Financial stability, economic growth, and the banking sector

IJtsma, Pieter Adolf

Financial stability, economic growth, and the banking sector

Pieter IJtsma

Publisher: University of Groningen
Groningen, The Netherlands

Printed by: Ipskamp Drukkers B.V.
Enschede, The Netherlands

ISBN: 978-94-034-0269-7 (printed version)
978-94-034-0270-3 (electronic version)

Financial stability, economic growth, and the banking sector

PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. E. Sterken
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Thursday 30 November 2017 at 11.00 hours

by

Pieter Adolf IJtsma

born on 14 May 1988
in Leeuwarden

Supervisors
Prof. L. Spierdijk
Prof. B.W. Lensink

Assessment committee
Prof. J.A. Bikker
Prof. C.J. Green
Prof. L.J.R. Scholtens

Preface

When I started working as a PhD candidate in September 2014, I could not have imagined how much my life was going to change in the next three years. During this period I broke my leg (and fully recovered again), Sjoerdtje and I got married, we bought a house and moved to Hoogkerk, and we are currently expecting our first child. In the meantime, I also somehow managed to write this PhD thesis, although not without the support of many colleagues, family and friends.

I would like to thank, first of all, my supervisors Laura Spierdijk and Robert Lensink. Thank you for your guidance and expertise, and for being such kind colleagues these three years. During my time as a PhD candidate, not only did you always make time to discuss problems and ideas with me, you also showed an interest in my personal well-being, which became especially apparent when I was recovering from my leg injury. I met Laura when I was following the Research Master programme at the University of Groningen, and have successfully cooperated with her ever since. Her expertise in econometrics and mathematics have proved invaluable both to the writing of my Master's and PhD theses and to my personal development as a researcher. I met Robert during my time as a Research Master student as well, when I took one of his courses. His knowledge in a wide range of economic disciplines has helped me keep in mind the bigger economic picture in the process of writing this thesis. As such, your skills and expertise have been quite complementary, which made you a truly great team. It has been a privilege to work under your supervision.

In addition, I am grateful for the efforts of the reading committee, consisting of Jaap Bikker, Christopher Green and Bert Scholtens. Thank you for taking the time to carefully read my thesis and for providing valuable comments, which were helpful in the process of improving this text.

I would like to thank all members of the department of Economics, Econometrics and Finance for hosting me and for providing me with a great working environment. I am especially grateful to Lammert-Jan Dam, Paul Elhorst and Machiel Mulder, all of whom took the time to read my work and provide helpful comments and suggestions at the SOM PhD conference. In addition, I thank Rob Alessie, who was always prepared to help me with questions of a technical nature. Furthermore, I want to thank Maarten Allers, Jelle van Essen, Tom de Greef, Corine Hoeben, Klaas Kwakkel, Anouk Schippers, Irina Stanga, Eduard Suari-Andreu and Jakob Veenstra for numerous interesting discussions (and in the case of Tom, chess games) during lunch and coffee breaks.

Special thanks to my former officemates Gert-Jan Romensen and Wim Siekman, with whom I have had many interesting conversations during my time as a PhD candidate. Being your officemate has been great fun.

On a personal level, I first and foremost thank Sjoerdtje, the love of my life. As I write this, we have been married exactly two years. Thank you for your love, loyalty and support. I am looking forward to many more great years with you, and with our future child. Thanks also to Sigo; you have been a great friend ever since we met in high school. In addition, I want to thank my parents, Anne and Imka, for their unconditional love and support. You were there for me in a number of difficult episodes in my life, and for that I will always be grateful. Gratitude also goes to my loving siblings: my sisters Femmie, Agnes, Douwine, Andrea and Roelien, and my brother Rinze. Words cannot describe how proud I am to be part of this family.

Last but not least, I thank my great friend Wesley, who is always there to keep me company at home. May your hopping and thumping continue for many years!

Pieter IJtsma

Contents

Chapter 1

Introduction

The regulation and supervision of the financial sector have been widely debated issues for decades, and the topic has received a surge of attention among both academics and policymakers since the outbreak of the global financial crisis in 2008. What distinguishes the financial sector from the real sector of the economy is the importance of risk and the interdependency both among financial institutions and between financial institutions and firms in the real economy. Financial institutions are typically highly leveraged, which makes their business model inherently risky. Furthermore, since many firms in the real sector are dependent upon the financial sector for the funding of investments, a crisis in the financial sector is likely to have far wider repercussions than a crisis in a particular sector of the real economy. As a result, financial stability is increasingly recognized as an important objective of central banks and other regulators, even though a consenus about the exact definition of financial stability has yet to be reached.[1] In addition, market imperfections in the financial sector are likely to have effects beyond their immediate impact on consumers of financial services. For instance, when a lack of competition in the banking sector results in large interest rate spreads, investments in the real economy are likely to suffer, with negative repercussions for economic growth. This thesis contributes to the literature dealing with the analysis of regulation of the financial sector. Among other things, we analyze the effects of increased banking market concentration in the EU and of the deregulation

[1] Chapter 2 of this thesis delves more deeply into the concept of financial stability and presents several definitions that have been proposed in the academic literature.

of competitive restrictions in the banking sector of the United States. Furthermore, we use a theoretic model to analyze how liquidity requirements are related to financial stability, through their effect on liquidation prices in the event of failures of financial institutions. A detailed description of the various chapters is given below.

In Chapter 2, a critical review is presented of the existing theoretical and empirical literature dealing with the effects of banking competition on economic growth and financial stability. The chapter starts with a detailed review of the various ways in which banking competition and financial stability are measured, discussing both strong points and weaknesses of the different measures. We show that, especially when it comes to the measurement of financial stability, important improvements can be made. We then present the most important theoretical and empirical contributions to the debates about (i) the relationship between banking competition and financial stability, and (ii) the relationship between banking competition and economic growth. The picture that emerges is that neither of these debates has been settled. More specifically, theoretical arguments as well as empirical evidence suggest that an increase in banking competition could have either beneficial *or* detrimental effects on financial stability and economic growth. Further research on the effects of banking competition is therefore necessary, and this thesis constitutes a step in that process. We finish the chapter by identifying a number of key gaps in the scientific literature, some of which are dealt with in the subsequent chapters of this thesis.

Chapter 3 is a theoretical contribution to the literature that deals with the measurement of financial stability.[2] Before the outbreak of the financial crisis that started with the fall of Lehmann Brothers in 2008, the majority of practitioners and academics in banking assumed that the stability of a financial system can be safeguarded by ensuring that the individual financial institutions in the system are stable. As a result, measures of financial stability were typically bank-specific, focusing on the stability of financial institutions in isolation. For instance, the z-score, which was the most widely used measure of financial stability before the outbreak of the crisis, uses information about banks' equity buffers, expected returns and return volatility to give an estimate of their stability. By using only bank-specific information, this measure ignores the possibility that the stability of banks can be interdependent, either because the balance sheets of banks are directly linked through interbank loans and syndicated loans,

[2]This chapter is based on IJtsma, P. and Spierdijk, L. (2017). Systemic risk with endogenous loss given default. *Journal of Empirical Finance*, forthcoming.

or because banks have similar investment portfolios and are therefore likely to suffer losses at the same time. After the outbreak of the crisis, the attention for *systemic* measures of financial stability has increased significantly. A systemic measure of financial stability does not only take into account the stability of individual banks in isolation, but also incorporates information about interdependencies in banks' stability. As such, it deals not only with banks' individual risks, but also takes into account *systemic risk*. Although a number of systemic measures of financial stability currently exist, these do not acknowledge that in addition to default probabilities, the *losses given default* (LGDs) of banks are also systemically determined. That is, the LGD of a particular bank depends not only on the characteristics of the bank itself, but also on those of the other banks in the financial system. To illustrate why this is the case, we build a model in which the LGDs of banks are endogenously determined. In the model, a bank's LGD depends on the liquidation price of its assets. This liquidation price is determined by the demand for and supply of similar assets on the market, which in turn depend on the number and size of failed banks as well as the liquidity of the surviving banks in the system. Since an increase in the number and size of failed banks lowers the demand for liquidated assets while increasing the supply, liquidation prices will typically be lower during times of industry-wide distress in the financial sector. We show how banks optimally choose the amount of liquidity on their balance sheet and how financial stability will be overestimated when the above-mentioned process is not taken into account. Moreover, we show that time-varying liquidity requirements could significantly reduce systemic risk. These would force banks to build up a liquidity buffer that can be used to purchase the assets of failed banks during times of distress in the financial sector, thereby significantly reducing LGDs. In our analysis, we assume that there may be indirect linkages between the solvency of banks due to common risk exposures, leading to positive asset return correlations between banks. We abstract from the possibility that a crisis occurs due to direct linkages between banks, such as interbank loans, which may lead to contagion.[3] An interesting avenue for future research would thus be the inclusion of such contagion effects into the model. When banks are directly connected, the failure of one bank will affect the stability of other banks, who may have to write off a significant portion of their loan portfolio. In this scenario, a firesale can be expected to have even larger

[3]Contagion occurs when the failure of one bank causes other banks to fail as well, leading to a domino effect.

detrimental effects, as it may lead to additional failures by banks which would have remained solvent in the absence of a firesale. Hence, we expect liquidity requirements to be even more important when banks are connected through loans on the interbank market.

In Chapter 4, an empirical study is performed which analyzes the relationship between the degree of market concentration in the banking sector and financial stability.[4] We first illustrate how the logic behind the z-score can be applied to the financial system as a whole to obtain a systemic measure of financial stability. This so-called *aggregate z-score* takes into account the return correlations of banks, in addition to their capital buffers, expected returns and return volatilities. We then show that the conventional and aggregate z-score only contain the same information in the unlikely case of perfectly positive return correlations between all banks in the system. Hence, in the likely case in which banks do not have perfectly positive return correlations, the aggregate z-score provides valuable information which is not captured by the conventional z-score. In the remainder of the chapter, data from the EU-25 during the 1998-2014 period is used to empirically investigate the relationship between banking market concentration and financial stability. To analyze whether the level of analysis matters, we use both invidual (bank-level) and aggregate (country-level) z-scores as measures of stability. The results indicate that there is no economically significant relationship between concentration and stability, irrespective of the level of analysis. This suggests that neither individual bank risk nor systemic risk is significantly affected by a change in the degree of banking market concentration. This finding is reassuring for regulators, as it suggests that supervisory restructurings are an attractive alternative to bail-outs as a way to safeguard the stability of the financial system during times of distress. This is important because, unlike restructuring mergers, bail-outs have the tendency to give rise to moral hazard on the part of bank managers. In addition, our finding indicates that the trend of an increasing degree of concentration in European banking markets is unlikely to have negative consequences for financial instability. A limitation of the study is that the analysis only includes data for commercial banks, thereby ignoring savings banks and cooperative banks. Unlike commercial banks, it cannot be taken for granted that savings banks and cooperative banks maximize profits, as these types of banks often have other objectives.

[4]This chapter is based on IJtsma, P., Spierdijk, L. and & Shaffer, S. (2017). The Concentration-Stability Controversy in Banking: New Evidence from the EU-25. *Journal of Financial Stability*, forthcoming.

In addition, savings banks and cooperative banks tend to retain profits, whereas commercial banks often distribute profits to shareholders, and cooperative banks and savings banks are generally more focused on traditional financial intermediation than commercial banks. As such, we may expect a different relationship between market concentration and financial stability when analyzing savings banks and cooperative banks. We leave this issue open for future research.

Chapter 5, finally, consists of an empirical study in which the growth effects of the deregulation of competitive restrictions in the U.S. banking sector are analyzed. Prior to 1970, most states in the U.S. did not allow their banks to freely open or acquire branches with the state, while not a single state allowed out-of-state-banks to freely operate on their market. In the period from 1970 to 2000, state legislatures incrementally relaxed these competitive restrictions on intrastate branching and interstate banking, thereby allowing banks to compete more freely within their home state as well as across state borders. Since different states deregulated their banking industry at different points in time, both cross-sectional and temporal variation exists in banking (de)regulation, which allows for the identification of a possible effect of deregulation on economic growth. The main innovation of the study is that, unlike earlier studies, it takes potential spillover effects of deregulations into account. This is important for two reasons. First, firms can typically borrow funds from banks in neighboring states and are therefore affected by deregulations in the banking sector of neighboring states. Second, an increase in economic activity in one state is likely to stimulate growth in neighboring states, since states are connected by trade linkages and commuters. If the deregulation of competitive restrictions in banking affects economic growth, it is therefore likely to do so not only in the deregulating state itself, but also in neighboring states. Ignoring these potential spillover effects will result in biased estimates of the effect of deregulations on growth. We deal with this issue by estimating a spatial model, which explicitly takes into account spillover effects and estimates their size and statistical significance. The results indicate that spatial spillover effects of interstate banking deregulation are indeed present. In addition, they provide evidence for a statistically and economically significant effect of interstate banking deregulation on economic growth in the deregulating state as well as in neighboring states. No evidence is found for an effect of intrastate branching deregulation on growth, however. To determine whether the estimated relationship represents a causal effect, we delve deeper into the issue by analyzing economic growth on the level of the county or metropolitan statistical area (MSA). More specifically, we estimate the effect of deregulation on growth in a matched-pairs setting, where counties or MSAs are matched in pairs on the basis of economic, demographic and geographic characteristics in 1970. The results suggest that counties or MSAs from states which had relaxed restrictions on interstate banking grew faster compared with counties or MSAs from states which had not yet relaxed these restrictions, but with otherwise similar characteristics. Since the decision to deregulate was made at the state level, this finding suggests that simultaneity is not an issue, so that the estimates are likely to represent a causal effect of interstate banking deregulation on economic growth. We further analyze whether the effect of interstate banking deregulation on growth can be explained by an increase in the competitiveness of the banking industry. This is done by considering three potential channels through which an increase in competition may affect growth, namely (i) a decrease in interest margins, (ii) an increase in banks' cost efficiency, and (iii) an increase in banks' profit efficiency. The results suggest that the average profit efficiency of banks increased with approximately 3% following interstate banking deregulation, whereas only weak evidence is found for a positive effect on cost efficiency and no evidence is found for an effect on interest margins. This suggests that interstate banking deregulation increased economic growth by allowing banks to become more profit efficient, for instance by making it easier for banks to direct their funds to the most profitable investment opportunities. However, given the large growth effects of deregulation, it seems unlikely that the (modest) increase in profit efficiency associated with deregulation can fully explain the relationship between deregulation and economic growth. Investigating other potential channels through which interstate banking deregulation affects growth is thus an interesting avenue for future research.

To conclude, this thesis presents a multifaceted study into the nexus between banking competition, financial stability and economic growth. Chapter 2 provides an up-to-date discussion of the existing scientific literature on this subject, while Chapter 3 is a theoretical contribution to the literature that deals with the measurement of financial stability and its counterpart, systemic risk. The reader who is more interested in empirical studies is referred to Chapters 4 and 5, which provide empirical studies of the relationship between banking competition, concentration, financial stability and economic growth.

Chapter 2

Competition, stability and growth: A critical review of the literature

Abstract. *This chapter summarizes and critically discusses the literature dealing with the effect of banking competition on financial stability and economic growth. We discuss a variety of measures that are used in the empirical literature and summarize the main arguments in the debate on the effects of banking competition. We then summarize the empirical findings on this subject. With regard to the relationship between banking competition and financial stability, the empirical evidence is conflicting, but it should be noted that most studies use measures of individual bank risk rather than systemic risk to analyze financial stability. The empirical evidence on the relationship between banking competition and economic growth suggests that competition is likely to have a positive effect on growth. However, very few papers study this relationship directly, so that future research is necessary to draw a firm conclusion.*

2.1 Introduction

The recent financial crisis has highlighted the important role that banks play in the economy. Financial development is an important prerequisite for economic growth (Levine, 2005), but at the same time the banking sector is susceptible to the occurrence of financial crises, with extremely negative repercussions for the economy as a whole. Banking crises affect banks' stakeholders (depositors, shareholders, borrowers, taxpayers) directly, and tend to trigger macroeconomic recessions through sharp contractions in lending. Indeed, the average cumulative output loss of a financial crisis is estimated to be somewhere between 15% and 20% of annual GDP (Hoggarth et al., 2002; Allen & Gale, 2004).

The aim of this chapter is to review the scientific literature that examines the effects of competition in the banking sector on financial stability and economic growth. Banking competition has traditionally been considered a source of instability, and in many countries regulatory measures such as entry restrictions, activity restrictions and interest rate regulations were used to limit competition during much of the 20th century (Beck et al., 2010). In the latter part of the last century, however, policymakers began to consider the potential benefits of banking competition. In theory, competition should lead to more innovation and result in higher consumer welfare as well as better access to finance for firms. A process of deregulation in banking has therefore taken place from 1970 onwards, with the permission of interstate bank branching in the U.S. and increasing market integration in Europe. Moreover, competition authorities, especially the European Commission, have started to take competition in the financial sector seriously by opposing anti-competitive behavior as well as mergers that might hamper competition (Carletti, 2008). The recent financial crisis, however, has resulted in massive government interventions in the financial sector, in the form of bail-outs, state aid, and increases in the coverage of deposit insurance funds. These measures were taken to safeguard financial stability, but have also resulted in competitive distortions because banks that have received state support are often legally prohibited from undercutting the borrowing rate of their competitors. Some argue that this is not a problem and that financial stability should take priority over all other concerns, while others worry about the negative consequences of competitive distortions and are in favor of a more stringent application of competition policy in reaction to government intervention in the sector (Beck et al., 2010).

The difficulty in assessing the effect of banking competition on economic growth and financial stability lies in the fact that neither banking competition nor financial stability are directly observable. Competition is a rather abstract concept and is consequently difficult to measure. Financial stability is a multifaceted concept, which currently still lacks a widely accepted definition. Moreover, financial instability is only observable during episodes of systemic crises, while it typically builds up in the years prior to a crisis. Because of these difficulties, we extensively discuss issues associated with the measurement of banking competition and financial stability below.

The structure of the remainder of this chapter is as follows. Section 2.2 discusses issues associated with the measurement of banking competition and financial stability. The most widely used measures of these concepts are introduced here, and a critical review of their strenghts and weaknesses is provided. Section 2.3 discusses research on the relationship between banking competition and financial stability. After introducing the most important theories regarding this relationship, we give an overview of the empirical literature on the topic. The same structure is applied in Section 2.4, which discusses the literature that deals with the relationship between banking competition and economic growth. Finally, some concluding thoughts follow in Section 2.5.

2.2 Measurement issues

As was argued in the introduction, neither banking competition nor financial stability is directly observable. As a result, their measurement is an important issue in the analysis of the relationship between banking competition, financial stability and economic growth. Below, we first discuss the measurement of financial stability and then turn our attention to banking competition.

2.2.1 Financial stability

Of the three phenomena of interest in this chapter, financial stability is arguably the most difficult to operationalize and measure. An important reason for this is that there is not even any consensus yet on the definition of financial (in)stability as such. Mishkin (1992) defines financial instability as follows: "A financial crisis is a disruption to financial markets in which adverse selection and moral hazard problems become much worse, so that financial markets are unable to efficiently channel funds to those who have the most productive investment opportunities." Although this definition is often referred to in textbooks, Allen & Wood (2006) criticize it because of the fact that the definition is not expressed in terms of observable variables. They define financial crises as episodes in which such a large number of parties face financial difficulties that there are adverse macro-economic effects which hurt innocent bystanders. They then propose to define financial stability as "a state of affairs in which an episode of financial instability is unlikely to occur, so that fear of financial instability is not a material factor in economic decisions taken by households or business." Note that there is an important difference between these two definitions of financial stability. Whereas the definition of Mishkin (1992) refers to the absence of disruptions in the *functioning* of the financial system in a general sense, the definition of Allen & Wood (2006) focuses on *losses* incurred by the parties affected by episodes of financial instability. This difference in perspective has important consequences for the way in which financial (in)stability should be measured. From the perspective of Mishkin (1992), it makes sense to operationalize the definition of financial stability by looking at sudden changes in interest rates, sudden decreases in investments and asset prices, bank holidays, deposit freezes and/or foregone GDP growth associated with financial instability. The definition of Allen & Wood (2006), on the other hand, suggests to look at (potential) fiscal costs of bank bailouts, and (potential) losses to savers and other creditors of banks associated with the failure of financial institutions.

The above-mentioned definitions are only two examples of how financial stability could be defined, and many more have been suggested.[1] What most definitions of financial stability have in common, however, is that they refer to the state of the financial system *as a whole*. In other words, financial instability is interpreted as a state of affairs in which many financial institutions fail or are in distress *simultaneously*. What is surprising in this respect, is that most empirical studies which investigate financial stability focus not on threats to system-wide stability (systemic risk), but on the stability or risk of *individual* banks. This is problematic, since systemic risk and individual bank risk are fundamentally different concepts. For instance, a financial system can be relatively robust even though the individual banks in the system take a lot of risk. This would be the case if (i) different banks take on different types of (independent) risks, and (ii) the returns of banks are not interdependent. For exam-

[1] See Allen & Wood (2006) for an overview.

ple, when banks do not diversify, but instead specialize in making loans to a specific sector of the economy, they are quite susceptible to shocks in that sector. However, as long as different banks specialize in different sectors and do not engage in interbank lending, the system might be relatively robust, since it is unlikely that every sector of the economy is hit at the same time. In such a system, the likelihood that any particular bank fails is relatively large, but it is unlikely that many banks in the system fail simultaneously. Conversely, a financial system can be fragile even if the individual banks in the system appear to be stable. This would be the case if all or most of the banks in the system have diversified their risks in the same manner, or when the returns of banks are highly interdependent due to e.g. interbank lending. In such a scenario, failures are higly correlated, so that the likelihood that many or all banks in the system fail is relatively large.[2] Since individual bank risk and systemic risk are fundamentally different concepts, it is quite surprising that most studies in the empirical literature on financial stability use measures of individual bank risk as proxies of financial stability. Only in more recent years has the measurement of systemic risk received more attention. Papers which have applied systemic risk measures are still scarce, however.

In the remainder of this section, we first review non-systemic measures of financial stability, after which a brief overview will be given of the most widely used measures of systemic risk.[3]

Non-systemic measures

As mentioned above, the majority of empirical studies that investigate financial stability use bank-level proxies of stability. These measures typically reflect the credit risk or solvency risk of individual banks. The most widely used measures in this respect are the z-score, distance-to-default, and the non-performing loans (NPL)-ratio.

Z-score. The widely used z-score (Roy, 1952; Hannan & Hanweck, 1988; Boyd & Runkle, 1993) is a measure of a bank's solvency, which combines information about the bank's profitability, capital buffer and return volatility. It is defined as follows:

$$z_i = \frac{E(r_i) + k_i}{\sigma(r_i)}, \tag{2.1}$$

[2]See Shaffer (1994), De Vries (2005) and Wagner (2010a, 2011) for more information on the relationship between diversification and systemic risk.

[3]For a complete overview of systemic risk measures, we refer to Bisias et al. (2012) and Benoit et al. (2016).

where z_i is the z-score of bank i, $E(r_i)$ is the bank's expected return on assets, k_i is the bank's capital ratio and $\sigma(r_i)$ is the standard deviation of the bank's return on assets. Intuitively, the z-score gives the number of standard deviations by which the bank's return can fall below its expected return before the bank becomes insolvent. If its returns are normally distributed, the bank's probability of default is $1 - \Phi(z)$, where Φ is the standard normal cdf. Note that, since the bank's expected return is unobserved, it is typically proxied by either the bank's return in the previous period or by its mean return over a number of periods. The standard deviation of the bank's return is also unobserved, and is typically estimated as the standard deviation of the bank's return over a number of recent periods.

The z-score requires relatively little data and has a straightforward interpretation. A drawback of the measure, however, is that it might underestimate systemic risk for three reasons. First, the measure implicitly assumes that returns are normally distributed, in which case the expected return and the return standard deviation provide a complete description of the return distribution. In reality, the mean and standard deviation of the return may not accurately describe the negative tail of the return distribution, which is precisely the most relevant part of the distribution when estimating insolvency risk. Second, the z-score is a static measure of insolvency risk and ignores the timing of returns. As such, it is unable to identify a negative sequence of returns, which would clearly be an indication of increased insolvency risk (De Nicolo & Kwast, 2002). Finally, the z-score typically uses historical accounting data to give a sense of the stability of a bank, and is therefore a backward-looking risk measure. During times of distress, past returns might not provide an accurate description of a bank's expected return, which would result in an underestimation of risk. Because of these drawbacks, the z-score is more useful as an indication of the evolution of risk over time than as an absolute measure of risk at a certain point in time.

Distance-to-default. The distance-to-default (DD) is a measure which is conceptually quite similar to the z-score. It is defined as the difference between the market value of a bank's assets and its default point, divided by the volatility of the value of the assets. Hence, as is the case for the z-score, the DD indicates the stability of a bank in terms of the distance to its default point measured in standard deviations. Unlike the z-score, however, the DD is calculated on the basis of market data and can therefore be interpreted as a forward-looking measure. The DD is based on the model of Black & Scholes (1973) and Merton (1974), in which the market value of a firm's equity is interpreted as a call option on the firm's assets. A bank is considered solvent as long as the market value of its assets is higher than the market value of its debt. Under the assumptions of the model, the DD can be expressed as:

$$DD_i^t = \frac{\ln(v_i/d_i) + (\mu_i - \sigma_i^2/2)t}{\sigma_i\sqrt{t}}, \tag{2.2}$$

where v_i is the current market value of the bank's assets, d_i is the market value of its debt, μ_i and σ_i are the expected return and the standard deviation of the return on assets, respectively, and t is the number of time-periods that are taken into account (i.e. the number of time periods that we are "looking forward to"). The probability of default is $1 - \Phi(DD)$, where Φ is the standard normal cdf.

Compared with the z-score, a major benefit of the DD is that it is a forward-looking measure of stability. Its drawback, however, is that the market value of a bank's assets is not observed and must therefore be estimated. Moreover, this estimation is typically done on the basis of the market value of a bank's equity, so that DD is in practice only calculated for listed banks. Finally, the measure is based on the rather restrictive assumption that the market value of the assets follows a log-normal stochastic process, which is not necessarily realistic.

NPL-ratio. A final non-systemic risk measure that is often used to analyze financial stability is a bank's ratio of non-performing loans to total assets. Note that this ratio is a measure of credit risk, not solvency risk. Hence, it is doubtful whether the NPL-ratio is useful for analyzing financial stability, since a bank with a high ratio of non-performing loans to total assets can be quite stable as long as its capital buffers are large enough. Nonetheless, this meaure is widely used in the empirical literature as a proxy of individual bank risk.

Systemic measures

Since the outbreak of the financial crisis in 2008, much attention has been devoted to the development of systemic risk measures, which monitor the stability of the financial system as a whole. The literature on this topic can be broadly classified into two strands. The first focuses on interbank lending and how the failure of one bank might negatively affect the solvency of other banks, thereby leading to potential contagion. Studies which take this approach typically use network models and use simulations to analyze the vulnerability of financial systems to the failure of particular banks. The second strand of the literature focuses on asset return correlations across banks. The idea of this approach is that the degree of asset return correlations across banks is an important determinant of financial stability. If many banks have made similar investments, they are likely to face adverse shocks at the same time, thereby threatening system-wide stability. A complete overview of systemic risk measures can be found in Bisias et al. (2012). Here, we discuss the measures which have been applied in empirical work. These consist of crisis dummies, the aggregate z-score, SRISK and Conditional Value-at-Risk (CoVaR).

Crisis dummies. Traditionally, studies of financial stability have tended to use stability measures which are binary in nature and indicate whether or not a particular financial system is in distress at a certain point in time. A widely used measure is the indicator proposed by Demirgüç-Kunt & Detragiache (2002), who define a financial crisis as a situation in which i) emergency measures are taken to assist the banking system, such as bank holidays, deposit freezes, or guarantees to depositors, ii) large-scale nationalizations of banks have taken place, iii) non-performing assets are at least 10 percent of total banking assets, or iv) the cost of rescue operations of banks exceeds 2 percent of GDP.

The benefit of a crisis indicator variable is that, since it is based on outcomes rather than causes of financial instability, it does not focus on any particular aspect of stability, but captures a wide range of phenomena associated with it. An important downside, however, is that a dummy variable does not contain information about the *intensity* of a crisis or the risk of instability in the *absence* of a crisis. In addition, binary measures are by definition backward-looking, and since they are typically based on government *responses* to a crisis, they are likely to identify crises too late (Von Hagen & Ho, 2007). Because of these drawbacks, crisis dummies are hardly used in more recent studies of financial stability.

Aggregate Z-score. The aggregate z-score (Uhde & Heimeshoff, 2009) is the aggregated counterpart of the traditional z-score. It gives an indication of the solvency of the financial system as a whole. For a system with n banks, the aggregate z-score is calculated as:

$$z_n = \frac{\sum_{i=1}^{n} w_i(E(r_i) + k_i)}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij}}}, \tag{2.3}$$

where z_n is the aggregate z-score, w_i is the market share of bank i in terms of assets, and ρ_{ij} is the return correlation of banks i and j. Note that in a system with two banks, the aggregate z-score can be written as:

$$z_2 = \frac{w_1\left[E(r_1) + k_1\right] + w_2\left[E(r_2) + k_2\right]}{\sqrt{w_1^2\sigma^2(r_1) + w_2^2\sigma^2(r_2) + 2w_1w_2\sigma(r_1)\sigma(r_2)\rho(r_1, r_2)}}. \tag{2.4}$$

It follows that the aggregate z-score is *not* a linear combination of the individual z-scores of the banks in the system, unless their returns are perfectly correlated. In general, the higher is the return correlation across banks, the lower will be the aggregate z-score. This makes sense intuitively: when the banks in the system are more similar, it is more likely that they will become insolvent at the same time. As a result, it is also more likely that the financial system as a whole will become insolvent.

The benefit of using the aggregate z-score instead of banks' individual z-scores is that the aggregate z-score not only takes into account the solvency of the invidiual banks in the system, but also the degree to which returns are correlated. When the banks in a financial system all diversify in the same way, this raises their individual z-scores, even though the system as a whole does not necessarily become more stable. The aggregate z-score takes this into account through the inclusion of the correlation term, so that the aggregate z-score does not necessarily increase when banks diversify. A drawback of the aggregate z-score is that its interpretation is not straightforward. The measure gives an indication of the solvency of the portfolio of banks in a financial system, but it is extremely unlikely that an entire financial system will become insolvent. In practice, financial instability results from the failure of individual banks. For instance, the failure of one large bank in the system could result in a financial crisis, even when the system as a whole remains solvent. Hence, two financial systems with the same aggregate z-score could be quite different when it comes to financial stability. Nonetheless, we believe that the aggregate z-score is a useful addition to the conventional z-score, especially when it is used to monitor changes in financial stability over time. By taking into account return correlations across banks, the measure picks up an additional dimension of systemic risk which is not accounted for by the conventional z-score.

SRISK. This measure of systemic risk was developed by Acharya et al. (2012) and Brownlees & Engle (2016). SRISK measures the expected capital shortfall of a bank conditional on the occurrence of an episode of systemic distress, where the capital shortfall is defined as the difference between the equity the bank is required to hold at minimum (due to, say, capital requirements) and the firm's actual equity. It can be expressed as:

$$SRISK_{it} = kd_{it} - (1-k)e_{it}[1 + \mathrm{E_t}(r_{it+1}|r_{mt+1} < c)], \tag{2.5}$$

where $SRISK_{it}$ is the SRISK of bank i at time t, k is the required capital ratio, d_{it} is the bank's debt, e_{it} is the market value of the bank's equity, r_{it+1} is the bank's return in the coming period, r_{mt+1} is the market return in the coming period, and c is the threshold defining a systemic event. Hence, SRISK is a function of the size of the bank, its degree of leverage, and its expected equity loss conditional on a severe market decline. The measure can be used to rank banks in terms of their contribution to systemic risk. Moreover, the sum of SRISK over all banks in the financial system is a measure of overall systemic risk. This number can be interpreted as the expected amount of capital the government will have to provide to bail out the financial system should a crisis occur.

SRISK is a forward-looking risk measure, which can be applied at the bank-level, yet has a clear link with systemic risk. Moreover, it requires relatively little data and does not rely on structural assumptions such as normally distributed returns. Its largest drawback, however, is that it requires the estimation of banks' conditional return distributions, which may be difficult to obtain in practice. In addition, it is difficult to compare the overall risk of different financial systems with this measure, since SRISK conditions on a distress event, whereas the probability of such an event may differ between systems. As a result, the measure is only useful for evaluating the evolution of systemic risk *within* a system over time.

CoVaR. The Conditional-Value-at-Risk (CoVaR) (Adrian & Brunnermeier, 2016) is the systemic counterpart of Value-at-Risk (VaR), the measure which the majority of financial institutions use to monitor and manage risk.[4] Whereas VaR focuses on the risk of an individual institution, CoVaR captures the tail-dependence between the financial system as a whole and a particular institution. A bank's CoVaR is defined as the VaR of the whole financial system conditional on the bank being in distress.

[4]The α%-VaR is that dollar value for which the probability that the bank incurs losses smaller than this amount is exactly $\alpha/100$. Formally, the VaR is defined such that:

$$P(L \leq VaR_\alpha) = \alpha/100, \tag{2.6}$$

where P is the probability operator and L is the bank's loss expressed in dollars. Note that the VaR can also be expressed as the *minimum loss* given that the loss is in the upper $(100-\alpha)$% of the loss distribution. In practice, typical choices for α are 95 and 99.

Formally:

$$P\big([L_j|C(X_i)] \leq \text{CoVaR}_\alpha^{j|C(X_i)}\big) = \alpha/100, \tag{2.7}$$

where L_j is the loss of the financial system as a whole and $C(X_i)$ is the event in which the loss of bank i is greater than X. A typical choice for X is the bank's VaR at confidence level α. The contribution of a particular financial institution to systemic risk can then be expressed as the difference between the institution's CoVaR (at confidence level α) under the conditioning event that its loss equals its VaR at confidence level α, and its CoVaR (at confidence level α) under the conditioning event that the institution has made a return equal to the median of its return distribution:

$$\Delta\text{CoVaR}_\alpha^{j|i} = \text{CoVaR}_\alpha^{j|X_i=\text{VaR}_\alpha^i} - \text{CoVaR}_\alpha^{j|X_i=\text{VaR}_{50}^i} \tag{2.8}$$

An increase in a bank's ΔCoVaR indicates that the bank's contribution to systemic risk has increased because the system has become more vulnerable to losses of that particular bank. A major benefit of (Δ)CoVaR is that, even though it is a bank-specific measure, (Δ)CoVaR captures precisely the component of individual bank risk which is relevant for the system as a whole. A drawback of the measure is that it requires estimation of the conditional distribution of the VaR of the financial system as a whole, which may be difficult to do reliably. Moreover, CoVaR does not consider risk outside of the confidence interval determined by the value of α, whereas it is precisely tail risk which is most relevant for financial stability. Finally, CoVaR does not contain information about capital buffers, and therefore does not have a direct connection with failure probabilities. When the banking system is well capitalized, a high CoVaR is far less of a problem compared with a case in which capital buffers are small. Hence, CoVaR is only a useful measure of systemic risk if it is combined with additional information.

Other measures. Since the occurrence of the financial crisis, the attention for systemic risk measurement has increased substantially and many new measures have been proposed as a result. Notable examples of such measures are the Systemic Expected Shortfall and Marginal Expected Shortfall (Acharya et al., 2017), the Distress Insurance Premium (Huang et al., 2009), Co-Risk (Chan-Lau et al., 2009) and measures based on the modelling of banks' joint returns or joint default probabilities (Lehar, 2005; Segoviano Basurto & Goodhart, 2009). Since these measures have not been applied yet, we will not go into them here. For a complete description and overview of existing systemic risk measures, we refer to Bisias et al. (2012) and Benoit et al. (2016).

2.2.2 Banking competition

Since competition is by definition unobservable, the banking literature has used a variety of proxies to measure the effects of banking competition. In this section, we describe these measures. We begin by introducing a number of concentration indices, which are typically used in the application of antitrust policy in the banking sector. We then discuss a variety of indicators, including the Panzar-Rosse H-statistic, the Lerner index, the Boone indicator and indicators based on the concept of conjectural variation.

Concentration indices. Traditionally, the banking literature has often used a number of concentration indices as proxies of competition in the banking industry. The theoretical ground for the use of concentration indices is the so-called Structure-Conduct-Performance (SCP) paradigm (Bain, 1968). The SCP explains banks' market performance as the result of an exogenously given market structure, which influences the competitive conduct of banks. It assumes that collusion among market participants is easier in a concentrated market, so that an increase in market concentration reduces the degree of competition in the market (Bikker & Haaf, 2002). The most widely used concentration indices are the k Bank Concentration Ratio (CR_k) and the Herfindahl-Hirschmann Index (HHI). They are defined as the combined market share of the largest k banks in the market, and the sum of the squared market shares of all banks in the market, respectively. In both cases, higher values indicate a more concentrated market. The CR_k is a straightforward and easily interpretable measure, but its drawback is that it necessarily only includes information about the market share of a rather arbitrary number of banks. The HHI does not suffer from such an arbitrary cut-off point, but it has the drawback of being sensitive to the entry of a large number of small banks (Hart, 1975; Rhoades, 1995). Other, less-often used indices of market concentation are the Hall-Tademan Index (Hall & Tideman, 1967), the Comprehensive Industrial Concentration Index (Horvath, 1970), the U Index (Davies, 1979), the Hannah and Kay Index (Hannah & Kay, 1977), and the Haussa Index (Hause, 1977). In an empirical application, Bikker & Haaf (2002) calculate the above-mentioned indices for the banking sector of 20 developed countries in 1997 and conclude that the ranking of the countries is quite similar for these different indices.

Since concentration indices reflect changes in the degree of market concentration as a result of mergers as well as market entry and exit, they are used in the application of antitrust policies. For instance, in the U.S., a merger of two banks is typically approved without further investigation as long as the market's HHI does not increase by more than 0.02 and does not exceed 0.18 after the merger has taken place (Bikker & Haaf, 2002). It should be noted, however, that concentration is not necessarily a good proxy of competition. For instance, the *contestability theory* maintains that a highly concentrated market can be quite competitive as long as there is free entry and exit (Baumol, 1982; Corvoisier & Gropp, 2002). According to this theory, it is not the degree of concentration but the contestability of the market which determines its competitiveness. In addition, the *efficiency theory* argues that market structure is itself endogenous and that a highly concentrated market might be the result of intense competition, due to which only the most efficient firms in the markets have managed to survive (Peltzman, 1977; Brozen & Bittlingmayer, 1982; Baumol, 1982). Moreover, if an increase in competition reallocates market share from inefficient to efficient firms, the market might become more concentrated even though competition has increased (Van Leuvensteijn et al., 2011). Furthermore, concentration indices do not reflect a number of important determinants of a firm's market power, such as the degree to which substitutes in consumption or production are available, excess capacity of competitors, or the ocurrence of explicit or tacit collusion between firms (Landes & Posner, 1981). Finally, the measurement of concentration indices requires a clear definition of the product market and geographic market for which they are calculated, which may be problematic.

Overall, concentration indices are thus a problematic proxy of competition. Indeed, empirical evidence indicates that once market share is accounted for, the degree of market concentration has no effect on profitability (Smirlock, 1985; Berger, 1995). More recent evidence also indicates that market concentration is generally a poor measure of competition (Ausubel, 1991; Calem & Mester, 1992; Shaffer, 1993, 1999, 2002; Shaffer & DiSalvo, 1994; Claessens & Laeven, 2004). Moreover, in some of the above-mentioned studies, markets are found to be much more competitive than their degree of concentration suggests, whereas in other cases, banks are found to have more market power than implied by the market structure. Bikker et al. (2012) conclude that "since the mismatch can run in either direction, concentration is an extremely unreliable measure of performance." As such, it is rather surprising that many studies still use concentration measures as proxies of competition (Boyd & De Nicolo, 2005; De Nicolo & Loukoianova, 2007; Boyd et al., 2009b; Martinez-Miera & Repullo, 2010; Jiménez et al., 2013), although the problems associated with its use are increasingly acknowledged in the banking literature (Bikker, 2004; Beck et al., 2006; Schaeck et al., 2009; Uhde & Heimeshoff, 2009).

H-statistic. Perhaps the most widely used measure of competition in banking is the so-called H-statistic, developed by Panzar & Rosse (1987). The H-statistic is calculated as the sum of the elastiticies of a bank's total revenue with respect to input prices. In their seminal article, Panzar & Rosse (1987) argue that $H = 1$ for banks in a market characterized by long-run competitive equilibrium, whereas $H < 0$ for a standard profit-maximizing monopolist. Finally, the case in which $0 < H < 1$ is claimed to be consistent with banks operating in a market characterized by either monopolistic competition or conjectural variation oligopoly. Since the calculation of the H-statistic requires relatively little data, it is not surprising that the measure has become extremely popular in the empirical banking literature. Unfortunately, recent theoretical work indicates that the H-statistic is, by itself, not a useful measure of competition. First, Bikker et al. (2012) demonstrate that competitive banks can have $H < 0$ if their market is in structural disequilibrium or when average costs are constant over some range of output within which the bank chooses to produce. Second, Shaffer & Spierdijk (2015) illustrate that $H > 0$ is possible in a wide range of non-competitive scenarios. Since the H-statistic can be either positive or negative for any degree of competition, and since it can be either increasing or decreasing in the degree of competition (Bikker et al., 2012), Shaffer & Spierdijk (2015) conclude that without additional information, "neither the sign nor the magnitude of the H-statistic can reliably identify the degree of market power." Nevertheless, the H-statistic is still applied in recent empirical work, e.g. Schaeck & Cihak (2012); Hoxha (2013).

