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Oana Peia

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Four essays on finance and the real economy

Oana PEIA

UNIVERSITÉ DE CERGY-PONTOISE

ANNÉE 2016

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THESE

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ESSEC
BUSINESS SCHOOL

Four essays on finance and the real economy

A dissertation submitted in fulfillment of the requirements for the degree of

**PHD IN BUSINESS ADMINISTRATION
FROM ESSEC BUSINESS SCHOOL**

Publicly defended on October, 12 2016 by

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Introduction

The 2008 Global Financial Crisis has emphasized the crucial role played by finance in economics and led to a resurgence of interest in the field of financial economics (Allen et al., 2014).¹ Recent contributions have reshaped our view of how financial intermediaries interact and, importantly, our understanding of how these interactions impact the real economy. This PhD thesis draws on and contributes to different strands of research in financial economics by employing various methodological approaches to understand the impact of financial development and crises on economic growth and investment.

The first chapter entitled “Banking crises, R&D investment and slow recoveries” focuses on the real effects of banking crises. The magnitude of the recent financial crisis has, once again, brought attention to the built-in fragility of the financial sector. Traditionally, two main views have been employed to explain the origins of financial crises. The first is that they are the result of panic or coordination failures among depositors who end up running on the bank due to self-fulfilling beliefs about the behavior of other depositors (Bryant, 1980; Diamond and Dybvig, 1983). In this view, banking crises are sunspot phenomena, as in Cass and Shell (1983), as multiple equilibria can occur. The alternative argument is that banking crises are the result of a deterioration of bank fundamentals over the business cycle (Jacklin and Bhattacharya, 1988; Allen and Gale, 1998). Empirically, it is difficult to disentangle between panic and bad fundamentals, as crisis episodes are generally associated with both (Demirgüç-Kunt and Detragiache, 1998; Hertzberg et al., 2011). However, recent developments in games with imperfect information, called “global games”, bring together these two views of financial crises (Goldstein, 2010; Angeletos and Lian, 2016). By letting agents have heterogeneous information about aggregate shocks hitting the economy, crises can be modeled as pinned down by bad fundamentals, but still self-fulfilling as they would not occur if agents did not expect them to occur (Morris and Shin 1998, 2001, 2004; Goldstein and Pauzner, 2005). The use of global games to model coordination frictions in the financial sector is a common thread in my PhD thesis.

¹Financial economics, as a field, includes the study of financial intermediaries and markets, but also issues of corporate finance and asset pricing.

In the first chapter, I employ this methodology to model a banking sector crisis that matches some key features of the recent financial crisis. Specifically, this chapter proposes a model of bank runs triggered by a coordination failure among bank creditors, who run on the bank when they observe pessimistic signals about the real economy. Previous research has employed global games to model how bank runs occur and can be mitigated.² At difference, the crisis in my model results from a squeeze in liquidity coming from both sides of a bank's balance sheet, as both firms and depositors simultaneously demand liquid funds. This is motivated by recent empirical evidence, which finds that, together with the repo market runs by short-term bank creditors (Gorton and Metrick, 2012), and a deposits inflow freeze (Acharya and Mora, 2015), banks also saw a drain of liquidity coming from the assets side of their balance sheets, as firms massively drew down their credit lines (Ivashina and Scharfstein, 2010).

The second contribution of the chapter is to embed this static bank run model in an overlapping generation model and study the dynamics of investment and economic growth over the financial cycle. Traditionally, macroeconomic models have largely ignored financial intermediaries or treated them as a veil and, as a result, have not anticipated key empirical phenomena that played out during the recent financial crisis (Gertler and Kiyotaki, 2010). For example, Borio (2014) highlights the existence of "financial cycles" characterized by some distinctive patterns, such as a lower frequency compared to business cycles, or the fact that their peak is associated with a banking crisis. Moreover, when banking crises occur, they are not only associated with large output losses, but also slower economic recoveries.³ Reinhart and Rogoff (2014) find that it takes, on average, eight years for countries to recover and reach their pre-crisis levels of output. Similarly, Boissay et al. (2015) show that recessions that follow banking crises last 40% longer than other recessions.

A recent stream of research has thus tried to incorporate financial intermediaries in general equilibrium models to account for some of these stylized facts.⁴ In these models, crises are generally generated through adverse financial shocks or occasionally binding collateral constraints (see, among others, Bianchi and Mendoza, 2011; Kiyotaki and Moore, 2012; Jermann and Quadrini, 2012; Brunnermeier and Sannikov, 2014). At difference with these general equilibrium models, the framework proposed in Chapter 1 focuses on the long-term effects

²See, for example, Morris and Shin (2001) and Rochet and Vives (2004) who build the two workhorse models of banking crises in a global games framework. Goldstein and Puzner (2005) study how returns on bank deposits can impact the probability of a bank run. Bechuk and Goldstein (2011) show how different policies can mitigate credit market freezes, while Liu (2016) shows how interbank creditor runs arise from a shrinking of the pool of aggregate liquidity.

³Laeven and Valencia (2012) identify 147 systemic banking crises episodes over the past four decades that have been accompanied by an average output loss of 23%.

⁴In earlier works such as Kiyotaki and Moore (1997) and Bernanke et al. (1999), financial frictions mattered through a so-called "balance sheet effect", as tightening credit constraints due to a procyclical borrower net worth amplified negative productivity shocks.

of financial sector distress by modelling a richer characterization of real sector investment patterns. The model aims to identify a potential channel that can provide a theoretical micro-foundation for the longer-term effects of banking crises on growth. I show that financial sector distress impacts not only the volume, but also the composition of real sector investment over the financial cycle. By disproportionately disrupting investments in innovation, banking crises can have a long-lasting effect on growth as documented by recent empirical evidence. This channel is then confirmed empirically using cross-country, cross-industry data on Research and Development (R&D) spending, as a proxy for investments in innovation.

The empirical evidence in this chapter contributes to a large literature that studies the effects of financial sector distress on the real economy. The immediate consequences of financial crises are, by now, well understood. Banking sector distress is generally followed by a sizeable squeeze in bank lending (Ivashina and Scharfstein, 2010; Chava and Purnanandam, 2011; Cornett et al., 2011; Bord and Santos, 2014; Iyer et al., 2014). For example, the 2008 liquidity dry-up in the banking sector was followed by a 47% drop in new loans at the peak of the crisis (Ivashina and Scharfstein, 2010). This credit crunch generally leads to depressed corporate investment, employment and capital spending (Duchin et al., 2010; Campello et al., 2010; Chodorow-Reich, 2014; Garicano and Steinwender, 2015). The central debate in this literature is whether these effects occur mostly via a bank lending channel or a firm balance sheet channel. Disentangling the “exogenous” effects of contractions in credit supply has been empirically challenging as banking crises are generally followed by economic recessions (Demirgüç-Kunt and Detragiache, 1998; Kahle and Stulz, 2013). As such, several identification strategies have been proposed in the literature. For example, Chava and Purnanandam (2011) use the 1998 Russian crisis as an exogenous capital shock to bank capital to study the effects of contractions in credit supply. Iyer et al. (2014) and Cingano et al. (2016) use matched firm-bank datasets from Portugal and Italy, respectively, to quantify the direct impact effects of bank shocks on investment following the 2008 Global Financial Crisis. Furthermore, Chodorow-Reich (2014) shows that borrowers of weaker banks could not simply switch to healthier banks during this crisis, which resulted in a 50% lower probability of receiving a loan after the crisis. Overall, this evidence points to the importance of contractions in credit supply, in particular on borrowers highly dependent on bank lending.

In the first chapter, I employ a “difference-in-difference” identification strategy to document a novel effect of credit supply shocks on investments in innovation. I show that industries that generally depend more on the banking sector to obtain external funds have a disproportionately lower share of R&D in total investment after banking crises. These differential effects suggest that the drop in R&D investment is the result of contractions in credit supply, and not just a

consequence of demand side conditions specific to the business cycle.

The use of frictions in coordination in macroeconomic models is central to this PhD thesis and is employed in the subsequent two chapters as well. Specifically, Chapter 2, entitled “The cost of capital in a model of financial intermediation with coordination frictions” studies a financial intermediation model in the presence of coordination frictions in financial markets. In the model in Chapter 1, banking crises occurred when banks themselves were funding constrained, as a result of a simultaneous demand for liquidity from depositors and firms. In this second chapter, I study another type of funding constraint that arises when financial intermediaries seek to raise capital in financial markets to finance real sector projects. The financing structure analysed best describes large capital investments, such as “project finance”, which are funded through bond markets. In the model, an investment bank aims to raise capital from a continuum of small investors to fund a capital intensive project. I study the optimal return set by this intermediary, which faces a trade-off between attracting more investors to the project and lowering its cost of capital. The model admits a “socially optimal” return on capital, however coordination frictions result in an interest rate higher than the socially optimal one. This generates a market inefficiency in the spirit of theories of credit market rationing. The model provides a new explanation to the observed high costs of financial intermediation (Philippon, 2015). Classical arguments for these costs rely on imperfect competition in the lending market (Sharpe, 1990; Rajan, 1992; Petersen and Rajan, 1995; Dell’Ariccia et al., 1999; Demirgüç-Kunt and Levine, 2004) or imperfect information about borrowers’ risk (Stiglitz and Weiss, 1981; Besanko and Thakor, 1987). In this chapter, a high cost of capital is the response of financial intermediaries to investor coordination frictions and arises in equilibrium despite the absence of lender market power or information asymmetries between borrowers and lenders.

Chapter 3 complements the previous two by studying how the coordination failures that generate bank runs arise in a controlled laboratory experiment. The use of experimental economics to address macroeconomic issues, such as bank runs, has gained a lot of attention recently (for recent surveys, see Duffy, 2014; Cornand and Heinemann, 2014; Dufwenberg, 2015). Limited data availability on depositor behavior during bank runs make controlled laboratory experiments a natural testing ground for the mechanisms that might influence withdrawals during episodes of bank distress. As such, a growing experimental literature has proposed different versions of the classical Diamond and Dybvig (1983) model of panic-based runs. This thesis contributes to this literature by analyzing the role of deposit insurance in mitigating the risk of bank runs. While deposit insurance schemes are crucial elements of modern financial safety nets, recent research has pointed out that, in most countries, they are grossly underfunded (Demirgüç-Kunt and Laeven, 2013). This chapter shows that depositors’

uncertainty about the size of insured deposit coverage is an important propagator of bank runs. These findings can provide a potential explanation for why we have observed many recent bank run episodes in countries with generous deposit insurance schemes in place.

Finally, while the first three chapters are concerned with crises and inefficiencies in the financial sector, the last chapter takes a longer-term perspective and looks at the impact of a deepening financial system on economic development. Prior to the 2008 Global Financial Crisis, a large consensus in the financial economics literature supported a positive impact of financial development on growth. The severity of this recent crisis has led to a reassessment of this relationship (Beck, 2011; Arcand et al., 2015; Demetriades and Rousseau, 2016). Chapter 4 re-examines the long-run finance-growth nexus using a series of novel cointegration and causality techniques. Employing a sample of countries with developed financial sectors, the results show that causality patterns between finance and growth depend on whether countries' financial development stems from the stock market or the banking sector. Stock market development tends to cause economic development in the long-run, while a reverse causality is mostly present between banking sector development and output growth. These findings contribute to a large literature that tries to understand the role of finance in economic development and suggest that the dynamics between the two might be more complex than previously thought.

Chapter 1

Banking crises, R&D investments and slow recoveries*

Abstract

This chapter studies the effect of banking crises on the composition of investment and economic growth. It builds a partial equilibrium growth model with a banking sector and two types of investment: a low return one and an innovative, high productivity one. Investments in innovation are risky, as they are hit by a liquidity cost that firms cover by borrowing from banks. When bank creditors are sufficiently pessimistic about the aggregate liquidity needs of the real sector, they will run on the bank and cause a credit freeze. Tighter credit supply after the crisis leads firms to invest disproportionately less in innovation, which slows down economic growth. An empirical investigation, employing industry-level data on R&D investment around 13 recent banking crises, confirms this hypothesis. Industries that depend more on external finance, in more bank-based economies, invest disproportionately less in R&D following episodes of banking distress. These industries also have a relatively lower share of R&D in total investment, suggesting a shift in the composition of investment after the crisis. 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.

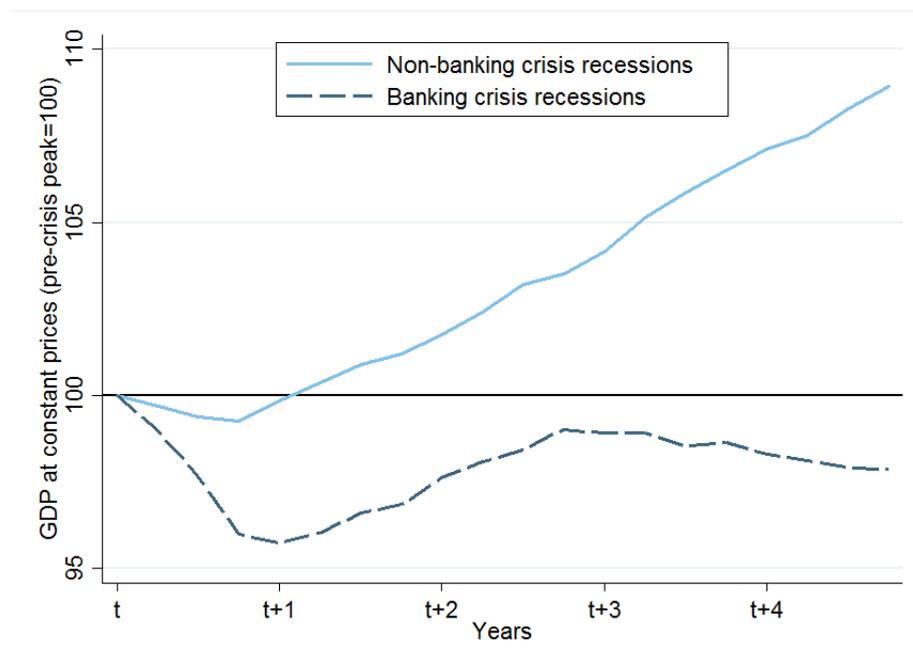
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1.1 Introduction

Banking crises are generally associated with large and persistent economic disruptions (Cerra and Saxena, 2008; Laeven and Valencia, 2008; Furceri and Mourougane, 2012; Ball, 2014; Boissay et al., 2015). Looking at 100 systemic banking crises, Reinhart and Rogoff (2014) find that it takes, on average, eight years for countries to reach their pre-crisis levels of GDP per capita. Figure 1.1 confirms this slower recovery associated with banking crises by showing the evolution of the average real GDP per capita following several recent crisis episodes as compared to other non-banking crisis recessions in the same set of countries.¹

This chapter proposes a new channel to explain this medium- to long-term effect of banking crises on real economic growth. It first builds an endogenous growth model to show how banking crises can impact not only the volume, but also the composition of real sector investment. In the model, banking sector distress has long-lasting effects on growth by disproportionately reducing investments in innovative projects. This channel is then supported empirically, by providing causal evidence of the impact of banking crises on investments in innovation.

Figure 1.1: Evolution of average GDP following 12 banking vs non-banking crises recessions



The magnitude of the 2007-08 Global Financial Crisis has emphasized the importance of

¹The countries included are: Austria (2008; 2001), Belgium (2008; 2001), France (2008; 1975), Germany (2008; 2003), Italy (2008; 1992), Japan (1997; 2008), Portugal (2008; 2002), Slovenia (2008; 2001), Spain (2008; 1992), Turkey (2000; 2007), United Kingdom (2008; 1990) and United States (2007; 2001), where the first date in parenthesis is the starting year of a systemic banking crisis episode identified in Laeven and Valencia (2012), while the second date is the start of a recession as classified in the FRED Economic Data database of the St. Louis Federal Reserve Bank.

liquidity dry-ups in the banking sector. At the onset of the crisis, an aggregate liquidity shock hit banks on both sides of their balance sheets, 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., 2015). This chapter models a banking crisis that captures some of these stylized facts. In the model, crises are triggered by a coordination failure among depositors who run on the bank when they observe pessimistic signals about the demand for liquidity of the real sector. In a global games framework (Morris and Shin, 1998; Goldstein and Pauzner, 2005), this coordination problem yields a unique equilibrium, which pins down the probability of a bank run and an optimal credit supply.

This static bank run model is then embedded in an overlapping generations model of entrepreneurs who can invest in two different technologies: a safe, low return, short-term technology and a risky, high return, long-term technology. Long-term technologies can be seen as investments in innovation, which are more productive but risky, as they are subject to a random liquidity shock. Entrepreneurs borrow from the bank to cover these extra costs and invest more in innovation when credit conditions are more relaxed, because the probability that these investments survive the liquidity shock is higher. The focus on heterogeneous technologies in this chapter is inspired by Matsuyama (2007) and Aghion et al. (2010), who also emphasize the importance of financial frictions on the composition of investment via a credit demand channel. In this chapter, however, the focus is on a bank lending channel as contractions in credit supply, rather than demand, affect investments in innovation.

The new insight here is to model how these credit conditions evolve over the financial cycle and how they impact real sector investment patterns.² The mechanism through which this happens is as follows. As long as banking crises do not occur, increases in aggregate wealth result in higher deposit inflows and a more leveraged banking sector. This causes banks to relax credit conditions by lending a higher share of their assets to the real sector. Higher credit supply further encourages investment in innovation. Once a banking crisis occurs, credit to the real sector is frozen and long-term investments fail. At the same time, lower aggregate wealth in the next period causes banks to deleverage and decrease their loan-to-assets ratios. This tighter credit supply after the crisis discourages investments in innovation leading 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 can have long lasting ef-

²The procyclical evolution of credit supply featured in the model 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).

fects on growth by disproportionately discouraging investments in innovative, growth-enhancing technologies. This channel is tested empirically using data on Research and Development (R&D) spending, as a proxy for investments in innovation. I study the dynamics of 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 the “exogenous” effect of credit supply conditions on R&D investment, this chapter employs the difference-in-difference methodology proposed in [Rajan and Zingales \(1998a\)](#). The identification comes from the fact that tight credit conditions following banking crises should have a greater impact on bank-dependent borrowers.

I find that industries more dependent on external finance invest disproportionately less in R&D, significantly in countries that rely more on the banking sector to obtain funding. These cross-country, cross-industry effects are consistent with the idea that borrowers in more bank-based economies cannot circumvent the banking sector and raise outside funds directly in capital markets. By focusing on an interaction between an industry level-measure of dependence on external finance and a country-level measure of dependence on bank credit, this study suggests that contractions in credit supply affect bank-dependent borrowers’ investment patterns. In particular, I show that not only the amount 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.³

The sensitivity of these findings is subjected to a variety of robustness checks. These include: (i) different horizons over which the effect of the crisis is expected to materialize; (ii) different measures of dependence on external finance; (iii) the inclusion of economic recessions; (iv) as well as various econometric specifications and fixed effects identification 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 chapter is organized as follows. The next section discusses previous research and the motivation of the paper. Section 1.3 presents the theoretical model and derives the main testable implications. Section 1.4 lays out the empirical strategies employed and presents the results. Finally, section 1.5 concludes.

³The importance of R&D investments in driving productivity growth is largely accepted both theoretically ([Aghion and Howitt, 2009](#)) and empirically ([Hall et al., 2010](#)).

1.2 Relation to literature

This work relates and contributes to several branches of the literature. Theoretically, there is a large literature modelling financial crises, which mainly focuses on how crises occur and can be mitigated (for a review, see [Goldstein, 2010](#)). The two main views of financial crises are that they occur as a result of panic and coordination failures ([Diamond and Dybvig, 1983](#)) or a deterioration of bank fundamentals ([Allen and Gale, 1998](#)). Recent developments in global games bring together these two views by modelling crises pinned down by bad fundamentals, but which are still self-fulfilling, as they would not have occurred if agents did not expect them to occur ([Carlsson and Van Damme, 1993](#); [Morris and Shin 1998, 2001, 2004](#); [Goldstein and Pauzner, 2005](#)). The introduction, in this framework, of imperfect information eliminates the multiplicity of equilibria which generally characterizes bank run models and allows agents to coordinate around a unique threshold equilibrium.⁴ For example, in a set-up close to the one in this chapter, [Rochet and Vives \(2004\)](#) model a “modern” form of bank runs, where large investors refuse to renew their credit to a bank. They study bank regulation policies that can help mitigate this coordination problem and eliminate runs on otherwise solvent banks.

This chapter, however, embeds a static bank run model in a dynamic framework, to study how the probability of a crisis occurring evolves as a result of the decisions of agents in the real economy. This theoretical framework is used to provide a micro-foundation for some stylized facts regarding the real effects of banking crises. More specifically, recent research shows that banking crises are not only followed by large contractions in economic activity, but also by long-lasting recessions and slower economic recovery ([Reinhart and Rogoff, 2014](#); [Ball, 2014](#); [Boissay et al., 2015](#)). However, despite this medium- to longer-term effect of banking crises, theoretical literature generally treats separately the analysis of long-run growth and short-term instability. A large literature that studies the effects of financial development on growth generally overlooks shocks and crises (for an overview, see [Levine, 2005](#)). Real business cycle models, on the other hand, emphasize the role of credit market constraints in propagating and amplifying productivity shocks, but largely treat financial intermediaries as a veil ([Bernanke et al., 1999](#); [Gertler and Kiyotaki, 2010](#)). The recent macroeconomic literature that models the role of financial frictions generally relies on random financial shocks as a 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. \(2015\)](#) in which adverse selection in the interbank market, and not binding

⁴By and large, this methodology has remained static and is primarily concerned with understanding the triggers of crises and how they can be mitigated. One exception is [Angeletos et al. \(2007\)](#) who build a dynamic model of currency attacks in which agents learn from previous actions.

collateral constraints, causes occasional financial market runs. They model a financial cycle with credit booms prior to the banking crisis similar to the one in this chapter. At difference, however, here the focus is on the real side of the economy and the long-term effects of financial sector distress.

One potential link between short- and long-run economic dynamics is represented by investments that drive growth, such as investments in innovation or Research and Development (R&D). Investment in R&D is generally considered the main driving force of productivity growth in the endogenous growth literature and its importance is largely acknowledged empirically.⁵ At the same time, recent empirical findings show that R&D spending tends to be strongly pro-cyclical despite the traditional neoclassical 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 (Aghion et al., 2010; Ouyang, 2011). The idea is that pro-cyclical profits make financial constraints more binding in recessions, which affects firms' ability to borrow and discourages investments in innovation.⁶ Aghion et al. (2010) formalize this idea in a partial equilibrium model in which investments in innovation have higher liquidity risks, which makes them pro-cyclical in the presence of credit constraints. They show that this pro-cyclicality highlights a new propagation mechanism through which credit market imperfections can explain both the lower mean growth and the higher volatility of economies with tighter credit conditions. They confirm this hypothesis 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 procyclical in firms that

⁵Hall et al. (2010) review a large literature measuring the returns to investments in innovation. In a standard growth accounting framework, this literature estimates an elasticity of output to investments in R&D between 0.05 to 0.12, which is somewhat higher than for ordinary capital investment. Furthermore, the time frame over which we expect the effects of R&D investment on output growth to materialize is around two periods in cross-country regressions (Guellec and van Pottelsberghe de la Potterie, 2001), and between 1 to 4 years for firms-level studies (Hall et al., 2010). It should be noted that these studies make a distinction between private/business R&D and public or R&D spillovers. Public or basic research generally requires very long time periods to translate into productivity improvements (see also Artuç and Pourpourides, 2014 and Eberhardt et al., 2013, for empirical evidence on R&D spillovers).

⁶Firm-level evidence on the importance of financial conditions on investments in R&D and innovation is generally scarce. Studies employing Euler investment equations find mixed evidence on the importance of liquidity constraints in R&D investments (Bond et al., 2005; Brown et al., 2012). Cross-country and industry studies, on the other hand, point towards a strong relation between the structure of a country's financial system, industrial characteristics and investments in R&D (Calderon and Liu, 2003). For example, Hsu et al. (2014) show that financial development matters for investment in innovation, but find a stronger impact of equity and not credit markets on R&D spending. Their results are based, however, on investments of publicly listed companies, which generally tend to rely less on bank credit to finance innovation. Indeed, Nanda and Nicholas (2014) show that during the Great Depression of the 1930s' bank distress was associated with a shift away from high-risk R&D projects relatively more for private firms as compared to publicly traded firms.

face tighter credit constraints.⁷ This chapter builds on the idea that financial constraints impact investments in innovation by studying situations in which these constraints are likely to be more binding, i.e. following banking crises. In particular, it is concerned with highlighting the *exogenous* effect of a bank lending channel on investments in innovation. The basic argument is that changes in credit standards or credit supply can cause a shift in the composition of investment 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 chapter 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 (1998a) by focusing on bank-dependent borrowers and not external finance dependent industries, 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 2007-08 Global Financial Crisis, firms shifted investments away from long-term to short-term ones. Schmitz (2014) shows that smaller firms exhibit a greater contraction in R&D following financial shocks and, since these smaller firms also have a higher innovative capacity, the effect of these financial shocks on productivity growth tends to be persistent over time. Nanda and Nicholas (2014) employ a difference-in-difference methodology to show that firms significantly reduced investments in innovation in particular in counties with higher bank distress during the Great Depression in the US in the 1930s. Finally, Fernández et al. (2013) document that industries more dependent on external finance have a lower share of intangible assets during periods of bank distress.

⁷Barlevy (2007) provides an alternative explanation to the pro-cyclicality of R&D investments in a model in which the gains from innovation are immediate for the innovator, but lost if imitated. This can explain why it is more profitable to innovate in booms when the gains from new ideas are larger.

1.3 Theoretical model

1.3.1 The static model

This section presents a three-period game between entrepreneurs, investors and a bank and derives the main implications of this model for investment cycles.

Agents and technologies

The economy consists of three agents: entrepreneurs, investors and a bank. All agents are risk-neutral and protected by limited liability. The real sector of the economy is represented by a continuum of homogeneous entrepreneurs with unit mass who live three periods $[0,1,2]$ and invest in two different productive technologies.⁸ Entrepreneurs have no wealth and borrow from the bank to invest. The financial sector is represented by a bank which obtains funding from investors and lends to entrepreneurs. There is a continuum $[0,1]$ of investors who place their endowment of wealth in the bank at the beginning of their lives ($t = 0$).⁹

Investment projects

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, innovative technology, which takes two periods to become productive and generate Y_2 . Entrepreneurs have no initial wealth and borrow from the bank to invest in the two linear technologies. Given the inelastic demand for funds, the amount of borrowing in $t = 0$ depends on the availability of credit from the financial sector. Denote by I the total amount of capital the entrepreneur can borrow in $t = 0$ and by k the share of this capital invested in the innovative technology. Given this share, the output of the two technologies in periods 1 and 2 is given by:

$$Y_1 = \sigma_1(1 - k)I \quad \text{and} \quad Y_2 = \sigma_2 kI, \quad (1.1)$$

where σ_1 and σ_2 are the productivity parameters of the short- and long-term technology, with $\sigma_2 > \sigma_1$ such that the productivity of the long-term investment is higher than the short-term one. The distinction between these two types of investment projects follows [Aghion et al. \(2010\)](#). They interpret long-term investments as R&D spending, fixed investments or

⁸A zero discount factor between periods is assumed.

⁹As usual, I assume that, due to severe information asymmetries, investors cannot lend directly to the real sector and do so through the bank. At the same time, the bank has a classical role of channeling funds from the financial to the real sector. It is also assumed that in doing so, the bank can also perfectly monitor the entrepreneurs such that the model does not feature any moral hazard or strategic default on the real side of the economy.

adoption of new technologies which tend to enhance productivity and growth. 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.

At the same time, investments in innovation are risky since they are subject to a liquidity shock in the form of a random expense, C , which occurs in period $t=1$. If the entrepreneur is successful in covering the liquidity shock, then production in period 2 will take place and yield output Y_2 , otherwise the long-term investment becomes obsolete and is scrapped, i.e. $Y_2 = 0$. As in [Aghion et al. \(2010\)](#), I assume that, if the liquidity shock is covered and the production of the long-term technology takes place, the entrepreneur will receive an extra benefit C in the last period such that the value of the long-term investment remains unaffected by the liquidity shock. This assumption guarantees that long-term investments, when they survive the liquidity costs, are still more productive than short-term investments.¹⁰

The liquidity shock specific to long-term investments captures a salient feature of investments in innovation, which is the high uncertainty associated with their output ([Hall and Lerner, 2010](#)). Furthermore, the choice of modeling an *aggregate* liquidity shock is motivated by [Holmstrom and Tirole \(1998\)](#) who 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 the presence of *aggregate* liquidity needs, the real sector is no longer able to insure itself. In their model, however, banking crises are ruled out, as investors cannot claim assets in the intermediate period. Their main result is that governments can improve market liquidity by issuing bonds. This chapter studies the case in which bank runs can occur and, as a result, it does not consider any type of government-injected liquidity in the system.¹¹

This modeling approach has also strong empirical foundations. The first motivation for introducing a liquidity need of entrepreneurs at the center of the crisis comes from the empirical literature documenting the events lining up to the 2007-08 financial crisis. [Ivashina and Scharfstein \(2010\)](#) show that, together with the liquidity freeze in the banking sector, 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 what the aggregate liquidity shock captures in a stylized manner. Second, since the liquidity shock affects all firms to the same extent, they will all rely on the banking sector to raise the additional funds to cover it. This

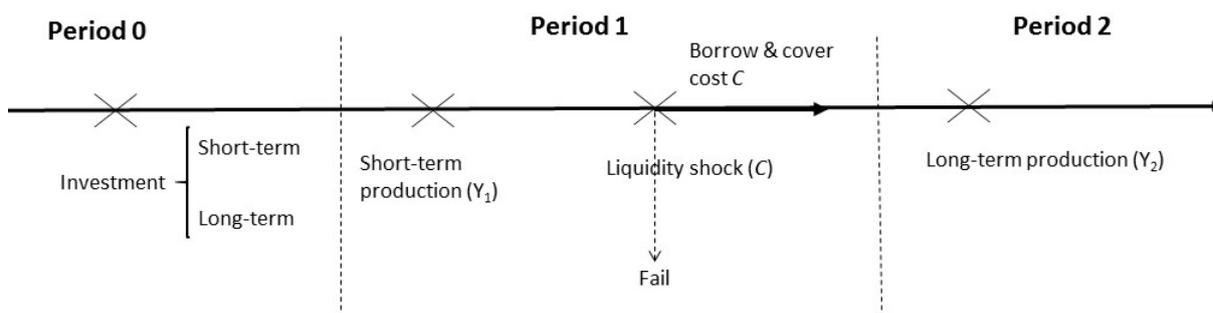
¹⁰This assumption does not affect the equilibrium composition of investment. However, for tractability, I will ignore the possibility that the net present value of the long-term investment is diminished by the liquidity cost.

¹¹Government bailouts or central bank liquidity would naturally dampen the effects of the crisis in the model, however, empirical evidence following the 2007-08 Global Financial Crisis shows that only a limited amount of this liquidity was channeled towards the real sector ([Cornett et al., 2011](#)).

again reflects empirical findings. While some big firms can circumvent the banking sector and raise outside funds directly in capital markets (see, [Adrian et al., 2012](#)), most borrowers do not have this option and distress in the banking sector limits their ability to borrow ([Iyer et al., 2014](#); [Chodorow-Reich, 2014](#)).

The timing of the events is presented in Figure 1.2. At the beginning of their life entrepreneurs borrow and decide the share of capital to invest in the short- and long-term technology, respectively. In period 1, short-term production, Y_1 , is realized and the long-term investment 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, $t = 2$, long-term investments become productive only if the liquidity shock is covered and entrepreneurs consume their total life-time income after which they die.

Figure 1.2: Timing of the real sector



The outputs of the two technologies are divided between the bank and the entrepreneur in fixed proportions, with a fraction α going to the bank.¹² Thus entrepreneurs receive $(1 - \alpha)\sigma_1(1 - k)I$ from the short-term technology and $(1 - \alpha)\sigma_2kI$ from the long-term one, respectively. The entrepreneur's expected profit is thus:

$$\Pi_E(k) = (1 - \alpha)\sigma_1(1 - k)I + e(1 - \alpha)\sigma_2kI, \quad (1.2)$$

¹²This approach can be rationalized in several ways (see [Aghion and Howitt, 2009](#)). For example, consider that output is produced through a new-classical production function of the form:

$$Y = AK^\alpha L^{1-\alpha}$$

with capital K and labor L as inputs. Following [Romer \(1986\)](#), the scale parameter A , which measures aggregate productivity, depends on the aggregate capital stock: $A = aK^\gamma$, with $\gamma = 1 - \alpha$. Moreover, assuming a fixed labor supply, $L = \bar{L}$, yields a standard AK model: $Y = \sigma K$ with $\sigma = a\bar{L}^{1-\alpha}$. If input markets are competitive, capital and labor are remunerated at their marginal productivity, such that their shares of final output are given by the usual formulas:

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

[Aghion et al. \(1999\)](#) use a similar production function to study endogenous investment cycles. However, instead of introducing an aggregate capital accumulation externality in the spirit of [Romer \(1986\)](#), they assume an unlimited labor supply at a constant real wage, which generates a similar AK technology.

where e is an indicator function taking value 1 if the entrepreneur covers the liquidity shock and 0 otherwise. Whether or not entrepreneurs are able to cover the liquidity shock, as well as their borrowing capacity, will depend on the constraints in the banking sector to which I turn to next.

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 $t = 0$.¹³ The bank promises to pay a per-unit return $r > 1$ in period $t = 2$. Investors can, however, withdraw their deposit at $t = 1$ and get back their initial investment. If they wait until the last period, they receive the promised return only if long-term investments survive the liquidity shock.¹⁴ This funding structure makes the banking sector prone to runs if enough depositors withdraw and deprive the financial institution of funds in the intermediate period.

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

Assets	Liabilities
$I(\text{loans})$	D
M	E

In this representation, I is the volume of loans granted to entrepreneurs, M is the amount of cash reserves held by the bank, D represents the volume of deposits investors place in the bank and E is the bank's equity, which is assumed to be fixed and exogenous. For simplicity, the liabilities side of the bank's balance sheet can be expressed as a function of the level of deposits (D), as follows:

$$D + E = \left(1 + \frac{E}{D}\right) D \equiv \phi D,$$

where, $\phi \equiv 1 + \frac{E}{D}$, can be interpreted as a measure of leverage of the bank. The lower ϕ , the

¹³The terms investors, bank creditors and depositors are used interchangeably throughout the model. They represent the only source of external funding for the bank. Given that the model assumes no discount between the three periods of the game, the funds obtained by the bank can be equally thought of as deposits or short-term interbank debt obligations.

¹⁴This assumption implies limited liability for the bank. Failure of long-term investment projects is tantamount to a bank failure in this model. This implies that the residual, i.e. short-term production is split only between the entrepreneur and the bank. Assuming the alternative, i.e. that investors receive the residual of the short-term production leaves the results of the model unchanged, but is mathematically less tractable.

higher the level of deposits as compared to that of equity and the more leveraged the bank is. Given this size of the balance sheet, the bank will decide how much funds to place in risky assets (loans to entrepreneurs) and in safe assets (M). This is tantamount to deciding a loan-to-assets ratio, denoted by μ , such that a proportion $\mu\phi D$ of total assets is invested in the real sector. Moreover, given that the model features no moral hazard or adverse selection between the bank and the entrepreneur, this loan-to-assets ratio also represents the extent of credit constraints in lending to the real sector.

In this stylized representation of the banking sector, early withdrawals can cause a collapse of the bank if the funds demanded are higher than the liquid assets available to the bank, M . At the same time, entrepreneurs who face an exogenous liquidity shock seek to borrow from the bank implying a further demand for funds that the bank needs to cover at $t = 1$. This drain of liquidity coming from both sides of the balance sheet is another well-documented feature of the 2007-08 financial crisis, as together with the run by short-term creditors, there was a simultaneous run by firms who drew down their credit lines, squeezing the banking sector of liquidity from both sides of the balance sheet (Ivashina and Scharfstein, 2010).

