Three essays on banking risk

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Contents

List of Tables

List of Figures

List of Abbreviations

ALLL	Allowance for Loan and Lease Losses
alt.	alternative
BEA	Bureau of Economic Analysis
BHC	Bank holding company
C&I Loans	Commercial and Industrial Loans
CAR	Capital Asset Ratio
CDFI	Community Development Financial Institution
CPI	Consumer Price Index
CSR	Corporate social responsibility
ECB	European Central Bank
EDF	Expected default frequency
EU	European Union
FE	Fixed effects
FEBEA	Fédération Européenne de Finances et Banques Ethiques et Alternatives
FDIC	Federal Deposit Insurance Corporation
GABV	Global Alliance for Banking on Values
GDP	Gross Domestic Product
GMM	Generalized method of moments
HHI	Herfindahl-Hirschman Index
INAISE	International Association of Investors in the Social Economy
IV	Instrumental variables
LLP	Loan loss provisions
LTF	Long-term funding
MP	Monetary policy
MSA	Metropolitan Statistical Area
NCIF	National Community Investment Fund
NPL	Non-performing loan
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
RCFD	Foreign and Domestic Call Report
RCON	Domestic Call Report
ROA	Return on Assets
SME	Small and medium enterprise
STF	Short-term funding
TA	Total Assets
U.S.	United States
USD	US Dollar
VaR	Value at risk

Erklärung über Zusammenarbeit mit Ko-Autoren und Vorveröffentlichungen

Der erste Aufsatz dieser Dissertation, “Bank risk-taking and monetary policy. Regional evidence from U.S. commercial banks.” wurde nicht vorveröffentlicht und ist in alleiniger Autorschaft entstanden. Er wurde auf der Jahrestagung des Vereins für Socialpolitik 2012, der 2012 Barcelona Banking School und dem Magdeburg 2012 Workshop on Banking and Financial Markets vorgetragen. Der Klarheit halber weise ich darauf hin, dass meine Diplomarbeit mit dem Titel “The risk-taking channel of monetary policy. Evidence from the U.S. banking system” sich ebenfalls mit dem Risikokanal der Geldpolitik in den Vereinigten Staaten beschäftigt. Das erste Papier dieser Dissertation unterscheidet sich jedoch deutlich von der Diplomarbeit und geht an mehreren Punkten über sie hinaus. Unter anderem wird durch die Verwendung von Summary-of-Deposit Daten die geographische Zuordnung der Aktivität von Banken ermöglicht, der Stand der Geldpolitik durch Geldpolitikregeln nach dem Typ der Taylor-Regel evaluiert, eine große Zahl von Risikomaßen verwendet und Interaktionen mit anderen Bankcharakteristika erkundet.

Der zweite Aufsatz dieser Dissertation “Are ethical and social banks less risky? Evidence from a new dataset” erhielt den Best Paper Award “Welfare Wealth Work for Europe”, eines Forschungsprojekts innerhalb des 7. Forschungsrahmenprogramms der Europäischen Kommission. In diesem Zusammenhang wurde er in einer leicht gestrafften Version unter dem gleichen Titel als Discussion Paper des DIW Berlin und als Working Paper No. 96 des Forschungsprogramms “Welfare Wealth Work for Europe” veröffentlicht. Er ist in alleiniger Autorschaft entstanden. Er wurde beim 2014 Halle Financial Markets Workshop, dem Bologna Workshop on Social Economy for Young Economists 2014 und dem 4. Workshop Banken und Finanzmärkte der Universitäten Augsburg, Magdeburg und der Deutschen Bundesbank in Eltville vorgetragen.

Der dritte Aufsatz “Riskiness of ethical and social banks in the United States” wurde nicht vorveröffentlicht und ist in alleiniger Autorschaft entstanden.

Chapter 1

Introduction

This dissertation contributes to the research on two topics that relate to the riskiness of banks. The first paper of the dissertation studies the effects of monetary policy on bank riskiness, while both the second and the third paper investigate the connection of ethical and social behavior in banks and their riskiness.

These two topics are, in a way, quite distinct. Monetary policy is a macroeconomic topic as it is centrally decided and affects all banks in an economy to some degree. The ethical and social behavior of banks is institution-specific. When looking at the riskiness of social and ethical banks the perspective is more microeconomic. However, the three papers of this dissertation have more in common than the fact that they use data on small and medium-sized banks. Both topics, the setting of monetary policy as well as the behavior of individual agents in financial markets have been discussed widely as contributing factors to the global financial crisis that started in 2007. Even though the outbreak of the financial crisis is no longer recent, these two topics continue to be of interest from the perspective of financial stability, monetary policy and bank supervision today.

As interest rates in the Eurozone remain at historic lows, the effects of mismatched monetary policy on bank risk-taking remain a concern. For example, the last Financial Stability Review of the ECB, published in November 2015, states that "prolonged periods of low interest rates combined with non-standard monetary policy measures may have unintended and localized financial stability effects"(ECB, 2015, p.159). This is especially important in a monetary union where financial and business cycles are not synchronized across countries and regions. My first paper contributes to this debate as it studies the effects of the stance of monetary policy on bank risk-taking when evaluated against regional economic conditions.

The second and third paper study the riskiness of social and ethical banks, that is, banks that pursue ethical, social, sustainable, environmental or other "added social value" goals as a core part of their business strategy. Social and ethical banks could be less risky than conventional banks as they are generally risk-averse, focused on the real economy and tend to avoid speculative activities.

While social and ethical banks make up only a tiny fraction of the banking market, the discussion on the importance of ethics in banking is ongoing (G30 Working Group, 2015). This becomes apparent in a recent speech by Danièle Nouy, chair of the Supervisory Board of the Single Supervisory Mechanism, who states that "[c]ulture and ethics are at the heart of banks' decisions in terms of risk-taking and safe and sound management practices" (Nouy, 2015). She continues that this is a "soft" topic that is difficult to grasp.

Still, the second paper of this dissertation develops a comprehensive database of social and ethical banks in EU and OECD countries (excluding the United States), matches them with comparable conventional banks and thus allows for a systematic assessment of the riskiness of social and ethical banks. It also offers some insight into their stability in the global financial crisis. The third and final paper extends this study to social and ethical banks in the United States.

Chapter 2

Bank risk-taking and monetary policy. Regional evidence from U.S. commercial banks.

2.1 Introduction

In the aftermath of the global financial crisis, an increased interest in linkages between monetary policy and financial system stability has emerged. Academics and policy makers discuss how and to what extent monetary policy affects financial stability and if monetary policy should take financial stability into account (Smets, 2014). Especially in the run-up to the great recession, unusually loose monetary policy has been linked to an increase in risk-taking by economic agents in general, and banks in particular (Taylor, 2014). As interest rates remain at historical lows even years after the financial crisis of 2007–2008, this link continues to be of interest. This paper contributes to the discussion of the link between risk-taking and monetary policy for the case of small commercial banks and also offers suggestions for macroprudential policy.

Rajan (2006) was the first to argue that technological and financial innovation changed the way that risk is viewed and taken, especially through the possibility of transferring risks off the balance sheet. Borio and Zhu (2012) coined the term "risk-taking channel of monetary policy" and defined it as the "link between monetary policy and the perception and pricing of risk by economic agents". The risk-taking channel describes the "impact of changes in policy rates on either risk perceptions or risk-tolerance and hence on the degree of risk in the portfolios, on the pricing of assets, and on the price and non-price terms of the extension of funding" (Borio and Zhu, 2012, p.242). During times of lower interest rates, the risk-taking channel leads financial institutions to take on additional risks.

The risk-taking channel for banks operates in several different ways. Banks or bank managers may set themselves a target nominal rate of return. During times of lower interest rates this high nominal rate can only be achieved through riskier investments. Institutional factors, for example performance-based remuneration of bank managers, may increase their incentive to search for yield. Also, lower interest rates increase the value of assets, collateral and expected cash flows, income, and profits. This can change perceptions and make a transaction appear less risky or make an economic agent more willing to bear the increased risk (Borio and Zhu, 2012). The central bank can also affect risk-taking through forming market anticipations.

This paper adds to the literature on monetary policy and bank risk-taking through the study of small and medium-sized banks. Small banks that act locally and depend on local economic conditions may be particularly suited to study this field. They have relatively simple balance sheets and usually do not engage in securitization or off-balance sheet activities. Their riskiness can therefore be observed where it originates. Also, using small banks mitigates endogeneity problems that are inherent to the link of banks, monetary policy and economic outcomes. Most existing studies relying on loan-level or bank-level data usually consider only one monetary area. Consequently, all banks operate in the same interest rate environment and it is difficult to differentiate the risk that is taken on due to monetary policy from other factors influencing risk. I mitigate this problem by exploiting differences in economic condition in the various regions of the United States. In the econometric analysis, I estimate the effect of monetary policy on bank risk-taking using a dataset of over 2,000 U.S. commercial banks in 23 different Metropolitan Statistical Areas (MSAs). The stance of monetary policy is then evaluated in relation to the regional economic condition using monetary policy rules of the Taylor-type. As the Federal Reserve cannot react to diverging regional economic conditions, monetary policy is not endogenous for these small, regionally active banks.

The estimation results provide some evidence in favor of a risk-taking channel of monetary policy. Comparatively loose monetary policy is associated with a lower capital asset ratio, higher balance sheet risk and higher use of non-traditional funding sources. Risk measures that rely on non-performing loans show the opposite effect. Here, if monetary policy is comparatively loose in a region, the economy is doing relatively well and there is a low ratio of troubled loans. Bank liquidity seems to mitigate the effect of comparatively loose monetary policy on bank risk-taking and could be a protective or stabilizing factor.

The rest of the paper is organized as follows. In section 2, I explore from a theoretical perspective how the risk-taking channel may work for a small commercial bank. Section 3 describes the data, the methodology and the risk measurement. Section 4 discusses the econometric model and results. The last section concludes.

2.2 Bank risk and monetary policy: Theory and evidence

2.2.1 The risk-taking channel for small commercial banks

In the context of monetary policy transmission, the risk-taking channel is closely linked to the credit channel. Via the credit channel, monetary policy can influence both the ability to supply loans (bank lending channel) and the demand of loans (balance sheet channel). The risk-taking channel may be viewed as an amplification of both of these channels (Alpanda and Aysun, 2012). It thus introduces a new facet into the transmission mechanism of monetary policy. It studies the link between changes in monetary policy rates and risks taken on by economic agents (Borio and Zhu, 2012).

Interest rates influence the way economic agents perceive risks and their degree of risk aversion (Gambacorta, 2009). Specifically, bank risk-taking increases when interest rates are too low. This changed behavior of banks affects their credit standards. Therefore, low interest rates may not only lead to an increase in bank loans but also in their riskiness. This risk-taking channel may work in several ways. For the purpose of this paper it is of interest which mechanisms of the risk-taking channel may be particularly strong or highly visible in small commercial banks.

First, low interest rates may intensify the banks' and bank managers' search for yield. Lower interest rates make it more difficult to meet sticky target rates of return. Target rates of return can be sticky due to a wide range of psychological and institutional reasons (Bank for International Settlements, 2004). As high nominal returns become rare in a low interest rate environment, the decision makers may make unsound investments. Money illusion may lead the bank managers to try and replicate the high nominal return that they became used to during boom times. To achieve this, they are willing to increase their risk. During good times, economic agents can also fall prey to "irrational exuberance" and fail to consider business cycle fluctuations. For small commercial banks, this may be especially true in the mortgage business. Even if the risk perception is not affected, search for yield can increase risk tolerance of banks. Banks that are already struggling may further increase their risk-taking in a gamble for resurrection.

This increased search for yield may also be institutionalized in the bank. An example would be a certain nominal rate of return that the bank has committed to in long-term contracts (Gambacorta, 2009). Banks that hold a large amount of fixed interest rate long-term liabilities must increase their risk-taking when interest rates are lowered in a gamble to remain solvent. Smaller banks, which are less involved in the interbank market and have to rely more on long-term liabilities, may be especially affected.

Second, interest rates affect the valuations and cash flows of projects and thus their perceived riskiness (Borio and Zhu, 2012). In a straightforward example, the net present value of an investment project increases if the discount rate decreases. Low cost of capital strengthens a firm's balance sheets and lets it take on additional external funding. Projects that would normally have a negative net present value now become feasible. As low interest rates change projects' valuations, the risk measurement of these projects is also changed. Consequently, the average project banks take on could become riskier. This aspect of the risk-taking channel is closely related to the balance-sheet channel. As Ongena et al. (2013) find that large and multinational banks flee domestic regulation with riskier foreign credits, which may not show up as such on balance sheets, this effect may also be more visible in small banks who do not have this possibility.

Third, many banks target specific financial indicators, such as a certain leverage and regulatory capital ratio. When asset prices rise in response to loose monetary policy, bank's balance sheets become stronger, and the bank net worth increases. This implies that their leverages (defined as the ratio of total assets to equity) decline. If total assets rise, while a bank does not adjust its equity, then leverage growth is inversely related to total assets. But banks want to reduce costly excess capital in order to return to their preferred leverage, and meet targets for credit rating and performance measures such as return on equity (Adrian and Shin, 2010). This means, that after a monetary easing, banks need to expand their balance sheets. Adrian and Shin (2008) find a strong correlation between loose monetary policy and expanding balance sheets. They present evidence that banks actively manage their leverage and aim to keep it fixed at a certain rate.

To expand their balance sheet, commercial banks take on more debt on the liability side and increase their lending on the asset side. If the pool of potential borrowers is fixed, which is probably true for a bank that operates in only one region, a greater lending supply leads to lower interest rates, which can be interpreted as lower risk premia (Adrian and

Shin, 2010). Also, some of the additional lending may be extended to new borrowers of lower credit-worthiness. Lending standards decline in both cases.

In addition to the change in absolute values, the volatility of asset prices also affects risk measurement. During good times, asset price volatility tends to decline. As a consequence, risk measured via Value at Risk (VaR) or similar methodologies declines, too. This frees up the bank's risk reserves (Gambacorta, 2009). Again, banks will seek to remain only slightly above the costly reserve requirements. However, lower volatility may have no influence on the probability of tail risks (Rajan, 2006). These are, by construction, excluded in VaR methodologies so that in a low interest rate environment banks may hold too little buffer against extreme events. A similar point can be made for a targeted return on equity. Banks adjust their amount of equity compared to the profitability and riskiness of their assets. If the profitability and measured risk are lowered due to a lower interest rate, equity will also have to decline during times of loose monetary policy to keep a targeted return on equity. For small commercial banks that do not necessarily use sophisticated risk management models, this effect may be less pronounced.

All of the above working mechanisms of the risk-taking channel lead to the same result: an increase in bank risk-taking when interest rates are too low in comparison with the macroeconomic environment. The importance of the risk-taking channel may have increased with technological progress and the deregulation of the banking system. Securitization and structured products make risk-shifting possible (ECB, 2008, p.90). The possibility of credit-risk transfer allows banks to originate more credit than they keep on their balance sheets. Technological and financial innovation made it possible to transfer risks off-balance sheet and construct complicated financial products (Rajan, 2006). Loans can be issued, with much of the profits remaining with the originator while most of the loan risk is sold to someone else.

The mechanisms of the risk-taking channel may affect different aspects of bank risk. Aspects of risk could be different types of lending, different riskiness of lending, increased leverage or resort to cheaper sources of funding. For a commercial bank, search for yield would lead to an increased risk in lending. Targeting key figures might also lead to a decline in relative equity capital. By loading up on real estate loans, banks can increase their risk-taking in several dimensions: they increase their counterparty risk and maturity mismatch, due to long-term contracts. Commercial and industrial loans are short-term and relatively safe but also yield high interest rates (Den Haan et al., 2007). Although the risk-taking channel may also affect other areas of banks than the credit origination, such as trading and off-balance sheet activities, the focus for small banks is likely to be bank credit and balance sheet expansion. I use several different types of risk measures that capture these different ways to increase risk.

There are other reasons why smaller banks are especially suited for this study. In their discussion of the bank lending channel, Kashyap and Stein (1995) argue that banks exhibit cross-sectional differences in the way their balance sheets respond to a monetary policy shock. Small banks are perceived as inherently riskier and therefore more subjected to capital market imperfections than big banks. That is why they have more difficulty in switching between deposit and non-deposit sources of funding. The authors find that monetary policy has a stronger impact on small banks than on big banks. This stronger impact can also be expected for the risk-taking channel.

Using smaller banks has the added advantage that it could also mitigate the endogeneity of the condition of banks and the regional economic conditions. With large banks, causality is likely to run in both directions. Small banks are, of course, affected by regional economic conditions, but have less of an influence on the regional economic conditions through their lending behavior. Evidence on the importance of banks for the real economy is mixed. Research by Driscoll (2004) shows that the influence of bank lending on economic output is limited, although banks react to loan demand. However, Garmaise and Moskowitz (2006) find that a worsening of terms of credit on a local level is associated with worse economic outcomes.

2.2.2 Related literature

This paper contributes to the analysis of the risk-taking channel of monetary policy, or, more generally, to the analysis of the link between monetary policy and financial stability. The empirical literature on monetary policy and bank risk can be grouped into three categories by the source of data they are using. First, there are studies using individual loan data, second, studies using results from survey data and third, papers relying on bank balance sheet data. An introduction into the literature on the risk-taking channel of monetary policy can be also found in De Nicolò et al. (2010) as well as in Smets (2014).

As representatives for the first category, two studies by Jiménez et al. (2014) and Ioannidou et al. (2009) address the identification problem by using individual loan data from Spain and Bolivia, respectively. Both find that lower interest rates are associated with a softening of lending standards. In the second category, studies reviewing the responses of the ECB Bank Lending Survey and the Federal Reserve Senior Loan Officer Survey (Maddaloni and Peydró, 2011) find that lending standards for corporate and household loans as reported by the banks themselves decline during times of low interest rates. Similarly, Buch et al.

(2014) make use of the Federal Reserve's Survey of Terms of Business Lending. They find evidence for a risk-taking channel of monetary policy particularly for small, domestic banks.

This paper falls in the third category. Although some papers that use balance sheet data from the United States or the euro area exist, many of them suffer from two drawbacks: First, they often use data on large, listed banks (Altunbas et al., 2014; Delis and Kouretas, 2011). Large banks may however do business in several countries and currencies so that they are less affected by their home country's interest rate. Also, they are more likely to have off-balance sheet positions that make it difficult to assess their true riskiness. Second, the explanatory variable, that is the stance of monetary policy, has no variation across the cross-sectional dimension of the panel as most studies rely on only one currency area. One exception is Altunbas et al. (2014) who estimate separate Taylor rules for the countries of the euro area. However, the authors use data from listed banks, which are often active on international financial markets, and therefore less exposed to the national economy. For the United States, Dell'Ariccia et al. (2013) also control for regional economic conditions via the inclusion of regional economic control variables or Taylor rule residuals calculated on a regional basis. They only use the headquarters of the bank to identify its location. Especially for large or transnational banks, the location of the headquarters may be chosen for tax reasons or be due to historical reasons. It may therefore have little to do with the locations of the activities of the bank. However, their results are robust to the exclusion of large banks. Therefore, this paper additionally controls for the location of bank branches to ensure that only banks enter the analysis that have the focus of their business activities in the region considered. Two other papers that use U.S. data exist (Paligorova and Santos, 2013; Delis et al., 2011) that combine bank balance sheet data with the use of loan-level data from commercial or business loans.

This paper contributes to the existing literature in several ways. First, it focuses on small banks in the United States. This is in contrast to existing evidence that often focuses on large, international banks. This yields a much more comprehensive picture of the risk-taking channel. Second, to the best of my knowledge, it is the only one that uses detailed data on the location of bank activities and therefore allows to exploit regional variation in economic condition. This makes it possible to study the effect of regional economic differences on the behavior of banks in one monetary policy regime. Third, it makes it possible to consider the effects of mismatched monetary policy in an economically diverse country which is similar to the situation in the euro area. Lastly, the paper also contributes to the analysis of the behavior of small banks as well as the analysis of regional economic effects of monetary policy.

2.3 Methodology and data

2.3.1 Identification strategy

In identifying the effect of monetary policy on bank risk, three other effects have to be taken into account. First, a reduction in interest rates implies a reduction of already existing credit risks. This may be due to lowered refinancing costs and an increased net worth of the borrower (Jiménez et al., 2014). Borrowers find it easier to pay back existing loans without any changes in bank behavior and a bank's capitalization may improve. Second, the interest rate is usually lowered to combat an economic slowdown. A declining macroeconomic environment can lead to more credit events, which raises the credit risk indicators, without changing bank behavior. These two effects can both obscure the direct effect of monetary policy on bank risk-taking. Third, a closely related point is the possibility that the stability of the banking sector directly affects monetary policy decisions (Altunbas et al., 2014).