Lerner index. The Lerner index is a measure of a firm's market or "monopoly" power, calculated as the relative difference between the market price and a firm's marginal cost (Amoroso, 1930; Lerner, 1934; Landes & Posner, 1981). A major benefit of the Lerner index in comparison with concentration indices is that the Lerner index is a firm-specific measure and therefore does not require the definition of a product or geographic market (Lerner, 1934). The index also has the attractive feature that it is based on a clear theoretical foundation. When there is perfect competition, the price should be equal to marginal cost, so that the Lerner index has a value of zero. A positive Lerner index thus suggests the existence of market power, and higher values are associated with a higher degree of market power. Moreover, by comparing price and marginal cost, the Lerner index expresses the degree of market power in terms of the deviation from the social optimum of marginal-cost pricing (Elzinga & Mills, 2011; Shaffer & Spierdijk, 2017).

The Lerner index also has a number of drawbacks, however. First, marginal cost is typically unobserved and therefore has to be estimated in order to calculate the Lerner index.[5] Second, prices might deviate from marginal costs for other reasons than the existence of market power. For instance, when there are scale economies or when banks make risky loans, the price will typically be above marginal cost to cover fixed costs (Lindenberg & Ross, 1981) or expected losses (Maudos & de Guevara, 2004). Third, the Lerner index is a static measure of competition and does not capture a monopolist's tendency to use its market power to pursue a "quiet life" rather than maximize profits (Elzinga & Mills, 2011). Fourth, if an increase in competition results in a reallocation of market share from inefficient firms (with a low Lerner index) to efficient firms (with a higher Lerner index), the average Lerner index in the industry may increase even though the industry has become more competitive (Boone, 2008; Van Leuvensteijn et al., 2011). Spierdijk & Zaouras (2017) argue that these limitations of the Lerner index are especially relevant for the banking industry, which is clearly characterized by the existence of economies of scale (Feng & Serletis, 2010; Wheelock & Wilson, 2012; Hughes & Mester, 2013; Beccalli et al., 2015). They therefore conclude that the Lerner index should not be interpreted as a measure of market power, but as an indication of the social loss due to market imperfections, which may include the presence of market power. As such, marginal-cost pricing indicates the absence of market power, but a positive Lerner index does *not* necessarily indicate the *presence* of market power. Hence, the Lerner index represents an upper bound of the degree of market power.

Conjectural variation. The concept of conjectural variation is related to the belief of a firm about how competitors will respond to a change in its output. More specifically, the conjectural variation of a firm with regard to all of its competitors is defined as

[5] The Lerner index can also be calculated without an estimate of marginal cost if the firm's price elasticity of demand is known. This variable, however, is typically unobserved as well.

the firm's expectation of the ratio of the change in the aggregate output of the firm's competitors to a change in its own output. Formally:

$$\lambda_i = E\left(\frac{\partial Q_{-i}}{\partial q_i}\right) = E\left(\frac{\partial Q}{\partial q_i}\right) - 1, \tag{2.9}$$

where λ_i is the conjectural variation of firm i with respect to its competitors, q_i is the output of firm i and Q_{-i} is the market output net of the firm's own output. As shown by Iwata (1974), Bresnahan (1982) and Lau (1982), a firm maximizes profits by choosing its quantity supplied in such a way that the following equality holds:

$$p(Q) - \frac{dp(Q)}{dQ}(1+\lambda_i)q_i - c(q_i) = 0, \tag{2.10}$$

where $p(Q)$ is the output price and c is the marginal cost of production. Solving Equation (2.10) for λ_i, and rewriting, gives the conjectural variation as an elasticity-adjusted Lerner index:[6]

$$\lambda_i = \frac{Q}{q_i}\left(\frac{dQ}{dp}\frac{p}{Q}\right)\left(\frac{p-c}{p}\right) - 1 = \frac{\varepsilon}{s_i}L_i, \tag{2.11}$$

where ε is the price elasticity of market demand, $s_i = q_i/Q$ is the bank's market share and L_i is its Lerner index. Note that in the case of perfect competition, we have $\frac{dQ}{dq_i} = 0$, so that $\lambda_i = -1$. From equation (2.10), this gives $p = c(q_i)$, which implies that there is marginal-cost pricing. In case of Cournot competition, firms take the output of their competitors as given, so that $\frac{dQ}{dq_i} = 1$ and $\lambda_i = 0$. This gives $p(q_i) - \frac{dp(q_i)}{dq_i} = c(q_i)$, which is the usual Cournot outcome. Finally, when there is pure collusion, the firm expects its competitors to retaliate in response to an increase in output to retain market share. Hence, $\frac{dQ}{dq_i} = \frac{Q}{q_i}$ and $\lambda_i = \frac{Q}{q_i} - 1$. Given a market with n firms, the average conjectural variation parameter thus ranges from -1, signalling perfect competition, to $(n-1)$, indicating pure collusion. An increase in the conjectural variation parameter is associated with a decrease in the degree of competition.

The conjectural variation as a measure of competition is based on the same reasoning as the Lerner index, which is that deviations from marginal-cost pricing indicate the presence of market power. As such, it shares with the Lerner index most ad-

[6]Market demand is assumed to be locally linear.

vantages and drawbacks. The measures differ in their data requirements, however. More specifically, since the conjectural variation requires the estimation of a supply and demand equation, it is more data-demanding than the Lerner index and, unlike the Lerner index, requires defining a geographic and product market. In practice, therefore, the Lerner index is much more widely used than conjectural variation as a proxy of banking competition.

Boone indicator. The most recently developed measure of banking competition is the so-called Boone indicator (Hay & Liu, 1997; Boone, 2008). The Boone indicator measures the strength of the relationship between a firm's efficiency and its performance in terms of profits and market share. The idea behind this approach is twofold. First, more efficient firms perform better (in terms of profits and/or market shares) than less efficient firms. Second, an increase in the degree of competition benefits the most efficient firms at the expense of their less efficient counterparts by reallocating market share from inefficient to efficient firms (Goldberg & Rai, 1996; Smirlock, 1985). Hence, we expect a positive relationship between efficiency and performance, and the higher is the degree of competition in the market, the stronger will be this relationship. The strength of the relationship between efficiency and performance is thus an indicator of the degree of competition.

The most important benefit of the Boone indicator is that it is monotonically related to the degree of competition in an industry under relatively mild assumptions.[7] Its drawback, however, is that it is a data-demanding measure and that it relies on estimates of efficiency and of the relationship between efficiency and performance. Indeed, since measurement errors and unobserved heterogeneity are less likely to vary over time than across industries (Van Leuvensteijn et al., 2011), the Boone indicator is more useful as a tool for evaluating changes in the degree of competition in an industry over time than for comparing the competitiveness of different industries at a particular moment in time.

2.3 Banking competition and financial stability

In this section, we review the theoretical and empirical literature which investigates the relationsip between banking competition and financial stability. Traditionally,

[7] The most important assumption is that that economies of scale are controlled for, see Spierdijk & Zaouras (2017).

many scholars and regulators have argued that a stringent competition policy may not be beneficial when it comes to the banking sector due to its special nature (Vives, 2001). Banks are typically highly leveraged and risk plays a larger role in the financial sector compared with other sectors of the economy. As a result, a highly competitive banking system may be the source of financial instability, with negative repercussions for the real economy. For this reason, competition in the banking sector has been restricted in many developed economies until the latter part of the 20st century. As shown below, however, there is no scientific consensus about the effect of banking competition on financial stability, neither in the theoretical nor in the empirical literature. Below, we first review the theoretical literature on the subject, which is divided into a so-called *competition-fragility view*, which argues that competition is detrimental to stability, and a *competition-stability view*, which claims that competition enhances stability. After discussing these two views on the relationship between banking competition and stability, we give an overview of the empirical literature dealing with this important question.

2.3.1 Theory: the competition-fragility view

According to the competition-fragility view, an increase in banking competition is likely to have a detrimental effect on financial stability. Proponents of this view argue that an increase in banking competition increases banks' incentives to take risk due to a charter value effect, and lowers their incentives to screen borrowers. We elaborate upon these arguments below.

Charter value effect. The traditional view on banking competition is based on an extension of the model of Merton (1977) on the pricing of deposit insurance. Merton (1977) illustrates that, for a bank, the value of deposit insurance is akin to the value of a put option on its assets. Since the value of an option is an increasing function of the variability in the value of the underlying asset, a bank with insured deposits has an incentive to maximize the variability in the value of its assets. This strategy maximizes the value of the bank's equity in the presence of deposit insurance, but also maximizes insolvency risk. Marcus (1984) and Keeley (1990) extend this analysis by showing that the existence of a valuable bank charter gives rise to bankruptcy costs, since the charter is lost in case of failure.[8] When a bank's charter is valuable

[8]The value of a bank's charter is sometimess referred to as its *franchise value*. It is equal to the present value of the bank's expected future profits.

enough, any increase in the value of deposit insurance due to additional risk-taking is outweighted by an increase in expected bankruptcy costs, so that the bank finds it optimal to *minimize* rather than maximize insolvency risk. However, an increase in competition for deposits erodes banks' rents and future profits, thereby lowering banks' charter values, so that more banks find it optimal to choose a risk-maximizing strategy. As a result, competition is likely to be negatively associated with financial stability. Hellmann et al. (2000) generalize the analysis to the case in which there are capital requirements in place. They show that deposit-rate ceilings, which limit competition for deposits, are an effective way to increase stability due to their charter value-enhancing effect. Repullo (2004) confirms the above-mentioned findings in a model with spatial competition.[9]

Screening incentives. Cordella & Yeyati (2002) develop a model in which banks influence their degree of risk by choosing an optimal degree of screening of loan applicants. They illustrate that the benefits of screening fall with an increase in the degree of competition. As a result, banks reduce their screening effort, and thereby become more risky, when competition increases.[10] Hauswald & Marquez (2006) find a similar relationship between the degree of competition and banks' screening incentives. Finally, Marquez (2002) shows that screening becomes more difficult with an increase in the number of banks in the market because each bank becomes informed about a smaller proportion of the pool of borrowers. As a result, more low-quality borrowers obtain financing, with negative repercussions for financial stability.

2.3.2 Theory: the competition-stability view

Proponents of the competition-stability view argue that banking competition is beneficial for financial stability. They do so by turning the arguments for the competition-fragility view around. Below, we summarize their arguments.

Moral hazard effect. Boyd & De Nicolo (2005) argue that banks with market power charge higher loan rates, which give rise to a moral hazard problem on the part borrowers, as in Stiglitz & Weiss (1981). These borrowers will increase their risk when faced with higher interest costs, thereby increasing the risk of their bank's portfolio.

[9] See also Besanko & Thakor (2003) Allen & Gale (2000), Boot & Thakor (2000) Bolt & Tieman (2004), De Nicolo & Lucchetta (2013) and Matutes & Vives (2000).

[10] See also Chan et al. (1986), Gehrig (1998), Caminal & Matutes (2002) and Dell'Ariccia & Marquez (2006).

An increase in competition for loans is thus beneficial for stability, since it reduces loan rates and thereby alleviates moral hazard problems on the part of borrowers. The mechanism described above is similar to the one underlying the charter value effect, but works in the opposite direction. The charter value effect is based on the assumption that banking competition takes place on the *deposit* market. An increase in competition raises deposit rates and reduces bank profits, so that banks find it optimal to increase their risk. The moral hazard effect, on the other hand, is based on the assumption that competition takes place on the *loan* market. An increase in competition lowers loan rates and enhances the profits of borrowers, who find it optimal to *reduce* their risk. In practice, banking competition is likely to occur on both the deposit and the loan market, so that both channels are likely to be present. It should be noted that Boyd & De Nicolo (2005) assume that loan defaults are perfectly correlated. Martinez-Miera & Repullo (2010) demonstrate that, in the more realistic case of imperfect loan default correlation, there is also a margin effect because higher interest payments from performing loans can provide a buffer to cover losses from defaulting loans. They show that in this case, a U-shaped relationship follows between competition and stability. That is, when banks have a high degree of market power, an increase in competition is beneficial for stability, but when the degree of competition reaches a certain threshold, further increases in competition are detrimental to stability. Finally, Wagner (2010b) shows that when banks can choose between borrowers with different levels of default risk, the moral hazard effect becomes irrelevant and banking competition is unambiguously detrimental to financial stability. The reasoning is that even though an increase in competition lowers loan rates and thereby lowers the default risk of individual borrowers, the associated decrease in bank profits incentivizes banks to switch lending to more risky borrowers due to the charter value effect.

Diversification effect. A second argument in favor of the competition-stability view uses the reasoning of the charter value effect, but turns its conclusion upside down. The argument is that when banks have market power, they indeed have an incentive to reduce risk in order to protect the value of their charters. However, they are likely to do decrease their risk in a way which increases systemic risk, and which is therefore detrimental to financial stability, namely by means of diversifiying their asset portfolio. As was explained in section 2.2.1, diversification lowers a bank's individiual probability of failure, but it also makes banks more similar and thereby makes systemic crises more likely (De Vries, 2005; Wagner, 2010a). Moreover, according to the "too-many-to-fail" theory of Acharya & Yorulmazer (2007), banks with market power have an incentive to diversify irrespective of the associated decrease in individual bank risk. The idea is that banks with valuable charters want to take correlated risks, as this ensures that they only fail when many other banks are in distress as well, which in turn increases the likelihood that they will be rescued when in distress. In either case, an increase in competition decreases charter values and thereby lowers banks' incentives to diversify, which is beneficial for financial stability even though it may increase individual bank risk.

Too-big-to-fail effect. A final argument in favor of the competition-stability view is that uncompetitive environments are more likely to produce large, too-big-to-fail (TBTF) banks. By itself, the existence of TBTF-banks is already a threat to financial stability, since these banks are a major source of contagion risk (Nier et al., 2007). In addition, managers of a TBTF bank know that it is likely that their bank will be rescued when in distress and therefore have an incentive to take excessive risks (Mishkin, 1999; Stern & Feldman, 2004; Mishkin, 2006). This moral-hazard problem further aggravates the problems associated with TBTF-banks. It should be noted that the TBTF argument relies upon the assumption that less competitive markets tend to be more concentrated and that an increase in competition is thus associated with a decrease in the degree of market concentration. As discussed above, this is not necessarily the case.

2.3.3 Empirical evidence

Since conflicting theories exist about the effect of banking competition on financial stability, the sign of the relationship between these two phenonema is ultimately an empirical question. Unfortunately, the empirical literature on this subject is conflicting as well. Table 2.1 gives an overview of the studies which have empirically investigated the relationship between banking competition and financial stability, along with their most important characteristics. The table groups these studies into those which support the competition-fragility view, those that give evidence in favor of the competition-fragility hypothesis, and those that give mixed evidence. The picture that emerges from the table is that overall, the empirical evidence does not appear to favor one theory over the other. Indeed, Beck et al. (2013) report large cross-country heterogeneity in the relationship between banking competition and financial stability. Moreover, a meta-analysis by Zigraiova & Havranek (2015) suggests that on the whole, the empirical literature provides little evidence of a significant relationship between banking competition and financial stability of either sign.

It should be noted, however, that a large majority of studies analyze the effect of banking competition on individual bank risk, rather than systemic risk. This is problematic, because the effect of competition on individual bank risk is not necessarily the same as the effect on systemic risk, and it is systemic risk which matters most for financial stability. Indeed, Leroy (2016) finds that banking competition increases individual bank risk, but reduces systemic risk. Moreover, the few studies which use systemic measures of risk all find evidence in favor of the competition-stability view. However, since so few studies make use of a systemic risk measure, it is too early to conclude that the empirical evidence favors the competition-stability view. Indeed, an interesting avenue for future research would be to replicate the results of some of the studies which offer support for the competition-fragility view, using systemic rather than individual measures of risk. For instance, studies which use the z-score as the measure of financial stability could be replicated using the aggregate z-score rather than banks' individual z-scores as the dependent variable. It would be quite interesting to see whether this change in the level of analysis of the dependent variable affects the results. In Chapter 4, we do something similar in our analysis of the relationship between the degree of banking market concentration and financial stability in the EU in the period between 1998 and 2014. More specifically, we analyze the effect of changes in concentration on financial stability using both individual (bank-specific) and aggregate (country-specific) z-scores, thereby capturing different aspects of financial stability. The results suggest that in this particular context, the relationship between banking market concentration and z-scores does not depend on the level of analysis.

2.4 Banking competition and economic growth

As was the case with the relationship between banking competition and financial stability, two opposing views exist with regard to the relationship between banking competition and economic growth. We will refer to these views as the *competition-growth* and the *competition-stagnation* view. The theoretical arguments for these two

Table 2.1: Overview of empirical studies of the competition-stability relationship.

Paper	Individual risk measure	Systemic risk measure	Competition measure	Country/region	Period
Competition-fragility view					
Agoraki et al. (2011)	Z-score, NPL-ratio	-	Lerner index	Eastern Europe	1998-2005
Beck et al. (2013)	Z-score	-	Lerner index	Worldwide	1994-2009
Berger et al. (2009)	Z-score, NPL-ratio, cap. ratio	-	Lerner index, HHI	Developed countries	1999-2005
Fungáčová & Weill (2013)	Default indicator	-	Lerner index	Russia	2001-2007
Jiménez et al. (2013)	NPL-ratio	-	Lerner, HHI, CR5	Spain	1988-2003
Salas & Saurina (2003)	Capital ratio	-	Tobin's q	Spain	1968-1998
Turk-Ariss (2010)	Z-score	-	Lerner index	Developing countries	1999-2005
Yaldiz & Bazzana (2010)	Z-score, NPL-ratio	-	Lerner index	Turkey	2001-2009
Yeyati & Micco (2007)-	Z-score	-	H	Latin America	1993-2002
Competition-stability view					
Anginer et al. (2014)	Z-score, Distance-to-default	CoVaR	Lerner, H, HHI, CR3	Worldwide	1997-2009
Beck et al. (2006)	-	Crisis dummy	Regulatory restrictions	Worldwide	1980-1997
Boyd et al. (2006)	Z-score		HHI	Developing countries	1993-2004
Chen (2007)	NPL-ratio	-	H	Europe	1990-1999
Čihák & Hesse (2010)	Z-score	-	HHI	Islamic countries	1993-2004
De Nicolo & Loukoianova (2007)	Z-score	-	HHI	Developing countries	1993-2004
Fiordelisi & Mare (2014)	Z-score	-	Lerner index	Western Europe	1998-2009
Leroy (2016)	Z-score, Distance-to-default	SRISK	Lerner index	Europe	2004-2013
Liu et al. (2012)	Z-score	-	H, CR3	South East Asia	1998-2008
Schaeck & Čihák (2008)	Z-score	-	Boone indicator	Europe/United States	1995-2005
Schaeck & Cihak (2012)	Capital ratio	-	H	Europe	1999-2005
Schaeck & Cihák (2014)	Z-score, NPL-ratio	-	Boone indicator	Western Europe	1995-2005
Schaeck et al. (2009)	-	Crisis dummy	H	Worldwide	1980-2005
Uhde & Heimeshoff (2009)	-	Agg. Z-score	HHI, CR5, CR3	Europe	1997-2005
Mixed evidence					
Fu et al. (2014)	Z-score, Distance-to-default	-	CR3, Lerner index	Asia Pacific	2003-2010
Jeon & Lim (2013)	Z-score	-	Boone ind., HHI, CR5	South Korea	1999-2011
Kick & Prieto (2015)	Distress/default indicator	-	Lerner index, Boone ind.	Germany	1994-2010
Liu & Wilson (2013)	Z-score	-	Lerner index	Japan	2000-2009
Liu et al. (2013)	Z-score	-	Lerner index	Western Europe	2000-2008
Tabak et al. (2012)	Z-score	-	Boone indicator	Latin America	2003-2008

Notes: This table gives an overview of the empirical studies that have investigated the relationship between banking competition and financial stability. A distinction is made between studies that give evidence in favor of the competitition-stability view, those that give evidence in favor of the competition-fragility view, and those that give mixed or ambiguous evidence. *NPL-ratio* refers to the ratio between non-performing loans and total assets. *Cap. ratio* refers to the equity-to-assets ratio. *Agg. Z-score* refers to the aggregate (country-level) Z-score. *HHI* refers to the Herfindahl-Hirschmann index, *H* refers to the H-statistic, CR5 and CR3 refer to the five-bank and three-bank concentration ratio, respectively.

views are outlined below, after which a summary of the empirical literature on the subject follows.

2.4.1 Theory: the competition-growth view

The traditional view on the relationship between banking competition and economic growth is that an increase in the competitiveness of the banking sector is beneficial for growth. Three arguments have been provided by proponents of this view, which are discussed below.

Interest margin effect. The most important argument for the competition-growth view is that an increase in the degree of banking competition reduces the margin between deposit and loan rates by increasing deposit rates and reducing loan rates. This reduction in the interest rate margin improves the welfare of borrowers and savers, and stimulates both savings and investments. The increase in investments, in turn, has a positive impact on the growth rate of the economy. As a result, an increase in banking competition results in higher economic growth (Hannan, 1991; Besanko & Thakor, 1992; Pagano, 1993; Smith, 1998; Guzman, 2000).

Efficiency effect. A second argument in favor of the competition-growth view is that a high degree of competition in the banking sector forces banks to become more efficient, as only the most efficient banks are able to survive in a highly competitive environment. An increase in the competitiveness of the banking industry thus raises the efficiency of the banking sector. The increase in banks' efficiency allows a larger proportion of savings to be used for investments, which has a positive effect on economic growth (Pagano, 1993; Allen & Gale, 2000; Vives, 2001).

Hold-up effect. A final argument in favor of the competition-growth view is that an increase in competition may alleviate hold-up problems for borrowers. The idea is that when banks have market power, it is difficult for bank borrowers to switch to another bank. As a result, the bank is able to extract rents from its borrowers by raising loan rates after a lending relationship has been established. This increase in loan rates has a detrimental effect on investments and thereby reduces growth. An increase in banking competition reduces the market power of banks and thereby alleviates this hold-up problem. As a result, it will have a positive impact on economic growth (Sharpe, 1990; Rajan, 1992; Claessens & Laeven, 2005).

2.4.2 Theory: the competition-stagnation view

Proponents of the competition-stagnation view argue that an increase in banking competition is associated with a decrease in economic growth. Two arguments support this idea.

Relationship lending. The most important argument for the competition-fragility view is that an increase in banking competition makes it more difficult for banks to engage in relationship lending with clients (Mayer, 1988; Petersen & Rajan, 1995; Claessens & Laeven, 2005). Young and innovative firms are typically not profitable in their early years, but may become profitable in the future. As a result, banks are only willing to give such firms credit if they can extract rents in the future through the formation of a lending relationship. In a competitive banking industry, however, firms which have become profitable can easily switch to a competing bank, thereby preventing their initial bank from extracting rents and sharing in the surplus generated by the firm. As a result, banks in a competitive environment will be unwilling to lend to young firms, which hampers investment, innovation, and growth.

Screening incentives. As was explained in section 2.3, the benefits of screening decrease with an increase in the degree of banking competition (Cordella & Yeyati, 2002; Marquez, 2002; Hauswald & Marquez, 2006). This is not only detrimental to financial stability, but may also effect economic growth, since one of the purposes of screening is to ensure that funds are directed towards the most profitable investment opportunities. Hence, an increase in banking competition may hamper economic growth by making it less attractive for banks to properly screen borrowers and thereby worsening the efficient channeling of funds to the most profitable investment opportunities.

2.4.3 Empirical evidence

In contrast to the abundant empirical literature on the relationship between banking competition and financial stability, few studies (Valverdie et al., 2003; Hoxha, 2013; Koetter, 2013; Gaffeo & Mazzocchi, 2014; Liu et al., 2014) have directly investigated the effect of banking competition on economic growth. The majority of studies in the empirical literature use indirect proxies of either economic growth or banking competition instead. For instance, a number of studies (Jayaratne & Strahan, 1996; Krol & Svorny, 1996; Freeman, 2002; Strahan, 2003; Huang, 2008) analyze the effect

Table 2.2: Overview of empirical studies of the competition-growth relationship.

Paper	Direct growth measure	Indirect growth measure	Competition measure	Country/region	Period
Competition-growth view					
Jayaratne & Strahan (1996)	GDP growth	-	Deregulation dummy	United States	1972-1992
Krol & Svorny (1996)	GDP growth	-	Deregulation dummies	United States	1970-1988
Shaffer (1998)	Household income growth	-	Number of banks	United States	1979-1989
Cetorelli & Gambera (2001)	-	Industry growth	CR5, CR3	Worldwide	1980-1990
Black & Strahan (2002)	-	Rate of new incorporations	Deregulation dummies	United States	1970-1994
Strahan (2003)	State income growth	-	Deregulation dummy	United States	1976-1996
Demirgüç-Kunt et al. (2004)	-	Net interest margin	Entry restrictions	Worldwide	1995-1999
Peria & Mody (2004)	-	Interest rate spread	HHI, CR3	Latin America	1995-2001
Claessens & Laeven (2005)	-	Industry growth	H	Worldwide	1980-1997
Koetter (2013)	GDP growth	-	Lerner index	Germany	1993-2011
Gaffeo & Mazzocchi (2014)	GDP growth	-	Boone indicator	Worldwide	1997-2010
Liu et al. (2014)	Value added	-	Boone indicator, CR5	Worldwide	1993-2007
Ryan et al. (2014)	-	Investment	Lerner index	Europe	2005-2008
Léon (2015)	-	Probability of loan	Boone ind., Lerner, H	Worldwide	2006-2011
Competition-stagnation view					
Inklaar et al. (2012)	-	SME output growth	Lerner index, HHI	Germany	1996-2006
Ogura (2012)	-	Probability of loan	Interest margin	Japan	1993-2003
Hoxha (2013)	Value added	-	H, HHI, CR5	Worldwide	1994-2006
Leroy (2016)	-	Total factor productivity	Boone indicator	Europe	1999-2009
Mixed evidence					
Berger et al. (2001)	-	Small business lending	HHI	United States	1993-1998
Freeman (2002)	GDP growth	-	Deregulation dummy	United States	1972-1992
Valverdie et al. (2003)	GDP growth	-	Lerner index, H, HHI	Spain	1986-1998
Deidda & Fattouh (2005)	GDP growth	Industry growth	CR3	Worldwide	1980-1990
Huang (2008)	GDP growth	-	Deregulation dummy	United States	1975-1990
de Guevara & Maudos (2011)	-	Industry growth	Lerner index, H	Worldwide	1993-2003

Notes: This table gives an overview of the empirical studies that have investigated the relationship between banking competition and economic growth. A distinction is made between studies that give evidence in favor of the competitition-growth view, those that give evidence in favor of the competition-stagnation view, and those that give mixed or ambiguous evidence. *HHI* refers to the Herfindahl-Hirschmann index, *H* refers to the H-statistic, CR5 and CR3 refer to the five-bank and three-bank concentration ratio, respectively.

of deregulations of competitive restrictions in the banking sector on economic growth. The assumption is that these deregulations have increased the competitiveness of the banking industry, which has in turn affected economic growth. Other studies measure competition more directly, but look at the effect of banking competition on lending, interest rate spreads, investments, productivity, or industry growth. The idea is that these variables are important determinants of economic growth, so that it can be assumed that an increase in, say, investments, results in higher growth. Clearly, we can only regard the results of these studies as indirect evidence of a relationship between banking competition and economic growth.

Table 2.2 gives an overview of the studies that directly or indirectly study the link between banking competition and economic growth. The overview clearly illustrates that the majority of studies find that an increase in the competitiveness of the banking industry results in higher growth. Nevertheless, a number of studies, some of which are quite recent, find mixed evidence or a negative relationship between competition and growth. Hence, although the empirical literature on the whole appears to favor the competition-growth view, a consensus on the relationship between banking competition and economic growth has yet to be reached. We believe that more empirical research is necessary to establish the sign of the relationship, especially given the relatively small amount of studies which have analyzed the relationship directly. In Chapter 5, we make a start with this by studying the effect of deregulations of banking competition on economic growth, and subsequently assessing whether banking competition is the channel through which these deregulations affect growth.

2.5 Conclusion

This chapter has critically reviewed the scientific literature regarding the effect of banking competition on financial stability and economic growth. We have shown that the measurement of banking competition and financial stability is difficult because these phenomena are not directly observable. Various measures of competition and stability have been discussed, along with their strenghts and weaknesses. It has become clear from this discussion that completely satisfactory measures of competition or banking competition do not yet exist. Fortunately, improvements in the measurement of competition and financial stability are still being made. Indeed, the attention for the measurement of financial stability in particular has increased substantially after the outbreak of the financial crisis in 2008. In Chapter 3, we contribute to this growing literature by illustrating how the potential for firesales affects the measurement of systemic risk when banks take correlated risks; a dimension of systemic risk which so far has largely been ignored in the measurement of financial stability.

After a discussion of the measurement of the three phenomena of interest in this chapter, we focused on the relationship between banking competition and financial stability. We have shown that the theoretical literature dealing with this relationship is divided, with some studies arguing in favor of the view that banking competition is beneficial for financial stability, and others supporting the view that competition has detrimental effects on stability. An important issue in this respect is whether competition between banks mostly takes place on the deposit market or on the loan market. Given the ambiguity of the theoretical literature, the sign of the effect of an increase in banking competition on financial stability is ultimately an empirical question. Unfortunately, the empirical literature does not paint a clear picture on this issue either. Moreover, we have shown that most studies use measures of individual bank risk as a proxy of financial stability, even though *systemic* risk is the concept which is relevant for financial stability. Moreover, we have argued that systemic risk is conceptually quite different from individual bank risk, since an increase in individual bank risk does not necessarily imply an increase in systemic risk, or vice versa. As such, we believe that more studies are necessary, in particular studies which use measures of systemic risk to identify the effect of banking competition on financial stability. An interesting avenue for future research would be to replicate existing studies on the relationship between banking competition and financial stability while replacing individual measures of stability at the bank level with their systemic counterparts. In Chapter 4, we do something similar when studying the relationship between banking market concentration and financial stability. More specifically, we analyze the relationship between banking market concentration and stability using both individual (bank-specific) and aggregate (country-specific) z-scores.

Finally, we discussed the literature on the relationship between banking competition and economic growth. As was the case with the relationship between banking competition and financial stability, the theoretical literature dealing with this relationship consists of two strands. On the one hand, proponents of the competition-growth view argue that an increase in the degree of banking competition lowers interest rate margins and reduces hold-up problems, thereby stimulating investments and economic growth. On the other hand, proponents of the competition-stagnation view believe that an increase in banking competition reduces banks' incentives to engage in relationship lending and to screen loan applicants. As a result, the efficient allocation of savings to the most profitable investment opportunities is reduced, which results in lower economic growth. The empirical literature dealing with the effect of banking competition on economic growth appears to favor the competition-growth view. However, most studies analyze the effect of indirect measures of competition, such as deregulations of competitive restrictions in banking, on growth. Hence, we believe that more research is necessary before it can be concluded that banking competition is beneficial for growth. In Chapter 5, we do a first attempt in this respect, by using a spatial econometric model to analyze the effects of deregulations in the banking sector on economic growth and subsequently exploring whether banking competition is the channel through which these deregulations affect growth.

Chapter 3

Systemic risk with endogenous loss given default

Abstract. *When many financial institutions fail simultaneously, the remaining institutions in the system are unlikely to have sufficient liquidity to acquire all failed institutions. As a result, some assets will have to be liquidated and sold to outsiders at firesale prices, giving rise to a potentially high losses given default (LGDs) for creditors of failed institutions. This study analyzes the consequences of this firesale mechanism for systemic risk. Our findings suggest that systemic risk is likely to be heavily underestimated when the potential for firesales, and thereby the endogenous nature of LGDs, is not taken into account. The magnitude of the negative bias increases with asset return correlations, banks' return variability, the degree of asset specificity of bank loans and the degree of concentration in the banking sector. The analysis suggests that time-varying liquidity requirements are an effective way to reduce the potential for firesales and thereby lower systemic risk.*

This chapter is based on IJtsma, P. and Spierdijk, L. (2017). Systemic risk with endogenous loss given default. *Journal of Empirical Finance*, forthcoming.

3.1 Introduction

Since the outbreak of the global financial crisis that started with the fall of Lehmann Brothers in September 2008, macroprudential regulation of the financial system has become a major concern to regulators and policymakers. The main objective of macroprudential regulation is to safeguard the stability of the financial system as a whole, in order to prevent the occurrence of a systemic crisis in which many financial institutions fail simultaneously. Such systemic crises tend to be costly because they are associated with high fiscal costs and lead to large output losses due to disruptions in lending to the real economy (Hoggarth et al., 2002; Allen & Carletti, 2013). Consequently, a growing body of economic research analyzes and measures systemic risk.

This study adds to the literature by analyzing how the potential for a firesale during times of distress in the financial system affects systemic risk through the effect of firesales on losses given default (LGDs).[1] Although there are a number of studies in the literature that show how firesales can result from the joint failure of multiple financial institutions (Shleifer & Vishny, 1992; Acharya & Yorulmazer, 2008), their consequences for systemic risk have not yet been analyzed. We analyze these consequences and quantify them using the widely used concept of Expected Shortfall (ES).[2] Our analysis thereby bridges a gap in the literature that exists between those studies dealing with firesales during periods of systemic distress and those that deal with the measurement of systemic risk.

Following Acharya (2009), we define systemic risk as the risk that creditors of financial institutions incur large losses as a result of the joint failure of multiple institutions due to correlated returns on the asset side of their balance sheets.[3] While most studies take LGDs as exogenously given, we show that when there is a potential for firesales, LGDs become endogenous. Our study illustrates that LGDs depend, among other things, on the degree of return correlation across banks' loan portfolios as well as the aggregate liquidity in the financial system, the latter of which is

[1] A firesale occurs when during a bankruptcy, assets are sold at extremely discounted prices. This is especially likely to happen when the failing firm's sector is in distress (Shleifer & Vishny, 1992; Acharya & Yorulmazer, 2008; James & Kizilaslan, 2014). Loss given default is the share of an asset that is lost when a borrower defaults, and which is thus not recovered by the lender.

[2] The $\alpha\%$ Expected Shortfall is the *average* loss of the $\alpha\%$ worst losses. As such, Expected Shortfall is a measure of tail risk.

[3] Note that *systemic* risk is a concept that is fundamentally different from *systematic* risk, which is the risk of a particular firm that can be explained by the risk of the market as a whole.

endogenous in our model. Monte Carlo simulations indicate that systemic risk is underestimated when LGDs are assumed to be exogenous. Furthermore, the magnitude of the negative bias increases with an increase in banks' asset return variability, the return correlations of their loan portfolios, the asset-specificity of loans and the degree of concentration in the banking system.

Our findings emphasize the importance of appropriately modeling LGDs associated with joint defaults of multiple financial institutions. Furthermore, they show that liquidity plays an important role in this respect, and suggest that regulations regarding minimum liquidity ratios for systemically important financial institutions (SIFIs) are an effective way to reduce the potential for firesales and thereby lower systemic risk. More specifically, during normal times (when there is no threat of firesales occurring) SIFIs should be required to hold a certain proportion of their assets in the form of a liquidity buffer, which could be used to purchase the assets of failed institutions during times of systemic distress.

The outline of the remainder of this chapter is as follows. Section 3.2 embeds our study in the existing literature. Firesales and LGDs are modeled in Section 3.3. The effects of firesales on systemic risk are then analyzed in Section 3.4. Finally, some concluding thoughts follow in Section 3.5.

3.2 Overview of the literature

This section summarizes the literature on systemic risk and elaborates on the literature dealing with firesales and LGDs. Finally, we position our study in these two strands of the literature.

3.2.1 Systemic risk

The literature on systemic risk can largely be categorized into two strands. The first strand deals with the possibility of contagious defaults, which occur when the failure of an individual financial institutions spreads as a contagion through the financial system, causing other institutions to fail as well. These studies generally focus on direct interlinkages between financial institutions (i.e. interbank loans), using network models and simulations to assess the vulnerability of a particular system to contagious defaults. Studies that use this approach are Furfine (2003), Upper & Worms (2004), Müller (2006), Hałaj & Kok (2013) and Peralta & Zareei (2016). For an overview of this strand of the literature, see Upper (2011). The second strand of the literature – to which the current study contributes in particular – analyzes how systemic risk arises as a result of correlations in the returns on institutions' asset portfolios.[4] The rationale for this approach is that simultaneous defaults might occur even in the absence of direct connections between financial institutions if their asset portfolios are very similar. When asset portfolios are similar, different institutions are likely to incur large losses at the same time. As a result, failures are likely to be correlated. Since bank-specific risk measures do not take such indirect linkages into account, a number of new measures related to systemic risk have been developed, which we discuss below.

Early contributions by Lehar (2005) and Kuritzkes et al. (2005) define systemic risk as the risk that a (hypothetical) deposit insurer, which has insured the liabilities of all financial institutions in the system, incurs significant losses. In this framework, the liability of the deposit insurer can be interpreted as a portfolio of short put options on correlated assets, so that the Merton (1974) model can be applied to obtain an estimate of systemic risk. Adrian & Brunnermeier (2016) propose a measure (called CoVaR) to capture the contribution of individual institutions to systemic risk. Their measure is calculated as the Value-at-Risk (VaR) of the financial system as a whole conditional on a particular financial institution being in distress. Acharya et al. (2017) introduce a measure that is conceptually quite similar to CoVaR. Their Systemic Expected Shortfall (SES) refers to the propensity of a financial institution to be undercapitalized when the system as a whole is undercapitalized. Again, by conditioning on a systemic event, SES measures the *contribution* of a particular bank to systemic risk rather than systemic risk itself. This also holds for the SRISK measure developed by Brownlees & Engle (2016). Huang et al. (2009, 2012) construct a so-called Risk Insurance Premium, which measures the insurance premium that protects against distressed losses of a hypothetical debt portfolio consisting of the total liabilities of all financial institutions in a system. They estimate this premium by combining information about CDS spreads of individual institutions and asset return correlations across banks. Jobst & Gray (2013) analyze systemic risk by looking at the multivariate distribution of losses associated with the default of different combi-

[4]We only summarize the most relevant studies below. For a complete overview of this strand of the literature, please refer to Bisias et al. (2012).

nations of institutions in a financial system and subsequently derive the distribution of the aggregate loss.

3.2.2 Firesales and LGDs

In addition to contributing to the systemic risk literature, our analysis is also related to the growing literature on firesales and LGDs in the context of systemic events. This literature took off with an important study by Shleifer & Vishny (1992), who argue that LGDs tend to be higher during episodes of industry-wide distress. Their argument is that industry peers of failed firms are unlikely to be able to purchase liquidated assets during such episodes. As a result, some assets will have to be sold to outsiders, who typically lack the expertise to manage them and are therefore not willing to pay a high price. The resulting fall in liquidation prices, typically referred to as a firesale, increases LGDs. Empirical evidence for this phenomenon is provided by Pulvino (1998), Brown et al. (2006), Acharya et al. (2007) and James & Kizilaslan (2014). Allen & Gale (1994) elaborate on the idea with the concept of *cash-in-the-market pricing*. They show that if participation in a market is limited, the liquidity of market participants plays an important role in determining equilibrium prices because their aggregate liquidity (the cash in the market) may put an upper limit on the equilibrium price. These ideas are combined by Acharya & Yorulmazer (2008), who formally derive the equilibrium price of liquidated assets following bank failures in a system with n equally sized banks and outsiders. They show that when the number of failures is above a certain threshold, the equilibrium price is determined by the available cash in the market (i.e. the aggregate liquidity of surviving banks and outsiders), so that LGDs increase with the number of bank failures.

3.2.3 Position of our study in the existing literature

Firesales and their consequences for systemic risk have been analyzed previously by a number of other studies, such as Cifuentes et al. (2005) and Brunnermeier & Pedersen (2009). However, the channel through which this effect takes place is entirely different from our analysis. While those studies analyze potential contagion effects of firesales in a situation in which banks' assets are marked-to-market, we focus on the effect of firesales on LGDs and rule out contagion effects. Hence, our study adds to this strand of the literature by highlighting a different channel through which firesales affect systemic risk. Our analysis is also related to Huang et al. (2009, 2012) and Jobst & Gray (2013). The difference between Huang et al. (2009, 2012) and our approach is that we explicitly model LGDs, whereas they make an assumption about LGDs and then derive default probabilities (PDs) from CDS spreads. We believe that their approach is somewhat problematic, because if the assumed LGDs are inaccurate, the implied PDs will be inaccurate as well. The main difference between our approach and that of Jobst & Gray (2013) is that we explicitly model LGDs, whereas they take LGDs as exogenously given. Finally, the way in which we model the optimal liquidity holdings of banks resembles the approach of Wagner (2011). However, whereas Wagner (2011) studies the portfolio choice decision of investors in a setting with two risky assets and a liquid asset, we take the composition of banks' portfolio of risky assets as given and analyze loss given default and systemic risk in a setting where banks choose their optimal holdings of liquidity.