Hence, at $t = 1$, the bank faces two types of liquidity needs. On the one hand, some investors withdraw their initial investment, D . On the other hand, entrepreneurs seek to borrow $C - Y_1$, given the liquidity shock C and their own funds at $t = 1$, i.e., the production of the short-term technology, Y_1 . Denoting the proportion of investors who demand early withdrawal by ℓ , the demand for funds the bank faces in the intermediate period is:

$$\ell D + C - Y_1 > M \tag{1.3}$$

Equation (1.3) above implies that the bank is in a liquidity crunch if the liquid assets, M , cannot cover the demand of funds coming from *both* the investors and the entrepreneurs. The equilibrium solution in the financial sector can be split in two parts. First, I solve for the equilibrium of the investors' coordination problem employing a global games methodology. Then, I solve for the bank's maximization problem considering the equilibrium outcomes of the entrepreneurs' and investors' optimization problems.

Investors' coordination problem

Equation (1.3) characterizes the run threshold of the bank: $\ell D + C^* = M + Y_1$. For liquidity shocks below C^* , the demand for funds the bank faces in $t = 1$ can be satisfied by its liquid funds M and hence long-term investments survive. However, when $C > C^*$, the bank cannot cover the demand for liquidity and, as a result, entrepreneurs cannot borrow and long-term

investments fail. This situation represents a bank run or a liquidity crunch in the model.

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 for others to do so, since the chances that the bank can fulfill the demand for liquidity are lower. This means that panic-based runs can occur depending on investors' self-fulfilling beliefs. This brings about a classical coordination problem in the spirit of [Diamond and Dybvig \(1983\)](#), which is known to have multiple equilibria. However, a recent literature in global games has shown that introducing imperfect information in this framework can eliminate this multiplicity of equilibria ([Morris and Shin, 1998, 2004](#); [Goldstein and Pauzner, 2005](#)). I follow this approach and assume that investors have imperfect information about the size of the liquidity shock entrepreneurs need to cover in order for the investment in innovation to succeed. More specifically, at $t = 1$, investors only observe the liquidity shock with a noise:

$$x_i = C + \epsilon_i,$$

where x_i is investor's i signal, C is the cost drawn by nature from a uniform distribution over the interval $[0, \bar{c}D]$ and ϵ_i is an idiosyncratic noise which is independent of C and uniformly distributed over $[-\epsilon, \epsilon]$.

Using this global games approach, the occurrence of the liquidity crisis is the result of depositor panic, but is still linked to the fundamentals in the real economy, which are represented by the liquidity shock C . Proposition 1 states the basic equilibrium result.

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:

$$C^* = M + Y_1 - \frac{D}{r} \tag{1.4}$$

Proof See Appendix

Given this unique threshold, the probability of bank runs, which is also the probability that innovative investments fail, is given by $Prob[C > C^*]$. Based on the characterization of the equilibrium critical cost in Equation (1.4), this probability is decreasing in Y_1 , M and r . The intuition behind this result is straightforward. As entrepreneurs invest more in the long-term technology, the income available at $t = 1$, Y_1 , decreases, which means the bank has to service a higher liquidity demand in the interim period. This will increase the probability

that depositors panic and withdraw their funds. Similarly, if the bank holds more liquid assets, higher M , this decreases the probability the long-term investments fail. Finally, higher returns required by investors, r , facilitates their coordination and decreases the probability of runs. Given this equilibrium probability of bank runs, the bank has to decide in $t = 0$ how much to invest in the real sector and how much funds to place in the safe asset, i.e., its optimal loan-to-assets ratio, μ .

Equilibrium

In equilibrium, the bank chooses μ to maximize its profits, given the equilibrium investment decisions of entrepreneurs and the equilibrium probability of bank runs from the investors' coordination problem:

$$\begin{aligned} \text{Max}_{\mu} \quad & \lambda[\alpha\sigma_2k\mu\phi D + \alpha\sigma_1(1-k)\mu\phi D - rD] + (1-\lambda)\alpha\sigma_1(1-k)\mu\phi D + (1-\mu)\phi D \\ & \text{given } k \text{ and } \lambda, \end{aligned}$$

where λ is the probability that long-term investments survive, $\alpha\sigma_2k\mu\phi D$ 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 assets stored in liquid assets. 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.¹⁵

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 $\phi < \bar{\phi}$.

Proof See *Appendix*.

The first result of Lemma 1 states that the probability of survival of innovative investments is increasing in μ . From Equation (1.4), 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 decreases the amount of liquid assets (M) of the bank in the intermediate period, making it less likely

¹⁵An 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, however it does make the exposition of the proof cumbersome.

to cover the depositors and, thus, increasing the probability of bank 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 $\phi < \bar{\phi}$, i.e. when banks are sufficiently leveraged.¹⁶ 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 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 $t = 0$. In the model in this chapter, the credit multiplier, μ , is the loan-to-assets ratio of the bank. Hence, a higher μ means more funds are borrowed by firms in $t = 0$. This higher access to funds will then induce entrepreneurs to undertake more long-term investments, as more borrowing in $t = 0$ increases the monetary gains from the safe investment as well (higher output Y_1) and reduces the amount of funds entrepreneurs need to borrow in $t = 1$.

With these results in mind, solving the bank's maximization problem yields the following result:

Proposition 2 As banks become more leveraged, ϕ decreases, their loan-to-assets ratio, μ , increases monotonically whenever $\phi < \bar{\phi}$.

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 ($\phi < \bar{\phi}$), beyond which bank creditors disproportionately 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 classical risk-and-return trade-off. The more leveraged the

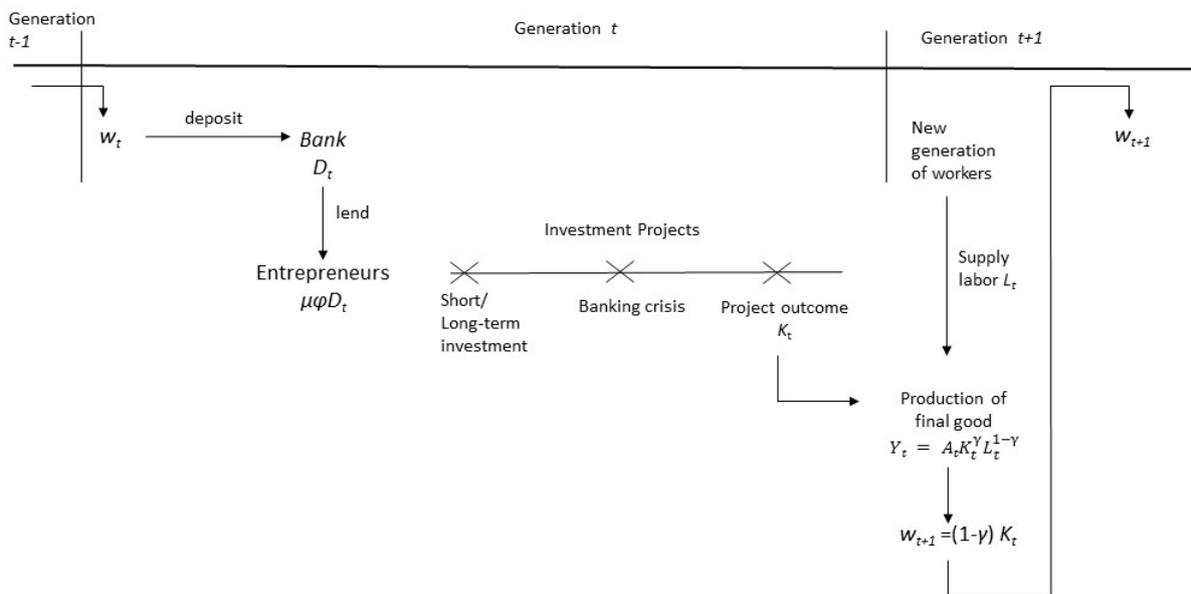
¹⁶This “minimum” level of ϕ puts a lower bound to bank leverage and is used as the starting level in numerical simulations. The interpretation for it is that the model pertains to a banking sector that is already sufficiently leveraged. This can be seen as a more developed financial system, where banks are also more prone to take some risk, i.e. invest in the real economy as opposed to keeping most of their funds in liquid assets.

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 extend this trade-off in the context of a simple dynamic model to study its implications for real sector investment patterns around banking crises.

1.3.2 The dynamic model

This section embeds the static three-period 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 capital directed towards the long-term technology. However, the coordination game between investors, as well as the entrepreneur-bank and bank-investor relationships 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.

Figure 1.3: Timing of the OLG model



The OLG model is summarized in Figure 1.3. 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 thus become the pool of deposits, D_t ,

the bank has access to and represent the aggregate wealth in the economy. Thus, workers are introduced in the model to simply to pass along the wealth in the economy 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 1.3. The output from the two investments represents the accumulated capital of entrepreneurs at the end of their lives:

$$K_t = (1 - \alpha)\sigma_1(1 - k_t)\mu_t\phi_t D_t + e_t(1 - \alpha)\sigma_2 k_t \mu_t \phi_t D_t, \quad (1.5)$$

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

Thus, the level of capital at 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:

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

with capital K_t and labor L as inputs and a scale parameter, A_t , measuring aggregate productivity. 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 is:

$$w_{t+1}L = (1 - \gamma)F_t \equiv w(K_t). \quad (1.6)$$

Since this young generation of workers consumes when they are old, they will place their labor income, $w(K_t)$ in the bank such that their wealth represents the aggregate level of deposits at $t + 1$:

$$D_{t+1} = w_{t+1}L = w(K_t). \quad (1.7)$$

In the last period of their lives, old entrepreneurs consume all the final production in t , i.e., F_t , and die. Old workers also consume their income deposited in the bank and die. Furthermore, the 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 depositing them in the banking sector in the first periods of their lives. These savings, consequently, become the

capital available for investment to the $t + 1$ generation of entrepreneurs.

To fully characterize the dynamics of the economy, we also need to study the evolution of the bank's balance sheet. For convenience, this balance sheet is reproduced in Figure 1.4. At time t , the pool of deposits, D_t , available to the bank is just the aggregate wealth in the economy, specified in Equation (1.7). Given the assumption that capital fully depreciates at the end of each period, the equity of the bank stays constant over time.¹⁷ 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.

Figure 1.4: Bank balance sheet in period t

Assets	Liabilities
$I_t = \mu_t \phi_t D_t$	D_t
$M = (1 - \mu_t) D_t$	E

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 wealth dynamics of the economy.

Proposition 3 (i) As long as a bank run does not occur, higher savings increase the leverage of the bank and its loan-to-assets ratio μ_t . This increases the share of investments in innovations and leads to higher wealth growth.

(ii) A bank run decreases savings in the next generation 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.

¹⁷An 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 Equation (1.6). 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 the 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 chapter.

(iii) Tighter credit conditions after the banking crisis, lead to a lower share of investment in innovation, which slows down the recovery.

Proof Part (i) 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 (1.5) and (1.7) 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.

Figure 1.5: Dynamics of output around financial versus other recessions

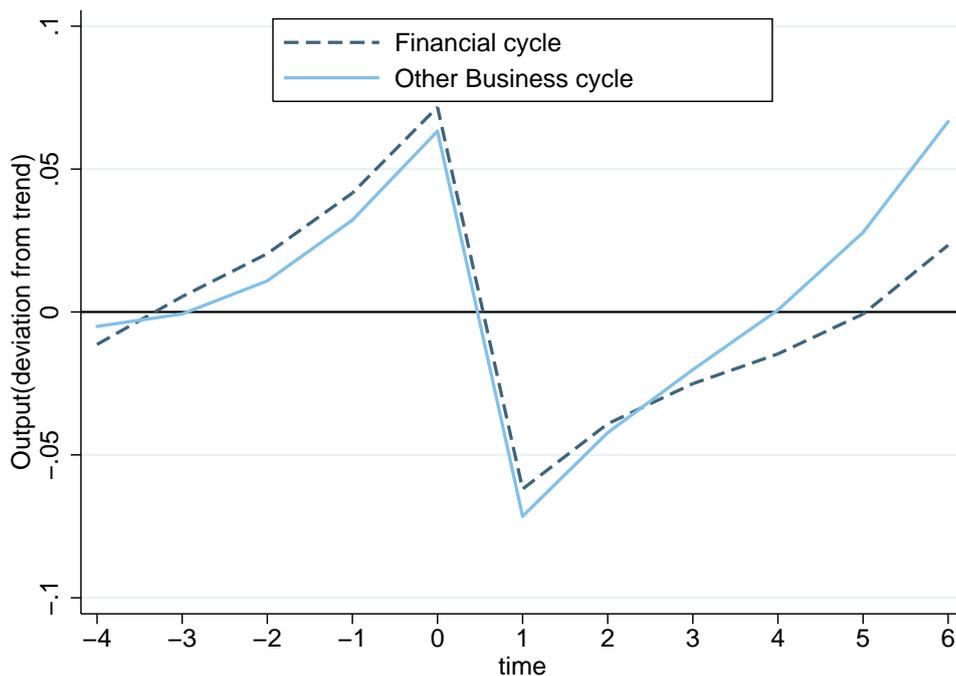


Figure 1.5 plots the simulation of the financial cycle described in Proposition 3, based on the structural parameter values in Appendix Table 1.8. This is represented by the dashed line which shows the deviation of output (F_t) from its long-run trend around a banking crisis occurring in time 0. A counter-factual 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 1.5, 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 chapter has a higher growth prior the crisis, captured by the higher deviation of output from its long-run trend in Figure 1.5 (dashed line). However, the opposite occurs after the crisis, since it takes five periods for output to reach its 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. This longer duration of financial recessions is in line with empirical evidence in [Boissay et al. \(2015\)](#) who find that recessions following the last 78 banking crises, lasted, on average, eight months longer than other “regular” recessions.

This stylized model is intended to capture some central features of banking crises. Prior to the crisis, the economy experiences a credit boom in the long-term technology, since entrepreneurs direct a larger share of their total investment to innovative projects. A large empirical literature shows that financial crises are typically followed by periods of high credit growth ([Jordà et al., 2011](#)). The boom is ended by a bank run, which causes a tightening in credit supply in subsequent periods. The pro-cyclical evolution of credit supply and bank leverage featured in the model is another well-documented empirical pattern across the financial cycle ([Asea and Blomberg, 1998](#); [Lown and Morgan, 2006](#); [Adrian et al., 2012](#); [Kahle and Stulz, 2013](#); [Becker and Ivashina, 2014](#)).

The main empirical implication of this simple model is that one channel through which banking crises can have a long-lasting effect on growth is through affecting investments in innovation. The remainder of this paper tests empirically this prediction.

1.4 Empirical evidence

This section provides an empirical test of the main theoretical prediction in the previous section by providing causal evidence of the impact of banking crises on investments in innovation. One common proxy for investments in productivity-enhancing projects is Research and Development (R&D) expenditures across sectors. The importance of R&D investments in driving productivity growth is well-recognized both theoretically and empirically. At the same time, the strong pro-procyclicality of R&D make it an ideal proxy to create a link between short- and long-run dynamics as suggested by the theoretical model in the previous section ([Comin and Gertler, 2006](#); [Barlevy, 2007](#); [Aghion et al., 2010](#); [Ouyang, 2011](#)). Yet, this procyclical evolution of R&D also implies that an identification strategy is needed in order to disentangle

the causal effect of banking crises on R&D spending from the fluctuations explained by regular balance sheet effects over the business cycle. In other words, we aim to assess whether the observed cyclicity of R&D investments is caused by supply-side effects, i.e., tightening of credit conditions, as opposed to demand-side factors such as lower investment opportunities during economic downturns.

1.4.1 Identification strategy

This chapter employs the classical [Rajan and Zingales \(1998a\)](#) “difference-in-difference” approach to estimate the differential effect of banking crises on R&D spending across sectors and countries.¹⁸ [Rajan and Zingales \(1998a\)](#) argue that there is a technological or economic 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 \(1998a\)](#) 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 which depend the most on obtaining external financing ([Kroszner et al., 2007](#)).

This chapter uses a similar identification strategy by focusing on cross-industry, cross-country effects, to disentangle a causal link from banking distress to the composition of investment. The main hypothesis tested is that, following a banking crisis, firms in industries more dependent on external finance, in countries that rely more on the banking sector for obtaining funds, will decrease their investments in R&D disproportionately more than firms in less dependent industries. Identification thus comes from an interaction between a country characteristic (reliance on bank finance) and an industry characteristic (external financial dependence) to isolate the effect of financial conditions (banking crisis) on R&D investment. Finding evidence of these cross-country, cross-industry differences in the data would therefore

¹⁸Similar identification strategies are employed in many recent studies. For example, [Aghion et al. \(2009\)](#) look at the impact of exchange rate volatility on productivity growth at different levels of financial development. [Manova \(2008\)](#) investigates the impact of equity market liberalization on export growth in more financially dependent industries. [Hsu et al. \(2014\)](#) look at the differential impact of financial development on innovation in financially dependent industries. See also [Braun and Larrain \(2005\)](#), [Levchenko et al. \(2009\)](#), [Nanda and Nicholas \(2014\)](#), for similar difference-in-difference identification techniques.

provide indirect, but strong support for the presence of a causal effect of banking crises on R&D investments. This methodological specification differs from previous approaches which generally focus on an interaction between industry external dependence and country financial development, measured by the ratio of private credit to GDP (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 which have 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 (for a similar argument, see Nanda and Nicholas, 2014). Again, this effect should be stronger for firms that rely mostly on the banking sector to obtain external finance. As a result, the disproportionate effect of banking crises on external finance dependent borrowers should be stronger in countries that rely more on the banking sector to obtain funding, i.e., more bank-based economies.

The baseline specification follows Kroszner et al. (2007) and implements an event study analysis. More specifically, the model tested is as follows:

$$\Delta R\&D_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i * Bank_c + \beta_2 Share_{ic} + \epsilon_{ic}, \quad (1.8)$$

where $\Delta R\&D_{ic} = R\&D_{ic,crisis} - R\&D_{ic,pre-crisis}$ is the difference in average real growth of R&D investment 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 $Share_{ic}$ 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.

Equation (1.8) is estimated cross-sectionally since it employs only one observation per country-sector: the change in average growth in R&D spending around a banking crisis.

The coefficient of interest is β_1 and we expect $\beta_1 < 0$, meaning the growth rate of R&D after the crisis as compared to the pre-crisis is lower in more financially dependent industries in countries with bigger banking sectors as compared to stock markets. The identification then comes from industries that rely more on external finance, in countries that rely more on the banking sector to obtain external finance. This cross-industry, cross-country effect is captured by the interaction term $ExtDep_i * Bank_c$, whose negative coefficient suggests that the reduction in the growth rate of R&D is greater for financially dependent firms in more bank-based economies.

Model (1.8) also includes the share of an industry's R&D in total research and development spending in a country to capture any industry size or "convergence" effects, i.e., the tendency of larger industries to experience a slower growth in general and in investment, in particular (see also [Rajan and Zingales, 1998a](#); [Kroszner et al., 2007](#); [Dell'Ariccia et al., 2008](#)). To avoid any potential endogeneity problems, pre-crisis levels of the industry share of R&D are used.¹⁹

Finally, the inclusion of industry and country fixed effects permits to control 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. This array of fixed effects reduces concerns of omitted variable bias or model mis-specification and allows us to focus on within country, between industries, variations.

1.4.2 Data and descriptive statistics

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

¹⁹One 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 ([Rajan and Zingales, 1998a](#)). 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 with the exclusion of the share variable from the model.

To date banking crisis years, I use the [Laeven and Valencia \(2012\)](#) dataset. The timing of the banking crises and the availability of R&D data from ANBERD limits the sample to 13 country-crisis years and 29 two- and three-digit ISIC level manufacturing sectors.²⁰

Data on total investment comes from the OECD Structural Statistics of Industry and Services database. The Gross Investment in Tangible Goods (GITG) data series capture the investments in land, existing buildings and structures, plant, machinery and equipment and new buildings and structures. Total investment is then calculated as the sum of R&D spending and gross 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 which require R&D expenses to be accounted as an investment, rather than consumption. As a result, the data on gross investment at industry level does not incorporate R&D expenditure.²¹

Finally, I also 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 ([Levine, 2002](#)).

Measures of external dependence

The main measure of an industry's reliance on external finance follows [Rajan and Zingales \(1998a\)](#). External dependence (*ExtDep*) is defined as the share of capital expenditure not financed with cash-flow from operations. [Rajan and Zingales \(1998a\)](#) build their measure based on a sample of US manufacturing firms from Compustat during 1980s.²² To preserve the sample size, I re-compute their index for 29 two- and three-digit ISIC level manufacturing industries for which matching R&D data in the ANBERD database is available. The firm level data used is also from Compustat and comprises 106,000 US firm-year observations over the period 1990-1999. Following [Rajan and Zingales \(1998a\)](#), 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 whole period. Two important assumptions underlie this approach: (i) this measure of external dependence reflects technological characteristics of an industry that are stable over time and (ii) employing US data is motivated by the fact that the use of finance by US Compustat firms is less likely to be skewed by constraints on the supply-side and should

²⁰The 13 banking crises covered are: Austria (2008), Belgium (2008), France (2008), Germany (2008), Italy (2008), Japan (1997), South Korea (1997), Portugal (2008), Slovenia (2008), Spain (2008), Turkey (2000), United Kingdom (2007) and United States (2007). The 29 industries covered are presented in Appendix 1.E.

²¹The date of implementation of the SNA framework differs across OECD countries, however for the sample of countries considered only the United States has implemented the standard in 2013, while all EU member countries in 2014.

²²[Rajan and Zingales \(1998a\)](#) compute a firm's dependence on external finance as Capital expenditures (*Compustat item* CAPX) plus Acquisitions (*Compustat item* AQC) minus Cash Flow from Operation divided by Capital Expenditures. Cash flow from operations is the sum of *Compustat items*: IBC, DPC, TXDC, ESUBC, SSPIV, FOPO, RECCH, INVCH, APALCH.

Table 1.1: R&D investment growth around a banking crisis

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

Country	Crisis year	Low Financial Dependence			High Financial Dependence		
		Nb of Industries	before	after	Nb of Industries	before	after
AUSTRIA	2008	17	0.07	-0.01	11	0.00	0.03
BELGIUM	2008	17	0.01	0.04	6	0.04	0.41
FRANCE	2008	17	0.08	0.00	6	0.09	-0.01
GERMANY	2008	17	0.02	0.01	6	0.07	0.01
ITALY	2008	17	0.12	0.01	6	0.09	0.01
JAPAN	1997	10	0.00	-0.01	3	0.01	0.03
SOUTH KOREA	1997	17	0.04	-0.03	6	0.25	-0.13
PORTUGAL	2008	10	0.24	0.02	5	0.15	-0.03
SLOVENIA	2008	13	0.23	0.11	5	0.13	0.08
SPAIN	2008	17	0.03	-0.01	6	0.07	-0.12
TURKEY	2000	11	0.19	0.06	3	0.47	0.03
UK	2008	8	0.02	0.00	5	0.12	0.08
USA	2008	13	0.02	0.01	8	0.06	0.02
Median			4.1%	0.7%		8.9%	2.0%
Difference			-3.4%*			-6.9%**	

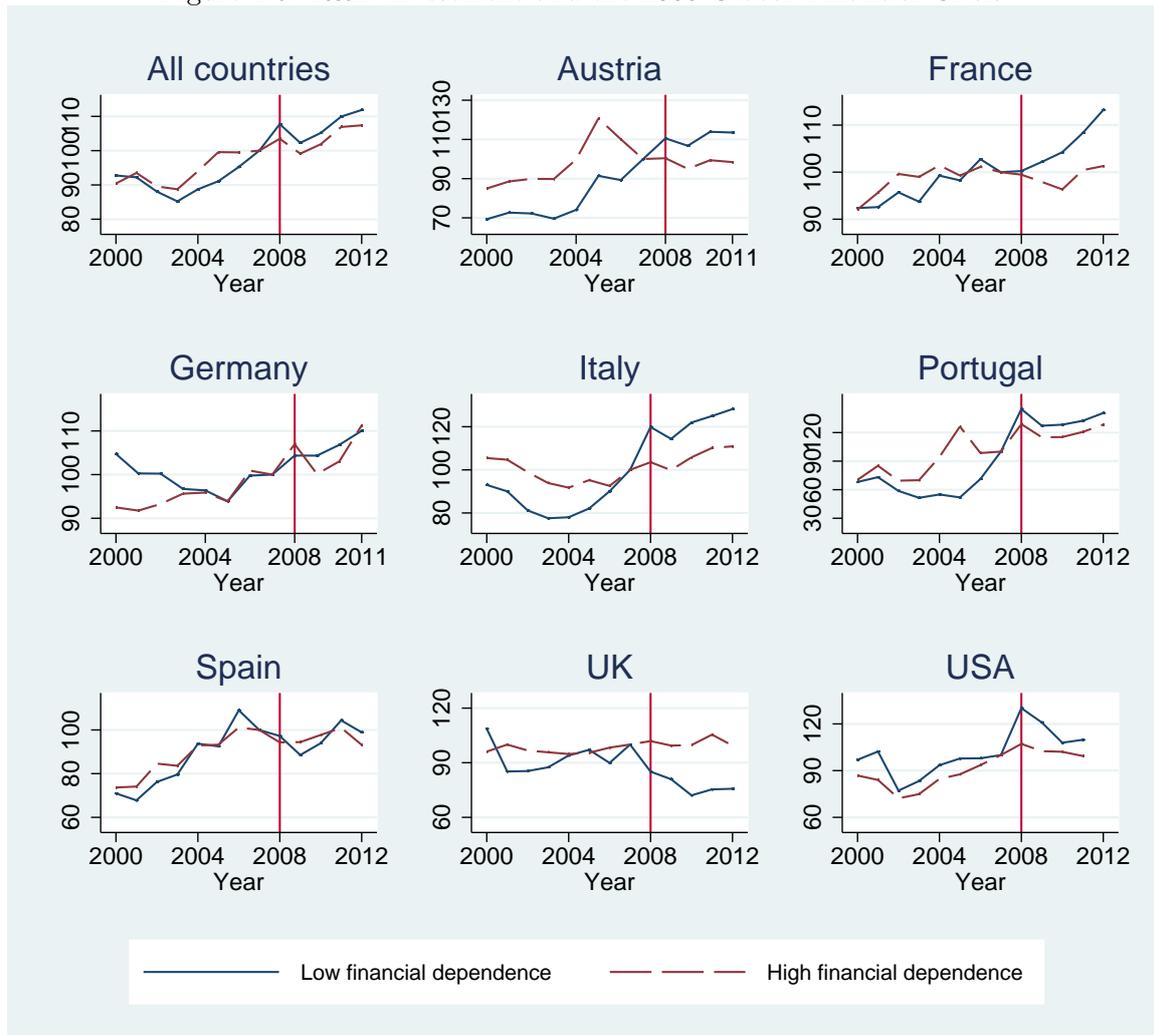
*/** represent significance at the 5%/1% for the Pearson's chi-squared (MOOD) test under the null hypothesis that the medians of the samples are identical.

reflect more their demand for external finance as compared to companies in countries with less advanced financial systems. The time-invariant, industry-level index of external finance dependence is presented in Appendix 1.E. This re-computed index is comparable to the one developed by [Rajan and Zingales \(1998a\)](#) or [Raddatz \(2006\)](#). It labels, for example, industries like Pharmaceuticals (ISIC level 21), Electronics (ISIC level 264) or Medical supplies (ISIC level 325) as being highly dependent on external finance, while Leather (ISIC level 15), Wearing apparel (ISIC level 14) and Textiles (ISIC level 13) among the least dependent.

Descriptive statistics

As a first glance of the data, I perform a simple split-sample analysis by looking at the investments in research and development around a banking crisis. In particular, I compute the average R&D growth in the periods $[t - 3, t - 1]$ and $[t + 1, t + 3]$ around a crisis occurring in year t for each of the 13 crises episodes covered. I then split the sample in industries that have

Figure 1.6: R&D investment and the 2008 Global Financial Crisis



Figures show the evolution of R&D spending by type of industry for a selection of countries in the dataset. They compare an index of R&D investment in industries below (Low financial dependence) and above (High Financial dependence) the median external dependence index. The base year is 2007 and industry indexes are aggregated in the two categories using the share of an industry's R&D spending in the total R&D spending of the country as a weight. The first graph is computed as a simple average of the individual country indexes.

a financial dependence index below/above the median. The statistics are presented in Table 1.1. In most countries, growth in R&D investment drops in the years following a banking crisis and, more importantly, this drop appears greater in sectors that rely more on external funds. The overall difference in median growth in R&D around a crisis year is -3.4% in low dependent industries, versus -6.9% in highly dependent ones.

Another way of visualizing the data is to look at the evolution of research and development spending over time. Figure 1.6 plots an index of R&D investment per industry for a selected sample of countries that were hit by the 2008 Global Financial Crisis. The index is set to 100 in the base year 2007 and is computed for each industry, in each country. The data is then aggregated at the country level using the share of an industry's R&D spending in the

total R&D spending of the country as a weight. The index thus tracks the changes in R&D investment over time. Several interesting patterns can be noticed. First, for most countries, the index of high financial dependence industries (dashed line) prior to the crisis is above that of low financial dependence (full line) suggesting a higher growth rate. This trend clearly reverses after 2008, in particular, if we look at the graph in the first panel which shows an average of all the countries affected by the 2008 Global Financial crisis. Second, this reversal appears more pronounced in countries generally considered as bank-based economies such as Germany, Austria, or Italy and to a lower extent in stock-market based economies such as UK or USA.

The patterns observed in the descriptive statistics above 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. In the next section, these dynamics are analysed in a more rigorous way.

1.4.3 The effect of banking crises on R&D investment: baseline results

The first set of results investigate the effect of banking sector distress on the growth in R&D spending. Columns (1)-(5) in Table 1.2 present the estimates of model (1.8), 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. 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, in particular for the pre-crisis period, to mitigate any concerns regarding investment booms occurring before the banking crisis. So Column (2) uses the average R&D in the 4 years after the crisis and the 8 years prior to a crisis in year t : $[t + 1, t + 4]$ 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 $[t - 4, t - 1]$.²³

²³See Kroszner et al. (2007) and Manova (2008) for similar pre- and post-crisis time frames.

Table 1.2: 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 used to compute averages 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 crisis countries 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 industry-level measure of external dependence measure following [Rajan and Zingales \(1998a\)](#) 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. Share $_{t-3}$ is the share of the sector's R&D investment in total R&D investment lagged by three periods. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. Constant term included, but not reported. *** significance at 1% level, ** significance at 5% level, * significance 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*** (0.00580)	-0.0152*** (0.00528)	-0.0259*** (0.00641)	-0.0187** (0.00633)	-0.0152*** (0.00541)					
ExtDep*Bank*Crisis						-0.0104*** (0.00284)	-0.0115*** (0.00336)	-0.0113*** (0.00367)	-0.00875*** (0.00287)	
ExtDep*Crisis										-0.0202* (0.0108)
Share $_{t-3}$	0.274 (0.600)	-0.346 (0.389)	-0.0694 (0.519)	0.274 (0.680)	0.632 (0.499)	-0.368*** (0.101)	-0.658*** (0.230)	-0.446*** (0.0956)	-0.596*** (0.143)	-0.372*** (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			

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 investments in the crisis period compared to the pre-crisis one is lower in industries that are more dependent on external finance, in countries with more developed banking sectors as compared to financial markets. In other words, industries that depend more on bank credit see a greater reduction of investment in R&D from the pre-crisis to the crisis period. Given this differential impact, we can conclude that the effect of the banking crisis manifests itself, at least partly, through a bank lending channel, as industries that depend more on finance have a disproportionately lower growth of R&D investment after the crisis. Furthermore, this effect is economically significant. Looking at column (1) estimates, a sector in the 75th percentile of external dependence, in a country in the 75th percentile of banking sector dependence, experiences, on average, a 21% smaller real R&D growth following a banking crisis as compared to a sector in the 25th percentile of external dependence and 25th of bank dependence.

The estimations 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](#)). Furthermore, in column (5), model (1.8) is estimated for a restricted sample of countries that were hit by the 2008 Global Financial Crisis. This assures us that the results are consistent with more recent banking crises episodes, as well. The results are consistent across these alternative specifications.

The aggregation strategy in Eq. (1.8), which collapses the time dimension, has been shown to be an effective methodology to account for any serial correlation in the dependent variable, which can result in biased 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. This more econometrically demanding setting can also allow us to control for various two-level fixed effects. More specifically, the model tested is:

$$R\&D_{ict} = \alpha_i + \mu_c + \lambda_t + \beta_1 ExtDep_i * Bank_c * Crisis_{ct} + Share_{ic} + \epsilon_{ict}, \quad (1.9)$$

where $R\&D_{ict}$ is the annual real growth in R&D in sector i of country c , in year t ; α_i are industry fixed effects; μ_c are country fixed effects and λ_t time fixed effects. $Crisis_{ct}$ is a banking crisis dummy that takes the value 1 in the first three years following a banking crisis

and 0 otherwise.²⁴ The triple interaction term captures the differential impact of dependence on external finance in countries that rely more on the banking sector, during periods of bank distress.

The results presented in column (6) of Table 1.2 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 spend disproportionately less on Research and Development, especially if they operate 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 predominantly present in countries which have a relatively larger banking sector as opposed to stock markets. This implies that identification is obtained from industries that are generally more dependent 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 sets of fixed effects. Column (7) in Table 1.2 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. (1.9), 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.

²⁴Results are robust when considering two years after the crisis and are available upon request.

Table 1.3: 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. ExtDep*Bank is the interaction term of the industry-level measure of external dependence measure following [Rajan and Zingales \(1998a\)](#) 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. Share $_{t-3}$ is the share of the sector's R&D investment in total R&D investment lagged by three periods. Growth observations are winsorized at +100% and -100%. Robust standard errors are reported in parentheses. Errors are clustered at country level in column (4). Column (5) replicates the model in column (1) for the 2008 Global Financial Crisis countries only. Constant term included, but not reported. *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

	$\Delta(R\&D/TI) = (R\&D/TI)_{crisis} - (R\&D/TI)_{pre-crisis}$					Panel regressions: $R\&D/TI$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ExtDep*Bank	-0.0104*** (0.00333)	-0.00570 (0.00346)	-0.0278*** (0.00816)	-0.0104** (0.00392)	-0.0107*** (0.00336)				
ExtDep*Bank*Crisis						-0.00562** (0.00245)	-0.00474* (0.00243)	-0.00312 (0.00318)	-0.00588** (0.00300)
Share $_{t-3}$	-0.0962 (0.153)	0.0354 (0.179)	0.0916 (0.510)	-0.0962 (0.127)	-0.106 (0.171)	0.263** (0.105)	0.0243 (0.0243)	0.404*** (0.0960)	0.616*** (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		

The coefficient of this interaction term is negative, however statistically significant only at a 10% level. Given the strongly significant coefficient of the triple interaction term in columns (6)-(9), we can confirm that identification does come from external finance dependent industries *in* countries with a predominant banking sector financing.

In sum, the results in Table 1.2 provide strong support for the importance of credit market conditions for investments in innovations. Yet, in the theoretical model in the previous section a shift in the composition of corporate investment from R&D to other safer investments was responsible for the slower economic recovery. The next section provides a more direct test of this hypothesis, by looking at the share of R&D investment in total investment.

1.4.4 Effects of banking crises on the composition of investment

Having established the importance of changes in financial constraints for investments in R&D, I now investigate whether this drop in research and development spending is also associated with a shift in corporate 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 disproportionately more by changes in financial conditions. In other words, banking crises discourage significantly more investments in innovation, as compared to other types of investment.