Here, the first effect is taken into account via employing several measures of bank risk that should capture different dimensions of risk. Specifically, I use "forward-looking" measures of bank risk that should react immediately and "backward-looking" measures of risk, like distressed loans, that materialize only later or in times of crisis. For forward-looking risk measures, two strategies are used to mitigate the second and third effect. First, I consider the stance of the federal funds rate in relation to a Taylor-type monetary policy rule on a regional level. This implicitly takes the macroeconomic environment into account. As the timing, length and amplitude of business cycles can vary significantly between U.S. states (Owyang et al., 2005; Hamilton and Owyang, 2011), monetary policy is by necessity not always adapted to the economic situation of a specific U.S. state. Especially states that are dominated by agriculture or oil-production can experience separate recessions. Also, the business cycle of individual states may be ahead or behind the national business cycle.

As monetary policy has to be set on a national level, it cannot react to diverging economic situations on a regional level. Therefore, the deviation of monetary policy from its hypothetical optimal stance can reasonably be considered exogenous. Also, the focus on banks that are active only on a regional level implies that the banks considered here are comparatively small and not systemically important. This, again, makes it less likely that monetary policy directly reacts to their risk level or stability. Furthermore, to counteract the third effect, the analysis is stopped at the end of the year 2007. At this point, it becomes unlikely that monetary policy did not directly take the economic situation of the banks into account.

2.3.2 Construction of the dataset

Bank Balance Sheet data

The first main data source for the econometric analysis is balance sheet and income statement data from U.S. commercial banks retrieved from the publicly available "Reports of Condition and Income" (Call Reports). They include balance sheet items, income statements and some regional and structural information for federally insured U.S. commercial banks. The data cover the period from 1990 through 2007. The time span studied encompasses a full business cycle with times of both low and high interest rates. This yields a broad picture of different monetary policies. The analysis deliberately ends in 2007, to exclude the effects of the financial crisis, and the subsequent unconventional monetary and economic policy measures which could obfuscate the results.

A series of scans was applied to the data to ensure data integrity and in order to filter out banks that are unlikely to have the same risk-taking channel mechanism as an "ordinary" commercial bank. I drop grandfathered non-bank banks and banker's banks, as their balance sheet characteristics differ substantially from the other commercial banks and they are not always subject to reserve requirements. For similar reasons, I do not consider banks engaging primarily in credit card activity. They behave very differently from the rest of the sample (e.g. they report zero loans), but are too few to merit a separate analysis. Banks with foreign owners are not considered, as they probably have other refinancing and investment options than national banks. Their business decisions are therefore not only subject to the local economic environment. Scans to ensure data integrity are explained in more detail in the appendix. The appendix also includes detailed definitions of variables in table 2.3. As Kashyap and Stein (2000) were among the first to use Call Reports to study the bank lending channel, this paper follows their variable definitions when feasible.

The call report data is reported for the individual bank and not aggregated in case that the bank belongs to a bank holding company. This means that a bank may appear as being relatively small although it is owned by a larger bank holding company (Ashcraft, 2001). This membership in a larger financial group may lessen financial constraints a small bank faces and therefore dampen its reaction to monetary policy. Ashcraft (2006) finds that the loan supply of banks affiliated with a bank holding company reacts less to the federal funds rate. Therefore, the membership in a large bank holding company is controlled for in robustness checks.

Data on bank location

The balance sheet and income statement data is merged with a second dataset, Summary of Deposits data. This dataset contains detailed information on the number and location of the individual branches of banks as well as the amount of deposits that were collected in each branch. Therefore, using Summary of Deposits data, it is possible to pinpoint the geographic areas in which a bank is active. It is a popular data source in research that considers the regional activities of banks (e.g. Goetz, 2011) or regional effects such as competition or the effects of distance on lending (Berger et al., 2005; Carlson et al., 2013).

By using the Summary of Deposits data, it can be assured that the banks in the analysis are mostly active on a local level and are therefore subjected to the regional economic environment. This makes it possible to identify the effect of the stance of monetary policy in relation to the regional economic situation on bank risk. Larger banks and banks that are active in a larger region or have cross-border activities can balance out local economic differences. Also, the balance sheet and organizational structure of small banks is simple in comparison to larger banks which makes it more straightforward to assess their riskiness.

Using Summary of Deposits data, I am able to identify banks that are active in only one Metropolitan Statistical Area (MSA). To achieve this, only banks that are headquartered in one of the MSAs considered and have at least 95% of their branches in that MSA are included in the analysis. This ensures that only banks that act regionally and are primarily affected by local economic conditions are included in the analysis.

As Summary of Deposits data is available only since 1994, banks are excluded that leave the sample before 1993. This has no impact on the results, because a minimum of three consecutive years of data is a requirement for the econometric analysis anyway. If a bank had at least 95% of its branches in one MSA in 1994, then it is assumed that this was the case also from 1990 – 1994. This is a very weak assumption, as in later years, very few switches of location can be observed for banks.

When using Summary of Deposits data to localize the activities of a bank, the implicit assumption is that banks extend loans in the MSA where they have their branches and collect deposits. While this may be less clear for large banks, the literature on relationship lending shows that smaller banks may profit from the smaller distances between their loan officers and their borrowers as well as between the loan officers and management to process soft information which arises in opaque borrowers (Brevoort and Hannan, 2004; Berger et al., 2005). While technological progress and the increase in securitization activities has increased the possibility to lend at arm's length, recent research by Gilje et al. (2013) shows that branch networks are still important for the lending activities of banks. The assumption that banks are active where their branches are located is therefore reasonable.

There are still a large number of banks that act primarily locally and therefore do not have the possibility to diversify between different regions or countries. Goetz (2011) shows that a significant number of banks only have one office and the geographic concentration of banks is still high. In 2006, over half of all banks still serve only one county. In this analysis, as only banks that act locally are included in the regression, most are of a small and medium size.

Regional economic data

Regional data is used on the level of Metropolitan Statistical Areas (MSAs). MSAs are chosen by the Census Bureau to represent joined areas of economic activity (Marcoot, 1985) and are often used in the banking literature to define a local market (for example Berger et al., 1999, 2005; Ambrose and Pennington-Cross, 2000). MSAs consist of multiple counties and can extend over several states. For 23 of the largest MSAs, there are local consumer price, unemployment and personal income data available, which is used for the regression analysis. Table 2.1 in the appendix gives an overview of the 23 MSAs and their macroeconomic situation.

Due to the limited availability of consumer price index (CPI) data on a regional level, the dataset is based on yearly data. This is not unusual in the case of an analysis based on bank balance sheet data. From an economic perspective, the transmission of monetary policy via bank balance sheets takes time and making use of higher-frequency data would not necessarily capture the economic relationships better, but would definitively increase the noise in the data and decrease the size of the dataset.

Summary statistics

Table 2.4 provides summary statistics of the regression dataset and table 2.5 shows the development of bank balance sheet over time. The final dataset contains a total of 2,551 individual banks which is about one fourth of all commercial banks in the U.S. during that time. The number of banks decreases by about one third over time, which, again, is in line with the general trend.

With an average balance sheet size of 375 million USD in 1990 and 862 million USD in 2007 the banks in the dataset are comparatively, but not excessively, small. For comparison, Berger et al. (2005) categorize banks with total assets under 100 million USD as "small" and banks with total assets between 100 million and 1 billion as medium-sized. However, Berger and Bouwman (2012) define a bank as small if it has assets under one billion USD.

On the asset side, average holdings of cash and securities decrease over time while the fraction of loans increases. Especially real estate loans increase from 32% of total assets in 1990 to 53% in 2007. On the liability side, average equity capital increases from 9% in 1990 to 13% in 2007. The banks remain mainly financed through deposits (88% in 1990 and 81% in 2007). The median number of bank branches is 3 and the average about 5. About 10% of all banks have 10 branches or more. The number of bank branches per bank is very stable over time.

2.3.3 Bank risk measures

The complex nature of bank risk calls for several indicators to capture diverse aspects of bank risk-taking. As risk is difficult to measure, most indicators have some drawbacks. Several issues are apparent and are considered in the choice of risk measures.

First, banks can take on and be exposed to several kinds of risks, most importantly market risk, credit risk, interest rate risk, risk from maturity mismatch and operational risk. Most risk measures can only capture one or a few of these different dimensions. Second, the effects of the risk-taking channel depend on the time horizon studied. For example, in the short term a reduction of the policy rate has been shown to reduce the outstanding credit risk. At the same time, it encourages more risk-taking which may only materialize in the medium to long term. The true riskiness of a loan portfolio may only become apparent after all loans have been repaid or have defaulted.

As I focus on the behavior of small and medium-sized banks, my analysis has to rely solely on risk measures available from bank balance sheet and revenue data. Market based indicators are infeasible as there is usually no market information available for smaller banks. However, this does not have to be a drawback. Market information does not perfectly capture risk inherent in banks. The lack of reliable risk measurement is widely named as one of the factors leading to the market turmoil in 2007. Rating agencies were criticized in the aftermath of the financial crisis as their ratings failed to reflect the risk. The dramatic jump in yield spreads during the crisis, which are used for risk measurement, indicates that market information did not incorporate the risk inherent in the system. Also, market risk indicators such as risk premia are often lowest shortly before the downturn of the market.

As the balance sheet data is public, risk indicators based on it can only reflect the risk that the bank management and market participants also are aware of. The same is true for risk indicators based on survey data. Balance sheet indicators are a basic instrument compared to more sophisticated ratings. But the simplest measures may be the most robust and the ones that are the least affected by balance sheet arithmetic.

In order to obtain a comprehensive view of the many facets of bank riskiness, I use a large array of bank risk measures. They can be grouped in three categories. The first category are the "ex-ante" risk measures which can be expected to give information about the current and future stability of the bank. The main risk measure used here is the capital asset ratio (CAR), that is the ratio of equity capital to total assets, or the inverse of the leverage ratio. It measures the capitalization of banks and, thus, their ability to withstand adverse events. The riskiness of a bank is lowered if equity capital increases. Equity capital acts as a buffer against risks and it can be viewed as a measure of distance to default. On average, banks' capital asset ratios have increased during the time studied.

Other risk measures in this group are two balance sheet risk measures, which approximate the amount of risk a bank has on the asset side of its balance sheet. They are used in a similar definition in Angeloni et al. (2010). Risky assets are approximated here with the fraction of real estate loans and loans to individuals (Balance risk I) or alternatively with holdings of residential mortgages and loans to individuals (Balance risk II) over total assets. Balance sheet risk measures are particularly meaningful for smaller banks, as these make less use of securitization, credit default swaps or other means of transferring their risky positions off their balance sheet. Nevertheless, the regression robustness checks include controls for these activities as far as possible.

The following two risk measures capture not the level, but the increase (or decrease) in the riskiness of a bank. "Credit Growth" is the yearly growth rate of total loans and leases. Strong growth rates of bank lending should be associated with riskier lending if the pool of potential borrowers remains unchanged in quality and quantity. Köhler (2015) and Altunbas et al. (2012) both find that high growth rates of credit are a good indicator for increasing bank risk. On a macroeconomic level, excessive credit growth has also been shown to be a good predictor for financial instability (Eidenberger et al., 2015). "Expansion Real Estate" is the 12-month difference in the fraction of real estate loans over total assets of the bank and is also used in Angeloni et al. (2010). For these four risk measures, a higher value denotes higher risk.

The second category are the "ex-post" risk measures which are all based on similar notions of the ratio of troubled or non-performing loans. They are measures of credit risk. However, the risk may materialize only years after it has been taken, when the risky loan eventually fails. The main risk measure here is "Problem loans I" which is the ratio of loans late and loans not accruing over total assets. This measure of loan performance is relatively objective and, contrary to loan loss provisions, gives little freedom to managers to decide when a loan should be classified as non-performing (Campello, 2002). Again, a high value stands for high risk. The other risk measures of that category are described in detail in the appendix.

While the previous two categories of risk measures focused on bank capitalization and asset allocation, the third category of risk measures is geared towards the riskiness or instability of bank funding. The ratio of non-deposit funding over total liabilities equally indicates higher bank risk if the value is higher. Köhler (2015) finds that retail banks with higher ratios of non-deposit funding are less stable while investment banks are more stable. However, Altunbas et al. (2012) find, using a sample of listed banks, that a lower fraction of customer deposits in the bank funding mix is associated with higher risk.

The exact definition of all risk measures and their summary statistics may be found in tables 2.2 and 2.4 in the appendix. The correlations in table 2.6, unsurprisingly, show that some risk measures, such as the two balance sheet risk measures, are highly correlated while other risk measures show very little correlation.

2.3.4 Monetary policy measures

The economic data on the level of MSAs is used to evaluate the stance of monetary policy on a regional level using a monetary policy rule of the Taylor-type. In the case of the United States, data on unemployment, inflation and personal income growth is available on a regional level for 25 different Metropolitan Areas of which 23 are used for this analysis[1]. These areas are defined based on regional centers of economic activity. As the business cycles in the different parts of the U.S. are not completely synchronized and some areas enjoy stronger growth than others, regional differences can be used to study the effect of mismatched monetary policy on banks. I evaluate the stance of monetary policy using the residual obtained as the difference between the hypothetical interest rate prescribed by a regional monetary policy rule of the Taylor-type and the actual federal funds rate.

Monetary policy decisions are made to best fit the country as a whole. Specifically, the Federal Reserve cannot react to unemployment or inflation conditions in only one region. This means that the stance of monetary policy can then be seen as quasi exogenous for an individual MSA. This approach has previously been used for the countries of the Eurozone, where for example Altunbas et al. (2014) and Maddaloni and Peydró (2011) use Taylor rules to evaluate the stance of monetary policy using national economic data in the context of monetary policy and bank riskiness. For the United States, only Dell'Ariccia et al. (2013) use Taylor-rule residuals on a state level to this effect. However, using MSAs

[1] The Metropolitan Areas of Anchorage and Honolulu are excluded from the analysis. Although CPI data exists for them, they are not home to a sufficient number of banks to yield reliable regression results. However, they would have to be considered as outliers anyway due to their geographical location as well as different demographics (Williams, 1996).

I am able to include more years of data in my analysis. Also, this paper is the first to not only rely on the location of the headquarters of the bank but also on the location of its branches in order to determine its location. Especially for larger banks, the location of the headquarters may not be meaningful for the center of its activities.

The Taylor rule (Taylor, 1993) offers a descriptive measure of the adaptedness of monetary policy to the economic environment. Although it is a quite simple measure, Judd and Rudebusch (1998) find that "simple Taylor-type reaction functions [...] perform almost as well as optimal, forecast-based reaction functions" and continue that "the general form of the Taylor rule may be a good device for capturing the key elements of policy in a variety of policy regimes".

While the traditional Taylor rule is constructed using data on inflation and some measure of the output gap, the monetary policy rule used here relies on unemployment data rather than GDP data as the former is available on county level. The county level data is then aggregated on the level of the MSA, weighted by population of the counties, to match the aggregation level of the CPI data. The monetary policy rules are calculated at a yearly frequency. That is, core inflation is the inflation rate for the last 12 months and unemployment is the average of the last 12 months unemployment rates. The inflation measure is the change in the core consumer price index (CPI) which excludes food and energy prices and may therefore be better suited to depict real inflation that can be influenced by monetary policy. The use of unemployment data is not untypical in the literature that augments Taylor-type rules with regional information (Coibion and Goldstein, 2012; Jung and Latsos, 2014). Also, as the dual mandate of the Federal Reserve is to promote maximum employment *and* stable prices it is not inferior from a theoretical point of view.

In its baseline specification, the monetary policy rule used here is based on Mankiw (2002) who estimates a simple Taylor-type rule based on the unemployment rate and the core consumer price index. The coefficients were chosen to match the decade of the 1990s best, which is seen as a decade where monetary policy was doing reasonably well (Mankiw, 2002).

Normally, central banks have an interest to avoid sudden shocks in their monetary policy and therefore tend to adjust their interest rates only gradually in response to macroeconomic changes. I therefore add a lagged value of the predicted federal funds rate as a smoothing parameter to the above monetary policy rule, which is similar to Judd and Rudebusch (1998) or Altunbas et al. (2014). The current predicted value of the federal funds rate is weighted with 0.8 and the previous predicted value with 0.2. The initial value in the first year is not smoothed. The stance of monetary policy (MP) that would theoretically be best suited to the individual MSA then results from the following equation:

$$\begin{aligned} Predicted\,MP_t &= 0.8 * (8.5 + 1.4 * (Core\,Inflation - Unemployment\,rate)) \\ &\quad + 0.2 * Predicted\,MP_{t-1} \end{aligned} \tag{2.1}$$

The inflation rates of the average of the MSAs in the sample and the national average are very highly correlated with over 90%. The correlation between the average unemployment rate in the counties studied and nationwide unemployment rate is over 99%. This means that results obtained here cannot be due to systematic differences between the MSAs studied and the situation in the whole of the United States. When calculated with national unemployment and inflation data, this monetary policy rule follows the actual path of monetary policy quite closely as seen in figure 2.2.

The identification strategy hinges on the point that the macroeconomic environment in the MSAs can be fundamentally different from the overall macroeconomic situation of the United States which is considered by the Federal Reserve. Due to differences between CPI and unemployment rate on the level of MSAs and the national rates, monetary policy may be "mismatched" when compared to a hypothetical regional monetary policy rule. Two examples of conflicting regional Taylor rules are the Metropolitan Areas of Denver-Boulder-Greeley and Los Angeles-Riverside-Orange County (figure 2.6 and 2.7 in the appendix). For other regions, such as Pittsburgh, the actual federal funds rate follows the regional Taylor rule prescription quite closely. Figure 2.1 in the Appendix shows the location of the MSAs and the deviation of the regional Taylor rules from the federal funds rate in 1990. It illustrates that, at the same time, the same federal funds rate is relatively loose in some regions and relatively restrictive in others. More importantly, the boxplot of the stance of monetary policy relative to economic conditions in the MSAs (figure 2.4) shows that in nearly every year, some MSAs experience monetary policies that are too restrictive and others experience monetary policies that are too loose. Also, there is no MSA that consistently experiences a stance of monetary policy that is always too restrictive or always too loose.

In an alternative estimation of the monetary policy rule, rather than relying on coefficients of weights for unemployment and inflation suggested in the literature, I also estimate the coefficients using OLS regression. Here, as well as in the previously presented monetary policy rules, the implicit assumption is that all regions have the same preferences regarding the relative weight of unemployment and inflation in the determination of monetary policy. As information about these hypothetical preferences would be almost impossible to obtain, the assumption is made that the overall national preferences are equal to those of the regions. For the regression, I only use data until the end of 2006 to estimate the coefficients. This owes to the fact that after the onset of the financial crisis and the subsequent introduction of unconventional monetary policy measures traditional monetary policy rules hit the zero lower bound. The inflation target is set to 2%. This yields the following monetary policy rule with regression based coefficients:

$$\begin{aligned} Predicted\,MP &= .1083477 + 1.828929 * (Core\,Inflation - 0.02) \\ &\quad -1.446808 * Unemployment\,rate \end{aligned} \tag{2.2}$$

When calculated with national unemployment and inflation data, this monetary policy rule also follows the real path of monetary policy quite closely as seen in figure 2.3. Again, the boxplot in figure 2.5 shows that the de facto federal funds rate is within the scope of the hypothetical regional rates set by the monetary policy rules in most years. That is, in most years, some MSAs are below the actual federal funds rate and some above.

The robustness section of this paper shows results based on different specifications of monetary policy rules. It provides evidence that results obtained here are not qualitatively dependent on the exact specification of the rule.

2.4 Econometric model and results

2.4.1 Econometric model and control variables

Equation 2.3 regresses the value of the bank risk measure on a constant, a lagged value of itself, the monetary policy rule residual, a set of bank control variables and a set of year dummies. The dependent variable is one of the bank risk measures discussed in the previous section. The main explanatory variable is the monetary policy residual, which is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The econometric model is inspired by Delis and Kouretas (2011).

$$\begin{aligned} risk_{it} &= \alpha + \beta\, risk_{i,t-1} + \gamma_1\, MP\, residual_{j,t} \\ &\quad + \gamma_2\, controls_{i,t} + \delta\, Year_t + \epsilon_{i,t} \end{aligned} \tag{2.3}$$

As the commercial banks in the sample can be heterogeneous, measures of bank size, profitability, efficiency and liquidity are included as control variables. In the baseline specification, the number of controls is kept rather small in the interest of a parsimonious model specification, however, further controls are added in the robustness section. Most bank-level controls are standard in the related literature and an overview including summary statistics and more details on definitions may be found in the appendix.