3.3 Modeling firesales and LGDs

In this section, we model firesales and derive the LGDs associated with them. Our approach generalizes the model of Acharya & Yorulmazer (2008) by allowing for an arbitrary bank size distribution and endogenizing the aggregate liquidity in the system. Furthermore, while they model the liquidation procedure as a common-value share auction, we let the seller of the assets simply set a price and derive the demand for the assets for any given price. Modeling the liquidation procedure as an auction is problematic, as shown by Wilson (1979). The equilibrium price in such auctions is much lower than suggested by Acharya & Yorulmazer (2008), since the bidders have an incentive to understate their demand for the assets.

The model consists of one period with financial institutions (banks), outsiders (e.g. foreign banks, pension funds, governments, etc) and a regulator, all of which are risk neutral. Banks are financed with insured deposits and equity and invest in a combination of risk-free liquid assets (liquidity) and risky illiquid assets (loans) at the beginning of the period.[5] They fail if they are insolvent at the end of the period, which happens when the fundamental (book) value of their assets falls below the value

[5]The investment in liquidity can be interpreted as the purchase of Treasury securities with a risk-free rate that is normalized to zero. This investment can generate a positive return, however, in the case of a firesale at the end of the period, when it can be used to purchase liquidated loans at discounted prices.

of their liabilities. More specifically, bank i fails when:

$$d_i > \ell_i + a_i(1 + R_i) - \alpha_i d_i, \tag{3.1}$$

where d_i refers to the deposits of bank i, while ℓ_i and a_i are the bank's liquidity and loans, respectively. Furthermore, $R_i \sim N(\mu_i, \sigma_i)$ is the bank's return on loans, which is the source of uncertainty in the model, and α_i is the bank's deposit insurance premium. Rewriting Equation (3.1) gives the critical return on loans (c_i) below which the bank fails:

$$c_i = \frac{d_i(1 + \alpha_i) - \ell_i}{a_i} - 1 = \frac{d_i^*}{a_i} - 1, \tag{3.2}$$

where $d_i^* = d_i(1 + \alpha_i) - \ell_i$ refers to the bank's liabilities net of its liquidity. When a bank fails, the regulator, who has insured the deposits, takes over the bank's loan portfolio and liquidates the loans by selling them to the surviving banks and/or outsiders. Surviving banks attach a relatively high value of $\bar{p}$ per unit to the loans ($0 < \bar{p} \leq 1$), but have limited liquidity. Outsiders have unlimited aggregate liquidity, but are inefficient at managing loans and therefore value liquidated them at a lower value of $\underline{p}$ per unit.[6] This notion captures the idea that bank loans are asset-specific, in the sense that they cannot easily be managed by outsiders. The parameter $\underline{p}$ measures the degree of loans' asset-specificity, with a lower value corresponding to a higher degree of asset-specificity.[7] The regulator knows the aggregate amount of liquidity held by surviving banks and its objective is to minimize its loss by maximizing the proceedings from the liquidation. The liquidation procedure is as follows: First, the regulator announces the liquidation price. Then, the surviving banks and outsiders indicate the quantity of loans they wish to purchase. Finally, the regulator distributes the loans over the surviving banks and outsiders. The problem for the regulator is thus to set the price in such a way as to maximize the proceedings from the liquidation. To find this optimal price, we first derive the demand schedule for the loans.

Demand The surviving banks maximize profits, taking the liquidation price and their holdings of liquidity (which is chosen at the beginning of the period) as given.

[6] We assume that the aggregate liquidity of outsiders is unlimited in order to simplify the model. The results of our analysis do not hinge on this assumption.

[7] Shleifer & Vishny (1992) provide a theoretical justification for this approach, while James (1991) shows that losses given default are significantly higher when failing banks are not acquired by surviving banks.

Since they value the assets at $\bar{p}$ per unit, they want to purchase as many loans as possible when the liquidation price is below $\bar{p}$, and will not purchase any loans when it is above $\bar{p}$.[8] It follows that their aggregate demand for liquidated loans can be expressed as:

$$q_b = \begin{cases} \frac{\ell_S}{p} & \text{if} \quad 0 < p \leq \bar{p} \\ 0 & \text{if} \quad p > \bar{p}, \end{cases} \tag{3.3}$$

where q_b is the surviving banks' aggregate demand and ℓ_S is the aggregate liquidity of the surviving banks. A similar reasoning holds for outsiders. Hence, their demand can be expressed as:

$$q_o = \begin{cases} \frac{w}{p} & \text{if} \quad 0 < p \leq \underline{p} \\ 0 & \text{if} \quad p > \underline{p}, \end{cases} \tag{3.4}$$

where q_o is the outsiders' aggregate demand and w is the aggregate liquidity held by outsiders. As mentioned above, we assume that outsiders have unlimited aggregate liquidity. Hence, their demand is unlimited whenever $p \leq \underline{p}$, and 0 otherwise.

The regulator The regulator determines the liquidation price, taking the amount of loans to be liquidated and the demand curve of surviving banks and outsiders as given. Its maximization problem can be formulated as:

$$\begin{aligned} \max_{p} \quad & \pi = p(q_b + q_o) \\ \text{s.t.} \quad & q_b \leq \frac{\ell_S}{p} \\ & (p - \bar{p})q_b \leq 0 \\ & (p - \underline{p})q_o \leq 0 \\ & q_b + q_o \leq q, \end{aligned} \tag{3.5}$$

[8] We assume that banks can use all of their liquidity to purchase liquidity. In practice, banks are constrained in their use of liquidity through liquidity requirements. Hence, the liquidity that we refer to here could be interpreted as banks' *excess liquidity*, i.e. liquidity in excess of the requirement. Note also that it could be argued that, in practice, banks are able to borrow from the central bank to obtain additional liquidity with which to purchase assets. However, this requires an additional assumption that banks have excess capital, i.e. capital in excess of the capital requirement, since borrowing from the central bank will increase leverage. We abstract from this possibility in this study.

where π refers to the revenues of the liquidation procedure, q_b is the quantity of loans sold to surviving banks, q_o is the quantity of loans sold to outsiders and q is the quantity of loans to be liquidated. The optimal price is:[9]

$$p^* = \begin{cases} \bar{p} & \text{if} \quad q \leq \frac{\ell_S}{\bar{p}} \\ \frac{\ell_S}{q} & \text{if} \quad \frac{\ell_S}{\bar{p}} < q \leq \frac{\ell_S}{\underline{p}} \\ \underline{p} & \text{if} \quad q > \frac{\ell_S}{\underline{p}}. \end{cases} \tag{3.6}$$

Hence, as long as the quantity of loans to be liquidated is below some threshold, they can be liquidated for the high price $\bar{p}$. Whenever it is larger than this threshold, however, a firesale occurs in the sense that the loans will have to be sold for a price below the value that surviving banks attach to them. The liquidation price will continue to fall with an increase in the amount of loans to be liquidated until it equals $\underline{p}$, after which a further increase does not affect the price because liquidity-abundant outsiders participate in the liquidation procedure from then on. As such, the proceedings from the liquidation are:

$$\pi^* = \begin{cases} \bar{p}q & \text{if} \quad q \leq \frac{\ell_S}{\bar{p}} \\ \ell_S & \text{if} \quad \frac{\ell_S}{\bar{p}} < q < \frac{\ell_S}{\underline{p}} \\ \underline{p}q & \text{if} \quad q > \frac{\ell_S}{\underline{p}}. \end{cases} \tag{3.7}$$

The loss given default, which is defined as the loss of the regulator, equals the difference between the liabilities of failed banks net of their liquidity and the proceedings from the liquidation. It can be expressed as:

$$S = \begin{cases} d_F^* - \bar{p}q & \text{if} \quad q \leq \ell_S \\ d_F^* - \ell_S & \text{if} \quad \frac{\ell_S}{\bar{p}} < q \leq \frac{\ell_S}{\underline{p}} \\ d_F^* - \underline{p}q & \text{if} \quad q > \frac{\ell_S}{\underline{p}}, \end{cases} \tag{3.8}$$

where S is the (systemic) loss given default and $d_F^* = \sum_{i \in F} \left[d_i(1 + \alpha_i) - \ell_i \right]$, where F is the set of failed banks. Note that if $\underline{p} = \bar{p}$ (i.e. bank loans are not asset-specific), the loss is always equal to $d_F^* - \bar{p}q$, which implies that there is no firesale mechanism,

[9] This is actually one of many solutions, but they all give the same revenue, which is what we are ultimately interested in. A proof is given in Section 3.B.1.

prices are deterministic, and loss given default is exogenous. Hence, exogenous LGDs follow from a special case of the model.[10]

Deposit insurance premium The deposit insurer charges a risk-based deposit insurance premium, according to the following pricing rule:

$$\alpha_i = \beta\omega_i, \tag{3.9}$$

where ω_i is the bank's loan-to-assets ratio. It follows that the bank's deposit insurance premium increases linearly in its loans-to-assets ratio and that the bank only pays a premium when it holds a strictly positive amount of loans. This is reasonable, since a bank which holds only liquidity has a zero failure probability and therefore a zero probability of generating losses for the deposit insurer. In the spirit of Acharya et al. (2010), we additionally assume that deposit insurance premia are actuarially fair in the aggregate, so that the deposit insurer's revenues are equal to the expected systemic loss. This gives the following equilibrium condition:

$$E(S) = \beta\sum_{i=1}^{n}\omega_i d_i \tag{3.10}$$

When Equation (3.10) is satisfied, the regulator's income from insurance premia is exactly sufficient to cover its expected loss, so that it breaks even in expectation.[11]

Optimal liquidity Given the auction procedure described above, banks determine their optimal holdings of liquidity at the beginning of the period. Since banks are risk neutral, they maximize their ex-ante expected return on overall assets. This return is a weighted average of the bank's expected return on loans and expected return on liquidity. We can thus write the bank's expected return on overall assets as:[12]

$$E(ROA_i) = \omega_i E(R_i) + (1-\omega_i)E\left[\bar{p} - p^*(\omega_i)\middle|R_i > c_i(\omega_i)\right] - \alpha_i(\omega_i)(1-k), \tag{3.11}$$

[10]We have also derived the equilibrium under the assumption that the regulator is able to price discriminate between surviving banks and outsiders. This affects the results in a quantitative sense, but not the mechanism illustrated here. Proofs are available upon request.

[11]As long as the loans of failed banks are liquidated by one agent, an alternative interpretation of our model is a situation in which banks borrow from (uninsured) creditors rather than insured depositors. In this case, the deposit insurance premium would be replaced by a premium paid to creditors, which is charged to cover their expected losses. This case might be relevant in the context of e.g. shadow banking. We thank an anonymous referee for pointing this out.

[12]See section 3.B.2 in the mathematical appendix for a derivation.

where ROA_i is the bank's return on overall assets and k_i is its capital ratio. Taking the derivative of Equation (3.11) with respect to ω_i and substituting the pricing rule of the deposit insurer gives the bank's equilibrium condition for determining its optimal amount of liquidity:[13]

$$E(R_i) - \beta(1-k_i) = \frac{\partial}{\partial \omega_i}\Big((1-\omega_i)E\big[\bar{p} - p^*(\omega_i)|R_i > c_i(\omega_i)\big]\Big) \tag{3.12}$$

The left-hand side of Equation (3.12) is the expected marginal net return on loans after taking into account the costs of deposit insurance. The right-hand side is the expected marginal return on liquidity, which depends on the expected equilibrium price of liquidated assets conditional on the bank's survival. This expected equilibrium price, in turn, depends on the aggregate liquidity in the banking sector and therefore on the bank's asset composition. An increase in a bank's liquidity affects its return on liquidity in two ways. First, it ensures that the bank can sustain larger losses before it fails. If the returns on banks' loan portfolios are positively correlated, this implies that there is a higher probability that the bank survives when there is a firesale. As a result, the expected equilibrium price of liquidated loans conditional on the bank's survival will fall, thereby increasing the bank's return on liquidity. Second, an increase in a bank's liquidity increases the aggregate pool of liquidity in the system, thereby increasing the expected equilibrium price of liquidated loans and decreasing the expected return on liquidity. This effect is mostly relevant for large banks, of which the liquidity constitutes a large portion of aggregate liquidity, and gives large banks an incentive to choose a strategically low amount of liquidity in an attempt to lower the expected equilibrium price of liquidated loans.

To conclude this section, Table 3.A.1 gives an overview of the most important variables included in the model, distinguishing between variables of which the value is endogenously determined by the model and those that are taken as exogenously given.

[13] Note that there are also two corner solutions, where banks choose to invest only in loans or liquidity, respectively. See section 3.B.2 in the mathematical appendix for details.

3.4 Modeling systemic risk

This section assesses the consequences of the above-mentioned firesale mechanism for systemic risk. Our conceptualization of systemic risk is similar to Lehar (2005) and Kuritzkes et al. (2005), but we adopt a more realistic framework. While the latter studies assume that banks' assets can always be liquidated for their fundamental value, we explicitly model the equilibrium price for which bank loans are liquidated. Our approach is more realistic, since it is unlikely that the demand for the loans of failed institutions is sufficiently high to liquidate them for their fundamental value during episodes of system-wide distress.

We interpret systemic risk as the risk that the regulator incurs large losses and refer to the loss of the regulator as the *systemic loss* in the remainder of this section. We use simulations to get a sense of the quantitative effects of firesales. In our simulations, we explicitly calculate the banks' liquidity-to-assets ratios (liquidity ratios), thereby recognizing that it is an endogenous variable. We also demonstrate how systemic risk is affected by changes in (i) the degree of asset-specificity of bank loans, (ii) the return correlation across banks' loan portfolios, (iii) banks' failure probabilities, and (iv) the degree of market concentration in the banking sector.

3.4.1 Analytical illustration

For the sake of exposition, we first derive the probability distribution function of the systemic loss in a system with two banks and show analytically how the distribution is affected by the potential occurrence of firesales. Note that in this illustration, we take the aggregate liquidity in the system as given even though it is endogenous in the model. The reason for this is that we do not have a closed-form expression of equilibrium aggregate liquidity. We believe that an analytical approach in a two-bank setting is nevertheless useful because it highlights the mechanism through which firesales affect systemic risk. When the banking system consists of two banks, the systemic loss can be expressed as a function of their (random) returns, which we denote $S(R_x, R_y)$. When both banks fail, the banks' loans are necessarily purchased by outsiders, so that the liquidation price equals $\underline{p}$. Furthermore, when neither bank fails, the loss is equal to 0. Finally, when one of the two banks fails, the liquidation price is given by Equation (3.6). Combining these cases gives the expression stated below in Equation (3.13).[14] Here S is the systemic loss, d_i^* denotes the book value of liabilities (including the deposit insurance premium) of bank i net of its liquidity, while a_i refers to the book value of its loans. Furthermore, $c_i = \frac{d_i^*}{a_i} - 1$ denotes the critical return of bank i below which it fails, so that the systemic loss is zero when the return of both banks is above c_i, while it is equal to the expression in the first line when the return is below c_i for both banks. In addition, $\tau_x = \frac{\ell_y}{\bar{p} a_x} - 1$ is the critical return of bank x below which bank y, if y survives, has sufficient liquidity to purchase the loans of x for the high price (and vice versa for τ_y). If the return of the failed bank is below this critical value, the liquidation price is equal to $\bar{p}$, which implies a loss equal to the second or third line of Equation (3.13). In the same spirit, $\eta_x = \frac{\ell_y}{\underline{p} a_x} - 1$ is the critical return of x above which the regulator maximizes its revenues by setting the price equal to $\underline{p}$ when x fails and y survives (and vice versa for η_y). If the return of the failed bank is above this critical value, the liquidation price will be $\underline{p}$, which implies a loss equal to line 6 or 7 of Equation (3.13). Finally, when the return of the failed bank is between the critical values τ_i and η_i, the regulator charges the price in such a way that the surviving bank has exactly sufficient liquidity to purchase the assets of the failed bank, which implies a systemic loss equal to the expression in line 4 or 5 of Equation (3.13) below:

$$S(R_x, R_y) = \begin{cases} d_x^* + d_y^* & \\ -\underline{p}\big[(1+R_x)a_x + (1+R_y)a_y\big] & \text{if} \quad R_x < c_x \text{ and } R_y < c_y \\ d_x^* - \bar{p}(1+R_x)a_x & \text{if} \quad R_x < \min[\tau_x,\, c_x] \text{ and } R_y \geq c_y \\ d_y^* - \bar{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } R_y < \min[\tau_y,\, c_y] \\ d_x^* - \ell_y a_y & \text{if} \quad \tau_x \leq R_x < \min[\eta_x,\, c_x] \text{ and } R_y \geq c_y \\ d_y^* - \ell_x & \text{if} \quad R_x \geq c_x \text{ and } \tau_y \leq R_y < \min[\eta_y,\, c_y] \\ d_x^* - \underline{p}(1+R_x)a_x & \text{if} \quad \eta_x \leq R_x < c_x \text{ and } R_y \geq c_y \\ d_y^* - \underline{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } \eta_y \leq R_y < c_y. \\ 0 & \text{if} \quad R_x \geq c_x \text{ and } R_y \geq c_y. \end{cases} \tag{3.13}$$

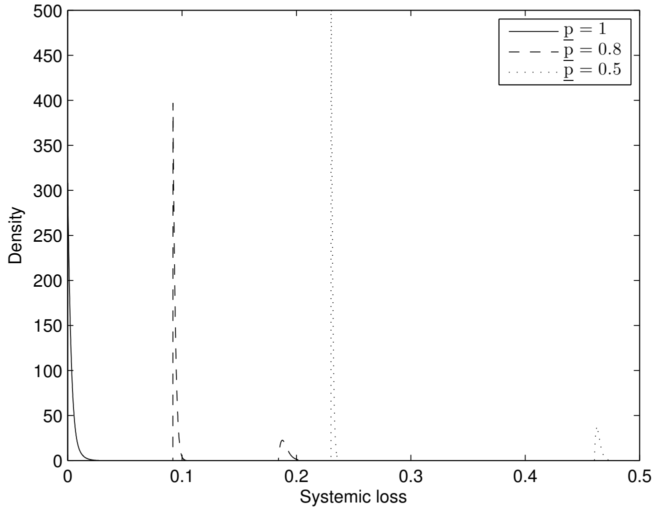
Note that when $\underline{p} = \bar{p}$, there is no firesale mechanism and the expression collapses to:

$$S(R_x, R_y) = \begin{cases} d_x^* + d_y^* - \bar{p}\big[(1+R_x)a_x + (1+R_y)a_y\big] & \text{if} \quad R_x < c_x \text{ and } R_y < c_y \\ d_x^* - \bar{p}(1+R_x)a_x & \text{if} \quad R_x < c_x \text{ and } R_y \geq c_y \\ d_y^* - \bar{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } R_y < c_y \\ 0 & \text{if} \quad R_x \geq c_x \text{ and } R_y \geq c_y. \end{cases} \tag{3.14}$$

[14] A formal proof is given in Section 3.B.3.

As an illustration, Figure 3.1 gives, for different values of $\underline{p}$, the pdf of the systemic loss conditional on the loss being positive, i.e. $f_S(s|S > 0)$. This picture arises when the banks are of equal size and have multivariate normally distributed returns with means of 0.01, standard deviations of 0.0172, and a correlation of 0.75. Furthermore, they are assumed to have a debt-to-assets ratio of 0.97, a liquidity ratio of 0.05, and to value each others' assets at their book value (i.e. $\bar{p} = 1$).[15] Note that the systemic loss is expressed as a fraction of the size of the banking system in terms of assets.

Figure 3.1: Systemic loss distribution of a financial system with two equal banks.



Notes: This figure presents the probability distribution of the systemic loss of a system with two banks of equal size. The pdf is conditional on the systemic loss being strictly positive. The loss is measured relative to the size of the banking system in terms of assets. The banks' returns are assumed to be multivariate normally distributed with a mean of 0.01, a standard deviation of 0.0172, and a correlation of 0.75. Banks are assumed to have a debt-to-assets ratio of 0.97 and a liquidity ratio of 0.05, and to value each others' assets at their book value.

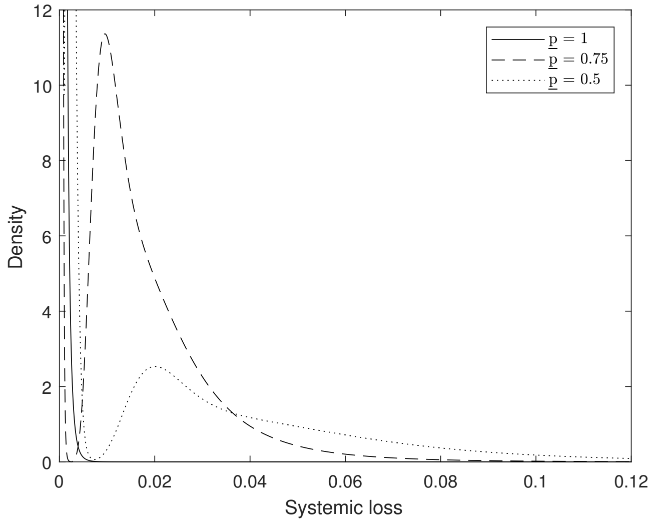
[15]These parameters imply a failure probability of approximately 1% for both banks. We choose an expected return on loans of 1%, which is the approximate mean return on assets of a sample of European banks in the period from 1998 to 2014. The debt-to-assets ratio of 0.97 corresponds with the 3% capital requirement of the Basel III framework. Note that we take liquidity as exogenous here even though it is endogenous in the model because we do not have a closed-form solution for aggregate liquidity. Moreover, determining the equilibrium conditions for the optimal amount of liquidity in a two-bank system is not straightforward. We present the pdf thus purely for illustrative purposes. The general expression of the pdf as well as its derivation are given in Section 3.B.3.

As illustrated by the solid line in Figure 3.1, the loss distribution is described by a relatively steep downward-sloped curve when their is no firesale mechanism (i.e. when $\underline{p} = \bar{p} = 1$). Hence, the probability of observing large losses is negligible in this case. The reason for this is that when the assets can always be liquidated for their fundamental value, large losses only occur as a result of a bank failing by a large margin, which is very unlikely. When outsiders value bank loans lower than banks do, however, the probability of large losses becomes significant. In a system with two equally sized banks with a relatively low liquidity ratio, a failure by one bank will automatically trigger a firesale. This is because the surviving bank will never have sufficient liquidity to purchase the failed bank for the high price. As a result, a large loss will occur even when one of the banks fails by only a slight margin. Consequently, the pdf of the systemic loss consists of two peaks. The first peak is related to the probability that one bank fails, whereas the much smaller second peak is associated with the simultaneous failure of both banks. A decrease in the value of $\underline{p}$ shifts both peaks to the right, as illustrated by the dotted line in Figure 3.1.

3.4.2 Simulations

How strongly does the above-mentioned firesale mechanism affect systemic risk? To get an idea of the quantitative effect, we use simulations to determine the equilibrium liquidity ratios and deposit insurance premia in a system with 50 banks of equal size, and analyze the associated distribution of the systemic loss. The simulation procedure consists of repeatedly taking a million draws from a 50-dimensional multivariate normal distribution with means of 0.01, standard deviations of 0.0172 and correlations of 0.25 to obtain the distribution of the banks' joint returns, and calculating the systemic loss for each draw. During the procedure, we continuously update the banks' deposit insurance premia and liquidity ratios until the conditions in Equations (3.10) and (3.12) of Section 3.3 are simultaneously satisfied. We apply numerical differentiation to calculate the right-hand side of Equation (3.12). As before, we assume that banks have debt-to-assets ratios of 0.97 and value each other's assets at their book value.

Figure 3.2: Systemic loss distribution of a financial system with 50 equal banks.



Notes: This figure presents Kernel density estimates of the probability distribution of the systemic loss of a system with 50 banks of equal size. The pdf is conditional on the systemic loss being strictly positive. The loss is measured relative to the size of the banking system in terms of assets. Banks have debt-to-assets ratios of 0.97 and expected returns and return standard deviations of 0.01 and 0.0172, respectively, which corresponds with a failure probability of approximately 1%. All bivariate return correlations are 0.25 and banks are assumed to value each other's assets at their book value. The parameter $\underline{p}$ refers to the ratio between the value that outsiders attach to banking assets and their book value. The kernel density estimates are calculated in Matlab using the *kdensity* command with the bandwidth parameter set to 1/3.

Figure 3.2 gives the kernel density estimates of the pdf of the loss distribution in the equilibrium for various values of $\underline{p}$. As can be observed in the figure, the probability of observing large losses is negligible when outsiders value bank loans at their fundamental value. Indeed, the systemic loss is never above 1% of the size of the system in terms of assets in this case. When outsiders value bank loans less than banks do, however, the systemic loss could be substantial under the assumptions given above. More specifically, when outsiders value the loans at 50% or less of their book value, the systemic loss could exceed 10% of the size of the banking system in terms of assets.

Tables 3.A.2, 3.A.3 and 3.A.4 give the equilibrium deposit insurance premium, equilibrium liquidity ratio and 1% ES of the deposit insurer under various parameter values for the case in which banks have failure probabilities of approximately 0.5%, 1% and 2% respectively, depending on the chosen return variance of the loan portfolio. The results illustrate that the equilibrium deposit insurance premium increases with an increase in the asset-specificity of loans and with an increase in return correlations. The latter finding is in line with Acharya et al. (2010), who argue that actuarially fair deposit insurance premia should increase in joint failure risk. Note, however, that even in the worst case scenario, with high return correlations across banks and a high degree of asset-specificity of banks loans, deposit insurance premia remain relatively low (around 0.3%). Since the premium is proportional to the expected systemic loss, this finding indicates that the *expected* systemic loss is (in absolute terms) hardly affected by the potential for firesales for any reasonable combination of parameters. This finding is not surprising, since in our model the surviving banks ensure that the expected return on liquidity does not exceed the expected return on loans. Banks will thus increase their holdings of liquidity in response to an increase in joint failure risk or in the asset-specificity of loans, since such changes increase the expected return on liquidity. This mechanism can clearly be observed in the above-mentioned tables, where liquidity ratios increase when moving from the northwest to the southeast corner of the tables. Even though the average loss of the deposit insurer is hardly affected by the potential for firesales, the same cannot be said for its tail risk, as measured by the 1% ES. Indeed, we find that tail risk is almost negligible when assets can always be liquidated for their fundamental value, but that it increases sharply with a decrease in the outsider price and an increase in return correlations of loan portfolios. For example, when banks have a 1% failure probability, return correlations are 0.25 and outsiders are willing to pay 50% of the fundamental value of banks' loans, the 1% ES is 5.6% of the size of the banking system as a whole. In the worst-case scenario, with high failure probabilities, return correlations and asset specificity, the 1% ES is no less than 20% of the size of the system. This contrasts sharply with the case in which loans are always sold for their fundamental value, in which case the 1% ES is smaller than 0.1% of the size of the system. We find this effect for a wide range of parameter values, which suggests that systemic risk is likely to be heavily underestimated when it is assumed that banks' assets can always be sold for their fundamental value.

3.4.3 The role of concentration

The numerical analysis so far has only dealt with a banking system consisting of a large number banks of equal size, whereas in reality many financial systems are dominated by a few large banks. This fact is relevant in the context of our model, since the probability of a firesale is likely to be an increasing function of the concentration of a banking system. Indeed, when the system is dominated by a few large banks, the failure of a single bank might already constitute a systemic event and lead to a firesale. As such, we would expect the firesale mechanism to have a stronger effect on systemic risk in a more concentrated banking system. We analyze whether this is the case by repeating the simulation procedure for (i) a system with 10 equally sized banks, (ii) a system with 10 banks of heterogeneous size, and (iii) a system with two banks of equal size.[16] Tables 3.A.5, 3.A.6 and 3.A.7 report the results for the case in which banks have a failure probability of approximately 1%. As expected, the effect of the firesale mechanism on systemic tail risk generally increases with an increase in the degree of concentration in the banking system, even though liquidity ratios also increase due to the higher probability of a firesale. Indeed, in the worst-case scenario the increase in liquidity ratios is so large, that it more than compensates the increase in the probability of a firesale, so that the effect of the firesale mechanism on tail risk becomes smaller with an increase in concentration. In all other cases, however, concentration increases tail risk. For instance, tail risk in the case with a medium degree of asset-specificity and return correlations increases from 5.6% in the 50-bank case, to 8.4% in the 10-bank case, to 12.1% and 13.7% in the case of 10 heterogeneous banks and 2 banks, respectively. Another interesting finding is that for the heterogeneous bank case, we find an almost perfectly negative correlation between a bank's size and its equilibrium liquidity ratio. This finding indicates that, ceteris paribus, a bank's optimal liquidity ratio is a negative function of its size that is close to linear. Intuitively this outcome makes sense, since a large bank knows that its asset portfolio choice will affect the expected price of liquidated loans. Hence, the larger is a bank, the stronger will be incentive to choose a strategically low liquidity ratio in an attempt to lower the expected price of liquidated loans.

[16] To obtain 10 banks of heterogeneous size, we take 10 random draws from a generalized Pareto distribution with the location parameter set to 0 and the shape parameter set to 1 and normalize the values so that they sum to 1. We obtain a vector of bank sizes in which the largest bank has a market share of 29.3%, whereas the smallest bank has a market share of 3.8%.

3.4.4 The role of liquidity

Overall, our findings suggest that taking LGDs as exogenously given is likely to heavily understate systemic tail risk. They also suggest that liquidity ratios are an important determinant of systemic risk through their effect on liquidation prices and that in concentrated financial systems, banks have an incentive to strategically choose low liquidity ratios. As a last exercise, therefore, we exogenously set the aggregate liquidity ratio equal to 0.2 and repeat the simulation procedure described above. This scenario resembles a situation in which banks are forced to hold at least 20% of their assets in liquid form, and are allowed to use this liquidity to purchase liquidated loans in case of bank failures. As shown in Table 3.A.8, tail risk is indeed substantially reduced by this policy. Indeed, when the system consists of at least 10 banks, the 1% ES is never above 5% of the size of the banking system for any reasonable combination of parameters. As such, our analysis indicates an important role for time-varying liquidity requirements in macroprudential regulation. More specifically, financial institutions should be required to hold a relatively large amount of liquidity during 'normal times'. By lowering the liquidity requirement during times of systemic distress, financial institutions can then be allowed to use their liquidity buffer to clear the market for liquidated loans of failed banks. This should significantly lower the severity of firesales and thereby reduce systemic risk.

3.5 Conclusion

This study has analyzed how the possibility that bank loans are liquidated at firesale prices affects systemic risk, where systemic risk is defined as the risk that creditors of financial institutions incur significant losses as a result of the joint failure of multiple institutions. While other studies using this definition of systemic risk assume that liquidation prices are deterministic and thereby take losses given default (LGDs) as exogenously given, we endogenize LGDs by explicitly modeling liquidation prices. In addition, we model the portfolio decision of banks with regard to the choice between loans and liquidity, thereby endogenizing the amount of aggregate liquidity in the system, and show how this affects systemic risk.

Our analysis indicates that systemic risk is likely to be underestimated when LGDs are assumed to be exogenous. Furthermore, we show that the degree of underestimation increases in the correlation of financial institutions' loan portfolio returns, the degree of asset-specificity of loans, and the degree of concentration in the banking system. Moreover, even for intermediate return correlations and a reasonable degree of asset-specificity, tail risk is severely underestimated when LGDs are taken as exogenous. As such, the analysis in this study illustrates the importance of modeling LGDs when measuring systemic risk. In addition, our findings indicate that liquidity is not only important due to liquidity risk (i.e. the risk that a financial institution might fail because of illiquidity), but that it also indirectly affects systemic risk through its effect on LGDs during systemic events.

A policy prescription following from the analysis is the introduction of time-varying liquidity requirements. Financial institutions should be required to hold a relatively large amount of liquidity during normal times, so that liquidity requirements can be lowered during times of systemic distress. The resulting liquidity buffer allows surviving financial institutions to clear the market for liquidated loans during times of systemic distress, thereby reducing the probability and severity of firesales and limiting systemic risk.

An interesting avenue for future research would be the inclusion of contagion effects into the model. In the current setup, banks are assumed to only be indirectly connected through common exposures leading to correlations in the return on their asset portfolios. In the real world, banks are also connected directly via e.g. interbank loans. As such, the failure of one bank will affect the stability of other banks, who may have to write off a significant portion of their loan portfolio. In this scenario, a firesale can be expected to have even larger detrimental effects, as it may lead to additional failures by banks which would have remained solvent in the absence of a firesale. Hence, we expect liquidity requirements to be even more important when banks are connected through loans on the interbank market.

3.A Appendix: Tables

Table 3.A.1: Overview of the most important variables of the model.

Endogenous variables	**Exogenous variables**
Liquidity ratio (ω)	Return on loans (R)
Liquidation price (p^*)	Debt-to-assets ratio $\left(\frac{d}{a+\ell}\right)$
Deposit insurance premium (α)	Insider price ($\bar{p}$)
Systemic loss (S)	Outsider price ($\underline{p}$)

Table 3.A.2: Simulation outcomes for a financial system with 50 equal banks with a failure probability of approximately 0.5%.

Variable	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
Dep. ins. prem.	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.000	0.001	0.001
	Medium (0.50)	0.000	0.001	0.001
	Low (0.25)	0.000	0.001	0.001
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.019	0.030	0.030
	Medium (0.50)	0.023	0.035	0.047
	Low (0.25)	0.024	0.036	0.053
1% ES	Book (1.00)	0.000	0.001	0.001
	High (0.75)	0.011	0.023	0.045
	Medium (0.50)	0.018	0.043	0.084
	Low (0.25)	0.018	0.055	0.113

This table presents our quantitative results when analyzing a banking system consisting of 50 equally sized banks with failure probabilities of approximately 0.5%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium (*Dep. ins. prem.*) is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The 1% expected shortfall (*1% ES*) is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3.A.3: Simulation outcomes for a system with 50 equal banks with a failure probability of approximately 1%.

Variable	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
Dep. ins. prem.	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.000	0.001	0.001
	Medium (0.50)	0.000	0.001	0.002
	Low (0.25)	0.000	0.001	0.002
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.034	0.048	0.056
	Medium (0.50)	0.035	0.056	0.079
	Low (0.25)	0.035	0.057	0.090
1% ES	Book (1.00)	0.001	0.001	0.002
	High (0.75)	0.015	0.034	0.065
	Medium (0.50)	0.025	0.064	0.118
	Low (0.25)	0.026	0.080	0.156

This table presents our quantitative results when analyzing a banking system consisting of 50 equally sized banks with failure probabilities of approximately 1%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium (*Dep. ins. prem.*) is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The 1% expected shortfall (*1% ES*) is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.0172. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3.A.4: Simulation outcomes for a system with 50 equal banks with a failure probability of approximately 2%.

Variable	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
Dep. ins. prem.	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.001	0.001	0.002
	Medium (0.50)	0.001	0.002	0.002
	Low (0.25)	0.001	0.002	0.003
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.050	0.076	0.099
	Medium (0.50)	0.051	0.090	0.119
	Low (0.25)	0.051	0.094	0.144
1% ES	Book (1.00)	0.001	0.002	0.005
	High (0.75)	0.020	0.049	0.087
	Medium (0.50)	0.031	0.091	0.162
	Low (0.25)	0.032	0.107	0.201

This table presents our quantitative results when analyzing a banking system consisting of 50 equally sized banks with failure probabilities of approximately 1%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium (*Dep. ins. prem.*) is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The 1% expected shortfall (*1% ES*) is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.0195. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3.A.5: Simulation outcomes for a system with 10 heterogeneous banks with a failure probability of approximately 1%.

Variable	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
Dep. ins. prem.	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.001	0.002	0.002
	Medium (0.50)	0.002	0.002	0.003
	Low (0.25)	0.002	0.003	0.003
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.079	0.080	0.079
	Medium (0.50)	0.080	0.084	0.089
	Low (0.25)	0.081	0.086	0.104
1% ES	Book (1.00)	0.002	0.002	0.003
	High (0.75)	0.027	0.051	0.074
	Medium (0.50)	0.041	0.102	0.152
	Low (0.25)	0.050	0.135	0.197

This table presents our quantitative results when analyzing a banking system consisting of 10 equally sized banks with failure probabilities of approximately 1%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium (*Dep. ins. prem.*) is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The 1% expected shortfall (*1% ES*) is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3.A.6: Simulation outcomes for a system with 10 heterogeneous banks with a failure probability of approximately 1%.

Variable	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
Dep. ins. prem.	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.002	0.002	0.002
	Medium (0.50)	0.002	0.003	0.003
	Low (0.25)	0.003	0.003	0.003
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.080	0.081	0.078
	Medium (0.50)	0.113	0.121	0.152
	Low (0.25)	0.131	0.144	0.167
1% ES	Book (1.00)	0.000	0.003	0.003
	High (0.75)	0.074	0.080	0.096
	Medium (0.50)	0.147	0.157	0.170
	Low (0.25)	0.159	0.167	0.183

This table presents our quantitative results when analyzing a banking system consisting of 10 banks of heterogeneous size with failure probabilities of approximately 1%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium (*Dep. ins. prem.*) is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The 1% expected shortfall (*1% ES*) is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3.A.7: Simulation outcomes for a system with 2 equal banks with a failure probability of approximately 1%.

Variable	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
Dep. ins. prem.	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.005	0.005	0.006
	Medium (0.50)	0.004	0.005	0.005
	Low (0.25)	0.004	0.004	0.004
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.009	0.009	0.005
	Medium (0.50)	0.140	0.137	0.138
	Low (0.25)	0.193	0.192	0.191
1% ES	Book (1.00)	0.005	0.005	0.005
	High (0.75)	0.131	0.143	0.171
	Medium (0.50)	0.213	0.221	0.241
	Low (0.25)	0.295	0.302	0.319

This table presents our quantitative results when analyzing a banking system consisting of equally sized banks of with failure probabilities of approximately 1%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium (*Dep. ins. prem.*) is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The 1% expected shortfall (*1% ES*) is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3.A.8: Expected 1% shortfall for the different banking systems when liquidity-to-asset ratios are exogenously set to 0.2 and banks have failure probabilities of approximately 1%.

Banking system	Outsider price \ Corr.	Low (0.00)	Medium (0.25)	High (0.50)
50 equal banks	Book (1.00)	0.000	0.000	0.001
	High (0.75)	0.000	0.001	0.007
	Medium (0.50)	0.000	0.001	0.010
	Low (0.25)	0.000	0.001	0.011
10 equal banks	Book (1.00)	0.001	0.001	0.001
	High (0.75)	0.001	0.002	0.011
	Medium (0.50)	0.001	0.003	0.018
	Low (0.25)	0.001	0.003	0.021
10 unequal banks	Book (1.00)	0.001	0.001	0.001
	High (0.75)	0.018	0.019	0.025
	Medium (0.50)	0.026	0.029	0.041
	Low (0.25)	0.026	0.030	0.047
2 equal banks	Book (1.00)	0.001	0.001	0.001
	High (0.75)	0.057	0.058	0.057
	Medium (0.50)	0.114	0.114	0.114
	Low (0.25)	0.167	0.168	0.168

This table presents the 1% expected shortfall of the different banking systems when liquidity-to-asset ratios are exogenously set to 0.2 and failure probabilities are approximately 1%. *Corr.* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The 1% expected shortfall (*1% ES*) is expressed relative to the size of the banking system (in terms of total assets). Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.072. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

3.B Appendix: Proofs

3.B.1 Loss given default

We solve the problem by finding the optimal price set by the regulator given that it decides to include or exclude outsiders from the liquidation procedure and then determining when outsiders should be included and excluded.

Outsiders excluded

When outsiders are exluded from the liquidation procedure (which can be done simply by setting the price above the threshold $\underline{p}$), we have $q_o = 0$. The third constraint is thus redundant, so that the Lagrangian is:

$$\mathcal{L} = pq_b + \lambda_1[\ell_S - pq_b] + \lambda_2[\bar{p} - p] + \lambda_3[q - q_b]. \tag{3.B.1}$$

The first-order conditions are:

$$\begin{aligned}
&\frac{\partial \mathcal{L}}{\partial p} = [1 - \lambda_1]q_b - \lambda_2 = 0 \\
&\frac{\partial \mathcal{L}}{\partial \lambda_1} = \ell_S - pq_b \geq 0, \qquad && \lambda_1 \geq 0, \quad \lambda_1[\ell_S - pq_b] = 0 \\
&\frac{\partial \mathcal{L}}{\partial \lambda_2} = \bar{p} - p \geq 0, && \lambda_2 \geq 0, \quad \lambda_2[\bar{p} - p] = 0 \\
&\frac{\partial \mathcal{L}}{\partial \lambda_3} = q - q_b \geq 0, && \lambda_3 \geq 0, \quad \lambda_3[q - q_b] = 0.
\end{aligned} \tag{3.B.2}$$

We can subsequently distinguish between 8 cases:

Case 1: $\lambda_1 = \lambda_2 = \lambda_3 = 0$. This gives $q_b = 0,\ p \leq \bar{p}$ and $\mathcal{L} = 0$.

Case 2: $\lambda_1 > 0, \lambda_2 = \lambda_3 = 0$. This gives $q_b = \frac{\ell_S}{p}$, $\frac{\ell_S}{q} \leq p \leq \bar{p}$, $\mathcal{L} = \ell_S$ and implies $q \geq \frac{\ell_S}{\bar{p}}$.