To test this prediction, a modified version of the cross-sectional model in Eq. (1.8) that takes into account the composition of investment, is used:

$$\Delta(R\&D/TI)_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i * Bank_c + \beta_2 Share_{ic} + \epsilon_{ic}, \quad (1.10)$$

where $R\&D_{ic}/TI_{ic}$ is now the ratio of R&D spending to total investment in sector i in country c .

Results are presented in Table 1.3 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, not only the total spending on R&D drops, but also its share in total investment as a result of tighter credit conditions following episodes of bank distress. Coupled, these two empirical results suggest a potential new channel through which banking crises can have long-lasting consequences on the real economy and lend broad support to the qualitative

implications of the theoretical model presented in the previous section.

The remaining columns in Table 1.3 propose the same empirical exercises as the ones in Table 1.2. 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 1.3 extend the event analysis to a panel setting. Thus, a modified version of model (1.9) is performed employing 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 $ExtDep_i * Bank_c * Crisis_{ct}$ 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. Results 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.

1.4.5 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:

$$R\&D_{ict} = \alpha_i + \mu_c + \lambda_t + \beta_1 ExtDep_i * Bank_c * Crisis_{ct} + \beta_2 ExtDep_i * Bank_c * Recession_{ct} + \beta_3 Share_{ic} + \epsilon_{ict}, \quad (1.11)$$

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.²⁵ $Recession_{ct}$ is a recession dummy which takes the value 1 in the years between the peak and

²⁵Results are robust when considering two years after the crisis and available upon request.

Table 1.4: 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 . Share $_{t-3}$ 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 and not just crisis countries. Constant term included, but not reported. *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

	<i>R&D</i> growth					<i>R&D/TI</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ExtDep*Bank*Crisis	-0.00943*** (0.00264)	-0.0112*** (0.00330)	-0.0107*** (0.00386)	-0.00741*** (0.00284)	-0.0102*** (0.00335)	-0.00617** (0.00285)	-0.00441** (0.00209)	-0.00862** (0.00415)	-0.00561* (0.00286)
ExtDep*Bank*Recession	-0.00246 (0.00626)	0.00181 (0.00737)	0.00137 (0.00933)	-0.00812 (0.00795)	-0.00382 (0.00554)	-0.0242*** (0.00765)	-0.00414 (0.00585)	-0.0353*** (0.0123)	-0.0298*** (0.00830)
Share $_{t-3}$	-0.359*** (0.103)	-0.631*** (0.222)	-0.430*** (0.0992)	-0.623*** (0.164)	-0.380*** (0.107)	0.465*** (0.162)	0.0250 (0.0247)	0.682*** (0.144)	1.189*** (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	

the trough of the cyclical component of real GDP following the methodology proposed by [Braun and Larrain \(2005\)](#).²⁶ The coefficient of interest is still β_1 and the hypothesis is that the negative effect of banking crises captured by it, is still statistically significant once the effect of economic recessions is taken into account.

The results in Table 1.4 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*Bank*Recession* is mostly negative, but statistically significant only in a few cases. On the other hand, triple interaction *ExtDep*Bank*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 may have experienced only economic recessions over the period 1987-2013.²⁷ The results obtained for this extended sample are presented in column (5) and are consistent, confirming the strongly significant effect of banking crises on investments in innovation, and, to a lesser extent, that of balance sheet conditions during economic recessions.

Finally, columns (6)-(9) in Table 1.4 estimate model (1.11) considering the share of R&D in total investment as a dependent variable. When considering this model, the coefficient of the interaction term *ExtDep*Bank*Recession* is now statistically significant in two of the three specifications. Nonetheless, the effect of banking crises on the composition of investment is still significant across all fixed effects identification strategies in columns (6)-(9). Overall, these results 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.

²⁶More 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.

²⁷More 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 1.5: Banking crises versus non-crises periods

The dependent variable in columns (1)-(4) is the average growth in R&D during non-crises ((1)-(2)) and crises ((3)-(4)) periods, respectively. Columns (2) and (4) are performed on 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. $Share_{avg}$ is the average share of a sector's R&D investment in total R&D investment over the period considered. $Share_{t-3}$ 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. Constant term included, but not reported. *** significance at 1% level, ** significance at 5% level, * significance 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* (0.0035)	0.0046* (0.0026)	-0.0074* (0.0043)	-0.008* (0.004)	0.0043 (0.0034)	0.0007 (0.0025)	-0.012*** (0.003)	-0.0046* (0.0025)
Share _{avg}	0.402** (0.183)	0.395** (0.183)	-0.216 (0.228)	0.0028 (0.289)				
Share _{t-3}					-0.513** (0.220)	0.303* (0.177)	-0.447** (0.203)	0.85*** (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 FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE					YES	YES	YES	YES
Year FE					YES	YES	YES	YES

1.4.6 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 1.1 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, 1998a). 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. Indeed, 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 American firms did reduce disproportionately

their R&D spending during the Great Depression in the 1930s.

This chapter tests the hypothesis that financially dependent industries have different investment rates in innovation during non- versus crisis periods. A first specification considers the average investment in R&D in the two sub-periods separately, in the following model:

$$R\&D_{ic} = \alpha_i + \mu_c + \beta_1 ExtDep_i * Bank_c + \beta_2 Share_{avg} + \epsilon_{ic}, \quad (1.12)$$

where $R\&D_{ic}$ represents the average investment in R&D during crisis and non-crisis periods, separately, and $Share_{avg}$ now represents the average share of R&D of industry i in total country c 's R&D investment, over the two separate periods, as well.

Results are presented in columns (1)-(4) of Table 1.5. 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 two sample averages might include different country-industry observations in the non- and crisis periods, respectively. This was not the case in the event-study regressions in Tables 1.2 and Table 1.3 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, meaning the same number of country-industry observations are 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 column (5)-(8). Columns (5) and (6) refer to the growth in R&D, while columns (7) and (8) to the share of R&D in total investment. Similarly to the aggregated estimations, the positive, albeit less precisely estimated, impact of $ExtDep * Bank$ during non-crisis periods (columns (5)-(6)) is reversed after banking crises. These split sample results provide strong evidence for the importance of financial conditions for investments in innovation. They also suggest an explanation for the mixed results in previous literature as dependence on external finance appears to matter for R&D investments, in particular in countries that rely on the banking sector to obtain funding. This implies that bank financing does 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.

1.4.7 Alternative measures of financial dependence

This section employs alternative measures of financial dependence to test the robustness of the results previously obtained. 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, 2012](#)). The identification strategy proposed in this chapter, 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.

This second measure is 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 only a limited number of two- and three- digits industry codes, I recompute their measure using a sample of both listed and non-listed firms in the two more 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 2004-2007.²⁸ Using an approach similar the construction of the *ExtDep* measure, an industry index is obtained by taking the median of firm-level data for each industry level.

This alternative measure of dependence, denoted by *BankDep*, is presented in Appendix 1.E. Some descriptive statistics with respect to this industry-level index of bank dependence are also presented in Appendix 1.E, Table 1.9. They include a similar split sample analysis as in the previous section, by looking at the average growth in R&D in each country prior and post a banking crisis, in industries below and above the median value of *BankDep*. The patterns of R&D growth are similar to the ones uncovered employing the [Rajan and Zingales \(1998a\)](#) measure. Across countries, R&D growth is, on average, 2.4% lower in the post crisis period in industries less dependent on bank finance and 7.4% lower for those that rely extensively on the banking sector. These different growth rates suggest similar dynamics of R&D around banking crises as compared to the main measure employed throughout this chapter. I then go on and estimate model (1.8) employing this alternative measure of bank

²⁸The 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 $\text{Total Assets}_{t-1}$ less the Depreciation in year t .

Table 1.6: 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. Share $_{t-3}$ 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%. Robust standard errors are reported in parentheses. Constant term included, but not reported. *** significance at 1% level, ** significance at 5% level, * significance 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** (0.003)	-0.006* (0.003)	0.001 (0.001)	-0.005 (0.004)				
ExtDep*Credit					-0.041** (0.018)	-0.072*** (0.023)	-0.032** (0.012)	-0.081*** (0.024)
Share $_{t-3}$	0.105 (0.599)	0.0453 (0.489)	0.119 (0.178)	0.0411 (0.517)	-0.251 (0.395)	0.388 (0.649)	0.182 (0.208)	0.484 (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
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

dependence. The results obtained are presented in columns (1)-(4) of Table 1.6. Columns (1)-(2) use the growth of R&D as a dependent variable and two alternative time frames for the crisis and pre-crisis averages, namely $[t+1, t+3]$, $[t-3, t-1]$ and $[t, t+2]$, $[t-4, t-1]$, 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. Result 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. Part of the reason is that this index is constructed using a smaller time-frame and sample of companies as compared to the [Rajan and Zingales \(1998a\)](#) index, making it a less precise measure of external dependence.

A second robustness analysis refers to an alternative measure of the country-level index of reliance of banking sector funding. The main estimations employed the ratio of Private Credit to Stock Market Capitalization to classify countries as more bank-based following a well-

established banking literature. 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 $ExtDep*Credit$, are presented in Table 1.6, columns (5)-(8). The model estimated is the event study analysis in (1.8) considering 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 and support the main hypothesis of a shift in the composition of corporate investment around banking crises.

Table 1.7: Falsification strategies: hypothetical crisis date

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. * 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)
Share $_{t-3}$	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
Country FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

1.4.8 Robustness check: falsification strategies

One last robustness check considered is a falsification strategy as suggested by [Bertrand et al. \(2004\)](#). In particular, I repeat the analysis in Table 1.2 by changing the crisis year to a hypothetical crisis date. Table 1.7 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 $ExtDep^*Bank$ 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 a different set 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 following 2008, 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.

1.5 Conclusions

The 2007-08 Global Financial Crisis has given renewed impetus to the study of the causes and consequences of financial crises. A large empirical literature looks at how the funding constraints faced by banks at the onset of the crisis have led to a credit freeze to the real sector, and how, in turn, this affected corporate investment and performance ([Ivashina and Scharfstein, 2010](#); [Duchin et al., 2010](#); [Campello et al., 2010](#)). Yet, this literature is generally concerned with the short-run effects of such credit crunches. This chapter aims to build a bridge between static models of financial crises and studies of long-term growth. I do so by integrating a bank run model into a growth model, which allows me to study the growth implications of credit market freezes. This builds on recent theoretical contributions that stress the importance of credit constraints not only on the volume of real sector investments but also on their composition ([Matsuyama, 2007](#); [Aghion et al., 2010](#); [Favara, 2012](#)).

In a partial equilibrium growth model, it can be shown that contractions in credit supply that follow banking crises cause firms to shift their investments from long-term, innovative investments, to short-term, low-productivity ones. By impacting the type of investments undertaken, banking crises can have long-lasting effects on economic activity as documented by recent empirical evidence.

This theoretical prediction is confirmed empirically, employing a sample of 13 recent sys-

temic 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. Estimations consider both the size of R&D and the share of these investments in total investment as dependent variables, 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 disproportionately lower R&D spending following episodes of bank distress.

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, thus explaining the slow recovery following episodes of systemic banking crises. These results hold several policy implications. First, they are in line with the view that bank dependent borrowers cannot circumvent the banking sector in crisis times. Hence support to the banking sector or policy measures that provide alternative sources of funding 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 various policy interventions that support R&D spending in particular following banking crises. Clearly, more investigation at the firm level is needed to fully understand the implications of such policies, which remains an important avenue for future research.

Appendices

1.A Proof of Proposition 1

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

The intuition behind the proof can be best understood by applying the logic of backward induction. Note first that the space of liquidity costs $[0, \bar{c}H]$ 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, $k = 1$.²⁹ 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 slightly 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 to withdraw. At the same time, investors receiving

²⁹These 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 1.8](#).

a signal slightly below C_{max} is pessimistic about the probability of survival of the long-term investment projects and prefers not to lend. Again, we can apply a backward reasoning and establish a boundary well below C_{max} above which investors withdraw. The mathematical proof rests in showing that these two boundaries coincide.

I show this following the steps of the proof of [Morris and Shin \(1998\)](#). First, for any given profile of strategies, denote by $\pi(x)$ the proportion of investors who demand early withdrawal in $t = 1$ upon observing a signal x . The *actual* proportion of investors who end up withdrawing depends on the state C drawn by nature and is denoted by $\ell(\pi, C)$. Given the fact that C and ϵ are drawn from uniform distributions over $[0, \bar{c}D]$ and $[-\epsilon, \epsilon]$, respectively, signals $x_i = C + \epsilon_i$ are also uniformly distributed over $[C - \epsilon, C + \epsilon]$. We have that:³⁰

$$\ell(\pi, C) = \frac{1}{2\epsilon} \int_{C-\epsilon}^{C+\epsilon} \pi(x) dx \quad (1.13)$$

Denote by $\ell^*(C)$ the threshold number of investors who need to run on the bank to trigger the liquidity freeze. From Eq. (3.4) it follows that:

$$\ell^*(C) = \frac{M + Y_1 - C}{D} \quad (1.14)$$

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

$$A(\pi) = \{C | \ell(\pi, C) \leq \ell^*(C)\} \quad (1.15)$$

Thus the payoff of investors, given the strategy π they follow, is rD if $C \in A(\pi)$ and zero otherwise. The actual payoff of investors depends on the realization of C . Since, C is not observed, the *expected* payoff from leaving the money in the bank depends on the posterior distribution of C conditional on the signal x . Given the distribution of signals, the posterior distribution of C is uniform over $[x - \epsilon, x + \epsilon]$.³¹ So the expected utility from leaving the

³⁰Following [Morris and Shin \(1998\)](#), I assume that $2\epsilon < \min[C_{min}, \bar{c}D - C_{max}]$. This condition assures 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 believes that C is in the “safe” region where long-term investments always survive.

³¹The actual posterior distribution of C is $[\max(0, x-\epsilon), \min(\bar{c}D, x+\epsilon)]$. To avoid carrying around the min, max operators we restrict our analysis to the states that are at least ϵ distance away from the bounds of prior belief. In other words, $x \in [\epsilon, \bar{c}D - \epsilon]$.

money in the bank conditional on the signal x and the true C is:

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

Given this information structure and payoffs, the first step in Morris and Shin's (1998) proof rests in showing that investors decisions are strategic complements, i.e., the more investors leave their funds in the bank, the higher the incentives of others to do so. This means that given two strategy profiles π and π' , if $\pi(x) \geq \pi'(x)$ for every x , then the payoff of leaving the money in the bank is higher when more investors leave their money in the bank, or $u(x, \pi) \geq u(x, \pi')$ for all x . To show this, note that if $\pi(x) \geq \pi'(x)$, i.e., strategy π entails a higher proportion of withdrawals for the same signal, x , then $\ell(\pi, C) \geq \ell(\pi', C)$ for every C , given the definition of ℓ in (1.13). Furthermore, from (1.15), $A(\pi) \supseteq A(\pi')$, which implies that:

$$u(x, \pi) = \frac{1}{2\epsilon} \int_{A(\pi) \cap [x-\epsilon, x+\epsilon]} rD \, dC \geq \frac{1}{2\epsilon} \int_{A(\pi') \cap [x-\epsilon, x+\epsilon]} rD \, dC = u(x, \pi'). \quad (1.16)$$

Next, recall that investors can withdraw their funds at $t=1$ and get back their initial investment, D . Assume now that investors follow a simple rule where they withdraw if $u(x, \pi) < D$ and leave their money in the bank if $u(x, \pi) \geq D$. In other words, investors withdraw if the expected utility from leaving the money in the bank is lower than the sure payoff of D . Thus investors have a simple strategy profile where they withdraw if their signals is less than a threshold signal, x^* . Consider the following indicator function I_{x^*} to depict the aggregate withdrawals in $t=1$:

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

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

$$u(x^*, I_{x^*}) = D, \quad (1.17)$$

where $u(x^*, I_{x^*})$ is the expected payoff from leaving the money in the bank, when all the others follow a switching strategy around x^* .³²

³²To prove existence, we first need to check that $u(x^*, I_{x^*})$ is continuous and strictly decreasing in x^* . The arguments are similar to the proof of Lemma 2 in Morris and Shin (1998). Denote by C^* the threshold cost at which bank failure occurs. Given Eq. (1.14), this threshold cost solves: $\ell^*(C^*) = \frac{M+Y_1-C^*}{D}$. Thus long-term investments survive, if and only if C lies in the interval $[0, C^*]$, and so the payoff function $u(x^*, I_{x^*})$ can be written as:

$$u(x^*, I_{x^*}) = \frac{1}{2\epsilon} \int_{x^*-\epsilon}^{C^*} rD \, dC,$$

The intuition behind the proof of existence is the following. Consider first a very low signal, say \underline{x}_1 , for which leaving the money in the bank is an optimal strategy no matter what the others do. The marginal investor with signal, \underline{x}_1 , knows that the liquidity costs must be below the lower limit C_{min} where investment projects always succeed. In this region, the payoff from leaving the money in the bank is always greater than D , the payoff of withdrawing at $t=1$, i.e., $u(\underline{x}_1, I_{\underline{x}_1}) > D$. Similarly, for a sufficiently large signal, \bar{x}_1 , the marginal speculator knows that investment projects always fail, such that $u(\bar{x}_1, I_{\bar{x}_1}) < D$. Given the monotonicity of $u(x, I_x)$, there exists a unique value of x for which, $u(x, I_x) = D$, and this is defined by x^* . Having showed the existence of a strategy threshold, x^* , [Morris and Shin \(1998\)](#) show that it is also unique (Lemma 3 in their paper). This proof is similar to theirs and, for brevity, I do not include it here.

The final step of the proof rests in computing the threshold signal, x^* . Denote by C^* the threshold cost at which bank failure occurs. Given Eq. (1.14), this threshold cost solves: $\ell^*(C^*) = \frac{M+Y_1-C^*}{D}$. The equilibrium values of x^* and C^* can be easily computed given the two equations:

$$\begin{aligned}\ell(I_{x^*}, C^*) &= \ell^*(C^*) \\ u(x^*, I_{x^*}) &= D.\end{aligned}$$

Given the strategy profile, I_{x^*} , the proportion of investors who run are those receiving a signal above the threshold x^* :

$$\ell(I_{x^*}, C^*) = Prob(x_i > x^* | C^*) = Prob(C + \epsilon_i > x^* | C^*) = 1 - \frac{1}{2\epsilon}(x^* - C^* + \epsilon), \quad (1.18)$$

since x_i is uniformly distributed over $[C - \epsilon, C + \epsilon]$. Given (1.14), the first equation that defines the threshold signal x^* as a function of C^* is:

$$x^* = C^* - \epsilon - \frac{2\epsilon}{rD}(M + Y_1 - C^*) \quad (1.19)$$

The second equation is given by the indifference condition of an investor who receives the

since, conditional on $x_i = x^*$, $C \sim \text{unif}[x^* - \epsilon, x^* + \epsilon]$. Note that the upper bound the integral should be $\min(C^*, x^* + \epsilon)$. However, as long as $rD > 1$, it can be shown that $\min(C^*, x^* + \epsilon) = C^*$. Suppose the opposite. If, $x^* + \epsilon < C^*$, then $Prob[C < C^* | x^*] = 1$, i.e. a depositor with the threshold signal always knows that everyone leaves their money in the bank for any realization of C . Then x^* cannot be the signal of the indifferent depositor. This contradicts the initial assumption.

Given the payoff above, it follows directly that $u(x^*, I_{x^*})$ is strictly decreasing in x^* is C^* is decreasing in x^* . To verify the last statement it is easy to see that $\ell(I_{x^*}, C^*) = \frac{M+Y_1-C^*}{D}$, so $\frac{\partial C^*}{\partial x^*} = -\frac{\partial \ell(I_{x^*}, C^*)}{\partial x^*} < 0$, since the number proportion who withdraw is increasing in x^* .

threshold signal, x^* . The expected utility of this marginal investors is given by:³³

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

Plunging this into equation (1.19) gives us the equation in Proposition 1:

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

QED

1.B Proof of Lemma 1

The entrepreneur's maximization problem in Eq. (1.2) yields the following first order condition:

$$-\sigma_1 + \frac{\partial \lambda}{\partial k} \sigma_2 k + \lambda(k) \sigma_2 = 0. \quad (1.20)$$

where $\lambda(k)$, the ex-ante probability that long-term investments survive, is given by the equilibrium condition in the investors' coordination problem in Eq. (1.4):

$$\lambda(k) = Prob[C < C^*] = \frac{(1-\mu)\phi + \sigma_1(1-k)\mu\phi}{\bar{c}} - \frac{1}{\bar{c}r}. \quad (1.21)$$

Replacing this equilibrium probability in the FOC above yields an optimal k equal to:

$$k_{opt} = \frac{\sigma_1 - 1}{2\sigma_1} - \frac{(\bar{c}\sigma_1 - \phi\sigma_2)r + \sigma_2}{2\mu\sigma_1\sigma_2\phi r} \quad (1.22)$$

Thus $\frac{\partial k}{\partial \mu} = \frac{(\bar{c}\sigma_1 - \phi\sigma_2)R_D + \sigma_2}{2\mu^2\sigma_1\sigma_2\phi r}$, is positive if and only if $\phi < \frac{\bar{c}\sigma_1}{\sigma_2} + \frac{1}{r} \equiv \bar{\phi}$.

This result states the share of long-term investment is increasing in the loan-to-assets ratio of the bank. In other words, the higher the share of bank assets lent to the real sector, i.e. the lower the credit constraints in the economy, the more entrepreneurs will invest in R&D as a share of total investment. Figure 1.7 depicts numerically this relationship for the set of parameters in Table 1.8.

The second part of Lemma 1 states that the ex-ante probability that long-term investments survive, λ , is increasing in μ . Again, this follows directly from the equilibrium probability of

³³Since, conditional on $x_i = x^*$, $C \sim \text{unif}[x^* - \epsilon, x^* + \epsilon]$, the upper bound the integral should be $\min(C^*, x^* + \epsilon)$. However, Morris and Shin (1998) as long as $rD > 1$, $\min(C^*, x^* + \epsilon) = C^*$. Suppose the opposite. If, $x^* + \epsilon < C^*$, then $Prob[C < C^* | x^*] = 1$, i.e. the indifferent depositor always knows that a everyone renews their investment for any realization of C . Then x^* cannot be the signal of the indifferent depositor. This contradicts the initial assumption.

survival of innovative investments in Eq. (1.21):

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

Replacing $k(\mu)$ with its equilibrium value in Eq. (1.22) yields:

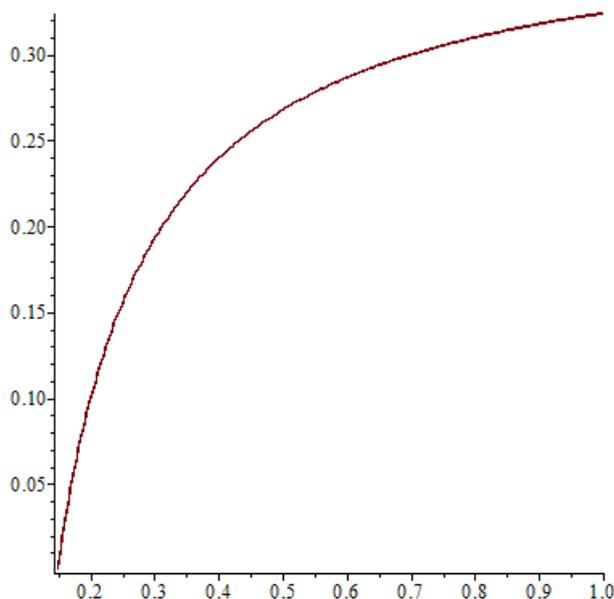
$$\frac{\partial \lambda(\mu)}{\partial \mu} = \frac{\phi}{\bar{c}} \left[-1 - \sigma_1 \frac{(\bar{c}\sigma_1 - \phi\sigma_2)r + \sigma_2}{2\mu\sigma_1\sigma_2\phi r} + \sigma_1 \left(1 - \frac{\sigma_1 - 1}{2\sigma_1} + \frac{(\bar{c}\sigma_1 - \phi\sigma_2)r + \sigma_2}{2\mu\sigma_1\sigma_2\phi r}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

which is simply equal to:

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

given that $\sigma_1 > 1$. *QED*

Figure 1.7: Share of R&D investment as a function of credit conditions



1.C Numerical simulations

Table 1.8: 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 on C	uniform over $[0, \bar{c}D]$	$[0, 2D]$
Investors' unit return	r	1.1

1.D Proof of Proposition 2

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

$$\text{Max}_{\mu} \lambda(\alpha\sigma_2 k\mu\phi D + \alpha\sigma_1(1-k)\mu\phi D - rD) + (1-\lambda)\alpha\sigma_1(1-k)\mu\phi D + (1-\mu)\phi D, \quad (1.23)$$

which yields the following FOC:

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

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:

$$\frac{d\mu}{d\phi} = -\frac{\partial J/\partial \phi}{\partial J/\partial \mu} < 0 \quad (1.24)$$

To show this consider:

$$\frac{\partial J}{\partial \mu} = \frac{\partial^2 \lambda}{\partial^2 \mu} \left(k\alpha\mu\sigma_2 - \frac{r}{\phi} \right) + 2 \frac{\partial \lambda}{\partial \mu} \frac{\partial k}{\partial \mu} \alpha\mu\sigma_2 + 2k \frac{\partial \lambda}{\partial \mu} \alpha\sigma_2 + \underbrace{\frac{\partial^2 k}{\partial^2 \mu} \alpha\mu(\lambda\sigma_2 - \sigma_1) + 2 \frac{\partial k}{\partial \mu} \alpha(\lambda\sigma_2 - \sigma_1)}_0$$

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. (1.21), 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, $\frac{\partial^2 \lambda}{\partial \phi \partial \mu} = \frac{\sigma_1 - 1}{2c} > 0$, $\frac{\partial k}{\partial \phi} = \frac{c\sigma_1 r + \sigma_2}{2\mu\sigma_1\sigma_2\phi^2 r} > 0$ and $\frac{\partial \lambda}{\partial \phi} = \frac{1 + \mu(\sigma_1 - 1)}{2c} > 0$, given that, by definition, $\sigma_1 > 1$. This proves that $\frac{\partial J}{\partial \phi} > 0$ and thus $\frac{\partial \mu}{\partial \phi} < 0$.

1.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 \(1998a\)](#) measure of dependence of external finance computed for a sample of US Compu-stat for the period 1990-1999. BankDep index in the last column is the measure of bank dependence proposed by [Calderon and Liu \(2003\)](#).

Table 1.9: R&D investment growth around a banking crisis: alternative measure of dependence on external finance

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

Country	Crisis year	Low Financial Dependence			High Financial Dependence		
		Nb of Industries	before	after	Nb of Industries	before	after
AUSTRIA	2008	11	0.05	0.04	15	0.11	-0.02
BELGIUM	2008	9	-0.02	0.35	13	0.03	0.08
FRANCE	2008	9	0.02	0.03	13	0.24	-0.01
GERMANY	2008	9	0.03	0.04	13	0.05	0.01
ITALY	2008	9	0.11	0.02	13	0.28	0.03
JAPAN	1997	5	0.00	-0.02	6	0.00	-0.02
KOREA	1997	9	0.19	-0.18	13	0.08	-0.01
PORTUGAL	2008	9	0.51	-0.02	6	0.30	0.08
SLOVENIA	2008	7	0.15	0.12	9	0.58	0.23
SPAIN	2008	9	0.02	-0.04	13	0.08	-0.03
TURKEY	2000	5	0.40	0.13	7	0.33	0.08
UK	2008	7	0.08	0.06	5	0.05	0.00
USA	2008	9	0.03	-0.02	10	0.07	0.06
Median			5.1%	2.7%		8.2%	0.8%
Difference			-2.4%			-7.4%*	

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

Chapter 2

The cost of capital in a model of financial intermediation with coordination frictions¹

Abstract

This chapter studies the impact of coordination frictions in financial markets on the cost of capital of real sector projects. In the model, a financial intermediary seeks to raise funds to finance a risky capital-intensive project. Capital is owned by a large number of small investors, who observe noisy signals about the project's implementation cost. Employing a global games equilibrium refinement, we characterize a unique threshold equilibrium of the coordination game between investors. We then show that the relationship between the probability of success of the project and the rate of return on capital is non-monotonic. There exists a “socially optimal” price of capital, which maximizes the probability that the project is profitable. However, fee-maximizing intermediaries will generally set an interest rate that is higher than the socially optimal rate, highlighting a form of inefficiency in the intermediation process. The model best characterizes project finance investments funded through the bond market and yields implications for the cost of capital of such projects.

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2.1 Introduction

Financial intermediation is the central institution in the savings-investment process in most of the world's economies nowadays (Gorton and Winton, 2003). Bank-like intermediaries' role in producing information, pooling funds and monitoring economic agents is a pervasive feature of financial intermediation associated, at times, with high costs of capital (Philippon, 2015). Economic theory generally explains these high costs of intermediation through imperfect competition in the lending market (Petersen and Rajan, 1995; Dell'Araccia et al., 1999; Demirgüç-Kunt and Levine, 2004), adverse selection mechanisms in markets with asymmetric information about borrowers' risk (Stiglitz and Weiss, 1981; Besanko and Thakor, 1987) or informational monopolies of banks that result in hold-up problems (Sharpe, 1990; Rajan, 1992; Boot, 2000). This paper aims to provide a complementary explanation, in which a high cost of capital is the response of intermediaries to coordination frictions in capital markets, despite the absence of lender market power or information asymmetries between borrowers and lenders.

The general context of our analysis refers to a financial intermediary that seeks to raise external capital from many small investors to finance a large, risky real sector project. The intermediary's goal is to maximize the participation to the project, as it earns a fixed fee per unit of capital raised. It will thus set a return on capital in line with this objective. Project risk takes the form of a stochastic overrun cost occurring during project implementation. The investment is capital-intensive, with its output increasing in the amount of capital according to a linear technology. In this context, raising more capital increases the probability that the project pays off, which leads to a typical coordination problem, as investors' actions are strategic complements.

In a perfect information set-up, such coordination problems are known to present multiple equilibria, in the spirit of Diamond and Dybvig (1983), which makes it difficult to address issues such as the optimal price of capital. However, a recent literature has shown that the introduction of incomplete information offers a useful method for eliminating the perfect coordination of agents' actions and beliefs and, therefore, the possibility of multiple equilibria (Morris and Shin, 2001; Angeletos and Lian, 2016). Such games with strategic complementarities and imperfect information about a pay-off relevant variable, called "global games", present a unique threshold equilibrium (Carlsson and Van Damme, 1993; Morris and Shin 1998, 2004).

We follow this approach and assume that investors do not perfectly observe the true implementation cost of the real sector project. They receive, instead, only a noisy signal about the project's costs, which makes investors' beliefs no longer common knowledge. The coordination

problem between investors can thus be solved as a typical global game. We characterize the threshold equilibrium of the game and show that the project succeeds if the realized implementation cost is below a cut-off value and fails otherwise.

The main contribution of the chapter is to show that this equilibrium cut-off cost depends in a non-monotonic way on the fixed return on capital set by the financial intermediary. The impact of this return on the cut-off cost is driven by two opposite effects. On the one hand, a higher return raises the cost of capital of the project and decreases its probability of success. On the other hand, a higher return mitigates coordination frictions by attracting more investors and thus increasing the amount of funds pooled into the project, which implicitly increases its probability of success. It can be shown that there exists a “socially optimal” price of capital for which the probability of success of the project is the highest. However, we show that fee-maximizing intermediaries will generally set an interest rate that is higher than the socially optimal rate. The wedge between these two returns does not necessarily reflect the intermediary’s market or informational power, but is a direct consequence of the type of financial contract studied. This result highlights an inefficiency that stems from the coordination frictions that the intermediary aims to mitigate.

While our model could be extended to various forms of financial intermediation, it best describes *project finance* investments funded through a bond issuance (see [European Commission, 2012](#); [Esty, 2014](#)).² Bond issuance, as source of funding for capital-intensive projects, has gained momentum in the aftermath of the 2007-09 global financial crisis and is considered by many observers to be the future of infrastructure investments.³ In this particular form of financial contract, an investment bank seeks to fund a large, risky real project (owned by a special purpose vehicle) and raises external capital by issuing bonds. The bank acts as a bond-trustee that promises a fixed return on investment if the project is successful. Returns in this type of investment are generated by the cash flow of the project, which is typically associated with a high risk of cost overrun ([Esty, 2003](#); [Esty and Matysiak, 2004](#)). As such, the returns promised to investors are generally high due to the perceived riskiness of such capital intensive projects. Our analysis suggests that part of this high cost of capital might be due to the coordination frictions among investors that the financial intermediary strives to overcome.

Our model is related to a growing literature in financial economics that studies coordination

²Project finance investments are loosely defined as: “the rising of funds to finance an economically separable capital investment project in which the providers of funds look primarily for the cash flow from the project as the source of funds to service their loans” ([Finnerty, 2013](#)).

³The issuance of project bonds recorded an all-time high level of \$49 billion in 2013, representing approximately half of the total world-wide number of project finance investments that year. See also [Deloitte \(2015\)](#) and [PricewaterhouseCoopers \(2015\)](#).

problems in a global games framework (for a survey, see [Jorge and Rocha, 2015](#)). In particular, the model in this chapter is closest to several papers which study financial intermediation issues. For instance, [Morris and Shin \(2004\)](#) study the coordination risk of creditors of a distressed borrower. They show that creditors foreclose on a loan based on signals they receive about a “generic” state variable that represents a firm’s ability to meet external obligations. By contrast, in our model, project failure is directly related to the cost uncertainty specific to capital-intensive investment projects. At the same time, in our model, the return paid by the project owner is an endogenous variable set by the bank. [Goldstein and Pauzner \(2005\)](#) also study how interest rates on deposits set by banks affect the probability of runs. In their model, however, higher interest rates make banks more vulnerable to runs because they increase depositors’ expected utility of withdrawing early. By contrast, in our model, up to a point, higher interest rates favour coordination by increasing the pool of funds raised by the financial intermediary.

Thus, this chapter focuses on a different coordination problem compared to most global games models, which analyse the risk of runs by depositors or investors, on banks or other financial institutions (see, *inter alia*, [Morris and Shin, 2001](#); [Goldstein and Pauzner, 2005](#); [Morris and Shin, 2009](#); [He and Xiong, 2012](#); [Liu, 2016](#)). In our model, the financial intermediary does not face a run problem, but aims to raise external funds from investors who must overcome coordination difficulties. Other parallel approaches to bank runs include [Li \(2013\)](#), who studies the systemic bankruptcy risk of firms with investment complementarities. Similar to our analysis, she highlights a non-monotonic relationship between lenders’ expected profits and the interest rate. However, in her model, coordination frictions result from investment decisions in the real sector, whereas our model focuses on investor coordination. Finally, [Bebchuk and Goldstein \(2011\)](#) analyse systemic risk as a coordination failure among banks to fund non-financial firms. In their model, real sector projects are highly interdependent, and in this context, the failure of some banks to lend may prompt all projects to collapse. They study how policy responses can move an economy out of a credit-market freeze.

By highlighting an inefficient shortage of funds to real sector projects, our work also relates to theories of credit market rationing (for a survey, see [Jaffee and Stiglitz, 1990](#)). [Stiglitz and Weiss \(1981\)](#) show that, in an asymmetric information set-up about borrower riskiness, a higher interest rate may attract worse risk borrowers (adverse selection) or prompt borrowers to undertake riskier investments (moral hazard). This entails a non-monotonic relationship between the interest rate and the expected return of the bank. In their model, the optimal interest rate that maximizes the expected return of the bank does not necessarily clear the market (credit rationing). The model in this chapter also features a non-monotonic relationship

between interest rates and the bank's expected return. However, this result is now obtained in the absence of adverse selection or moral hazard among borrowers. In contrast to [Stiglitz and Weiss \(1981\)](#), in our model, the emphasis falls on the supply of funds, with the financial intermediary raising interest rates to attract investors, while simultaneously weighting the negative consequence of a higher interest burden on the success of the project. Although in our framework fee-maximizing intermediaries choose an interest rate that is higher than the socially optimal rate, there is no credit rationing per se because the demand for capital is infinitely elastic and the market clears at the interest rate set by the intermediary.