Bank size is linked to ease of funding of the bank. It is approximated with the log of total assets. As in Kashyap and Stein (2000), bank liquidity is approximated by the ratio of securities to total assets. In general, liquidity and risk-taking are interconnected and can have mutual effects on each other. For example, an asset that is perceived to be low-risk has a higher liquidity, which again leads to lower perceived risk (Borio and Zhu, 2012). A similar argument can be made for commercial banks. For them, holding liquid assets implies lower risk stemming from maturity mismatch and similar risk factors. Also, banks that hold a lot of liquid assets can use them to smooth the effects of monetary policy (Campello, 2002; Bernanke and Blinder, 1992).

Bank profitability is defined as profits before taxes over total assets. Delis and Kouretas (2011) argue that the effect of profitability on bank risk-taking is complex. More risk-taking increases profits, which can be used to take on even more risky credit. Eventually, too much risky credit may diminish profits. A particularly unprofitable bank may also try to increase its profitability by taking on more risk. Also, a profitable bank can more easily build up or replenish a capital buffer.

A final control variable is bank efficiency which is approximated as the ratio of total operating income to total expenses. A higher value of the control variable indicates higher efficiency. The motivation for the inclusion of this control variable is that technically efficient banks could also be more efficient at risk management. Wheelock and Wilson (1995, 2000) find that more efficient banks are also better at screening and monitoring loans and less efficient banks have higher probabilities of failure. Also, Jonas and King (2008) find that the lending of more cost-efficient banks reacts stronger to monetary policy changes.

For the estimation of the econometric model a general method of moments (GMM) estimator for dynamic panel data, as developed by Arellano and Bover (1995) and Blundell and Bond (1998), called system GMM, is used. The use of the system GMM estimator is well established in the empirical bank risk-taking literature. Delis and Kouretas (2011) and Altunbas et al. (2010) both use system GMM in similar model specifications. Via the dynamic estimator, the lagged bank risk measure can be included as an explanatory variable in the regression. This is helpful, as individual bank risk is highly persistent (Delis and Kouretas, 2011). Bank risk persists for example due to the long-term nature of credit contracts, relationship lending, limited off-balance sheet activities of small banks and the risk culture established in a bank.

The system GMM estimator is suitable for dynamic panels with "small T and large N" datasets. As the time dimension is comparatively large (17 years), I restrict the number of lags used as instruments and collapse the instrument set (Roodman, 2007). In the choice of the number of lags I also experiment with principal component analysis as suggested in Mehrhoff (2009), however, this did not improve results. As recommended by Roodman (2006), a set of year dummies is included in each regression.

The estimator uses suitable lagged values of variables (in levels and differences) as instrumental variables for endogenous variables. This makes it possible to include potentially endogenous regressors even if no other good instrumental variables are available. When analyzing bank risk, many bank characteristics are expected to be endogenous. The estimator is not affected by the dynamic-panel or Nickell bias (Nickell, 1981) which arises in fixed effects models that include a dynamic term. System GMM does not break down in the presence of unit roots.

Bank-specific characteristics, such as profitability, are potentially endogenous in risk equations. Therefore, they enter the regression as endogenous variables. Bank size is treated as predetermined. While the federal funds rate would have to be considered as endogenous to the overall banking system, the monetary policy rule residual offers an element of exogeneity.

2.4.2 Results on baseline specification

Category 1: Ex-ante risk measures

The first set of regression results in table 2.7 reports the results for the group of ex-ante risk measures. Note that for the capital asset ratio a lower value indicates a higher risk. For the other risk measures, a higher value indicates a higher risk.

For the capital asset ratio as a risk measure, I find a significant negative coefficient of the monetary policy residual on the level of the capital asset ratio. This means that a federal funds rate that is too low in relation to the stance indicated by the monetary policy rule is associated with lower bank capitalization. In the case of the other risk measures, the coefficients are significant and positive. This result points in the same direction in terms of bank risk. The two measures of balance sheet risk that signal the amount of particularly risky assets on bank's balance sheet show that levels of balance sheet risk in banks are higher where monetary policy is comparatively loose.

Also, the risk measures of growth of credit and expansion of risky assets on bank balance sheets are significant and positive. This indicates that banks do not only have higher levels of risk when interest rates are too low in comparison to regional economic surroundings, but they are actively engaged in risk-taking. As the banks' riskiness increases when the stance of monetary policy is too low, these results show strong evidence in favor of the existence of the risk-taking channel for small commercial banks. When expressing the regression coefficients in the form of standardized beta coefficients, a one standard-deviation increase in the monetary policy rule residual is associated with a 0.012 to 0.015 standard deviation decrease in capital asset ratios of a bank. Results for the balance sheet risk measure are in a similar range. While this indicates that the effect of the monetary policy residual on bank risk is relatively small, it may be still relevant on a macroeconomic level.

The estimated coefficients of the lagged risk measure confirm that bank risk-taking is persistent over time. Interestingly, even the risk measures that indicate the expansion or growth of risky positions on banks' balance sheets show a significant dynamic coefficient. The results table 2.7 also repeats the regressions for residuals obtained from the two different specifications of the monetary policy rule as introduced in the previous section. Coefficient signs and sizes are very robust to these changes.

Category 2: Ex-post risk measures

The next set of regression results in table 2.8 shows the results of the same regression equation for the ex-post risk measures. As these risk measures are expected to pick up the riskiness of the loan portfolio only after a few years, it is less likely that these capture the immediate effect of the risk-taking channel.

Indeed, results indicate that if monetary policy is too low in relation to the regional economic situation, all measures of loan performance are better, that is, the loan portfolio is less risky. This is probably due to the comparatively good economic situation the banks and the local borrowers are facing. Using this regression specification, not surprisingly, no effect of the risk-taking channel is found.

This finding demonstrates that it is not easy to distinguish between the effect of the regional economic environment and the effect of monetary policy. However, a similar positive effect of the economy on the risk level could also have been reasonable for the capital asset ratio as a risk measure, but this was not the case. This, again, points towards the existence of a risk-taking channel for this group of banks.

Category 3: Risk-taking on the deposit side

There are multiple ways for a bank to increase their risk-profile. Banks can increase their risk-taking via their asset-side (for smaller banks most often via loan quality and loan quantity), but risk can also increase through riskier funding. The regression results in table 2.9 therefore use the ratio of non-deposit funding of the bank as a risk measure. Again, non-traditional funding sources have been linked with higher bank risk (Köhler, 2015). The results here confirm that banks increasingly make use of non-deposit funding when interest rates are comparatively low. Small, regionally active banks can attract only a limited amount of additional deposits without raising their deposit rates. An expansion of risk on the balance sheet via credit growth may have to be refinanced with higher amounts of non-deposit funding. An increase in non-deposit funding can therefore be seen as complementary to the increase in the balance sheet and capitalization risk measures; as the other side of the coin of the risk-taking channel.

2.4.3 Extension of the baseline model

Addition of interaction terms

In the next step, the model is extended to include interaction terms of bank-specific variables and the monetary policy residual. More information about the types of banks that are especially susceptible to increase their risk-taking in times of low interest rates is interesting for current policy analysis and possible micro- and macroprudential policy measures.

$$\begin{aligned} risk_{it} &= \alpha + \beta\, risk_{i,t-1} + \gamma_1\, MP\, resid_{j,t} + \gamma_2 MP\, resid_{j,t} * controls_{i,t} \\ &\quad + \gamma_3\, controls_{i,t} + \delta\, Year_t + \epsilon_{i,t} \end{aligned} \tag{2.4}$$

In separate regressions, each of the baseline bank control variables liquidity, profitability and efficiency is interacted with the monetary policy residual (*MP resid*). The interaction term also includes other bank characteristics that might influence the reaction of banks to the relative stance of monetary policy, specifically the loan to deposit ratio, the bank lending rate and an indicator for membership in a bank holding company.

Here, a significant effect is found for the interaction of bank liquidity with the monetary policy residual. Results in table 2.10 show that the coefficient sign and significance of the monetary policy residual by itself is robust to the inclusion of the interaction effect. The coefficient of liquidity by itself (positive for the capital asset ratio as a risk measure, negative for the other risk measures) indicates that banks that are more liquid are less risky.

The negative coefficient of the interaction term indicates that liquidity may have a protective effect on bank risk-taking: Banks that have above-average liquidity and are exposed to a monetary policy that is too low with regard to the regional economic conditions are less risky and increase their risk-taking less than their less liquid counterparts. In case of the capital asset ratio, the coefficient does not have the expected sign but is also not significant. One possible concern may be that as bank liquidity is approximated with the banks holdings of securities, lower amounts of risky credit may simply result from higher holdings of securities. Three of the four balance sheet risk measures do however display very low or negative correlations with bank liquidity, which alleviates this concern.

The monetary policy transmission literature also stresses the importance of bank liquidity. Kashyap and Stein (2000) find that less liquid banks also react stronger to a tightening in monetary policy than their more liquid counterparts. They restrict their lending more in response to a higher federal funds rate. This holds especially for small banks. Gambacorta (2005) also finds that liquidity is important for a bank's reaction to a monetary policy tightening. More liquid banks decrease their lending less in response to tighter monetary policy.

2.4.4 Robustness of results

This section explores the econometric validity of results and reports the results of a series of robustness tests and different specifications of the equation of interest.

Addition of explanatory variables

First, the robustness of results is confirmed by adding a variety of different control variables that may also influence the riskiness of banks or their reaction to monetary policy, but which were omitted in the baseline specification in the interest of parsimony. Table 2.11 repeats the regression using the capital asset ratio as a risk measure and includes one additional explanatory variable in each column. In the first column, an indicator variable for membership in a large bank holding company is included. Ashcraft (2006) finds that the loan supply of banks affiliated with a bank holding company (BHC) reacts less to the federal funds rate. This could also imply that the risk-taking channel of monetary policy is stronger for small banks that are not part of a BHC. However, Berger et al. (2005) find that in the case of banks that are part of a BHC, the size of the bank and not the size of the bank holding company matters for their lending behavior. Here, banks that are part of a large BHC have higher capital asset ratios, but the effect of the monetary policy residual remains qualitatively unchanged.

In columns 2 and 3, indicator variables control for off-balance sheet activities and the use of credit derivatives by the bank. Both dummy variables are not significant and do not change results. As very few banks in the sample engage in these activities this result may not transfer to larger banks. Column 4 includes the bank lending rate as banks with particularly low lending rates may have an additional incentive to increase their riskiness. Column 5 adds the demand deposit ratio. Banks with very unstable funding may be forced to keep higher capital. Both coefficients are not significant.

The last two columns include the personal income per capita at the MSA level. In column 6 it is expressed as a moving average of the last three years while column 7 includes the personal income per capita as a second lag. This additional economic control variable should capture the past economic situation of the MSA which may also have contributed to the risk profile of the bank. Again, results remain robust.

Results table 2.12 repeats the same regression using the first balance sheet risk measure instead of the capital asset ratio. Here, only the significant negative coefficient of the demand deposit ratio indicates that banks with more short-term funding may be wary of increasing their risk. Again, the baseline results are robust to the inclusion of additional explanatory variables.

Robustness to the specification of the monetary policy rule

One of the assumptions that has to be made for the analysis is that the stance of monetary policy can be captured reasonably well using a monetary policy rule. Here, a Taylor-type rule is chosen. However, there exist a large number of possible specifications of monetary-policy rules and some of the more established specifications are not possible due to lack of economic data at the MSA level. Therefore, it is important to demonstrate that the results obtained in this paper do not significantly depend on the exact choice of the monetary policy rule.

That is why table 2.13 repeats the regression results for six different specifications of the monetary policy-type rule. The first two columns repeat the two specifications already described in the previous section in equations 2.1 and 2.2. Column 3 is based on the monetary policy rule described in equation 2.1 but uses only the first part of the rule, that is, without the smoothing term. Columns 4 and 5 are also based upon the monetary policy rule described in equation 2.1 but use different coefficients as re-estimated by Krugman (2010). Column 4 includes the smoothing term and column 5 excludes it. Lastly, column 6 is based on the monetary policy rule in equation 2.2 but in contrast to the baseline specification which only uses data until the year 2006 it uses all years of available data in the estimation of the parameters.

The coefficients remain virtually unchanged in all different specifications of the monetary policy rule shown in table 2.13. In all specifications, the coefficient of the deviation from the monetary policy rule remains negative and significant. Therefore, results are robust to the exact specification of the monetary policy rule.

Econometric validity of results

Both the Hansen and the Sargan test are tests of joint validity of all instruments. Their null hypothesis is that the population moment conditions are correct (Cameron and Trivedi, 2010). But they can also be seen as a test of structural specification. If important explanatory variables are omitted, variation could be moved into the error term and lead to correlation with the instruments (Roodman, 2007). The Sargan test requires more restrictive assumptions than the Hansen test as it assumes homoscedastic errors for consistency. This is rarely the case. The Hansen test can be severely biased by instrument proliferation. Given the large size of the dataset and the restricted number of lags in the instrument set, the Hansen test can be considered to be more robust for this analysis. Therefore, I apply the Hansen test for tests of model specification. It points towards the correct specification of the instrument set in nearly all reported regressions.

The Arellano-Bond test for autocorrelation in first differences tests the key assumption that the ϵ_{it} are serially uncorrelated (Arellano and Bond, 1991). First-order autocorrelation in errors is to be expected as the regression runs on first differences. However, the null hypothesis of no second or higher order autocorrelation in errors should not be rejected. This is the case in all reported regressions. All regressions are run using the two-step estimator which obtains in a first estimation the optimal weighting matrix for the second step (Cameron and Trivedi, 2010). Standard errors in the two-step model can be downward biased if the sample is small and the instrument count large. Windmeijer's finite sample correction is used to counter this problem (Roodman, 2006). Small-sample bias should not be an issue in this large dataset.

The coefficient of the lagged dynamic variable in a system GMM estimation should lie in between the coefficients of an OLS and a fixed effects (FE) regression of the same equation. Both OLS and FE results are expected to be biased, however, in different directions. As an additional check of the method employed here, the results tables 2.14, 2.15 and 2.16 also report OLS and fixed effects regression results. In nearly all cases the coefficient lies in between the coefficients of the OLS and FE regression. There are some very few cases where it lies just outside the range. As this happens rarely and the regression results are generally unchanged and all other tests point towards a correct specification of the model, this should not give rise to excessive doubts.

2.5 Conclusion

I study the effect of monetary policy on the risk-taking of small U.S. commercial banks that act primarily regionally. Regression results provide evidence that comparatively loose monetary policy is associated with a lower capital asset ratio, higher level of balance sheet risk, higher growth of balance sheet risk and less stable funding sources. Risk measures based on non-performing loans show lower levels of risk. This is probably due to the benign economic environment the bank is active in. It is therefore important to employ a large variety of risk measures in order to capture the different facets at work in bank risk-taking. Banks that are especially liquid seem to be protected from the increase in risk-taking. Although establishing the causality would necessitate further research, the introduction of additional liquidity regulations in Basel III may be beneficial from a balance sheet risk perspective.

It becomes evident that risk measurement is one of the key challenges of studying the risk-taking channel – especially for small banks where no market data is available. Risk measurement also has regulatory implications. Especially in light of the risk-taking channel, banking regulation needs to take into account how banks perceive and measure risks. An improvement of risk measurement might be to require risk measurement over longer time horizons. This could lead banks to focus more on the risk of changing interest rates and to consider the long-term default probabilities of their credit portfolios. Borio and Zhu (2012) suggest that this could lead to more prudent behavior.

When considering the economic relevance of the results one has to keep in mind that small commercial banks are only one type of financial institutions through which the risk-taking channel may take effect. Large commercial banks are probably exposed to the same incentives if monetary policy is mismatched on a larger scale. Other institutions, such as insurance firms, investment banks or investment funds, will also take on additional risk during times of low interest rates. For these, the risk-taking channel may work with a modified mechanism. For institutions that are less regulated than commercial banks, the effect of the risk-taking channel is likely to be more pronounced.

2.6 Appendix to chapter 2

2.6.1 Data sources and data description

A series of scans was applied to the call report data to ensure the exclusion of obviously faulty data or obvious outliers: Individual observations are deleted in the rare case of negative or zero loans, equity, deposits or assets. As the econometric model requires differences and lagged values, banks with less than three consecutive observations are excluded from the dataset. I obtained a comprehensive list of failed banks from the FDIC. Failed banks are deleted in the last reported year as the last observations often include negative or extreme values.

In Call Reports, balance sheet data is provided for the domestic dealings of banks only (RCON series) as well as on a consolidated basis for foreign and domestic holdings (RCFD series). Here, the consolidated series is used. For banks without foreign operations, the RCFD and the RCON series are usually identical (Federal Reserve Bank of Chicago, 1998). In this analysis of small banks the differences should be minimal. However, as some variables do not exist on a consolidated basis, occasionally the domestic series is used. See the variable definition table for details when this is the case.

A little over one fifth of the different commercial banks (552 of 2,551) in the dataset are observed in all years. As the number of banks in my sample decreases from 1,858 in 1990 to 1,190 in 2007, data inconsistencies through mergers may pose a problem. Data on bank mergers is confidential and in the case of mergers, the bank continues to exist under the same ID. To correct for mergers, I follow Den Haan et al. (2002, p. 9) and drop an observation from the sample if the loan growth rate diverges by more than 5 standard deviations from the cross-sectional mean loan growth rate of that quarter. Random checks of some banks thus excluded showed that this procedure did filter out observations during mergers and takeovers. Also, Kishan and Opiela (2006), who study the effects of monetary policy on loan growth using Call Report data, find that they obtain similar results with merger-adjusted and non merger-adjusted data.

Banks are only included if they are active in one of the Metropolitan Statistical Areas considered. This means that in the event that a bank moves its headquarters out of an MSA considered it will exit the sample at that point in time (or vice versa, if it moves its headquarters into one of the MSAs considered). This effect is, however, small. There was only one case in the dataset where a bank moved its headquarters from one MSA to the other.

Data on the federal funds rate was obtained from the Federal Reserve System website. Unemployment and Consumer Price Index data was retrieved from the Bureau of Labor Statistics website. Data on CPI, GDP and personal income was obtained from the U.S. Department of Commerce Bureau of Economic Analysis. The regional CPI data are based on the 1990 definitions of MSAs. Data on personal income and unemployment rates are available on county level and were aggregated at MSA level using population weights also obtained from the Bureau of Economic Analysis. The list of failed banks was obtained from the FDIC. Information on the composition of MSAs was obtained from the U.S. Census Bureau. While data on unemployment is available at monthly frequency, for some of the MSAs, CPI data is available only at a bi-yearly level. Therefore, the analysis is based on a yearly level, using year-end data unless specified otherwise.

The econometric analysis is performed with Stata using the xtabond2 module as described by Roodman (2006).

Table 2.1: Metropolitan Statistical Areas overview

Metropolitan Area Name	includes parts of States	no. of banks in 1990	2010	population (million) in 1990	2010	unemployment 1990 - 2010	core inflation 1990 - 2010
New York-Northern New Jersey-Long Island	NY-NJ-CT-PA	178	109	19.78	22.18	6.13%	2.90%
Philadelphia-Wilmington-Atlantic City	PA-NJ-DE-MD	94	54	5.89	6.49	5.79%	2.70%
Boston-Brockton-Nashua	MA-NH-ME-CT	83	27	6.53	7.23	5.43%	2.71%
Pittsburgh	PA	27	10	2.40	2.29	5.58%	2.59%
Chicago-Gary-Kenosha	IL-IN-WI	394	161	8.24	9.53	6.22%	2.40%
Detroit-Ann Arbor-Flint	MI	56	29	5.19	5.32	7.10%	2.33%
St. Louis	MO-IL	116	63	2.49	2.72	5.60%	2.34%
Cleveland-Akron	OH	23	13	2.86	2.88	5.97%	2.24%
Minneapolis-St. Paul	MN-WI	153	102	2.54	3.28	4.07%	2.46%
Milwaukee-Racine	WI	57	24	1.61	1.75	4.96%	2.49%
Cincinnati-Hamilton	OH-KY-IN	41	20	1.82	2.10	5.21%	2.38%
Kansas City	MO-KS	134	70	1.58	1.97	5.17%	2.23%
Washington-Baltimore	DC-MD-VA-WV	131	60	6.73	8.61	4.41%	2.46%
Dallas-Fort Worth	TX	187	91	4.04	6.44	5.33%	2.28%
Houston-Galveston-Brazoria	TX	142	57	3.73	5.89	5.82%	2.43%
Atlanta	GA	93	58	2.96	5.11	4.99%	1.90%
Miami-Fort Lauderdale	FL	68	41	3.19	4.24	6.56%	2.90%
Los Angeles-Riverside-Orange County	CA	180	98	14.53	17.88	7.00%	2.52%
San Francisco-Oakland-San Jose	CA	77	41	6.25	7.41	5.62%	2.73%
Seattle-Tacoma-Bremerton	WA	37	33	2.97	4.02	5.55%	2.97%
San Diego	CA	29	19	2.50	3.10	5.62%	2.98%
Portland-Salem	OR-WA	19	14	1.79	2.61	5.96%	2.80%
Denver-Boulder-Greeley	CO	202	30	1.98	2.98	4.75%	2.96%

The Washington-Baltimore Metropolitan Area has inflation data available only since 1998 and is excluded from the regression before that time.