Case 3: $\lambda_1 = 0,\ \lambda_2 > 0,\ \lambda_3 = 0$. This gives $q_b \leq \frac{\ell_S}{\bar{p}}$, $p = \bar{p}$, $\lambda_2 = q_b$ and $\mathcal{L} \leq \ell$.

Case 4: $\lambda_1 = \lambda_2 = 0,\ \lambda_3 > 0$. This gives $q_b = 0,\ p \leq \bar{p}$ and $\mathcal{L} = 0$.

Case 5: $\lambda_1 > 0, \lambda_2 > 0, \lambda_3 = 0$. This gives $q_b = \frac{\ell_S}{\bar{p}}, p = \bar{p}, \mathcal{L} = \ell_S$ and implies $q \geq \frac{\ell_S}{\bar{p}}$.

Case 6: $\lambda_1 > 0,\ \lambda_2 = 0,\ \lambda_3 > 0$. This gives $q_b = q,\ p = \frac{\ell_A}{q}$, $\mathcal{L} = \ell_S$ and implies $q \geq \frac{\ell_S}{\bar{p}}$.

Case 7: $\lambda_1 = 0, \lambda_2 > 0, \lambda_3 > 0$. This gives $q_b = q$, $p = \bar{p}$, $\mathcal{L} = \bar{p}q$ and implies $q \leq \frac{\ell_S}{\bar{p}}$.

Case 8 : $\lambda_1 > 0, \lambda_2 > 0, \lambda_3 > 0$. This gives $q_b = q, p = \bar{p}, \mathcal{L} = \ell_S$ and implies $q = \frac{\ell_S}{\bar{p}}$.

It follows that case 7 is the solution when $q < \frac{\ell_S}{p}$, case 8 is the solution when $q = \frac{\ell_S}{p}$ and cases 2, 5, 6 and 7 are the solutions when $q > \frac{\ell_S}{p}$. When outsiders are exluded from the liquidation procedure, we thus have that:

$$\begin{aligned}\mathcal{L} &= \begin{cases} \bar{p}q & \text{if} \quad q \leq \frac{\ell_S}{\bar{p}} \\ \ell_S & \text{if} \quad \bar{q} > \frac{\ell_S}{\bar{p}} \end{cases} \\ &= \min[\bar{p}q, \ell_S]. \end{aligned} \tag{3.B.3}$$

Outsiders included

Consider now the case in which outsiders are included in the liquidation procedure, which requires that $p \leq \underline{p}$. This condition makes the second constraint redundant, so that the Lagrangian is:

$$\mathcal{L} = p[q_b + q_o] + \lambda_1[\ell_S - pq_b] + \lambda_2[\underline{p} - p] + \lambda_3[q - q_b - q_o]. \tag{3.B.4}$$

The first-order conditions are:

$$\begin{aligned} &\tfrac{\partial \mathcal{L}}{\partial p} = [1 - \lambda_1]q_b - \lambda_2 = 0 \\ &\tfrac{\partial \mathcal{L}}{\partial \lambda_1} = \ell_S - pq_b \geq 0, \qquad \lambda_1 \geq 0, \quad \lambda_1[\ell_S - pq_b] = 0 \\ &\tfrac{\partial \mathcal{L}}{\partial \lambda_2} = \underline{p} - p \geq 0, \qquad \lambda_2 \geq 0, \quad \lambda_2[\underline{p} - p] = 0 \\ &\tfrac{\partial \mathcal{L}}{\partial \lambda_3} = q - q_b - q_o \geq 0, \qquad \lambda_3 \geq 0, \quad \lambda_3[q - q_b - q_o] = 0. \end{aligned} \tag{3.B.5}$$

We can again distinguish between 8 cases:

Case 1: $\lambda_1 = \lambda_2 = \lambda_3 = 0$. This gives $q_b = 0,\ q_o \leq q,\ p \leq \underline{p}$ and $\mathcal{L} \leq \underline{p}q$.

Case 2: $\lambda_1 > 0,\ \lambda_2 = \lambda_3 = 0$. This gives $q_b = \frac{\ell_S}{p},\ q_o \leq q - \frac{\ell_S}{p},\ p \leq \underline{p}$ and $\mathcal{L} \leq \underline{p}q$.

Case 3: $\lambda_1 = 0,\ \lambda_2 > 0,\ \lambda_3 = 0$. This gives $q_b \leq \frac{\ell_S}{p},\ q_o \leq q - q_b,\ p = \underline{p}$ and $\mathcal{L} \leq \underline{p}q$.

Case 4: $\lambda_1 = \lambda_2 = 0,\ \lambda_3 > 0$. This gives $q_b = 0,\ q_o = q,\ p \leq \underline{p}$ and $\mathcal{L} \leq \underline{p}q$.

Case 5: $\lambda_1 > 0,\ \lambda_2 > 0,\ \lambda_3 = 0$. This gives $q_b = \frac{\ell_S}{\underline{p}},\ q_o \leq q - \frac{\ell_S}{\underline{p}},\ p = \underline{p}$ and $\mathcal{L} \leq \underline{p}q$.

Case 6: $\lambda_1 > 0,\ \lambda_2 = 0,\ \lambda_3 > 0$. This gives $q_b = \frac{\ell_S}{p},\ q_o = q - \frac{\ell_S}{p},\ p \leq \underline{p}$ and $\mathcal{L} \leq \underline{p}q$.

Case 7: $\lambda_1 = 0,\ \lambda_2 > 0,\ \lambda_3 > 0$. This gives $q_b \le \frac{\ell_S}{\underline{p}},\ q_o = q - q_b,\ p = \underline{p}$ and $\mathcal{L} = \underline{p}q$.

Case 8: $\lambda_1 > 0,\ \lambda_2 > 0,\ \lambda_3 > 0$. This gives $q_b = \frac{\ell_S}{\underline{p}},\ q_o = q - \frac{\ell_S}{\underline{p}},\ p = \underline{p}$ and $\mathcal{L} = \underline{p}q$.

It follows that case 7 and 8 are the solutions. When outsiders are included in the liquidation procedure, we thus have that $\mathcal{L} = \underline{p}q$.

General solution

Since the regulator can choose whether or not to include outsiders in the liquidation procedure, we have that:

$$\begin{aligned}\mathcal{L}^* &= \max\big[\underline{p}\bar{q},\ \min[\bar{p}q,\ \ell_S]\big] \\ &= \begin{cases} \bar{p}q & \text{if} \quad q \le \frac{\ell_S}{\bar{p}} \\ \ell_S & \text{if} \quad \frac{\ell_S}{\bar{p}} < q \le \frac{\ell_S}{\underline{p}} \\ \underline{p}q & \text{if} \quad q > \frac{\ell_S}{\underline{p}}. \end{cases}\end{aligned} \tag{3.B.6}$$

The optimal price follows straightforwardly.

3.B.2 Optimal liquidity

The bank's profit function is:

$$E(\Pi_i) = a_i R_i + \ell_i\big[\bar{p} - p^*(\ell_i)\big] - \alpha_i(\ell_i)d_i, \tag{3.B.7}$$

where Π_i is the profit of bank i. The first term on the right hand side refers to the bank's profits on investments in loans, the second term to profits associated with the purchase of liquidated loans of failed banks, and the last term to the costs of deposit insurance. The bank's expected return on overall assets is thus:

$$E(ROA_i) \quad = \quad \omega_i E(R_i) + (1-\omega_i)E\big[\bar{p} - p^*(\omega_i)\big] - \alpha_i(\omega_i)(1-k_i), \tag{3.B.8}$$

where $\omega_i = \frac{a_i}{a_i+\ell_i}$ is the bank's loans-to-assets ratio ($0 \le \omega_i \le 1$) and $k_i = 1 - \frac{d_i}{a_i+\ell_i}$ is the bank's capital ratio. Taking the derivative of Equation (3.B.8) with respect to ω_i gives:

$$\frac{\partial E(ROA_i)}{\partial \omega_i} = E(R_i) - \frac{\partial}{\partial \omega_i}\Big((1-\omega_i)E\big[\bar{p} - p^*(\omega_i)|R_i > c_i(\omega_i)\big]\Big) - (1-k_i)\frac{d\alpha_i}{d\omega_i} \tag{3.B.9}$$

We assume that $\alpha_i = \beta\omega_i$. Substituting this expression into Equation (3.B.9) and setting the derivative equal to zero gives:

$$E(R_i) - \beta(1-k_i) = \frac{\partial}{\partial\omega_i}\left((1-\omega_i)E\big[\bar{p} - p^*(\omega_i)|R_i > c_i(\omega_i)\big]\right) \tag{3.B.10}$$

Equation (3.B.10) gives the equilibrium condition for an interior solution for ω_i. It states that the expected marginal return on loans should be equal to the expected marginal return on liquidity. Note that if the LHS is greater than the RHS for $\omega_i = 1$, we obtain a corner solution in which the bank only invests in loans. Similarly, if the LHS is smaller than the RHS for $\omega_i = 0$, we obtain a corner solution in which the bank only invests in liquidity.

3.B.3 Systemic loss with two banks

In this section we derive the (pdf of the) systemic loss in terms of the random returns of two banks. We start with the expression in Equation (3.8):

$$S = \begin{cases} d_F^* - \bar{p}q & \text{if} \quad q \leq \frac{\ell_S}{\bar{p}} \\ d_F^* - \ell_S & \text{if} \quad \frac{\ell_S}{\bar{p}} < q < \frac{\ell_S}{\underline{p}} \\ d_F^* - \underline{p}q & \text{if} \quad q \geq \frac{\ell_S}{\underline{p}}, \end{cases} \tag{3.B.11}$$

where $d_F^* = d_F(1+\alpha) - \ell_F$ refers to the aggregate liabilities of all failed banks net of their liquidity, q refers to the aggregate risky assets of failed banks, and ℓ_S refers to the aggregate liquidity of surviving banks. To obtain an expression of the systemic loss in terms of R_x and R_y, we need to distinguish between four cases:

Both banks fail. This case implies that:

$$\begin{aligned} R_x &< c_x \\ R_y &< c_y \\ d_F^* &= d_x^* + d_y^* \\ q &= (1+R_x)a_x + (1+R_y)a_y \\ \ell_S &= 0. \end{aligned}$$

It follows that:

$$S = d_x^* + d_y^* - \underline{p}\big[(1+R_x)a_x + (1+R_y)a_y\big] \text{ if } R_x < c_x \text{ and } R_y < c_y. \tag{3.B.12}$$

Bank x fails, y survives. This case implies that:

$$\begin{aligned} R_x &< c_x \\ R_y &\geq c_y \\ d_F^* &= d_x^* \\ q &= (1+R_x)a_x \\ \ell_S &= \ell_y. \end{aligned}$$

It follows that:

$$S = \begin{cases} d_x^* - \bar{p}(1+R_x)a_x & \text{if} \quad R_x < \min\left[\frac{\ell_y}{\bar{p}a_x} - 1,\ c_x\right] \text{ and } R_y \geq c_y \\ d_x^* - \ell_y & \text{if} \quad \frac{\ell_y}{\bar{p}a_x} - 1 \leq R_x < \min\left[\frac{\ell_y}{\underline{p}a_x} - 1,\ c_x\right] \text{ and } R_y \geq c_y \\ d_x^* - \underline{p}(1+R_x)a_x & \text{if} \quad \frac{\ell_y}{\underline{p}a_x} - 1 \leq R_x < c_x \text{ and } R_y \geq c_y. \end{cases} \tag{3.B.13}$$

Bank x survives, y fails. This is the mirror image of case 2. It follows that:

$$S = \begin{cases} d_y^* - \bar{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } R_y < \min\left[\frac{\ell_x}{\bar{p}a_y} - 1,\ c_y\right] \\ d_y^* - \ell_x & \text{if} \quad R_x \geq c_x \text{ and } \frac{\ell_x}{\bar{p}a_y} - 1 \leq R_y < \min\left[\frac{\ell_x}{\underline{p}a_y} - 1,\ c_y\right] \\ d_y^* - \underline{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } \frac{\ell_x}{\underline{p}a_y} - 1 \leq R_y < c_y. \end{cases} \tag{3.B.14}$$

Both banks survive. This case implies that:

$$\begin{aligned} R_x &\geq c_y \\ R_y &\geq c_y \\ d_F^* &= 0 \\ q &= 0 \end{aligned}$$

It follows that:

$$S = 0 \text{ if } R_x \geq c_x \text{ and } R_y \geq c_y. \tag{3.B.15}$$

Combining the four cases above gives:

$$S(R_x, R_y) = \begin{cases} d_x^* + d_y^* \\ -\underline{p}\big[(1+R_x)a_x + (1+R_y)a_y\big] & \text{if} \quad R_x < c_x \text{ and } R_y < c_y \\ d_x^* - \bar{p}(1+R_x)a_x & \text{if} \quad R_x < \min[\tau_x,\, c_x] \text{ and } R_y \geq c_y \\ d_y^* - \bar{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } R_y < \min[\tau_y,\, c_y] \\ d_x^* - \ell_y a_y & \text{if} \quad \tau_x \leq R_x < \min[\eta_x,\, c_x] \text{ and } R_y \geq c_y \\ d_y^* - \ell_x & \text{if} \quad R_x \geq c_x \text{ and } \tau_y \leq R_y < \min[\eta_y,\, c_y] \\ d_x^* - \underline{p}(1+R_x)a_x & \text{if} \quad \eta_x \leq R_x < c_x \text{ and } R_y \geq c_y \\ d_y^* - \underline{p}(1+R_y)a_y & \text{if} \quad R_x \geq c_x \text{ and } \eta_y \leq R_y < c_y. \\ 0 & \text{if} \quad R_x \geq c_x \text{ and } R_y \geq c_y. \end{cases} \tag{3.B.16}$$

With $f(r_x, r_y)$ the simultaneous probability density of (R_x, R_y), let us define the following parameters:

$$\begin{aligned}
\tau_x &= \frac{\ell_y}{\bar{p}a_x} - 1 \\
\tau_y &= \frac{\ell_x}{\bar{p}a_y} - 1 \\
\eta_x &= \frac{\ell_y}{\underline{p}a_x} - 1 \\
\eta_y &= \frac{\ell_x}{\underline{p}a_y} - 1 \\
\kappa_x &= d_x^*(1-\underline{p}) \\
\kappa_y &= d_y^*(1-\underline{p}) \\
\theta_x &= d_x^* - \ell_y \\
\theta_y &= d_y^* - \ell_x \\
\alpha_x(s) &= \frac{1}{\underline{p}a_x}\int_{c_y}^{\infty} f\left(\frac{d_x^*-s}{\underline{p}a_x} - 1,\, r_y\right) dr_y \\
\alpha_y(s) &= \frac{1}{\underline{p}a_y}\int_{c_x}^{\infty} f\left(r_x,\, \frac{d_y^*-s}{\underline{p}a_y} - 1\right) dr_x \\
\beta_x &= \int_{\tau_x}^{\min[c_x,\,\eta_x]}\int_{c_y}^{\infty} f(r_x, r_y)dr_y dr_x \\
\beta_y &= \int_{c_x}^{\infty}\int_{\tau_y}^{\min[c_y,\,\eta_y]} f(r_x, r_y)dr_y dr_x \\
\gamma_x(s) &= \frac{1}{\bar{p}a_x}\int_{c_y}^{\infty} f\left(c_x - \frac{s}{\bar{p}a_x},\, r_y\right) dr_y, \\
\gamma_y(s) &= \frac{1}{\bar{p}a_y}\int_{c_x}^{\infty} f\left(r_x,\, c_y - \frac{s}{\bar{p}a_y}\right) dr_x \\
\delta(s) &= \frac{1}{\underline{p}a_y}\int_{\frac{d_x^*+(1-\underline{p})d_y^*-s}{\underline{p}a_x}-1}^{c_x} f\left(r_x,\, \frac{d_x^*+d_y^*-s}{\underline{p}a_y} - \frac{[1+r_x]a_x}{a_y} - 1\right) dr_x.
\end{aligned}$$

To obtain an expression of the pdf, we need to distinguish between eight cases.

Both banks fail.

$$\begin{aligned} S &= d_x^* + d_y^* - \underline{p}\big[(1+R_x)a_x + (1+R_y)a_y\big] \\ R_x &< c_x \\ R_y &< c_y. \end{aligned}$$

The system above implies that:

$$S > (1-\underline{p})(d_x^* + d_y^*) = \kappa_x + \kappa_y$$

$$P(S \leq s,\ R_x < c_x,\ R_y < c_y)$$

$$= P\Big(d_x^* + d_y^* - \underline{p}\big[(1+R_x)a_x + (1+R_y)a_y\big] \leq s,\ R_x < c_x,\ y < c_y\Big)$$

$$= P\left(R_x < c_x,\ \frac{d_x^*+d_y^*-s}{\underline{p}a_y} - \frac{[1+R_x]a_x}{a_y} - 1 \leq R_y < c_y\right)$$

$$= P\left(\frac{d_x^*+[1-\underline{p}]d_y^*-s}{\underline{p}a_x} - 1 < R_x < c_x,\ \frac{d_x^*+d_y^*-s}{\underline{p}a_y} - \frac{[1+R_x]a_x}{a_y} - 1 \leq R_y < c_y\right)$$

$$= \int_{\frac{d_x^*+(1-\underline{p})d_y^*-s}{\underline{p}a_x}-1}^{c_x} \int_{\frac{d_x^*+d_y^*-s}{\underline{p}a_y} - \frac{(1+r_x)a_x}{a_y} - 1}^{c_y} f(r_x, r_y)dr_y dr_x.$$

Taking the derivative of the latter expression with respect to s gives:

$$\frac{\partial}{\partial s}\left(\int_{\frac{d_x^*+(1-\underline{p})d_y^*-s}{\underline{p}a_x}-1}^{c_x} \int_{\frac{d_x^*+d_y^*-s}{\underline{p}a_y} - \frac{(1+r_x)a_x}{a_y} - 1}^{c_y} f(r_x, r_y)dr_y dr_x\right)$$

$$= \frac{1}{\underline{p}a_y}\int_{\frac{d_x^*+(1-\underline{p})d_y^*-s}{\underline{p}a_x}-1}^{c_x} f\left(r_x,\ \frac{d_x^*+d_y^*-s}{\underline{p}a_y} - \frac{[1+r_x]a_x}{a_y} - 1\right)dr_x = \delta(s).$$

The contribution of this event to the pdf is thus equal to $\delta(s)$ if $s > \kappa_x + \kappa_y$ and 0 otherwise.

Bank x fails, y survives, no firesale.

$$\begin{aligned} S &= d_x^* - \bar{p}(1+R_x)a_x \\ R_x &< \min[\tau_x,\ c_x] \\ R_y &\geq c_y. \end{aligned}$$

The system above implies that:

$$S > \max[0,\ d_x^* - \ell_y] = \max[0,\ \theta_x]$$

$$P\big(S \leq s,\ R_x < \min[\tau_x,\ c_x],\ R_y \geq c_y)$$

$$= P(d_x^* - \bar{p}[1+R_x]a_x \leq s,\ R_x < \min[\tau_x,\ c_x],\ R_y \geq c_y\big)$$

$$= P\left(c_x - \frac{s}{\bar{p}a_x} \leq R_x < \min[\tau_x,\ c_x],\ R_y \geq c_y\right)$$

$$= \int_{c_x - \frac{s}{\bar{p}a_x}}^{\min[\tau_x,\ c_x]} \int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x.$$

Taking the derivative of the latter expression with respect to s gives:

$$\frac{\partial}{\partial s} \int_{c_x - \frac{s}{\bar{p}a_x}}^{\min[\tau_x,\ c_x]} \int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x = \frac{1}{\bar{p}a_x} \int_{c_y}^{\infty} f\left(c_x - \frac{s}{\bar{p}a_x}, r_y\right) dr_y = \gamma_x(s).$$

The contribution of this event to the pdf is thus equal to $\gamma_x(s)$ if $s > \max[0,\ \theta_x]$ and 0 otherwise.

Bank x survives, y fails, no firesale.

$$\begin{aligned} S &= d_y^* - \bar{p}(1+R_y)a_y \\ R_x &\geq c_x \\ R_y &< \min[\tau_y,\ c_y]. \end{aligned}$$

This is the mirror image of case 2. The contribution of the event to the pdf is thus equal to $\gamma_y(s)$ if $s > \max[0,\ \theta_y]$ and 0 otherwise.

Bank x fails, y survives, firesale without outsider participation.

$$
\begin{aligned}
&S = d_x^* - \ell_y \\
&\tau_x \leq R_x < \min[\eta_x,\ c_x] \\
&R_y \geq c_y.
\end{aligned}
$$

The system above implies that the contribution of this event to the pdf is only defined for $s = d_x^* - \ell_y = \theta_x > 0$. To obtain the contribution of this event to the pdf, we proceed as follows:

$$
\begin{aligned}
P(S = d_x^* - \ell_y,\ \tau_x \leq R_x < \min[\eta_x,\ c_x],\ R_y \geq c_y) &= P(\tau_x \leq R_x < \min[c_x,\ \eta_x],\ R_y \geq c_y) \\
&= \int_{\tau_x}^{\min[\eta_x,\ c_x]} \int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x \\
&= \beta_x.
\end{aligned}
$$

It follows that this contribution is equal to β_x if $s = \theta_x > 0$ and 0 otherwise.

Bank x survives, y fails, firesale without outsider participation.

$$
\begin{aligned}
&S = d_y^* - \ell_x \\
&R_x \geq c_x \\
&\tau_y \leq R_y < \min[\eta_y,\ c_y].
\end{aligned}
$$

This is the mirror image of case 4. The contribution of the event to the pdf is thus equal to β_y if $s = \theta_y > 0$ and 0 otherwise.

Bank x fails, y survives, firesale with outsider participation.

$$
\begin{aligned}
&S = d_x^* - \underline{p}(1 + R_x)\underline{p}a_x \\
&\eta_x \leq R_x < c_x \\
&R_y \geq c_y.
\end{aligned}
$$

The system above implies that $d_x^*(1 - \underline{p}) < S \leq d_x^* - \ell_y$, which can be written as

$\kappa_x < S \leq \theta_x$. Furthermore:

$$\begin{aligned} P(S \leq s,\, \eta_x \leq R_x < c_x,\, R_y \geq c_y) &= P(d_x^* - \underline{p}(1+R_x)a_x \leq s,\, \eta_x \leq R_x < c_x,\, R_y \geq c_y) \\ &= P\left(\max\left[\frac{d_x^*-s}{\underline{p}a_x} - 1,\, \eta_x\right] \leq R_x < c_x,\, R_y \geq c_y\right) \\ &= \int_{\max\left[\frac{d_x^*-s}{\underline{p}a_x}-1,\, \eta_x\right]}^{c_x} \int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x. \end{aligned}$$

Taking the derivative of the latter expression with respect to s gives:

$$\frac{\partial}{\partial s}\left(\int_{\frac{d_x^*-s}{\underline{p}a_x}-1}^{c_x} \int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x\right) = \begin{cases} \frac{1}{\underline{p}a_x}\int_{c_y}^{\infty} f\left(\frac{d_x^*-s}{\underline{p}a_x} - 1, r_y\right) dr_y = \alpha_x(s) & \text{if} \quad s < \theta_x \\ 0 & \text{if} \quad s \geq \theta_x. \end{cases}$$

The contribution of this event to the pdf is thus equal to $\alpha_x(s)$ if $\kappa_x < s < \theta_x$ and 0 otherwise.

Bank x survives, y fails, firesale with outsider participation.

$$\begin{aligned} &S = d_y^* - \underline{p}a_y(1+R_y) \\ &R_x \geq c_x \\ &\eta_y \leq R_y < c_y. \end{aligned}$$

This is the mirror image of case 6. It follows that the contribution to the pdf of this event is equal to $\alpha_y(s)$ if $\kappa_y < s < \theta_y$ and 0 otherwise.

Both banks survive.

$$\begin{aligned} &S = 0 \\ &R_x \geq c_x \\ &R_y \geq c_y. \end{aligned}$$

It follows immediately from the system above that the contribution of this event to the pdf is only defined for $s = 0$ and that it is equal to $\int_{c_x}^{\infty}\int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x$. Aggregating over the eight subcases gives:

$$f_S(s) = \begin{cases} 0 & \text{if} \quad s < 0 \\ \int_{c_x}^{\infty}\int_{c_y}^{\infty} f(r_x, r_y) dr_y dr_x & \text{if} \quad s = 0 \\ 0 & \text{if} \quad 0 < s \leq \min[\kappa_x,\ \kappa_y] \text{ and } s < \min[\theta_x,\ \theta_y] \\ \alpha_y(s) & \text{if} \quad \kappa_y < s \leq \kappa_x \text{ and } s < \min[\theta_x,\ \theta_y] \\ \beta_y & \text{if} \quad 0 < s \leq \kappa_x \text{ and } s = \theta_y < \theta_x \\ \gamma_y(s) & \text{if} \quad \max[0,\ \theta_y] < s \leq \kappa_x \text{ and } s < \theta_x \\ \alpha_x(s) & \text{if} \quad \kappa_x < s \leq \kappa_y \text{ and } s < \min[\theta_x,\ \theta_y] \\ \alpha_x(s) + \alpha_y(s) & \text{if} \quad \max[k_x,\ k_y] < s \leq \kappa_x + \kappa_y \text{ and } s < \min[\theta_x,\ \theta_y] \\ \alpha_x(s) + \beta_y & \text{if} \quad \kappa_x < s \leq \kappa_x + \kappa_y \text{ and } s = \theta_y < \theta_x \\ \alpha_x(s) + \gamma_y(s) & \text{if} \quad \max[\kappa_x,\ \theta_y] < s \leq \kappa_x + \kappa_y \text{ and } s < \theta_x \\ \alpha_x(s) + \alpha_y(s) + \delta(s) & \text{if} \quad \kappa_x + \kappa_y < s < \min[\theta_x,\ \theta_y] \\ \alpha_x(s) + \beta_y + \delta(s) & \text{if} \quad \kappa_x + \kappa_y < s < \theta_x \text{ and } s = \theta_y \\ \alpha_x(s) + \gamma_y(s) + \delta(s) & \text{if} \quad \max[\theta_y,\ \kappa_x + \kappa_y] < s < \theta_x \\ \beta_x & \text{if} \quad 0 < s \leq \kappa_y \text{ and } s = \theta_x < \theta_y \\ \beta_x + \alpha_y(s) & \text{if} \quad \kappa_y < s \leq \kappa_x + \kappa_y \text{ and } s = \theta_x < \theta_y \\ \beta_x + \beta_y & \text{if} \quad s = \theta_x = \theta_y \leq \kappa_x + \kappa_y \\ \beta_x + \gamma_y(s) & \text{if} \quad s = \theta_x \leq \kappa_x + \kappa_y \text{ and } s > \theta_y \\ \beta_x + \alpha_y(s) + \delta(s) & \text{if} \quad s = \theta_x < \theta_y \text{ and } s > \kappa_x + \kappa_y \\ \beta_x + \beta_y + \delta(s) & \text{if} \quad s = \theta_x = \theta_y > \kappa_x + \kappa_y \\ \beta_x + \gamma_y(s) + \delta(s) & \text{if} \quad s = \theta_x > \max[\theta_y,\ \kappa_x + \kappa_y] \\ \gamma_x(s) & \text{if} \quad \max[0,\ \theta_x] < s \leq \kappa_y \text{ and } s < \theta_y \\ \gamma_x(s) + \alpha_y(s) & \text{if} \quad \max[\theta_x,\ \kappa_y] < s \leq \kappa_x + \kappa_y \text{ and } s < \theta_y \\ \gamma_x(s) + \beta_y & \text{if} \quad s = \theta_y \leq \kappa_x + \kappa_y \text{ and } s > \theta_x \\ \gamma_x(s) + \gamma_y(s) & \text{if} \quad \max[\theta_x,\ \theta_y] < s \leq \kappa_x + \kappa_y \\ \gamma_x(s) + \alpha_y(s) + \delta(s) & \text{if} \quad \max[\theta_x,\ \kappa_x + \kappa_y] < s < \theta_y \\ \gamma_x(s) + \beta_y + \delta(s) & \text{if} \quad s = \theta_y > \max[\theta_x,\ \kappa_x + \kappa_y] \\ \gamma_x(s) + \gamma_y(s) + \delta(s) & \text{if} \quad s > \max[\theta_x,\ \theta_y,\ \kappa_x + \kappa_y]. \end{cases} \tag{3.B.17}$$

Chapter 4

The Concentration-Stability Controversy in Banking: New Evidence from the EU-25

Abstract. *This chapter explores whether the relationship between banking market concentration and financial stability is affected by the level of analysis; i.e., bank-level versus country-level stability. The diverging results in the literature suggest that we may expect differences between the two levels. With the z-score as the measure of financial stability, our theoretical analysis confirms that we may find such differences. Yet our empirical analysis for the EU-25 during the 1998 – 2014 period finds no economically significant effect of concentration on either the bank-level or the country-level z-score. This finding is an indication of robustness in the empirical concentration-stability relation not previously established in the literature. This finding further suggests that neither supervisory restructuring, nor normal market-driven mergers, are likely to be substantially harmful to financial stability.*

This chapter is based on IJtsma, P., Spierdijk, L. and & Shaffer, S. (2017). The Concentration-Stability Controversy in Banking: New Evidence from the EU-25. *Journal of Financial Stability*, forthcoming.

4.1 Introduction

The recent financial crisis has witnessed massive government interventions in the financial sector, which have consisted mainly of the arrangement of restructuring mergers and bail-outs. Although these measures have been successful in preventing an immediate collapse of the financial system during the recent crisis, they might have detrimental long-run consequences for the financial system. Bailout expectations have been shown to lead to additional risk taking by banks (Dam & Koetter, 2012). Moreover, while restructuring mergers are less likely to lead to the above-mentioned moral hazard problem, they reinforce a trend of an increasing degree of market concentration in the financial sector (Vives, 2011). Some theoretical studies indicate that this trend of consolidation is likely to make the financial system more fragile (Boyd & De Nicolo, 2005; Nier et al., 2007; De Nicolo & Lucchetta, 2009). Others, however, believe that a positive association exists between the degree of banking market concentration and financial stability (Marcus, 1984; Keeley, 1990; Repullo, 2004).

Bank failures directly increase subsequent market concentration, whether handled by acquisition or liquidation. It is therefore crucial for regulators and policymakers to know the impact of banking market concentration on financial stability. The recent focus on systemic risk and macroprudential regulation indicates that regulators are not only concerned with the stability of individual banks, but also with the stability of a country's financial system as a whole. It is therefore important to explore whether the level of analysis – bank-level versus country-level stability – affects the observed concentration-stability relation.

Surprisingly, the role of the level of analysis has been ignored by the existing literature on the concentration-stability nexus. Existing studies typically focus on either bank-level or country-level stability, instead of analyzing the concentration-stability nexus at both levels. Furthermore, the literature yields conflicting evidence on the impact of concentration on stability (e.g., Boyd et al., 2009b; Jiménez et al., 2013; Fiordelisi & Mare, 2014). Among the bank-level studies that use the z-score as the measure of financial stability, both negative and positive effects have been found. The only study using the country-level aggregate z-score as the measure of financial stability establishes a negative effect of concentration (Uhde & Heimeshoff, 2009).

The goal of our study is to explore the role of the level of analysis in the study of the relationship between banking market concentration and financial stability, both theoretically and empirically. In the study, we use the z-score at both the bank level and the country level as the measure of financial stability. Our study is, to our best knowledge, the first to systematically analyze the relation between banking market concentration and financial stability at both levels in a coherent way and to make the comparison between both levels of analysis.

The theoretical part of our analysis shows that the aggregate z-score, unlike the bank-level z-score, incorporates the correlations across banks' returns on assets and thereby accounts for systemic risk. In this way, the bank-level and country-level z-scores measure different aspects of financial stability in the common scenario of imperfect return correlations. We may therefore expect empirical differences in the way concentration affects the z-score at both levels of analysis.

The empirical part of our analysis builds upon Uhde & Heimeshoff (2009) and focuses on commercial banks in the EU-25. We analyze the relation between banking market concentration and the z-score at both the bank level and the country level, using as much as possible the same model variables and econometric methodology for both approaches. In some of our models, we find a significantly negative effect of concentration on stability. Nevertheless, all estimated models indicate that the effect of concentration on stability is economically speaking small at both the bank level and the country level. Our finding that concentration hardly affects stability at both levels of analysis is an indication of robustness in the empirical concentration-stability relation not previously established in the literature.

Our findings are somewhat reassuring for regulators. They suggest that restructuring mergers, which are often arranged in order to restore financial stability during banking crises, will not contribute substantially to instability, nor will ordinary market-driven mergers and acquisitions.

The rest of the chapter is organized as follows: in Section 4.2, the existing theoretical and empirical literature is reviewed. Our methodology is elaborated upon in Sections 4.3 and 4.4. Section 4.5 presents the empirical results. Section 4.6 concludes.

4.2 Literature review

As mentioned in the introduction, the theoretical literature is inconclusive about the relation between banking market concentration and financial stability. Moreover, the empirical literature does not paint a clear picture either. We briefly review the literature below.

The concentration-stability controversy can be summarized as follows. Advocates of the so-called *concentration-stability view* argue that banks in more concentrated markets tend to be more stable for one of the following reasons. First, the *charter value hypothesis* maintains that a bank's charter is more valuable when the bank operates in a less competitive environment with high expected future profits. Banks in more concentrated markets will therefore engage less in excessively risky lending (Marcus, 1984; Chan et al., 1986; Keeley, 1990; Allen & Gale, 2000, 2004; Repullo, 2004) and will screen loan applicants better (Cordella & Yeyati, 2002; Hauswald & Marquez, 2006) to protect the value of their charter. Both outcomes are beneficial for financial stability.[1] Second, in more concentrated markets, banks become informed about a larger proportion of borrowers. As a result, they make more informed decisions and are less exposed to credit risk (Marquez, 2002). Third, when the failure of a bank threatens the stability of the system, banks in more concentrated markets may find it easier to reach an agreement to rescue the troubled bank to prevent contagion. In more diffuse markets, an agreement is less likely to be reached because of a coordination problem. Hence, contagion is less likely to occur in more concentrated markets (Sáez & Shi, 2004). Finally, some argue that it is easier to monitor a system with only a few large banks than one with many small banks.[2]

Proponents of the *concentration-fragility view*, on the other hand, argue that banking market concentration is *detrimental* to financial stability. First, if the level of competition decreases with the degree of market concentration, banks in more concentrated markets can charge higher loan rates. This aggravates moral hazard problems on the part of borrowers, who will be induced to invest in more risky projects. As a result, the riskiness of the bank's asset portfolio increases (Boyd & De Nicolo, 2005; De Nicolo & Lucchetta, 2009). Second, banks in concentrated markets are more likely to be too-big-to-fail, which gives rise to a moral hazard problem on the part of bank managers (Mishkin, 1999).[3] Third, the ex-ante risk of financial contagion is higher

[1] A crucial assumption behind this line of reasoning is that concentrated markets are less competitive. This view is challenged by the *contestability theory* (Baumol, 1982; Corvoisier & Gropp, 2002) and the *efficiency theory* (Demsetz, 1973; Smirlock, 1985; Berger, 1995).

[2] Another often-mentioned argument in favor of the concentration-stability view is that banks in more concentrated markets are larger and therefore better able to diversify idiosyncratic risk. However, De Vries (2005) and Wagner (2010a) show that diversification cannot raise the stability of the system as a whole, even though it may increase the stability of *individual* banks.

[3] Dam & Koetter (2012) provide evidence that bank managers who expect to be bailed out in case of failure engage in more risky behavior.

in more concentrated markets, since the probability that a particular bank is large enough to impact the rest of the system increases with the degree of market concentration (Nier et al., 2007). Finally, some argue that the supervision of concentrated banking markets is more difficult because banks in such markets tend to be larger and more complex than their counterparts operating in more diffuse markets (De Nicolo et al., 2004; Beck et al., 2006).

Table 4.1: Overview of empirical studies of the concentration-stability relationship.

Paper	Level	Dependent variable	Effect	Inst.
Demirgüç-Kunt & Detragiache (2002)	Country	Crisis dummy	Positive	No
De Nicolo et al. (2004)	Bank	Z-score	Negative	No
Beck et al. (2006)	Country	Crisis dummy	Positive	Yes
De Nicolo & Loukoianova (2007)	Bank	Z-score	Negative	No
Berger et al. (2009)	Bank	Z-score	Positive	Yes
Schaeck et al. (2009)	Country	Crisis dummy	Positive	No
Uhde & Heimeshoff (2009)	Country	Aggregate z-score	Negative	Yes
Boyd et al. (2009a)	Bank	Z-score / Loan losses	Positive	Yes
Boyd et al. (2009b)	Country	"Crisis indicators"	Negative	Yes
Jiménez et al. (2013)	Bank	NPL-ratio	Non-linear	Yes
Fiordelisi & Mare (2014)	Bank	Z-score	Ambiguous	Yes
Fu et al. (2014)	Bank/Country	Z-score / Dummy	Negative	Yes

Notes: This table presents an overview of empirical studies that have investigated the relationship between banking market concentration and financial stability. The reported effects are significant at the 10% level at the least. The last column indicates whether the study controls for reverse causality by instrumenting the concentration measure with an exogenous variable.

Empirical studies of the relation between banking market concentration and financial stability tend to focus solely on either the bank level or the country level. Analyses at the country level typically look at real episodes of financial crises. Using a crisis indicator variable, Beck et al. (2006) and Schaeck et al. (2009) find that higher levels of banking market concentration lower the probability of a financial crisis. Boyd et al. (2009b), on the other hand, show that banking market concentration is positively associated with the probability of a sharp decline in lending, which is indicative of a crisis. Although a focus on real episodes of crises is intuitively appealing, it has the important drawback that an indicator variable does not provide information about the *intensity* of a crisis or about the fragility of the system in the *absence* of a crisis. For this reason, most bank-level analyses use the z-score as a proxy of the solvency of individual banks. As shown by the overview in Table 4.1, however, these studies tend to give conflicting evidence. Finally, Uhde & Heimeshoff (2009) combine aspects of the country-level and bank-level approaches mentioned above. They aggregate bank-level data to obtain an *aggregate* z-score, which can be interpreted as measuring the solvency of a country's financial sector as a whole. Looking at the EU-25 in the period between 1997 and 2005, Uhde & Heimeshoff (2009) obtain strong results which indicate a *negative* relation between banking market concentration and financial stability. The next sections will explore the role of the level of analysis in more detail, using the z-score as the measure of financial stability.

4.3 Measuring concentration and financial stability

This section explains how we measure concentration and how we calculate the bank-level and country-level z-scores. We also make a comparison between the bank-level and country-level z-scores.

4.3.1 Measuring market concentration

In both the country-level and the bank-level analysis, we use the *five-bank concentration ratio* (CR_5) and the *Herfindahl-Hirschman index* (HHI) as measures of the degree of market concentration. The CR_5 is defined as the combined market share in terms of assets of the largest five banks operating in a country. Higher values thus indicate a more concentrated market. Although the CR_5 is a straightforward measure, its drawbacks are that the cut-off point of five banks is arbitrary and that it ignores the market shares of all other banks in the country. As a result, the CR_5 could be the same for markets with rather different structures (Bikker, 2004). The HHI does not suffer from an arbitrary cut-off point, but it has the drawback of being sensitive to the entrance of a large number of small banks (Rhoades, 1995). According to Bikker (2004), differences in the CR_5 across countries are mainly determined by the skewness of the size distribution of banks, whereas differences in the HHI result mainly from differences in the number of banks operating in the market. We therefore use both concentration measures. Note that both the CR_5 and the HHI are measured at the country level. As such, we assume that countries represent banking markets, as is common in the literature (e.g., Bikker et al., 2012).

4.3.2 The bank-level and country-level z-scores

We use the z-score as our measure of financial stability, which is based on bank balance sheet data (Roy, 1952; Hannan & Hanweck, 1988; Boyd et al., 1993). The z-score is a widely used solvency measure, which combines information about *profitability*, *capital buffers* and *return volatility*. The z-score of bank i at time t is defined as:

$$z_{it}^{B} = \frac{E(r_{it}) + k_{it}}{\sigma(r_{it})}. \tag{4.1}$$

Here, $E(r_{it}) = E\left(\frac{\pi_{it}}{a_{it}}\right)$ is the bank's expected return on assets at time t, calculated as expected net income in the coming period ($E(\pi_{it})$) divided by total assets (a_{it}). Furthermore, $k_{it} = \frac{e_{it}}{a_{it}}$ is the equity ratio at time t, calculated as total equity (e_{it}) divided by total assets. Finally, $\sigma(r_{it})$ is the standard deviation of the return on assets.[4] If returns are normally distributed, the bank's probability of default is equal to $1 - \Phi(z_{it}^{B})$, where Φ is the standard normal cdf.