This paper is organized as follows. The next section presents the main assumptions. Section 3 shows the equilibrium of the model, while Section 4 studies the relationship between returns and the equilibrium threshold. The optimal interest rate set by the bank is analysed in Section 5. Section 6 considers some possible extensions of the model, and the last section concludes.

2.2 Main assumptions

The model features a continuum of small investors, a financial intermediary and an investment project. Investors are the only agents endowed with wealth, however the endowment of each individual investor is small with respect to the amount required by the project. The project, then, will be funded via a debt contract through a financial intermediary that pools capital from investors.

A. The investment project

We consider a large, capital-intensive investment project such as an infrastructure investment. The cash flow generated by the project, denoted by Y , is increasing linearly in the amount of capital available: $Y = (1 + A)K$, where K denotes capital and A is a positive parameter characteristic of the marginal product of capital $(1 + A)$.

The assumption of a linear technology allows us to address the investment problem when capital is in scarce supply in a straightforward manner. With a concave production function and no shortage of capital, the firm will use capital until its marginal productivity equals its cost; this notional demand of capital will thus depend on the interest rate. If the interest rate is large enough, then the demand for capital will be low, which may render the question of the availability of capital irrelevant. The use of a linear technology allows us to rule out such trivial situations. With a linear technology the demand elasticity of capital is infinite

(provided that the cost of capital is below A), and the availability of capital becomes critical.⁴

Project risk takes the form of a stochastic fixed cost denoted by c . In the context of project finance investments, this scale-invariant cost can be best thought of as cost overruns, specific to large infrastructure projects. These can be the result of several factors, such as completion delays, macroeconomic conditions, political instability or technological and operating risks. The true size of this cost is not known at the beginning of the game. We assume that it follows a normal distribution: $c \rightsquigarrow N(\bar{c}, \sigma^2)$, with a mean value $\bar{c} > 0$ and a precision $\alpha = 1/\sigma^2$.⁵ Given this assumption, the (stochastic) output/cash flow of the project after interest expenses and cost overruns are paid-off is:

$$\pi(K, R^K, c) = (1 + A)K - (1 + R^K)K - c = (A - R^K)K - c, \quad (2.1)$$

where we denote by R^K the return on capital to be paid to the financial intermediary, with $R^K \leq A$.

B. The Financial Intermediary

The financial intermediary can be viewed as an investment bank that raises external capital from investors to invest in the real sector project. Funds are collected through a bond issuance such that the risk of the project is borne by the investors who hold the bonds. As a result, the intermediary is assumed to earn a fixed fee τ per unit of capital raised, with $\tau > 0$. In the specific context of project finance, τ can be interpreted as the up-front arrangement fee generally paid to the lead arranger (or the bond trustee) (Gatti, 2013).⁶ The fee covers the intermediary's operating costs such as salaries or rentals, but it may also include a mark-up that reflects the intermediary's market power. In our main set-up, we consider this fee to be exogenously given. This assumption is most realistic when applied to a highly competitive sector of financial intermediation, in which the profit margin is close to zero and the fee merely covers the operating costs.⁷

Given this fixed cost of financial intermediation, the pricing of the financial contract takes

⁴The key insight of our model does not change if, instead of the linear technology, we use a more standard decreasing returns to scale technology, provided that the production function is not "too" concave, such that the "short side" of the market is still determined by the supply of capital.

⁵Naturally, negative costs are of no interest for our analysis. Hence, we restrict our attention to the case in which the mean is sufficiently large and variance sufficiently small, such that $\Pr[c < 0]$ is negligible.

⁶This institutional context motivates our assumption of a fixed τ that is upheld by the investment bank together with the return paid to investors.

⁷In an imperfect competition, financial intermediaries dispose of some market power, and a larger τ will include a market-determined profit margin. In this context, the financial intermediary could strategically manipulate its profit margin to influence the probability of success of the project. This possibility would make our model intractable. Nonetheless, in the Extension section, we consider an alternative fee structure, in which τ increases with the number of investors participating to the project, as a proxy for the intermediary's market share.

the following form:

$$R^K = R + \tau, \tag{2.2}$$

where we denote by R the return the intermediary commits to paying investors. Because the financial intermediary earns a fee for each unit of capital raised, its aim is to maximize the amount of funds invested in the project. Thus, the intermediary will set a rate of return, R , that maximizes the number of investors participating to the project.

C. Investors

There is a continuum $n = 1$ of risk-neutral investors, each endowed with one unit of wealth. They have the choice of either investing in a project that pays a return R per unit invested or placing their funds in a safe asset that yields a return $r > 0$. The safe return can also be thought of as the investors' opportunity cost of capital. The return promised to debt holders by the financial intermediary, R , is risky and depends on the success of the project. If the cash flow generated by the project is sufficiently high, then investors receive $R \geq r$. However, if the project's profit is negative, then the project fails, and investors can only recover a residual value. For simplicity, we assume this residual value to be zero. We denote the proportion of investors that places their funds in the investment project by ℓ , with $\ell \in [0, 1]$.

As noted above, at the outset of the game, the true size of the cost overruns incurred by the project is unknown to all market participants and is drawn from a normal distribution, with mean \bar{c} and precision α . Furthermore, following the standard approach in global games, information about this cost is "heterogeneous": each investor receives a private signal about the true value of c that takes the following form:

$$x_i = c + \epsilon_i, \tag{2.3}$$

where x_i is the signal and ϵ_i the idiosyncratic bias, which is also normally distributed among investors with zero mean and precision β . One way to think of this private signal is that it represents each investor's private assessment of the true risk of the project.

The investors' payoffs, contingent upon their decision and the outcome of the project, itself depending on the realization of the shock c , can be summarized as follows:

$$U = \begin{cases} \text{invest in risky project} & \begin{cases} 1 + R & \text{if } \pi \geq 0 \\ 0 & \text{if } \pi < 0 \end{cases} \\ \text{invest in safe asset} & 1 + r \end{cases}$$

D. Timing

The timeline of the game is represented in Figure 2.1. In the first period ($t = 0$), the financial intermediary proposes a financial contract that promises a return R for each unit of capital invested. Investors then decide whether to participate in the investment project, given their private beliefs about the costs and the return R promised by the intermediary. Thus, the supply of funds for the project is equal to the number of investors, ℓ , who choose the participation strategy. At time $t = 2$, the cash flow of the project is realized, and if sufficiently large, the return on capital R^K , which comprises the intermediary's fee and the investors' return, is paid to the financial intermediary. If the cash flow is negative, then the project is scrapped and investors gain zero.

Figure 2.1: Timing

t=0	t=1	t=2
<ul style="list-style-type: none"> • The intermediary sets R and proposes a financial contract to investors 	<ul style="list-style-type: none"> • Investors observe a noisy signal about the cost overruns • Investors decide on participating to the project or investing in a safe asset 	<ul style="list-style-type: none"> • Cash flow of the project is realized • Investors receive $1+R$ if project is successful and 0 otherwise

Given this sequential structure, the game is solved backwards. We first characterize the optimal decision of investors who must choose between participating in the project or investing in a safe asset, based on the signals they receive and a given R . We then solve the maximization problem of the financial intermediary, which decides R , taking into account the investors' optimal decision.

2.3 The Equilibrium

Given the linear technology in Equation (2.1), the demand for capital is infinitely elastic, and the equilibrium capital is given by the supply of funds, i.e., the number of investors who decide to participate to the investment project: $K = \ell$. The project's stochastic profit can then be re-written as follows:

$$\pi = (A - \tau - R)\ell - c, \tag{2.4}$$

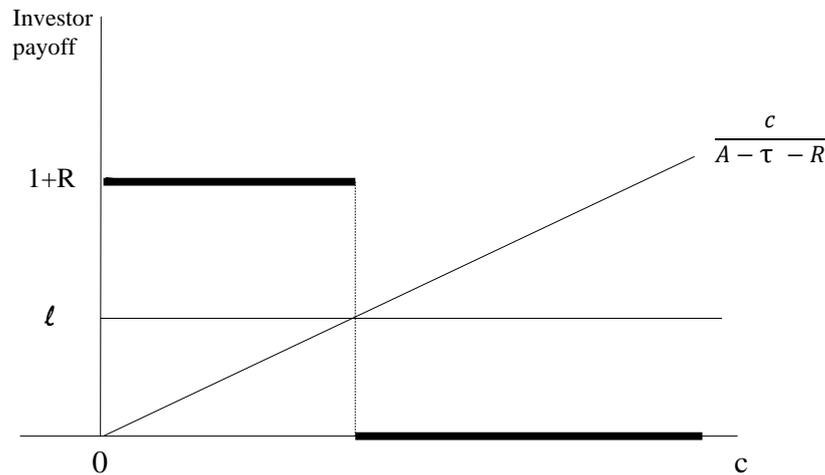
given that $R^K = R + \tau$.

Equation (2.4) indicates the importance of coordination among investors: the higher ℓ is,

the higher the probability that the project is successful and, hence, the higher the expected return of each individual investor who chose the participation strategy. This implies a strategic complementarity among investors' actions.

To provide more intuition on the nature of the coordination game, we take as given a participation rate, $\ell \in (0, 1)$, and study the individual payoff of an investor who decides to participate to the project, depending on the cost overrun c . He/she earns a return $(1 + R)$ if the profit delivered by the project is positive ($\pi > 0$), and zero otherwise. Figure 2.2 represents this payoff structure. When the cost is relatively low such that $\frac{c}{A - \tau - R} < \ell$, the participation to the project is sufficiently large to cover the overrun cost, and the investor will receive a return $(1 + R)$ (represented by the bold upper line). However, if $\frac{c}{A - \tau - R} > \ell$, then the payoff from participating in the project will be zero (represented by the bold lower line) because the funds pooled into the project do not make it possible to cover the overrun cost. All things being equal, if the participation rate ℓ is reduced (increased), then the range of costs c for which the project generates a positive profit shrinks (grows). In other words, the more investors participate, the better are the ex-ante chances that the project succeeds and investors make a positive payoff.

Figure 2.2: Investor payoff from participating to the project



Under perfect information, this investor coordination problem presents multiple equilibria. If $c = 0$, the project makes a positive profit even if a single investor decides to participate. Consequently, all investors have a dominant action to participate. However, if $c > A - \tau - R$, the project fails even if all investors participate. Clearly, none of them should then invest. However, when c lies in the intermediate region $(0, A - \tau - R)$, there is a coordination problem

among investors. If all investors participate, the project yields a positive cash flow and pays a return $(1 + R) > (1 + r)$. However, if no one participates, then the investment project fails, and the return is $0 < r$.

This indeterminacy is removed under our information structure. Not only is c now a random variable, but also investors receive an idiosyncratic, noisy signal x_i about this realized cost. Thus investors' beliefs are no longer common knowledge and the problem can be analysed as a standard global game. Carlsson and Van Damme (1993) and Morris and Shin (1998; 2004) have shown that such games present a unique "threshold" equilibrium characterized by a "cut-off" value of a key state variable, above which the project succeeds and below which the project fails. Related to this cut-off state value, there is a single critical signal such that an individual who receives a signal above the critical one will take the action leading to the high-payoff and below which he/she follows a "wait-and-see" strategy. Their proof proceeds by the successive elimination of dominated strategies. For the sake of parsimony, we do not repeat their proof of existence of a single threshold. Instead, we follow Veldkamp (2011) and assume and then verify that the solution takes the form of a threshold rule.

First, given investors' threshold strategies, we define the critical signal x^* such that an investor who receives a signal below x^* chooses to participate to the project, whereas an investor with a signal above x^* chooses the safe asset. Furthermore, based on the assumption of normal distribution for the overrun cost, when nature draws a realization of c , the signals investors receive are also normally distributed around the realization of c , with a variance β^{-1} . At the same time, recall that the total population of investors has been normalized to one. Hence, the proportion of investors who participate to the project (ℓ) is equal to the frequency of investors who receive a signal below the critical signal, i.e. $\ell(c) = \Pr(x_i < x^* | c)$.⁸

Second, we define a cut-off cost, c^* , such that, when $c > c^*$, the project fails and, when $c < c^*$, the project succeeds. Thus cut-off can be obtained as the solution to $\pi = 0$ or:

$$c^* = (A - \tau - R)\ell(c^*). \quad (2.5)$$

Given this cut-off cost, the "pivotal" investor who receives exactly the signal x^* should be indifferent between participating to the project or not. With risk-neutral individuals, his/her indifference condition can be written as follows:

$$(1 + R) \Pr(c < c^* | x^*) = (1 + r), \quad (2.6)$$

⁸This frequency is the c.d.f. of the distribution of x_i s, centered on the realization of c , and evaluated at x^* , i.e., $F(x^* | c) = \Pr(x_i < x^* | c)$.

where $\Pr(c < c^*|x^*)$ is the probability that the project succeeds, as evaluated by an investors with signal x^* . An equilibrium of the game is a couple (c^*, x^*) jointly satisfying Equations (2.5) and (2.6). Leaving the detailed resolution steps for Appendix A, Proposition 1 states our basic equilibrium result.

PROPOSITION 1. The investors' coordination problem presents a unique threshold equilibrium provided that the precision of the signal is large enough, more precisely, if $\frac{\alpha}{\sqrt{\beta}} \leq \frac{\sqrt{2\pi}}{A - \tau - R}$. The equilibrium critical cost, below which the firm's project succeeds, is implicitly defined by the following equation:

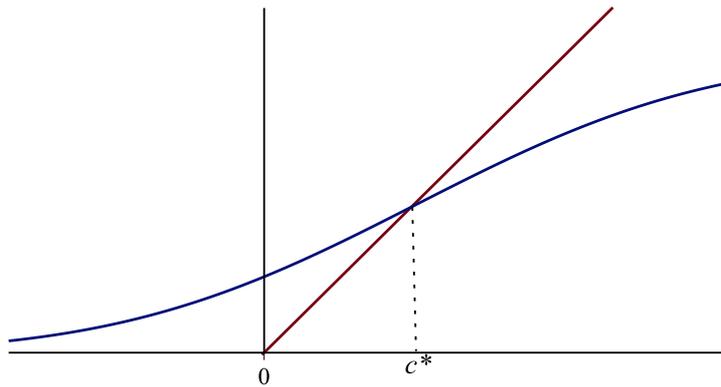
$$c^* = (A - \tau - R)\Phi\left(\frac{\alpha}{\sqrt{\beta}}\left[c^* - \bar{c} - \frac{\sqrt{\alpha + \beta}}{\alpha}\Phi^{-1}\left(\frac{1+r}{1+R}\right)\right]\right), \quad (2.7)$$

where $\Phi(\cdot)$ is the c.d.f. of the standard normal distribution.

PROOF. See Appendix A

Graphically, the equilibrium cut-off cost is presented in Figure 2.3 at the intersection of the 45° line and the scaled-up cumulative normal distribution with mean $\left[\bar{c} + \frac{\sqrt{\alpha + \beta}}{\alpha}\Phi^{-1}\left(\frac{1+r}{1+R}\right)\right]$ and standard deviation $\frac{\alpha}{\sqrt{\beta}}$. The uniqueness of this solution is guaranteed if condition $\frac{\alpha}{\sqrt{\beta}} \leq \frac{\sqrt{2\pi}}{A - \tau - R}$ holds (see discussion in Appendix).

Figure 2.3: The equilibrium critical cost



Clearly, there exists a range of costs for which viable projects fail due to the lack of coordination among investors. In particular, for $c \in (c^*, A - \tau - R)$, the project will succeed if all investors coordinate and participate (but they do not). This leads to a form of inefficient supply of funds, which is the consequence of strategic uncertainty among investors.

The uniqueness of the equilibrium allows us to analyse how the cut-off cost responds to

changes in the parameters of our model. Moreover, changes in c^* are tantamount to changes in the probability of success of the project because $\Pr[c < c^*] = \Phi(\sqrt{\alpha}(c^* - \bar{c}))$ is monotonously increasing in c^* . We derive all comparative statics in the Appendix.

A lower risk-free rate, r , prompts more investors to participate, and thus raises the probability of success of the project. This may correspond to an expansionary monetary policy which lowers long-term interest rates and, in our model, will favour investment in real sector projects. A similar effect occurs for lower average overrun costs, \bar{c} , which can occur in more stable economic environments that decrease certain types of project finance risks, such as the political or operating risk. An increasing wedge τ , as a result of higher management costs or the market power of financial intermediaries, leads to a decline in c^* and thus a decrease in the probability of success of the firm's project.

Finally, a key determinant of the equilibrium cut-off cost is the return R chosen by the financial intermediary. We turn our attention to this relationship next.

2.4 The relationship between the return on capital and the equilibrium cut-off cost

Intuitively, the relationship between c^* (and hence the probability of success of the project) and R is driven by two opposite effects. On the one hand, a higher return R should facilitate investors' coordination by making the decision to invest in the project more appealing. A higher number of investors who participate should, in turn, increase the chances that the project succeeds because more capital is available to cover the fixed cost c . On the other hand, a higher R raises the interest burden of the project, $R + \tau$, which increases its probability of default. We can state the following result:

PROPOSITION 2. The equilibrium cut-off cost $c^*(R)$ admits at least one maximum for R in the interval $[r, (A - \tau)]$.

PROOF. First, from Equation (2.7), it is straightforward that, for $R \in [r, (A - \tau)]$, the function $c^*(R)$ is continuous, positive and lower than $(A - R - \tau)$. Moreover, at the extremes of the interval $[r, (A - \tau)]$, we have that the critical cost converges to zero, as $\lim_{R \rightarrow r} c^*(R) = 0$ and $\lim_{R \rightarrow A - \tau} c^*(R) = 0$.⁹ To characterize the relationship between c^* and R within this interval, we apply the implicit function theorem to Equation (2.7) and obtain the following relation (see

⁹Using the properties of the standard normal distribution: $\Phi^{-1}(1) = \infty$ and $\Phi(-\infty) = 0$.

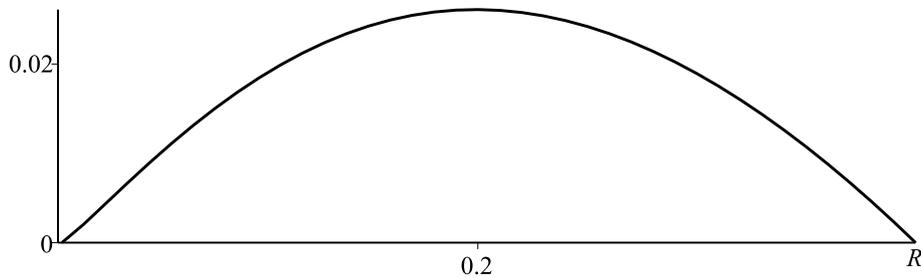
the derivation of this expression in Appendix B):

$$\frac{dc^*}{dR} = \frac{\sqrt{\frac{\alpha + \beta}{\beta}} \frac{(1+r)(A - \tau - R)}{(1+R)^2} \frac{\varphi(H)}{\varphi\left(\Phi^{-1}\left(\frac{1+r}{1+R}\right)\right)} - \Phi(H)}{1 - (A - \tau - R) \frac{\alpha}{\sqrt{\beta}} \varphi(H)}, \quad (2.8)$$

where $H = \frac{\alpha}{\sqrt{\beta}} \left[c^* - \bar{c} - \frac{\sqrt{\alpha + \beta}}{\alpha} \Phi^{-1}\left(\frac{1+r}{1+R}\right) \right]$ and $\varphi(\cdot)$ is the p.d.f of the standard normal distribution. We can show that for the maximal value of R , namely, $A - \tau$, the expression in Equation (2.8) is negative, i.e., that $\left[\frac{dc^*}{dR}\right]_{R=A-\tau} < 0$. First, given the equilibrium uniqueness condition, $\frac{\alpha}{\sqrt{\beta}} \leq \frac{\sqrt{2\pi}}{A-\tau-R}$, the denominator of expression (2.8) is always positive since $1 - (A - \tau - R) \frac{\alpha}{\sqrt{\beta}} \varphi(\cdot) \geq 1 - (A - R - \tau) \frac{\alpha}{\sqrt{\beta}} \frac{1}{\sqrt{2\pi}} > 0$. Second, as the first term of the numerator is zero when $R = A - \tau$, the sign of the derivative is the sign of $-\Phi(H)$. It can be easily seen that $\Phi(H) > 0$, for $R = A - \tau$. As $c^*(R)$ is zero for the minimum value of R and is decreasing to zero towards the maximum, this suffices to prove that $c^*(R)$ admits at least one maximum on the interval $[r, A - \tau]$. *Q.E.D.*

We denote the return that maximizes c^* by \tilde{R} . As the probability of success of the firm, $\Pr[c < c^*(\tilde{R})]$, is monotonic in $c^*(R)$, this interest rate will also maximize the probability that the firm obtains a profit. To bring additional intuition to this result, Figure 2.4 presents a numerical simulation of the evolution of the critical cost c^* as a function of R . The parameter values are $c \sim N(0.1, \frac{1}{10})$, $\epsilon \sim N(0, \frac{1}{100})$, $r = 0.01$, $A = 0.5$ and $\tau = 0.1$. The function $c^*(R)$ has an inverse U -shape, with a maximum at $\tilde{R} = 0.2$. This value corresponds to a probability of success of the project of 40.8%.

Figure 2.4: Evolution of threshold equilibrium c^* as a function of R



The non-linear relationship between the optimal return and the probability of success of the project highlights the importance of coordination frictions in the financial market. Project-

specific risk related to cost overruns can be mitigated by pushing down the interest rate and relaxing the interest-rate burden. However, in the presence of coordination frictions, lower returns on capital imply that fewer funds are directed towards the project, which lowers its chances of success. It should be noticed that, because $\lim_{R \rightarrow r} c^* = 0$, the optimal return is always higher than the risk-free rate, $\tilde{R} > r$.¹⁰

As a numerical counterfactual, we study what would be the interest rate that risk neutral investors require to participate to this project in absence of any coordination frictions. We can rule out coordination problems by assuming that, for example, capital is provided by a single large investor ($K = 1$). The return that such a risk-neutral investor would require is such that he/she is compensated for the project risk, i.e., the risk that overrun cost are so large that the project fails. This return, denoted by R' , can be determined by the zero trade-off condition:

$$(1 + R') \Pr[c < (A - R' - \tau)] = 1 + r \quad (2.9)$$

Setting the same parameters as before, the interest rate demanded by the single investor is $R' = 0.012$, which is 20% higher than r , but significantly lower than $\tilde{R} = 0.2$. Thus, the large wedge between these two interest rates is the direct consequence of coordination frictions between investors. The sharp decline in the probability of success of the project from 99.8% when financed by a single large investor to 40.8% in the case of multiple investors, could be interpreted as a measure of the allocative inefficiency specific to the type of decentralized intermediation studied in this chapter.

2.5 The optimal cost of capital

In this section, we compare the return that maximizes the critical cost with the optimal interest rate set by the financial intermediary. The former return can be thought of as a “socially optimal” interest rate because it maximizes the probability of success of real sector projects. We have shown that a socially optimal return does not necessarily imply setting interest rates close to the opportunity cost of capital, whenever coordination frictions can arise in financial markets. We will argue next that, given the intermediary’s organizational structure, the interest rate it will set is higher than the socially optimal rate.

¹⁰Our main result becomes even sharper in a special case of the game in which private signals become infinitely precise, i.e. $\beta \rightarrow \infty$. Under this assumption the condition for uniqueness always holds and x^* and c^* will converge to the same value:

$$c_{\beta \rightarrow \infty}^* = (A - \tau - R) \Phi \left(-\Phi^{-1} \left(\frac{1+r}{1+R} \right) \right) = \frac{(A - \tau - R)(R - r)}{1 + R}.$$

This function is concave, with a maximum cut-off cost obtained for a \tilde{R} solving: $1 + \tilde{R} = \sqrt{(1+r)(1+A-\tau)}$.

The intermediary charges a transaction fee τ for every unit of capital raised. Thus, if the project succeeds, its total profit will be $\Pi = \tau\ell$, as the proportion of investors participating, ℓ , is also the total amount of funds raised. Naturally, the intermediary sets the return to be paid to investors, R , at the outset of the game, before the shock c is realized. As a result, it must take into account the fact that the actual proportion of investors who end up participating to the project is conditional on the realization of c . Thus, the decision problem of the financial intermediary is to maximize its ex-ante expected income given by:

$$\text{Max}_R E[\Pi] = \tau E[\ell(x^*(R), c)] = \tau \int_{-\infty}^{c^*(R)} \ell(x^*(R), c) f(c) dc, \quad (2.10)$$

given the ex-ante distribution of shocks c and the equilibrium values of c^* and x^* as a function of R . We denote the return that maximizes Equation (2.10) by \hat{R} . It can be shown that:

PROPOSITION 3. The optimal interest rate set by the financial intermediary, \hat{R} , is higher than the socially optimal return that maximizes the probability of success of the project, \tilde{R} .

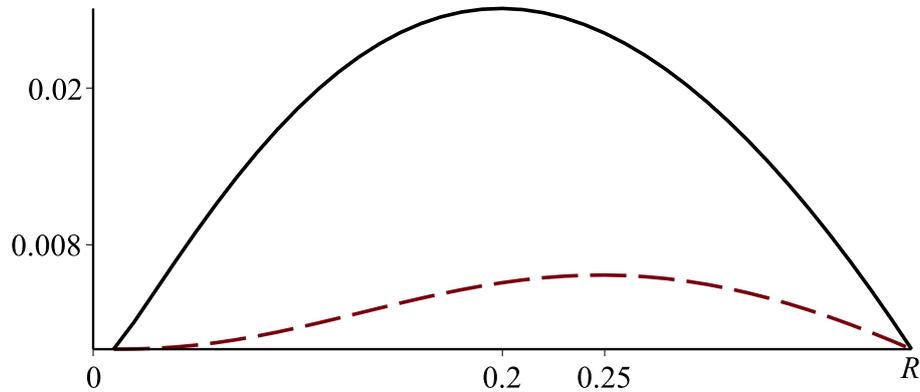
PROOF. *See Appendix.*

The intuition behind the result in Proposition 3 is as follows: in the presence of coordination frictions, the intermediary aiming to maximize the pool of funds invested in the project will set a price of capital that is higher than the socially optimal rate. The wedge between the two returns is not necessarily the result of rents extracted by the financial intermediary. On the contrary, the higher interest rate is a coordination device that enables more funds to be directed towards the project. The inefficiency that results from this, is thus the consequence of the financial contract studied in this chapter.

As it is higher than the socially optimal return, the interest rate set by the intermediary is also associated with a lower probability of success of the project. Figure 2.5 numerically simulates the two maxima obtained in Propositions 2 and 3. The full line represents the evolution of the threshold equilibrium cost c^* as a function of R using the same parameter values as in Figure 2.4. The dashed line shows the evolution of the total funds attracted by the bank, $E[\ell(c^*(R))]$ as a function of R , with the peak at $\tilde{R} = 0.25$, which is the optimal return set by the bank. The maximum probability of success of the firm of 40.8% is reached for $\tilde{R} = 0.20$. Consequently, under the return set by the financial intermediary, this probability drops to 40.5%.

The non-monotonic relationship in Figure 2.5 is reminiscent of the well-known trade-off in Stiglitz and Weiss (1981) between bank profit and interest rates. In their model, the

Figure 2.5: Social versus bank optimal return



expected return of the bank is a hump-shaped function of interest rates: due to the imperfect information about borrowers' type or actions, the direct benefit of higher rates is offset by a sorting of the worse-risk borrowers or increased moral hazard. We obtain a similar trade-off, but through a completely different mechanism. In our model, there is no adverse selection or moral hazard on the borrower side and higher interest rates increase the probability of default of the project only due to the increase in the interest burden. However, this negative effect is offset by the increase in the amount of capital that is attracted as a result of an increase in interest rates. Although our model suggests that the optimal interest rate is higher than the socially optimal rate that maximizes project success and the amount of credit, there is no “credit rationing” as defined by [Stiglitz and Weiss \(1981\)](#) because, in our case, the demand for capital is infinitely elastic.

Our analysis thus suggests a different type of credit market inefficiency that stems from the supply rather than the demand of credit. We show that constraints in the supply of credit can be the result of coordination frictions in capital markets and can lead to higher interest rates. In what follows, we discuss some of the implications of this result and consider several possible extensions of the model.

2.6 Discussion and extensions

In this section, we discuss the implications of our model by considering several extensions. First, we consider an alternative fee structure for the financial intermediary, in which its mark-up increases with the number of investors participating to the project. Second, we analyse the limit when bank fees are negligible and the intermediary maximizes investors' expected returns.

A. Alternative fee structure

In Section 5, we have shown that the interest rate set by the arranger of the financial contract is higher than the rate that maximizes the probability that the project turns profitable. This result holds regardless of the size of the fixed fee charged by the intermediary. We now consider an extension in which the size of the fee reflects some form of market power. It is natural to assume that the higher the number of investors attracted to the project is, the greater the market share of the intermediary. This would result in a fee τ that is increasing in the number of investors who participate to the project, $\tau(\ell)$. In this context, the intermediary's maximization problem becomes:

$$\text{Max}_R E[\Pi] = E[\tau(\ell(R, c))\ell(R, c)], \quad (2.11)$$

where now $\tau(\ell(R, c))$ is an increasing function of the number of investors who participate.

If we assume a simple linear form for this relationship such that $\tau(\ell) = \ell \leq 1$, then the intermediary's income as a function of R is depicted in Figure 2.6 for the same parameters used throughout the paper. Figure 2.6 compares the intermediary's revenue under this alternative fee structure (full line) with our main model (dashed line). Clearly, the optimal return set by the bank is higher when fees are increasing with market power. For the same parameters as before, this corresponds to an increase in R from 0.24 to 0.27, which results in a drop in the probability of project success of 0.2 percentage points. While we cannot compare analytically the maximum in Equation (2.11) with the optimal return in Proposition 3, intuitively, if we let the bank's fee increase with the number of investors participating, then this increase in bank income will lower the probability of success of the project, which will prompt investors to demand a higher return.

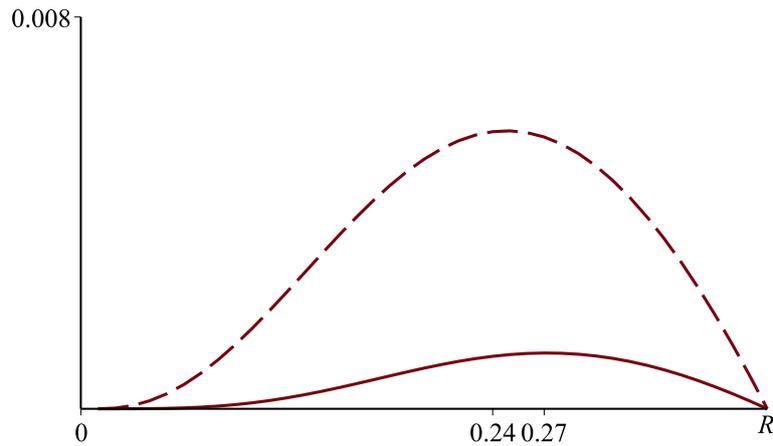
B. Alternative goal of the intermediary

So far, the analysis considered that the intermediary's fee is strictly positive. Another extension of the model consists in analyzing the behavior of a financial intermediary in the limit case where fees are negligible, $\tau \rightarrow 0$. This would also reflect the limiting case of perfect competition. In this case, an alternative goal for the intermediary would be to maximize the expected return of its creditors as in [Diamond and Dybvig \(1983\)](#). This maximization problem can be written as:

$$R^\circ = \underset{R}{\text{argmax}} \{ \Pr[c < c^*(R)](1 + R) \}.$$

From the first order condition we can show that:

Figure 2.6: Alternative bank fee structure



$$\frac{dc^*}{dR} = -\frac{\Phi(\sqrt{\alpha}(c^* - \bar{c}))}{\varphi(\sqrt{\alpha}(c^* - \bar{c}))}(1 + R)^{-1} < 0.$$

Thus, similar to the proof of Proposition 3, we can show that the rate R° that maximizes investors' expected return is necessarily higher than the socially optimal return that maximizes $c^*(R)$, which is set such that $[\frac{dc^*}{dR}]_{R=\tilde{R}} = 0$. This is because R° necessarily falls on the downward sloping part of the curve $c^*(R)$, i.e., $[\frac{dc^*}{dR}]_{R=R^\circ} < 0$, and, as a result, $R^\circ > \tilde{R}$. In numerical simulations, at $R^\circ = 0.39$, the interest rate that maximizes investors' expected return is well above the optimal return, $\tilde{R} = 0.2$. In this case, the probability of success of the project is as low as 37.8%.

2.7 Concluding remarks

This chapter presents a model of an investment bank that seeks to pool funds from a large number of investors into a capital-intensive project. The possibility that these investors fail to coordinate leads to a strategic risk that compounds its effect on the project specific risk, which takes the form of a random overrun cost. We analyse the equilibrium behaviour of investors in a standard global games approach and show that there exists an equilibrium critical cost that separates the failure and success states of the project. The higher this critical cost is, the lower the probability of default of the project.

The main contribution of the model is to show that this cut-off cost (and the probability of default) depends in a non-monotonic manner on the return on capital set by the financial intermediary. On the one hand, a higher return mitigates the coordination frictions among investors, increasing the volume of available funds. On the other hand, a higher interest rate

increases the project's financing costs, lowering its probability of success. It can be shown that there exists a socially optimal price of capital that maximizes the chances that the project is successful. Coordination frictions push this interest rate well above the rate demanded to compensate a single investor for the project's operating risk. This highlights a new source of inefficiency in decentralized capital markets. We then show that intermediaries aiming to maximize the amount of funds pooled into the project (and their fee-based income) will set a return that is higher than the rate that maximizes the probability of success of the project. This result holds even in the presence of perfect competition in the intermediation sector or alternative fee structures of the bank.

The model best describes a particular form of project finance investment in which capital is raised through a bond issuance in the capital market. The recent global financial crisis has increased the use of this type of financial arrangement to fund large-scale, capital-intensive projects. This increase in project bond financing is partly due to: (i) tighter capital requirements that have forced banks to deleverage; (ii) a search for yield by institutional investors in a post-crisis low interest environment ([Thompson, 2013](#)); (iii) but also active efforts by governments and international organizations to promote this type of alternative market funding for large capital-intensive projects, such as the Europe 2020 Project Bond Initiative ([European Commission, 2012](#)). Project finance bonds require investment banks to pool many investors towards a common goal in the absence of a strong coordination mechanism. Our model shows that this type of funding may be prone to coordination frictions that translate into a high cost of capital for the project.

Our model can also have some implications for traditional bank finance, particularly in the case when banks themselves are financially constrained. Recent empirical evidence suggests that credit rationing can also be the result of banks' funding constraints and not only the quality of the pool of borrowers.¹¹ In the light of our analysis, the ability of banks to raise external finance themselves may impact their lending to the real economy and result in an inefficient allocation of capital. The severity of such liquidity shortages is likely to be harsher during economic downturns. For example, empirical findings show that, during the 2007-09 financial crisis, firms borrowing from liquidity constrained banks paid higher loan spreads ([Santos, 2011](#)). Our theoretical model also suggests that banks' ability to obtain funding is closely related to their loan pricing.

Despite the limitations of a highly stylized model of bond-based financing, our approach

¹¹Such studies relate exogenous shock to banks' liquidity to their lending to the real sector. For example, [Khwaja and Mian \(2008\)](#) study a large liquidity shock to Pakistani banks and find that a 1% drop in bank liquidity resulted in a 0.87% drop in lending to small firms. Similarly, [Paravisini \(2008\)](#) shows how Argentinian local banks expand credit by \$0.66 in response to an additional dollar of external financing.

highlights how coordination frictions can affect real sector outcomes and emphasizes the use of the return on capital by banks as an investor coordinating device.