Table 2.2: Bank risk measures overview

Variable name	ID / Definition	Description
CAR	$rcfd3210/rcfd2170$	Capital asset ratio, total equity capital / total assets
Balance sheet risk I	$\frac{rcfd1410+rcfd1975}{rcfd2170}$	Real estate loans + loans to individuals / total assets
Balance sheet risk II	$\frac{rcon1430+rcfd1975}{rcfd2170}$	Residential mortgages + loans to individuals)/total assets
Credit growth	$\frac{rcfd1400-L.rcfd1400}{L.rcfd1400}$	Growth rate of total loans and leases, yearly
Expansion real estate	$\frac{rcfd1410}{rcfd2170}_t - \frac{rcfd1410}{rcfd2170_{t-1}}$	Yearly difference in the fraction of real estate loans over total assets
Problem loans I	$\frac{rcfd1407+rcfd1403}{rcfd2170}$	Loans late and loans not accruing over total assets
Problem loans II	$\frac{rcfd1407+rcfd1403}{rcfd1400}$	Loans late and loans not accruing over total loans
Loans not accruing	$rcfd1403/rcfd1400$	Total loans not accruing over total loans
Loans late	$rcfd1407/rcfd1400$	Loans 90 days or more late over total loans
Non-deposit funding	$\frac{rcfd2950-rcfd2200}{rcfd2950}$	Non-deposit funding over total liabilities

Table 2.3: Bank characteristic variables

Variable name	ID / Definition	Description
Cash	$rcfd0010$	Cash and balances due from depository institutions
Total assets	$rcfd2170$	Sum of all asset items
Total liabilities	$rcfd2948$	Total liabilities, incl. subordinated debt
Securities	$rcfd0390 + rcfd2146$	Investment securities (book value) plus assets held in trading accounts (until 1993)
	$rcfd1754 + rcfd1773$	Total securities, held to maturity and available for sale assets (since 1994)
Total loans	$rcfd1400$	Gross book value of total loans and leases
Real estate loans	$rcfd1410$	All loans secured by real estate
C&I loans	$rcfd1766$	Commercial and industrial loans
Total deposits	$rcfd2200$	Total deposits
Equity	$rcfd3210$	Total equity capital
Profitability	$riad4000/rcfd2170$	Total operating income (last 12 months) over total assets
Liquidity	$\frac{rcfd1754+rcfd1773}{rcfd2170}$	Ratio of securities to total assets
Efficiency	$riad4000/riad4130$	Total operating income over total operating expenses (in last 12 months)
Bank size	log (rcfd2170)	Log of total assets
Multi-BHC member	Inferred from rssd9348 and rssd9348	Membership in a bank holding company that holds multiple banks
Off-balance sheet indicator	Inferred from rcfd8764 and rcfd8764	Equals 1 if there is credit exposure across all off-balance sheet derivative contracts
Credit derivatives indicator	Items rcfda535 and rcfda535	Equals 1 if the bank is beneficiary of credit derivatives
Bank lending rate	$riad4107/rcfd1400$	Interest income from loans over total loans
Demand deposit ratio	$rcfd2210/rcfd2200$	Demand deposits over total deposits

The balance sheet variables follow the specifications in Kashyap and Stein (1995, 2000) and the notes by the Federal Reserve Bank of Chicago (1998) where possible. Variable descriptions are summarized from the MDRM data dictionary and Reports of Condition and Income glossary.

Table 2.4: Summary statistics regression dataset

	N	mean	sd	min	max
as a fraction of total assets					
Cash	26,794	.06	.048	0	.77
Securities	26,794	.25	.15	0	.98
Total Loans	26,794	.60	.16	0	1
Total Deposits	26,794	.85	.092	0	1
Equity Capital	26,794	.099	.054	.001	.99
Risk measures					
Capital asset ratio	26,794	.099	.054	.001	.99
Balance risk I	26,794	.46	.16	0	1
Balance risk II	26,794	.22	.14	0	1
Credit growth [yearly]	23,989	.29	9.5	-1	1,368
Ex. real estate [yearly]	25,778	.014	.063	-.84	.56
Problem loans I	26,793	.008	.012	0	.24
Problem loans II	26,793	.013	.021	0	.65
Loans late	26,794	.003	.008	0	.22
Loans not accruing	26,793	.009	.018	0	.65
Non deposit funding	26,794	.052	.088	0	1
Other explanatory and control variables					
Residual MP rule (Type 1)	25,353	.005	.022	-.07	.069
Residual MP rule (Type 2)	25,978	.003	.025	-.077	.076
Liquidity	26,794	.25	.15	0	.98
Profitability	26,794	.081	.16	0	25
Efficiency	26,789	1.3	.43	-3.4	59
Bank size	26,794	12	1.2	7.4	19
Multi-BHC membership	26,794	.2	.4	0	1
Off-balance sheet indicator	26,794	.027	.16	0	1
Credit derivatives indicator	26,794	.001	.032	0	1
Bank lending rate	26,794	.51	33	0	5,162
Demand deposit ratio	26,794	.19	.10	0	1
Personal income (per-capita, USD)	26,794	30.839	7.674	19.482	58.711

Table 2.5: Balance sheet size and composition of banks in regression dataset over time

Year	1990	2000	2007
Number of banks	1,858	1,327	1,190
Mean Assets (million USD)	375	602	862
Median Assets (million USD)	67	125	179
Fraction of total assets (in %)			
Cash	.079	.054	.041
Securities	.23	.23	.17
Total Loans	.58	.62	.70
Real estate loans	.32	.41	.53
C&I loans	.14	.14	.12
Deposits	.88	.84	.81
Demand deposits	.16	.15	.11
Equity Capital	.093	.10	.13

Table 2.6: Correlation table of risk measures and main independent variables

	CAR	Balance risk I	Balance risk II	Credit growth	Ex. real estate	Probl. loans I	Probl. loans II	Loans late	Loans n. accruing	Resid. MP rule	Liqui- dity	Profit- ability	Effi- ciency	Bank size
Capital asset ratio	1													
Balance risk I	-0.11	1												
Balance risk II	-0.14	0.46	1											
Credit growth	0.13	-0.01	0.00	1										
Ex. real estate	0.06	0.21	0.04	0.07	1									
Problem loans I	-0.11	0.06	-0.00	-0.01	-0.07	1								
Problem loans II	-0.10	-0.08	-0.05	-0.01	-0.11	0.89	1							
Loans late	-0.04	-0.04	0.07	-0.01	-0.06	0.54	0.54	1						
Loans not accruing	-0.10	-0.07	-0.09	-0.01	-0.11	0.81	0.93	0.20	1					
MP rule residual	0.03	0.03	0.03	0.00	0.07	-0.19	-0.19	-0.09	-0.18	1				
Liquidity	-0.07	-0.59	-0.13	0.00	-0.12	-0.16	-0.03	0.01	-0.03	-0.01	1			
Profitability	0.06	-0.02	0.03	0.01	-0.03	0.03	0.03	0.02	0.02	-0.02	-0.02	1		
Efficiency	0.04	0.06	0.01	-0.01	-0.03	-0.08	-0.08	-0.03	-0.08	0.03	0.01	0.01	1	
Bank size	-0.19	0.09	-0.04	-0.02	-0.06	-0.00	-0.01	-0.06	0.01	-0.04	0.02	-0.03	0.18	1

2.6.2 Figures and regression results

Figure 2.1: Metropolitan Areas with deviation from monetary policy rule in 1990

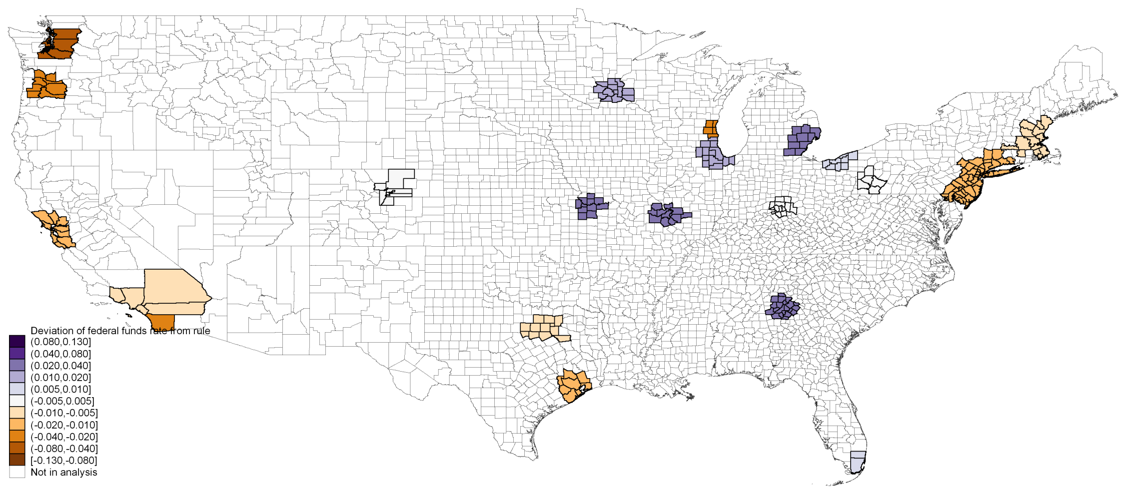


Figure 2.2: Federal funds rate and monetary policy rule (equation 2.1)

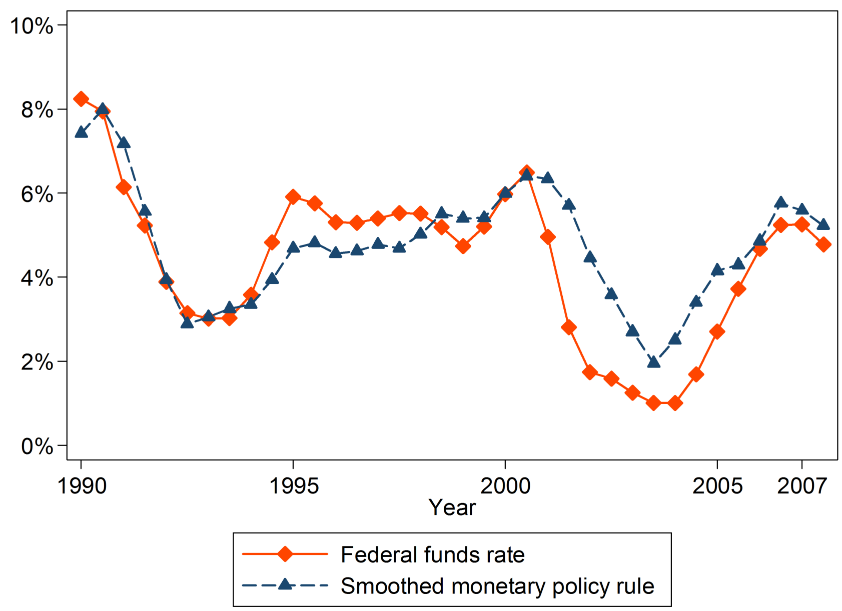


Figure 2.3: Federal funds rate and monetary policy rule (equation 2.2)

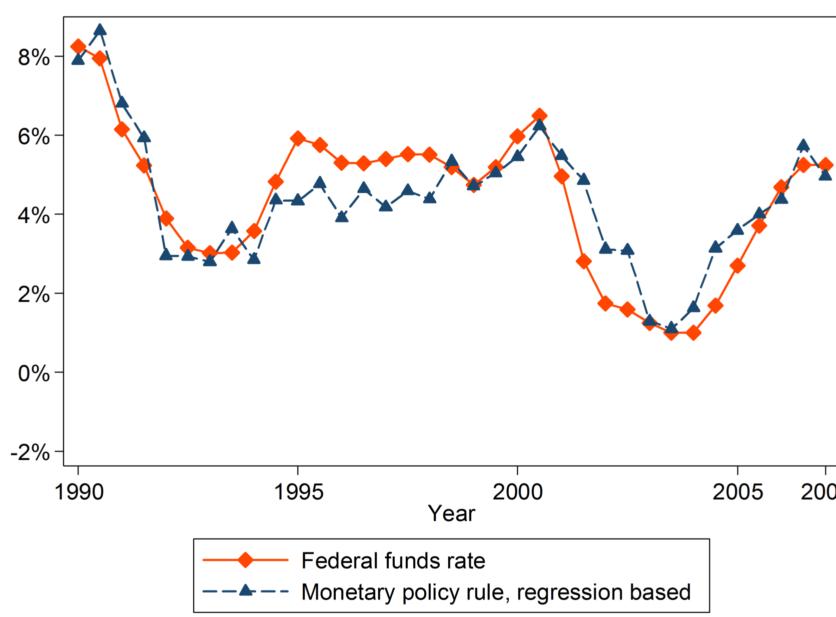


Figure 2.4: Dispersion of the stance of monetary policy across MSAs (equation 2.1)

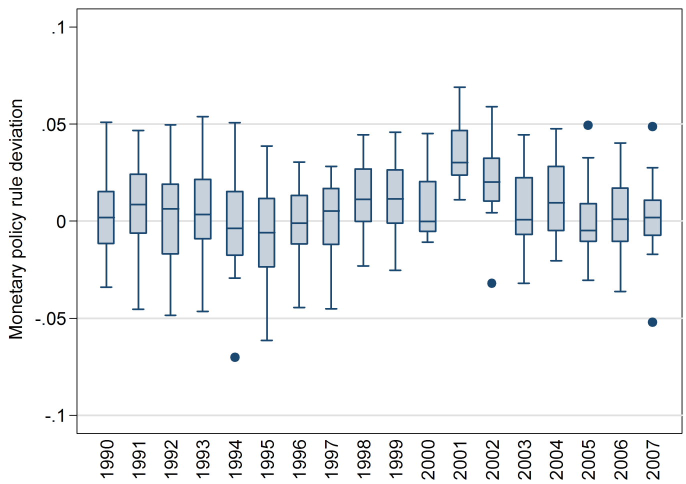


Figure 2.5: Dispersion of the stance of monetary policy across MSAs (equation 2.2)

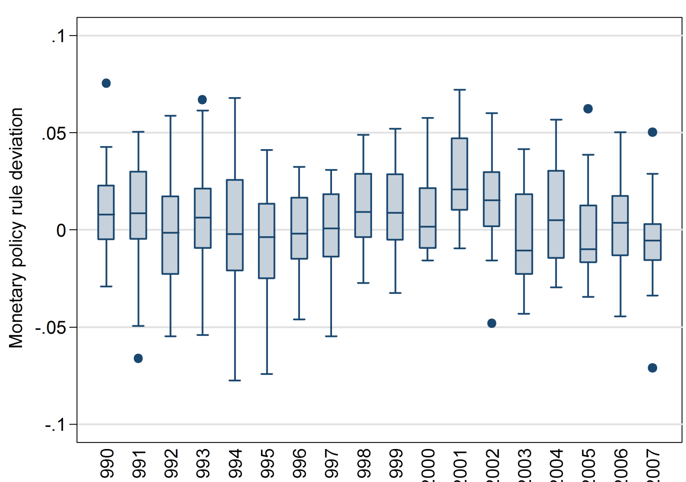


Figure 2.6: Stance of monetary policy in Denver-Boulder-Greeley MSA (equation 2.1)

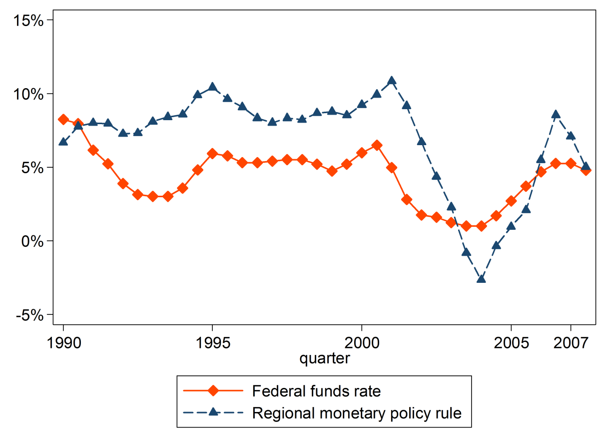


Figure 2.7: Stance of monetary policy in Los Angeles-Riverside-Orange County MSA (equation 2.1)

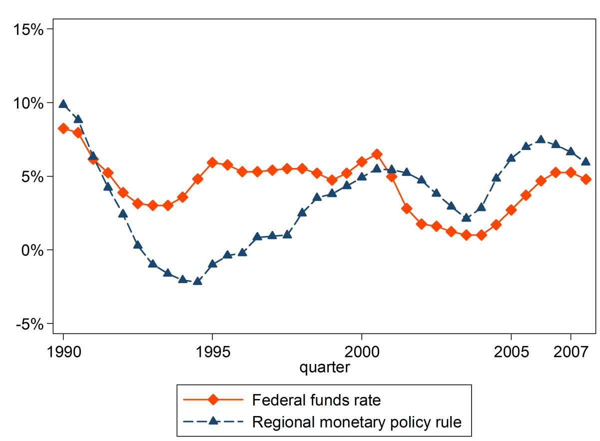


Table 2.7: Regression results. Ex-ante risk measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Risk measure	CAR		Balance risk I		Balance risk II		Credit growth		Ex. real estate	
Lagged Risk measure	0.441***	0.448***	0.928***	0.928***	0.964***	0.966***	0.002***	0.002***	0.030*	0.024
	[0.042]	[0.039]	[0.041]	[0.041]	[0.031]	[0.031]	[0.000]	[0.000]	[0.016]	[0.015]
Residual MP rule (1)	-0.040*		0.124***		0.092***		2.655***		0.118***	
	[0.023]		[0.026]		[0.023]		[0.603]		[0.041]	
Residual MP rule (2)		-0.029**		0.096***		0.069***		1.862***		0.096***
		[0.013]		[0.021]		[0.019]		[0.399]		[0.028]
Liquidity	0.010	0.011	0.020	0.018	0.034	0.029	-1.181***	-1.255***	-0.002	-0.008
	[0.026]	[0.025]	[0.049]	[0.049]	[0.021]	[0.021]	[0.280]	[0.279]	[0.032]	[0.030]
Profitability	0.494***	0.493***	0.021	0.014	0.037	0.034	-2.223	-2.346	-0.084	-0.106
	[0.160]	[0.176]	[0.136]	[0.140]	[0.184]	[0.199]	[4.496]	[4.770]	[0.239]	[0.242]
Efficiency	0.059***	0.061***	0.004	0.004	0.001	0.001	-0.317	-0.333	-0.004	-0.005
	[0.013]	[0.012]	[0.004]	[0.004]	[0.003]	[0.004]	[0.552]	[0.550]	[0.010]	[0.010]
Bank size	-0.005*	-0.005**	-0.005***	-0.005***	-0.001**	-0.001**	-0.153**	-0.145**	-0.004*	-0.003**
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.062]	[0.064]	[0.002]	[0.002]
Constant	-0.014	0.004	0.109***	0.111***	0.011	0.014	2.760***	2.726***	0.066**	0.073***
	[0.035]	[0.033]	[0.031]	[0.031]	[0.021]	[0.019]	[0.600]	[0.601]	[0.029]	[0.026]
Observations	22,697	23,291	22,697	23,291	22,697	23,291	20,154	20,715	21,834	22,395
No. of banks	2,450	2,551	2,450	2,551	2,450	2,551	2,376	2,471	2,379	2,474
No. of instruments	27	27	27	27	27	27	28	28	27	27
Hansen test (p-value)	0.168	0.197	0.593	0.548	0.694	0.657	0.155	0.145	0.467	0.539
AR 1 (p-value)	0.00464	0.0123	0	0	5.93e-09	3.20e-09	0.231	0.229	2.50e-08	5.07e-06
AR 2 (p-value)	0.779	0.829	0.770	0.630	0.940	0.819	0.284	0.279	0.310	0.240
Wald test (p-value)	0	0	0	0	0	0	0	0	0	0