We now turn to a country's *aggregate* z-score. Without loss of generality, we assume that only two banks are active in the country. Similar to the individual z-score, the aggregate z-score of two banks, say i and j, is defined as:

$$z_{ij,t}^{C} = \frac{E(r_{ij,t}) + k_{ij,t}}{\sigma(r_{ij,t})}, \tag{4.2}$$

where the subscript ij refers to aggregate values.[5] Here,

$$E(r_{ij,t}) = E\left(\frac{\pi_{it} + \pi_{jt}}{a_{it} + a_{jt}}\right) = \frac{a_{it}E(r_{it}) + a_{jt}E(r_{jt})}{a_{it} + a_{jt}} = w_{it}E(r_{it}) + w_{jt}E(r_{jt}), \tag{4.3}$$

where $w_{it} = \frac{a_{it}}{a_{it}+a_{jt}}$ and $w_{jt} = \frac{a_{jt}}{a_{it}+a_{jt}}$ are the asset weights of bank i and j, respec-

[4] For the empirical calculation of z-scores, we need estimates of expected returns and return standard deviations. Throughout, we proxy these variables by realized returns in the last period and the standard deviation of the realized returns over the sample period, respectively. This approach is common in the literature. Alternatively, some studies use a rolling window to obtain a time-varying estimate of the standard deviation of the return. Even though this approach is conceptually attractive, a rolling window has the drawback that it requires a relatively long sample to deliver reliable estimates. As such, Lepetit & Strobel (2013) find that using the entire sample period for calculating the standard deviation of returns gives better estimates of the return volatility.

[5] Please refer to Equation 2.3 for the mathematical expression of the aggregate z-score in a system with n banks.

tively, at time t. Using a similar exercise, we can write $k_{ij,t}$ as:

$$k_{ij,t} = w_{it}k_{it} + w_{jt}k_{jt}. \tag{4.4}$$

The standard deviation $\sigma(r_{ij,t})$ equals:

$$\begin{aligned}\sigma(r_{ij,t}) &= \sigma(w_{it}r_{it} + w_{jt}r_{jt}) \\ &= \sqrt{w_{it}^2\sigma^2(r_{it}) + w_{jt}^2\sigma^2(r_{jt}) + 2w_{it}w_{jt}\sigma(r_{it})\sigma(r_{jt})\rho(r_{it}, r_{jt})}, \end{aligned} \tag{4.5}$$

where $\rho(r_{it}, r_{jt})$ is the correlation between the banks' returns on assets. Substitution of (4.3), (4.4) and (4.5) into (4.2) gives:

$$z_{ij,t}^C = \frac{w_{it}(E(r_{it}) + k_{it}) + w_{jt}(E(r_{jt}) + k_{jt})}{\sqrt{w_{it}^2\sigma^2(r_{it}) + w_{jt}^2\sigma^2(r_{jt}) + 2w_{it}w_{jt}\sigma(r_{it})\sigma(r_{jt})\rho(r_{it}, r_{jt})}}. \tag{4.6}$$

The aggregate z-score of two banks can be interpreted as the z-score corresponding to a portfolio that consists of a weighted combination of the two individual banks. The aggregate z-score indicates the number of standard deviations by which the return of the portfolio could fall below its expected value before before exhausting the portfolio's capital buffer.

We thus see that the aggregate z-score is generally *not* a weighted average of the banks' individual z-scores due to the presence of imperfect return correlation between banks. The return correlation is a measure of banks' interconnectedness. Because the aggregate z-score uses banks' return correlations, it reflects systemic risk, which has become a primary focus of prudential regulation in recent years. Indeed, the aggregate z-score goes to infinity when two equally sized banks with the same return standard deviation have a perfectly negative return correlation, even when the individual z-scores of the two banks are finite. More formally, we observe that $\sigma(r_{it}) > 0,\ \sigma(r_{jt}) > 0$ and $-1 \leq \rho(r_{it}, r_{jt}) \leq 1$. We must therefore have:

$$\frac{w_{it}(E(r_{it}) + k_i) + w_{jt}(E(r_{jt}) + k_j)}{w_{it}\sigma(r_{it}) + w_{jt}\sigma(r_{jt})} \leq z_{ij,t}^C \leq \frac{w_{it}(E(r_{it}) + k_i) + w_{jt}(E(r_{jt}) + k_j)}{|w_{it}\sigma(r_{it}) - w_{jt}\sigma(r_{jt})|}. \tag{4.7}$$

Consequently, the aggregate z-score of two banks could be very high even though both banks are quite fragile, as long as their return correlation is low enough. It is readily seen that, if $\rho(r_{it}, r_{jt}) = 1$, the aggregate z-score in Equation (4.6) can be written as

$z^C_{ij,t} = v_{ij,t} z^B_{it} + (1 - v_{ij,t}) z^B_{jt}$, where $v_{ij,t} = \frac{w_{it}\sigma(r_{it})}{w_{it}\sigma(r_{it}) + w_{jt}\sigma(r_{jt})} = \frac{a_{it}\sigma(r_{it})}{a_{it}\sigma(r_{it}) + a_{jt}\sigma(r_{jt})}$. The appendix provides a complete proof of the next result.

Result 4.1: *The aggregate z-score is a weighted average of banks' individual z-scores if and only if banks' returns on assets are perfectly correlated.*

We can thus distinguish two cases. In the unlikely scenario that banks' returns are perfectly correlated, the aggregate z-score equals the asset-weighted average of the individual z-scores. Then the aggregate z-score uses exactly the same information as the individual bank-level z-scores. In the common scenario that banks' returns are imperfectly correlated, the country-level z-score is no longer equal to the weighted average of banks' individual z-scores. The aggregate z-score then additionally incorporates the return correlation across banks and thereby accounts for systemic risk. In this way, the bank-level and country-level z-scores measure different aspects of financial stability. We may therefore expect empirical differences in the way concentration affects stability at both levels. This will be explored in the next sections.

4.4 Econometric models

This section discusses the bank-level and country-level models that we will use in our empirical analysis to estimate the impact of concentration on financial stability as measured by the z-score.

4.4.1 Bank-level model

Our bank-level analysis will be based on the following model:

$$z^B_{it} = \beta_i + \beta CONC^*_{it} + \sum_k \beta_{x,k} x_{it,k} + \sum_\ell \beta_{y,\ell} y_{it,\ell} + \sum_t \beta_{time,t} d_t + \varepsilon_{it}, \tag{4.8}$$

where the subscripts i and t denote the bank and year, respectively. The variable z^B_{it} refers to the (logarithmically transformed) z-score of bank i in year t, while $CONC^*_{it}$ represents one of the two (logarithmically transformed) measures of banking market concentration in the country where bank i is located. Moreover, $x_{it,k}$ refers to the k-th bank-specific control variable for bank i in year t and $y_{it,\ell}$ to the ℓ-th country-specific control variable for bank i in year t. In addition, the model includes a bank-specific individual effect β_i that will be further specified later, year dummies d_t and a zero-mean error term ε_{it}. The main coefficient of interest is β, which measures the percentage change in the individual z-score following a percentage change in the degree of market concentration.

Similar to Uhde & Heimeshoff (2009), we control for the following macroeconomic variables: the rate of *real GDP growth*, the level of *GDP per capita*, the rate of *inflation*, and the *real interest rate*. In addition to the macroeconomic controls, five bank controls are included in the analysis. These are the bank's *total assets*, *net interest margin*, ratio of *loan loss provisions* (LLP) to total assets, *cost-income ratio*, and *loan-assets ratio*.

On the basis of the existing literature, we expect the following coefficient signs. GDP growth and GDP per capita are expected to have a positive effect on financial stability (Laeven & Majnoni, 2003), whereas the effects of the rate of inflation and the real interest rate are theoretically ambiguous (Uhde & Heimeshoff, 2009). We expect a negative coefficient for total assets (Boyd & Runkle, 1993; De Nicolo, 2000). The net interest margin is a measure of profitability, which is expected to have a positive effect on stability. The ratio of loan loss provisions to total assets, on the other hand, is a measure of credit risk and is expected to have a negative effect. The cost-income ratio is a measure of bank inefficiency and is expected to negatively affect financial stability (Uhde & Heimeshoff, 2009). Finally, the loan-asset ratio measures the extent to which banks are specialized in making loans as opposed to obtaining other sources of income. Its effect is not a-priori clear (Berger et al., 2009; Beck et al., 2013).

4.4.2 Country-level model

We specify the following country-level model:

$$z_{jt}^C = \gamma_j + \gamma CONC_{jt}^* + \sum_k \gamma_{x,k} x_{jt,k}^C + \sum_\ell \gamma_{y,\ell} y_{jt,\ell} + \sum_t \gamma_{time,t} d_t + \eta_{jt}, \tag{4.9}$$

where z_{jt}^C is the (logarithmically transformed) aggregate z-score of country j in year t and $CONC_{jt}^*$ is the (logarithmically transformed) degree of market concentration in country j's banking sector in year t. In addition, $x_{jt,k}^C$ refers to the k-th country-aggregated bank control variable and $y_{jt,\ell}$ to the ℓ-th macroeconomic control variable in country j at time t. The model includes a country-specific individual effect γ_j

that will be specified later, year dummies d_t and a zero-mean error term η_{jt}. The coefficient of interest is γ, which measures the percentage change in the aggregate z-score following a percentage change in the degree of market concentration.

We include the same control variables as used in the bank-level analysis. Yet the country-level model includes country-aggregated values of total assets, net interest margin, loss provisions ratio, cost-income ratio, and loan-assets ratio. These bank controls are calculated as an asset-weighted average of the banks in a country, with the weight of bank i in year t equal to $\frac{a_{it}}{\sum_k a_{kt}}$. Table 4.2 lists the variable definitions and data sources for both the country-level and the bank-level model.

4.5 Empirical analysis

We use Bankscope EU-25 bank data to run both a bank-level and a country-level analysis. We assess the impact of banking market concentration on financial stability as measured by the z-score. This section discusses the data and the empirical results based on the bank-level and country-level models.

4.5.1 Data description

Our empirical analysis uses bank balance sheet data from the EU-25 in the period between 1998 and 2014, obtained from Bankscope. The bank-level sample includes commercial banks in the EU-25 for which Bankscope provides data for at least five different years. We drop observations with statements that are under processing by Fitch ratings, of branches with no statement, of no longer existing banks without statements, and of banks with no statement. We use consolidated data where possible (Bikker et al., 2012) and apply the Duprey-Lé algorithm to iteratively drop duplicates for any given bank while keeping the time series for each bank as long as possible (Duprey & Lé, 2015).

Panel (a) of Figure 4.1 shows the evolution over time of the aggregate z-scores of the five major European economies in the period from 1998 to 2014. The figure shows substantial variation in the z-score.[6] Figure 4.1 also illustrates the degree of banking market concentration in the five major European economies, as measured by the CR_5 (panel b) and the HHI (panel c). The process of increasing market concentration in

[6]Since we hardly have any data for Spanish banks in 2004, the z-score for this observation is a sharp outlier. We omit this observation for illustrative purposes.

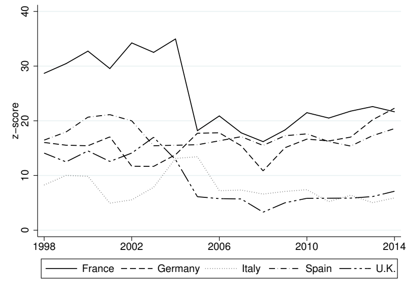
Table 4.2: Variable definitions and data sources

Variable	Definition	Source
Dependent variable		
Z-score	(Capital ratio + return on assets)/SD(return on assets)	Authors' calculations
Capital ratio	Ratio of equity to total assets	Bankscope
Return on assets	Return on average assets before taxes	Bankscope
SD(return on assets)	Standard deviation of return on assets over the sample period	Authors' calculations
Explanatory variables		
CR_5	Combined market share in assets of largest 5 banks in the country	ECB statistics
HHI	Sum of squared market shares in assets of all banks in the country	ECB statistics
Country controls		
GDP growth	Rate of real GDP growth (%)	World Development Indicators
GDP per capita	Ratio of nominal GDP to population (US $)	World Development Indicators
Inflation	Rate of growth of GDP deflator (%)	World Development Indicators
Real interest rate	3-month money market interest rate minus GDP deflator (%)	Eurostat, OECD
Bank controls		
Assets	Total assets (US $)	Bankscope
Net interest margin	Bank's net interest revenue as a share of interest-bearing assets (%)	Bankscope
LPP ratio	Loan loss provisions / total assets (%)	Bankscope
Cost-income ratio	Ratio of overhead costs to total revenue (%)	Bankscope
Loan-asset ratio	Ratio of outstanding loans to total assets (%)	Bankscope

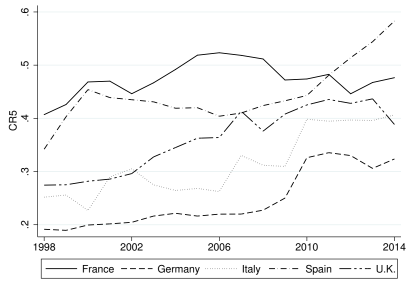
Notes: This table presents an overview of the variables included in our empirical analyses, as well as their source.

these countries, especially after the 2007 – 2008 financial crisis, can clearly be seen. The exception is France, where neither of the two concentration measures exhibit a tendency to increase over time.

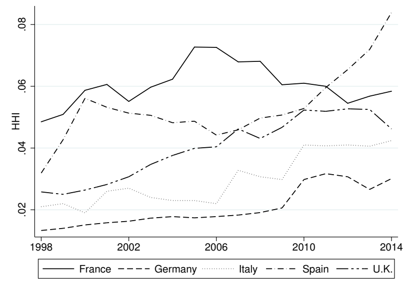
Figure 4.1: Aggregate z-scores (a), five-bank concentration ratio (b) and Herfindahl-Hirschman index (c) of the banking sector in the five major European economies.



(a)



(b)



(c)

4.5.2 Preliminary analysis

Descriptive statistics of all model variables are shown in Table 4.3. We divide the sample into a pre-crisis and a (post-)crisis period to show the structural change due to the global and financial crisis that started with the fall of Lehman Brothers in September 2008. We thus distinguish between the full sample period (1998 – 2014), the pre-crisis period (1998 – 2007) and the (post-)crisis period (2008 – 2014). The pre-crisis and (post-)crisis sample differ in various ways. For instance, we observe a noticeable drop in GDP growth and real interest rates after the onset of the crisis and a substantial increase in banks' average total assets.[7]

Unit roots. We have applied the Im-Pesaran-Shin (IPS) panel unit root test (Im et al., 2003) to both the bank-level and country-level data sets. The distribution of the IPS test statistic is derived under fixed-$T/N \to \infty$ asymptotics, which may be problematic given our small-T/small-N country-level data set. We therefore report the results for the country-level IPS tests with some caution. At the bank-level though, fixed-$T/N \to \infty$ asymptotics seem reasonable. Only for (log) per-capita income, the IPS test cannot reject the null hypothesis of non-stationarity. Given the evidence for non-stationarity of the log per-capita income variable, we will exclude this variable from the analysis.

Return correlations. As explained in Section 4.3.2, we expect imperfect return correlation across banks. To get a feel for these correlations, we run an explorative analysis. For each bank i in country j in year t, we calculate the equally-weighted return on assets of the *other* banks in country j in year t (denoted r_{jt}^{-i}). We interpret this as a 'market return' (in a factor-model sense). Subsequently, we calculate, for each country j, the sample correlation between the market return and banks' individual return on assets as an estimate of $\rho_j = \text{Cor}(r_{it}, r_{jt}^{-i})$. The ρ_js give a rough indication of the return correlation across banks in a country and are reported in Table 4.4. We have only done this for the full sample period to ensure a sufficient amount of observations for calculating the sample correlation. Table 4.4 shows that the ρ_js are positive for all countries with the exception of Malta, the Netherlands and Portugal.

[7] We notice that the countries Cyprus and Malta are only available in the post-crisis period; we will later investigate the consequences of this in our robustness analysis. Furthermore, initially we also considered a credit growth variable taken from the World Development Indicator. However, this variable had relatively many missing values, thus reducing the sample. Because of the limited significance of this variable in our preliminary model estimations, we have excluded this variable altogether.

Table 4.3: Sample statistics

	1998 – 2014				1998 – 2007				2008 – 2014			
Bank level	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
z-score	21.68	21.50	-0.22	165.42	21.25	20.72	-0.02	165.42	22.12	22.28	-0.22	163.89
CR_5	0.47	0.17	0.19	0.99	0.45	0.19	0.19	0.99	0.48	0.16	0.23	0.95
herfindahl	0.07	0.06	0.01	0.41	0.07	0.06	0.01	0.41	0.07	0.05	0.02	0.37
per capita income	37.44	19.25	2.98	116.61	32.29	16.36	2.98	104.84	42.83	20.55	11.32	116.61
gdp growth	1.65	2.94	-14.81	11.90	3.05	2.17	-1.13	11.90	0.18	2.92	-14.81	7.58
inflation rate	1.99	1.89	-9.69	20.13	2.35	2.14	-1.26	20.13	1.61	1.48	-9.69	11.84
real interest rate	0.77	2.18	-9.54	25.21	1.44	2.05	-9.54	15.34	0.07	2.09	-5.30	25.21
total assets (mln. US$)	41.81	202.15	0.00	3,065.09	25.75	141.41	0.00	2,833.80	58.65	249.40	0.01	3,065.09
net interest margin	2.52	1.62	0.03	10.58	2.71	1.75	0.03	10.52	2.31	1.44	0.03	10.58
LLP-asset ratio	0.51	0.87	-1.24	6.23	0.38	0.73	-1.21	6.23	0.66	0.97	-1.24	6.09
cost-income ratio	0.67	0.25	0.12	2.38	0.66	0.24	0.12	2.38	0.67	0.26	0.12	2.38
loan-asset ratio	0.53	0.25	0.01	0.98	0.50	0.26	0.01	0.98	0.55	0.25	0.01	0.98
# obs.	9,485				4,855				4,630			
# banks	1,051				883				858			
# countries	25				23				25			
# years	17				10				7			
Country level	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
z-score	14.37	9.82	0.29	79.82	14.30	8.91	2.57	79.82	14.49	10.98	0.29	53.91
CR_5	0.58	0.19	0.19	0.99	0.57	0.20	0.19	0.99	0.60	0.18	0.23	0.95
herfindahl	0.11	0.08	0.01	0.41	0.11	0.09	0.01	0.41	0.11	0.07	0.02	0.37
per capita income	30.10	19.85	2.98	116.61	23.05	15.22	2.98	88.68	36.23	21.15	11.25	113.73
gdp growth	2.16	3.65	-14.81	11.90	3.76	2.55	-1.13	11.90	0.51	4.11	-14.81	11.09
inflation rate	2.54	2.61	-9.69	20.13	3.25	2.75	-1.26	19.96	2.07	2.69	-9.69	20.13
real interest rate	0.79	2.84	-9.54	25.21	1.41	2.73	-7.27	15.34	0.42	3.01	-9.54	25.21
mean total assets (mln. US$)	234.49	415.70	0.03	1,890.74	103.73	226.94	0.11	1,263.00	378.71	510.29	3.04	1,766.82
net interest margin	2.42	1.27	0.48	6.55	2.80	1.48	0.28	9.52	2.07	1.06	0.54	5.43
LLP-asset ratio	0.52	0.68	-0.46	3.51	0.37	0.67	-2.11	6.81	0.75	1.11	-0.71	7.82
cost-income ratio	0.63	0.18	0.37	2.38	0.67	0.29	0.35	3.75	0.60	0.18	0.38	1.86
loan-asset ratio	0.54	0.14	0.16	0.89	0.51	0.14	0.15	0.88	0.57	0.13	0.25	0.80
# obs.	378				205				173			
# country	25				23				25			
# years	17				10				7			

Notes: This table presents descriptive statistics of the variables included in our empirical analysis. *CR5* refers to the five-bank concentration ratio, *herfindahl* refers to the Herfindahl-Hirschmann index, *LLP-ratio* refers to the ratio between loan loss provisions and total assets.

The ρ_js range between -0.62 (Malta) and 0.65 (Ireland) and its average value over all 25 countries equals 0.21.

Table 4.4: Sample correlations per country (1998 – 2014)

country	**corr.**	**country**	**corr.**
Austria	0.11	Latvia	0.39
Belgium	0.07	Lithuania	0.44
Cyprus	0.29	Luxembourg	0.11
Czech Republic	0.18	Malta	-0.62
Denmark	0.49	The Netherlands	-0.03
Estonia	0.52	Poland	0.09
Finland	0.17	Portugal	-0.04
France	0.07	Slovak Republic	0.15
Germany	0.01	Slovenia	0.52
Greece	0.46	Spain	0.09
Hungary	0.37	Sweden	0.16
Ireland	0.65	United Kingdom	0.26
Italy	0.22		

Notes: This tables presents country averages of the return correlations between banks. For each bank in country i in year t, we have calculated the equally-weighted return on assets of the other banks in country i in year t ('market return'). Subsequently, we have calculated for each country the sample correlation between banks' individual return on assets and the market return. The resulting correlations are reported in the table.

4.5.3 Bank-level model

Since the z-score is heavily skewed to the right, we use a logarithmic transformation of the z-score as the dependent variable.[8] To avoid losing observations with negative z-scores, we add a constant equal to the sample median before taking the logarithm. The transformed z-score is thus calculated as $\tilde{z}_{it}^B = \log(z_{it}^B + z^m)$, where z^m is the sample median of the z-score. The effect of a unit change in the degree of banking market concentration on the z-score is therefore:

$$\frac{\partial \tilde{z}_{it}^B}{\partial CONC_{it}^*} = \frac{dz_{it}^B}{d\tilde{z}_{it}^B}\frac{\partial \tilde{z}_{it}^B}{\partial CONC_{it}^*} = \beta(z_{it}^B + z^m). \tag{4.10}$$

[8] As shown by Lepetit & Strobel (2015), the logarithm of the z-score is negatively proportional to an upper bound of the log odds of insolvency.

For a bank with a z-score equal to the median, this gives:

$$\frac{\partial z_{it}^B / \partial CONC_{it}^*}{z_{it}^B} = 2\beta \tag{4.11}$$

Hence, multiplying the estimate of β in Equation (4.8) by 2 gives the estimated percentage change in the z-score due to a percentage change in the degree of market concentration, for a bank with a z-score equal to the sample median.

The fixed-effects (FE) estimator for Equation (4.8) is attractive, because it allows for unobserved bank-specific heterogeneity that is correlated with the observed covariates. However, similar to Uhde & Heimeshoff (2009) we find that the amount of time variation in the concentration measures is limited. We therefore incur the risk that part of the effect of concentration on stability is absorbed by the fixed effect. This could lead to a seemingly minor estimated effect of concentration on stability, while the true effect is much larger. We therefore also use the random-effects (RE) estimator. In contrast to the FE estimator, (nearly) time-invariant variables pose no problem for the RE estimator. However, the RE estimator assumes that any unobserved bank-specific heterogeneity is uncorrelated with the observed covariates, which may be unrealistic. We will later show that the point estimates obtained by the FE estimator are very similar to those generated by the RE estimator, suggesting that the limited amount of time variation in the concentration measures poses no problem for the FE estimator.

For the moment we assume that a sufficient way to deal with various sorts of endogeneity in Equation (4.8) is to account for time-invariant and bank-invariant omitted variables correlated with the observed variables. We do this by using the FE estimator in combination with year dummies. We will verify the validity of this assumption in Section 4.5.5.

The RE and FE models are estimated for the full sample period 1998 − 2014 and contain either the CR_5 or the HHI as the concentration measure. The estimated coefficients are reported in Table 4.5. For all models, the reported standard errors are robust to time series correlation and heteroskedasticity.

The negative point estimates of the FE and RE estimators are of a similar magnitude, suggesting that the limited amount of time variation is not a problem for the FE estimator. Because the RE models are rejected by a Hausman test, we proceed with the FE models, whose adjusted R^2s equal 0.23. The FE models indicate that

Table 4.5: Estimation results (RE and FE estimator, bank-level, 1998 – 2014)

	CR5							
	RE				**FE**			
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
intercept	5.2809	0.1612	32.7536	0.0000				
concentration (transformed)	-0.1068	0.0294	-3.6368	0.0003	-0.1006	0.0335	-3.0011	0.0027
gdp growth	-0.0021	0.0012	-1.8026	0.0715	-0.0024	0.0012	-1.9483	0.0514
inflation	0.0002	0.0020	0.0807	0.9357	0.0013	0.0021	0.6222	0.5338
real interest rate	-0.0003	0.0018	-0.1468	0.8833	0.0003	0.0019	0.1470	0.8831
total assets (log)	-0.1404	0.0109	-12.9319	0.0000	-0.1857	0.0153	-12.1529	0.0000
net interest margin	0.0329	0.0047	7.0263	0.0000	0.0315	0.0050	6.2784	0.0000
LLP-asset ratio	-0.0333	0.0035	-9.4515	0.0000	-0.0304	0.0035	-8.6510	0.0000
cost-income ratio	-0.1031	0.0163	-6.3104	0.0000	-0.1119	0.0170	-6.5838	0.0000
loan-asset ratio	0.0427	0.0320	1.3338	0.1823	0.0362	0.0334	1.0831	0.2788
adj. R^2	0.45				0.23			
	HHI							
	RE				**FE**			
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
intercept	5.1789	0.1619	31.9888	0.0000				
concentration (transformed)	-0.0658	0.0165	-3.9885	0.0001	-0.0641	0.0195	-3.2929	0.0010
gdp growth	-0.0022	0.0012	-1.8170	0.0692	-0.0024	0.0012	-1.9646	0.0495
inflation	0.0001	0.0020	0.0518	0.9587	0.0012	0.0021	0.5980	0.5498
real interest rate	-0.0002	0.0018	-0.1230	0.9021	0.0003	0.0019	0.1677	0.8669
total assets (log)	-0.1405	0.0108	-12.9548	0.0000	-0.1859	0.0153	-12.1832	0.0000
net interest margin	0.0331	0.0047	7.0731	0.0000	0.0318	0.0050	6.3206	0.0000
LLP-asset ratio	-0.0331	0.0035	-9.3810	0.0000	-0.0302	0.0035	-8.5820	0.0000
cost-income ratio	-0.1020	0.0163	-6.2479	0.0000	-0.1108	0.0170	-6.5371	0.0000
loan-asset ratio	0.0421	0.0320	1.3137	0.1889	0.0354	0.0335	1.0588	0.2897
adj. R^2	0.45				0.23			

Notes: This table reports the estimation results for the bank-level model (Equation 4.8). The standard-errors are robust for time-series correlation and heteroskedasticity. The time fixed-effects are not reported. *Est.* refers to the point estimates.

the effect of concentration on stability is *negative* and significant at the 1% level. In terms of the CR_5, a 1% increase in concentration leads to a *decrease* in stability of about $2 \times 0.1006 = 0.20\%$ with associated 95% confidence interval $[0.07, 0.33]\%$, while for the HHI a 1% increase in concentration leads to a *decrease* in stability of about $2 \times 0.0641 = 0.13\%$ with corresponding 95% confidence interval $[0.05, 0.20]\%$. We thus see that the economic significance of the effect of concentration on stability is limited, despite the statistical significance.[9] With the exception of GDP growth, the signs of the control variables' coefficients are in line with our theoretical predictions whenever they are significant; see Table 4.7.

The estimated models rely on the standard assumption in the literature that banking markets coincide with individual countries; see e.g. Bikker et al. (2012). In this way, the focus of our models is on the relation between bank stability and *national* concentration measures, which – from a policy perspective – seems the most relevant focus. For some commercial banks in our country the standard assumption about the extent of the market may be incorrect, such as banks with a regional focus or banks that are active in multiple countries. For the first type of banks, the impact of a national concentration measure will probably be weaker than that of a regional concentration measure. Regarding the latter type of bank, we notice that the individual effects in our models will correct for time-invariant missing information about the extent of the market.

4.5.4 Country-level model

We estimate the country-level model of Equation (4.9) with the logarithmically-transformed z-score as the dependent variable. Using similar arguments as for the bank-level analysis, we apply FE and RE estimators. We estimate the country-level models for the full sample period 1998 – 2014 using either the CR_5 or the HHI as the concentration measure. By definition, the country-level models focus on the relation between bank stability and *national* concentration measures. The estimated coefficients are reported in Table 4.6. As before, the reported standard errors are robust to time series correlation and heteroskedasticity.[10]

[9] Statistical significance is a necessary but not a sufficient condition for economic significance. For more details about statistical versus economic significance, see e.g. Granger (1998).

[10] Because the number of countries is relatively small in the country-level analysis, the formula-based clustered standard errors may be problematic (since they are based on the assumption that the number of countries is large). We therefore report the most conservative standard errors, where we choose between the standard errors based on a wild panel bootstrap (Cameron et al., 2008) and

Table 4.6: Estimation results (RE and FE estimator, country-level, 1998 – 2014)

	CR5							
	RE				FE			
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
intercept	4.3036	0.3384	12.7191	0.0000				
cr5	-0.4866	0.1117	-4.3547	0.0000	-0.3795	0.1661	-2.2845	0.0223
gdp growth	0.0134	0.0095	1.4055	0.1599	0.0145	0.0090	1.6140	0.1065
inflation	-0.0088	0.0083	-1.0696	0.2848	-0.0062	0.0079	-0.7829	0.4337
real interest rate	0.0110	0.0100	1.1007	0.2710	0.0129	0.0098	1.3083	0.1908
mean total assets (log)	-0.1485	0.0164	-9.0648	0.0000	-0.1509	0.0166	-9.0950	0.0000
net interest margin	0.1581	0.0212	7.4711	0.0000	0.1618	0.0201	8.0488	0.0000
LLP-asset ratio	-0.1744	0.0527	-3.3103	0.0009	-0.1680	0.0536	-3.1343	0.0017
cost-income ratio	-0.1946	0.0846	-2.3005	0.0214	-0.1584	0.0868	-1.8256	0.0679
loan-asset ratio	-0.4918	0.2861	-1.7190	0.0856	-0.3353	0.2878	-1.1650	0.2440
adj. R^2	0.5600				0.5600			
	HHI							
	RE				FE			
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
intercept	3.7538	0.3439	10.9163	0.0000				
HHI	-0.1437	0.0155	-9.2680	0.0000	-0.2814	0.0794	-3.5463	0.0004
gdp growth	0.0134	0.0094	1.4170	0.1565	0.0144	0.0090	1.5967	0.1103
inflation	-0.0087	0.0078	-1.1081	0.2678	-0.0060	0.0076	-0.7856	0.4321
real interest rate	0.0111	0.0098	1.1338	0.2569	0.0130	0.0095	1.3703	0.1706
mean total assets (log)	-0.3044	0.0467	-6.5181	0.0000	-0.1450	0.0153	-9.4642	0.0000
net interest margin	0.1668	0.0204	8.1842	0.0000	0.1716	0.0188	9.1070	0.0000
LLP-asset ratio	-0.1710	0.0515	-3.3226	0.0009	-0.1637	0.0521	-3.1438	0.0017
cost-income ratio	-0.1836	0.0840	-2.1869	0.0288	-0.1491	0.0847	-1.7592	0.0785
loan-asset ratio	-0.5177	0.2723	-1.9015	0.0572	-0.3900	0.2672	-1.4600	0.1443
adj. R^2	0.5800				0.5800			

Notes: This table reports the estimation results for the country-level model (Equation 4.9). The standard-errors are robust for time-series correlation and heteroskedasticity. The time fixed-effects are not reported. *Est.* refers to the point estimates.

Again the RE and FE models provide negative point estimates of a similar magnitude, so there is no need for concerns about the FE estimator. Because the RE models are rejected by a Hausman test, we proceed with the FE models, whose adjusted R^2s equal 0.57 – 0.58. The effect of concentration on stability is *negative* and significant at the 5% level. In terms of the CR_5, a 1% increase in concentration leads to a *decrease* in stability of 0.38%, with associated 95% confidence interval $[0.05, 0.71]$%. In terms of the HHI, a 1% increase in concentration leads to a *decrease* in stability of 0.28%, with associated 95% confidence interval $[0.13, 0.44]$%. The economic relevance of the effect of concentration on stability is larger than in the bank-level model, but economically speaking still modest. Throughout, the signs of the control variables' coefficients are in line with theory whenever they are significant; see Table 4.7.

Table 4.7: Signs of covariates' coefficients in the bank-level and country-level models

		CR_5				**HHI**			
		RE		**FE**		**RE**		**FE**	
	exp. sign	**bank**	**country**	**bank**	**country**	**bank**	**country**	**bank**	**country**
concentration (log)	**?**	–	–	–	–	–	–	–	–
gdp growth	+	–	NS	–	NS	–	NS	–	NS
inflation rate	?	NS	NS	NS	NS	NS	NS	NS	NS
real interest rate	?	NS	NS	NS	NS	NS	NS	NS	NS
total assets (log)	–	–	–	–	–	–	–	–	–
net interest margin	+	+	+	+	+	+	+	+	+
LLP-asset ratio	–	–	–	–	–	–	–	–	–
cost-income ratio	–	–	–	–	–	–	–	–	–
loan-asset ratio	?	NS	–	NS	NS	NS	–	NS	NS

Notes: This table summarizes the signs of the covariates in the bank-level and country level models (Equations 4.8 and 4.9). 'NS' stands for 'not significant' at the 10% level. The column 'expected effects' indicates what the expected sign is according to the literature, where a question mark indicates a lack of consensus in the literature about the expected effect.

4.5.5 Robustness checks

The control variables in both the bank-level and country-level models include year dummies. In each model, the number of dummies equals the number of years in the sample minus one; so $17 - 1 = 16$ in total. With only 378 bank-years, the country models may be overfit due to the large amount of year dummies (Babyak, 2004), thus capturing noise rather than a meaningful economic effect. We therefore re-estimate the FE country-level models including a single time dummy for the (post-)crisis period

the formula-based standard errors.

(2008 – 2014); see Table 4.8. The estimated coefficients of concentration are all negative as before (-0.0312 for the CR_5 and -0.1317 for the HHI), but no longer statistically significant (p-values of 0.87 and 0.19, respectively). The significance of some of the control variables also changes, but the signs are still in line with theory.

We verify the robustness of the estimates to the exclusion of currently inactive banks. Secondly, we analyze separately the subsample of the largest 25% of banks in terms of total assets. Thirdly, we redo the main analysis without the countries Cyprus and Malta, since they are only available during the post-crisis period. In all cases, we find similar estimation results as before.[11]

We also estimate the effect of concentration on stability separately for the pre-crisis period (1998 – 2007) and the (post-)crisis period (2008 – 2014) using a difference-in-difference approach; see Table 4.9. The estimation results show that the effect of concentration on stability does not significantly differ between the two periods. We also draw this conclusion in the country-level model with a single time dummy, in which case the effect of concentration is not significant either.

Simultaneity of stability and concentration is a potential issue. This would arise if a drop in the stability of a (too-big-to-fail) bank results in a restructuring merger and an increase in the CR_5 or HHI. Such simultaneity would result in omitted, unobserved variables correlated with the concentration measure in Equations (4.8) and (4.9). In our previous estimations, we have assumed that the FE estimator, in combination with year dummies, is able to deal with this sort of endogeneity. We investigate the validity of this assumption by means of a FE-2SLS approach; see Table 4.10. At the bank level, we use log population as an instrument in the preferred specification, the FE model. The underlying motivation is that small countries are expected to be more concentrated than larger ones and that the instability of individual banks will not affect a country's population. At the country level, we use investment freedom from the Heritage Foundation as the instrument. The intuition is that this freedom indicator is an exogenous feature of the (financial) economy, which determines its development and thereby the degree of banking concentration. At both the bank level and the country level the first-stage F-statistic is above the value 10. Hence, the instruments are strong enough (Stock et al., 2002). At the bank level, the coefficients of concentration equal 0.08 (CR_5) and 0.09 (HHI), but they are not statistically significant.

[11] Since the results of the robustness checks are very similar to the ones already presented, we do not report them here. They are available upon request.

Table 4.8: Estimation results with fewer time dummies (FE estimator, country level, 1998 – 2014)

	CR$_5$				**HHI**			
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
concentration (log)	-0.0312	0.1973	-0.1583	0.8742	-0.1317	0.1001	-1.3160	0.1882
gdp growth	0.0060	0.0049	1.2351	0.2168	0.0055	0.0050	1.1044	0.2694
inflation rate	-0.0436	0.0080	-5.4400	0.0000	-0.0443	0.0085	-5.2386	0.0000
real interest rate	-0.0298	0.0082	-3.6466	0.0003	-0.0308	0.0083	-3.7148	0.0002
total assets (log)	-0.0896	0.0178	-5.0475	0.0000	-0.0836	0.0163	-5.1353	0.0000
net interest margin	0.1460	0.0330	4.4232	0.0000	0.1539	0.0317	4.8533	0.0000
LLP-asset ratio	-0.1486	0.0577	-2.5749	0.0100	-0.1447	0.0557	-2.5960	0.0094
cost-income ratio	-0.1488	0.1294	-1.1500	0.2502	-0.1423	0.1261	-1.1290	0.2589
loan-asset ratio	-0.0197	0.2932	-0.0673	0.9464	-0.1043	0.2785	-0.3746	0.7080
adj. R^2	0.44				0.44			

Notes: This table reports the estimation results for the country-level model (Equation 4.9), with a single time dummy to avoid overfitting. The standard-errors are robust for time-series correlation and heteroskedasticity. The time fixed-effect is not reported. *Est.* refers to the point estimates.

Table 4.9: Robustness check: the effect of the crisis on the concentration-stability relation

	CR_5				**HHI**			
bank-level								
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
concentration	-0.0968	0.0316	-3.0632	0.0022	-0.0607	0.0180	-3.3724	0.0007
concentration$\times I(t \geq 2008)$	0.0143	0.0197	0.7247	0.4686	0.0098	0.0109	0.8974	0.3695
country-level								
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
concentration	-0.3762	0.1621	-2.3206	0.0203	-0.2813	0.0790	-3.5603	0.0004
concentration$\times I(t \geq 2008)$	0.0279	0.1277	0.2187	0.8269	0.0010	0.0712	0.0134	0.9893

Notes: This table reports the estimated coefficient of the (log) concentration variable in the FE difference-in-difference models (Equations 4.8 and 4.9). The standard-errors are robust for time-series correlation and heteroskedasticity. *Est.* refers to the point estimates.

At the country level, we find coefficients of −0.66 (CR_5) and −0.30 (HHI). Also here the coefficients of concentration are no longer statistically significant. Throughout, the magnitude and significance of the control variables is similar as before. The loss of statistical significance of the concentration coefficient in the FE-2SLS models reinforces our prior conclusion that the effect of concentration on stability is economically speaking limited.

In sum, our robustness checks confirm that the effect of concentration on stability is economically speaking limited, although sometimes statistically significant.

Table 4.10: Robustness check: results for FE-2SLS estimation

	CR_5				**HHI**			
bank-level								
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
concentration	0.0811	0.2561	0.3164	0.7517	0.0906	0.2900	0.3126	0.7546
first-stage F-statistic	129.8				94.9			
country-level								
	est.	*s.e.*	*t-value*	*p-value*	*est.*	*s.e.*	*t-value*	*p-value*
concentration	-0.6632	1.0660	-0.6221	0.5339	-0.3000	0.4652	-0.6450	0.5190
first-stage F-statistic	12.5				13.8			

Notes: This table reports the estimated coefficient of the (log) concentration variable in the FE models, estimated by means of 2SLS. The standard-errors are robust for time-series correlation and heteroskedasticity. The first-stage F-statistics are also reported. *Est.* refers to the point estimates. In the bank-level model, log population is used as the instrument. In the country-level model, the investment freedom indicator of the Heritage Foundation is used as the instrument.

4.6 Conclusion

The recent focus on systemic risk and macroprudential regulation indicates that regulators are not only concerned with the stability of individual banks, but also with the stability of a country's financial system as a whole. It is therefore important to explore whether the level of analysis – bank-level versus country-level stability – affects the observed concentration-stability relation. The diverging results in the literature suggest that we may indeed expect differences between the two levels.

Our theoretical analysis has shown that the country-level aggregate z-score, unlike the bank-level z-score, incorporates the correlations across banks' returns on assets and thereby accounts for systemic risk. In the common scenario of imperfect return correlations, the bank-level and country-level z-scores measure different aspects of financial stability. We may therefore expect differences in the empirical concentration-stability relation between both levels of analysis.

The empirical part of our study has used bank data from the EU-25 during the 1998 – 2014 period to investigate the causal relation between banking market concentration and the z-score at both the bank level and the country level. At both levels of analysis, we find that the effect of concentration on stability is economically speaking limited. Our finding that market concentration hardly affects stability at both levels of analysis is an indication of robustness in the empirical concentration-stability relation not previously established in the literature.

Our findings are somewhat reassuring for regulators. They suggest that restructuring mergers, which are often arranged in order to restore financial stability during banking crises, will not substantially contribute to instability, nor will ordinary market-driven mergers and acquisitions. Since existing research has indicated that bail-outs lead to increased bank risk taking by raising expectations of future bail-outs, our findings support the idea that restructuring mergers are a viable alternative to bail-outs when a troubled bank is deemed too important to fail.