Appendices

2.A Proof of Proposition 1

Following standard resolution steps (Morris and Shin, 2001; 2004), we assume that investors follow a switching strategy around a threshold signal x^* , such that they invest when they receive a signal lower than x^* . Then, the proportion of investors who invest, denoted by ℓ , is just the probability that any particular investor invests. Given the switching equilibrium, for a given cost c , this probability is given by:

$$\ell = \Pr(x_i < x^* | c) = \Pr(\epsilon_i < x^* - c) = \Phi(\sqrt{\beta}(x^* - c)). \quad (2.12)$$

Next, define by c^* the cut-off cost for which the project is on the edge between failing and succeeding, i.e., the level at which the profits are zero such that, $c^* = (A - \tau - R)\ell$. Thus, given Equation (2.12), c^* is implicitly defined by:

$$c^* = (A - \tau - R)\Phi(\sqrt{\beta}(x^* - c^*)). \quad (2.13)$$

This gives us a first relation which defines c^* as a function of x^* .

Second, given our assumptions about the normality of the distributions of costs and signals, when an investor i receives a signal x_i , his posterior distribution of c is also normal, with mean $\left(\frac{\alpha\bar{c} + \beta x_i}{\alpha + \beta}\right)$ and precision $(\alpha + \beta)$. So, for an investor with signal x_i , the probability of success of the project is the following:

$$\Pr(c < c^* | x_i) = \Phi\left(\sqrt{\alpha + \beta}\left[c^* - \frac{\alpha\bar{c} + \beta x_i}{\alpha + \beta}\right]\right). \quad (2.14)$$

Moreover, at the switching point, an investor receiving the critical signal x^* is indifferent between participating or not to the project. His indifference condition can be written as:

$$(1 + R)\Pr(c < c^* | x^*) = (1 + r), \quad (2.15)$$

which is equivalent to:

$$\Phi\left(\sqrt{\alpha+\beta}\left[c^* - \frac{\alpha\bar{c} + \beta x^*}{\alpha+\beta}\right]\right) = \frac{1+r}{1+R}. \quad (2.16)$$

After some calculations it follows that:

$$x^* - c^* = \frac{\alpha}{\beta}(c^* - \bar{c}) - \frac{\sqrt{\alpha+\beta}}{\beta}\Phi^{-1}\left(\frac{1+r}{1+R}\right), \quad (2.17)$$

which defines x^* as a function of c^* .

The equilibrium critical thresholds x^* and c^* are thus the solution to the system of Equations (2.13) and (2.17). By substituting Equation (2.17) in (2.13), we obtain the equation in Proposition 1:

$$c^* = (A - \tau - R)\Phi\left(\frac{\alpha}{\sqrt{\beta}}\left[c^* - \bar{c} - \frac{\sqrt{\alpha+\beta}}{\alpha}\Phi^{-1}\left(\frac{1+r}{1+R}\right)\right]\right). \quad (2.18)$$

Graphically, the equilibrium cut-off cost is obtained at the intersection of the 45° line and the scaled-up cumulative normal distribution with mean $\left[\bar{c} + \frac{\sqrt{\alpha+\beta}}{\alpha}\Phi^{-1}\left(\frac{1+r}{1+R}\right)\right]$ and standard deviation $\frac{\alpha}{\sqrt{\beta}}$ (see Figure 2.3). The uniqueness of this solution is guaranteed when the slope of the right hand-side of Equation (2.18) is less than one, that is: $(A - \tau - R)\varphi(\cdot)\frac{\alpha}{\sqrt{\beta}} < 1$, where $\varphi(\cdot)$ is the p.d.f. of the standard normal distribution. Given that $\varphi(\cdot) \leq \frac{1}{\sqrt{2\pi}}$, then the unique solution exists if condition $\frac{\alpha}{\sqrt{\beta}} \leq \frac{\sqrt{2\pi}}{A - \tau - R}$ holds. *Q.E.D.*

2.B Comparative statics

In this Appendix, we analyze how the equilibrium cut-off cost c^* varies with the various parameters of the model. This follows from applying the implicit function theorem to Equation (2.7). Consider the function:

$$I(c^*, R, r, \bar{c}, \tau) = c^* - (A - \tau - R)\Phi\left(\frac{\alpha}{\sqrt{\beta}}\left[c^* - \bar{c} - \frac{\sqrt{\alpha+\beta}}{\alpha}\Phi^{-1}\left(\frac{1+r}{1+R}\right)\right]\right) = 0$$

We have that:

$$\frac{\partial I}{\partial c^*} = 1 - (A - \tau - R)\frac{\alpha}{\sqrt{\beta}}\varphi(H) \geq 1 - (A - R)\frac{\alpha}{\sqrt{\beta}}\frac{1}{\sqrt{2\pi}} > 0,$$

given the imposed condition for equilibrium uniqueness $\frac{\alpha}{\sqrt{\beta}} \leq \frac{\sqrt{2\pi}}{A-R}$, and

$$\begin{aligned}\frac{\partial I}{\partial R} &= \Phi(H) - (A - \tau - R)\varphi(H) \frac{\sqrt{\alpha + \beta}}{\sqrt{\beta}} \frac{1}{\varphi(\Phi^{-1}(\frac{1+r}{1+R}))} \frac{1+r}{(1+R)^2} \\ \frac{\partial I}{\partial r} &= (A - \tau - R)\varphi(H) \frac{\sqrt{\alpha + \beta}}{\sqrt{\beta}} \frac{1}{\varphi(\Phi^{-1}(\frac{1+r}{1+R}))} \frac{1}{1+R} > 0 \\ \frac{\partial I}{\partial \bar{c}} &= (A - \tau - R)\varphi(H) \frac{\alpha}{\sqrt{\beta}} > 0 \\ \frac{\partial I}{\partial \tau} &= \tau\Phi(H) > 0,\end{aligned}$$

where $H = \frac{\alpha}{\sqrt{\beta}} \left[c^* - \bar{c} - \frac{\sqrt{\alpha + \beta}}{\alpha} \Phi^{-1} \left(\frac{1+r}{1+R} \right) \right]$ and φ is the p.d.f of the standard normal distribution. From the implicit function theorem, it follows that:

$$\begin{aligned}\frac{dc^*}{dR} &= -\frac{\partial I / \partial R}{\partial I / \partial c^*} \\ \frac{dc^*}{dr} &= -\frac{\partial I / \partial r}{\partial I / \partial c^*} < 0 \\ \frac{dc^*}{d\bar{c}} &= -\frac{\partial I / \partial \bar{c}}{\partial I / \partial c^*} < 0 \\ \frac{dc^*}{d\tau} &= -\frac{\partial I / \partial \tau}{\partial I / \partial c^*} < 0.\end{aligned}$$

2.C Proof of Proposition 3

The maximization problem in Equation (2.10) yields the following first order condition:

$$\tau \frac{d}{dR} \int_{-\infty}^{c^*(R)} \ell(R) f(c) dc = 0,$$

where $\ell(R) = \Phi[\sqrt{\beta}(x^*(R) - c)]$ given Equation (2.12) and $f(c) = \sqrt{\alpha}\varphi[\sqrt{\alpha}(c - \bar{c})]$ is the ex-ante density function of c . Dividing by τ and applying Leibniz's Rule we obtain:

$$\int_{-\infty}^{c^*(R)} \frac{\partial}{\partial R} \Phi \left[\sqrt{\beta}(x^*(R) - c) \right] f(c) dc + \frac{\partial c^*(R)}{\partial R} \Phi \left[\sqrt{\beta}(x^*(R) - c^*(R)) \right] f(c^*(R)) = 0$$

Differentiating under the integral yields:

$$\begin{aligned}\frac{\partial x^*(R)}{\partial R} \int_{-\infty}^{c^*(R)} \sqrt{\beta}\varphi \left[\sqrt{\beta}(x^*(R) - c) \right] \sqrt{\alpha}\varphi \left[\sqrt{\alpha}(c - \bar{c}) \right] dc \\ + \frac{\partial c^*(R)}{\partial R} \Phi \left[\sqrt{\beta}(x^*(R) - c^*(R)) \right] \sqrt{\alpha}\varphi \left[\sqrt{\alpha}(c^*(R) - \bar{c}) \right] = 0\end{aligned}\quad (2.19)$$

The product of the two standard normal p.d.f. under the integral sign becomes: $\sqrt{\beta}\varphi \left[\sqrt{\beta}(c - x^*(R)) \right] \cdot \sqrt{\alpha}\varphi \left[\sqrt{\alpha}(c - \bar{c}) \right] = \sqrt{\frac{\alpha\beta}{\alpha+\beta}} \varphi \left[\sqrt{\frac{\alpha\beta}{\alpha+\beta}}(x^*(R) - \bar{c}) \right]$.

$\sqrt{\alpha + \beta} \varphi \left[\sqrt{\alpha + \beta} \left(c - \frac{\beta x^*(R) + \alpha \bar{c}}{\alpha + \beta} \right) \right]$, using standard properties of the normal distribution.¹²

Thus Equation (2.19) becomes:

$$\begin{aligned} & \frac{\partial x^*(R)}{\partial R} \sqrt{\frac{\alpha\beta}{\alpha+\beta}} \varphi \left[\sqrt{\frac{\alpha\beta}{\alpha+\beta}} (x^*(R) - \bar{c}) \right] \int_{-\infty}^{c^*(R)} \sqrt{\alpha + \beta} \varphi \left[\sqrt{\alpha + \beta} \left(c - \frac{\beta x^*(R) + \alpha \bar{c}}{\alpha + \beta} \right) \right] dc \\ & + \frac{\partial c^*(R)}{\partial R} \Phi \left[\sqrt{\beta} (x^*(R) - c^*(R)) \right] \sqrt{\alpha} \varphi \left[\sqrt{\alpha} (c^*(R) - \bar{c}) \right] = 0 \end{aligned} \quad (2.20)$$

But $\int_{-\infty}^{c^*(R)} \sqrt{\alpha + \beta} \varphi \left[\sqrt{\alpha + \beta} \left(c - \frac{\beta x^*(R) + \alpha \bar{c}}{\alpha + \beta} \right) \right] dc = \Phi \left[\sqrt{\alpha + \beta} \left(c^*(R) - \frac{\beta x^*(R) + \alpha \bar{c}}{\alpha + \beta} \right) \right] = \Phi \left[\Phi^{-1} \left(\frac{1+r}{1+R} \right) \right] = \frac{1+r}{1+R}$, where we have replaced $x^*(c^*(R)) = \frac{\alpha+\beta}{\beta} c^*(R) - \frac{\alpha}{\beta} \bar{c} - \frac{\sqrt{\alpha+\beta}}{\beta} \Phi^{-1} \left(\frac{1+r}{1+R} \right)$. Also since $\frac{\partial x^*(R)}{\partial R} = \frac{\alpha+\beta}{\beta} \frac{\partial c^*(R)}{\partial R} + \frac{\sqrt{\alpha+\beta}}{\beta} \frac{1}{\varphi(\Phi^{-1}(\frac{1+r}{1+R}))} \frac{1+r}{(1+R)^2}$, Equation (2.20) becomes:

$$\begin{aligned} & \sqrt{\frac{\alpha\beta}{\alpha+\beta}} \varphi \left[\sqrt{\frac{\alpha\beta}{\alpha+\beta}} (x^*(R) - \bar{c}) \right] \frac{1+r}{1+R} \left[\frac{\alpha + \beta}{\beta} \frac{\partial c^*(R)}{\partial R} + \frac{\sqrt{\alpha + \beta}}{\beta} \frac{1}{\varphi(\Phi^{-1}(\frac{1+r}{1+R}))} \frac{1+r}{(1+R)^2} \right] + \\ & \frac{\partial c^*(R)}{\partial R} \Phi \left[\sqrt{\beta} (x^*(R) - c^*(R)) \right] \sqrt{\alpha} \varphi \left[\sqrt{\alpha} (c^*(R) - \bar{c}) \right] = 0 \end{aligned}$$

Thus, we obtain that:

$$\begin{aligned} \frac{\partial c^*(R)}{\partial R} &= - \frac{1}{\sqrt{\frac{\alpha(\alpha+\beta)}{\beta}} \varphi \left[\sqrt{\frac{\alpha\beta}{\alpha+\beta}} (x^*(R) - \bar{c}) \right] \frac{1+r}{1+R} + \Phi \left[\sqrt{\beta} (x^*(R) - c^*(R)) \right] \sqrt{\alpha} \varphi \left[\sqrt{\alpha} (c^*(R) - \bar{c}) \right]} \\ & \left[\sqrt{\frac{\alpha}{\beta}} \frac{(1+r)^2}{(1+R)^3} \frac{\varphi \left[\sqrt{\frac{\alpha\beta}{\alpha+\beta}} (x^*(R) - \bar{c}) \right]}{\varphi(\Phi^{-1}(\frac{1+r}{1+R}))} \right] < 0 \end{aligned} \quad (2.21)$$

In the proof of Proposition 2, we have shown that there exists a return \tilde{R} that maximizes $c^*(R)$, i.e. $\left[\frac{dc^*}{dR} \right]_{R=\tilde{R}} = 0$. From condition (2.21) above it follows that the optimal interest rate set by the financial intermediary, \hat{R} , is reached on the downward slope of the curve $c^*(R)$, because $\left[\frac{dc^*}{dR} \right]_{R=\hat{R}} < 0$. Thus, this interest rate is necessarily higher than the one that maximizes the firm's probability of success ($\hat{R} > \tilde{R}$). This result holds regardless of the size of the intermediary's fee, $\tau > 0$.

¹²This follows from a well-know property of the normal distribution. If $x \rightsquigarrow N(\mu, \sigma^2)$ then $\frac{1}{\sigma} \varphi \left(\frac{x-\mu}{\sigma} \right) \frac{1}{\sigma'} \varphi \left(\frac{x-\mu'}{\sigma'} \right) = \frac{1}{\sigma^*} \varphi \left(\frac{\mu-\mu'}{\sigma^*} \right) \frac{\sigma^*}{\sigma\sigma'} \varphi \left(\frac{x-\mu^*}{\sigma^*} \right)$, where $\sigma^* = \sqrt{\sigma^2 + \sigma'^2}$ and $\mu^* = \frac{\sigma'^2 \mu + \sigma^2 \mu'}{\sigma^2 + \sigma'^2}$. See, for example, Corollary 4.2. in Aldershof et al. (1995).

Chapter 3

Experimental Evidence on Bank Runs under Partial Deposit Insurance¹

Abstract

This chapter proposes a laboratory experiment to study the impact of partial deposit insurance schemes on the risk of deposit withdrawals. In the experiment, depositors decide whether to withdraw or leave their money in a bank, triggering a default when too many participants choose to withdraw. When a bank run occurs, the amount of wealth each depositor can recover depends on the number of withdrawals and a deposit insurance fund whose size cannot cover in full all depositors. We consider two treatments: (i) a perfect information case when depositors know the size of the insurance fund and (ii) a heterogeneous information setting when they only observe noisy signals about its size. Our results show that uncertainty about the level of deposit coverage exerts a significant impact on the propensity to run. The frequency of runs is relatively high in both treatments, despite the large gains from coordinating on the payoff dominant equilibrium. Bank runs are more likely when depositors have heterogeneous information and as the size of the deposit insurance fund increases. In both settings, a majority of subjects follow a threshold strategy consistent with a risk-dominant equilibrium selection.

¹This chapter is co-authored with Radu Vranceanu from ESSEC Business School and THEMA. We would like to thank Delphine Dubart for her help in organizing the experimental sessions, Vittorio LaroCCA and participants to the 7th International Conference of the French Association of Experimental Economics (Cergy) for useful comments and suggestions.

3.1 Introduction

Deposit insurance schemes are crucial elements of modern financial safety nets. Demirgüç-Kunt and Laeven (2013) find that 60% of countries worldwide have a form of explicit deposit insurance scheme (DIS) in place.² Economic theory generally argues that a full and credible deposit insurance can prevent bank runs (Diamond and Dybvig, 1983). However, the majority of DIS appear grossly underfunded: in more than half of the countries in Demirgüç-Kunt and Laeven's (2013) sample, the size of the deposit insurance fund is less than 50% of the total deposits that need to be covered (in a third of the countries, it is less than 10% of insured deposits). These underfunded deposit insurance schemes can call into question the ability of governments to cover the full amount of insured deposits. As a result, even holders of insured deposits can suffer substantial losses, in particular if depositors rush to withdraw their funds from all the banks simultaneously (Ennis and Keister, 2009). This perspective of a systemic banking crisis is likely to increase the risk of runs at individual banks.³ Indeed, in recent years many bank runs occurred in countries with extensive deposit insurance schemes in place, such as the UK in 2008 (Northern Rock), the Netherlands in 2009 (DSB Bank), Latvia in 2012 (Swedbank), Bulgaria in 2014 (two banks), the systemic bank run in Cyprus in 2013, as well as the slow moving “run” on deposits in Greece between 2010 and 2012.

These recent events call into question the effectiveness of deposit insurance schemes in alleviating the risk of deposit withdrawals. This chapter proposes a laboratory experiment to study the role of partial deposit insurance schemes in preventing bank runs. In particular, we investigate whether the size and coverage of the deposit insurance fund has an impact on individuals' propensity to withdraw. Our framework has two key features. First, we consider *partial* deposit coverage, since the resources available in the insurance fund do not generally cover the total amount of insured deposits in the banking sector. Second, we consider a setting in which a bank run is equivalent to a systemic crisis, such that depositor rushing to the bank need to be compensated by the deposit insurance fund. This allows us to test the efficiency of deposit insurance schemes in mitigating system-wide bank runs.

In the experiment, five subjects play the role of depositors at a bank for ten identical

²The source of funding and deposit coverage ratio varies markedly across countries. For example, the coverage limit ranges from a low of \$406 in Moldova to a high of \$1.5 million in Thailand.

³This has also been suggested by several empirical studies that look at the cross-country effects of financial safety nets. For example, Demirgüç-Kunt and Detragiache (2002) find that explicit deposit insurance tends to be detrimental to bank stability whenever the coverage is extensive, the insurance scheme is run by the government and the institutional environment is weak. Similarly, Hoggarth et al. (2005) show that countries with explicit *unlimited* insurance are ex-ante more likely to experience a banking crisis, while those with explicit but *partial* insurance are less likely. This evidence suggests that whenever deposit coverage is extensive, but depositors believe that governments are not likely to commit to cover the everyone in case of system-wide bank distress, bank runs tend to be more likely.

rounds. At the beginning of each round, they each receive a 10 Euro deposit. Participants must decide whether to withdraw their deposit or leave the money in the bank. Payoffs depend on individual decisions, as well as the decisions of others. If less than three depositors withdraw, the “patient” depositors (those who wait) can make a substantial profit. If three or more participants withdraw, the liquidity reserves of the bank are exhausted and it can no longer repay depositors. Whenever such a bank run occurs, what depositors can recover from their initial endowment depends on a deposit insurance fund. The size of this fund is randomly drawn from the interval $[0, 50]$. If this fund is large enough, depositors who withdraw can recover their initial deposit. Otherwise, the fund is equally split between those who withdraw. Those who wait get nothing in case of bank failure. This is a typical coordination game with strategic complementarity as in [Diamond and Dybvig \(1983\)](#). Given the multiplicity of equilibria of such coordination games, we employ two equilibrium refinements to characterize the aggregate behavior of players.

These are modeled in two experimental treatments related to the type of information depositors receive about the deposit insurance fund. In a first treatment, subjects were asked to play the wait/withdraw game under a *perfect information* setting in which they observe the actual size of the deposit insurance fund in each round. Under perfect information, the two pure-strategy equilibria of the game are: (i) a payoff-dominant equilibrium where all players choose the “wait” strategy and (ii) a bank-run equilibrium in which all players choose the “withdraw” strategy. While standard theory lacks a clear prediction about which of these two equilibria will prevail, a well-known equilibrium refinement, defined as risk-dominance in [Harsanyi and Selten \(1988\)](#), offers a useful guidance to understanding aggregate behavior. The intuition behind this concept is that a player chooses the action that maximizes his/her expected payoff, under the assumption that others play either of “wait” or “withdraw” action with an equal probability (see also [Heinemann et al., 2004](#)).

In a second treatment, we consider an *heterogeneous information* variant of this game. In this set-up, individuals no longer know the size of the deposit insurance fund and receive also noisy, idiosyncratic signals about it in each round. Such coordination games with strategic complementarity and heterogeneous information are referred to as global games. [Carlsson and Van Damme \(1993\)](#) and [Morris and Shin \(1998\)](#) have shown that they present a single “threshold equilibrium” in which players pick the strategy that coincides with the risk-dominance criterion, even when the payoff-dominant one is available.⁴ We find that players’ behavior in each of the two treatments is consistent with these two equilibrium selection criteria.

⁴Several experimental papers have shown that this threshold equilibrium is a valid characterization of players’ behavior in various global games frameworks ([Heinemann et al., 2004, 2009](#)).

Our main experimental result consists in showing that bank runs occur quite often, in a spontaneous way, despite the significantly higher payoff of the no-run equilibrium. We refer to a “bank run” as a situation in which more than two depositors withdraw and the deposit insurance scheme must compensate depositors. Depending on the treatment, the frequency of runs ranges from 2.5% to 45% of the cases and is significantly higher in the heterogeneous information case compared to the perfect information one. Our results thus suggest that uncertainty about the coverage of deposit insurance exerts a significant impact on the propensity to withdraw. We analyze individual behavior and show that a majority of players resort to “threshold strategies”, i.e., there is critical cutoff value of the observed or perceived (in the heterogeneous information case) size of the deposit insurance fund around which they switch between waiting and withdrawing. Thus, using the two equilibrium refinements, we can characterize a fairly predictable equilibrium behavior.

In both treatments, the frequency of participants who withdraw is increasing in the size of the deposit insurance fund. This is in line with a risk dominant equilibrium selection as the payoff from playing the “safe” action, i.e. withdraw, is increasing with the size of the fund. Thus, a very low deposit insurance actually reduces the probability of runs, as the expected payoff from withdrawing is very low.⁵ However, for very high levels of deposit insurance, depositors are more prone to running on the bank, as the payoff from the “safe” option is high. Thus, from a policy perspective, extensive, explicit deposit insurance can actually be detrimental to bank stability, when the size of the deposit insurance fund is not sufficient to cover all deposits. Such arguments can also explain why empirical evidence that looks at episodes of systemic banking crises tends to associate an extensive deposit coverage with a higher ex-ante probability of bank distress ([Demirgüç-Kunt and Detragiache, 2002](#); [Hoggarth et al., 2005](#)). Thus, while deposit insurance schemes can be an efficient way to contain runs at individual banks, they might amplify or accelerate a systemic crisis.

These results bring new evidence to a growing body of literature that studies bank runs in an experimental setting.⁶ Generally, these studies generate panic-based runs by (i) forcing some of the subjects to withdraw early ([Madies, 2006](#); [Kiss et al., 2012](#); [Garratt and Keister, 2009](#)); (ii) introducing uncertainty about banks’ returns and observability of actions ([Schotter and Yorulmazer, 2009](#); [Brown et al., 2016](#); [Chakravarty et al., 2014](#)) or (iii) varying the coordination parameter needed for the payoff-dominant equilibrium to occur ([Arifovic et al., 2013](#)). For example, [Garratt and Keister \(2009\)](#) use a payoff structure similar to ours, but

⁵This is in line with the results of other coordination games such as minimum effort experiments. [Brandts and Cooper \(2006\)](#) show that a lower attractiveness of the safe action relative to the risky action leads to a higher occurrence of the Pareto-optimal equilibrium.

⁶For surveys on applying experimental methods to macroeconomic issues including banking crises, see [Duffy \(2014\)](#), [Cornand and Heinemann \(2014\)](#) and [Dufwenberg \(2015\)](#).

force some players to withdraw early. Interestingly, in a treatment with no forced withdrawals, they find no evidence of runs and show that players always coordinate on the payoff-dominant equilibrium. At difference with this study, our setting does not require any “exogenous” triggers of runs. We show that the strategic uncertainty about the decision of other depositors and hence, the coverage provided by the deposit insurance fund, suffices to generate runs.

Several experimental papers also explicitly consider the effects of deposit insurance on the probability of panic-based runs. [Madies \(2006\)](#) studies the effectiveness of partial insurance schemes in a standard Diamond and Dybvig bank run setting. He finds no link between the levels of insurance and subjects’ propensity to withdraw. [Schotter and Yorulmazer \(2009\)](#), in an experiment with multiple withdrawal opportunities, find that insurance postpones the time of withdrawal, hence slowing down the bank run. [Kiss et al. \(2012\)](#) find that deposit insurance decreases the probability of a run, but this effect disappears when depositors can observe the number of withdrawals that took place before them. However, in all these settings, depositors’ payoffs, if they decide to withdraw their funds from the bank, are certain, and they are informed about the coverage of deposit insurance. We consider an alternative setting in which the exact size of deposit coverage is uncertain, as it depends on the number of subjects running on the bank. We show that this uncertainty is a strong propagator of runs, the more so, when subjects receive heterogeneous information. These findings draw attention to a possible inefficiency of underfunded deposit insurance schemes.

The remainder of this chapter is organized as follows. The next section introduces our experimental design. Section 3 sketches a theoretical and numerical solution to the depositor decision problem. Section 4 presents the experimental results, while Section 5 concludes.

3.2 Experimental design

We conducted six experimental sessions at the ESSEC Experimental Lab between May 2015 and June 2016 with 120 participants recruited among the student population of ESSEC Business School. Each session involved 20 subjects who participated in 10 successive decision rounds. In each session, subjects were divided into groups of five, which represented the pool of depositors at a bank. Groups were rematched after every round in a typical stranger design. All interactions were computerized using the z-Tree package ([Fischbacher, 2007](#)) and the anonymity of the subjects was guaranteed.

At the beginning of each decision round, each player receives an endowment of 10 Euro as a deposit in a bank. Depositors choose between two actions: “withdraw” their deposit or “wait” until the end of the round, when they can potentially receive a higher payoff. The final payoff

at the end of each round depends on the number of depositors who decide to withdraw their funds from the bank. Specifically, if everyone decides to wait, at the end of the round, the initial deposit becomes R , with $R > 10$. We follow [Diamond and Dybvig \(1983\)](#) and assume that, as long as a bank run does not occur, the return of those who wait decreases smoothly with the number of depositors (Table 3.1). Furthermore, subjects are informed that the bank is able to absorb at most *two* withdrawals before it liquidates all its reserves and must call in the deposit insurance scheme (we implicitly assume the bank cannot fire-sale assets).⁷ If the bank's resources are exhausted, depositors who wait get nothing.

Table 3.1 presents the structure of payments conditional on the withdrawal decision. If two depositors or less withdraw, the bank can repay in full their deposit of 10 Euro. If three or more withdraw, the bank's liquidity reserves are depleted, and depositors are covered by the deposit insurance fund. In each round, the computer draws the amount of reserves of this fund, denoted by D , from the set of integers uniformly distributed over $[0,50]$. Those who withdraw receive the minimum between D/n and 10, where $n \in \{3, 4, 5\}$ is the number of depositors withdrawing (see Table 3.1). This implies that the deposit insurance fund is evenly split among depositors who withdraw and, naturally, it will not reimburse more than the initial deposit.

Table 3.1: Promised returns

Number of depositors who withdraw	Payoff if withdraw	Payoff if wait
0	-	R €
1	10 €	R-1 €
2	10 €	R-2 €
3	minimum{D/3, 10} €	0
4	minimum{D/4, 10} €	0
5	minimum{D/5, 10} €	-

This payoff structure reveals the strategic complementarity in actions. For $n \leq 2$, the more depositors wait, the higher the payoff from waiting. When $n > 2$, the bank fails and subjects have a dominant action to withdraw. If all depositors withdraw, they each get $D/5 < 10$.⁸

Details on the six experimental sessions are presented in Table 3.2. We consider a standard between-subjects design, with participants attending only one of the six experimental sessions.

⁷The bank's balance sheet has a similar structure to that used by [Garratt and Keister \(2009\)](#). At difference, we assume that the amount depositors can recover in case of runs is no longer fixed, but depends on the size of the deposit insurance fund.

⁸Note that coordination threshold is set at 60%. This is a significantly lower requirement than in classical coordination problems such as the minimum effort game ([Van Huyck et al., 1990; 1991](#)). [Arifovic et al. \(2013\)](#) explicitly test for the level of coordination in bank runs models and show that whenever it is less than 50% (or more than 80%) subjects play only the payoff dominant (respectively run) equilibrium. Our coordination coefficient lies in the intermediate region where multiple equilibria are likely to occur.

Table 3.2: Sessions

Treatments	Number of Students	Date
Perfect information, Low return	20	January, 2016
Perfect information, High return	40	Feb/June, 2016
Heterogeneous information, Low return	20	May, 2015
Heterogeneous information, High return	40	May, 2015/June 2016

The experiment has two main treatments. In the perfect information treatment, participants are informed about the size of the deposit insurance fund, D , drawn randomly in each round. In the imperfect information treatment, they receive idiosyncratic hints, which are uniformly distributed around the true value of D . We performed three sessions under each treatment. Within each treatment, we considered two variations of the maximum payoff attainable, R . Out of the six sessions, four were performed with a “high” return, $R^H = 16$, and two with a “low” return, $R^L = 14$. We vary the level of the return to test whether changes in payoff dominance affect behavior in any way. Previous research has shown that changing the level of risk-dominance affects equilibrium outcomes, while changes in the level of payoff dominance do not (Schmidt et al., 2003).

In two of the four heterogeneous information treatments, subjects were also asked to guess the number of withdrawals before they make their decision. This guess was incentivized, such that a better estimation of the number of withdrawals allowed subjects to increase their payoff by a maximum of 5 Euro.⁹

At the end of each of the ten rounds, subjects learn their payoff from the round and how many depositors have withdrawn in that round. In the heterogeneous information treatments they are also informed about the true value of D . At the end of the experiment, one of the ten rounds is selected randomly to determine the subjects’ remuneration from the experiment, to which a 5 Euro participation fee is added.¹⁰ On average, participants earned 18.68 Euro and sessions lasted around 45 minutes, including the time to read out loud the instructions.

3.3 Theoretical predictions

This section describes the equilibrium selection theories employed to characterize aggregate behavior and computes numerically the solutions they imply.

⁹The extra payment was according to the formula: $5/(1 + error)$, where *error* is the absolute difference between their guess and the actual number of withdrawals.

¹⁰Previous experiments in coordination have found that random payments give the higher possible impact of risk aversion and induces players to avoid hedging (Heinemann et al., 2004).

3.3.1 Perfect information setting

In the perfect information setting, subjects are informed at the beginning of each round about the size of the deposit insurance fund, D . This game has two Nash equilibria in pure strategies. In the payoff-dominant equilibrium, all depositors choose the “wait” strategy and receive the large payoff, $R > 10$. An individual depositor who unilaterally deviates (plays withdraw) would get at most 10 Euro. In the second equilibrium, all players choose the “withdraw” strategy and receive $D/5$. Since the bank is now bankrupt, a player who unilaterally deviates (plays wait), would get zero. The first equilibrium is Pareto-dominant, but it is risky insofar as it requires a majority of players to coordinate on leaving their funds in the bank. The second equilibrium eliminates this strategic risk, while still providing a positive, but smaller, payoff.

Harsanyi and Selten (1988) have defined a risk-dominance concept in such games with two possible actions and symmetric payoffs, in which players choose a “safe” strategy by trying to minimize losses. Under this equilibrium refinement, players’ optimal strategy consists in choosing the higher expected payoff under the assumption that the other players will choose either of the two actions available to him/her with equal probability. In our case, this concept implies that players should withdraw as long as the expected utility from withdrawing is higher than the expected utility of leaving the money in the bank. We proceed to compute these expected utilities in a multiple players set-up following Heinemann et al. (2004). Let n be the number of players who withdraw. Then the payoff from leaving the deposit in the bank (wait) can be written as:

$$\text{Payoff}_{\text{WAIT}}(n) = \begin{cases} R - n & \text{if } n \leq 2 \\ 0 & \text{if } n > 2 \end{cases} \quad (3.1)$$

Thus, the expected payoff from waiting is the return obtained given that none, one or two of the other depositors decide to withdraw. The probability that at most two other depositors withdraw given that each subject withdraws with a probability of $p = 50\%$ can be represented by the binomial probability function. We denote this binomial probability by $B(n, 4, p)$, where n is the number of the other 4 depositors who decide to withdraw, when each withdraws with a probability p . Then the expected payoff from waiting is simply:

$$EP_{\text{WAIT}} = \sum_{n=0}^4 B(n, 4, p) \text{Payoff}_{\text{WAIT}}(n). \quad (3.2)$$

Similarly, the payoff from withdrawing is 10 Euro if the bank does not fail. However, if the bank fails ($n > 2$), the deposit is covered as long as the deposit insurance fund has enough

funds to repay all the depositors who withdraw, i.e., if $D \geq 10n$. Otherwise, each depositor who withdraws gets an equal share of D (D/n). More precisely, this payoff is:

$$\text{Payoff}_{\text{WITHDRAW}}(n) = \begin{cases} 10 & \text{if } n \leq 2 \\ 10 \cdot \text{Prob}[D \geq 10n] + \frac{D}{n} \cdot \text{Prob}[D < 10n] & \text{if } n > 2 \end{cases} \quad (3.3)$$

As D is uniformly distributed over $[0,50]$, this payoff is a linearly increasing function of D for all $n > 2$. Same as before, the expected payoff from withdrawing is the return from withdrawing given that none, one, two, three or four of the other depositors also withdraw:

$$EP_{\text{WITHDRAW}} = \sum_{n=0}^4 B(n, 4, p) \text{Payoff}_{\text{WITHDRAW}}(n). \quad (3.4)$$

Solving the indifference equation:

$$\sum_{n=0}^4 B(n, 4, p) \text{Payoff}_{\text{WITHDRAW}}(n) = \sum_{n=0}^4 B(n, 4, p) \text{Payoff}_{\text{WAIT}}(n) \quad (3.5)$$

we obtain a threshold, denote by \hat{D} , above which the expected utility from withdrawing is higher. The risk-dominant equilibrium refinement thus suggests that players will withdraw for $D > \hat{D}$, as the expected payoff from choosing the “safe” strategy, i.e. to withdraw, is increasing in the size of the deposit insurance fund. Similarly, for $D < \hat{D}$, players choose to leave their money in the bank, as the expected payoff from withdrawing is low.

Solving the problem (3.5) numerically, we obtain the thresholds $\hat{D}_{14} = 15.43$ for $R = 14$ and $\hat{D}_{16} = 25.45$ for $R = 16$. Clearly, for $D > \hat{D}$, the payoff-dominance and risk-dominance selection criteria generate conflicting recommendations. [Harsanyi and Selten \(1988\)](#) posit that the payoff dominant equilibrium should prevail if players “trust each other to play the payoff dominant strategy”. However, how much players “trust” each other may depend on the risk and payoff characteristics of the game. For example, [Schmidt et al. \(2003\)](#) find that, in a 2-player coordination game, players’ willingness to trust others to play the payoff dominant equilibrium is influenced by the size of the safe payoff. In our case, as well, the variability of the safe payoff should make subjects more likely to play the “safe” option and withdraw when D is relatively large, in line with a risk-dominant equilibrium selection.

In the context of our framed experiment, we posit that a potential a fear of bank runs would make players even more sensitive to changes in risk dominance. This would induce them to withdraw for higher levels of deposit insurance, as the payoff from the “safe” action is higher. In the context of real world bank runs, this corresponds with situations when deposit

coverage tends to be extensive, yet depositors fear that the size of the fund might not be large enough to cover all insured deposits.