This table reports the regression estimates of equation 2.3. All regressions include year dummies. The dependent variable is ex-ante bank risk measure as detailed in the header. "Residual MP rule" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. Two different specifications of the monetary policy rule residual are used to show robustness to the exact specification of the monetary policy rule. The monetary policy rules may be found in equations 2.1 and 2.2. GMM regression with robust standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Regression results. Ex-post risk measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk measure	Problem loans I		Problem loans II		Loans late		Loans not accruing	
L. Risk measure	0.662***	0.659***	0.490***	0.491***	0.245***	0.248***	0.538***	0.540***
	[0.069]	[0.068]	[0.039]	[0.039]	[0.040]	[0.040]	[0.047]	[0.046]
Residual MP rule (1)	-0.021***		-0.058***		-0.014***		-0.048***	
	[0.007]		[0.015]		[0.005]		[0.011]	
Residual MP rule (2)		-0.019***		-0.049***		-0.010***		-0.040***
		[0.006]		[0.010]		[0.003]		[0.007]
Liquidity	-0.012***	-0.012***	-0.002	-0.001	-0.001	-0.001	-0.001	0.000
	[0.003]	[0.003]	[0.009]	[0.009]	[0.003]	[0.003]	[0.007]	[0.007]
Profitability	0.005	0.004	0.215	0.209	0.020	0.019	0.172	0.169
	[0.014]	[0.014]	[0.192]	[0.184]	[0.049]	[0.046]	[0.149]	[0.144]
Efficiency	-0.000	-0.000	-0.008	-0.007	-0.002	-0.002	-0.006	-0.006
	[0.000]	[0.000]	[0.006]	[0.006]	[0.001]	[0.001]	[0.005]	[0.005]
Bank size	0.000*	0.000*	0.001	0.001	-0.000	-0.000	0.001	0.000
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]
Constant	0.003*	0.006***	-0.011	-0.006	0.004	0.004	-0.010	-0.007
	[0.001]	[0.002]	[0.017]	[0.018]	[0.003]	[0.003]	[0.014]	[0.015]
Observations	22,695	23,289	22,695	23,289	22,697	23,291	22,695	23,289
No. of banks	2,450	2,551	2,450	2,551	2,450	2,551	2,450	2,551
No. of instruments	27	27	27	27	27	27	27	27
Hansen test (p-value)	0.626	0.651	0.0398	0.0431	0.297	0.342	0.0503	0.0507
AR 1 (p-value)	0	0	0.319	0.310	0.124	0.0942	0.306	0.296
AR 2 (p-value)	0.0758	0.0781	0.887	0.868	0.0698	0.0718	0.511	0.501
Wald test (p-value)	0	0	0	0	0	0	0	0

This table reports the regression estimates of equation 2.3. All regressions include year dummies. The dependent variable is ex-post bank risk measure as detailed in the header. “Residual MP rule” is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. Two different specifications of the monetary policy rule residual are used to show robustness to the exact specification of the monetary policy rule. The monetary policy rules may be found in equations 2.1 and 2.2. GMM regression with robust standard errors in brackets. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.9: Regression results. Risk-taking on the deposit side

	(1)	(2)	(3)	(4)
Risk measure	Non-deposit funding ratio			
L. Non-depos. funding	0.612***	0.803***	0.604***	0.797***
	[0.051]	[0.043]	[0.052]	[0.043]
Residual MP rule (1)	0.094**	0.044**		
	[0.038]	[0.019]		
Residual MP rule (2)			0.072***	0.036***
			[0.028]	[0.013]
Liquidity	-0.009	0.019	-0.008	0.015
	[0.022]	[0.018]	[0.022]	[0.020]
Profitability	-0.359	-0.229	-0.362	-0.347
	[0.219]	[0.416]	[0.221]	[0.470]
Efficiency	-0.004	0.003	-0.005	0.001
	[0.021]	[0.006]	[0.021]	[0.006]
Bank size	0.012***	0.005***	0.012***	0.005***
	[0.002]	[0.002]	[0.002]	[0.001]
Constant	-0.073**	-0.025	-0.074**	-0.010
	[0.035]	[0.053]	[0.034]	[0.051]
Observations	22,697	22,697	23,291	23,291
No. of banks	2,450	2,450	2,551	2,551
No. of instruments	27	27	27	27
Hansen test (p-value)	0.663	0.426	0.569	0.635
AR 1 (p-value)	0.316	0.136	0.311	0.0961
AR 2 (p-value)	0.290	0.247	0.291	0.275
Wald test (p-value)	0	0	0	0

This table reports the regression estimates of equation 2.3. The dependent variable is the ratio of non-deposit funding of the bank. This risk measure captures an increase in risk-taking on the deposit side of the banks. “Residual MP rule” is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. Two different specifications of the monetary policy rule residual are used to show robustness to the exact specification of the monetary policy rule. The monetary policy rules may be found in equations 2.1 and 2.2. All regressions include year dummies. GMM regression with robust standard errors in brackets. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.10: Regression results. Interaction with liquidity

Risk measure	(1) CAR	(2) Balance risk I	(3) Balance risk II	(4) Credit growth	(5) Ex. real estate
L.Risk measure	0.426***	0.794***	0.941***	0.002***	0.026*
	[0.044]	[0.029]	[0.030]	[0.001]	[0.014]
Residual MP rule (Type 1)	-0.045**	0.148***	0.115***	2.774***	0.150***
	[0.018]	[0.026]	[0.023]	[0.642]	[0.031]
Resid. MP rule (1) * Liquidity	-0.145	-0.604***	-0.249*	-7.858**	-0.765***
	[0.209]	[0.173]	[0.146]	[3.693]	[0.175]
Liquidity	0.015*	-0.189***	-0.037***	-2.219***	-0.070***
	[0.008]	[0.021]	[0.012]	[0.395]	[0.006]
Profitability	0.438**	-0.048	-0.005	-5.348	-0.027
	[0.179]	[0.253]	[0.282]	[7.569]	[0.155]
Efficiency	0.062***	0.000	-0.001	0.406	-0.013
	[0.012]	[0.006]	[0.005]	[0.376]	[0.011]
Bank size	-0.005***	-0.003***	-0.001	-0.213***	-0.002*
	[0.002]	[0.001]	[0.001]	[0.056]	[0.001]
Constant	-0.004	0.157***	0.025	2.495***	0.057**
	[0.028]	[0.032]	[0.027]	[0.803]	[0.025]
Observations	22,697	22,697	22,697	20,154	21,834
No. of banks	2,450	2,450	2,450	2,376	2,379
No. of instruments	27	27	27	30	27
Hansen test (p-value)	0.114	0.201	0.537	0.00789	0.498
AR1 test (p-value)	0.0665	0	0	0.219	0
AR2 test (p-value)	0.902	0.713	0.994	0.255	0.435
Wald test (p-value)	0	0	0	0	0

This table reports the regression estimates of equation 2.4 which includes an interaction effect of the monetary policy rule residual and bank characteristics, here bank liquidity. All interacted variables are demeaned for ease of interpretation (See Balli and Sørensen, 2013; Brambor et al., 2006). The dependent variable is an (ex-ante) risk measure as detailed in the regression header. "Residual MP rule (1)" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The monetary policy rule may be found in equation 2.1. All regressions include year dummies. GMM regression with robust standard errors in brackets. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.11: Regression results. Robustness to additional bank-specific and macroeconomic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L. CAR	0.382***	0.428***	0.440***	0.400***	0.398***	0.441***	0.441***
	[0.033]	[0.053]	[0.042]	[0.031]	[0.031]	[0.044]	[0.043]
Residual MP rule (1)	-0.056***	-0.047**	-0.041*	-0.045*	-0.042**	-0.040	-0.040*
	[0.020]	[0.023]	[0.022]	[0.023]	[0.018]	[0.025]	[0.024]
Liquidity	0.009	0.012	0.010	0.008	0.013	0.010	0.010
	[0.014]	[0.023]	[0.025]	[0.008]	[0.016]	[0.025]	[0.025]
Profitability	0.176	0.392**	0.485***	0.200	0.336*	0.494***	0.494***
	[0.146]	[0.167]	[0.163]	[0.144]	[0.182]	[0.157]	[0.158]
Efficiency	0.055***	0.059***	0.059***	0.059***	0.054***	0.059***	0.059***
	[0.013]	[0.013]	[0.013]	[0.015]	[0.014]	[0.013]	[0.013]
Bank size	-0.006***	-0.005**	-0.005**	-0.005***	-0.005***	-0.005*	-0.005*
	[0.001]	[0.003]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
Multi-BHC member	0.008***						
	[0.003]						
Off-balance sheet		0.007					
		[0.008]					
Credit derivatives			0.019				
			[0.017]				
Bank lending rate				-0.000			
				[0.000]			
Demand deposit ratio					-0.015		
					[0.028]		
Pers. income, 3-yr ma						-0.000	
						[0.000]	
Pers. income (L2)							0.000
							[0.000]
Constant	0.035	0.006	-0.011	0.045***	0.019	-0.022	0.007
	[0.023]	[0.049]	[0.035]	[0.016]	[0.031]	[0.033]	[0.035]
Observations	22,697	22,697	22,697	22,697	22,697	22,697	22,697
No. of banks	2,450	2,450	2,450	2,450	2,450	2,450	2,450
No. of instruments	29	29	29	29	29	28	28
Hansen test (p-value)	0.0196	0.0793	0.252	0.0945	0.205	0.171	0.171
AR1 (p-value)	0.227	0.0809	0.00692	0.218	0.171	0.00476	0.00477
AR2 (p-value)	0.646	0.925	0.791	0.661	0.929	0.778	0.777
Wald test (p-value)	0	0	0	0	0	0	0

This table reports the regression estimates of equation 2.3 which is extended with additional explanatory variables. It shows the robustness of results towards the inclusion of additional bank-specific and macroeconomic variables that may play a role in bank risk and bank behavior. "Residual MP rule (1)" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The monetary policy rule may be found in equation 2.1. All regressions include year dummies. The dependent variable is the capital asset ratio. GMM regression with robust standard errors in brackets. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.12: Regression results. Robustness to additional bank-specific and macroeconomic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L. Balance risk I	0.938***	0.930***	0.919***	0.925***	0.904***	0.927***	0.928***
	[0.039]	[0.040]	[0.045]	[0.040]	[0.042]	[0.041]	[0.041]
Residual MP rule (1)	0.123***	0.125***	0.124***	0.125***	0.119***	0.126***	0.125***
	[0.025]	[0.026]	[0.026]	[0.026]	[0.025]	[0.026]	[0.026]
Liquidity	0.030	0.024	0.010	0.017	0.002	0.020	0.020
	[0.045]	[0.048]	[0.053]	[0.048]	[0.048]	[0.049]	[0.049]
Profitability	0.047	0.034	0.010	0.007	0.045	0.021	0.021
	[0.046]	[0.130]	[0.151]	[0.106]	[0.143]	[0.135]	[0.135]
Efficiency	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Bank size	-0.005***	-0.004***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Multi-BHC member	0.003						
	[0.007]						
Off-balance sheet		-0.015					
		[0.012]					
Credit derivatives			-0.037				
			[0.045]				
Bank lending rate				-0.000			
				[0.000]			
Demand deposit ratio					-0.074**		
					[0.036]		
Pers. income, 3-yr ma						-0.000	
						[0.000]	
Pers. income (L2)							-0.000
							[0.000]
Constant	0.070***	0.098***	0.114***	0.111***	0.140***	0.082**	0.113***
	[0.025]	[0.029]	[0.033]	[0.029]	[0.038]	[0.032]	[0.032]
Observations	22,697	22,697	22,697	22,697	22,697	22,697	22,697
No. of banks	2,450	2,450	2,450	2,450	2,450	2,450	2,450
No. of instruments	29	29	29	29	29	28	28
Hansen test (p-value)	0.289	0.643	0.647	0.700	0.801	0.595	0.595
AR1 (p-value)	0	0	0	0	0	0	0
AR2 (p-value)	0.791	0.804	0.777	0.761	0.822	0.769	0.770
Wald test (p-value)	0	0	0	0	0	0	0

This table reports the regression estimates of equation 2.3 which is extended with additional explanatory variables. It shows the robustness of results towards the inclusion of additional bank-specific and macroeconomic variables that may play a role in bank risk and bank behavior. "Residual MP rule" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The monetary policy rule may be found in equation 2.1. All regressions include year dummies. The dependent variable is the Balance Risk measure I. GMM regression with robust standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 2.13: Regression results. Robustness to the specification of the monetary policy rule

Residual MP rule	(1)	(2)	(3)	(4)	(5)	(6)
L. CAR	0.441***	0.448***	0.448***	0.448***	0.441***	0.447***
	[0.042]	[0.039]	[0.039]	[0.039]	[0.042]	[0.039]
Residual MP rule	-0.040*	-0.029**	-0.037**	-0.029**	-0.031*	-0.037**
	[0.023]	[0.013]	[0.017]	[0.013]	[0.018]	[0.018]
Liquidity	0.010	0.011	0.011	0.011	0.010	0.011
	[0.026]	[0.025]	[0.025]	[0.025]	[0.026]	[0.025]
Profitability	0.494***	0.493***	0.494***	0.494***	0.494***	0.491***
	[0.160]	[0.176]	[0.177]	[0.177]	[0.160]	[0.175]
Efficiency	0.059***	0.061***	0.061***	0.061***	0.059***	0.061***
	[0.013]	[0.012]	[0.012]	[0.012]	[0.013]	[0.012]
Bank size	-0.005*	-0.005**	-0.005**	-0.005**	-0.005*	-0.005**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Constant	-0.014	0.004	0.004	0.004	-0.014	0.004
	[0.035]	[0.033]	[0.033]	[0.033]	[0.035]	[0.034]
Observations	22,697	23,291	23,291	23,291	22,697	23,291
No. of banks	2,450	2,551	2,551	2,551	2,450	2,551
No. of instruments	27	27	27	27	27	27
Hansen test (p-value)	0.168	0.197	0.197	0.197	0.168	0.197
AR 1 (p-value)	0.00464	0.0123	0.0125	0.0125	0.00464	0.0125
AR 2 (p-value)	0.779	0.829	0.826	0.826	0.779	0.831
Wald test (p-value)	0	0	0	0	0	0

This table reports the regression estimates of equation 2.3 showing the robustness of results towards a series of different specifications of the monetary policy rule. Columns 1 and 2 repeat the two specifications already described in the main text (equations 2.1 and 2.2). Column 3 is based on the monetary policy rule described in equation 2.1 but uses only the first part of the rule, that is, without the smoothing term. Columns 4 and 5 are also based upon the monetary policy rule described in equation 2.1 but use different coefficients ($Predicted\,MP_t = 9 + 1.8 * (Core\,Inflation - Unemployment\,rate)$) as re-estimated by Krugman (2010). Column 4 adds the smoothing term and column 5 excludes it. Column 6 is based on the monetary policy rule in equation 2.2 but in contrast to the baseline specification which only uses data until the year 2006 uses all years of available data in the estimation of the monetary policy rule parameters. All regressions include year dummies. The dependent variable is the capital asset ratio. GMM regression with robust standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 2.14: Regression robustness of ex-ante risk measures (I). Comparison with OLS and FE regression

	(1) OLS	(2) FE	(3) GMM	(4) OLS	(5) FE	(6) GMM	(7) OLS	(8) FE	(9) GMM
Risk measure		CAR			Balance risk I			Balance risk II	
L. RM	0.665***	0.426***	0.441***	0.828***	0.496***	0.928***	0.926***	0.640***	0.964***
	[0.021]	[0.035]	[0.042]	[0.005]	[0.013]	[0.041]	[0.004]	[0.013]	[0.031]
Residual MP rule	0.005	0.031**	-0.040*	0.140***	0.198***	0.124***	0.123***	0.160***	0.092***
	[0.009]	[0.013]	[0.023]	[0.021]	[0.037]	[0.026]	[0.015]	[0.026]	[0.023]
Liquidity	0.005***	-0.005	0.010	-0.142***	-0.373***	0.020	-0.017***	-0.139***	0.034
	[0.001]	[0.004]	[0.026]	[0.004]	[0.012]	[0.049]	[0.002]	[0.008]	[0.021]
Profitability	0.021***	0.006***	0.494***	-0.018***	-0.001	0.021	-0.006**	-0.003*	0.037
	[0.008]	[0.001]	[0.160]	[0.006]	[0.001]	[0.136]	[0.003]	[0.002]	[0.184]
Efficiency	0.008*	-0.000	0.059***	-0.002***	0.001	0.004	-0.001	-0.000	0.001
	[0.004]	[0.003]	[0.013]	[0.001]	[0.002]	[0.004]	[0.001]	[0.001]	[0.003]
Bank size	-0.000	-0.008***	-0.005*	-0.002***	0.009***	-0.005***	-0.001**	-0.006**	-0.001**
	[0.000]	[0.002]	[0.002]	[0.000]	[0.003]	[0.001]	[0.000]	[0.003]	[0.001]
Constant	0.026***	0.160***	-0.014	0.163***	0.239***	0.109***	0.018***	0.169***	0.011
	[0.005]	[0.022]	[0.035]	[0.006]	[0.041]	[0.031]	[0.004]	[0.034]	[0.021]
Observations	22,697	22,697	22,697	22,697	22,697	22,697	22,697	22,697	22,697
No. of banks		2,450	2,450		2,450	2,450		2,450	2,450
No. of instruments			27			27			27
R^2	0.691	0.385		0.850	0.648		0.882	0.585	
Hansen test (p-value)			0.168			0.593			0.694
AR1p			0.00464			0			5.93e-09
AR2p			0.779			0.770			0.940
Wald test (p-value)			0			0			0

This table reports the regression estimates of equation 2.3. The results are repeated using ordinary least squares and fixed effects estimation. In the case of GMM estimation, the coefficient of the lagged dynamic variable should lie in between the (biased) coefficients of the OLS and FE estimation. "Residual MP rule" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The monetary policy rule may be found in equation 2.1. All regressions include year dummies. Robust standard errors in brackets. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.15: Regression robustness of ex-ante risk measures (II). Comparison with OLS and FE regression

	(1) OLS	(2) FE	(3) GMM	(4) OLS	(5) FE	(6) GMM
Risk measure	Credit growth			Exp. real estate		
L. RM	0.003**	0.001	0.002***	-0.020**	-0.109***	0.030*
	[0.001]	[0.002]	[0.000]	[0.009]	[0.009]	[0.016]
Residual MP rule	1.492**	0.984***	2.655***	0.143***	0.216***	0.118***
	[0.737]	[0.339]	[0.603]	[0.020]	[0.032]	[0.041]
Liquidity	-0.102	-0.321**	-1.181***	-0.040***	-0.113***	-0.002
	[0.161]	[0.160]	[0.280]	[0.003]	[0.007]	[0.032]
Profitability	0.116	0.004	-2.223	-0.010***	-0.008***	-0.084
	[0.183]	[0.079]	[4.496]	[0.001]	[0.001]	[0.239]
Efficiency	0.042	0.017	-0.317	-0.000	0.000	-0.004
	[0.068]	[0.076]	[0.552]	[0.001]	[0.001]	[0.010]
Bank size	0.010	0.043	-0.153**	-0.002***	-0.010***	-0.004*
	[0.009]	[0.072]	[0.062]	[0.000]	[0.002]	[0.002]
Constant	-0.021	-0.313	2.760***	0.045***	0.154***	0.066**
	[0.099]	[0.753]	[0.600]	[0.005]	[0.023]	[0.029]
Observations	20,154	20,154	20,154	21,834	21,834	21,834
No. of banks		2,376	2,376		2,379	2,379
No. of instruments			28			27
R^2	0.005	0.003		0.032	0.048	
Hansen test (p-value)			0.155			0.467
AR1p			0.231			2.50e-08
AR2p			0.284			0.310
Wald test (p-value)			0			0

This table reports the regression estimates of equation 2.3. The results are repeated using ordinary least squares and fixed effects estimation. In the case of GMM estimation, the coefficient of the lagged dynamic variable should lie in between the (biased) coefficients of the OLS and FE estimation. "Residual MP rule" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The monetary policy rule may be found in equation 2.1. All regressions include year dummies. Robust standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 2.16: Regression robustness of ex-post risk measures. Comparison with OLS and FE regression