A limitation of our study is that we have restricted the analysis to include only data for commercial banks, thereby ignoring savings banks and cooperative banks. Whereas the assumption that banks maximize profits seems reasonable for commercial banks, savings banks and cooperative banks may have other objectives (Ayadi et al., 2010; Fiordelisi & Mare, 2014). Furthermore, commercial banks tend to distribute profits to their shareholders, whereas cooperative banks and savings banks generally retain profits (Salas & Saurina, 2002; Fonteyne, 2007; Ayadi et al., 2010), and cooperative banks and savings banks are generally more focused on traditional financial intermediation than commercial banks, potentially making them more vulnerable to changes in lending rates (Hesse & Cihák, 2007). As such, we may expect a different relationship between market concentration and financial stability when analyzing savings banks and cooperative banks. We leave this issue open for future research.

4.A Appendix: Proof of Result 4.1

Result 4.1: The aggregate z-score is a weighted average of banks' individual z-scores if and only if banks' returns on assets are perfectly correlated.

Proof: Without loss of generality, we confine the proof to the case of two banks. If $\rho(r_{it}, r_{jt}) = 1$, the aggregate z-score in Equation (4.6) can be written as $z^C_{ij,t} = v_{ij,t} z^B_{it} + (1 - v_{ij,t}) z^B_{jt}$, where $v_{ij,t} = \frac{w_{it}\sigma(r_{it})}{w_{it}\sigma(r_{it}) + w_{jt}\sigma(r_{jt})} = \frac{a_{it}\sigma(r_{it})}{a_{it}\sigma(r_{it}) + a_{jt}\sigma(r_{jt})}$. Conversely, assume that $z^C_{ij,t} = \tilde{v}_{ij,t} z^B_{it} + (1 - \tilde{v}_{ij,t}) z^B_{jt}$. From Equation (4.6) it becomes clear that we must have:

$$\tilde{v}_{ij,t} = \frac{w_{it}\sigma(r_{it})}{\sqrt{w^2_{it}\sigma^2(r_{it}) + w^2_{jt}\sigma^2(r_{jt}) + 2w_{it}w_{jt}\sigma(r_{it})\sigma(r_{jt})\rho(r_{it}, r_{jt})}}. \tag{4.A.1}$$

However, because the weights must sum to unity, we have to get rid of the square root in the denominator of (4.A.1). This is only possible for $\rho(r_{it}, r_{jt}) = 1$, yielding $\tilde{v}_{ij,t} = v_{ij,t}$.

Chapter 5

Did banking deregulation in the U.S. strengthen economic growth? The role of spatial spillovers

Abstract. *This chapter analyzes the effects of deregulations in the banking industry on economic growth in the United States. We find robust evidence in favor of a positive effect running from interstate banking deregulation to growth, whereas no evidence is found for an effect of intrastate branching deregulation. In addition, we find that there are strong spatial spillover effects of interstate banking deregulation. The presence of spillovers suggests that previous studies, which do not take spatial effects into account, are likely to give misleading results. Our analysis suggests that the positive effect of interstate banking deregulation on growth can at least partly be attributed to an increase in banks' profit efficiency following deregulation.*

5.1 Introduction

Liberalization and deregulation of the banking industry have traditionally been seen as important drivers of economic growth. By fostering efficiency and competition, these measures were believed to lead to improved lending conditions for borrowers and a better allocation of savings to profitable investment opportunities. These improvements, in turn, should have a positive effect on the efficiency and growth of the real sector of the economy (Besanko & Thakor, 1992; Smith, 1998).

More recently, however, the potential downsides of liberalization and deregulation have received more attention. By facilitating expansion across state borders, for instance, deregulations have allowed some banks to grow so large that they are considered too-big-to-fail (Mishkin, 1999). The resulting increase in risk-taking by these large banks can be very disruptive to the economy, as we have observed during the recent financial crisis. Some also argue that an increase in the competitiveness of the banking industry, to which deregulation is supposed to contribute, might not necessarily foster economic growth. The argument is that banks which operate in a highly competitive environment may be inhibited from forming long-term lending relationships with small and medium-sized enterprises (SMEs). Since SMEs are important drivers of innovation but are typically dependent on bank credit, a highly competitive banking industry might be detrimental to economic growth (Petersen & Rajan, 1995; Cetorelli & Peretto, 2012).

This chapter analyzes the effects of deregulations in the banking industry on economic growth in the United States. Following much of the existing literature, we use the incremental relaxation by state legislatures of intrastate branching and interstate banking restrictions in the 1970s, 80s and 90s as a natural experiment. Since different states deregulated their banking industries at different points in time, the resulting combination of cross-sectional and temporal variation allows for a clear identification of the effects of deregulation. The contribution of our study to the existing literature is threefold. First, we take into account the possibility that the effect of deregulations on growth may produce *spillovers* to neighboring states. In the context of the relationship between banking sector deregulations and economic growth, spillover effects can be expected because (i) firms may be able to borrow funds from banks in neighboring states, and (ii) the economies of adjacent states are typically connected by trade linkages and commuters. Controlling for potential spillovers is important, because if spillovers are present, ignoring them will lead to biased estimates of the effect of deregulations on economic growth. Second, we critically analyze the robustness of our findings by comparing local growth rates in a matched-pairs setting. Since the decision to deregulate the banking sector is taken at the state level, a local analysis is necessary to rule out the possiblity that the observed relationship between deregulation and economic growth is due to simultaneity, i.e. due to a change in state-level economic growth leading to deregulation. Finally, we delve deeper into the deregulation-growth nexus by analyzing whether the relationship between deregulation and growth can be explained by changes in the degree of competition in the banking industry resulting from deregulation.

The rest of the chapter is structured as follows. Section 5.2 summarizes the existing theoretical and empirical litature on the relationship between banking sector deregulation and economic growth. Our empirical strategy is elaborated upon in Section 5.3. A description of the data then follows in Section 5.4. Section 5.5 reports the results of our main analysis, after which the role of banking competition is analyzed in Section 5.6. Some concluding thoughts follow in Section 5.7.

5.2 Related literature

The theoretical literature that analyzes the real effects of banking deregulation took off with the seminal study by Besanko & Thakor (1992), who build a spatial model to illustrate the effects of a relaxation of entry barriers into banking. Their model shows that banking deregulation raises competition and thus improves the welfare of borrowers and savers by lowering loan rates and increasing deposit rates. Both savings and investments would be expected to increase, with beneficial effects for economic growth. Petersen & Rajan (1995), on the other hand, argue that a more competitive banking sector does not necessarily lead to higher growth rates because competition might hamper relationship lending. Young and innovative firms are typically not profitable in their early years, but might become so when they mature. When banks have market power, relationship lending allows them to extract rents from such firms once they become profitable. In a competitive banking industry, however, borrowers can turn to a competing bank once they are profitable, so that the initial lender cannot expect to share in the future surplus of the borrower. As a result, young firms may not be able to obtain a loan in the first place. Another reason why a more competitive banking sector might hamper economic growth is that it may lead to less efficient screening by banks. As a result, lending rates might actually be pushed *up* rather than down (Marquez, 2002). In addition, investments in information acquisitions might become less worthwile and therefore fall, resulting in less efficient lending decisions (Hauswald & Marquez, 2006). The potentially ambiguous effect of banking competition on growth is confirmed by Cetorelli & Peretto (2012), who build a model in which banks can choose between lending at arm's length and relationship lending. They show that an increase in competition lowers banks' incentive to engage in relationship lending, which lowers the *quality* of investments. However, competition also lowers interest rate spreads, which positively affects the *quantity* of lending. As a result, the overall effect of a change in banking competition on growth is theoretically ambiguous.

Given the ambiguity of the theoretical literature, we now turn to empirical studies of the relationship between banking sector deregulation and economic growth. This literature kicks off with a study by Jayaratne & Strahan (1996), who study the growth effects of the relaxation of intrastate bank branching restrictions in the United States in the 1970s and 80s. They find that these deregulations had a positive and large, significant effect on growth rates. Moreover, their study suggests that this posivite effect cannot be explained by increases in savings and lending following deregulation. Instead, Jayaratne & Strahan (1996) find that it can be explained by the fact that better banks grow at the expense of their less efficient rivals after deregulation. As a result, the performance of the banking sector as a whole improves. The results of Jayaratne & Strahan are corroborated by a number of studies. Black & Strahan (2002) find that the rate of new incorporations increases after states relax branching restrictions. Strahan (2003) also finds an increase in entrepreneurial activity, as well as growth rates, after deregulation. Moreover, studies by Dick (2006) and Rice & Strahan (2010) indicate that interest rate spreads fall after deregulation. Finally, Koetter et al. (2012) find that banks become more efficient after deregulation, while the results of Amore et al. (2013) and Chava et al. (2013) indicate that interstate banking deregulation spurred innovation by public and private firms. These findings, and especially the earlier studies, have received a fair amount of criticism, however, with the main point being that deregulation might be endogenous to state-level economic conditions. For example, Freeman (2002) uses an event study methodology to argue that states have tended to deregulate their banking system during times of econonomic distress. Hence, the increase in growth rates observed after deregulation could be attributed to a recovery from a recession rather than to a causal effect. Wall (2004) finds that the positive relationship between deregulation and entrepreneurship becomes ambiguous once regional effects are taken into account. Finally, Huang (2008) compares the growth rates in counties on opposite sides of state borders and concludes that the evidence for a causal effect running from deregulation to growth is weak. He argues that the observed correlation between deregulation events and subsequent growth spurts at the state level could instead by explained by expectations of future growth opportunities inducing state legislatures to deregulate their banking sectors.

The argument of Huang (2008) fits well into an old debate about the relationship between growth and finance. In this debate, one side is of the Schumpeterian viewpoint that financial development causes economic growth (Schumpeter, 1934), whereas the other side argues that "where the economy leads, finance follows" (Robinson, 1952). In the banking deregulation literature, an important study which analyzed the determinants of deregulation has been conducted by Kroszner & Strahan (1999). Their findings indicate that the relative strength op potential winners (large banks and small firms) and losers (small banks and insurance firms) can explain the timing of intrastate branching deregulation across states. A spatial analysis by Garrett et al. (2005), which takes into account the fact that that state-level banking deregulations are highly spatially correlated (i.e. states tend to deregulate when their neighbours have recently done so), largely confirms these findings. Since the idea that the strength of these interest groups is determined by growth rates seems far-fetched, this would suggest that deregulations can safely be assumed to be exogenous when analyzing their effect on economic growth. Nevertheless, given the findings of Freeman (2002) and Huang (2008), causality running from economic growth to relaxations of banking restrictions cannot be ruled out. We therefore take this possibility into account in our analysis.

5.3 Empirical strategy

This section discusses the empirical strategy used to analyze the effect of banking sector deregulation on economic growth. As was mentioned in the introduction, we study the incremental relaxation of restrictions on intrastate branching and interstate banking in the U.S. in the 1970s, 80s and 90s as a natural experiment. Intrastate branching restrictions refer to state-level regulations which prohibit or restrict banks from expanding *within* a state by acquiring branches of existing banks or by establishing new branches. In 1970, only a handful of states allowed banks to freely expand within their borders. Most states restricted intrastate branching in some way, with some states going so far as to only allow *unit banking*, which means that banks were only allowed to have one branch. Interstate banking restrictions, on the other hand, refer to regulations that prevent out-of-state banks from expanding *across* borders into the regulated state. Interstate banking was even more restricted in 1970, when not a single state allowed out-of-state banks to freely enter its market. In the period between 1970 and 1997, both intrastate branching and interstate banking restrictions were gradually relaxed, until the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) removed the remaining barriers to intrastate branching and interstate banking in 1997.

In assessing the effect of the above-mentioned deregulations on economic growth, the empirical challenge is the fact that there might be a two-way causality between banking deregulation and economic growth. That is, deregulation might not only affect growth, but (expectations of future) growth might also induce deregulation. Since it is difficult to convincingly rule out simultaneity with only a state-level analysis, we need additional evidence from an analysis at a more local level to determine the causal relationship of state-level banking deregulation on economic growth. A complicating factor is that economic growth, deregulations and the relationship between them can be expected to be spatially correlated. An increase in economic growth in a certain area is likely to have a positive spillover effect on growth in neighboring areas. Furthermore, it has been shown by Garrett et al. (2005) that states tend to deregulate when their neighbors have recently done so. Finally, deregulations can have spillover effects in the sense that they might not only affect growth in the deregulated state itself, but also growth in neighboring states. These spillover effects could occur either because deregulation in one state directly affects growth in neighboring states, or because a change in a state's growth rate following deregulation spills over to neighboring states. The former type of spillover is typically referred to as a *local spillover*, whereas the second type is referred to as a *global spillover*. If the growth effects of deregulation indeed spill over to neighboring states, it is not surprising that the study by Huang (2008), which focuses on differences in growth rates between counties on opposite sides of state borders, does not find strong evidence in favor of a causal effect running from deregulation to growth. The reason for this is that, while the county in the deregulated state is expected to experience higher growth due to the direct effect of deregulation, the county on the opposite of side of the border is expected to experience higher growth as well, due to the spillover effect of deregulation on growth. Hence, a higher rate of economic growth would be expected on *both* sides of the border. We therefore need a different strategy to obtain evidence on the deregulation-growth nexus at the local level if the data suggest that spillovers are present.

To tackle the above-mentioned issues, we procede as follows. First, we study the relationship between deregulation and growth at the state level and analyze whether or not the data suggest the presence of spillover effects. Next, we analyze the relationship between deregulation and growth at the local level, using a matched-pairs setting, in which growth rates are compared within pairs of counties that are located in states which deregulated their banking sectors at different points in time. The approach of Huang (2008) is appealing in this respect, since contiguous counties on opposite sides of state borders are likely to be similar in terms of unobservable characteristics. However, in the presense of spillovers, identifying an effect of deregulation on growth might be difficult in this setup, as explained above. In the matching of local areas, there is thus a tradeoff between the *comparability* of local areas and the *identifiability* of an effect of deregulation on growth. Matching areas that are located further away from one another should make it easier to identify a relationship between deregulation and growth, since spillovers effects can be expected to decrease with distance. At the same time, this makes it more difficult to convincingly argue that the identified relationship represents a causal effect, since the two areas can be expected to be less comparable with respect to unobservable characteristics. We therefore try to strike a balance between comparability and identifiability by matching areas based on observable characteristics instead of geographic location, while requiring matched areas to be located in the same geographic region.[1]

Below, we elaborate upon the state-level component of our empirical analysis. In the next subsection, we provide more details about the matching procedure used in the local-level component of our study.

[1]These regions are the West, Midwest, South and Northeast of the United States. We follow Jayaratne & Strahan (1996) in the grouping of states.

5.3.1 State-level analysis

We begin our state-level analysis by estimating the base model of Jayaratne & Strahan (1996):

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \beta_t + \boldsymbol{X}_t\boldsymbol{\gamma} + \boldsymbol{\varepsilon}_t, \tag{5.1}$$

where $\boldsymbol{y}_t$ is a vector of per capita income growth rates at time t, $\boldsymbol{\alpha}$ is a vector of state-specific constants included to capture unobserved state heterogeneity, and β_t is a time-specific constant included to control for country-wide business cycle effects.[2] Furthermore, $\boldsymbol{X}_t$ is a matrix that includes two vectors of deregulation dummies with a value of 1 in the years following intrastate branching or interstate banking deregulation and a value of 0 otherwise. The parameters of interest are included in the vector $\boldsymbol{\gamma} = [\gamma_1, \gamma_2]$, which captures the effects of intrastate branching and interstate banking deregulation on growth. Finally, ε_{it} is a zero-mean error term, which is assumed to be uncorrelated with the explanatory variables. As explained above, we suspect that deregulations may produce spillover effects. If this is the case, the estimates of Equation (5.1) will be inconsistent due to omitted variable bias. Furthermore, we expect the spillover effects to be captured by the error term since they are not accounted for by the model, in which case the error terms will be spatially correlated. That is, we expect a positive correlation between the error in one state in a particular period and the errors in neighboring states in the same period. As a first test of the presence of spillovers, we estimate a so-called Spatial Error Model (SEM) (Anselin, 1988; Anselin et al., 1996), which captures the presence of spatial correlation in the error term:

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \beta_t + \boldsymbol{X}_t\boldsymbol{\gamma} + \boldsymbol{u}_t \tag{5.2}$$

$$\boldsymbol{u}_t = \lambda \boldsymbol{W}\boldsymbol{u}_t + \boldsymbol{\varepsilon}_t. \tag{5.3}$$

Here, $\boldsymbol{u}_t$ is a vector of (potentially) correlated error terms and $\boldsymbol{W}$ is an N-dimensional *spatial weight matrix* which describes the spatial structure of the states in our analysis.[3] We use a so-called *binary contiguity (BC) matrix*, with entry (i,j) equal to the

[2] In fact, this constant captures any time-varying variable that is constant over all states. For instance, it captures the total number of states which have deregulated their banking sector at a certain point in time.

[3] Note that the model in Equation (5.2) and (5.3) can be written as: $\boldsymbol{y}_t = \boldsymbol{\alpha} + \beta_t + \boldsymbol{X}_t\boldsymbol{\gamma} + (\boldsymbol{I}_N - \lambda\boldsymbol{W})^{-1}\boldsymbol{\varepsilon}_t$. Since this is a non-linear model, we estimate it by means of Maximum Likelihood estimation using Stata's *xsmle* package.

inverse of the number of neighbors of state i if states i and j share a border and 0 otherwise.[4] Intuitively, this means that it is assumed that the error of a particular state in year t depends on the average error of its neighbors in the same period. Note that the expression of the error term in Equation (5.3) is similar to that of the error in a first-order autoregressive (AR(1)) model, with the difference that it includes the term $\boldsymbol{W}\boldsymbol{u}_t$ (a spatial lag) rather than $\boldsymbol{u}_{t-1}$ (a temporal lag). Indeed, the SEM model with a BC matrix can be interpreted as the spatial counterpart of an AR(1) model. Where the AR(1) model assumes that the error in one period is only directly affected by the error in the previous period, the SEM with a BC matrix assumes that the error in one state is only directly affected by the errors in its immediate neighbors. We test for the presence of spillovers by testing the significance of λ, which would indicate spatial correlation in the error term, and by comparing the estimates of the SEM with those of the base model using a spatial Hausman test based on Pace & LeSage (2008). In the presence of spillovers, we expect a significant difference between the estimates of the two models and a positive and significant estimate of λ.

If the results of the models above suggest that spillover effects are present, these spillovers can be modelled in different ways. First, deregulation in one state could directly affect growth in neighboring states. This is called a *local* spillover, because the spillover effect crosses only one border in any direction. This type of spillover may occur if firms from neighboring states are able to borrow from banks in a deregulating state, so that deregulation affects the funding of firms in neighboring states. In contrast, a *global* spillover would occur if changes in growth itself spill over to neighboring states. This type of spillover may occur if states are economically dependent on one another, for instance due to trade linkages or commuters. If this is the case, the change in the growth rate of neighboring states will in turn spill over to neighbors of those neighbors, and so on, which is why the process is referred to as a global spillover. Obviously, local and global spillover effects are not mutually exclusive and may occur simultaneously. Since we want to take into account the potential occurrence of both local and global spillovers, we estimate the so-called Spatial Durbin Model (SDM) (Anselin, 1988; LeSage & Pace, 2009).[5] This model allows for spillovers of both types

[4] We also considered a so-called *inverse distance matrix*, in which entry (i, j) equals the inverse of the geographical distance between the centroids of states i and j. However, Bayesian posterior model probabilities clearly indicate that a binary contiguity matrix better describes the spatial structure of the data.

[5] We also considered models which only allow for local spillovers. However, Bayesian posterior model probabilities suggest that the SDM best describes our data.

of spillovers and is specified as follows:

$$\boldsymbol{y}_t \quad = \quad \boldsymbol{\alpha} + \beta_t + \rho \boldsymbol{W} \boldsymbol{y}_t + \boldsymbol{X}_t \boldsymbol{\gamma} + \boldsymbol{W} \mathbf{X}_t \boldsymbol{\theta} + \boldsymbol{\varepsilon}_t. \tag{5.4}$$

Here, the inclusion of the term $\boldsymbol{W}\boldsymbol{y}_t$ captures the idea that an increase in the growth rate of a given state may effect growth in other states. Furthermore, the inclusion of the term $\boldsymbol{W}\mathbf{X}_t$, captures the idea that intastate branching and interstate banking deregulation in one state may effect growth in other states.[6] Estimation of the SDM allows for a distinction between the direct effect and the spillover effect of deregulation on growth. The direct effect refers to the effect of deregulation on growth in the deregulating itself, whereas the spillover effect refers to the cumulative effect of deregulation on growth in all other states. It should be noted, however, that the estimated coefficients of Equation (5.4) do not correspond directly with the marginal effects of deregulation. In the SDM, marginal effects typically vary by state and depend in a complicated way on the spatial structure of the data.[7] The interested reader is referred to LeSage & Pace (2009) and Elhorst (2014) for a more thorough discussion of the SDM model.

5.3.2 Local-level analysis

As Huang (2008) correctly points out, a state-level analysis has the drawback that it can never entirely rule out reverse causality running from (expectations of future) growth to deregulation, since the *decision* to deregulate is taken at the state level as well. For this reason, we continue our study by following Huang (2008) and analyzing the relationship between deregulation and growth at the local level. In accordance with the existing literature, we define a local banking market as either a county (for non-metropolitan counties) or a metropolitan statistical area (MSA). For simplicity, we refer to local banking markets as counties in the remainder of this chapter.

We perform our analysis by matching counties from different states into pairs

[6]The model in Equation 5.4 is non-linear, and can be written as $\boldsymbol{y}_t = (\boldsymbol{I}_N - \rho\boldsymbol{W})^{-1}\big(\boldsymbol{\alpha} + \beta_t + \boldsymbol{X}_t\boldsymbol{\gamma} + \boldsymbol{W}\mathbf{X}_t\boldsymbol{\theta} + \boldsymbol{\varepsilon}_t\big)$. We estimate it by means of Maximum Likelihood estimation using Stata's *xsmle* package.

[7]More specifically, whereas the (constant) marginal direct effects of deregulation correspond with the estimates in $\boldsymbol{\gamma}$ for the OLS and SEM, the (state-specific) marginal direct effects are represented by the diagonal elements of the N-dimensional matrix $\big[(\boldsymbol{I}_N - \rho W)^{-1}\gamma_k\big]$ for k $= 1, 2$ in the SDM. In a similar sense, the (state-to-state-specific) marginal spillover effects in the SDM are equal to the off-diagonal elements of the N-dimensional matrix $\big[(\boldsymbol{I}_N - \rho W)^{-1}(\gamma_k + \boldsymbol{W}\theta_k)\big]$. See Vega & Elhorst (2013) for a proof.

and analyzing how differences in economic growth within these pairs are related to differences in the timing of banking sector deregulation in the respective counties' states. We do this by estimating the following model:

$$y_{ipt} = \alpha_{ip} + \beta_{pt} + \gamma_1 intra_{ipt} + \gamma_2 inter_{ipt} + \boldsymbol{\delta}^T \boldsymbol{z}_{itp} + \varepsilon_{ipt}, \tag{5.5}$$

where y_{ipt} is the rate of per capita GDP growth in county i $(i = 1, 2)$ of county-pair p in year t, α_{ip} is a county-specific constant and β_{pt} is a pair-year-specific constant. Furthermore, $\boldsymbol{z}_{itp}$ is a vector of county-specific control variables, and $\boldsymbol{\delta}$ is a vector of coefficients which indicate their effect on GDP growth. By controlling for county and pair-year fixed effects, we only use the within-pair variation in growth rates to identify the effect of deregulations on growth. Our analysis thus takes only the other county in a given pair as the control county, whereas in a traditional regression analysis, *all* other counties are used as controls. Implicitly, a traditional regression analysis assumes that one county in the U.S. is as good a control as any other, whereas we specifically match counties to obtain appropriate controls.[8]

An important issue in our setup is the way in which counties are matched. As was explained above, we have to use a matching procedure which results in matched counties that are comparable with each other, without losing the ability to identify an effect of deregulation on growth in the presence of spillover effects. Since matching counties purely on the basis of geography, as is done by Huang (2008), gives high comparability but low identifiablity, we pursue a different approach. More specifically, our matching procedure is as follows. First, we collect data on the population, average level of education and per capita income of each county in 1970. We then do a principal component analysis, using these three variables and a dummy variable which indicates whether or not the county represents a metropolitan statistical area (MSA). We order the counties on the basis of their value on the resulting first principal component and match on the basis of that ordering. That is, the first county is matched with the second, the third with the fourth, and so forth. The idea behind this procedure is that we match counties which are relatively similar in terms of population size, educational attainment, income per capita and degree of urbanization. Given these observable variables, two counties in the same pair would therefore be expected to have undergone deregulations of their banking sector at approximately the same time. In this sense,

[8] Including pair-year fixed effects is conceptually equivalent to estimating the model at the county-pair level and expressing all variables as the difference between the two counties in the county-pair.

our procedure resembles that of propensity score matching (PSM), a procedure that is often used to estimate treatment effects in a cross-sectional setting.[9] In our case, *all* counties are eventually treated, but there is variation in the *timing* of the treatments. By comparing growth rates of counties that are expected to have been deregulated in the *same* year (given the data of 1970), but in reality were deregulated in *different* years, we are able to identify a causal effect of deregulation on growth. To check the robustness of our results, we repeat the above-mentioned procedure using OLS instead of PCA. Here, the intrastate branching and interstate banking dummies are used as the dependent variable, whereas the variables used in the PCA are included as explanatory variables. Using a similar reasoning as before, counties are matched on the basis of the predicted timing of their deregulations.

Note that we sort the counties by four main geographic regions in the U.S. before matching them, so that matched counties are always from the same region.[10] This ensures that counties are similar with respect to unobservable variables that are constant within regions. We prefer to account for geography in this way rather than by including a geographic variable in the PCA, since the latter strategy would likely result in county pairs consisting of neighboring or otherwise very approximate counties. As argued above, comparing counties that are geograpically very close to one another is problematic, due to the potential spillover effects that may result from deregulation.

5.4 Data

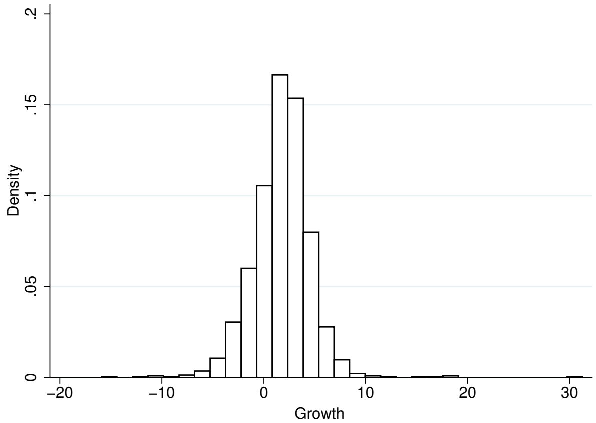
Our sample includes the 48 states of the contiguous United States and runs from 1970 to 2000. We collect state-level and county-level income data from the Bureau of Economic Analysis. Our dependent variable, economic growth, is calculated as the annual percentage change in the level of per capita personal income expressed in 1983 U.S. dollars. Nominal income figures are deflated using a national consumer price index taken from the Bureau of Labor Statistics. The average state-level growth rate in the sample period is 1.76%. As shown in Figure 5.1a, growth rates at the state level are typically between -10% and 10%, although there are a few outliers.

On the county level, the variation in growth rates around the mean of 1.93%

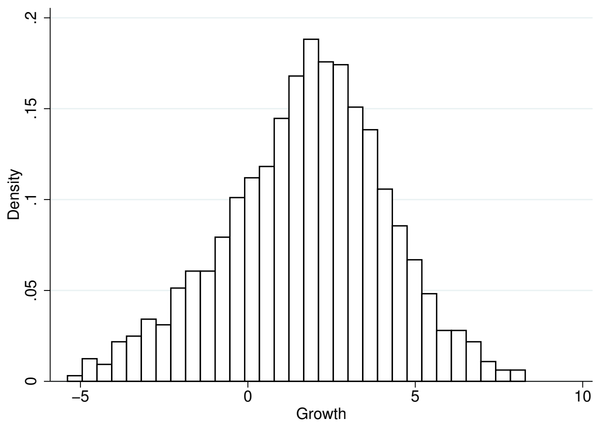
[9] See Rosenbaum & Rubin (1983) and Dehejia & Wahba (2002) for details about this method.

[10] These regions are the West, Midwest, Northeast and South. We follow Jayaratne & Strahan (1996) in this respect.

Figure 5.1: Distribution of state-level growth rates of real income per capita including (a) and excluding (b) the 1st and 99th percentile of the distribution.

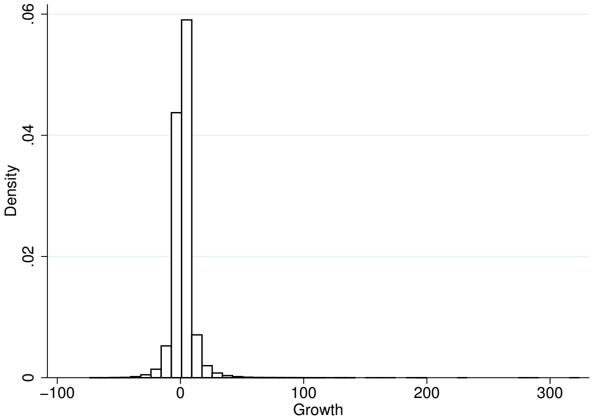


(a)

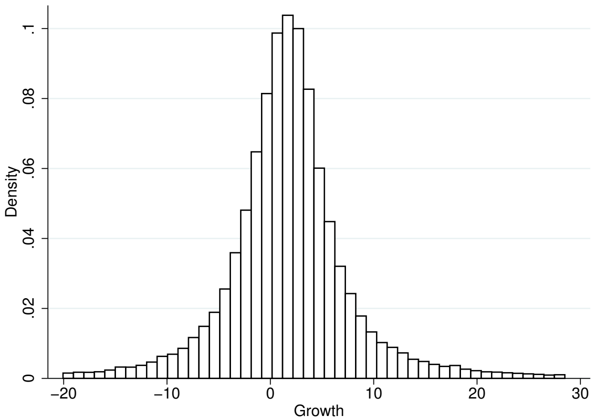


(b)

Figure 5.2: Distribution of local growth rates of real income per capita including (a) and excluding (b) the 1st and 99th percentile of the distribution.



(a)



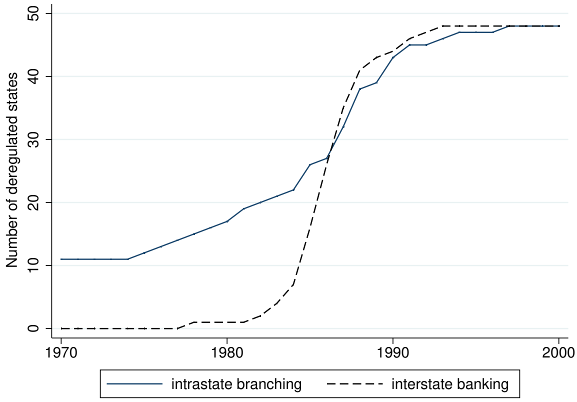
(b)

is significantly larger and outliers pose a bigger problem, as can be seen in Figure 5.2a. However, as Figures 5.1b and 5.2b illustrate, censoring the data at the 1% level removes all outliers. For this reason, we estimate the state-level models on winsorized data in a robustness check, where the growth rates are winsorized at the 1% level. Moreover, we estimate the local-level models on winsorized data only, since outliers are too large of a problem on the local level. Winsorizing the data ensures that our results are not be driven by outliers, without throwing away information. We apply the Harris-Tzavalis unit-root test and reject the null hypothesis of a unit root in both state-level and local growth rates. Hence, we can safely conclude that income growth is stationary on both levels.

The timing of intrastate branching and interstate banking deregulations are taken from Demyanyk et al. (2007). In the case of intrastrate branching restrictions, a distinction can be made between the year in which a state relaxed restrictions on branching through mergers and acquisitions (M&As) and the year in which it allowed branching through the establishment of new branches (de novo branching). We follow most of the literature by choosing the year in which states allowed branching through M&As as the deregulation year. As shown in Figure 5.3, intrastate branching restrictions had already been relaxed in 11 states at the beginning of our sample period. After 1970, the number of states that allowed intrastate branching without any restrictions gradually increased, until all 48 states did so in 1997. On the contrary, not a single state allowed out-of-state banks to enter its market in 1970, but most states relaxed interstate banking restrictions in the 1980s. Since we do not know the exact date at which states deregulated their banking sectors and since we expect that it will take some time before these deregulations affect economic growth, we construct our deregulation dummies in such a way that they have a value of 1 in the years *after* deregulation has taken place, and a value of 0 in the years before and the year of the deregulation.

Data on education in 1970 is taken from the U.S. Census Bureau, which distinguishes between four levels educational attainment. These four levels correspond to people with (i) less than a high school diploma, (ii) a high school diploma, (iii) some college, and (iv) four years of college or higher. For every county, we calculate an *educational attainment index* by giving 1 point to each person with less than a high school diploma, 2 points to persons with only a high school diploma, and so on, and then taking the average number of points per inhabitant. Data on GDP per capita and

Figure 5.3: Number of states that have relaxed restrictions with respect to intrastate branching and interstate banking.



the number of inhabitants per county in 1970 are taken from the Bureau of Economic Analysis. Finally, geographic data used to construct the spatial-weight matrices are obtained from Merryman (2005).

5.5 Results

We describe the results of our state-level estimations below. The results of the matched county-pairs analysis follow in the second subsection.

5.5.1 State-level analysis

Main analysis. The estimated coefficients of our state-level models are reported in Table 5.1. The estimates of the base model suggest that both intrastrate branching deregulation (intra) and interstate banking deregulation (inter) have a significant effect on growth (column 1). This finding is in line with earlier studies in the literature that use a state-level model to assess the effects of banking deregulation (Jayaratne & Strahan, 1996; Strahan, 2003). Once we allow for spatial autocorrelation in the error term by estimating the SEM model, however, the significance of both coefficients disappears (column 2). Moreover, the change from significant to non-significant coefficients does not result from an increase in the standard errors, but from a drop in the estimates. As explained in Section 5.3, this suggests that both the base model and the SEM are misspecified. To formally test for misspecification, we conduct a Hausman test based on Pace & LeSage (2008). The idea behind this test is the following: if the models are correctly specified, which means that the true data-generating process (DGP) is correctly described by either Equation (5.1) or Equation (5.2), the OLS estimates will be consistent, while the SEM estimates will be consistent and efficient. This implies that the estimated coefficients of the two models should be approximately the same. A significant difference between the estimates of the two models thus suggests that they are both misspecified. The Hausman test gives a chi-square statistic of 14.5, which is significantly different from zero at any reasonable significance level. We thus reject the null hypothesis that the two models have equal coefficients and conclude that they are misspecified. Since the estimated spatial correlation coefficient (lambda) is positive and highly significant, we interpret this finding as an indication that spillover effects may be present.

The estimates of the SDM confirm this interpretation (column 3). They suggest that interstate banking deregulation has had a significant effect on economic growth in both the deregulating state as well as neighboring states. The point estimates suggest that interstate banking deregulation resulted in an increase in growth of around 0.5 percentage points, whereas the spillover effect on other states is found to be approximately 2.3 percentage points. Both effects are found to be statistically significant at the 1% level of signifance. The spillover effect may seem unrealistically large, but it should be pointed out that the estimated spillover effect refers to the *cumulative* effect on *all* other states. This makes it difficult to compare the size of the spillover effect with the direct effect. One way in which this could be done is by dividing the point estimate of the cumulative spillover effect by 47, which gives an average spillover effect of approximately 0.05 percentage points on the growth rate of a random other state. Clearly, the estimated spillover effect is larger for neighboring states than for states located furher away, since (i) neighboring states are affected by both local and global spillover effects, whereas states located further away only experience global spillovers, and (ii) neighboring states experience first-order spilover effects, whereas other states are only affected by second-order or higher-order spillovers. As such, we believe that the statistical significance of the spillover effect is more relevant than its precise point estimate. In contrast to our results regarding interstate banking deregulation, we find only weak evidence in favor of a direct effect of intrastrate branching deregulation on economic growth, and no evidence for a spillover effect of intrastate branching deregulation.

Since the data indicate that there is a small probability that the Spatial Durbin Error model (SDEM) (LeSage & Pace, 2009) provides a better description of the data, we present its estimates in the final column.[11] The estimates confirm our findings, as we again find significant direct effects and spillover effects of interstate banking deregulation on growth, but no significant effect of intrastate branching deregulation. Tihs result is in line with Strahan (2003) and Stiroh & Strahan (2003), who find stronger effects of interstate banking deregulation than of intrastate branching deregulation on the number of acquisitions and the degree of market share reallocation in the banking industry.

Robustness checks. We perform a wide range of robustness checks. The results of the SDM are reported in Table 5.2 and those of the SDEM are reported in Table 5.3. Both tables have the same structure. In column (1), we report the results after having dropped Delaware from the sample. As explained by Jayaratne & Strahan (1996), Delaware passed a law in 1982 which provided a tax incentive for credit card banks to locate there. As a result, Delaware's banking industry grew extremely fast in the years following the passage of this law.[12] Column (2) gives the results when we use winsorized growth data, where the data are winsorized at the 1st and 99th percentile of the distribution. In column (3), we have changed the timing of the deregulation dummies so that they change to 1 in the year in which the deregulation event took place. In column (4), we have included a lagged dependent variable, while we have included lagged real income and its square in column (5). The columns (6) through (8) repeat the pattern of columns (2) through (4), but with lagged real income and its square included. Finally, we include the second lag of real income and its square in column (9), and additionally include a lagged dependent variable in the final column. The lags of real income are included to control for income convergence effects and are expected to have negative coefficients.

[11] The SDEM can be written as: $\boldsymbol{y}_t = \boldsymbol{\alpha} + \beta_t + \boldsymbol{X}_t\boldsymbol{\gamma} + \boldsymbol{W}\mathbf{X}_t\boldsymbol{\theta} + (\boldsymbol{I}_N - \lambda\boldsymbol{W})^{-1}\boldsymbol{\varepsilon}_t$. Hence, it captures local spillover effects and a spatially correlated error term, but no global spillover effects. Our Bayesian posterior model probabilities indicate that the probability that the DGP is best described by the SDM is about 4 times as large as the probability that it is best described by the SDEM. For this reason, our focus is on the SDM.

[12] Note that the exclusion of Delaware requires a new spatial weight matrix, with dimension 47 rather than 48. However, since Delaware is a coastal state with only three neighbors, the effect of this change in the spatial weight matrix on the results should be modest.

Table 5.1: Estimation results of the base model, SEM, SDM and SDEM.

Dependent variable: growth	(1) OLS	(2) SEM	(3) SDM	(4) SDEM
intra (direct effect)	0.410**	0.178	0.248*	0.247*
	(0.165)	(0.152)	(0.140)	(0.134)
intra (spillover effect)			0.604	0.365
			(0.486)	(0.315)
inter (direct effect)	0.894***	0.285	0.535**	0.544**
	(0.285)	(0.196)	(0.223)	(0.231)
inter (spillover effect)			2.376***	1.524***
			(0.840)	(0.562)
lambda		0.532***		0.523***
		(0.051)		(0.051)
rho			0.523***	
			(0.051)	
Observations	1,488	1,488	1,488	1,488
Number of states	48	48	48	48
R-squared	0.543	0.537	0.551	0.546
Log-likelihood		-2963.9	-2957.7	-2958.9

Notes: This table reports the estimation results of our state-level models. The standard errors are in parentheses and are clustered by state: *** p<0.01, ** p<0.05, * p<0.1. For the direct effect, the marginal effect of deregulation on growth in the state itself is reported. For the spillover effect, the cumulative marginal effect of deregulation of on growth in all other states is reported. Lambda and rho refer to the spatial correlation coefficient of the error term and of the dependent variable, respectively. The R-squared is calculated as the square of the correlation between actual growth and predicted growth, including the state fixed effect. *OLS* refers to the base model (Equation 5.1), *SEM* refers to the Spatial Error Model (Equation 5.2), *SDM* refers to the Spatial Durbin model 5.4, *SDEM* refers to the Spatial Durbin Error model (see footnote 11.

The robustness checks confirm our main findings: we find a positive direct effect of interstate banking deregulation, which is significant at the 5% level of significance at the least, in all specifications. The estimated effect on growth is somewhere in the range of 0.4 to 0.7 percentage points. The estimated spillover effect of interstate banking deregulation is statistically significant at the 1% level of significance in most instances, and at the 5% level in the remaining cases. In line with our baseline model, we do not find robust evidence in favor of an effect of intrastate branching deregulation on growth. The coefficients of lagged real income and its square are significant and have the expected sign. Consistent with the convergence hypothesis (Barro & Sala-i-Martin, 1995), we find that states with a high level of initial income grow slower, but that the marginal effect becomes less pronounced the higher is the level of income. This finding continues to hold when we include the second lag of real income and its square instead of the first lag. Finally, the coefficient of lagged growth is insignificant and quite close to zero, which suggests that a static model is appropriate.