3.3.2 Heterogeneous information setting

In this alternative setting, depositors are not informed about the value of D chosen by the computer in each round. Depositor i only receives a signal about the true size of D , which takes the following form:

$$x_i = D + \epsilon_i, \quad (3.6)$$

where D is uniformly distributed over $[0, 50]$ and ϵ_i is an individual-specific noise also uniformly distributed on the support $[-10, 10]$. Under these assumption, the problem can be solved as a typical global game, where subjects play a “threshold strategy” and switch between actions depending on the signal received. In particular, there exists a critical signal x^* such that individuals receiving a signal below x^* will wait and those receiving a signal $x_i > x^*$, will withdraw. The existence of threshold strategies rests on the idea that signals contain information not only about the true size of D , but also about the signals that the other players receive. Consider a player who receives a signal $x_i = 0$, then he/she has a dominant action to choose action “wait” as the expected payoff from withdrawing is lower (close to zero) regardless of the actions of the other players. Iterated domination arguments allow us to go further and find a threshold signal, x^* , below which the action “withdraw” is always dominated. Similarly, a player receiving a signal close to $x_i = 50$, should have a dominant action to withdraw, as he/she obtains a safe payoff of (almost) 10 Euro. Again, iterated elimination of dominated strategies shows that for signals above x^* , players have a dominant action to withdraw (see also [Morris and Shin, 2003](#); [Goldstein, 2010](#)). Note that the global games equilibrium refinement “forces” players to choose the risk-dominant equilibrium, even when the payoff-dominant option is available ([Carlsson and Van Damme, 1993](#)).

The equilibrium threshold, x^* , can be found by characterizing the expected utility of the depositor who receives exactly the threshold signal x^* and who is indifferent between withdrawing and waiting. We thus proceed to compute the expected utility of this “pivotal” agent. Let n be the number of players who withdraw. The expected utility from leaving the money in the bank is the utility from waiting given that at most two people withdraw. The probability that at most two people withdraw, given that players withdraw when they receive a signal above x^* , can be described by a binomial distribution, as in the perfect information case. Denote by p the probability that a single player gets a signal above x^* at state D , i.e.,

$p = Prob[x_i > x^*|D]$. Then the expected payoff of waiting can be expressed as:

$$EP_{WAIT}(x^*) = \sum_{n=0}^4 \left[\frac{1}{2\epsilon} \int_{x^*-\epsilon}^{x^*+\epsilon} B(n, 4, p) \text{Payoff}_{WAIT}(n) dD \right], \quad (3.7)$$

where B is the binomial probability function and Payoff_{WAIT} is the same as in the perfect information case in Equation 3.1.¹¹ Similarly, the expected payoff from withdrawing is the gain given that none, one, two, three or four of the others also withdraw:

$$EP_{WITHDRAW}(x^*) = \sum_{n=0}^4 \left[\frac{1}{2\epsilon} \int_{x^*-\epsilon}^{x^*+\epsilon} B(n, 4, p) \text{Payoff}_{WITHDRAW}(n) dD \right], \quad (3.8)$$

where $\text{Payoff}_{WITHDRAW}$ is given by Equation 3.3. Replacing p by $Prob[x_i > x^*|D^*] = 1 - \frac{x^*-D+\epsilon}{\epsilon}$, we can compute the threshold signal, as the signal received by the depositor who is indifferent between withdrawing and waiting: $EP_{WITHDRAW}(x^*) = EP_{WAIT}(x^*)$. The indifference equation is:

$$\sum_{n=0}^4 \left[\frac{1}{2\epsilon} \int_{x^*-\epsilon}^{x^*+\epsilon} B(n, 4, p) \text{Payoff}_{WAIT}(n) dD \right] = \sum_{n=0}^4 \left[\frac{1}{2\epsilon} \int_{x^*-\epsilon}^{x^*+\epsilon} B(n, 4, p) \text{Payoff}_{WITHDRAW}(n) dD \right]$$

The solution to this indifference condition yields the critical thresholds $x^* = 10.23$ for $R = 14$ and $x^* = 20.23$ for $R = 16$, respectively.

3.4 Experimental results

3.4.1 Observed behavior

Table 3.3 summarizes the observed individual and group behavior across the different sessions. We observe a large proportion of withdrawals across all sessions and treatments. On average, subjects chose to withdraw in approximately 24% of the cases, leading to a proportion of bank runs, i.e., situations in which three or more depositors withdraw, in 19% of the times. The number of withdrawals varies from 14% of the total number of withdrawal opportunities in Session 2 to a high as 45% in Session 5. This also results in a relatively high occurrence of bank runs. Runs occur from 3% of the cases to 45% of the total number of bank runs possible in Session 5. Notably, the occurrence of the payoff-dominant equilibrium where none of the depositors withdraw is similar, ranging from 4% (in Session 5) to 22% of the cases (in Session 2). Thus, the large majority of rounds experienced partial runs where two or less depositors

¹¹Note that in expression 3.7 above, we acknowledge the fact that the ex-post distribution of D is uniform over the interval $[x^* - \epsilon, x^* + \epsilon]$.

Table 3.3: Descriptive Statistics

Session	Treatment	% Withdrawals	% Bank runs
S1	Perfect information - Low Return	19%	18%
S2	Perfect information - High Return	14%	3%
S3	Perfect information - High Return	24%	13%
S4	Heterogeneous information - Low Return	22%	20%
S5	Heterogeneous information - High Return	45%	45%
S6	Heterogeneous information - High Return	19%	15%

The total number of observations per treatment is 200. The total number of possible bank runs per treatment is 40 (10 rounds x 4 banks/round). Sessions S4, S5 also included an incentivized guess.

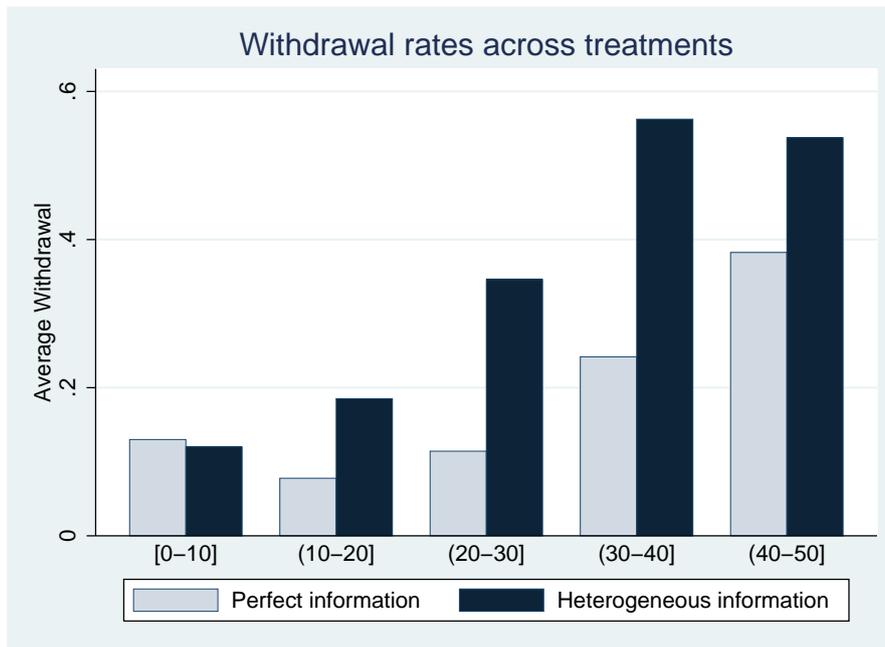
chose the withdraw strategy. We can state the following first result:

RESULT 1. The frequency of individuals who choose the withdraw strategy is relatively high and entails a large number of runs in most treatments.

Thus, the introduction of strategic uncertainty about the coverage of deposit insurance suffices to lead to a significant breakdown in subjects' coordination on the payoff-dominant outcome. This result is contrasting with the results of [Garratt and Keister \(2009\)](#), who also study a 5 depositors bank with a similar payoff structure. At difference, whenever bank runs occur in their experiment, the payoff from withdrawing is fixed and known a priori. In this setting, they observe no bank runs and the occurrence of the payoff dominant equilibrium in 100% of the cases. They then resort to forced withdrawals to generate panic-based runs. In a similar manner, previous bank-run experiments also resort to “exogenous” triggers of runs such as forcing some subjects to withdraw, allowing observability of actions of those who choose before the subject or varying the size of the coordination need to achieve the payoff-dominant equilibrium (for an overview of the literature, see [Duffy, 2014](#)). Classical unframed coordination games in the laboratory also see mixed results. The early experiments with minimum effort games by [Van Huyck et al. \(1990; 1991\)](#) largely suggested that coordination failure is a common phenomena in the laboratory. However, in these games reaching the payoff dominant equilibrium is extremely difficult, as deviations by a single player causes a breakdown in coordination. Stag-hunt games, which are closer to the bank-run model studied here, find largely mixed results depending of the attractiveness of the secure payoff or riskiness of the other action choices (see [Devetag and Ortmann, 2007](#)).

Regarding the difference between our two main treatments, we observe a higher propensity to withdraw in the heterogeneous information treatments for both the low and high return settings. The Wilcoxon-Mann-Whitney test that the median number of withdrawals is the same in the perfect vs heterogeneous Information treatments is rejected at a 1% confidence

Figure 3.1: Average withdrawal rate across treatments



level ($z = -6.982$). Similarly, the statistical difference between the perfect vs heterogeneous information treatments is present if we consider separately the low return $R^L = 14$ treatments ($z = -3.24$, $p = 0.0012$) or the high return, $R^H = 16$, ones ($z = -6.443$, $p = 0.0000$). This suggests a significantly higher propensity to run in the heterogeneous information treatment, regardless of the size of the payoff dominant return. Indeed, the size of R appears to have an ambiguous effect in the number of withdrawal, as the high return treatments can have either a higher or lower number of total withdrawals and bank runs in both the perfect and heterogeneous information treatments (see Table 3.3). We can state that:

RESULT 2. The frequency of withdrawals (and runs) is significantly higher in the heterogeneous information compared to perfect information treatments.

This is in line with [Heinemann et al. \(2004\)](#) who provide the first experimental test of equilibrium selection in global games and find that, in the perfect information setting, subjects coordinate more often on the payoff-dominant equilibrium, compared to the heterogeneous information one.

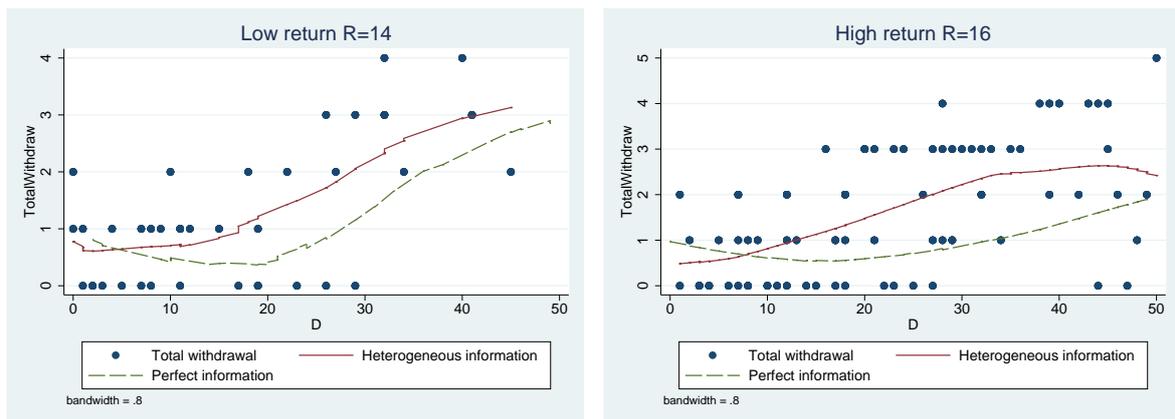
3.4.2 Deposit coverage and the number of withdrawals

Figure 3.1 presents the frequency of withdrawals across the distribution of D , in the perfect/heterogeneous information treatments. It shows the average withdrawal rate in each treatment, when pooling observations for the low and high return scenarios. In line with average results in Table 3.3, it can be observed that for each interval of D considered, the average

withdrawal rate is considerably higher under the heterogeneous information treatment compared to the perfect information one. In other words, uncertainty about the level of deposit insurance is associated with a higher withdrawal rate, at any level of the deposit insurance fund. Moreover, we can clearly observe that the average number of withdrawals is increasing in D (regardless of the information structure). This behavior is confirmed in Figure 3.2, which plots locally weighted regressions of the total number of withdrawals per bank for different realizations of D . These figures now consider the Low ($R = 14$) and High return ($R = 16$) scenarios of each treatment separately. Consistent with previous results, the noisy signals treatment is associated with a higher number of withdrawals, and the results appear similar regardless of the value of R . We can establish the following result:

RESULT 3. Regardless of the information structure, the frequency of withdrawals is increasing in the deposit coverage ratio.

Figure 3.2: Locally weighted regressions of the total number of withdrawals for different realizations of D



These results suggest that players' strategies are in line with a risk-dominant equilibrium selection, following the theoretical arguments in Section 3. In the perfect information case, we have argued that players would pick the withdraw strategy for higher values of D , as the expected return from running on the bank increases with the size of the deposit insurance fund. Similarly, in the heterogeneous information treatment, the global games equilibrium refinement entails that depositors with signals above a threshold, have a dominant action to withdraw. These equilibrium refinements yield a solution which can seem counterintuitive, as the frequency of withdrawals increases in the size of the deposit insurance. This is the result of the set-up of our model, which can be best seen as a model of systemic crises. As a bank run leads to a system failure and the reliance on deposit insurance to cover depositors, high levels of coverage prompts participants to pick the safe strategy which is to withdraw. On

the other hand, when the coverage is low, players prefer to coordinate on the risky strategy. Thus high deposit insurance coverage can breath instability, as depositors rush to the bank to recover their investment in full.

Overall, these results bring new evidence to the experimental literature that explicitly investigates the role of deposit insurance. [Madies \(2006\)](#) and [Kiss et al. \(2012\)](#) find only a small or negligible impact of the coverage ratio on the propensity to run. [Schotter and Yorulmazer \(2009\)](#) on the other hand, find a positive impact of deposit insurance on the probability of withdrawing. We show here that uncertainty about the ability of the deposit insurance fund to cover deposits prompts subjects to play the “safe” strategy more often and withdraw. This propensity to withdraw increases in the payoff of the safe strategy, which depends on the size of the deposit insurance fund. This highlights an inefficiency embedded in the design of deposit insurance schemes whenever they are underfunded. As we have argued in the introduction, deposit insurance funds can be subject to random shocks related to the ability of governments to commit to an explicit coverage, in particular whenever the macroeconomic conditions deteriorate. Such uncertainty about D might compound its effects with the strategic uncertainty embedded in a bank run model to increase the risk of depositor withdrawals.

Figures [3.1](#) and [3.2](#) also suggest that individuals follow some kind of “threshold strategy”. In [Heinemann et al. \(2004\)](#) an individual’s behavior is “consistent with a threshold strategy” if a player chooses to “wait” for some ordered states of the state variable (D in our problem) and to “withdraw” for others, and only switches once between the two. In the next section, we turn to an analysis of individual behavior and investigate whether this is consistent with such threshold strategies.

3.4.3 Additional evidence on threshold strategies

We study individual behavior to uncover whether players’ employ threshold strategies across the two treatments. Recall that, in each period, subjects choose between “wait” and “withdraw” for 10 randomly unordered values of the deposit insurance fund D . This design is similar to previous unframed experiments that focus on eliciting “threshold strategies” among players (see [Heinemann et al., 2004, 2009](#); [Shurchkov, 2013](#)). For example, [Heinemann et al. \(2009\)](#) propose an experiment to measure the size of strategic uncertainty among players and find that aggregate behavior is fairly stable and is characterized by a threshold strategy in line with a risk-dominant equilibrium selection. In our experiment, players should also find it intuitive to employ threshold strategies, as the expected payoff from withdrawing increases with the size of the deposit insurance fund, D , while the payoff from waiting stays constant across rounds.

RESULT 4. A majority of participants employed a threshold strategy.

An analysis of individual behavior across the 10 rounds, uncovers that 60% of the 120 participants employed a threshold strategy (including those who always choose the wait option in all 10 rounds). Table 3.4 presents the “empirical cut-offs” obtained from the individual decisions. These cut-offs are computed as the mean threshold for each treatment, when each individual’s probability of withdrawal is estimated by the cumulative logistic distribution:

$$\text{Prob}(\text{WITHDRAW}_i) = \frac{1}{1 + \exp(a - bx_i)}$$

where x_i is the signal received by an individual i in the heterogeneous information treatments or the size of the deposit insurance in the the perfect information treatments. Following [Heinemann et al. \(2004\)](#), the ratio a/b is interpreted as the mean threshold for each group. We compute these empirical thresholds for the two treatments and compare them with the theoretical ones calculated in the previous section.

Table 3.4: Threshold behavior

	Perfect information	Heterogeneous information
% playing threshold strategy	70%	47.5%
Theoretical cut-off		
R=14	15.43	10.23
R=16	25.45	20.23
Observed cut-off		
R=14	37.43	26.53
R=16	26.65	30.62

In Table 3.4, we observe that the empirical thresholds are relatively higher than the theoretical ones. This suggests that subjects are more prone to cooperate (play the wait strategy) than predicted theoretically. This is in line with the observations in [Heinemann et al. \(2004\)](#), albeit they do not observe such large differences. We also observe a higher propensity to employ threshold strategies in the perfect information case.

3.4.4 Regression analysis

We test the robustness of our results by analyzing the effect of deposit insurance on the probability of withdrawals in a random effects panel probit model. The dependent variable is an indicator taking the value 1 if an individual withdraws and 0 otherwise. Our key independent variables are D , the size of the deposit fund insurance and $Info$, a dummy variable taking the value 0 for the perfect information treatments and 1 for the heterogeneous ones.

Table 3.5: Probability of withdrawing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D	0.036*** (0.0036)	0.037*** (0.0036)	0.037*** (0.0036)	0.038*** (0.0037)	0.039*** (0.0039)	0.037*** (0.0036)	0.037*** (0.0036)	
Info		0.636*** (0.152)	0.637*** (0.152)	0.656*** (0.154)	0.721*** (0.155)	0.620*** (0.152)	0.215 (0.205)	
R			-0.0383 (0.159)					
Period				-0.056*** (0.0158)				
Previous run					0.0921 (0.129)			
First round						0.203 (0.167)		
Guess Session							0.606*** (0.212)	
Hint								0.016** (0.0071)
Estimation								0.874*** (0.0873)
Observations	1,200	1,200	1,200	1,200	1,080	1,200	1,200	400
Subjects	120	120	120	120	120	120	120	40

Panel probit regressions with random effects of the probability of withdrawing. D is the size of the deposit insurance fund in each round, $Info$ is a dummy variable taking value 1 for the heterogeneous information treatments. R is a dummy variable taking value 1 for the sessions where the payoff from action “wait” is higher, i.e., $R^H = 16$. Period is a scalar for the rounds. Previous run is a dummy taking value 1 if a run took place in the previous round. First round is a dummy for the first round. Guess session is a dummy for the sessions which included an incentivized guess. Hint is the hint number received in the heterogeneous information treatments. Estimation is the estimated number of withdrawals stated by subjects in the guess rounds. Constant term included, but not reported. Standard errors in parentheses. *** denotes significance at 1%, ** at 5% and * at 10% level respectively.

Results in Table 3.5 corroborate our previous findings. First, we observe that the probability of withdrawing is higher for larger values of D (columns (1)-(7)). This confirms the tendency of subjects to play risk-dominant strategies, as the expected return from withdrawing increases with the size of D . Furthermore, the probability of withdrawing is positively correlated with the $Info$ indicator suggesting that, for any value of D , the subjects in the heterogeneous information treatment have a higher propensity to run. In column (3), we control for the size of the payoff from waiting. R is a dummy variable taking value 1 for the sessions where the payoff from action “wait” is higher, i.e., $R^H = 16$. The coefficient of this variable is not statistically significant, suggesting that the size of the return of the payoff dominant equilibrium does not impact subjects’ probability to run.

In column (4) we control for any learning effects by including a Period variable. The negative and statistically significant coefficient suggests a propensity to coordinate on the payoff-dominant equilibrium in later periods. Unreported results controlling for individual period dummies show that the dummy variables for the last 3 periods are negative and statistically significant. This is a common outcome in repeated coordination games. However, by

contrast to minimum effort games like [Van Huyck et al. \(1990; 1991\)](#), subjects do not learn to coordinate on the inefficient equilibrium and coordination does not break down after the occurrence of the Pareto inferior outcome. We observe that a run occurring in previous period does not seem to affect behavior (column (5)) nor does the Period 1 outcome (column (6)).¹²

In two of the heterogeneous information sessions we also asked subjects to provide a guess of the number of players they believe will withdraw in that period. This incentivized guess seems to affect behavior and increases the propensity to withdraw (see column (7)). Finally, in the heterogeneous information treatments, we can control for the signal that subjects receive. This is captured by the *Hint* in column (8). We find that the signals are positively correlated with the propensity to withdraw. In this column, we also control for *Estimation*, i.e., participants' estimation of the number of withdrawals in the rounds with the incentivized guess. Results also show that subjects' behavior is in line with their stated beliefs, since their guess of the number of withdrawals is positively correlated with the probability of withdrawal in Column (8). This suggests that subjects withdraw for higher levels of deposit insurance because they believe others will do so as well.

3.5 Conclusion

The Great Recession that followed the 2007-08 Global Financial crisis exposed the fiscal fragility of many governments and a potential vulnerability of national deposit insurance scheme to large local shocks. Despite the extensive deposit coverage in place in most countries, a wave of bank runs that followed across Europe questioned the effectiveness of these national insurance schemes in mitigating bank runs. As a consequences, in November 2015, the European Union established a European Deposit Insurance Scheme to strengthen the protection of bank depositors across the union. Yet this supranational fund can only cover less than 1% of the total deposits of all banks in the EU.

In this paper, we study the effects of deposit insurance on the propensity to run on a bank, when the size of the deposit insurance fund may not suffice to cover all insured deposits. We replicate bank depositors' decisions in a typical coordination framework. However, contrary to previous studies, in our experiment there is no “exogenous” trigger of bank runs (such as forced withdrawals, contagion, informational cascades etc). We assume instead that the deposit coverage is uncertain and may not cover the deposit in full. This “uncertainty” about the actual level of coverage depends on (i) the size of the fund and (ii) the strategies of other

¹²By contrast, [Besancenot and Vranceanu \(2014\)](#) study a repeated investment coordination game with a partner design and show that investors present a long-memory of past defaults, being more reluctant to invest after a illiquidity default, and more tempted to invest prior to the first default.

players. At the same time, the return from waiting is common knowledge, and a payoff-dominant equilibrium in which all depositors wait is always feasible. We analyze two main contexts: (1) a perfect information setting in which depositors know the size of the deposit insurance fund; and (2) a heterogeneous information treatment in which subjects only observe an individual-specific, noisy signal about its size.

Our results show uncertainty about deposit coverage leads to a significant breakdown in coordination, the more so in the heterogeneous information treatment. Furthermore, we observe that the higher the deposit insurance fund is, the higher the frequency of withdrawals. This suggests that the coordination structure of the model “forces” players to adopt a risk-dominant strategy, even when the risk and payoff-dominant strategies yield conflicting recommendations. Moreover, in both treatments, a majority of players follow threshold strategies, i.e., have a critical cutoff value of the actual/perceived deposit insurance fund around which they switch between waiting and withdrawing.

Overall, our results cast doubt on the effectiveness of deposit insurance schemes, in particular when they are grossly underfunded, as in most countries nowadays, and the banking crisis is systemic. Moreover, banking crises, such as the one in Argentina in 2001, happen in periods of political turmoil and weak institutions, making commitments of deposit insurance difficult to achieve ([Ennis and Keister, 2009](#)). Our experiment highlights how such depositor uncertainty about the level of deposit coverage can create a strong ex-ante propensity to run.

Appendices

3.A Instructions - Heterogeneous information treatments

Thank you for participating in this economic experiment, in which you will be given the opportunity to earn money. We ask you not to communicate with each other from now on and turn off all mobile phones. If you have any questions, please raise your hand, and the instructor will come to you. The instructions below will explain to you the decisions you have to make throughout the experiment. Your identity will not be revealed to the other participants.

The experiment has 10 rounds. At the end of the experiment, one round will be randomly picked by the computer and you will receive the payoffs from that round.

At the beginning of each round you receive 10 Euro, which are deposited in a bank. A bank is formed of 5 depositors. Note that the depositors at a bank will change in each round, so the likelihood you will play with all the same people in future rounds is very low.

The bank will invest the money you and the other 4 depositors have placed with it in a project that will provide a known return. You have to decide whether to keep your money in the bank (**WAIT**) or withdraw your deposit (**WITHDRAW**).

Your payoff depends on your decision, but also on what the other players decide to do.

- If you **WAIT**, your payoff will decrease the more depositors at your bank withdraw as show in the table below.
- If you **WITHDRAW**, you get back your deposit of 10 Euro if less than 3 people (including yourself) decide to withdraw.

Deposit insurance

If 3 or more depositors at your bank decide to withdraw, the bank will fail and lose all its investment. How much you can recover from your deposit will then depend on a “**deposit insurance fund**”. This fund has an endowment, called **D**, which is unknown to all participants and is drawn randomly from the interval $[0, 50]$. All numbers in the interval $[0, 50]$ have the same probability to be drawn. This number is the same for everyone. When you make your

Number of depositors who withdraw	Payoff if you withdraw	Payoff if you wait
0	-	16 €
1	10 €	15 €
2	10 €	14 €
3	$\text{minimum}\{D/3, 10\} \text{ €}$	0
4	$\text{minimum}\{D/4, 10\} \text{ €}$	0
5	$\text{minimum}\{D/5, 10\} \text{ €}$	0

decision to withdraw or wait you will not know the chosen number D . You will however receive a hint about the drawn number D and this hint will be selected from the interval $[D-10, D+10]$. Each participant will receive his own hint number. On the basis of this hint you can decide whether to withdraw or not. If 3 or more depositors withdraw and the bank fails, depositors who withdraw get either the initial deposit of 10 Euro or an equal share of D , when D is not big enough to cover all depositors who withdraw. However, if the bank fails and you wait, you get nothing.

For example, the unknown number D drawn by the computer is 15. The 5 participants will receive hints from the interval $[5, 25]$ such as 6, 24, 9, 13, 22. The participant who receives hint 6 knows that D must be between 0 and 16. The participant who receives hint 24 knows that D must be between 14 and 34 etc. If 4 depositors withdraw, then they will each receive $D/4=3.75$ Euro, while those who wait receive 0.

Remember, you do not know the true value of D , you just receive a hit number which is an approximation of D . You also don't know the number of people who decide to withdraw. Therefore, you cannot *exactly* determine your payoffs in case the bank fails.

In each round you will see 2 screens. In the first screen, you will need to decide if withdrawing your deposit or leaving the money in the bank. You will also be asked to give your guess about the number of people you think will withdraw given the information received in that round. If your guess is correct you will get an additional payoff according to the formula $5+5/(\text{error}+1)$, thus the smaller the error (the closest your guess) the higher the payoff you can receive (if your guess is perfect you get 10 Euro). In the second screen you will see:

1. the actual number D
2. your decision
3. how many participants have withdrawn
4. your gain from the bank game in that round

Chapter 4

Finance and growth: time series evidence on causality¹

Abstract

This chapter re-examines the empirical relationship between financial and economic development while (i) taking into account their dynamics and (ii) differentiating between stock market and banking sector development. We study the cointegration and causality between finance and growth for 22 advanced economies. Our time series analysis suggests that the evidence in support of a finance-led growth is weak once we take into account the dynamics of financial and economic development. We show that, causality patterns depend on whether countries' financial development stems from the stock market or the banking sector. Stock market development tends to cause growth, while a reverse causality is mostly present between banking sector development and output growth. Our findings indicate that the direction of causality between finance and growth is likely to be different at high levels of development.

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4.1 Introduction

The importance of the relationship between financial development and economic growth is well recognized in the growth and financial literature alike. Economic theory predicts that well-functioning financial intermediaries and markets reduce information asymmetries, facilitate risk sharing and mobilize savings, which leads to a more efficient resource allocation and, thus, may foster long-term growth². A large empirical literature provides evidence that financial development matters for growth. However, there is less consensus as to whether the effect is mainly due to banks, stock markets or both. The “finance-led growth” hypothesis, according to which financial development exerts a positive and causal effect on real output is mainly supported in cross-country studies that focus on *bank* development proxies (King and Levine, 1993; Levine et al., 2000; Calderon and Liu, 2003; Christopoulos and Tsionas, 2004; Rioja and Valev, 2004; Loayza and Ranciere, 2006). Evidence when *stock market* development is also considered is more scarce or leads to less consistent results (Harris, 1997; Arestis et al., 2001).

This study provides new evidence that strengthens the notion that finance and growth co-move in a more complex way than previously thought. For this purpose, we investigate the relationship between economic and financial sector - banking and stock markets - development for 22 advanced economies during the period 1973-2011. Our empirical strategy is motivated by recent theoretical contributions that stress how banks and stock markets may relate differently to economic development. These studies argue that, because banks and stock markets affect economic outcomes through different channels, their effectiveness depends on a host of country-specific factors such as the legal and contractual environment (Deidda and Fattouh, 2008; Song and Thakor, 2010), stage of development (Boot and Thakor, 1997) or new technologies available (Allen and Gale, 1999). Thus, the role of finance in real sector outcomes may differ depending on whether financial development stems from securities markets or the banking sector. To capture these different causality patterns, we explore the link between finance and economic development for each country in our sample, over time, by employing a framework in which both financial and economic development are treated as endogenous variables.

Our results show that causality patterns indeed differ across countries and, in particular, with the type of financial institution considered. Stock market development generally causes economic development, while the causality between banking sector development and growth

²Theoretical models that capture the different channels through which financial intermediaries have a positive impact on real output, have been developed, among others, by Greenwood and Jovanovic (1990), Levine (1991), Bencivenga and Smith (1991), Greenwood and Smith (1997), Blackburn and Hung (1998). Together with a positive finance-growth nexus, the destabilizing effect of stock market crashes and financial crises is also recognized (Minsky, 1974; Kindleberger, 1978), however its impact on long-term growth is less clear (Cerra and Saxena, 2008; Ranciere et al., 2008).

goes in the reverse direction, most of the time. These findings suggest that the extensive empirical evidence that finance causes growth is sensitive to the type and dominance of a particular financial institution. Moreover, these causality patterns are robust to different estimations techniques and proxies for financial development.

Our research contributes to the finance-growth literature in several ways. First, we show that, among countries with relatively high levels of development, a finance-led growth hypothesis is supported only when financial development stems from security markets. In particular, this suggests that the strong causal link between banking sector development and growth appears to vanish when we consider a time period in which financial sectors have developed intensively. Second, our results suggest that finance and growth might relate differently in advanced economies. Empirical evidence generally shows that both stock markets and banks tend to become more developed as economies grow and that securities markets tend to develop more rapidly than banks (Demirgüç-Kunt and Levine, 2004). However, there is less consensus whether this financial system evolution matters for growth (Beck and Levine, 2002; Levine, 2002). Our findings show that, at higher levels of development, stock market development tends to have a causal impact on growth, while banking sector does not. Thus, the evolution of financial systems towards a more market-based structure does have an impact on real sector outcomes. These findings complement recent research that argues that not just the size, but also the structure of financial systems may matter for growth (Fecht et al., 2008; Luintel et al., 2008; Ergungor, 2008; Arestis et al., 2010; Demirgüç-Kunt et al., 2012).

The remainder of this chapter is organized as follows. Section 2 reviews theoretical and empirical contributions on this topic. Section 3 presents the variables and data used. Section 4 discusses the cointegration and causality tests employed and presents our main results and robustness checks performed. Section 5 concludes.

4.2 Motivation and previous research

Economists hold different opinions of the role of finance on economic growth and the developed theoretical literature mirrors these divisions. The theoretical underpinnings of this role can be traced back to Schumpeter (1934), who saw financial intermediaries as playing a pivotal role in output growth by channeling savings to the most productive investments. The alternative view is held by Robinson (1952), who argued that financial development simply follows economic growth which is generated elsewhere. Patrick (1966) characterizes these two possible relationships as the “supply-leading” and “demand-following” hypotheses. Both of his hypotheses, as well as possible interactions between them, have been further developed

by, among others, [Greenwood and Jovanovic \(1990\)](#), [Levine \(1991\)](#), [Bencivenga and Smith \(1991\)](#), [Greenwood and Smith \(1997\)](#), [Blackburn and Hung \(1998\)](#).

While both banks and stock markets perform important functions which affect real sector outcomes, their relative effectiveness might not be the same depending on the economic and contractual environment of a country. A recent theoretical literature analyses how banks and financial markets can affect economic outcomes through different channels and how this impact might depend on structural characteristics of the economy. For example, the well-functioning of stock markets depends on how important is the value of market information in real sector outcomes. [Boot and Thakor \(1997\)](#) argue that severe moral hazard attenuates the value of this information feedback through prices. They show that, in economies prone to such severe information asymmetries, banks can actually provide a better resolution of post-lending moral hazard and improve real sector decisions. The technological characteristics of an economy or the degree of agency problems it faces can also influence the comparative importance of banks and stock markets. In particular, [Allen and Gale \(1999\)](#) show that securities markets are better at financing new industries and technologies in economies characterized by high information uncertainty and diversity of opinion. Furthermore, in [Dewatripont and Maskin \(1995\)](#), a more market-based system provides better financial discipline in the presence of adverse selection by not committing to fund unprofitable projects.

The relative merits of banks and stock markets also depend on the stage of economic development and, in particular, on the legal and institutional framework of a country. [Rajan and Zingales \(1998b\)](#) argue that banks are more effective in weak legal systems with poor institutional infrastructure, whereas the well-functioning of stock markets relies on strong contractual environments and legal enforceability. This implies that market-based systems might prevail only at higher levels of development. Finally, the distribution of risk in the economy can also impact the link between finance and the real economy. [Boot \(2000\)](#) develop a model in which more mature and safe firms rely on equity markets, while small, riskier firms are better served by banks. Stock markets are also better at providing cross-sectional risk sharing, while banks allow for more inter-temporal risk-sharing ([Allen and Gale, 1997](#)). [Fecht et al. \(2008\)](#) show how this risk-sharing trade-off can lead to less investment in productive assets in bank-dominated economies and hence lower growth, as compared to market-based economies.

The arguments articulated in these theoretical models imply that the services provided by banks and stock markets should exert a different impact on economic activity at different levels of development or depending on a host of country-specific characteristics. Empirical research however, has mainly investigated the overall role of financial development in real

sector outcomes, and is less precise on the relative importance of either type of financial institution.

A large body of cross-sectional and panel studies generally supports a positive link between finance and growth and mainly addresses the issue of causality using IV and GMM techniques (see [King and Levine, 1993](#); [Levine and Zervos, 1998](#); [Levine et al., 2000](#); [Beck et al., 2000](#); [Beck and Levine, 2004](#)). This cross-country literature finds evidence in line with a “financial-service” view in which the overall size of the financial sector, and not necessarily its structure, matters for growth ([Levine, 2002](#); [Beck and Levine, 2002](#)). Time-series studies, however, show that these causality patterns may reflect only one side of the causal link (see [Demetriades and Hussein, 1996](#); [Arestis et al., 2001](#); [Christopoulos and Tsionas, 2004](#); [Ang, 2008](#); [Luintel et al., 2008](#)). Their results suggests that exploring the role of finance in economic development for a specific country, over time, may reveal causality patterns that cannot be inferred from pooled cross-sectional studies. One important caveat of pooling countries together in cross-sections is pointed out by [Rioja and Valev \(2004\)](#) who show that the link between finance and growth depends on the stage of economic development: highly and low developed economies are characterized by a weak link, while for developing countries, finance exerts a stronger influence on growth.