	(1) OLS	(2) FE	(3) GMM	(4) OLS	(5) FE	(6) GMM	(7) OLS	(8) FE	(9) GMM	(10) OLS	(11) FE	(12) GMM
Risk measure	Problem Loans I			Problem Loans II			Loans Late			Loans not accruing		
L. Risk Measure	0.633***	0.414***	0.512***	0.616***	0.385***	0.594***	0.433***	0.217***	0.245***	0.615***	0.385***	0.538***
	[0.017]	[0.027]	[0.061]	[0.036]	[0.022]	[0.111]	[0.031]	[0.052]	[0.040]	[0.047]	[0.021]	[0.047]
Residual MP rule	-0.036***	-0.043***	-0.079***	-0.068***	-0.079***	-0.051***	-0.016***	-0.014***	-0.014***	-0.059***	-0.070***	-0.048***
	[0.004]	[0.005]	[0.010]	[0.008]	[0.009]	[0.018]	[0.002]	[0.004]	[0.005]	[0.008]	[0.008]	[0.011]
Liquidity	-0.007***	-0.012***	-0.012***	-0.006***	-0.009***	-0.016**	-0.001	-0.003***	-0.001	-0.005***	-0.006***	-0.001
	[0.000]	[0.001]	[0.003]	[0.001]	[0.002]	[0.008]	[0.000]	[0.001]	[0.003]	[0.001]	[0.001]	[0.007]
Profitability	-0.000	-0.000	0.014	-0.001	-0.001***	0.046	0.000	0.000	0.020	-0.001	-0.001***	0.172
	[0.000]	[0.000]	[0.027]	[0.001]	[0.000]	[0.145]	[0.000]	[0.000]	[0.049]	[0.001]	[0.000]	[0.149]
Efficiency	-0.001	-0.001	-0.005**	-0.001	-0.001	-0.001	-0.000	-0.000	-0.002	-0.001	-0.001	-0.006
	[0.000]	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.005]
Bank size	0.000	0.002***	0.002***	0.000	0.002***	0.000	-0.000***	0.001**	-0.000	0.000**	0.001***	0.001
	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
Constant	0.009***	-0.007*	-0.010**	0.011***	-0.010	0.001	0.003***	-0.006*	0.004	0.009***	-0.004	-0.010
	[0.001]	[0.004]	[0.005]	[0.002]	[0.006]	[0.012]	[0.001]	[0.004]	[0.003]	[0.001]	[0.005]	[0.014]
Observations	22,695	22,695	22,695	22,695	22,695	22,695	22,697	22,697	22,697	22,695	22,695	22,695
No. of banks		2,450	2,450		2,450	2,450		2,450	2,450		2,450	2,450
No. of instruments			29			27			27			27
R^2	0.465	0.243		0.446	0.217		0.232	0.087		0.432	0.202	
Hansen test (p-value)			0.0196			0.271			0.297			0.0503
AR1 (p-value)			2.23e-06			0.167			0.124			0.306
AR2 (p-value)			0.0718			0.813			0.0698			0.511
Wald test (p-value)			0			0			0			0

This table reports the regression estimates of equation 2.3. The results are repeated using ordinary least squares and fixed effects estimation. In the case of GMM estimation, the coefficient of the lagged dynamic variable should lie in between the (biased) coefficients of the OLS and FE estimation. "Residual MP rule" is the deviation of the stance of monetary policy suggested by the monetary policy rule from the actual federal funds rate. The monetary policy rule may be found in equation 2.1. All regressions include year dummies. Robust standard errors in brackets. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Chapter 3

Are ethical and social banks less risky? Evidence from a new dataset

3.1 Introduction

Following the worldwide financial crisis that started in 2007, ethical and social banks have received increased and favorable attention in the media and by depositors. Their growing clientele sees them as a possible answer and reaction to the financial crisis (Weber and Remer, 2011). Mainly due to their increased popularity with small depositors ethical banks in Europe have doubled their assets between 2007 and 2010 (Benedikter, 2011). However, no comprehensive empirical evaluations of these banks exist. The small literature on social banking offers a few general descriptions of the business model of social banks (Benedikter, 2011; Weber and Remer, 2011) but there exists no comprehensive study that evaluates the stability of alternative banks in comparison to conventional banks. This may be due to the fact that despite their rapid growth, banks with an alternative business model remain a niche phenomenon and their impact on the financial system is accordingly small. Since the importance of social banks has nevertheless increased in the last few years and may continue to rise (Köhler, 2010), this paper aims to fill this gap in the literature by providing a comprehensive analysis of the riskiness of alternative banks in EU and OECD countries, especially during and since the financial crisis.

In the context of this paper the focus of the analysis lies on two areas of interest from the perspective of financial stability. First, bank riskiness and second, bank outcomes in the global financial crisis. Concerning the first point, bank riskiness, from a theoretical perspective alternative banks could be more or less risky than conventional banks. On the one hand, alternative banks could be less risky as they are generally risk-averse, focused on the real economy and tend to avoid speculative activities. On the other hand, alternative banks could be more risky, if, for example, they generate less profits that can be used to re-build capital buffers after crisis events. They could also be exposed to higher credit default risk if the "worthy causes" among their borrowers are not financially sound. In the second area of research, the development of alternative banks in and since the financial crisis, there are also two simultaneous effects. First, alternative banks are exposed to the general adverse effects of a troubled economy, second, they experience a period of accelerated growth due to an increase in customer deposits. Although most social banks did very well during the financial crisis, their rapid growth since could be a threat to their business model (Remer, 2011). For example, a strong influx of deposits may be difficult to match with a sufficient number of borrowers that fulfill the two criteria of being social or ethical as well as financially sound.

Accessing a large variety of sources, I develop a first and comprehensive overview of alternative banks in EU and OECD countries. I use balance sheet data from Bankscope to empirically evaluate their stability. Methodologically, I follow the literature on the evaluation of Islamic banking (see e.g. Beck et al., 2013; Čihak and Hesse, 2010) in comparing conventional and alternative banks. I match the alternative banks with a comparable set of conventional banks by size, country of origin, type of bank (commercial, savings or cooperative) and years of data observed. Matching is based on year 2006, that is, before the outbreak of the global financial crisis.

The main result is that alternative banks are significantly more stable than their conventional counterparts. This result is robust to different estimation methods and data specifications. Following the outbreak of the global financial crisis alternative banks also experienced a rapid growth in deposits and total assets. This occurred simultaneously with potential negative effects of the financial crisis. The effects of the crisis on bank stability are not easily distinguishable from the effects of the inflow of deposits. Results for the effects of the financial crisis on the stability of alternative banks are therefore less clear-cut.

This paper contributes to the literature on social and ethical banking in several ways. It introduces a comprehensive dataset of alternative banks and it matches alternative banks with an appropriate control group of conventional banks. This dataset is then used to address two research questions. First, it evaluates if alternative banks differ from their conventional counterparts in terms of risk. Second, it studies the stability and growth of alternative banks during and since the global financial crisis.

The remainder of this paper is organized as follows. Section 2 develops a definition of alternative banking, introduces the related literature and explores theoretically how the riskiness of alternative banks may differ from conventional banks. Section 3 describes the alternative bank dataset and the matching of the conventional bank control group. Section 4 presents regression results on bank stability and robustness tests. Section 5 concludes. A detailed methodological section may be found in the appendix.

3.2 Alternative banking and stability

3.2.1 Definition of an alternative bank

This paper defines "alternative banks" as those banks that pursue ethical, social, sustainable, environmental or other "added social value" goals as a core part of their business strategy. Banks with religious affiliations or roots are included as well if they follow a special code of ethics, engage in preservation of the environment or make similar adjustments to their business model.

The related literature offers no consistent terminology. Often, the terms "ethical" or "social" are used to discuss the same banks. I resort to the more general umbrella term "alternative" but also use the terms "ethical" or "social" when referencing specific literature. The above definition of alternative banks is close in spirit to Weber and Remer (2011, p.2) who define "social banking as banking that aims to have a positive impact on people, the environment and culture". Many social banks follow a "dual bottom line" approach, that is, their business decisions are made considering their own benefit as well as the benefit of the society. This can mean, for example, that they extend credit according to ethical or environmental criteria. San-Jose et al. (2011) find that the hallmark of an "ethical" bank is that it is striving for economic *and* social profitability, that is, having a dual bottom line.

These definitions show that there is some heterogeneity among alternative banks. They have different origins such as social reform movements, environmental preservation movements, or may hold themselves to ethical, christian or anthroposophical values (see Weber and Remer, 2011 for an overview). Although alternative banks have these different origins and have varying ways of doing business there is one unifying characteristic that makes it possible to group them together for analysis: This is their (explicit or implicit) dual- or triple bottom line approach which implies that alternative banks have different goals than conventional banks.

For the purpose of this study, I exclude banks engaging in microfinance, alternative banks in developing countries, and guarantee or business-development banks. Although they do share some characteristics with the alternative banks, they operate in completely different business environments. Alternative banks must further be distinguished from savings banks or cooperative credit unions which were also originally founded in the spirit of helping their members or disadvantaged groups in general. Although today most savings and cooperative banks do not explicitly take ethical considerations into account, many alternative banks are organized as cooperatives and there may exist some overlap with this banking type. To account for this, the banking type of the alternative banks (commercial, savings or cooperative) is controlled for in the further analysis. The country of origin of the bank is also controlled for, because characteristics of, for example, cooperative banks, also differ between countries.

3.2.2 Related literature

Although the global financial crisis drew much attention toward sustainable forms of banking and spurred interest in social banking in general society, the academic literature on social banking remains very small. This is also due to the very small size of the alternative banking sector. In Germany, for example, social and ecological banks have a market share of 0.2% of the private banking sector but 16 million of Germans are potentially interested in these types of banks (zeb, 2012). As alternative banks are seen as one answer to the financial crisis, this warrants study of their stability.

Weber and Remer (2011) provide an overview and introduction into social banking with descriptions of the history, business environment and challenges of social banks, while Benedikter (2011) discusses social banking against the backdrop of the financial crisis. Empirical studies that analyze multiple social banks do not exist as of yet, with the sole exception of Scheire and De Maertelaere (2009) who analyze the business models of social banks that are members of an association of social banks, the Global Alliance for Banking on Values (GABV). They provide an overview of the business strategies and balance sheets of 12 social banks that are GABV members for 2007 and 2008, finding that ethical banks are highly financed by deposits but do not always succeed in transforming these into loans. They do not, however, compare social banks with (appropriately matched) conventional banks. Most other literature on alternative banking studies individual banks only (e.g. Becchetti and Garcia, 2008; Harvey, 1995).

The relatively small size of the empirical ethical banking literature may also be due to several methodological challenges: first, no comprehensive overview of alternative banks exists, second, the econometric problems posed by their small sample size, and third, the question of an appropriate control group.

The methodological challenges to studying alternative banks are similar to those of studying Islamic banking. While for the former, to the best of my knowledge, no papers that compare between banking groups exist, the latter is studied in the academic literature. Especially, the performance of Islamic banks during the financial crisis received attention in several studies (Bourkhis and Nabi 2013; Hasan and Dridi 2011). Islamic banks are comparable to social banks in that they both subscribe to a certain set of (religious or moral) rules that constrain their behavior and may differentiate them from conventional banks in a number of ways. In both cases, there are religious or ethical/moral motivations for the bank's actions. Some similarities in the study of Islamic banks and social banks are that they have less or no focus on interest rates, that they are a small but quickly growing sector and that their business model differs from conventional banks. The methodological challenges are also similar due to the limited number of alternative banks which leads to few observations and the question of the choice of a suitable control group. That is why this paper takes a similar methodological approach as some of the Islamic banking literature. Specifically, I rely on matching methodology to obtain a comparable group of conventional banks (Bourkhis and Nabi, 2013) and the use of robust estimation techniques (Čihak and Hesse, 2010).

3.2.3 Riskiness and stability of alternative banks

1. Riskiness of alternative banks

From a theoretical perspective, alternative banks could be more or less risky than conventional banks. In general, alternative banks are relatively risk-averse and serve primarily the real economy. They avoid risky activities, such as highly structured financial products and speculative proprietary trading. They may also hold larger capital buffers than their conventional counterparts. Several of the ethical and social banks studied here are organized in a network of banks that follow sustainable standards, the Global Alliance for Banking on Values (GABV). Members of the GABV must comply with their "sustainable banking principles". These include among others the triple-bottom line approach ("profit, people, planet"), serving the community and the real economy, focusing on long-term relationships with clients, transparency and a long-term, self-sustaining business model[2]. These principles demonstrate that alternative banks aim to engage in little risk *taking* but they could still be equally risky or riskier than conventional banks because they may be subjected to unique risks stemming from their business model.

[2]Sustainable Banking Principles are summarized from www.gabv.org

Social banks may be exposed to higher credit default risk and concentration risk due to the specialized nature of their lending. For example, an environmental bank that grants a lot of credit to the renewable energy sector would be strongly affected by the curtailment of renewable energy subsidies. Also, some of the ethical lending might be inherently riskier as these "worthy causes" could be less well capitalized than typical borrowers. Then again, alternative banks are specialists in their field and therefore possess specific know-how that allows them to correctly assess the riskiness of a project. They are skilled in monitoring these creditors and some alternative banks provide business advice to their creditors that could lower riskiness, especially with inexperienced creditors (e.g. small and medium enterprises, first-time home buyers). Supporting this line of thought, Acharya et al. (2006) find that a sectoral specialization of banks is linked to better monitoring and higher quality of the loan portfolios. Additionally, social banks also engage in relationship lending that lessens information asymmetries. Also, as the customers of alternative banks choose their bank specifically for its ethical or social business strategy, the reputational risk of an alternative bank is likely to be higher than that of a conventional bank. The higher potential costs of a scandal should lead to more prudent business decisions and a clear focus on compliance.

It is a challenge for alternative banks to find highly qualified personnel who identify with the banks' values (von Passavant, 2011). The possibility exists that some of the employees of social banks have little experience in financial business and risk management. Employees and management of social banks usually accept wages that are below the industry average and bonus payments are small or nonexistent. This eliminates moral hazard and should lead to greater risk-aversion as well as less procyclical lending behavior than in conventional banks.

The stability of the bank can also be affected by its ability to generate profits. As alternative banks have other objectives besides generation of profit, it is likely that their profitability will be lower than that of conventional banks. One determinant of bank profitability is their interest rate setting. For alternative banks, interest rates are not purely set according to refinancing costs and risk premia, but also take social or environmental considerations into account. In alternative banks, interest rates are often, at least partially, set according to social considerations. For example, Cornée and Szafarz (2013) present data on business loans made by a French alternative bank and show that the bank charges interest rates that are below market rates for loans to social projects. While this furthers the social goals of the bank, it may also have less capacity to build up capital buffers or re-build capital after adverse events. Still, part of this loss of interest income may be offset by the banks' customers who also receive lower interest payments on their deposits. Two recent surveys explore the interest rates and riskiness of ethical banking in Germany. A survey study by the management consultancy zeb (2012) finds that German residents state that they would forgo 1.3% in remuneration to invest their money ethically. Irrespective of the questionable reliability of survey answers, one can state that clients of an ethical or social bank make a conscious choice to place their money there and are willing to forgo some part of their remuneration. A survey of German financial experts finds that these believe that social banks take fewer risks (Köhler, 2010).

To summarize, there are multiple factors that could lead alternative banks to be more risky or less risky than conventional banks. Also, these different factors could balance each other out so that there might be no difference in riskiness.

2. Stability of alternative banks in the global financial crisis

The stability of social banks during and since the financial crisis is of special interest due to the view that alternative banks could be an answer to the financial system fragility made apparent in the global financial crisis (Fessmann, 2013). There exist multiple and simultaneous channels through which the global financial crisis may have affected the stability of alternative banks. First, through the interbanking system and worsening financial markets conditions. Second, through the recession in the real economy. Third, through the rapid influx of customer deposits since the outbreak of the crisis.

Concerning the first channel, as alternative banks are predominantly financed by small depositors and largely independent from the interbank market (Scheire and De Maertelaere, 2009) they are mostly shielded from contagion and should therefore be more stable in times of crisis. They do not engage in speculative activities which could incur high losses in market downturns. Second, in real terms, alternative banks should enjoy greater stability than their conventional peers due to their emphasis on relationship lending, long-term funding and refusal to engage in high-risk business. Some of their lending, for example to social projects (pre-schools etc.) is less exposed to the business cycle than the manufacturing sector but may also be particularly affected in case of public spending cuts. Although most social banks emerged strengthened from the financial crisis (Remer, 2011), they were not immune to economic developments. For example, two of the 12 banks studied in Scheire and De Maertelaere (2009) no longer exist as of 2014.

Concerning the third channel, before the crisis ethical and social banking was mainly a niche phenomenon. Their rapid growth since then could be a threat to their business model. In conventional banks, strong growth of credit volume is associated with heightened bank risk (Köhler, 2015). This could lead to difficulties if the organizational structures of the banks are not equipped to handle this rapid influx of deposits. Also, rapid growth could destabilize the banks and pose a threat of dilution of core principles and values if, for example, not enough socially beneficial and economically sustainable projects can be found to match the increased inflow of deposits. Remer (2011) notes that this may be the case for some social banks. Specifically, in economically uncertain times and in a low interest-rate environment, a sudden increase in deposits and therefore total assets cannot immediately be translated in revenue-generating loans or other investments. Social banks find it more difficult to obtain equity capital than to obtain deposits (Becchetti, 2011). With the amount of equity capital remaining constant, capitalization-based risk-measures (leverage, z-score) will report an increase of the banks' riskiness after an inflow of deposits.

3.3 Data and Methodology

3.3.1 A new dataset of alternative banks

Comprehensive list of alternative banks

To the best of my knowledge, this is the first paper that studies alternative banking in OECD and EU countries using a comprehensive set of banks. In a first step, a comprehensive list of banks that are identified or self-identify as alternative is compiled using a large number of sources. A first source are the umbrella organizations (GABV, INAISE, FEBEA) that represent some of the social and ethical banks. Second, I obtain bank names from the social banking literature, for example an overview of social saving initiatives by the Réseau Financement Alternatif (2006) and case studies of ethical and social banks. Third, several dedicated websites (e.g. banksdaily.com) containing bank lists and bank overviews, websites of the banks themselves that often contain links to partnering banks and news sites are searched for keywords. Fourth, web searches of news sites and internet archival services yield information on alternative banks that are no longer active. Fifth, the websites of active alternative banks are scanned for defunct alternative banks by going through information on past mergers and acquisitions. Further, the websites are checked for joint ventures or daughters that are also alternative banks. Sixth, all banks available in the Bankscope database are searched for specific keywords or strings that are often contained in the names of alternative banks (e.g. "etic").

As these different approaches yield a large overlap of banks, I feel confident that my final dataset includes the vast majority of alternative banks[3]. When available, the dataset of

[3]The full overview of alternative banks is too unwieldy to include in this document but is available upon request as an Excel file.

alternative banks contains name, type, founding year, information on past mergers, and, if applicable, the year activity ceased.

Since the increase in popularity of social or ethical banking following the global financial crisis, one concern with the classification of alternative banking may be the threat of greenwashing. There is the possibility that terms like "ethical" or "sustainable" are used mainly for marketing purposes. Ordinary commercial banks may seek to improve their reputation by publicly announcing ethical standards that are mainly geared towards the media and potential customers. The credibility and efficiency of these announcements may then be doubtful.

In the construction of the alternative bank dataset, special care is taken to weed these banks out. Specifically, a bank can only be included in the group of alternative banks if it clearly states that its business model is substantially changed through its convictions. That is, the bank implicitly or explicitly has a dual bottom line. One possible caveat when relying on information collected from bank websites (CSR reports, mission statements, bank self descriptions) to obtain the information on bank characteristics and behavior, might be that banks simply do not distribute information about the social or ethical behavior they engage in. However, as banks have an incentive to inform their clients and potential clientele about their services and unique selling points (according to the principle "Do good and talk about it"), they have an incentive to provide detailed information about the implementation of their ethics guidelines. That is why it is reasonable to assume that if a bank does not mention a specific type of alternative or socially desirable behavior, it does not engage in it.

Therefore, banks are only included in the list if their ethics guidelines are strict and comprehensive enough to actually change the business structure of the bank. This may for example be the case if the bank is turning down business opportunities or avoiding market segments due to ethical considerations. Each bank website is checked individually for the manner in which the banks values manifest in the business model. In case of banks that are no longer active, I resort to alternative information sources such as newspaper articles or internet archives.