As an additional check, we store the residuals of our baseline models and regress them on a constant and two indicator variables that are equal to one in the three years before a state deregulated intrastate branching and interstate banking, respectively. If Freeman (2002) is correct in arguing that states typically deregulated their banking industry during a recession in an attempt to stimulate growth, we would expect growth rates in the years prior to deregulation to be significantly lower than predicted on the basis of our model. This implies that we should find negative coefficients when we regress the residuals on the two indicator variables. In reality, however, we obtain coefficients that are not significantly different from zero.[13] Hence, there is no evidence that states tended to deregulate their banking industries during economic downturns. Finally, since we apply a differences-in-differences estimator to panel data, the standard errors might be biased downward due to serial correlation, as illustrated by Bertrand et al. (2004). We therefore estimate the standard errors of the base model using a wild boostrap procedure with 10,000 replications. The resulting standard errors are actually slightly smaller than the clustered standard errors reported in Table 5.1.[14] We thus conclude that the significance of our results does not appear to be driven by a downward bias in the standard errors.

[13]The results are available upon request.

[14]Note that we can only apply the wild bootstrap to the base model, since this procedure destroys the spatial strucuture of the dependent variable that is exploited to estimate the SEM, SDEM and SDEM models. The results are available upon request.

Table 5.2: Robustness checks of the Spatial Durbin model (SDM).

Dependent variable: growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
intra (direct effect)	0.257*	0.297**	0.208*	0.254*	0.264	0.311**	0.189	0.250	0.224	0.252
	(0.144)	(0.133)	(0.119)	(0.134)	(0.180)	(0.156)	(0.166)	(0.175)	(0.167)	(0.173)
intra (global spillover)	0.548	0.395	0.653	0.615	1.445**	1.139**	1.376**	1.383**	1.205**	1.356*
	(0.490)	(0.479)	(0.482)	(0.520)	(0.640)	(0.493)	(0.693)	(0.700)	(0.514)	(0.700)
inter (direct effect)	0.552**	0.419**	0.574***	0.551**	0.683***	0.549***	0.636***	0.665***	0.584***	0.675***
	(0.229)	(0.207)	(0.192)	(0.235)	(0.251)	(0.190)	(0.220)	(0.256)	(0.221)	(0.259)
inter (global spillover)	2.458***	2.135***	2.511***	2.440***	2.714***	2.403***	2.516***	2.657***	2.318***	2.697***
	(0.856)	(0.628)	(0.820)	(0.942)	(0.997)	(0.671)	(0.824)	(1.028)	(0.863)	(1.038)
income (t-1)					-2.263***	-1.941***	-1.945**	-2.306***		
					(0.594)	(0.374)	(0.828)	(0.563)		
income-squared (t-1)					0.055***	0.047***	0.048**	0.056***		
					(0.014)	(0.009)	(0.020)	(0.014)		
income (t-2)									-2.068***	-2.283***
									(0.377)	(0.560)
income-squared (t-2)									0.051***	0.056***
									(0.010)	(0.014)
growth (t-1)								0.027		-0.078
								(0.045)		(0.065)
Observations	1,457	1,488	1,488	1,488	1,488	1,488	1,488	1,488	1,488	1,488
R-squared	0.551	0.631	0.553	0.625	0.580	0.577	0.579	0.581	0.579	0.579
Log-likelihood	-2903.6	-2624.9	-2957.1	-2957.4	-2908.8	-2568.6	-2909.8	-2908.1	-2916.3	-2910.3
Number of fips	47	48	48	48	48	48	48	48	48	48

Notes: This table reports the estimation results of the robustness checks of our state-level SDM models (Equation 5.4). The standard errors are in parentheses and are clustered by state: *** p<0.01, ** p<0.05, * p<0.1. For the direct effects, the marginal effect of deregulation on growth in the state itself is reported. For the spillover effect, the cumulative marginal effect of deregulation of on growth in all other states is reported. For the control variables, the estimated coefficients rather than the marginal effects are reported. The R-squared is calculated as the square of the correlation between actual growth and predicted growth, including the state fixed effect.

Table 5.3: Robustness checks of the Spatial Durbin Error model (SDEM).

Dependent variable: growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
intra (direct effect)	0.270**	0.304**	0.206*	0.254*	0.197	0.262*	0.122	0.187	0.177	0.193
	(0.137)	(0.129)	(0.119)	(0.133)	(0.183)	(0.149)	(0.172)	(0.179)	(0.163)	(0.177)
intra (local spillover)	0.382	0.279	0.387	0.384	0.794**	0.644*	0.748*	0.778**	0.672**	0.762**
	(0.316)	(0.333)	(0.302)	(0.327)	(0.377)	(0.341)	(0.403)	(0.384)	(0.324)	(0.383)
inter (direct effect)	0.563**	0.424**	0.588***	0.564**	0.677**	0.539***	0.648***	0.660**	0.595**	0.667**
	(0.236)	(0.214)	(0.190)	(0.237)	(0.267)	(0.202)	(0.227)	(0.269)	(0.233)	(0.271)
inter (local spillover)	1.601***	1.370***	1.647***	1.575***	1.735***	1.555***	1.654***	1.686**	1.523**	1.697**
	(0.582)	(0.447)	(0.518)	(0.589)	(0.662)	(0.505)	(0.543)	(0.663)	(0.591)	(0.666)
growth (t-1)				-0.034				0.037		-0.113
				(0.063)				(0.049)		(0.076)
income (t-1)					-3.020***	-2.564***	-2.983***	-3.110***		
					(0.782)	(0.475)	(0.793)	(0.734)		
income-squared (t-1)					0.071***	0.060***	0.071***	0.073***		
					(0.018)	(0.011)	(0.019)	(0.017)		
income (t-2)									-2.736***	-3.084***
									(0.455)	(0.715)
income-squared (t-2)									0.065***	0.073***
Observations	1,457	1,488	1,488	1,488	1,488	1,488	1,488	1,488	1,488	1,488
R-squared	0.547	0.625	0.547	0.546	0.579	0.657	0.577	0.579	0.573	0.577
Number of fips	47	48	48	48	48	48	48	48	48	48
Log-likelihood	-2904.5	-2626.2	-2958.2	-2958.0	-2900.0	-2558.8	-2901.1	-2898.8	-2911.0	-2901.3
Number of fips	47	48	48	48	48	48	48	48	48	48

Notes: This table reports the estimation results of the robustness checks of our state-level SDEM models (see footnote 11). The standard errors are in parentheses and are clustered by state: *** p<0.01, ** p<0.05, * p<0.1. For the direct effects, the marginal effect of deregulation on growth in the state itself is reported. For the spillover effect, the cumulative marginal effect of deregulation of on growth in neighboring states is reported. For the control variables, the estimated coefficients rather than the marginal effects are reported. The R-squared is calculated as the square of the correlation between actual growth and predicted growth, including the state fixed effect.

Overall, we conclude that it is important to control for spillover effects when estimating the effect of banking deregulation on state-level economic growth. Moreover, we find a strong effect of interstate banking deregulation on growth, both in the deregulating state itself and through spillovers on neighboring states. However, we do not find robust evidence in favor of an intrastate branching deregulation on growth. In the next subsection, we report the results of our county-level analysis, in which we further investigate whether the relationship between interstate banking deregulation and economic growth can be attributed to a causal effect of deregulation on growth.

5.5.2 Local-level analysis

We now turn to the results of our analysis at the local level. As explained in Section 5.3, we conduct a matched-pairs analysis at the local level to rule out the possibility that the positive relationship between deregulation and economic growth might be the result of reverse causality running from (expectations of) growth to deregulation. The main idea behind the procedure is to compare the growth rates of counties that have been deregulated at different points in time, but which have similar characteristics and which would therefore have been expected to deregulate at the same time given these characteristics. Conceptually, the analysis is quite similar to that of propensity score matching (PSM) in an experimental setting. Whereas PSM compares treated and non-treated subjects with an a priori equal *probability* of having been treated, we compare subjects with a different *timing* of the treatment and with an a priori equal *expected* timing of the treatment. We consider three different matching procedures.

The first procedure is based on a PCA, with the following variables: income per capita in 1970, the population in 1970, the average level of education in 1970 and a dummy indicating that the county is located in a metropolitan statistical area. The first principal component of these four variables explains more than half of the variation in these variables and has positive factor loadings on all variables. We match counties based on this first principal component, which has a correlation of 0.82, 0.53, 0.82 and 0.67, respectively, with the four variables. Hence, on one end of the spectrum we compare urban, high-income, high-education counties with each other, whereas on the other side of the spectrum we match rural, low-income, low-education counties. The second and third matching procedure are based on OLS, where we regress the timing of intrastate branching (2) and interstate banking (3) in the county on the above-mentioned observables. Counties are matched on the basis

Table 5.4: Estimated coefficients of the two regressions performed to match local markets.

	(1)	(2)
Dependent variable:	intra	inter
intercept	1,985.7***	1,981.1***
	(1.761)	(0.408)
income	-0.850**	0.059
	(0.384)	(0.089)
population	-1.755**	-0.417**
	(0.817)	(0.189)
education	0.736	3.541***
	(1.400)	(0.325)
metro	-2.791***	-1.561***
	(0.665)	(0.154)
Observations	2,271	2,271
R-squared	0.023	0.110

Notes: This table reports the estimation results of the two regressions performed to match local markets. The standard errors are conventional: *** p<0.01, ** p<0.05, * p<0.1. *intra* refers to intra-state branching restrictions, *inter* refers to inter-state banking restrictions. *Education* refers to the educational attainment index, as explained in 5.4. *Metro* refers to a dummy indicating whether the local market consists of a Metropolitan Statistical Area.

of the predicted timing of intrastate branching and interstate banking deregulation in the county's state. The results of the regressions are reported in Table 5.4. Since we are not interested in the estimates themselves, but only in the predicted timing of deregulations, we report conventional standard errors. The significance of the estimates should thus be interpreted with caution.

After having matched local banking markets on the basis of the three above-mentioned procedures, we estimate the effects of banking market deregulation by estimating Equation (5.5) with a wide range of alternative specifications. As can be seen in the equation, we include pair-specific time fixed effects in the model. The identification of the coefficients associated with intrastate branching and interstate banking deregulation is thus purely based on the variation in the timing of deregulations within each county pair. The results are reported in Tables 5.5, 5.6 and 5.7, where every table corresponds to one of the matching procedures. The three tables have the same structure. Column (1) gives the results of our baseline model, after which a wide range of robustness checks folllow. The results in column (2) arise once we omit all counties from Delaware from the sample. Column (3) gives the results when the timing of the deregulation dummies is such that they have a value of 1 in the deregulation year. In column (4), we have included a lagged dependent variable in the set of regressors. In columns (5) through (8) we repeat the pattern of columns (1) to (4) after having included the lag of real income and its square to the model. Finally, columns (9) through (12) repeat the pattern again, but now we have included the *second* lag of real income and its square instead of the first lag.

The picture that emerges from the three tables is that there is robust evidence in favor of the view that interstate banking deregulation has a positive effect on growth, which confirms the results of our state-level analysis. The estimate of the effect of interstate banking deregulation is statistically significant at the 1% or 5% level of significance in 31 of the 36 specifications. In the remaining specifications, it is significant at the 10% level of significance. The effect is also economically important: with a few exceptions, the estimate of the coefficient associated with the interstate banking deregulation dummy suggests an effect of deregulation on growth of 0.5 to 1.0 percentage points. Consistent with the results of the state-level model, we find that the intrastate branching deregulation dummy has a coefficient which is not significantly different from zero in the majority of cases. This finding is in line with the results of Huang (2008), who also obtains a statistically non-significant relationship between intrastate branching deregulation and economic growth in the majority of cases.

As expected, we find that counties with an initially high level of income per capita grow more slowly compared with counties with a low initial level of income per capita. Consistent with the convergence hypothesis, we also find the strenght of this relationship decreases with higher levels of (initial) income per capita. Most importantly, the estimated coefficient of interstate banking deregulation remains significant once we control for lagged income per capita. This suggests that our results are not explained by differences in growth opportunities between regulated and deregulated counties. The negative estimates of the coefficient associated with lagged economic growth could also be explained by a convergence effect: if a county grows relatively fast compared with the county with which it is paired, we might expect the other county to catch up in the next period, given that the two counties are relatively similar with respect

Table 5.5: Estimation results of local-level model, matching based on Principal Component Analysis.

Dependent variable: growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intra	0.227	0.229	-0.057	0.214	-0.198	-0.201	-0.494*	-0.164	0.083	0.083	-0.228	-0.143
	(0.182)	(0.182)	(0.147)	(0.214)	(0.276)	(0.277)	(0.282)	(0.266)	(0.173)	(0.173)	(0.150)	(0.252)
inter	0.882***	0.884***	0.763***	1.019***	0.940**	0.942**	0.619**	1.004***	0.803***	0.805***	0.656***	1.003***
	(0.293)	(0.294)	(0.261)	(0.348)	(0.354)	(0.355)	(0.239)	(0.372)	(0.291)	(0.292)	(0.217)	(0.364)
growth (t-1)				-0.192***				-0.083***				-0.300***
				(0.013)				(0.011)				(0.018)
income (t-1)					-4.777***	-4.778***	-4.782***	-4.338***				
					(0.405)	(0.405)	(0.404)	(0.392)				
income-squared (t-1)					0.091***	0.091***	0.091***	0.084***				
					(0.011)	(0.011)	(0.011)	(0.010)				
income (t-2)									-1.913***	-1.913***	-1.920***	-3.753***
									(0.169)	(0.169)	(0.168)	(0.292)
income-squared (t-2)									0.034***	0.034***	0.034***	0.066***
									(0.005)	(0.005)	(0.005)	(0.006)
Pair-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,308	70,246	70,308	68,040	70,308	70,246	70,308	68,040	68,040	67,980	68,040	68,040
R-squared	0.634	0.634	0.634	0.659	0.691	0.691	0.691	0.697	0.648	0.648	0.648	0.692

Notes: This table reports the estimation results of our local-level models in the case where local markets are matched by means of a principal component analysis. The standard errors are in parentheses and are clustered by state: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Intra* refers to intrastate branching restrictions, *inter* refers to interstate banking restrictions. For the control variables, the estimated coefficients rather than the marginal effects are reported. The R-squared is calculated as the square of the correlation between actual growth and predicted growth, including the state fixed effect.

Table 5.6: Estimation results of local-level model, matching based on OLS with intrastate branching.

Dependent variable: growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intra	0.414**	0.416**	0.169	0.410*	-0.077	-0.078	-0.387	-0.037	0.181	0.182	-0.092	-0.025
	(0.178)	(0.178)	(0.178)	(0.209)	(0.338)	(0.339)	(0.363)	(0.315)	(0.184)	(0.185)	(0.195)	(0.295)
inter	0.729**	0.731**	0.697**	0.863**	0.733*	0.734*	0.497*	0.796**	0.632*	0.634*	0.566**	0.804**
	(0.343)	(0.344)	(0.269)	(0.381)	(0.381)	(0.382)	(0.271)	(0.394)	(0.315)	(0.316)	(0.229)	(0.377)
growth (t-1)				-0.191***				-0.085***				-0.297***
				(0.012)				(0.010)				(0.022)
income (t-1)					-5.057***	-5.057***	-5.064***	-4.521***				
					(0.353)	(0.353)	(0.349)	(0.334)				
income-squared (t-1)					0.103***	0.103***	0.104***	0.093***				
					(0.009)	(0.009)	(0.009)	(0.008)				
income (t-2)									-2.086***	-2.086***	-2.093***	-4.074***
									(0.182)	(0.182)	(0.179)	(0.414)
income-squared (t-2)									0.042***	0.042***	0.042***	0.081***
									(0.004)	(0.004)	(0.004)	(0.011)
Pair-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,308	70,246	70,308	68,040	70,308	70,246	70,308	68,040	68,040	67,980	68,040	68,040
R-squared	0.634	0.634	0.634	0.660	0.693	0.693	0.693	0.699	0.647	0.647	0.647	0.693

Notes: This table reports the estimation results of our local-level models in the case where local markets are matched by means of OLS with the timing of intrastate branching deregulation as the dependent variable. The standard errors are in parentheses and are clustered by state: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*Intra* refers to intrastate branching restrictions, *inter* refers to interstate banking restrictions. The R-squared is calculated as the square of the correlation between actual growth and predicted growth, including the state fixed effect.

Table 5.7: Estimation results of local-level model, matching based on OLS with interstate banking.

Dependent variable: growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intra	0.312	0.314	0.097	0.277	-0.020	-0.013	-0.286	-0.019	0.124	0.127	-0.119	-0.031
	(0.223)	(0.223)	(0.164)	(0.257)	(0.288)	(0.289)	(0.284)	(0.286)	(0.212)	(0.212)	(0.175)	(0.282)
inter	0.617**	0.617**	0.594**	0.711**	0.795**	0.794**	0.629***	0.818**	0.604**	0.604**	0.578***	0.820**
	(0.287)	(0.287)	(0.261)	(0.336)	(0.336)	(0.336)	(0.222)	(0.353)	(0.282)	(0.282)	(0.212)	(0.343)
growth (t-1)				-0.188***				-0.084***				-0.290***
				(0.013)				(0.010)				(0.020)
income (t-1)					-4.715***	-4.715***	-4.714***	-4.296***				
					(0.385)	(0.385)	(0.383)	(0.363)				
income-squared (t-1)					0.093***	0.093***	0.093***	0.087***				
					(0.012)	(0.012)	(0.012)	(0.010)				
income (t-2)									-2.050***	-2.049***	-2.051***	-3.781***
									(0.141)	(0.141)	(0.140)	(0.332)
income-squared (t-2)									0.040***	0.040***	0.040***	0.072***
									(0.005)	(0.005)	(0.005)	(0.010)
Pair-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,308	70,246	70,308	68,040	70,308	70,246	70,308	68,040	68,040	67,980	68,040	68,040
R-squared	0.634	0.634	0.634	0.659	0.691	0.691	0.691	0.697	0.648	0.648	0.648	0.692

Notes: This table reports the estimation results of our local-level models in the case where local markets are matched by means of OLS with the timing of interstate banking deregulation as the dependent variable. The standard errors are in parentheses and are clustered by state: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Intra* refers to intrastate branching restrictions, *inter* refers to interstate banking restrictions. The R-squared is calculated as the square of the correlation between actual growth and predicted growth, including the state fixed effect.

to the characteristics on which they are matched.

Overall, we conclude that there is robust evidence in favor of a positive effect of interstate banking deregulation on economic growth. This effect is estimated to be somewhere in the range of 0.6 to 1 percentage point and remains significant after we control for spatial autocorrelation, local and global spillover effects, growth opportunities and potential reverse causality. The result also continues to hold when we use (panel-)bootstrapped instead of conventional (clustered) standard errors.[15] We do not obtain robust evidence in favor of an effect of intrastate branching deregulation on growth, however. This latter finding is in line with earlier work by Huang (2008), who compares contiguous counties across state borders to identify the effect of intrastate branching deregulations and also fails to find a robust effect on growth.

5.6 The role of competition

It is often argued that the deregulation of restrictions in banking may strengthen economic growth by increasing the degree of competition in the banking industry. For instance, Chava et al. (2013) argue that interstate banking deregulations decreased the local market power of banks and thereby allowed private firms dependent on banks for finance to innovate more. Cornaggia et al. (2015) even go so far as to equate interstate banking deregulation with an increase in banking competition. To test the hypothesis that interstate banking deregulation positively affected growth by increasing the degree of banking competition, we investigate two potential channels through which an increase in banking competition might affect growth. First, an increase in competition might reduce interest rate margins by increasing deposit rates and lowering loan rates. This reduction in interest margins should stimulate savings and investments, thereby contributing to growth (Hannan, 1991; Besanko & Thakor, 1992; Pagano, 1993; Smith, 1998; Guzman, 2000). Second, a higher degree of competition in the industry might force banks to become more efficient, since only the most efficient banks will be able to survive in a highly competitive environment (Koetter et al., 2012). The resulting increase in banks' efficiency allows a larger proportion of savings to be used for investments in the real economy, so that economic growth increases (Pagano, 1993; Allen & Gale, 2000; Vives, 2001). If the positive effect of interstate banking deregulation on economic growth can be explained by the effect

[15]The results are avaiable upon request.

of these deregulations on the competitiveness of the banking industry, we would thus expect a negative relationship between interstate banking deregulation and interest rate margins and/or a positive relationship between interstate banking deregulation and banks' efficiency.

To investigate this issue, we proceed as follows. We first estimate a translog cost function with one output (total assets) and three inputs (deposits, labor and physical capital) for each year in the period from 1976 to 2000, using data of one-state banks from the FDIC's Call Reports.[16] We follow Koetter et al. (2012) in our specification of the cost function, with the difference that we use one output (total assets), whereas Koetter et al. (2012) use two outputs (total loans and total securities). The variables included in the cost function are reported in Table 5.8.

The output of the estimated cost functions is used for two purposes. First, the output can be used to obtain an estimate of banks' marginal costs, which in turn is used to construct the Lerner index. More specifically, we obtain an estimate of a bank's marginal cost by taking the first derivative of the estimated translog cost function with respect to output. The Lerner index is then calculated as follows:

$$L_{it} = \frac{p_{it} - \widehat{mc}_{it}}{p_{it}} \tag{5.6}$$

where L is the Lerner index, p is the output price, calculated as the ratio of a bank's operating income to total assets, and $\widehat{mc}$ is the estimated marginal cost. We use the Lerner index to capture the above-mentioned interest margin effect of banking competition. The benefit of using the Lerner index rather than a direct measure of the interest margin is that the Lerner index takes into account changes in banks' operating costs. Note that the Lerner index should be zero in a perfectly competitive market, where price equals marginal cost, and that higher values of the Lerner index indicate a less competitive banking system. Second, we use the residuals of the estimated translog cost functions to obtain an estimate of banks' cost (in)efficiency using the "distribution-free approach" (DFA) of Berger (1993). The idea of this approach is that if banks are cost-efficient, estimation of a translog cost function should give residuals of which the average over time is approximately the same (and close to zero) for all banks. Persistent differences in residuals between banks are thus an indication of differences in efficiency. This implies that the efficiency of a bank in a certain period

[16] The banks that only operate in one state are identified through the use of the FDIC's Summary of Deposits (SOD).

Table 5.8: Overview of variables included in the estimation of cost and profit functions.

Variable	Description	Call Reports variable
Total assets	Total assets in US$	RCFD2170
Cost of labor	Salaries divided by number of FTEs	RIAD4135 / RIAD4150
Cost of fixed assets	Expenditures on fixed assets divided by fixed assets	RIAD4217 / RCFD2145
Cost of borrowed funds	Interest expenses on deposits and fed funds divided by sum of deposits and fed funds purchased	(RIAD4170 + RIAD4180) / (RCFD2200 + RCFD2800)
Total operating costs	Sum of salaries, expenditures on fixed assets and interest expenses on deposits and fed funds	RIAD4135 + RIAD4170 + RIAD4180 + RIAD4217
Profits before taxes	Difference between operating income and total operating costs	RIAD4000 - TOC

Note: This table presents the variables which are included in the translog cost and revenue functions which are estimated in section 5.6. Monetary values are deflated using a national GDP deflator.

can be calculated as follows:

$$EFF_i = \exp(\ln \hat{x}_{min} - \ln \hat{x_i}), \tag{5.7}$$

where EFF_i is the estimated efficiency of bank i, $\hat{x_i}$ is the average of the bank's residuals over the period and $\hat{x}_{min}$ is the average of the residuals of the bank with the lowest average residual. The calculation of banks' efficiency scores thus assumes that the bank with the lowest average residual is cost efficient. The efficiency level of other banks is expressed relative to this bank. Note that the method assumes that banks' efficiency is constant over time, which implies that the number of years used to calculate average residuals cannot be too high. We therefore calculate two averages for each bank. The first average is calculated over the period running from at most 7 years before the bank's state deregulated interstate banking until the year before it deregulated, while the second average is calculated for the period running from the first year after the bank's state deregulated until at most 7 years after the event. Estimated cost efficiencies before and after the deregulation event are then calculated for each bank by Equation (5.7), using either the most efficient bank over the entire U.S., or the most efficient bank in the bank's state in the respective period, as the anchor.[17] Using the most efficient bank over the entire U.S. requires the assumption that there is one cost frontier over the entire country, whereas the latter option allows cost frontiers to vary by state and to be affected by the deregulation event. Note that in addition to being cost-inefficient, banks may also be profit-inefficient. We therefore repeat the procedure above using the residuals from a translog revenue function to obtain estimates of profit (in)efficiency. We use our bank-specific estimates of the Lerner index, cost efficiency and profit efficiency as dependent variables and analyze whether they are affected by interstate banking deregulation.

Tables 5.9 and 5.10 report the number of one-state banks per state and year for which we have data. Note that the Call Reports are only available from 1976 onward, so that our sample period runs from 1976 to 2000. The distribution of Lerner indices is illustrated in Figure 5.4. Almost all observations are in the range of 0.2 to 0.5, which is a common finding in the banking literature and indicates that U.S. banks have some

[17] Note that we winsorize the distribution of residual averages at the 1% and 99% percentile before calculating efficiency levels. This is done to ensure that the estimated efficiencies are not driven by outliers that may arise due to a coincidental series of positive or negative noise in the residuals of a particular bank.

Table 5.9: Number of one-state banks per state and year, 1976 - 1988.

	1976	**1977**	**1978**	**1979**	**1980**	**1981**	**1982**	**1983**	**1984**	**1985**	**1986**	**1987**	**1988**
Alabama	150	155	158	161	162	164	165	167	168	172	174	177	185
Arizona	6	7	9	9	9	9	10	14	13	15	17	17	17
Arkansas	216	217	220	220	221	223	225	226	226	227	227	230	230
California	96	104	113	125	150	172	213	240	272	295	304	319	331
Colorado	164	171	175	182	189	198	210	224	231	241	247	259	262
Connecticut	60	60	61	21	21	21	21	21	20	24	26	30	32
Delaware	11	11	11	11	11	12	16	19	16	19	20	20	22
Florida	159	163	164	169	170	173	180	189	187	207	234	262	285
Georgia	256	259	258	260	262	261	263	263	268	279	285	296	317
Idaho	11	12	12	14	14	14	14	14	14	14	14	14	14
Illinois	808	818	828	834	839	845	846	844	839	841	837	844	850
Indiana	198	199	200	197	197	197	198	199	197	197	197	197	198
Iowa	475	483	486	488	489	490	491	493	495	500	501	502	504
Kansas	399	397	399	399	405	407	408	407	413	424	427	429	431
Kentucky	252	258	259	260	263	265	265	265	265	266	267	267	269
Louisiana	162	161	161	163	168	171	173	177	184	187	189	188	191
Maine	31	31	31	14	14	14	14	13	15	15	15	15	15
Maryland	56	56	56	56	57	57	58	58	59	61	63	65	68
Massachussetts	40	40	40	33	33	33	33	33	34	32	32	37	38
Michigan	176	176	176	177	178	180	182	183	181	182	182	183	183
Minnesota	507	508	514	518	521	522	527	526	529	531	532	536	536
Mississippi	98	99	100	100	100	100	99	99	99	99	101	101	101
Missouri	398	401	402	410	411	414	417	422	424	428	432	437	439
Montana	100	101	102	104	104	105	106	106	106	108	109	111	112
Nebraska	297	300	301	305	307	305	308	311	314	314	315	314	317
Nevada	5	5	6	6	7	9	10	10	12	13	13	13	13
New Hampshire	28	28	28	16	16	16	17	17	15	15	17	18	17
New Jersey	55	55	55	47	47	47	48	47	46	48	49	52	61
New Mexico	62	63	66	66	66	66	67	67	68	73	73	73	73
New York	142	144	148	101	104	105	106	106	92	90	96	99	103
North Carolina	24	24	25	25	25	25	27	31	31	33	35	40	43
North Dakota	117	116	118	119	119	121	122	123	124	124	124	125	125
Ohio	197	197	197	197	196	197	196	196	197	201	201	202	204
Oklahoma	271	282	285	292	295	301	305	314	320	325	325	328	332
Oregon	19	20	23	24	26	28	30	29	31	31	31	31	31
Pennsylvania	194	194	194	192	193	193	193	193	193	195	196	201	208
Rhode Island	6	6	6	4	4	4	4	4	2	3	3	3	3
South Carolina	49	49	49	49	49	49	49	49	49	50	52	57	62
South Dakota	99	100	100	100	100	101	101	101	101	102	104	111	110
Tennessee	183	186	187	188	188	191	192	194	190	193	195	201	206
Texas	683	700	709	722	728	751	776	824	861	896	941	955	962
Utah	18	18	22	23	23	24	24	21	26	29	32	32	31
Vermont	20	20	20	16	16	16	16	16	16	16	16	16	16
Virginia	91	93	96	100	100	103	106	102	108	114	119	123	131
Washington	39	41	44	44	46	48	50	50	48	49	51	51	55
West Virginia	108	110	111	112	112	113	114	114	116	116	117	117	117
Wisconsin	387	387	385	383	384	388	388	388	387	391	390	393	393
Wyoming	35	37	38	40	42	43	44	45	48	49	49	49	49
Total	**7958**	**8062**	**8148**	**8096**	**8181**	**8291**	**8427**	**8554**	**8650**	**8834**	**8976**	**9140**	**9292**

Table 5.10: Number of one-state banks per state and year, 1989 - 2000.

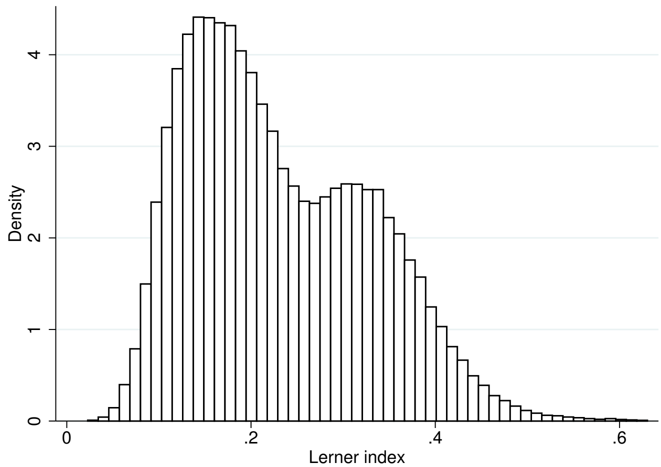
	1989	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**
Alabama	189	191	192	193	193	189	167	164	157	143	139	140
Arizona	18	20	23	24	25	25	25	26	30	29	30	30
Arkansas	231	233	242	243	243	246	233	223	214	191	183	173
California	340	357	370	372	374	359	336	315	291	287	282	267
Colorado	264	267	272	273	276	267	217	209	199	179	172	165
Connecticut	81	82	83	82	82	81	75	64	56	55	50	47
Delaware	24	25	24	23	22	23	24	23	23	22	21	19
Florida	313	326	333	337	339	333	312	268	246	230	252	244
Georgia	334	353	364	370	371	362	359	333	335	330	324	314
Idaho	15	14	16	16	17	15	16	12	11	11	10	11
Illinois	856	857	869	893	917	891	858	827	784	743	721	705
Indiana	202	203	202	203	209	208	200	192	172	155	144	137
Iowa	504	505	507	506	509	501	475	448	430	424	422	416
Kansas	433	435	435	434	438	419	393	381	370	360	350	340
Kentucky	273	278	279	282	285	275	265	262	257	248	236	220
Louisiana	193	196	196	196	199	190	175	162	146	139	143	139
Maine	32	33	34	35	35	35	35	35	32	32	30	29
Maryland	75	77	77	78	79	78	74	71	67	66	62	61
Massachussetts	216	216	218	219	220	211	208	205	199	187	183	184
Michigan	186	189	191	192	192	188	169	167	155	157	166	162
Minnesota	536	541	542	544	545	543	506	497	497	490	472	465
Mississippi	101	102	102	104	106	100	99	99	95	83	87	88
Missouri	442	443	446	445	447	438	423	392	370	348	335	330
Montana	113	114	115	115	115	110	102	98	94	87	83	82
Nebraska	318	319	322	325	327	325	309	301	299	286	278	249
Nevada	13	15	15	15	16	18	21	20	19	21	21	26
New Hampshire	35	38	40	40	40	39	35	34	30	27	25	22
New Jersey	76	85	86	95	103	99	90	81	85	83	81	89
New Mexico	73	73	74	75	75	66	64	63	53	52	47	46
New York	150	153	152	153	154	147	142	137	131	132	131	129
North Carolina	46	48	51	88	102	101	86	76	77	78	76	77
North Dakota	124	126	126	126	126	126	114	110	102	100	100	95
Ohio	207	209	213	215	230	241	243	242	227	208	209	204
Oklahoma	335	334	334	332	337	331	323	312	301	290	281	266
Oregon	31	34	36	36	36	35	35	32	31	33	35	32
Pennsylvania	219	226	236	256	266	261	238	232	226	212	209	205
Rhode Island	6	6	9	9	9	8	7	8	6	5	4	5
South Carolina	68	71	71	71	71	69	66	74	76	72	72	74
South Dakota	111	111	111	111	111	113	107	108	96	94	92	88
Tennessee	210	216	219	220	226	231	221	219	216	189	187	182
Texas	963	968	970	974	979	970	929	873	834	799	756	712
Utah	33	33	35	36	39	39	38	40	39	42	42	43
Vermont	21	21	21	21	21	21	21	19	18	18	17	16
Virginia	133	136	139	140	140	141	136	131	130	126	119	116
Washington	66	72	76	83	81	80	79	77	75	76	80	79
West Virginia	117	118	118	119	119	101	95	91	79	68	62	52
Wisconsin	396	399	400	402	419	397	385	359	355	341	335	309
Wyoming	49	49	49	49	49	47	47	48	47	46	43	39
Total	**9771**	**9917**	**10035**	**10170**	**10314**	**10093**	**9577**	**9160**	**8782**	**8394**	**8199**	**7923**

Table 5.11: Estimation results of Section 5.6.

Dependent variable:	(1) Lerner index	(2) Lerner index	(3) Cost efficiency	(4) Cost efficiency	(5) Cost efficiency	(6) Cost efficiency	(7) Profit efficiency	(8) Profit efficiency	(9) Profit efficiency	(10) Profit efficiency
inter	0.000	-0.001	0.003*	0.003*	0.003*	0.003*	0.014***	0.013***	0.014***	0.013***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Bank fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
State fixed effects	Yes	n.a..	Yes	n.a.	Yes	n.a.	Yes	n.a..	Yes	n.a.
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	207,514	207,210	86,111	85,868	86,111	85,868	86,111	85,868	86,111	85,868
R-squared	0.721	0.841	0.200	0.933	0.192	0.932	0.077	0.811	0.081	0.812

Notes: This table reports the estimation results of our state-level models in which the Lerner index, cost efficiency and profit efficiency are included as dependent variables. The standard errors are in parentheses and are clustered by state: *** p<0.01, ** p<0.05, * p<0.1. Columns 3, 5, 7 and 9 give the results when it is assumed that there is one country-wide cost or profit frontier. Columns 4, 6, 8 and 10 give the results when cost or pofit frontiers are allowed to vary by state and to depend on the deregulation event.

Figure 5.4: Distribution of estimated Lerner indices.



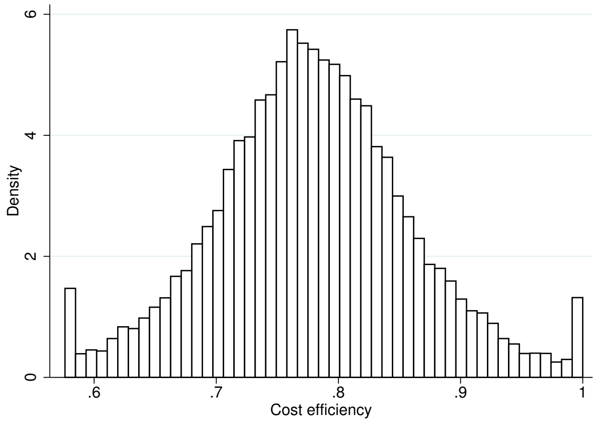
Note: The estimated Lerner indices are based on the estimation results of translog cost and profit functions.

market power.[18] Figure 5.5 illustrates the distribution of estimated cost efficiencies in our sample of banks. The average bank has a cost efficiency of about 80% compared to the most efficient bank, but there is substantial variation in cost efficiencies between banks. Finally, Figure 5.6 shows the distribution of profit efficiencies, which are typically lower than cost efficiencies. Indeed, the average bank has a profit efficiency that is somewhere between 60% and 70% of that of the most efficient bank. Again, there is substantial variation in efficiencies between banks.

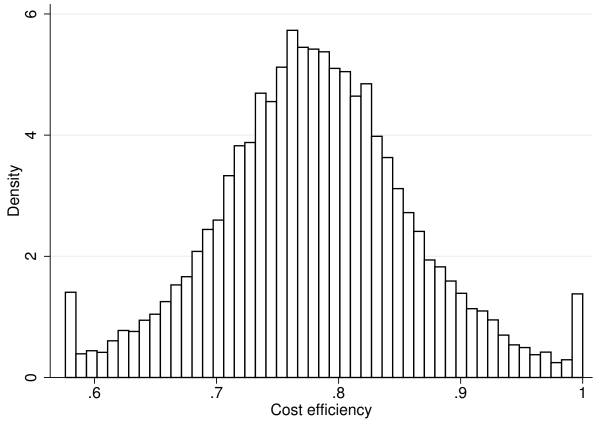
The results of our estimations are reported in Table 5.11. Note that columns 3, 4, 7 and 8 give the results when efficiencies are calculated relative to the most efficient bank country-wide, whereas columns 5, 6, 9 and 10 give the results obtained when efficiencies are calculated relative to the most efficient bank in the bank's state in the period before or after the deregulation event. The results indicate that there is no evidence for the interest margin channel, since Lerner indices appear to be unaffected by interstate banking deregulation. This suggests that banks were able to sustain

[18]We also find that, for 95% of the banks in the sample, marginal costs are below average costs, which indicates the presence of economies of scale.

Figure 5.5: Distribution of cost efficiencies relative to most efficient bank country-wide (panel a) or most efficient bank in the respective state (panel b).



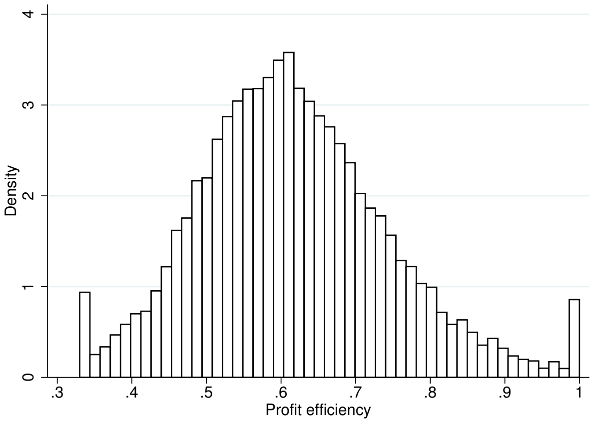
(a)



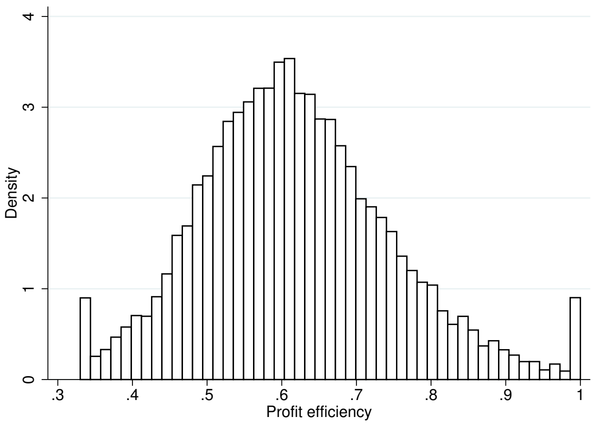
(b)

Note: Efficiency levels are calculated in the basis of winsorized data.

Figure 5.6: Distribution of profit efficiencies relative to most efficient bank country-wide (panel a) or most efficient bank in the respective state (panel b).



(a)



(b)

Note: Efficiency levels are calculated in the basis of winsorized data.

margins in the wake of deregulation events. The estimated effect of interstate banking deregulation on cost efficiency is weakly significant and has the expected positive sign. However, the effect is too small to be economically meaningful. Hence, cost efficiencies do not appear to be responsible for the effect of interstate banking deregulation on growth either. Finally, the estimated effect of interstate banking deregulation on profit efficiencies is positive and statistically significant at the 1% level of significance. The estimates suggest that banks' efficiency increased by 1.3 or 1.4 percentage points (relative to the most efficient bank) after interstate banking deregulation took place. Since the profit efficiency of the average bank in the sample is approximately 0.6, this amounts to a 3.2% to 3.5% increase in efficiency. We believe that this effect is modest, but economically meaningful. There is thus some evidence that interstate banking deregulation affected economic growth through an increase in banking competition, which forced banks te become more (profit) efficient. However, given the relatively large effect of deregulation on growth, it is unlikely that the associated increase in profit efficiency fully explains the growth effects of interstate banking deregulation.

5.7 Conclusion

This chapter has analyzed the effect of state-level deregulations of competitive restrictions in the banking industry on economic growth in the United States. Since these deregulations occured in a staggered way, with different states relaxing restrictions at different points in time, we were able to identify the effect of deregulation on growth. The evidence suggests that there are positive growth effects associated with the relaxation of restrictions on interstate banking, but no evidence is found for an effect of the relaxation of restrictions on intrastate branching. We additionally find that interstate banking deregulation produces spillover effects on neighboring states. A more detailed analysis at the local level confirms these findings. We find that counties in deregulated states experience higher growth compared with counties with similar characteristics that are from states which have not yet been deregulated.