To address these issues of country-specific effects, time series research identifies causality on a country-by-country basis, while accounting for the dynamics and cointegration properties of data ([Christopoulos and Tsionas, 2004](#)). Among the first to explore causality in this framework were [Demetriades and Hussein \(1996\)](#) and [Luintel and Khan \(1999\)](#) who mainly find a bi-directional relationship between banking sector development and growth in a sample of developing countries. Their results suggest that pooling countries with different levels of financial development in cross-sectional regressions may well suggest simpler than actual dynamics between finance and growth. [Arestis et al. \(2001\)](#), recognizing the low power of the Johansen cointegration test in small samples, limit their research to five developed nations, but find significantly different causality patterns among them. [Christopoulos and Tsionas \(2004\)](#) try to overcome the issues of low availability of data over long periods of time using panel cointegration techniques. Their findings are restricted to banking sector development and support a unidirectional causality going from financial depth to growth. Generally, the low data availability of measures of stock market development has restricted most of the time-series research to bank development proxies ([Demetriades and Hussein, 1996](#); [Luintel and Khan, 1999](#); [Rousseau and Wachtel, 1998](#); [Rousseau and Vuthipadadorn, 2005](#); [Ang and McKibbin, 2007](#))³.

³Recent evidence that benefits from the availability of longer time series, in particular with regards to

At the same time, when country-specific characteristics are taken into account, financial architecture also seems to matter (Arestis et al., 2001; Tadesse, 2002; Luintel et al., 2008). Luintel et al. (2008) show how, in assessing the role of financial structure on growth, cross-country data cannot be pooled due to significant cross-country heterogeneity. Tadesse (2002) finds that bank-based systems appear to be more effective in financially underdeveloped countries and in countries dominated by smaller firms, whereas market-based systems are more effective in financially developed countries and in economies dominated by larger firms. Furthermore, Demirgüç-Kunt et al. (2012) find that, as economies grow, the marginal increase in economic activity associated with an increase in bank development falls, while the one associated with stock market development rises. Thus, as economies develop, stock markets generate more growth than banking sector development.

The foregoing evidence implies that banks and stock markets might relate differently to the real economy depending on the level of development. Since advanced economies are more likely to have a strong legal and institutional framework, be less prone to severe agency problems and value more the information feedback coming from securities markets, we expect the impact of stock markets to be stronger in economies with highly developed financial sectors. The setting of our analysis allows us to test this hypothesis. First, by looking at both types of intermediaries, we can test whether causality patterns between the two financial sectors and economic development differ. Second, since our sample includes a set of countries with relative high levels of stock market development, we can examine whether, indeed, the services provided by financial markets tend to contribute more to real outcomes at higher levels of development.

4.3 Data

Consistent with theoretical specifications and previous studies (Demetriades and Hussein, 1996; Levine and Zervos, 1998; Arestis et al., 2001; Beck and Levine, 2004), we define *economic development* as the logarithm of real GDP per capita (GDP). We measure *stock market development* by the logarithm of the *ratio of stock market capitalization to nominal GDP* (STOCK) in line with Rousseau and Wachtel (2000), Arestis et al. (2001) and Shen and Lee (2006). Stock market capitalization, which measures the overall size of stock market activity, ought to capture the importance of financing through equity issues in the capital mobilization and resource allocation process. However, measures of stock market activity and liquidity have also been found to be closely connected with economic activity (see, for example, Rousseau

stock market data, has cast some doubts on the stylized positive relationship between financial development and growth. Shen and Lee (2006) find a negative relationship between bank development and growth, when controlling for the development of stock markets. Arcand et al. (2015) show that the relationship between financial development and economic growth turns negative for high levels of credit to GDP.

and Wachtel, 2000). As a result, we check the robustness of our findings using the *turnover ratio* defined as the value of the trades of shares divided by the total value of listed shares (market capitalization) (as in Beck and Levine, 2004)⁴. The *development of the banking sector* is captured by the logarithm of *domestic bank credit to the private sector divided by nominal GDP* (CRED). Several other measures of bank development are used in the literature⁵. However, domestic credit is argued to be more robustly linked to output growth and is more widely used in recent studies (Arestis et al., 2001; Loayza and Ranciere, 2006; Luintel et al., 2008). Appendix Table A.1. provides additional details on the construction of variables and data sources, while Appendix Table A.2. provides some basic descriptive statistics.

The theoretical arguments put forward in the previous section suggested that banks tend to be more closely related to economic outcomes at lower levels of development, while stock markets should exert a higher impact in more economically developed countries. As a result, we focus our analysis on a large sample of advanced economies for which data on both bank and stock market development is available for long periods of time. We follow the 2013 FTSE Global Equity Index Series Country Classification which splits countries in four groups according to their level of stock market development. We limit our research to the first group, i.e. Developed Capital Markets, which contains 25 countries. These countries are assessed to have (i) a free and well-functioning equity market with formal stock market regulatory authorities that actively monitor it, (ii) no legal impediments to trading, (iii) sufficient liquidity and (iv) reasonable transaction costs. We eliminate three countries from this sample due to a lack of sufficiently long time series of data and we are left with a sample of 22 countries⁶. Our empirical strategy follows the country-by-country approach of time series studies such as Demetriades and Hussein (1996), Luintel and Khan (1999) and Arestis et al. (2001) who study developing and advanced economies using either annual or quarterly data. Our variables are measured quarterly in line with Arestis et al. (2001) and cover a time span of around 40 years (1973-2011).

4.4 Empirical analysis

In this section, we briefly present the econometric methods we use and the results we obtain. The empirical literature on finance and growth builds on three econometric approaches: pure cross-sectional OLS studies, time series estimations and panel data analysis employing GMM

⁴We thank an anonymous referee for suggesting this robustness.

⁵These include the ratios of broad money (M2) and stock of liquid liabilities (M3) to GDP as measures of intermediary activity able to capture the notion of “financial depth”.

⁶Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, The Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, UK, USA.

(for an overview, see [Ang, 2008](#); [Beck, 2008](#); [Valickova et al., 2014](#)). We perform a country-by-country time series analysis which enables us to take into account country specific conditions and the cointegration properties of data. This also allows us to disentangle causality patterns between different types of financial intermediaries and real output across countries.

4.4.1 Cointegration between financial and economic development

Time series research on the finance-growth nexus has centered around cointegration ([Dimitriades and Hussein, 1996](#); [Luintel and Khan, 1999](#); [Arestis et al., 2001](#); [Christopoulos and Tsionas, 2004](#)). Consistent with this literature, we use the Johansen ([1988](#); [1992](#)) maximum likelihood procedures to test for the presence of cointegration in a vector autoregression with n variables integrated of order one, of the form:

$$y_t = b_1 y_{t-1} + b_2 y_{t-2} + \dots + b_k y_{t-k} + \Phi D_t + \varepsilon_t. \quad (4.1)$$

The $VAR(k)$ in (4.1) can be rewritten as a vector error correction model:

$$\Delta y_t = \pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \dots + \Gamma_{k-1} \Delta y_{t-(k-1)} + \Phi D_t + \varepsilon_t, \quad (4.2)$$

where y , in our case, is a vector with the three variables capturing economic development, stock market and banking sector development, i.e., $y = (\text{GDP STOCK CRED})'$, $\pi = \left(\sum_{i=1}^k b_i \right) - I_n$, $\Gamma_i = -(b_{i+1} - \dots - b_k)$, ($i=1, \dots, k-1$), D_t is a set of deterministic variables such as a constant, trend and dummies, and ε_t is a vector of normally distributed errors with zero mean and constant variance.

We test for cointegration through the rank r of the π matrix using [Johansen'](#) (1988) maximum likelihood statistics: the trace statistic $\lambda_{trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$ and the maximal-eigenvalue statistic: $\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$, where $\hat{\lambda}$ is the estimated value of the i^{th} ordered eigenvalue of π . We test sequentially for the presence of an increasing number of cointegrating vectors r , in favor of the alternative that there are $r+1$ (for λ_{trace}) or more than r (for λ_{max}), until we cannot reject the null hypothesis.

We carry out a number of standard steps prior to testing for cointegration in this framework. These include verifying the integration properties of each variable, setting the optimal number of lags, parameterizing the deterministic component D_t and testing for structural breaks in the cointegrating relationship. We refer the reader to [Appendix 4.B](#) for a more detailed account of these steps. Allowing for all these specifications assures us that the estimated VAR models are correctly specified. We thus check whether errors are independently,

identically, and normally distributed, which allows us to derive the likelihood function for testing cointegration under the [Johansen \(1988\)](#) procedure. These diagnostics tests are presented in Appendix Table 4.C. Generally, the estimated VAR for each country is well-specified and residuals are i.i.d. with a few cases in which the normality assumption is rejected, due to excess kurtosis. However, [Hendry and Juselius \(2001\)](#) argue that statistical inference is less sensitive to fat-tail distributions, under which parameter estimates are still consistent, but they may not be efficient.

Given all these specifications, we test for cointegration. The results are presented in Table 4.1. For brevity, we present only the trace statistic since the results of the maximum eigenvalue are qualitatively the same. When they differ, however, we put more weight on the trace statistic, which is more robust than the maximal eigenvalue in finite samples ([Cheung and Lai, 1993](#)). We find evidence of one cointegrating vector in all countries⁷.

Having established the presence of cointegration, the matrix π in equation (4.2) can be written as a product of two full rank matrices $\alpha \cdot \beta'$, with the β matrix containing the cointegrating vectors and the coefficients of α representing the speed of adjustment to the equilibrium relationship. We just-identify the cointegrating vector by normalizing it on GDP. However, when the coefficients of CRED or STOCK are not statistically significant, we impose over-identifying restrictions on the coefficients in β , to test whether all variables enter the cointegrating relationship ([Pesaran and Shin, 2002](#)). When such restrictions are imposed, we verify whether they are supported by the data. Column 3 in Table 4.2 presents the log-likelihood statistic (LR) of these tests. All imposed restrictions are accepted by the data. As a result, not both measures of financial development enter the cointegrating vectors. More precisely, we find a stable long-term relationship between both measures of financial development and GDP in only six of the countries (see Table 4.2). Stock market development is positively related to GDP in 14 of them, while a positive stable relationship between CRED and GDP is present in 13 of the countries. Overall, this evidence is consistent with the cross-country literature and points towards a positive finance-growth nexus⁸.

Having established the stable, long-run relationship between our variables of interest, we proceed to testing the direction of causality among them.

⁷We discuss in Appendix 4.B further robustness tests performed, as well as the specification of the cointegration tests when structural breaks are present.

⁸One exception is Singapore, where private credit enters negatively the cointegrating vector. This is surprising given the extensive financial liberalization undertaken in this country. However, stock market capitalization is positively related to GDP.

Table 4.1: Johansen Cointegration Test

Johansen cointegration test for the VAR in equation (4.2). Variables included in the VAR: logarithm of real GDP per capita (GDP), logarithm of the ratio of stock market capitalization to nominal GDP (STOCK), logarithm of the ratio of private credit to nominal GDP (CRED). Lags refers to the number of lags of the VAR model in equation (4.1). *SB* denotes the presence of structural breaks in: Germany (1991Q1), Ireland (1996Q3, 2003Q1), Italy (1992Q4, 1996Q4), the Netherlands (1988Q4), Sweden (1989Q4, 2004Q2) and USA(1984Q3, 1994Q3). For these countries estimations are performed using the [Johansen et al. \(2000\)](#) methodology detailed in the Appendix 4.B.

Country	Trace statistic under $H_0 = r$			Lags	Sample
	$r=0$	$r \leq 1$	$r \leq 2$		
Australia	53.67**	10.61	3.17	2	1984-2011
Austria	30.57*	11.51	3.72	2	1973-2011
Belgium	45.29**	8.61	0.55	2	1980-2011
Canada	36.67*	17.29	6.75	3	1973-2007
Denmark	41.60**	14.38	2.48	3	1977-2011
Finland	37.39**	14.51	2.26	2	1988-2011
France	31.38*	12.70	3.52	1	1973-2011
Germany ^{SB}	49.54**	19.40	7.20	3	1973-2011
Greece	29.82*	10.41	1.10	2	1988-2007
Ireland ^{SB}	72.22**	25.39	5.20	2	1973-2011
Italy ^{SB}	78.41**	38.07	17.90	2	1976-2011
Japan	52.63**	5.54	1.16	2	1979-2011
Netherlands ^{SB}	67.09**	21.97	8.49	2	1977-2011
New Zealand	32.72*	12.78	2.16	3	1988-2011
Norway	35.80**	14.43	2.21	3	1981-2011
Singapore	39.08**	14.72	1.12	2	1975-2011
South Korea	66.44**	18.61	5.41	2	1987-2011
Spain	36.19**	14.99	4.85	3	1987-2007
Sweden ^{SB}	80.42**	30.02	11.57	2	1982-2011
Switzerland	39.65**	10.35	2.57	2	1975-2011
United Kingdom	38.06**	8.69	2.41	2	1965-2011
USA ^{SB}	51.73**	23.64	7.70	2	1973-2011

* and ** denotes rejection of the hypothesis at the 5% and 1 % level. Critical values for the cointegration test are provided by [Mackinnon et al. \(1999\)](#).

4.4.2 Causality between financial and economic development

We test for a causal link between finance and growth in a simultaneous equation framework which allows us to uncover not only unidirectional causality, but also any potential bidirectional causality in which there is a feedback relationship between finance and economic development⁹. Time series evidence on causality between finance and growth generally focuses on long-term causal links ([Luintel and Khan, 1999](#); [Arestis et al., 2001](#)). However, short-term dynamics may also be important, as pointed out by recent evidence (see [Loayza and Ranciere, 2006](#)). In

Table 4.2: Cointegrating Vectors

Normalized cointegrating relationships based on the number of cointegration vectors in Table 4.1. Variables included in the VAR: logarithm of real GDP per capita (GDP), logarithm of the ratio of stock market capitalization to nominal GDP (STOCK), logarithm of the ratio of private credit to nominal GDP (CRED). LR test presents the p-value of a log-likelihood test under the null: $H_0: \beta_{ij}=0$, i.e. that variable j enters cointegrating relationship i . Non-rejection of this test means restrictions on the variables entering each cointegrating vector are binding.

Country	Cointegrating relationship	LR test
Australia	$C = GDP - 0.53 CRED - 8.80$ [-27.4]	0.99
Austria	$C = GDP - 1.17 CRED - 7.46$ [-15.3]	0.88
Belgium	$C = GDP - 0.21 STOCK - 8.68$ [-21.4]	0.64
Canada	$C = GDP - 0.20 STOCK - 7.99$ [-6.75]	0.69
Denmark	$C = GDP - 0.11 STOCK - 0.13 CRED - 10.81$ [-10.7] [-2.85]	-
Finland	$C = GDP - 0.29 STOCK - 0.30 CRED - 9.84$ [-10.3] [-3.92]	-
France	$C = GDP - 0.09 STOCK - 8.67$ [-8.79]	0.52
Germany	$C = GDP - 3.26 CRED - 3.38$ [-3.33]	0.08
Greece	$C = GDP - 1.19 CRED - 7.66$ [-3.98]	0.16
Ireland	$C = GDP - 2.33 CRED - 10.52$ [-5.49]	0.52
Italy	$C = GDP - 0.09 STOCK - 8.50$ [-3.75]	0.31
Japan	$C = GDP - 0.30 STOCK - 8.26$ [-8.31]	0.07
Netherlands	$C = GDP - 0.61 CRED - 8.04$ [-33.5]	0.06
New Zealand	$C = GDP - 7.50 STOCK - 7.86$ [-3.83]	0.65
Norway	$C = GDP - 0.89 CRED - 10.62$ [-8.54]	0.07
Singapore	$C = GDP - 1.21 STOCK + 1.16 CRED - 8.56$ [-7.33] [4.06]	-
South Korea	$C = GDP - 0.21 STOCK - 0.67 CRED - 14.47$ [-2.85] [-2.37]	-
Spain	$C = GDP - 0.23 STOCK - 8.39$ [-7.31]	0.99
Sweden	$C = GDP - 0.10 STOCK - 0.49 CRED - 10.34$ [-6.58] [-4.40]	-
Switzerland	$C = GDP - 0.78 CRED - 8.22$ [-15.8]	0.40
United Kingdom	$C = GDP - 0.36 STOCK - 8.13$ [-5.80]	0.16
USA	$C = GDP - 0.34 STOCK - 0.70 CRED - 11.32$ [-12.9] [-3.27]	-

t-statistics in [].

order to uncover the potential complex dynamics behind our variables of interest we perform a wide breadth of causality tests.

We first test for weak exogeneity. In the vector error correction model in (4.2), the equation determining ΔGDP_t when considering, for example, one cointegrating relationship and two lags, is written as:

$$\Delta GDP_t = \alpha_{11} ECT_{t-1} + \gamma_{11} \Delta GDP_{t-1} + \gamma_{12} \Delta STOCK_{t-1} + \gamma_{13} \Delta CRED_{t-1} + \varepsilon_{1t}, \quad (4.3)$$

⁹Christopoulos and Tsionas (2004) use a different approach to test for a bi-directional causality with a FMOLS framework by regressing both economic growth and financial development on each other. In their study a unidirectional causality from financial depth to growth is found for a sample of developing countries.

where $ECT_{t-1} = \beta_{11}GDP_{t-1} + \beta_{12}STOCK_{t-1} + \beta_{13}CRED_{t-1}$ is the error correction term, i.e. the cointegration relationship between the variables. A test of the null hypothesis $H_0 : \alpha_{11} = 0$ is a test of weak exogeneity since a non-rejection of the null means the lags of the variables in the error correction term do not enter in the equation determining GDP, i.e. GDP is exogenous to the system.

Rejection of the null hypothesis means there is evidence of long run causality going from the variables in the ECT to GDP. [Toda and Phillips \(1993\)](#) propose testing weak exogeneity as a joint test on both the α and β coefficients. We follow this approach and impose restrictions on the β coefficients to identify the cointegrating relationships as well as on the α coefficients to test whether the variables in the cointegrating vectors also enter each of the error-correction equation. Thus, a test of long-run causality going from STOCK to GDP is a joint test $H_0 : \beta_{12} = \alpha_{11} = 0$. Rejection of the null hypothesis implies that there is a causal link going from stock market capitalization to GDP in the long run. However, long-run causality does not mean causality in the Granger sense since it does not take into account the short-run dynamics. Therefore, we perform a second causality test: a short-run Granger non-causality test on the γ coefficients in equation (4.3). In this case, a test of short-run causality going from stock market capitalization to GDP is a test of the null hypothesis: $H_0 : \gamma_{12} = 0$.

The third causality test we perform is a stronger notion of exogeneity which involves testing the joint hypothesis of short-run and long-run causality ([Charemza and Deadman, 1992](#)). Hence the null hypothesis is $H_0 : \gamma_{12} = \alpha_{11} = 0$. The rejection of the null hypothesis implies an overall causality from STOCK to GDP without distinguishing between long-term and short-term causality.

All previous tests are based on likelihood ratios that follow a χ^2 distribution as long as all the parameters of equation (4.3) can be rearranged as coefficients of I(0) variables at the same time. However, rearranging all the parameters as coefficients of I(0) variables assumes the cointegration rank has been accurately estimated. [Toda and Yamamoto \(1995\)](#) derive a causality test which does not require any prior knowledge of the order of cointegration of the variables. Their methodology proposes testing for causality in the level VAR equation, by fitting an augmented $VAR(p+d)$ to the data, where d is the order of integration of the variables in the VAR with p lags. [Toda and Yamamoto \(1995\)](#) show that tests on the coefficients of the first p lags of such a model have standard asymptotic inferences which are assured by the additional lags added.

Our fourth causality test is the [Toda and Yamamoto \(1995\)](#) test on the augmented level VAR in equation (4.1) by one lag, since our variables are I(1). The equation determining

GDP, for example, in a VAR(2) becomes:

$$\begin{aligned} GDP_t = & b_{11}^{(1)}GDP_{t-1} + b_{12}^{(1)}STOCK_{t-1} + b_{13}^{(1)}CRED_{t-1} + b_{11}^{(2)}GDP_{t-2} + b_{12}^{(2)}STOCK_{t-2} \\ & + b_{13}^{(2)}CRED_{t-2} + b_{11}^{(3)}GDP_{t-3} + b_{12}^{(3)}STOCK_{t-3} + b_{13}^{(3)}CRED_{t-3} + \varepsilon_{1t} \end{aligned}$$

Toda and Yamamoto (1995) show that a F-test with the null that the first two lags of STOCK are zero: $H_0 : b_{12}^{(1)} = b_{12}^{(2)} = 0$ is asymptotically distributed as $\chi^2(2)$. Again, rejection of the null hypothesis points to causality going from STOCK to GDP, in the Granger sense.

All the causality tests performed are presented in Appendix Table 4.D. Given that the four tests capture different types of causality, results are not always consistent among them. We present a summary of all the causality tests in Table 4.3, where two (one) stars represents strong (weak) evidence of causality. We report a weak evidence of causality if half of the tests performed for a particular coefficient are significant at 5%. A higher number of significant tests and/or a stronger precision is reported as strong evidence of causality.

A clear pattern of causality can be observed in our sample of 22 advanced economies. First, evidence that bank development has an exogenous effect on GDP is present in only one country. On the other hand, we find strong evidence of reverse causality going from GDP to CRED in 16 of the countries, while a bi-directional causality is present in three. Looking at the causality patterns between stock market development and GDP, results are considerably different. Evidence of reverse causality is very scarce, with GDP causing STOCK in only three countries. The most compelling evidence points to a causal link going from stock market development to GDP, which is the case in 11 countries. A bi-directional link is also present, but only in four of the countries. Finally, evidence that both measures of financial development cause long-run economic development is present only in Finland¹⁰.

Overall, our results show an interesting pattern. The first notable implication of these findings is that countries experience rather different causality patterns and that these differences mainly stem from the type of financial institution considered. These results confirm previ-

¹⁰While most of the tests performed support a uni-directional causality, it should be noted that some evidence of a bi-directional link is also present. A feedback relationship between finance and growth is suggested by several theoretical models in which economic growth leads to the development of a financial structure, which then leads to more efficient investment that will generate even further growth (see Greenwood and Jovanovic, 1990). Our results support such a hypothesis, in particular when financial development stems from stock markets which display a strong bi-directional causal link with GDP in four countries. Interestingly, these countries exhibit some of the highest levels of stock market development as compared to bank development, as measured by the ratio of STOCK/CRED. While a bi-directional link does not refute the evidence of causality between finance and growth, it does point to more complex dynamics than previously considered. For example, the weak bi-directional causality between GDP and CRED found in three countries is mainly the result of a short-term causal impact of CRED on GDP. On the other hand, the bi-directional causality between GDP and STOCK is supported by both short- and long-run dynamics (see Appendix Table 4.D).

ous time series research that stresses the significant heterogeneity in the finance-growth link, such as [Demetriades and Hussein \(1996\)](#), [Luintel and Khan \(1999\)](#), [Arestis et al. \(2001\)](#) or [Luintel et al. \(2008\)](#). However, most of these findings are limited to proxies of banking sector development in developing countries (for example, [Ang and McKibbin, 2007](#); [Christopoulos and Tsionas, 2004](#); [Luintel and Khan, 1999](#); [Demetriades and Hussein, 1996](#)). We show here that, among countries with relatively high levels of development, a supply-leading hypothesis is supported only when financial development stems from security markets. One exception is [Arestis et al. \(2001\)](#), who test for long-run causality in a sample of five advanced economies. Their weak exogeneity tests yields similar results to ours (for example in the case of US, UK or Germany), however our general conclusion is slightly different, due to the fact that our evidence of causality rests on a wider breath of tests that imply both short- and long-run causality.

The second implication of our results, i.e. that stock markets contribute more to economic growth at higher levels of financial development is echoed in several theoretical models (see Section 2). One particular channel through which securities markets may matter more for growth is through the financing of novel, innovative investments that rely more on intangible inputs. For example, [Brown et al. \(2009\)](#) and [Brown et al. \(2012\)](#) highlight the importance of equity finance for US and European firms' research and development spending. Given the undeniable role of R&D investments in endogenous growth models, stock markets may be an important driver of growth, especially at higher levels of development. While our findings do not shed light on the particular channels through which market-based financial systems might contribute to higher growth, they provide empirical support for an increasing importance of stock markets. Indeed, our results suggest that, at higher levels of development, stock market development plays a causal role in the growth of economies, while the banking sector does not. These findings complement those of [Tadesse \(2002\)](#) and [Demirgüç-Kunt et al. \(2012\)](#), but bring a new perspective on how the finance-growth nexus is sensitive to the type of financial institution considered. [Tadesse \(2002\)](#) examines how industry-level performance varies in a cross-section of countries with different financial architectures. He finds that, depending on a set of country characteristics such as level of development or average firm size, market- or bank-based financial systems can disproportionately impact growth. We instead focus on the dynamics of financial development and its association with real economic performance over a long period of time. [Demirgüç-Kunt et al. \(2012\)](#) also look at the evolving contribution of banks and markets to real sector outcomes, however they do not explicitly identify a causal impact.

Finally, since we find very little evidence that both measures of financial development have

Table 4.3: Summary of causality tests

Country	GDP→CRED	CRED→GDP	GDP→STOCK	STOCK→GDP	GDP↔CRED	GDP↔STOCK
Australia	**					
Austria	**		*			
Belgium	**					**
Canada				**		
Denmark	**			**		
Finland		**		**		
France	**			*		
Germany	*					
Greece				*	*	
Ireland	*					
Italy	**			**		
Japan	*			**		
Netherlands					*	**
New Zealand				*		
Norway			**		*	
Singapore	**		**			
South Korea	**					
Spain	**			**		
Sweden	**			**		
Switzerland	**					**
UK	**			**		
USA	**					**

Tables present the summary of the four causality tests shown in Appendix Table 4.D.

"→"/"↔" symbolizes a unidirectional/bidirectional causality.

*/** represent a weak/strong evidence of causality. We consider the threshold for weak evidence of causality as half of the tests performed for a particular direction of causality being significant at 5%. A higher number of significant tests and/or a stronger precision is reported as strong evidence of causality.

GDP is the log of real GDP/capita, STOCK is the log of the ratio of stock market capitalization to nominal GDP, CRED is the log of the ratio of private credit to nominal GDP.

a causal impact on GDP, our findings suggest that the finance led-growth hypothesis requires modification. In particular, the strong causal link between banking sector development and growth appears to vanish when we consider a time period in which financial sectors have developed intensively. [Rousseau and Wachtel \(1998\)](#) document a strong causal link going from financial intermediaries to growth before the 1930's. We show that, at higher levels of financial development, this strong causality seems to vanish, and banking sector development simply follows that of the real economy. A theoretical intuition for this reversed effect is provided in [Deidda \(2006\)](#). He shows how, at high stages of development, financial intermediaries tend to become "too big" and their consumption of real resources offsets their contribution to economic growth.

The results summarized above reflect both a short- and long-term causal link. We also tested explicitly for short-term causality since recent empirical evidence has been concerned with the short-run effect that financial development might have on output growth ([Christopoulos and Tsionas, 2004](#); [Loayza and Ranciere, 2006](#)). Short-run Granger causality tests (SRG) are presented in Appendix Table 4.D and support our general results. Two interesting patterns are worth highlighting. First, evidence of short-run causality between banking sector development and GDP is weak, at best. Thus the causal link going from GDP to banking sector development highlighted above appears to be present only in the long-term¹¹. This is in line with the findings in [Christopoulos and Tsionas \(2004\)](#) who look at causality between between bank development and GDP in a sample of 10 developing countries. Second and more interestingly, the strong causal impact of stock market development on GDP is reflected in the short-run, as well¹². This distinction between short-run and long-run causality allows us to draw interesting policy implications. In particular, design of policies that boost stock market development can positively impact output in the both the short- and long-run. On the other hand, the fact that economic growth tends to be followed, in the long-run, by an increase in the size of the banking sector, should also raise policy concerns about the implications of this growth in financial intermediation. For example, [Greenwood and Scharfstein \(2013\)](#) document that, in fact, this growth in credit intermediation in the US over the past three decades has mainly been due to the expansion of household mortgage credit. This development can bring along significant social costs caused by an excessive household leverage. Similar evidence in [Beck et al. \(2014\)](#), shows that the recent growth of financial sectors in developed countries has mainly been driven by non-intermediation activities, which the authors find to be less correlated to economic performance.

¹¹We thank an anonymous referee for suggesting this discussion.

¹²The short-run coefficients of STOCK (not reported) are positive in all the countries, with the exception of two in which the coefficients are negative but not statistically significant.

4.4.3 Robustness checks

We check the robustness of our results along several lines. First, the Johansen cointegration procedure can be prone to falsely reject the null hypothesis of no cointegration in small samples (Reinsel and Ahn, 1992). We thus check the robustness of the estimated cointegrating relationships using two alternative econometric techniques: the fully modified OLS (FMOLS) estimator and panel unit roots and cointegration models. Second, we test the robustness of our main estimates using alternative measures of financial development.

FMOLS

We perform an alternative cointegration test proposed by Phillips and Hansen (1990) which corrects for finite-sample biases. The FMOLS procedure estimates cointegrating relationships by modifying the traditional OLS coefficients to account for endogeneity and serial correlation in the regressors. FMOLS is asymptotically equivalent to system methods like Johansen (1988), while it is less sensitive to lag lengths and performs better in small samples (Phillips and Hansen, 1990). We present the FMOLS estimators in Appendix Table 4.E. Using this procedure we identify the same stable long-term relationship as with the Johansen procedure and test for cointegration by examining the stationarity of the error term obtained. The results of the ADF test on the residuals are presented in column 3 of Appendix Table 4.E and generally confirm the stationarity of the residuals and, hence, of the estimated relationships¹³.

Panel cointegration and causality

We further test the robustness of our main results by implementing panel cointegration and causality tests. This methodological approach offers several advantages. First, we can, once again, correct for the Johansen small sample bias. Second, traditional panel techniques such as generalized method-of-moments (GMM) dynamic estimators generally require pooling individual cross-sections and only allow the intercept to differ across cross-sections. However, when dealing with panels where both the number of cross-sections and the time dimension are large, assuming a homogeneous slope may not be appropriate (see Petersen and Rajan, 1995; Im et al., 2003). Indeed, our country-by-country estimations in Section 4.1 suggest that the

¹³Overall, the identified cointegrating relationships are similar to the ones estimated under the Johansen procedure. In a few cases, FMOLS coefficients are not significant where the Johansen coefficients were (for example, Greece and New Zealand). This may be caused by the fact that the FMOLS procedure assumes that the variables on the right hand-side of the equation, hence the proxies for financial development, are exogenous. This is not always the case, as the causality tests presented in Appendix Table 4.D show. For this reason, we stress the importance of a simultaneous framework that allows for testing different feedback relationships. However, we estimate the FMOLS relationships using GDP as the explained variable just to allow for a consistent comparison with the Johansen normalized cointegration vectors.

coefficients of bank and stock market development can be significantly different among countries. Panel cointegration techniques can allow for such heterogeneous cointegrating vectors to be present in each country. Lastly, GMM dynamic estimators would be a valid approach if our data were averaged across large time periods, such that the time dimension of the panel is small (as in, [Levine et al., 2000](#); [Beck and Levine, 2004](#)). However, as we argue in Section 2, this may mask important dynamics. As a result, we follow novel estimation techniques for non-stationary heterogeneous panels ([Canning and Pedroni, 2008](#)).

The cointegration analysis of panel data consists of four steps which we briefly describe here. The first step rests in testing the integration properties of the panel data. To that end, we implement a panel unit root test proposed by [Im et al. \(2003\)](#) for each variable. This test allows each panel member to have a different autoregressive parameter and short-run dynamics. Appendix Table 4.F.1 presents the panel unit root tests. The null hypothesis of a panel unit root cannot be rejected for either of the three time series, while their first difference is stationary.

Having established that all our variables are $I(1)$, we test for panel cointegration. We follow the technique proposed by [Pedroni \(1999; 2004\)](#) which is robust to causality running in both directions, as our individual country tests suggest. Furthermore, this method also allows for both heterogeneous cointegrating vectors and short-run dynamics across countries which is, again, the case in our sample. More specifically, the cointegrating regression we estimate is:

$$GDP_{it} = \alpha_i + \beta_t + \gamma_i CRED_{it} + \delta_i STOCK_{it} + \epsilon_{it},$$

where we allow for country and time fixed effects. The residuals of this equation, ϵ_{it} , are then used to construct panel cointegration tests as proposed by [Pedroni \(1999; 2004\)](#). [Pedroni \(1999; 2004\)](#) develops two distinct tests. The first pools the autoregressive coefficients across countries and includes four statistics, while the second is based on averages of the individually estimated coefficients and includes three statistics (see Appendix Table 4.F.1). These tests confirm our previous results, since the null of no cointegration is rejected in six of the seven statistics proposed. Having confirmed the presence of a long-run relationship between the variables, we estimate this cointegrating relationship using the fully modified least square method (FMOLS) of [Pedroni \(2001\)](#). Using this method, we construct the error correction term: $\hat{\epsilon}_{it} = GDP_{it} - \hat{\alpha}_i - \hat{\beta}_t - \hat{\gamma}_i CRED_{it} - \hat{\delta}_i STOCK_{it}$. As a final step, following [Canning and Pedroni \(2008\)](#), we estimate the following error correction mechanisms:

$$\begin{aligned} \Delta GDP_{it} &= c_{1i} + \lambda_{1i} \hat{\epsilon}_{it-1} + \gamma_{11i} \Delta GDP_{i,t-1} + \gamma_{12i} \Delta STOCK_{i,t-1} + \gamma_{13i} \Delta CRED_{i,t-1} + \varepsilon_{1it} \\ \Delta CRED_{it} &= c_{2i} + \lambda_{2i} \hat{\epsilon}_{it-1} + \gamma_{21i} \Delta GDP_{i,t-1} + \gamma_{22i} \Delta STOCK_{i,t-1} + \gamma_{23i} \Delta CRED_{i,t-1} + \varepsilon_{2it} \\ \Delta STOCK_{it} &= c_{3i} + \lambda_{3i} \hat{\epsilon}_{it-1} + \gamma_{31i} \Delta GDP_{i,t-1} + \gamma_{32i} \Delta STOCK_{i,t-1} + \gamma_{33i} \Delta CRED_{i,t-1} + \varepsilon_{3it} \end{aligned} \quad (4.4)$$

where Δ denotes first difference¹⁴. Given that all variables in the error correction models in (4.4) are stationary, we carry out standard hypothesis tests on their coefficients. Evidence of causality in the Granger sense is a joint test on the coefficients of the error terms $\lambda_{1i}, \lambda_{2i}, \lambda_{3i}$ and the short-term dynamics coefficients γ_i in each equation in (4.4). For example, a test that STOCK Granger causes GDP is the joint test: $\lambda_{1i} = \gamma_{12i} = 0$ for each country in our sample. This test is equivalent to the strong exogeneity test (STE) presented in Appendix Table 4.D.

We present the causality tests for each country in Appendix Table 4.F.2. Results show the same patterns of causality: a mostly reverse causality between GDP and CRED, present in eight of the countries. At the same time, the strong evidence of causality going from STOCK to GDP is found in 15 of the countries also under this alternative estimation technique. While our general conclusion is supported under this alternative methodology, it should be noted that individual country causality tests are not always identical. The main reason for this is the manner in which these two tests are constructed. In the causality tests in Appendix Table 4.F.2, the error-correction term is constructed by including both financial development variables in the cointegrating relationship in all of the countries. The strong exogeneity tests in Appendix Table 4.D are performed after over-identifying restrictions are imposed on the cointegrating vectors, thus after excluding, in certain countries, either STOCK or CRED from the cointegrating relationship¹⁵.

Alternative measures of financial development

Lastly, we check the robustness of our results with regards to the proxies for financial development. As discussed in Section 3, measures of stock market liquidity have been found to be more closely related to real sector output. We thus re-test the causality between financial development and GDP, using the turnover ratio as a proxy for financial development. However, this measure is not available for all the countries in our sample for a sufficiently long time span and, as a result, we present the findings for a restricted sample of 17 countries. Results are reported in Appendix Table 4.G and are broadly similar to our baseline tests. We, once again, find significant evidence of reverse causality from CRED to GDP in 12 of the countries. There is less evidence of causality going from the turnover ratio to GDP, which is present in only two

¹⁴We estimate the error correction term allowing for one lag in the difference. We tested to higher order lags, but these were not significant.