For the banks included in the alternative bank dataset, this "alternative" behavior can take many different forms. Many banks adapt their investment and their lending to their business goals. Some have negative lists, that exclude certain areas of business from their activity, while others have positive lists and may, for example, only lend to socially or environmentally beneficial projects. Many of the alternative banks are very environmentally conscious, for example, they use exclusively renewable energy sources, compensate their CO_2 emissions or regularly audit their use of resources. Several alternative banks pursue their goals through the setting of interest rates. The interest rate on loans may be partially determined by the type of project financed. Discounts are given to social projects or ecological building renovations. Customers may also, for example, choose to forgo part of the interest rates they would receive on deposits to provide social or ecological projects with subsidized interest rates on loans. While most banks seek to be profitable, some explicitly state that they do not seek to maximize their profit. Often, part of the profit is donated. Employee remuneration may be competitive but may also be lower than in conventional banks. To stave off excessive payments to management, some banks define a maximum spread between highest- and lowest-earning employees while other banks make no or quite small bonus payments. These findings complement the work by San-Jose et al. (2011) who discuss the problem of identifying banks that are "truly" ethical and identify characteristics that distinguish ethical banks from conventional banks. They conclude that ethical banks distinguish themselves through high transparency and allocation of assets to create additional social profit.

Data sources and description

The final list of banks contains 65 banks. For 54 of these multiple years of balance sheet data are available in Bankscope[4]. The database may contain unconsolidated as well as consolidated bank balance sheets from the same bank. This could lead to double counting (see e.g. Buch and Neugebauer, 2011). The alternative banks in Bankscope have the consolidation codes C1 (consolidated statement without unconsolidated companion), C2 (consolidated statement with unconsolidated companion) and U1 (unconsolidated statement with no consolidation companion in Bankscope). Other consolidation codes such as U2 (unconsolidated statement with consolidated companion in Bankscope) are not present, which means that there is no danger of double counting of alternative banks. In the construction of the conventional comparison group I similarly use only the consolidation codes C1, C2 and U1. This specification follows a suggestion by Duprey and Lé (2014) and includes banks at their highest available consolidation status. All balance sheet data are in million USD and the Bankscope universal model data format is used. The data in the universal format is intended to facilitate comparability across different countries and accounting standards (Fitch Ratings and Bureau van Dijk, 2009).

[4]This excludes 15 alternative banks based in the U.S. that do not have, unfortunately, balance sheet data available in Bankscope. This is due to the fact that Bankscope focuses on the larger banks in each country. While it might be conceivable to supplement the U.S. data using regulatory data provided by the FDIC (Call Report Data), the Bankscope balance sheet data is treated to achieve comparability across different accounting standards. The U.S. regulatory data remains in the original format, thus introducing a source of bias. Also, as banks in the United States were at the epicenter of the financial crisis their riskiness might not be comparable to alternative banks overall.

The final dataset spans the years 1997 through 2012; however, the panel is quite unbalanced due to bank failures, mergers and acquisitions, as well as the representation of new banks in Bankscope. In order to achieve a reasonably balanced panel and allow the analysis of the effects of the global financial crisis, only banks that have balance sheet data available during the years 2006–2009 are included in the further analysis. There are 34 banks for which balance sheet data is available from 2006–2009 and that are used for the subsequent matching process. Some of the alternative banks do not have data available for the years 2006–2009 due to mergers and acquisitions or cease of activity as a bank. Most alternative banks that lack sufficient data were active during that time, but their balance sheets are not represented in Bankscope. These tend to be the comparatively smaller banks as well as relatively young banks. This could potentially be the source of some bias, however, it is unlikely that the inclusion into the Bankscope database differs systematically between alternative and conventional banks.

3.3.2 Control group of conventional banks

As alternative banks make up only a tiny fraction of the banking market, there is a large number of conventional banks that could be used to compare bank riskiness and financial crisis performance. Using all other banks as a control group is not feasible due to the small number of banks of interest. That is why I follow the matching literature and use pre-matching in the presence of a large and potentially heterogeneous control group (Imbens, 2014, Angrist and Pischke 2008). This pre-matching is implemented only to obtain an appropriate and less heterogeneous control group, not to obtain treatment effects that could be interpreted causally. Similar matching approaches are also used in the Islamic banking literature (Bourkhis and Nabi, 2013) and in the evaluation of socially responsible investment funds (Becchetti et al., 2014a).

The matching process follows two steps. First, the total number of banks is reduced to banks that have similar characteristics as the alternative banks and are therefore good potential controls. Specifically, to serve as a potential control, the conventional bank must be active in the same country as the alternative bank and have balance sheet data available for a long enough time frame (2006–2009). Only banks enter that are of the same banking type as the alternative bank (commercial, savings and cooperative)[5]. Banks that were part of large mergers are also dropped[6]. Banks must further be deposit-taking, as

[5]There exists also one alternative building society in the UK which is classified as a “Real Estate and Mortgage bank” in Bankscope and matched with other UK building societies.

[6]As Bankscope data does not contain information on mergers, merger control has to be somewhat approximate as in the related literature. Duprey and Lé (2014) recommend a cutoff of 50% of total assets

all alternative banks are deposit-taking. This leaves 3278 banks in the potential control group.

Second, the alternative banks are matched to conventional banks that closely resemble them using nearest neighbor matching. The banks are matched based on characteristics that are chosen to be important for the behavior and stability of the bank (e.g. bank size) and the business environment the bank acts in (e.g. country) but at the same time these characteristics should not be overly influenced by the status of the bank as being an alternative bank. Therefore, matching is done based on country of origin of the bank, total assets of the bank, bank type (savings, cooperative or commercial) and the last year that the bank is observed in the dataset.

The home country of the bank has effects on bank riskiness mainly through the macroeconomic environment but possibly also through national idiosyncrasies in accounting standards or banking supervision. Bank size is linked to bank capitalization and riskiness in multiple ways. Larger banks often have more sophisticated risk management techniques that allow them to keep lower capital ratios. Also, large banks may be more directly affected by turmoil on international financial markets. Smaller banks are typically less diversified and do not usually refinance themselves on the interbank market and therefore keep higher capital buffers (Jokipii and Milne, 2011). Bank type has also been linked with bank riskiness. For example, cooperative banks are found to be more stable than commercial banks (Hesse and Čihak, 2007).

To preserve the panel structure of the data, banks are matched in one specific year rather than matching each alternative bank with different banks each year. Banks are matched in the year 2006 in order of them to be unaffected by the outbreak of the financial crisis in summer 2007. Following a suggestion by Abadie et al. (2004), each bank is matched with four conventional controls. Using four controls yielded good mean-squared errors in simulations (Abadie and Imbens, 2002). See the appendix for a detailed technical description of the matching process and a discussion of multiple robustness checks of the matching methodology.

growth but some small alternative banks experienced higher self-sustained growth than that in the first years after being founded. I follow Demirgüç-Kunt et al. (2006) and exclude banks whose total assets growth is outside a range of four standard deviations of total assets growth. As some of the alternative banks were also involved in mergers, this technique excludes only large mergers and data errors.

3.3.3 Bank risk measures and control variables

Bank risk measures

The main bank risk measure is the z-score. It is defined as the fraction of the return on assets (ROA) plus the capital asset ratio (CAR) of the bank divided by its standard deviation of the return on assets.

$$z\text{-}score_{i,t} = \frac{ROA_{i,t} + CAR_{i,t}}{SDROA_i} = \frac{\frac{Net\,Income_{i,t}}{Assets_{i,t}} + \frac{Equity_{i,t}}{Assets_{i,t}}}{sd(\frac{Net\,Income}{Assets})_i} \tag{3.1}$$

I calculate the standard deviation over all years that the bank is present in the sample. The z-score states how many standard deviations the bank's return on assets can decline until the bank becomes insolvent. When the returns of the bank are normally distributed the z-score is the inverse of the probability of insolvency of the bank (Beck et al., 2009). A higher z-score therefore means greater bank stability. The z-score is well-established in the empirical banking literature (see e.g. Boyd and Runkle 1993; Laeven and Levine 2009) and has been used in similar studies analyzing the Islamic banking sector (Čihak and Hesse, 2010).

The two time-varying components of the z-score, ROA and CAR are affected differently by the financial crisis. First, the return on assets should decrease in times of crisis. This effect may be even stronger for alternative banks as they experienced a high inflow of assets. In a low interest-rate environment this increase in deposits would not generate the same returns as the old deposits. Second, the capital asset ratio may fall in the financial crisis if the bank experiences losses that reduce capital. In case of the alternative banks, it might also fall due to an inflow in deposits.

Although the z-score is a very widely used measure of banking stability, it can be quite high if the bank has very stable earnings over time. This leads to a very low volatility in ROA and therefore to a very high z-score. As this may happen in the sample studied here and due to the effect of deposit inflows on the z-score, I consider several alternative risk measures. First, I follow Čihak and Hesse (2010) and implement two modified z-scores that are based on downward volatility of return on assets rather than the overall volatility of return on assets. From a bank stability perspective, only downward spikes in return on assets are relevant. In the first modified z-score, downward volatility is proxied by the absolute value of the average negative deviations of the bank-specific ROA from its mean. In the second modified z-score, the downward volatility is proxied by the squared negative deviations of the bank-specific ROA from its mean (Hesse and Čihak, 2007). Lastly, I use the Regulatory Capital Ratio of banks, which is defined as the banks' total regulatory capital over its risk-weighted assets. While simple capital ratios are lowered by a strong inflow of deposits, which increases total assets without immediately increasing capital, the risk-weighted ratios are less affected by this.

Due to the relatively small size of all alternative banks, stock-market based risk measures cannot be employed. Information on non-performing loans (NPLs) is available for only about one-fifth of the banks sampled, which makes it unsuitable as a risk measure. Also, risk measures based on NPLs can be unreliable if troubled banks extend further credit to troubled creditors to avoid write-offs and tend to react with a time lag. Another possible venue of analysis of banking risk would be a comparison of bank failure rates via probit models or similar methods. However, due to very low numbers of observations this has to be left to future research.

Bank control variables

The regression equation includes an array of bank control variables. Many of them are adopted from the literature on riskiness of Islamic banks (see e.g. Čihak and Hesse, 2010) or have been found significant in explaining differences in bank riskiness. First, bank size is proxied by log total assets. Second, the bank's loans to assets ratio is included as a measure of the bank's balance sheet composition and its focus on traditional lending business. In some specifications the loan to deposit ratio is also included. It indicates how well the bank is able to transform deposits into interest-bearing loans. Third, the cost to income ratio is a measure of efficiency of the bank. Less efficient banks will generate lower returns and may also be worse at risk management. However, it may be not a meaningful efficiency measure for alternative banks that do not aim to generate income from their business.

Fourth, the income diversity measure introduced by Laeven and Levine (2007) is an indicator on how much the bank generates its income via granting of loans rather than other activities. This measure is also used by Čihak and Hesse (2010). A bank with diverse income sources can be more stable in times of low interest rates but it can also indicate that the bank is not focusing on traditional banking business. A high share of non-interest income has been linked with higher stability in German retail-oriented banks (Köhler, 2014). Lastly, the ratio of customer deposits to total assets is another indicator of traditional banking activity. Less reliance on wholesale deposit funding and the interbank market can be protective in crises and shows that the bank is closely connected to its community.

3.3.4 Descriptive statistics of the matched dataset

This section offers an overview of alternative banks and describes the matched dataset, which is used in the later regression analysis. Among the 34 alternative banks are 13 commercial banks, 15 cooperative banks, five savings banks and one building society. These alternative banks are headquartered in 12 different EU and OECD countries[7]. The average size of an alternative bank is 4474 million USD (Table 3.1). With a median of 1763 million USD, the size distribution is quite skewed. Table 3.2 provides summary statistics for the matched sample. It also compares the averages of the matched banks and the alternative banks and reports results from a significance test of sample means. Alternative banks are matched on size with conventional banks in the year 2006. Due to their higher rates of growth after 2006 they are on average slightly larger than conventional banks. Alternative banks have significantly lower loans to asset ratios (45% versus 57%) and loan deposit ratios than conventional banks (54% versus 71%). This confirms findings by Scheire and De Maertelaere (2009). These lower loan ratios may indicate that alternative banks have difficulties in finding enough viable borrowers but can also indicate that the banks prefer to keep larger liquidity buffers. The cost to income ratio is usually a measure of bank efficiency. The significantly higher cost to income ratio of alternative banks could therefore indicate that alternative banks are less efficient, but it could also be due to the fact that not all alternative banks are income-maximizing. The income diversity indicator shows that alternative banks have significantly less diverse income sources than conventional banks. This is probably due to their focus on core banking activities.

The ratio of customer deposits to total assets is significantly higher in alternative banks (77%) than in conventional banks (65%). This is to be expected due to the focus of alternative banks on the real economy. Without controlling for any other variables, the average z-score of alternative banks is significantly higher than that of conventional banks. In this sample of banks, z-scores in general are rather high, because many banks are rather well capitalized (high CAR). Additionally, the return on assets is rather low for both the alternative banks and for the matched sample when compared to the return on assets of all banks including large commercial and investment banks. For the second risk measure, the regulatory capital ratio, there is no significant difference between banking groups.

Figure 3.1 in the appendix shows the amount of total assets of the alternative banks and the matched conventional banks over time. Both banking groups experience increases in total assets over time, but since the outbreak of the financial crisis in 2007, the total assets of alternative banks have grown at a much higher rate than that of the matched

[7] Austria, Belgium, Denmark, France, Germany, Great Britain, Italy, Malta, the Netherlands, Norway, Spain and Switzerland

conventional banks. This is in line with Benedikter (2011) who states that total assets of ethical banks in Europe doubled between 2007 and 2010. The slight decrease of average total assets in 2012 is due to the fact that two rather large alternative banks exit the sample in 2011. Due to concerns that the growth in total assets may be driven by mergers or by large banks I restrict the data to banks that are available in the dataset from 2002–2012 and not involved in large mergers since the outbreak of the crisis. Figure 3.2 confirms the higher growth of alternative banks using the median total assets of this restricted sample.

The amount of customer deposits held by alternative banks is also steadily increasing and higher than that of the control group (Figure 3.3). This stronger increase in customer deposits after the financial crisis is again robust when using the restricted dataset (Figure 3.4). When looking at the development of current customer deposits (Figures 3.5 and 3.6) the increased inflow of deposits since the outbreak of the financial crisis becomes even more apparent.

3.4 Regressions and results

3.4.1 Riskiness of alternative banks

The following regressions evaluate the riskiness of alternative banks in comparison with conventional banks.

$$RISK_{i,t} = \alpha + \beta_1 \, Alt.\, Bank_i + \beta_2 \, B_{i,t} + \gamma \, Country_j + \delta \, Year_t + \epsilon_{i,t} \tag{3.2}$$

The dependent variable is the bank risk of bank i in year t. It is proxied by the z-score in the baseline specification. The effect of being an alternative bank (or not) is captured in the regression with the dummy variable "Alt. Bank" that equals one if the bank is an alternative bank and zero if it is a conventional bank. If the alternative banks had, for example, lower z-scores (were less stable) than the conventional banks, the dummy variable would have a negative coefficient sign in the regression. B is a vector of bank specific variables discussed in the previous section. It includes indicator variables of bank type (savings bank, cooperative or commercial bank), bank size proxied via log total assets, a measure of income diversity and the cost to income ratio as a measure of cost efficiency. It also includes the ratio of customer deposits to total assets and the ratio of loans to total assets, which has been shown to be significantly lower in alternative banks than in conventional banks (Table 3.2). Some specifications add the loan deposit ratio as a measure of conversion of deposits into loans. To account for country-specific characteristics and macroeconomic effects, the regression specification also includes country and year fixed effects. The inclusion of bank fixed effects is not possible as the status of being an alternative bank is also fixed over time. That is why the regression is implemented using pooled ordinary least squares (OLS) following Čihak and Hesse (2010).

Table 3.6 presents results for the baseline specification. In all specifications, the alternative bank status is associated with a significantly higher z-score and therefore greater stability. Larger banks and banks with a higher fraction of customer deposit funding are also more stable. Banks with more diverse income are less stable. As the cost to income ratio is insignificant in all regression specifications, it is not included in further regressions. Year fixed effects (columns 6 and 7) were found to be jointly insignificant and are also dropped.

Robustness to different risk measures

In Table 3.7 the regression is repeated using different specifications of the z-score. Column (1) includes a z-score calculated using the expected ROA, proxied by a moving average of the past 3 years rather than the current ROA, which leaves results virtually unchanged. From a perspective of financial stability only negative deviations from the average ROA are of interest (Čihak and Hesse, 2010). Columns (2) and (3) therefore report regression results using two z-scores based on downward volatility. Here, the alternative banks show even greater stability than conventional banks. This indicates that alternative banks are especially risk-averse. In column (4) the z-score is winsorized at the 1% and 99% level due to the concern that the regression results might be driven by outliers. Again, results are robust. However, the regression results using the regulatory capital ratio as a risk measure (columns 1 and 2 of Table 3.12) show no significant relationship between regulatory capital and alternative banking status. One caveat is that this alternative risk measure is only available for about one third of the banks in the sample.

Robust regression methods

Least squares regression methods are especially vulnerable to outliers due to the squared error term. In the case of alternative banking, the distribution of regression covariates is affected by some outliers. However, these are not data errors; rather this is due to the inherent heterogeneity of alternative banks. To ensure that the previous regression results do not depend on a few individual banks, I repeat the baseline regression using two different estimation techniques that are robust to outliers. Čihak and Hesse (2010) use the same robust regression techniques due to similar considerations for Islamic banks. Columns (1) and (2) in Table 3.8 present results using a weighted regression method that is robust to outliers. Specifically, the outlier-robust estimator described in Hamilton

(2012) identifies outliers in an iterative procedure and assigns them lower weights in the regression. Columns (3) and (4) present results using a median least squares regression. In both specifications, the coefficient values of the alternative bank indicator are somewhat lower but still positive and highly significant.

As an additional robustness check, equation 3.2 is modified by lagging all bank-specific explanatory variables by one year. This should mitigate potential issues of endogeneity. The results in table 3.9 show that the main result as well as the coefficients of bank-specific variables are very robust to the inclusion of lagged bank specific variables. As lagging the bank-specific variables leaves the main results unchanged but further reduces a rather small dataset, lagged terms are only included as a robustness exercise.

Inclusion of interaction terms

The regression results could be biased due to the presence of the bank characteristics, if they too are influenced by alternative banking status. As some of the bank specific variables collected in the vector B may be directly influenced by the alternative banking status, the above regression equation is modified to a fully interacted model where each regressor is interacted with the alternative bank dummy. This follows Čihak and Hesse (2010) who also include interaction variables of bank characteristics with the bank type when the bank characteristic differs between bank types.

$$RISK_{i,t} = \alpha + \beta_1\, Alt.\, Bank_i + \beta_2\, B_{i,t} + \beta_3\, Alt.Bank_i * B_{i,t} + \gamma\, Country_j + \delta\, Year_t + \epsilon_{i,t} \quad (3.3)$$

Results are presented in Table 3.10. While some of the interaction with bank characteristics are highly significant they leave the main result unchanged. The coefficient values of the alternative bank indicator remain very similar and highly significant. This indicates that the alternative bank indicator captures other stabilizing features of the banks that are not directly controlled for in the regression. These differences could be due to the different business culture of alternative banks, for example, a conservative loan portfolio, high-quality loan monitoring or a particularly dedicated staff.