We delved deeper into the issue by analyzing whether banking competition was the channel through which interstate banking deregulation affected growth. If interstate banking deregulation increased the degree of banking competition, we would expect a decrease in interest rate margins and an increase in banks' efficiency following deregulation. The data provide no evidence for an effect of deregulations on interest rate margins, but do indicate that banks increased their profit efficiency following interstate banking deregulation. This indicates that banking competition has likely played a role in the relationship between interstate banking deregulation and economic growth. Given the large growth effects of deregulation, however, we believe that it is unlikely that the (modest) increase in profit efficiency can fully explain the relationship between deregulation and growth. Investigating other potential channels through which interstate banking deregulation affects growth is therefore an interesting avenue for future research.

Bibliography

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, *5*, 224 – 255.

Acharya, V. V., Bharath, S. T., & Srinivasan, A. (2007). Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries. *Journal of Financial Economics*, *85*, 787 – 821.

Acharya, V. V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, *102*, 59–64.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *Review of Financial Studies*, *30*, 2–47.

Acharya, V. V., Santos, J., Yorulmazer, T. et al. (2010). Systemic risk and deposit insurance premiums. *New York FED Economic Policy Review*, (pp. 89–99).

Acharya, V. V., & Yorulmazer, T. (2007). Too many to fail – an analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation*, *16*, 1–31.

Acharya, V. V., & Yorulmazer, T. (2008). Cash-in-the-market pricing and optimal resolution of bank failures. *Review of Financial Studies*, *21*, 2705–2742.

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, *106*, 1705–1741.

Agoraki, M.-E. K., Delis, M. D., & Pasiouras, F. (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability*, *7*, 38–48.

Allen, F., & Carletti, E. (2013). What is systemic risk? *Journal of Money, Credit and Banking*, *45*, 121–127.

Allen, F., & Gale, D. (1994). Limited market participation and volatility of asset prices. *American Economic Review*, *84*, 933–955.

Allen, F., & Gale, D. (2000). *Comparing financial systems*. Cambridge, Massachusetts: MIT Press.

Allen, F., & Gale, D. (2004). Competition and financial stability. *Journal of Money, Credit, and Banking*, *36*, 453–480.

Allen, W. A., & Wood, G. (2006). Defining and achieving financial stability. *Journal of Financial Stability*, *2*, 152–172.

Amore, M. D., Schneider, C., & Žaldokas, A. (2013). Credit supply and corporate innovation. *Journal of Financial Economics*, *109*, 835–855.

Amoroso, L. (1930). La curva statica di offerta. *Giornale degli economisti e rivista di statistica*, *70*, 1–26.

Anginer, D., Demirgüç-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation*, *23*, 1–26.

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Dordrecht, Netherlands: Springer.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*, 77–104.

Ausubel, L. M. (1991). The failure of competition in the credit card market. *American Economic Review*, *81*, 50–81.

Ayadi, R., Llewellyn, D. T., Schmidt, R. H., Arbak, E., & De Groen, W. (2010). *Investigating Diversity in the Banking Sector in Europe: Key Developments, Performance and Role of Cooperative Banks*. Technical Report Centre for European Policy Studies.

Babyak, M. (2004). What you see may not be what you get: A brief, nontechnical introduction to overfitting in regression-type models. *Psychosomatic Medicine*, *66*, 411–421.

Bain, S. (1968). *Industrial Organisation*. New York: John Wiley & Sons.

Barro, R. J., & Sala-i-Martin, X. I. (1995). *Economic Growth*. Cambridge, Massachusetts: MIT Press.

Baumol, W. J. (1982). Contestable markets: An uprising in the theory of industry structure. *American Economic Review*, *72*, 1–15.

Beccalli, E., Anolli, M., & Borello, G. (2015). Are European banks too big? Evidence on economies of scale. *Journal of Banking & Finance*, *58*, 232–246.

Beck, T., Coyle, D., Dewatripont, M., Freixas, X., & Seabright, P. (2010). *Bailing out the banks: Reconciling stability and competition*. Technical Report Centre for Economic Policy Research.

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, *22*, 218–244.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance*, *30*, 1581–1603.

Benoit, S., Colliard, J.-E., Hurlin, C., & Pérignon, C. (2016). Where the risks lie: A survey on systemic risk. *Review of Finance*, *21*, 109–152.

Berger, A. N. (1993). "Distribution-free" estimates of efficiency in the U.S. banking industry and tests of the standard distributional assumptions. *Journal of Productivity Analysis*, *4*, 261–292.

Berger, A. N. (1995). The profit-structure relationship in banking – tests of market-power and efficient-structure hypotheses. *Journal of Money, Credit and Banking*, *27*, 404–431.

Berger, A. N., Goldberg, L. G., & White, L. J. (2001). The effects of dynamic changes in bank competition on the supply of small business credit. *European Finance Review*, *5*, 115–139.

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, *35*, 99–118.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, *119*, 249–275.

Besanko, D., & Thakor, A. V. (1992). Banking deregulation: Allocational consequences of relaxing entry barriers. *Journal of Banking & Finance*, *16*, 909–932.

Besanko, D., & Thakor, A. V. (2003). Relationship banking, deposit insurance and bank portfolio. In C. Mayor, & X. Vives (Eds.), *Capital Markets and Financial Intermediation* (pp. 292–318). Cambridge, U.K.: Cambridge University Press.

Bikker, J. A. (2004). *Competition and efficiency in a unified European banking market*. Cheltenham, U.K.: Edward Elgar Publishing.

Bikker, J. A., & Haaf, K. (2002). Measures of competition and concentration in the banking industry: A review of the literature. *Economic & Financial Modelling*, *9*, 53–98.

Bikker, J. A., Shaffer, S., & Spierdijk, L. (2012). Assessing competition with the Panzar-Rosse model: The role of scale, costs, and equilibrium. *Review of Economics and Statistics*, *94*, 1025–1044.

Bisias, D., Flood, M., Lo, A. W., & Valavanis, S. (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics*, *4*, 255–296.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*, 637–654.

Black, S. E., & Strahan, P. E. (2002). Entrepreneurship and bank credit availability. *Journal of Finance*, *57*, 2807–2833.

Bolt, W., & Tieman, A. F. (2004). Banking competition, risk and regulation. *Scandinavian Journal of Economics*, *106*, 783–804.

Boone, J. (2008). A new way to measure competition. *Economic Journal*, *118*, 1245–1261.

Boot, A. W., & Thakor, A. V. (2000). Can relationship banking survive competition? *Journal of Finance*, *55*, 679–713.

Boyd, J. H., & De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *Journal of Finance*, *60*, 1329–1343.

Boyd, J. H., De Nicolo, G., & Jalal, A. M. (2006). *Bank risk-taking and competition revisited: New theory and new evidence*. Working paper 06/297 IMF.

Boyd, J. H., De Nicolo, G., & Jalal, A. M. (2009a). *Bank Competition, Risk and Asset Allocations*. Working paper 09/143 IMF.

Boyd, J. H., De Nicolo, G., & Loukoianova, E. (2009b). *Banking crises and crisis dating: theory and evidence*. Working paper 09/141 IMF.

Boyd, J. H., Graham, S. L., & Hewitt, R. S. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of failure. *Journal of Banking & Finance*, *17*, 43–63.

Boyd, J. H., & Runkle, D. E. (1993). Size and performance of banking firms: Testing the predictions of theory. *Journal of Monetary Economics*, *31*, 47–67.

Bresnahan, T. F. (1982). The oligopoly solution concept is identified. *Economics Letters*, *10*, 87–92.

Brown, D. T., Ciochetti, B. A., & Riddiough, T. J. (2006). Theory and evidence on the resolution of financial distress. *Review of Financial Studies*, *19*, 1357 – 1397.

Brownlees, C., & Engle, R. F. (2016). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, *30*, 48–79.

Brozen, Y., & Bittlingmayer, G. (1982). *Concentration, mergers, and public policy*. New York: Free Press.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, *22*, 2201–2238.

Calem, P. S., & Mester, L. J. (1992). *Search, switching costs, and the stickiness of credit card interest rates*. Working paper 92-24 Federal Reserve Bank of Philadelphia.

Cameron, A., Gelbach, J., & Miller, D. (2008). Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics*, *90*, 414–427.

Caminal, R., & Matutes, C. (2002). Market power and banking failures. *International Journal of Industrial Organization*, *20*, 1341–1361.

Carletti, E. (2008). Competition and regulation in banking. In A. V. Thakor, & A. Boot (Eds.), *Handbook of Financial Intermediation and Banking* (pp. 449–482). Amsterdam, Netherlands: Elsevier.

Cetorelli, N., & Gambera, M. (2001). Banking market structure, financial dependence and growth: International evidence from industry data. *Journal of Finance*, *56*, 617–648.

Cetorelli, N., & Peretto, P. F. (2012). Credit quantity and credit quality: Bank competition and capital accumulation. *Journal of Economic Theory*, *147*, 967 – 998.

Chan, Y.-S., Greenbaum, S. I., & Thakor, A. V. (1986). Information reusability, competition and bank asset quality. *Journal of Banking & Finance*, *10*, 243–253.

Chan-Lau, J. A., Espinosa, M., Giesecke, K., & Sol, J. A. (2009). *Assessing the Systemic Implications of Financial Linkages*. Global Financial Stability Report 2 IMF.

Chava, S., Oettl, A., Subramanian, A., & Subramanian, K. V. (2013). Banking deregulation and innovation. *Journal of Financial Economics*, *109*, 759–774.

Chen, X. (2007). Banking deregulation and credit risk: Evidence from the EU. *Journal of Financial Stability*, *2*, 356–390.

Cifuentes, R., Ferrucci, G., & Shin, H. S. (2005). Liquidity risk and contagion. *Journal of the European Economic Association*, *3*, 556–566.

Čihák, M., & Hesse, H. (2010). Islamic banks and financial stability: An empirical analysis. *Journal of Financial Services Research*, *38*, 95–113.

Claessens, S., & Laeven, L. (2004). What drives bank competition? Some international evidence. *Journal of Money, Credit, and Banking*, *36*, 563–583.

Claessens, S., & Laeven, L. (2005). Financial dependence, banking sector competition, and economic growth. *Journal of the European Economic Association*, *3*, 179–207.

Cordella, T., & Yeyati, E. L. (2002). Financial opening, deposit insurance, and risk in a model of banking competition. *European Economic Review*, *46*, 471–485.

Cornaggia, J., Mao, Y., Tian, X., & Wolfe, B. (2015). Does banking competition affect innovation? *Journal of Financial Economics*, *115*, 189–209.

Corvoisier, S., & Gropp, R. (2002). Bank concentration and retail interest rates. *Journal of Banking & Finance*, *26*, 2155–2189.

Dam, L., & Koetter, M. (2012). Bank bailouts and moral hazard: Evidence from Germany. *Review of Financial Studies*, *25*, 2343–2380.

Davies, S. (1979). Choosing between concentration indices: The iso-concentration curve. *Economica*, *46*, 67–75.

De Nicolo, G. (2000). *Size, charter value and risk in banking: An international perspective*. Discussion Paper 9 Federal Reserve System.

De Nicolo, G., Bartholomew, P., Zaman, J., & Zephirin, M. (2004). Bank consolidation, internationalization, and conglomeration: Trends and implications for financial risk. *Financial Markets, Institutions & Instruments*, *13*, 173–217.

De Nicolo, G., & Kwast, M. L. (2002). Systemic risk and financial consolidation: Are they related? *Journal of Banking & Finance*, *26*, 861–880.

De Nicolo, G., & Loukoianova, E. (2007). *Bank Ownership, Market Structure and Risk*. Working Paper 07/215 IMF.

De Nicolo, G., & Lucchetta, M. (2009). *Financial intermediation, competition, and risk: a general equilibrium exposition*. Working paper 09/105 IMF.

De Nicolo, G., & Lucchetta, M. (2013). *Bank competition and financial stability: A general equilibrium exposition*. Working paper 11/295 IMF.

De Vries, C. G. (2005). The simple economics of bank fragility. *Journal of Banking & Finance*, *29*, 803–825.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, *84*, 151–161.

Deidda, L., & Fattouh, B. (2005). Concentration in the banking industry and economic growth. *Macroeconomic Dynamics*, *9*, 198–219.

Dell'Ariccia, G., & Marquez, R. (2006). Lending booms and lending standards. *Journal of Finance*, *61*, 2511–2546.

Demirgüç-Kunt, A., & Detragiache, E. (2002). Does deposit insurance increase banking system stability? An empirical investigation. *Journal of Monetary Economics*, *49*, 1373–1406.

Demirgüç-Kunt, A., Laeven, L., & Levine, R. (2004). Regulations, market structure, institutions, and the cost of financial intermediation. *Journal of Money, Credit and Banking*, *36*, 593–622.

Demsetz, H. (1973). Industry structure, market rivalry, and public policy. *Journal of Law and Economics*, *16*, 1–9.

Demyanyk, Y., Ostergaard, C., & Sørensen, B. E. (2007). U.S. banking deregulation, small businesses, and interstate insurance of personal income. *Journal of Finance*, *62*, 2763–2801.

Dick, A. A. (2006). Nationwide branching and its impact on market structure, quality, and bank performance. *Journal of Business*, *79*, 567–592.

Duprey, T., & Lé, M. (2015). *Bankscope dataset: Getting started*. Working Paper SSRN.

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Dordrecht, Netherlands: Springer.

Elzinga, K. G., & Mills, D. E. (2011). The Lerner index of monopoly power: Origins and uses. *American Economic Review*, *101*, 558–564.

Feng, G., & Serletis, A. (2010). Efficiency, technical change, and returns to scale in large U.S. banks: Panel data evidence from an output distance function satisfying theoretical regularity. *Journal of Banking & Finance*, *34*, 127–138.

Fiordelisi, F., & Mare, D. S. (2014). Competition and financial stability in European cooperative banks. *Journal of International Money and Finance*, *45*, 1–16.

Fonteyne, W. (2007). *Cooperative Banks in Europe – Policy Issues*. Working paper IMF.

Freeman, D. G. (2002). Did state bank branching deregulation produce large growth effects? *Economics Letters*, *75*, 383–389.

Fu, X. M., Lin, Y. R., & Molyneux, P. (2014). Bank competition and financial stability in Asia Pacific. *Journal of Banking & Finance*, *38*, 64–77.

Fungáčová, Z., & Weill, L. (2013). Does competition influence bank failures? *Economics of Transition*, *21*, 301–322.

Furfine, C. H. (2003). Interbank exposures: Quantifying the risk of contagion. *Journal of Money, Credit and Banking*, *35*, 111–128.

Gaffeo, E., & Mazzocchi, R. (2014). *Competition in the banking sector and economic growth: Panel-based international evidence*. Working paper SSRN.

Garrett, T. A., Wagner, G. A., & Wheelock, D. C. (2005). A spatial analysis of state banking regulation. *Papers in Regional Science*, *84*, 575–595.

Gehrig, T. (1998). Screening, cross-border banking, and the allocation of credit. *Research in Economics*, *52*, 387–407.

Goldberg, L. G., & Rai, A. (1996). The structure-performance relationship for European banking. *Journal of Banking & Finance*, *20*, 745–771.

Granger, C. (1998). Extracting information from mega-panels and high-frequency data. *Statistica Neerlandica*, *52*, 258–272.

de Guevara, J. F., & Maudos, J. (2011). Banking competition and economic growth: Cross-country evidence. *European Journal of Finance*, *17*, 739–764.

Guzman, M. G. (2000). Bank structure, capital accumulation and growth: A simple macroeconomic model. *Economic Theory*, *16*, 421–455.

Hałaj, G., & Kok, C. (2013). Assessing interbank contagion using simulated networks. *Computational Management Science*, *10*, 157–186.

Hall, M., & Tideman, N. (1967). Measures of concentration. *Journal of the American Statistical Association*, *62*, 162–168.

Hannah, L., & Kay, J. A. (1977). *Concentration in modern industry: Theory, measurement and the UK experience*. London, U.K.: Macmillan Press.

Hannan, T. H. (1991). Foundations of the structure-conduct-performance paradigm in banking. *Journal of Money, Credit and Banking*, *23*, 68–84.

Hannan, T. H., & Hanweck, G. A. (1988). Bank insolvency risk and the market for large certificates of deposit. *Journal of Money, Credit and Banking*, *20*, 203–211.

Hart, P. E. (1975). Moment distributions in economics: An exposition. *Journal of the Royal Statistical Society. Series A (General)*, *138*, 423–434.

Hause, J. C. (1977). The measurement of concentrated industrial structure and the size distribution of firms. In National Bureau of Economic Research (Ed.), *Annals of Economic and Social Measurement* (pp. 73–107). NBER volume 6.

Hauswald, R., & Marquez, R. (2006). Competition and strategic information acquisition in credit markets. *Review of Financial Studies*, *19*, 967–1000.

Hay, D. A., & Liu, G. S. (1997). The efficiency of firms: What difference does competition make? *Economic Journal*, *107*, 597–617.

Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American Economic Review*, *90*, 147–165.

Hesse, H., & Cihák, M. (2007). *Cooperative banks and Financial Stability*. Working paper IMF.

Hoggarth, G., Reis, R., & Saporta, V. (2002). Costs of banking system instability: Some empirical evidence. *Journal of Banking & Finance*, *26*, 825–855.

Horvath, J. (1970). Suggestion for a comprehensive measure of concentration. *Southern Economic Journal*, *36*, 446–452.

Hoxha, I. (2013). The market structure of the banking sector and financially dependent manufacturing sectors. *International Review of Economics & Finance*, *27*, 432–444.

Huang, R. R. (2008). Evaluating the real effect of bank branching deregulation: Comparing contiguous counties across US state borders. *Journal of Financial Economics*, *87*, 678–705.

Huang, X., Zhou, H., & Zhu, H. (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, *33*, 2036–2049.

Huang, X., Zhou, H., & Zhu, H. (2012). Systemic risk contributions. *Journal of Financial Services Research*, *42*, 55–83.

Hughes, J. P., & Mester, L. J. (2013). Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function. *Journal of Financial Intermediation*, *22*, 559–585.

Im, K., Pesaran, M., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*, 53 – 74.

Inklaar, R., Koetter, M., & Noth, F. (2012). *Who's afraid of big bad banks? Bank competition, SME, and industry growth*. Working paper 197 Frankfurt School of Finance & Management.

Iwata, G. (1974). Measurement of conjectural variations in oligopoly. *Econometrica*, *42*, 947–966.

James, C. (1991). The losses realized in bank failures. *Journal of Finance*, *46*, 1223–1242.

James, C., & Kizilaslan, A. (2014). Asset specificity, industry-driven recovery risk, and loan pricing. *Journal of Financial & Quantitative Analysis*, *49*, 599 – 631.

Jayaratne, J., & Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *Quarterly Journal of Economics*, *111*, 639–670.

Jeon, J. Q., & Lim, K. K. (2013). Bank competition and financial stability: A comparison of commercial banks and mutual savings banks in Korea. *Pacific-Basin Finance Journal*, *25*, 253–272.

Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, *9*, 185–195.

Jobst, A. A., & Gray, D. F. (2013). *Systemic contingent claims analysis – estimating market-implied systemic risk*. Working paper 13/54 IMF.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American Economic Review*, *80*, 1183–1200.

Kick, T., & Prieto, E. (2015). Bank risk and competition: Evidence from regional banking markets. *Review of Finance*, *19*, 1185–1222.

Koetter, M. (2013). *Market structure and competition in German banking*. Working paper 06/2013 German Council of Economic Advisors.

Koetter, M., Kolari, J. W., & Spierdijk, L. (2012). Enjoying the quiet life under deregulation? Evidence from adjusted Lerner indices for U.S. banks. *Review of Economics and Statistics*, *94*, 462–480.

Krol, R., & Svorny, S. (1996). The effect of the bank regulatory environment on state economic activity. *Regional Science and Urban Economics*, *26*, 531–541.

Kroszner, R. S., & Strahan, P. E. (1999). What drives deregulation? Economics and politics of the relaxation of bank branching restrictions. *Quarterly Journal of Economics*, *114*, 1437–1466.

Kuritzkes, A., Schuermann, T., & Weiner, S. M. (2005). Deposit insurance and risk management of the U.S. banking system: What is the loss distribution faced by the FDIC? *Journal of Financial Services Research*, *27*, 217–242.

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late? *Journal of Financial Intermediation*, *12*, 178–197.

Landes, W. M., & Posner, R. A. (1981). Market power in antitrust cases. *Harvard Law Review*, *94*, 937–996.

Lau, L. J. (1982). On identifying the degree of competitiveness from industry price and output data. *Economics Letters*, *10*, 93–99.

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, *29*, 2577–2603.

Léon, F. (2015). Does bank competition alleviate credit constraints in developing countries? *Journal of Banking & Finance*, *57*, 130–142.

Lepetit, L., & Strobel, F. (2013). Bank insolvency risk and time-varying z-score measures. *Journal of International Financial Markets, Institutions and Money*, *25*, 73–87.

Lepetit, L., & Strobel, F. (2015). Bank insolvency risk and z-score measures: A refinement. *Finance Research Letters*, *13*, 214–224.

Lerner, A. P. (1934). The concept of monopoly and the measurement of monopoly power. *Review of Economic Studies*, *1*, 157–175.

Leroy, A. (2016). Banking competition, financial dependence and productivity growth in Europe. *International Economics*, (p. forthcoming). Available online at https://doi.org/10.1016/j.inteco.2016.01.001.

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton, Florida: Taylor & Francis Group.

Levine, R. (2005). Finance and growth: Theory and evidence. In P. Aghion, & S. Durlauf (Eds.), *Handbook of Economic Growth, volume 1a* (pp. 865–934). Amsterdam, Netherlands: Elsevier.

Lindenberg, E. B., & Ross, S. A. (1981). Tobin's q ratio and industrial organization. *Journal of Business*, *54*, 1–32.

Liu, G., Mirzaei, A., & Vandoros, S. (2014). The impact of bank competition and concentration on industrial growth. *Economics Letters*, *124*, 60–63.

Liu, H., Molyneux, P., & Nguyen, L. H. (2012). Competition and risk in South East Asian commercial banking. *Applied Economics*, *44*, 3627–3644.

Liu, H., Molyneux, P., & Wilson, J. O. (2013). Competition and stability in European banking: A regional analysis. *The Manchester School*, *81*, 176–201.

Liu, H., & Wilson, J. O. (2013). Competition and risk in Japanese banking. *European Journal of Finance*, *19*, 1–18.

Marcus, A. J. (1984). Deregulation and bank financial policy. *Journal of Banking & Finance*, *8*, 557–565.

Marquez, R. (2002). Competition, adverse selection, and information dispersion in the banking industry. *Review of Financial Studies*, *15*, 901–926.

Martinez-Miera, D., & Repullo, R. (2010). Does competition reduce the risk of bank failure? *Review of Financial Studies*, *23*, 3638–3664.

Matutes, C., & Vives, X. (2000). Imperfect competition, risk taking, and regulation in banking. *European Economic Review*, *44*, 1–34.

Maudos, J., & de Guevara, J. F. (2004). Factors explaining the interest margin in the banking sectors of the European Union. *Journal of Banking & Finance*, *28*, 2259–2281.

Mayer, C. (1988). New issues in corporate finance. *European Economic Review*, *32*, 1167–1183.

Merryman, S. (2005). USSWM: Stata module to provide US state and county spatial weight (contiguity) matrices. Statistical Software Components, Boston College Department of Economics.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of finance*, *29*, 449–470.

Merton, R. C. (1977). An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory. *Journal of Banking & Finance*, *1*, 3–11.

Mishkin, F. S. (1992). Anatomy of a financial crisis. *Journal of Evolutionary Economics*, *2*, 115–130.

Mishkin, F. S. (1999). Financial consolidation: Dangers and opportunities. *Journal of Banking & Finance*, *23*, 675–691.

Mishkin, F. S. (2006). How big a problem is too big to fail? A review of Gary Stern and Ron Feldman's too big to fail: The hazards of bank bailouts. *Journal of Economic Literature*, *44*, 988–1004.

Müller, J. (2006). Interbank credit lines as a channel of contagion. *Journal of Financial Services Research*, *29*, 37–60.

Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, *31*, 2033–2060.

Ogura, Y. (2012). Lending competition and credit availability for new firms: Empirical study with the price cost margin in regional loan markets. *Journal of Banking & Finance*, *36*, 1822–1838.

Pace, R. K., & LeSage, J. P. (2008). A spatial Hausman test. *Economics Letters*, *101*, 282–284.

Pagano, M. (1993). Financial markets and growth: An overview. *European Economic Review*, *37*, 613–622.

Panzar, J. C., & Rosse, J. N. (1987). Testing for "monopoly" equilibrium. *Journal of Industrial Economics*, *35*, 443–456.

Peltzman, S. (1977). The gains and losses from industrial concentration. *Journal of Law and Economics*, *20*, 229–263.

Peralta, G., & Zareei, A. (2016). A network approach to portfolio selection. *Journal of Empirical Finance*, *38*, 157–180.

Peria, M. S. M., & Mody, A. (2004). How foreign participation and market concentration impact bank spreads: Evidence from Latin America. *Journal of Money, Credit and Banking*, *36*, 511–537.

Petersen, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *Quarterly Journal of Economics*, *110*, 407–443.

Pulvino, T. C. (1998). Do asset fire sales exist? An empirical investigation of commercial aircraft transactions. *Journal of Finance*, *53*, 939 – 978.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance*, *47*, 1367–1400.

Repullo, R. (2004). Capital requirements, market power, and risk-taking in banking. *Journal of Financial Intermediation*, *13*, 156–182.

Rhoades, S. A. (1995). Market share inequality, the HHI, and other measures of the firm-composition of a market. *Review of Industrial Organization*, *10*, 657–674.

Rice, T., & Strahan, P. E. (2010). Does credit competition affect small-firm finance? *Journal of Finance*, *65*, 861–889.

Robinson, J. (1952). *The Rate of Interest and Other Essays*. London, U.K.: MacMillan Press.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*, 41–55.

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica*, *20*, 431–449.

Ryan, R. M., O'Toole, C. M., & McCann, F. (2014). Does bank market power affect SME financing constraints? *Journal of Banking & Finance*, *49*, 495–505.

Sáez, L., & Shi, X. (2004). Liquidity pools, risk sharing, and financial contagion. *Journal of Financial Services Research*, *25*, 5–23.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, *22*, 203–224.

Salas, V., & Saurina, J. (2003). Deregulation, market power and risk behaviour in Spanish banks. *European Economic Review*, *47*, 1061–1075.

Schaeck, K., & Čihák, M. (2008). *How does competition affect efficiency and soundness in banking? New empirical evidence*. Working paper 932 ECB.

Schaeck, K., & Cihak, M. (2012). Banking competition and capital ratios. *European Financial Management*, *18*, 836–866.

Schaeck, K., & Cihák, M. (2014). Competition, efficiency, and stability in banking. *Financial Management*, *43*, 215–241.

Schaeck, K., Cihak, M., & Wolfe, S. (2009). Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, *41*, 711–734.

Schumpeter, J. A. (1934). *The theory of economic development: an inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge, Massachusetts: Harvard University Press.

Segoviano Basurto, M., & Goodhart, C. (2009). *Banking stability measures*. Working paper 09/4 IMF.

Shaffer, S. (1993). A test of competition in Canadian banking. *Journal of Money, Credit and Banking*, *25*, 49–61.

Shaffer, S. (1994). Pooling intensifies joint failure risk. *Research in Financial Services: Private and Public Policy*, *6*, 249–280.

Shaffer, S. (1998). The winner's curse in banking. *Journal of Financial Intermediation*, *7*, 359–392.

Shaffer, S. (1999). The competitive impact of disclosure requirements in the credit card industry. *Journal of Regulatory Economics*, *15*, 183–198.

Shaffer, S. (2002). Conduct in a banking monopoly. *Review of Industrial Organization*, *20*, 221–238.

Shaffer, S., & DiSalvo, J. (1994). Conduct in a banking duopoly. *Journal of Banking & Finance*, *18*, 1063–1082.

Shaffer, S., & Spierdijk, L. (2015). The Panzar–Rosse revenue test and market power in banking. *Journal of Banking & Finance*, *61*, 340–347.

Shaffer, S., & Spierdijk, L. (2017). Market power: Competition among measures. In J. A. Bikker, & L. Spierdijk (Eds.), *Research Handbook on Competition in Banking and Finance*. Cheltenham, U.K.: Edward Elgar Publishing.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance*, *45*, 1069–1087.

Shleifer, A., & Vishny, R. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance*, *47*, 1343–1366.

Smirlock, M. (1985). Evidence on the (non) relationship between concentration and profitability in banking. *Journal of Money, Credit and Banking*, *17*, 69–83.

Smith, R. T. (1998). Banking competition and macroeconomic performance. *Journal of Money, Credit and Banking*, *30*, 793–815.

Spierdijk, L., & Zaouras, M. (2017). Measuring banks' market power in the presence of economies of scale: A scale-corrected Lerner index. Unpublished manuscript.

Stern, G. H., & Feldman, R. J. (2004). *Too big to fail: The hazards of bank bailouts*. Washington, D.C.: Brookings Institution Press.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, *71*, 393–410.

Stiroh, K. J., & Strahan, P. E. (2003). Competitive dynamics of deregulation: Evidence from us banking. *Journal of Money, Credit, and Banking*, *35*, 801–828.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, *20*, 518–529.

Strahan, P. E. (2003). The real effects of US banking deregulation. *Federal Reserve Bank Of Saint Louis Review*, *85*, 111–128.

Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking & Finance*, *36*, 3366–3381.

Turk-Ariss, R. (2010). On the implications of market power in banking: Evidence from developing countries. *Journal of Banking & Finance*, *34*, 765–775.

Uhde, A., & Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking & Finance*, *33*, 1299–1311.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*, *7*, 111–125.

Upper, C., & Worms, A. (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review*, *48*, 827–849.

Valverdie, S. C., Humphrey, D., & Fernandez, F. R. (2003). Deregulation, bank competition and regional growth. *Regional Studies*, *37*, 227–237.

Van Leuvensteijn, M., Bikker, J. A., van Rixtel, A. A., & Sørensen, C. K. (2011). A new approach to measuring competition in the loan markets of the euro area. *Applied Economics*, *43*, 3155–3167.

Vega, S. H., & Elhorst, J. P. (2013). *On spatial econometric models, spillover effects, and W*. Working paper University of Groningen. Available online at http://hdl.handle.net/10419/123888.

Vives, X. (2001). Competition in the changing world of banking. *Oxford Review of Economic Policy*, *17*, 535–547.

Vives, X. (2011). Competition policy in banking. *Oxford Review of Economic Policy*, *27*, 479–497.

Von Hagen, J., & Ho, T.-K. (2007). Money market pressure and the determinants of banking crises. *Journal of Money, Credit and Banking*, *39*, 1037–1066.

Wagner, W. (2010a). Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation*, *19*, 373–386.

Wagner, W. (2010b). Loan market competition and bank risk-taking. *Journal of Financial Services Research*, *37*, 71–81.

Wagner, W. (2011). Systemic liquidation risk and the diversity–diversification trade-off. *Journal of Finance*, *66*, 1141–1175.

Wall, H. J. (2004). Entrepreneurship and the deregulation of banking. *Economics Letters*, *82*, 333–339.

Wheelock, D. C., & Wilson, P. W. (2012). Do large banks have lower costs? New estimates of returns to scale for U.S. banks. *Journal of Money, Credit and Banking*, *44*, 171–199.

Wilson, R. (1979). Auctions of shares. *Quarterly Journal of Economics*, (pp. 675–689).

Yaldiz, E., & Bazzana, F. (2010). The effect of market power on bank risk taking in Turkey. *Financial Theory and Practice*, *34*, 297–314.

Yeyati, E. L., & Micco, A. (2007). Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. *Journal of Banking & Finance*, *31*, 1633–1647.

Zigraiova, D., & Havranek, T. (2015). Bank competition and financial stability: Much ado about nothing? *Journal of Economic Surveys*, *30*, 944–981.

Chapter 6

Samenvatting (Dutch summary)

De regulering van en het toezicht op de financiële sector zijn uitvoerig besproken onderwerpen sinds het uitbreken van de financiële crisis in 2008. De financiële sector onderscheidt zich van de reële sector van de economie door de belangrijke rol die risico's spelen in de sector en door de sterke onderlinge afhankelijkheid en verwevenheid van financiële instellingen. Risico's zijn inherent aan het verdienmodel van financiële instellingen, die doorgaans met geleend geld investeringen doen. Bovendien zijn bedrijven in de reële sector van de economie voor de financiering van projecten vaak afhankelijk van banken, waardoor crises in de financiële sector zware consequenties kunnen hebben voor de reële sector. Om deze reden wordt het belang van financiële stabiliteit steeds meer erkend als een belangrijke doelstelling van centrale banken en toezichthouders, ondanks het feit dat er nog geen algemeen erkende definitie van het begrip *financiële stabiliteit* bestaat. Daarnaast kunnen marktimperfecties in de financiële sector effecten hebben die verder reiken dan slechts de consumenten van financiële diensten. Wanneer een tekort aan concurrentie tussen banken tot hoge rente-marges leidt, dan kan dit bijvoorbeeld leiden tot een afname van investeringen in de reële sector, met als gevolg een negatief effect op de economische groei.

Dit proefschrift levert een bijdrage aan de wetenschappelijke literatuur op het gebied van de regulering van de financiële sector. Het proefschrift bestaat uit een literatuuronderzoek, een theoretische studie en twee empirische studies. Hieronder volgt een korte samenvatting van deze vier studies.

Hoofdstuk 2 bevat een literatuuronderzoek naar wetenschappelijke studies die de effecten van concurrentie in de bankensector op economische groei en financiële stabiliteit bestuderen. Ook staat dit hoofdstuk uitgebreid stil bij de wijze waarop bankenconcurrentie en financiële stabiliteit in empirische studies worden gemeten. Met name op het gebied van het meten van financiële stabiliteit is nog veel ruimte voor verbetering, daar verreweg de meeste empirische studies op dit gebied zich richten op het meten van de stabiliteit van individuele banken, zonder oog te hebben voor de onderlinge afhankelijkheid en de verwevenheid van banken. Dit is een belangrijk punt, omdat een financiële systeem met sterk verweven banken zeer kwetsbaar kan zijn, zelfs wanneer de individuele banken relatief stabiel zijn. Na het uitbreken van de financiële crisis in 2008 is de aandacht voor de stabiliteit van de financiële sector als geheel toegenomen, maar recent ontwikkelde maatstaven van zogenoemde systeemrisico's zijn slechts zeer sporadisch toegepast. Ook bij het meten van bankenconcurrentie kan vooruitgang worden geboekt, aangezien veel studies de mate van marktconcentratie in de financiële sector als maatstaf gebruiken voor bankenconcurrentie. Hierbij wordt aangenomen dat meer geconcentreerde markten een lagere mate van concurrentie impliceren. Hoewel marktconcentratie in de bankensector op zichzelf zeer relevant kan zijn voor bijvoorbeeld financiële stabiliteit, is het gebruik van concentratie als maatstaf voor concurrentie problematisch. Zo kan een geconcentreerde markt zeer concurrerend zijn wanneer toetreding tot de markt relatief eenvoudig is, terwijl een minder geconcentreerde markt niet per definitie een hoge mate van concurrentie impliceert. In het algemeen kan uit de literatuurstudie in dit hoofdstuk worden geconcludeerd dat zowel de theoretische als de empirische literatuur ambigu is over de effecten van bankenconcurrentie op zowel economische groei als financiële stabiliteit.

Hoofdstuk 3 bestaat uit een theoretisch model, waarmee de rol van de liquiditeit van banken op de liquidatiekosten van banken tijdens financiële crises kan worden bestudeerd. Het model laat zien dat banken de neiging hebben om relatief weinig liquiditeit aan te houden, omdat banken met veel liquiditeit hun verwachte rendementen kunnen verhogen door liquiditeit om te zetten in leningen. Het gevolg hiervan is dat tijdens financiële crises de mogelijkheid ontstaat dat, door een gebrek aan liquiditeit in de bankensector, de leningen van omgevallen banken slechts voor een zeer lage prijs verkocht kunnen worden aan gezonde banken. De in de studie uitgevoerde simulaties tonen aan dit de kosten van de liquidatie van omgevallen banken via dit mechanisme zeer hoog op kunnen lopen. De simulaties laten daarnaast zien dat de kans op hoge liquidatiekosten aanzienlijk verkleind kan worden door regelgeving die banken dwingt tot het aanhouden van liquiditeitsbuffers, die aangesproken kunnen worden gedurende periodes van financiële turbulentie.

In hoofdstuk 4 staat de vraag centraal in hoeverre een toename van marktconcentratie in de bankensector van de EU-25 effect heeft gehad op de financiële stabiliteit van deze sector. Als maatstaf voor financiële stabiliteit wordt de zogenaamde Z-score toegepast. Deze maatstaf combineert informatie over kapitaalbuffers van banken met verwachte rendementen en de volatiliteit van rendementen. Hoewel de Z-score oorspronkelijk bedoeld was om de stabiliteit van individuele banken te meten, kan ze in aangepaste vorm ook worden toegepast op de financiële sector als geheel. De empirische analyse in dit hoofdstuk laat zien dat de toegenomen marktconcentratie in de bankensector van de EU-25 nauwelijks effect heeft gehad op zowel de individuele stabiliteit van banken als de stabiliteit van de financiële sector als geheel. Deze bevinding impliceert dat tijdens financiële crises, de herstructurering van banken door middel van fusies een aantrekkelijk alternatief zijn voor het redden van banken door middel van overheidsinjecties. De toename in marktconcentratie als gevolg van herstructurering lijkt immers geen schadelijke effecten te hebben, terwijl overheidsinjecties aan noodlijdende banken ongewenst gedrag in de hand kunnen werken.

Hoofdstuk 5, ten slotte, bevat een empirische studie naar de effecten van de deregulering van concurrentiebeperkende regelgeving in de bankensector van de Verenigde Staten op de economische groei in de periode tussen 1970 en 2000. Deze studie maakt gebruik van het feit dat concurrentiebeperkende regelgeving in de Verenigde Staten op staatsniveau zijn vastgelegd en dat het moment waarop deze regelgeving werd opgeheven per staat varieert. Door economische groei op staatsniveau te meten, kan op deze manier het verband tussen deregulering en groei worden vastgesteld. Een belangrijke innovatie van deze studie ten opzichte van de bestaande wetenschappelijke literatuur is dat de analyse rekening houdt met de mogelijkheid dat de bovengenoemde deregulering effecten kan hebben die zich over staatsgrenzen uitstrekken, zodat ook omliggende staten meeprofiteren van deregulering. Het bestaan van deze zogenaamde *spillover-effecten* ligt voor de hand, omdat banken in de Verenigde Staten zich bij het geven van leningen doorgaans niet storen aan staatsgrenzen en omdat een toename van economische groei in een gedereguleerde staat de vraag naar goederen en diensten in omliggende staten waarschijnlijk zal doen toenemen, waardoor ook de economische groei in omliggende staten wordt gestimuleerd. De resultaten van de empirische analyse in dit hoofdstuk tonen aan dat de deregulering van concurrentiebeperkende regelgeving in de Verenigde Staten tot een toename in de economische groei heeft geleid en dat de bovengenoemde spillover-effecten inderdaad hebben plaatsgevonden. Om de robuustheid van deze uitkomsten te onderzoeken, vervolgt de studie in dit hoofdstuk met een onderzoek naar de effecten van bovengenoemde deregulering op economische groei op lokaal niveau. In dit deel van de studie worden de economische groeicijfers van vergelijkbare lokale Amerikaanse gemeenschappen uit verschillende staten met elkaar vergeleken en wordt geanalyseerd in hoeverre verschillen in groeicijfers verband houden met de timing van deregulering. De uitkomsten van deze analyse op lokaal niveau bevestigen de bevindingen van de analyse op staatsniveau: lokale gemeenschappen in staten die concurrentiebeperkende regelgeving in de bankensector relatief vroeg hebben afgeschaft laten gemiddeld hogere groeicijfers zien in vergelijking met lokale gemeenschappen in staten die deze regelgeving relatief laat hebben afgeschaft. De conclusie van dit hoofdstuk is daarom dat concurrentiebeperkende regelgeving in de bankensector een remmende werking lijken te hebben op de economische groei.

De uitkomsten van de studies in dit proefschrift hebben drie belangrijke beleidsimplicaties. De eerste is dat de liquiditeit van banken een belangrijke rol speelt bij het bepalen van de liquidatiekosten van banken tijdens financiële crises en dat regelgeving die banken dwingt tot het aanhouden van een liquiditeitsbuffer daarom kan bijdragen aan het verlagen van de kosten van financiële crises. De tweede beleidsimplicatie is dat, gedurende periodes van financiële turbulentie, de stabiliteit van de bankensector bij voorkeur dient te worden versterkt door middel van de herstructurering van instabiele banken in plaats van overheidsinjecties. Ten slotte suggereren de uitkomsten in dit proefschrift dat concurrentiebeperkende regelgeving in de financiële sector onwenselijk is, aangezien dergelijke regelgeving een negatief effect heeft op de economische groei.