¹⁵Despite these different methodological approaches to testing causality, note that only 22 of the 88 tests performed using the panel causality approach do not match their equivalent strong exogeneity tests presented in Appendix Table 4.D. Nonetheless, we have further checked the robustness of these results by re-estimating the causality tests for several sub-samples. First, we exclude the 2007-2009 financial crisis window from our analysis. Second, we consider a sub-sample in which financial sectors have developed extensively, and include only the period 1990Q1- 2011Q4 in our panel. Finally, we have re-estimated the panel causality tests for a sub-sample between 1973 to 2000. These robustness tests give the same qualitative results and are available from the authors.

of the countries, however we do find stronger evidence in favor of a bi-directional causality, present in six of the countries. Reverse causality is also found in three cases, the same as in our main results. These slight differences can be attributed to the significantly smaller sample size for which the turnover ratio is available (the late 1980s for most countries). Nevertheless, our key findings still hold using this alternative proxy: bank development mostly follows that of the real economy, while stock market development appears to exert a stronger causal impact on GDP.

4.5 Conclusions

The growing importance of financial institutions over the past decades has fueled a large body of research over its effects on economic development. Despite the fact that the finance-growth nexus has been extensively analyzed, recent evidence and events have challenged many of the stylized facts derived during the 1990s.

This chapter contributes to the finance-growth literature by presenting evidence that causality patterns between finance and growth differ depending on whether financial development stems from the banking sector or stock markets.

We study the time series properties of economic and financial development for a sample of 22 advanced economies. We find that stock market development exerts a causal impact on GDP in 11 of the countries in our sample, while a reverse causal link is present between economic and bank development in 16 countries. These results suggest that the finance-led growth hypothesis derived from cross-country studies is supported only when financial development stems from stock markets. Banking sector development, on the other hand, seems to mainly follow the development of the real economy. Furthermore, since we look at countries with relatively advanced capital markets, our findings suggest that the impact of banking sector development is less strong at high levels development.

Our results confirm the need to reassess the causal link between the financial sector and economic growth; the general notion that finance causes growth may no longer be empirically valid when recent data is employed and both types of financial sectors are considered. Our results complement recent findings that suggest that not just the size, but also the structure of financial systems may matter for growth (Fecht et al., 2008; Luintel et al., 2008; Ergunçor, 2008; Arestis et al., 2010; Demirgüç-Kunt et al., 2012). Further empirical research may be directed towards disentangling the mechanisms through which the two different types of financial institutions affect the real sector. For example, Beck (2008) shows that banks disproportionately help the growth of small firms, Strieborny and Kukušková (2015) argue that

they promote growth by facilitating investment in relationship-specific assets, while [Brown et al. \(2009\)](#) and [Brown et al. \(2012\)](#) find evidence that stock markets lead to more funds being directed to innovative, young companies. Research along these lines can lead to the formulation of financial sector policies that shape its development in directions which bring a positive contribution to economic growth. More specifically, since our findings imply that financial system design has implications for real sector outcomes, then policies and institutions should be directed towards facilitating the evolution of financial sectors in directions in which their contribution to growth is the highest.

Appendices

4.A Variables definitions, sources and descriptive statistics

Table A.1: Definitions and sources of variables

Variable	Definition	Source
Real GDP* (GDP)	Logarithm of real GDP per capita (seasonally adjusted)	Authors' calculation based on nominal GDP data extracted from IMF-IFS Database, CPI and population data obtained from Datastream
Stock Market Capitalization (STOCK)	Logarithm of the ratio of stock market value to nominal GDP	Stock market value was obtained from Datastream (code: TOTMK...(MV))
Domestic Bank Credit (CRED)	Logarithm of the ratio of private sector bank credit to nominal GDP	Credit granted by banks to the private sector obtained from Bank of International Settlements Database: Long series on total credit and domestic bank credit to the private non-financial sector

*GDP data is seasonally adjusted, either from source or by the authors using the U.S. Department of Commerce quarterly seasonal adjustment method, X-12.

Table A.2.: Descriptive statistics

Variable	Mean	Std. Dev.	Max	Min
Log real GDP/capita	9.543	1.572	15.51	7.858
Private Credit/GDP	3.348	1.668	8.320	0.401
Stock market capitalization/GDP	2.199	2.246	11.88	0.002

4.B Johansen Cointegration

In this appendix, we discuss some of the caveats that the Johansen cointegration method faces in empirical applications and detail the steps we carry out prior to testing cointegration in this framework.

First, we test the integration properties of each variable using the Augmented Dickey-Fuller (ADF) as well as the Kwiatkowski et al. (1992) (KPSS) procedure. The null hypothesis of a unit root, in the presence of an intercept, cannot be rejected for any of variables considered in all the countries. Furthermore, all series are $I(0)$ in the first difference¹⁶.

Second, since the Johansen method has been shown to be sensitive to the lag length, we determine the proper number of lags using the Akaike (1974) and Schwarz (1978) information criteria. Hendry and Juselius (2001) argue that the lag length ought to be set such that the VAR residuals are free of autocorrelation, even if this implies longer lags than suggested by the information criteria. We follow both approaches to estimate the optimal lag length. However, if the information criteria suggest a lag length for which autocorrelation is still present, we set the number of lags such that the VECM residuals are uncorrelated, as the Johansen method proposes. As a robustness check, we re-test for the number of cointegrating vectors when different lag length are allowed. Generally, results are qualitatively the same.

Next, we parameterize the deterministic component D_t in equation (4.1). We allow for an unrestricted constant in the VAR which accounts for linear trends in the level data, but not for a trend in the cointegrating relationship. This unrestricted constant can be decomposed to allow for both linear trends in the data generating process and a non-zero intercept in the cointegrating vectors (Hendry and Juselius, 2001). Our data is best represented by this specification since the log variables are trending over time, while the cointegrating relationship does not present a trend in most cases. Exception are in the case of Canada, Korea, Singapore, Spain and UK, where we allow for a more relaxed assumption and restrict the constant term to lie in the cointegrating space, but we assume no linear deterministic trend in the data. Furthermore, D_t can also include unrestricted (innovational) dummies added to whiten the residuals. Following Hendry and Juselius (2001), we detect outliers larger than $\pm 3\hat{\sigma}$, for which we introduce unrestricted impulse dummies¹⁷. The introduction of impulse dummies leaves the asymptotic distributions of the cointegration model unaffected, while ignored innovational dummies have only minor consequences for small sample inferences of the cointegration rank (Bohn Nielsen, 2004).

Finally, we investigate the presence of structural breaks in the cointegrating relationships since various policy changes and macroeconomic events could have resulted in a structural break in the cointegrating relationship¹⁸. The presence of structural breaks in the model generally leads to an over-rejection of null of cointegration. We address this issue by applying the

¹⁶Results are available upon request.

¹⁷The list of impulse dummies introduced for each country is not presented here, but can be obtained from the authors.

¹⁸We thank an anonymous referee for suggesting this robustness.

Hansen and Johansen (1999) methodology of identifying structural breaks in the cointegrating relationship based on recursively estimated eigenvalues. The test consists in recursively estimating the eigenvalues of the β matrix and comparing them to the full-sample estimate. This recursive analysis can be regarded as a misspecification test to detect possible instabilities in the parameters when there is no prior knowledge of structural breaks in the parameters (Hansen and Johansen, 1999). Denote by $\lambda_i^{(\tau)}$ the i^{th} eigenvalue based on a sub-sample from the first τ observations only and let $\xi_i^{(\tau)} = \log \left(\frac{\lambda_i^{(\tau)}}{1-\lambda_i^{(\tau)}} \right)$. The test statistic compares $\xi_i^{(\tau)}$ to the full sample $\xi_i^{(T)}$, for every τ . Whenever the two values are significantly different, the null hypothesis of parameter stability is rejected. Using this methodology, we identify breaks in the cointegrating relationship in the following countries (dates): Italy (1992Q4, 1996Q4), Ireland (1996Q3, 2003Q1), Germany (1991Q1), the Netherlands (1988Q4), Sweden (1989Q4, 2004Q2) and USA (1984Q3, 1994Q3). These breaks correspond to major macroeconomic events like the German reunification (1991), Italy's exit from the ERM (1991), Sweden's credit crisis (1990) or important policy measures like the sudden tightening of monetary policy in the US (in 1984 and again in 1994). Furthermore, we tested whether our results are sensitive to including the period of the financial crisis. This is the case for Greece and Spain, for which we exclude the period after 2007Q3.

After breaks in the cointegrating relationship have been identified, we test for cointegration following the Johansen et al. (2000) procedure which restricts step dummies corresponding to these break dates in the cointegrating space. Evidence of one cointegrating vector is found in all of the countries where structural breaks are present. However, since these added step dummies should not impact the direction of causality, the estimations for the causality tests presented in Appendix Table 4.D do not include the step dummies¹⁹.

¹⁹These tests have been implemented using the JMulti Econometric package. Results are available upon request.

4.C Diagnostics Tests

Appendix Table C: Diagnostic tests for the Vector Autoregressive (VAR) Models

The Lagrange Multiplier is a test of residual autocorrelation under the null of no serial correlation at the lag order in Table 1. Columns 2 and 3 present the multivariate extensions of the Jarque-Berra residual normality test, under the null that the third (column 2) and fourth (column 3) moments of the residuals are comparable to those from the normal distribution. The joint test of residual normality for the three vectors in the VAR is presented in the last column, under the null hypothesis that residuals are multivariate normal.

Country	Lagrange Multiplier Test	Skewness	Kurtosis	Jarque-Berra
Australia	7.38 [0.60]	6.96 [0.07]	1.75 [0.62]	8.71 [0.19]
Austria	9.96 [0.35]	6.40 [0.09]	37.5 [0.00]	43.9 [0.00]
Belgium	12.4 [0.19]	8.39 [0.04]	4.16 [0.24]	12.6 [0.06]
Canada	12.6 [0.17]	62.5 [0.00]	215 [0.00]	278 [0.00]
Denmark	6.89 [0.64]	6.70 [0.08]	3.10 [0.37]	9.80 [0.13]
Finland	5.47 [0.79]	0.99 [0.80]	10.1 [0.02]	11.1 [0.08]
France	11.5 [0.24]	28.6 [0.00]	84.2 [0.00]	112 [0.00]
Germany	15.2 [0.08]	14.9 [0.01]	35.3 [0.00]	113 [0.00]
Greece	3.68 [0.93]	7.04 [0.07]	5.67 [0.13]	121 [0.00]
Ireland	9.97 [0.35]	6.46 [0.10]	4.53 [0.21]	11.0 [0.09]
Italy	6.92 [0.64]	7.56 [0.06]	5.18 [0.16]	12.7 [0.05]
Japan	10.4 [0.31]	2.88 [0.41]	4.49 [0.21]	7.38 [0.28]
Netherlands	10.7 [0.29]	4.13 [0.24]	33.5 [0.00]	37.7 [0.00]
New Zealand	14.5 [0.10]	3.42 [0.33]	3.75 [0.28]	7.17 [0.30]
Norway	9.13 [0.43]	3.86 [0.27]	0.39 [0.94]	4.26 [0.64]
Singapore	8.34 [0.50]	6.07 [0.10]	21.4 [0.00]	27.5 [0.00]
South Korea	3.57 [0.93]	1.35 [0.71]	5.95 [0.11]	7.31 [0.29]
Spain	12.1 [0.21]	9.85 [0.02]	22.6 [0.00]	32.5 [0.00]
Switzerland	12.8 [0.16]	8.42 [0.04]	39.9 [0.00]	48.4 [0.00]
Sweden	8.94 [0.43]	4.74 [0.19]	2.73 [0.43]	7.47 [0.27]
United Kingdom	11.8 [0.22]	4.33 [0.22]	374 [0.00]	379 [0.00]
USA	8.94 [0.43]	4.74 [0.19]	2.73 [0.43]	7.47 [0.27]

Figures in brackets represent p-values associated with the tests.

4.D Main Causality Tests

Appendix Table D: Main Causality Tests

Country	GDP → CRED				CRED → GDP				GDP → STOCK				STOCK → GDP			
	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y
Australia	38.7**	0.53	<u>43.5**</u>	<u>2.65</u>	2.34	0.21	<u>2.47</u>	<u>0.23</u>	1.22	0.07	<u>1.91</u>	<u>1.15</u>	-	3.71	-	5.80
Austria	13.5**	1.85	<u>13.8**</u>	<u>1.71</u>	0.12	0.15	<u>0.30</u>	<u>1.66</u>	5.02*	4.85*	<u>8.01*</u>	<u>4.27</u>	-	5.11*	-	3.57
Belgium	12.2**	3.65	<u>13.1**</u>	<u>9.92**</u>	-	1.65	-	<u>3.34</u>	0.29	7.25**	<u>7.33*</u>	<u>8.19*</u>	9.43**	1.93	<u>14.1**</u>	<u>4.01</u>
Canada	0.39	1.25	<u>1.43</u>	<u>1.26</u>	-	1.51	-	<u>0.99</u>	0.33	4.25	<u>4.26</u>	<u>0.78</u>	11.7**	2.50	<u>18.8**</u>	<u>10.1**</u>
Denmark	9.73**	14.1**	<u>43.6**</u>	<u>30.6**</u>	3.20	0.89	<u>4.77</u>	<u>2.13</u>	4.26*	4.22	<u>5.78</u>	<u>1.89</u>	3.20	6.45*	<u>14.6**</u>	<u>12.5**</u>
Finland	0.24	0.72	<u>0.77</u>	<u>0.10</u>	17.2**	0.07	<u>17.6**</u>	<u>1.28</u>	2.58	1.38	<u>3.06</u>	<u>1.26</u>	17.2**	1.32	<u>28.5**</u>	<u>17.4**</u>
France	8.61**	3.81	<u>10.5**</u>	<u>2.45</u>	-	1.08	-	<u>0.63</u>	1.86	0.02	<u>2.04</u>	<u>0.75</u>	6.88**	1.02	<u>7.93*</u>	<u>2.48</u>
Germany	1.64	6.99*	<u>12.1**</u>	<u>6.74</u>	2.95	2.19	<u>11.8**</u>	<u>6.06</u>	0.00	3.31	<u>6.55</u>	<u>5.32</u>	-	4.74	-	<u>5.84</u>
Greece	2.29	5.39*	<u>5.40</u>	<u>7.06*</u>	12.0**	0.27	<u>22.0**</u>	<u>1.28</u>	0.01	0.89	<u>1.53</u>	<u>2.08</u>	-	9.04**	-	<u>10.6**</u>
Ireland	5.45*	0.01	<u>7.33*</u>	<u>2.70</u>	0.01	2.53	<u>3.21</u>	<u>1.01</u>	5.12*	2.75	<u>5.39</u>	<u>4.89</u>	-	0.32	-	<u>0.22</u>
Italy	17.2**	1.77	<u>23.7**</u>	<u>2.18</u>	-	0.05	-	<u>1.41</u>	0.11	1.74	<u>1.75</u>	<u>4.17</u>	15.2**	0.36	<u>15.5**</u>	<u>2.37</u>
Japan	7.43**	1.17	<u>7.49*</u>	<u>4.80</u>	-	0.03	-	<u>0.05</u>	0.25	2.18	<u>2.23</u>	<u>2.26</u>	13.9**	1.29	<u>18.8**</u>	<u>6.81*</u>
Netherlands	22.2**	0.60	<u>28.6**</u>	<u>5.84</u>	0.57	6.35*	<u>6.53*</u>	<u>3.31</u>	7.80*	10.8**	<u>14.0**</u>	<u>7.29*</u>	-	13.3**	-	<u>13.7**</u>
New Zealand	0.10	0.31	<u>0.40</u>	<u>2.70</u>	-	1.14	-	<u>7.36</u>	1.96	1.76	<u>3.33</u>	<u>1.71</u>	7.54**	1.74	<u>9.39*</u>	<u>7.65</u>
Norway	12.8**	2.43	<u>19.9**</u>	<u>1.98</u>	0.27	8.44*	<u>8.50*</u>	<u>4.91</u>	0.06	9.62**	<u>10.1**</u>	<u>14.3**</u>	-	1.56	-	<u>2.24</u>
Singapore	11.7*	3.37	<u>13.7**</u>	<u>3.45</u>	0.41	0.07	<u>0.52</u>	<u>0.32</u>	9.70**	15.8**	<u>22.6**</u>	<u>15.6**</u>	0.40	0.01	<u>0.42</u>	<u>0.57</u>
South Korea	7.57**	2.08	<u>10.7**</u>	<u>0.64</u>	3.20	0.03	<u>3.21</u>	<u>0.97</u>	2.34	0.01	<u>2.36</u>	<u>1.78</u>	3.20	0.84	<u>5.18</u>	<u>1.85</u>
Spain	4.27*	17.9**	<u>18.2**</u>	<u>10.4**</u>	-	3.32	-	<u>2.41</u>	0.22	1.32	<u>1.34</u>	<u>5.58</u>	18.2**	7.08*	<u>28.8**</u>	<u>10.4*</u>
Sweden	11.7**	5.42*	<u>27.7**</u>	<u>8.31*</u>	0.03	1.59	<u>1.75</u>	<u>1.87</u>	0.06	0.68	<u>0.69</u>	<u>2.36</u>	0.03	6.07*	<u>6.44*</u>	<u>10.0**</u>
Switzerland	8.32**	1.01	<u>8.48*</u>	<u>0.33</u>	0.01	0.01	<u>0.01</u>	<u>4.12</u>	15.4**	7.81**	<u>19.4**</u>	<u>2.55</u>	-	7.41**	0	<u>8.84*</u>
UK	2.56	26.9**	<u>27.8**</u>	<u>5.35</u>	-	7.47**	-	<u>5.69</u>	0.25	2.97	<u>3.30</u>	<u>0.81</u>	22.6**	0.80	<u>25.4**</u>	<u>10.3**</u>
USA	0.01	23.1**	<u>23.2**</u>	<u>22.9**</u>	0.19	2.73	<u>3.15</u>	<u>2.72</u>	14.7**	1.05	<u>15.8**</u>	<u>0.27</u>	0.19	17.6**	<u>19.6**</u>	<u>18.5**</u>

Table presents the log-likelihood statistics of the causality tests distributed $\chi^2(1)$ for the statistics that are not underlined, $\chi^2(2)$ for the statistics underlined with one line and $\chi^2(3)$ for the statistics underlined with two lines.

GDP is the log of real GDP/capita, STOCK is the log of the ratio of stock market capitalization to nominal GDP, CRED is the log of the ratio of domestic credit to nominal GDP.

WEX is the weak exogeneity test under the null: $H_0 : \alpha_{ij} = \beta_{ij} = 0$.

SRG is the short-run Granger causality test under the null: $H_0 : \Gamma_{ij}^p = 0$, distributed $\chi^2(1)$.

STE is the strong exogeneity test under the null: $H_0 : \Gamma_{ij}^p = \alpha_{ij} = 0$.

T&Y is the Toda & Yamamoto(1995) causality test for level VARs.

*/** represent significance at 5%/1% level.

4.E Robustness checks: FMOLS estimation

Appendix Table E: FMOLS estimates

The estimated system is: $x_t = \gamma z_t + u_{1t}$; $z_t = z_{t-1} + u_{2t}$, where x_t is the normalized variable, GDP in the first cointegrating relationship and STOCK\CRED in the second and z_t is a vector of the other variables. The fully modified OLS estimate of γ is: $\gamma_{FMOLS} = \left(\sum_{t=1}^T z_t^2 \right)^{-1} \left[\left(\sum_{t=1}^T x_t^+ z_t \right) - T\delta^+ \right]$, where $x_t^+ = x_t - \hat{\omega}_{12}\hat{\omega}_{22}^{-1}\Delta z_t$, δ^+ is the bias correction term: $\delta^+ = \hat{\Lambda} \begin{bmatrix} 1 \\ -\hat{\omega}_{22}^{-1}\hat{\omega}_{21} \end{bmatrix}$, $\hat{\Lambda} = \sum_{k=0}^{\infty} E(u_{20}u_k')$ and the long-run variance is $\Omega = \{\omega_{i,j}\}_{i,j=1,2}$. ADF is the Augmented Dickey-Fuller test under the null of a unit root in the FMOLS residuals.

Country	Cointegrating relationship	ADF Test
Australia	$C = GDP - 0.44 CRED - 8.90$ [-20.8]	0.01
Austria	$C = GDP - 0.89 CRED - 7.75$ [-24.9]	0.02
Belgium	$C = GDP - 0.19 STOCK - 8.70$ [-16.6]	0.09
Canada	$C = GDP - 0.18 STOCK - 7.88$ [-19.7]	0.02
Denmark	$C = GDP - 0.12 STOCK - 0.13 CRED - 10.82$ [-15.8] [-3.88]	0.01
Finland	$C = GDP - 0.19 STOCK - 0.44 CRED - 9.27$ [-14.6] [-11.7]	0.01
France	$C = GDP - 0.12 STOCK - 8.68$ [-18.3]	0.01
Germany	$C = GDP - 1.37 CRED - 6.78$ [-10.1]	0.08
Greece	$C = GDP - 0.08 CRED - 8.09$ [-1.51]	0.01
Ireland	$C = GDP - 0.86 CRED - 10.3$ [-3.07]	0.08
Italy	$C = GDP - 0.21 STOCK - 8.60$ [-21.5]	0.01
Japan	$C = GDP - 0.34 STOCK - 8.28$ [-6.62]	0.10
Netherlands	$C = GDP - 0.60 CRED - 8.05$ [-33.7]	0.01
New Zealand	$C = GDP - 0.09 STOCK - 9.04$ [-1.76]	0.65
Norway	$C = GDP - 0.58 CRED - 10.9$ [-9.85]	0.05
Singapore	$C = GDP - 0.87 STOCK + 0.04 CRED - 8.04$ [-12.9] [0.31]	0.01
South Korea	$C = GDP - 0.32 STOCK - 0.92 CRED - 13.6$ [-9.97] [-7.42]	0.01
Spain	$C = GDP - 0.28 STOCK - 8.33$ [-15.0]	0.01
Sweden	$C = GDP - 0.12 STOCK - 0.27 CRED - 10.65$ [-11.0] [-3.51]	0.15
Switzerland	$C = GDP - 0.71 CRED - 8.36$ [-15.3]	0.02
United Kingdom	$C = GDP - 0.35 STOCK - 7.89$ [-11.6]	0.05
USA	$C = GDP - 0.31 STOCK - 0.44 CRED - 11.1$ [-19.5] [-3.61]	0.01

p-values in ().

4.F Robustness checks: Panel Cointegration

Table 4.F.1: Panel Unit Root and Cointegration tests

Panel unit root test Im et al. (2003)		
Variables	Level	First difference
GDP	0.67	-26.4**
STOCK	0.11	-43.4**
CRED	0.74	-15.4**
Panel cointegration test Pedroni (2004)		
Panel v	0.24	
Panel ρ	-6.75**	
Panel PP	-5.80**	
Panel ADF	-4.13*	
Group ρ	-2.73**	
Group PP	-3.26**	
Group ADF	-1.89*	

The first panel presents the [Im et al. \(2003\)](#) test under the null that the series presents a unit root. The second panel presents the [Pedroni \(2004\)](#) panel cointegration test under the null of no cointegration. The first four statistics are constructed by pooling the autoregressive coefficients across countries, while the last three are based on the averages of the individually estimated coefficients.

*/** represent significance at 5%/1% level.

Table 4.F.2.: Panel Causality tests

Country	GDP→ CRED	CRED→ GDP	GDP→ STOCK	STOCK→ GDP
Australia	1.74	1.11	0.65	5.74**
Austria	0.47	0.59	3.10*	2.13
Belgium	2.90	4.40*	1.84	4.47*
Canada	4.64*	2.03	0.99	4.75**
Denmark	8.97**	1.90	2.12	4.04*
Finland	4.01*	1.61	0.33	6.24**
France	0.87	0.32	2.59*	0.22
Germany	0.31	1.87	0.48	0.93
Greece	9.98**	12.5**	1.64	13.7**
Ireland	3.65*	2.19	0.29	1.41
Italy	9.29**	4.18*	3.30	3.26*
Japan	2.35	6.87**	1.24	8.08**
Netherlands	2.35	5.94**	2.47	10.2**
New Zealand	0.18	3.02	0.85	4.12*
Norway	6.97**	5.39**	4.03*	1.67
Singapore	0.89	1.19	5.74**	1.14
South Korea	1.52	2.52	0.26	3.58*
Spain	10.6**	2.20	1.78	2.08
Sweden	14.4**	2.23	0.58	4.75*
Switzerland	3.65*	0.16	2.93	3.87*
UK	1.93	4.25*	0.24	3.67*
US	7.84**	0.79	0.47	6.12**

Table presents a joint test that the coefficient of the error correction term λ_i and short-run dynamics coefficient γ_i enter each of the equations in system (4.4) for the variables of interest.

*/** represent significance at 5%/1% level.

4.G Robustness checks: Turnover ratio

Appendix Table 4.G: Causality tests (Robustness check using the turnover ratio)

Country	GDP → CRED				CRED → GDP				GDP → TUR				TUR → GDP			
	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y
Australia	45.17**	0.30	<u>50.45**</u>	<u>0.90</u>	0.48	0.26	<u>1.28</u>	<u>0.25</u>	7.72**	8.46**	<u>11.6**</u>	<u>5.13</u>	0.48	0.44	0.65	<u>1.81</u>
Austria	11.9**	0.14	<u>12.2**</u>	<u>1.43</u>	2.25	0.10	<u>2.58</u>	<u>2.18</u>	4.31*	0.01	<u>4.73</u>	<u>2.43</u>	-	0.51	-	<u>1.15</u>
Belgium	12.7**	8.21**	<u>15.4**</u>	<u>7.27*</u>	-	4.17*	-	<u>8.61*</u>	5.58*	0.01	<u>6.28*</u>	<u>0.01</u>	2.02	3.01	<u>6.55**</u>	<u>3.30</u>
Canada	0.08	<u>0.13</u>	<u>0.20</u>	<u>0.24</u>	-	<u>1.63</u>	-	<u>1.42</u>	10.1**	<u>0.39</u>	<u>12.6**</u>	<u>1.81</u>	2.27	<u>10.0**</u>	<u>10.0**</u>	<u>9.67*</u>
Denmark	34.1*	0.99	<u>37.7**</u>	<u>2.13</u>	2.20	0.46	<u>2.24</u>	<u>0.01</u>	0.07	0.53	<u>0.01</u>	<u>0.41</u>	2.20	5.19*	<u>6.25*</u>	<u>7.55*</u>
Finland	14.89**	1.26	<u>15.2**</u>	<u>2.41</u>	4.28*	0.94	<u>4.30</u>	<u>0.28</u>	0.26	0.01	<u>0.35</u>	<u>2.38</u>	-	0.01	-	<u>0.58</u>
France	15.5**	0.55	<u>19.1**</u>	<u>2.67</u>	0.28	0.36	<u>0.42</u>	<u>2.26</u>	0.39	1.14	<u>2.07</u>	<u>0.66</u>	0.28	1.03	<u>1.12</u>	<u>2.10</u>
Greece	25.3**	26.2**	<u>58.4**</u>	<u>27.6**</u>	10.8**	11.1**	<u>15.9**</u>	<u>15.5**</u>	0.01	0.56	<u>0.61</u>	<u>0.34</u>	-	3.48	-	<u>5.83</u>
Italy	25.5**	4.97*	<u>32.0**</u>	<u>4.33</u>	27.5**	9.69**	<u>30.3**</u>	<u>5.47</u>	7.07**	0.92	<u>7.71*</u>	<u>1.76</u>	27.5**	10.5**	<u>30.3**</u>	<u>4.13</u>
Japan	3.48	4.24*	<u>7.18**</u>	<u>4.06</u>	-	0.08	-	<u>0.29</u>	11.2**	0.01	<u>11.32**</u>	<u>0.97</u>	7.91**	5.58*	<u>10.3**</u>	<u>0.75</u>
Norway	3.47	4.46*	<u>9.40**</u>	<u>4.06</u>	-	6.53*	-	<u>4.01</u>	17.9**	.67	<u>17.8**</u>	<u>0.29</u>	0.11	0.23	<u>0.36</u>	<u>3.40</u>
Singapore	2.40	3.49	<u>3.92</u>	<u>3.96</u>	14.9**	0.22	<u>15.55**</u>	<u>0.38</u>	1.75	3.56	<u>3.71</u>	<u>6.08*</u>	14.9**	0.11	<u>14.9**</u>	<u>1.14</u>
South Korea	20.1**	0.51	<u>25.6**</u>	<u>0.18</u>	3.71	2.37	<u>4.24</u>	<u>0.09</u>	5.50*	2.39	<u>6.16*</u>	<u>2.66</u>	3.71	0.30	<u>3.72</u>	<u>2.27</u>
Sweden	17.2**	2.95	<u>38.1**</u>	<u>2.80</u>	0.03	0.71	<u>0.82</u>	<u>1.05</u>	3.21	2.18	<u>3.61</u>	<u>0.42</u>	0.03	0.96	<u>0.98</u>	<u>0.88</u>
Switzerland	0.68	1.73	<u>2.18</u>	<u>4.08</u>	2.87	0.06	<u>3.01</u>	<u>7.30*</u>	40.6**	1.62	<u>40.9**</u>	<u>3.40</u>	2.87	7.75**	<u>9.42**</u>	<u>5.70</u>
UK	31.1**	6.88**	<u>31.4**</u>	<u>3.02</u>	0.08	3.65	<u>4.25</u>	<u>5.49</u>	0.01	1.12	<u>1.66</u>	<u>0.84</u>	0.08	0.39	<u>0.57</u>	<u>0.33</u>
USA	3.59	36.9**	<u>41.5**</u>	<u>22.1**</u>	-	0.99	-	<u>2.83</u>	1.04	9.68**	<u>10.5**</u>	<u>1.74</u>	11.4**	0.40	<u>11.6**</u>	<u>1.13</u>

Table presents the log-likelihood statistics of the causality tests distributed $\chi^2(1)$ for the statistics that are not underlined, $\chi^2(2)$ for the statistics underlined with one line and $\chi^2(3)$ for the statistics underlined with two lines.

GDP is the log of real GDP/capita, TUR is the log of the ratio of value traded to stock market capitalization, CRED is the log of the ratio of domestic credit to nominal GDP.

WEX is the weak exogeneity test under the null: $H_0 : \alpha_{ij} = \beta_{ij} = 0$.

SRG is the short-run Granger causality test under the null: $H_0 : \Gamma_{ij}^p = 0$, distributed $\chi^2(1)$.

SET is the strong exogeneity test under the null: $H_0 : \Gamma_{ij}^p = \alpha_{ij} = 0$.

T&Y is the Toda & Yamamoto(1995) causality test for level VARs.

*/** represent significance at 5%/1% level.

Concluding remarks

Our understanding of the role of finance in real sector outcomes has been shaped by many important contributions, as well as major historical events. In the first issue of *Econometrica*, [Fisher \(1933\)](#) argued that the financial sector was largely responsible for the severity of the Great Depression in the 1930s. This view was later reinforced by [Schumpeter \(1934\)](#), [Gurley and Shaw \(1955\)](#) and [Goldsmith \(1969\)](#), who saw financial intermediaries playing a key role in the allocation of capital in the economy and, hence, in its growth. However, following the contributions of [Modigliani and Miller \(1958\)](#) and [Friedman and Schwartz \(1963\)](#), finance started to play a more passive role and was treated as a “veil” in most macroeconomic models. The incorporation of financial frictions in macroeconomic models was reintroduced much later by [Bernanke and Gertler \(1989\)](#), [Bernanke et al. \(1999\)](#) and [Kiyotaki and Moore \(1997\)](#), who highlighted their role in propagating real business shocks. Furthermore, the Great Moderation period throughout the 1990s corroborated the view of a large empirical literature suggesting that financial development is mostly beneficial for long-run growth ([Levine, 2005](#)). This literature largely overlooked the impact of systemic banking crises, which were seen as a concern for emerging economies solely.

The severity of the 2008 Global Financial Crisis reshaped many of these views. In particular, as financial intermediaries were at the center of the crisis, their role in, not just amplifying, but causing real sector disruptions has regained consensus in economic literature. Similarly, the positive role of finance in long-run growth is being reconsidered, in particular when the financial sector is “too big” ([Arcand et al., 2015](#)) or in weak institutional environments ([Demetriades and Rousseau, 2016](#)).

This thesis contributes to the financial economics literature by focusing on several ongoing issues. First, the recent crisis has revived the interest in understanding the extent to which financial frictions shape real sector outcomes. Recent contributions highlight the crucial role of financial constraints in explaining corporate investment and employment ([Nanda and Nicholas, 2014](#); [Chodorow-Reich, 2014](#)), international trade ([Amiti and Weinstein, 2011](#); [Chor and Manova, 2012](#)), international divergence in savings patterns ([Coeurdacier et al., 2015](#)),

housing market developments (Favara and Imbs, 2015) and the length and severity of business cycle fluctuations (Jermann and Quadrini, 2012; Brunnermeier and Sannikov, 2014; Boissay et al., 2015).

The first chapter of this thesis adds to this evidence by highlighting the effects of credit supply contractions that follow banking crises on the composition of corporate investment. It proposes a difference-in-difference identification strategy to show that banking crises affect disproportionately investments in innovation. By showing that industries that generally depend more on the banking sector to obtain funds invest less in R&D after the crisis, this chapter proposes a new channel that can explain the slower economic recovery following banking sector distress.

Together with understanding the impact of financial constraints, a recent stream of research also focuses on explicitly modeling the source of these frictions. While a large literature has studied numerous reasons why the market for external capital is subject to constraints (such as asymmetric information, moral hazard, or transaction and contract enforcement costs), recent contributions focus on financial sector frictions as the source of disruptions of funding towards the real economy (Bebchuk and Goldstein, 2011; Favara, 2012; Brunnermeier and Sannikov, 2014; Gorton and Ordoñez, 2014; Boissay et al., 2015). This thesis contributes to this literature by employing frictions in coordination in financial markets, as a way to model constraints in the supply of capital towards the real sector. It does so by employing a global games approach that allows for the introduction of incomplete information as method for eliminating the multiplicity of equilibria specific to coordination games (Angeletos and Lian, 2016). In particular, in the first chapter, I embed a classical bank run model in the spirit of Diamond and Dybvig (1983) in an endogenous growth model to show how banking crises affect real sector decisions by disproportionately discouraging investments in innovation. In the second chapter, I apply a similar methodology to study a model of financial intermediation in the presence of coordination frictions. The financing structure analysed best describes a type of project finance investment funded through a bond issuance. Finally, in the third chapter, I study how coordination frictions can generate bank runs in an experimental setting.

While the first three chapters are concerned with crises and inefficiencies in the financial sector, the final chapter of this thesis re-examines the long-run finance-growth nexus. Employing novel time series techniques, it shows that causality patterns between finance and growth depend on whether countries' financial development stems from the stock market or the banking sector. These findings contribute to a large literature that tries to understand the role of finance in economic development and suggest that the dynamics between the two might be more complex than previously thought.

The results presented in this thesis can also lead to further research in several directions. First, Chapter 1 proposes a stylized endogeneous growth model with a financial sector prone to banking panics. This partial equilibrium framework can be extended to a dynamic stochastic general equilibrium model in which banking crises arise endogenously. This would allow for enriched dynamics and new insights in the evolution of different types of investments over the business cycle. Second, the dynamics of industry-level investment patterns suggested in the first chapter could be investigated also at the firm level. One interesting context will be the study of European firm-level data that can provide some micro-level insights into the reasons behind the slow economic recovery in Europe during recent years.

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