3.4.2 Stability of alternative banks in the global financial crisis

The second area of research is the question if alternative banks were affected differently by the financial crisis. As the higher growth rates of alternative banks since the onset of the financial crisis have already been explored graphically in the previous section, this section focuses on the effect of the crisis on bank stability. This is evaluated by introducing a crisis indicator in the regression and interacting it with the alternative bank dummy. The use of a crisis dummy and the inclusion of interaction terms to capture crisis effects is typical in the literature (Beck et al., 2013). Two different crisis indicators are used, both based on GDP. As the alternative banks, as well as their matched counterparts, are comparatively small banks and few are active traders on financial markets, the financial crisis should most likely affect them via the real economy. The first measure, a crisis intensity measure, is the yearly *loss* of GDP, in percent, of the country where the bank is located. If the GDP grows, the crisis measure equals zero. This measure indicates the presence of a crisis for all countries in 2009 and for some countries in 2003, 2004, 2008, 2010 and 2012. The second crisis measure is a dummy that equals one if the home country of the bank experienced negative GDP growth that year.

$$\begin{aligned} RISK_{i,t} = {} & \alpha + \beta_1\, Alt.\, Bank_i + \beta_2\, B_{i,t} + \beta_3\, Crisis_{j,t} \\ & + \beta_4 Alt.\, Bank_i * Crisis_{j,t} + \gamma\, Country_j + \epsilon_{i,t} \end{aligned} \tag{3.4}$$

When using the z-score as a risk indicator I find no significant effect of the interaction term between the alternative bank dummy and the crisis indicator. The crisis indicator itself displays a negative, but not significant coefficient. In terms of z-score, there is no additional difference between alternative and conventional banks in times of crisis. This may be due to the multiple effects of the financial crisis on the z-scores of alternative banks discussed in section 3.2.3. Specifically, an inflow of deposits would c.p. increase total assets and therefore lower z-scores. That is why, in the following, a risk-weighted risk measure that should be less affected by capital inflows is used.

Table 3.12 presents results using the regulatory capital ratio as a risk measure. Both crisis indicators display negative coefficients, which indicates that both groups of banks lose in terms of regulatory capital in times of economic crisis. However, only the crisis intensity measure is significant. Interestingly, the alternative banking indicator is not significant when the regulatory capital ratio is used without including crisis measures (Columns 1 and 2). When crisis effects are included, it even becomes negative and significant. However, the interaction of both crisis measures with the alternative bank dummy is positive and significant in all specifications. This indicates that alternative banks proved more resilient in terms of regulatory capital in times of crisis than conventional banks. Due to the limited sample size for the regulatory capital ratio and the fact that no significant results are obtained using the z-score, results must be viewed as preliminary. When repeating these regressions using robust and quantile regression methods they lose significance.

When interpreting the results, it must not be forgotten that the control group consists of other small banks, many of them cooperative and savings banks, most of which were also not at the center of the financial crisis. The fast growth of alternative banks since the global financial crisis may obscure the pure crisis effects on the banks. While the final effect of the rapid growth of alternative banks remains to be seen, they were not less stable than the control group during the crisis.

3.5 Conclusion

This paper studies the riskiness of alternative banks in general and, specifically, during the financial crisis. This is the first study, that I am aware of, to compile a comprehensive dataset of alternative banks and evaluate their riskiness compared to an appropriate control group of conventional banks. The main result is that alternative banks, such as social and ethical banks, are significantly more stable than conventional banks. This result is confirmed using a wide array of robustness checks and is robust to different specifications of the main risk measure. The results are further confirmed using several robust regression methods. There is some evidence that in times of economic crisis alternative banks also prove to be more resilient in terms of regulatory capital than their conventional counterparts. The fast growth of alternative banks during and after the financial crisis makes bank risk measures based on total assets, such as the z-score, difficult to interpret. One avenue for further research is the analysis of alternative bank stability using risk measures that are less affected by bank growth.

When interpreting the results one must nevertheless keep in mind that the number of alternative banks used in the analysis is by necessity quite small. This is mostly due to the very small number of alternative banks in general and the limited number of years of data that were available for analysis. It must also be noted that by using balance sheet-generated risk measures, all results necessarily suffer from some survivorship bias. Some alternative banks did fail during the financial crisis and/or had to merge after financial difficulties. This, of course, also holds for conventional banks. A separate analysis of bank failure probabilities could be an avenue for future research assuming that the sample size of bank failures increases over time.

As alternative banks hold only a tiny fraction of banking system assets in Europe, the direct effect of alternative banking on financial stability is accordingly small. However, by their sheer existence alternative banks show that different ways of conducting banking business are possible, which may influence how other market participants act in turn. Supporting this line of thought, Becchetti et al. (2014b) develop a model where profit maximizing firms may find it optimal to adopt measures of corporate social responsibility when socially responsible, not profit maximizing, firms enter the market. Therefore, the fact that alternative banks do exist may be a positive influence on the behavior of conventional banks.

As a final note, it must be added that this paper studies alternative banking from a view of stability. Positive effects on the social economy, the environment and the society in general cannot be quantified here but are nevertheless a central aspect of alternative banking.

3.6 Appendix to chapter 3

3.6.1 Matching methodology and robustness

Matching methodology

As alternative banks make up only a tiny fraction of the banking market, there is a large number of conventional banks that could be used to compare bank riskiness and financial crisis performance. Using all other banks as a control group is not feasible due to the small number of banks of interest. That is why I follow the matching literature and use pre-matching in the presence of a large and potentially heterogeneous control group (Imbens, 2014; Angrist and Pischke, 2008). Notably, this means that the pre-matching process should not be associated with the matching methods used for obtaining causal inference in the context of treatment evaluation (e.g. propensity score matching).

The alternative banks are matched to conventional banks that closely resemble them in basic characteristics using nearest neighbor matching. The banks are matched based on characteristics that are chosen to be important for the behavior and stability of the bank (e.g. bank size) and the business environment the bank acts in (e.g. country) but at the same time these characteristics should not be overly influenced by the status of the bank as being an alternative bank. Matching is done based on country, bank specialization (savings, cooperative or commercial), bank size and the last year the bank was available in Bankscope. The bank specialization is assigned by Bankscope based on the annual report of the bank. One alternative bank is, most likely erroneously, classified as a "finance company" in Bankscope and reclassified as a cooperative bank for the analysis. One British alternative building society is classified as a "Real Estate and Mortgage bank" in Bankscope and is matched with other British building societies. Bank size is represented by total assets in 2006, that is, before the outbreak of the financial crisis. Of the banks that are available long enough for the regression analysis, three are not available until the end of the sample. One bank leaves the sample in 2009, two others in 2011. As one of the matching variables is the last year that the bank was observed in the data set, these are matched with banks that left the data set at a similar time. Both alternative banks and conventional banks in the matched data set are observed in Bankscope for 12 or 13 years, on average.

The matching process is implemented using the Stata command `nnmatch`. The nearest neighbor matching minimizes the Mahalanobis distance between the covariates. The Mahalanobis distance is invariant to scale and accounts for correlation of the matching variables (see e.g. Härdle and Simar, 2012).

To specify, this means that matching is done directly on the covariates and not on, for example, the propensity score. In the context of this paper, the more direct method is preferred as matching is employed only as a pre-matching and not for causal inference and there are few and mostly categorical covariates used for matching. For country and bank type exact matching is specified. This means in practice that these variables enter the weighting matrix with their original weight multiplied with 1000 (Abadie et al., 2004). Banks are matched with replacement which leads to higher quality matching than without replacement (Abadie and Imbens, 2002). Following a suggestion by Abadie et al. (2004), each alternative bank is matched with four conventional controls which yielded good mean-squared errors in simulations.

Robustness of results to matching specifications

This matched data set is used for all regressions except in Table 3.11 which presents a series of robustness checks of matching specification and data choice. Column (1) presents results for only the 1997–2011 period. The year 2012 is omitted from the regression because two alternative banks left the sample in that year. Column (2) repeats the matching using a sample that controls for mergers and panel attrition. Both the alternative banking groups as well as the other banks were involved in mergers and acquisitions during the time studied. In the baseline specification, only banks involved in large mergers are dropped from the sample. In column (2) banks are excluded from both groups if they experienced a total assets growth of 50% or more since 2006 (Duprey and Lé, 2014). Before 2006, banks are only subjected to the merger control following the baseline specification as some alternative banks experienced self-sustained growth greater than 50% just after founding. Bank mergers and acquisitions are one cause of sample attrition. Riskier banks could be more involved in take-overs, either as a receiving entity if they are more prepared to engage in potentially risky take-overs or as candidates for a takeover if past risk-taking destabilized their financial position. In order to control for possible effects of sample attrition, the data set used in column (2) also includes only banks with data available from 2003 through 2012 or longer. Column (3) does not use exact matching for country and bank type. While these are important variables in term of bank risk, the exact matching could lead to insufficient weight being placed on bank size. Columns (4) and (5) check whether the results are robust to the number of banks being matched and report results on 1:6 and 1:3 matching, respectively. Column (6) implements a bias adjustment that "adjusts the difference within the matches for the differences in their covariate values" (Abadie et al., 2004, p. 298). As this bias only occurs when more than one continuous variable is included in the matching or when the potential sample is too small, this bias adjustment is not included in the baseline specification (Abadie and Imbens, 2002). The matched data set in column (7) uses the inverse variance weighting matrix instead of the Mahalanobis distance. Column (8) checks whether the result is robust to the ordering of the matched variables. In the presence of categorical variables, the ordering of the variables in the matching process can affect the outcome of the match. Here, all matching variables, except the bank size, are categorical. That is why column (8) presents results from a different ordering of the matched variables. Lastly, the data set used in column (9) matches the banks in 2007 instead of 2006. While the turmoil on the U.S. housing markets began in summer 2007, the height of the crisis was reached only in summer 2008 with the collapse of Lehman Brothers. Therefore, alternative banks may have been still unaffected by the crisis in 2007 and this year could also be used to match the banks. For all different data sets and robustness tests collected in Table 3.11 the coefficient values remain of similar size and significant. Results therefore do not depend on the exact construction of the data set.

3.6.2 Data description and summary statistics

Table 3.1: Summary statistics for alternative banks

	Number	Mean	Standard deviation	Minimum	Maximum
Total Assets (Mill. USD)	381	4,474	9,867	21	78,229
Loans / Assets	381	45.20	21.69	1.72	89.05
Cost / Income	361	26.64	39.65	2.07	301.43
Income diversity	381	22.05	15.46	0.00	92.72
Customer deposits / Assets	381	76.80	15.37	10.23	96.73
Loan deposits ratio	381	53.84	28.88	1.80	140.16
z-score	381	88.73	135.82	1.89	983.70
z-score (expected ROA)	324	89.14	141.52	1.41	983.86
Downward z-score (I)	381	125.24	192.76	2.01	1,211.24
Downward z-score (II)	381	106.74	163.08	1.69	1,040.20
Regulatory Capital Ratio	147	16.84	6.12	9.50	69.10

Table 3.2: Summary statistics for all banks in matched sample

	N	Mean	Standard deviation	Min	Max	Mean conv. banks	Mean alt. banks	p-value
Total Assets (Mill. USD)	1,584	3,638	7,134	14	78,229	3,373	4,474	0.04
Loans / Assets	1,584	54.15	23.40	0.00	98.11	56.99	45.20	0.00
Cost / Income	1,484	20.07	59.01	0.42	1,937.74	17.96	26.64	0.00
Income diversity	1,584	32.52	22.35	0.00	100.00	35.84	22.05	0.00
Customer deposits / Assets	1,584	69.01	19.74	0.00	96.73	66.54	76.80	0.00
Loan deposits ratio	1,584	67.11	32.91	0.00	204.51	71.31	53.84	0.00
z-score	1,584	66.82	96.85	-2.52	983.70	59.88	88.73	0.00
z-score (expected ROA)	1,332	68.11	100.42	-0.41	983.86	61.35	89.14	0.00
Downward z-score (I)	1,584	89.89	123.21	-1.85	1,211.24	78.70	125.24	0.00
Downward z-score (II)	1,584	73.43	101.29	-1.20	1,040.20	62.88	106.74	0.00
Regulatory Capital Ratio	518	17.08	8.02	6.73	81.88	17.17	16.84	0.62

The p-values reported stem from a t-test of equality of the means of conventional banks and alternative banks. The test allows for the variance to be different between the banking types.

Table 3.3: Variable overview and definitions

Variable	Description / Calculation	Source
Risk measures and components thereof		
z-score	$= \frac{ROA_{i,t}+CAR_{i,t}}{SDROA_i}$	calculation based on Bankscope data
z-score (Expected ROA)	$= \frac{\frac{1}{3}*(ROA_{i,t}+ROA_{i,t-1}ROA_{i,t-2})+CAR_{i,t}}{SDROA_i}$	calculation based on Bankscope data
Downward z-score (I)	as standard z-score, but with downward absolute volatility of return on assets	calculation based on Bankscope data, specification following Hesse and Čihak (2007)
Downward z-score (II)	as standard z-score, but with downward squared volatility of return on assets	calculation based on Bankscope data, specification following Hesse and Čihak (2007)
Return on Assets (ROA)	Net income / Total assets	calculation based on Bankscope data
Capital Asset Ratio (CAR)	Total equity / Total assets	calculation based on Bankscope data
Regulatory Capital Ratio	Total regulatory capital ratio (%)	Bankscope
Control variables		
Alternative bank indicator	1 for alternative banks, 0 for conventional banks	own research
Bank type indicator	indicator variables for conventional, cooperative and savings banks	Bankscope
Bank size	log(total assets)	calculation based on Bankscope data
Income diversity	$= 1 - \lvert\frac{Net\,interest\,income - other\,operating\,income}{Total\,Operating\,Income}\rvert$	calculation based on Bankscope data, specification following Laeven and Levine (2007)
Loans / Assets	Net loans / Total assets	calculation based on Bankscope data
Cost to income ratio	(Interest + Non-interest expense)/ Net income	calculation based on Bankscope data
Customer Deposits / Assets	Customer deposits / Total assets	calculation based on Bankscope data
Loan deposit ratio	Net loans / (Total deposits, money market and short term funding)	calculation based on Bankscope data
GDP growth	percentage change yearly, current prices	Eurostat

To allow for correct interpretation, ratios relying on income data in numerator and denominator are set missing if the banks' income is negative.

Table 3.4: Correlation table of bank control variables

	Bank size	Loans/ Assets	Customer deposits/ Assets	Income diversity	Cost/ Income	Loan deposit ratio
Bank size	1					
Loans / Assets	0.07	1				
Customer deposits / Assets	-0.15	-0.06	1			
Income diversity	0.06	-0.29	-0.39	1		
Cost / Income	0.05	-0.07	0.04	0.02	1	
Loan deposit ratio	0.10	0.92	-0.24	-0.16	-0.08	1

Table 3.5: Number of alternative banks by year

Year	Bankscope data available	used in matched dataset
1997	21	18
1998	23	19
1999	23	19
2000	25	20
2001	25	21
2002	28	24
2003	26	23
2004	28	27
2005	33	32
2006	35	34
2007	35	34
2008	40	34
2009	42	33
2010	48	33
2011	48	33
2012	44	31

3.6.3 Figures

Figure 3.1: Total assets of alternative and conventional banks

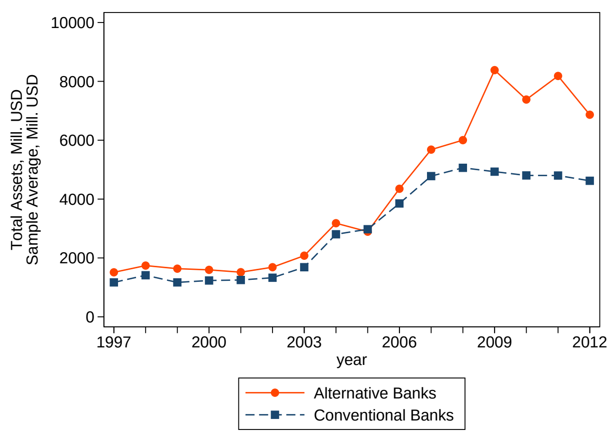
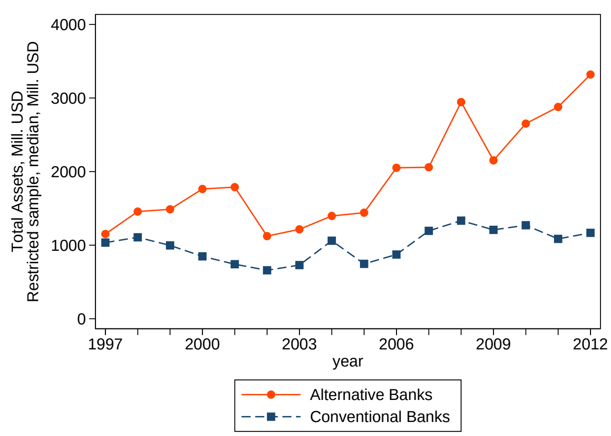


Figure 3.2: Total assets of alternative and conventional banks – outlier robust



This figure reports the total assets of alternative and conventional banks in an outlier-robust modification of the above figure. It reports the median total assets of a data set that is restricted to banks that are available in the data set from 2002–2012 and not involved in large mergers since the outbreak of the crisis.

Figure 3.3: Customer deposits of alternative and conventional banks

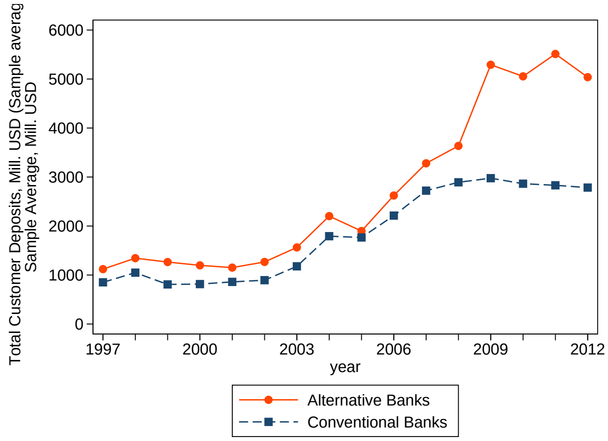
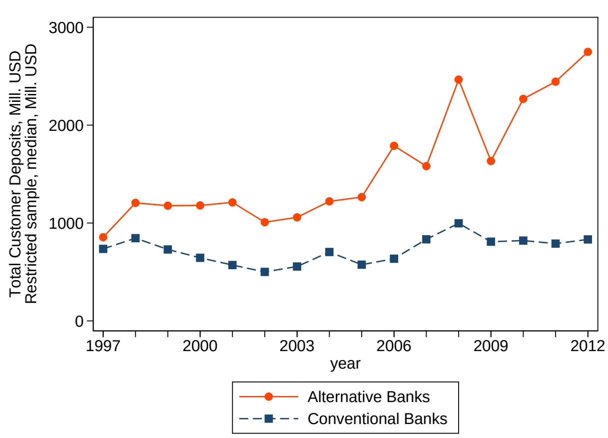


Figure 3.4: Customer deposits of alternative and conventional banks – outlier robust



This figure reports the customer deposits of alternative and conventional banks in an outlier-robust modification of the above figure. It reports the median total assets of a data set that is restricted to banks that are available in the data set from 2002–2012 and not involved in large mergers since the outbreak of the crisis.

Figure 3.5: Current customer deposits of alternative and conventional banks

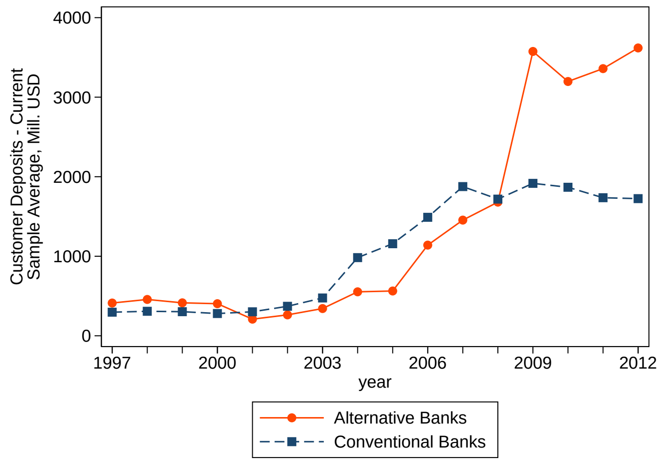
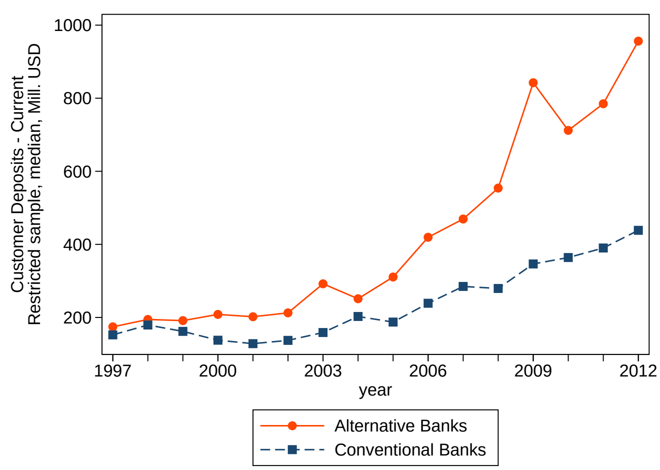


Figure 3.6: Current customer deposits of alternative and conventional banks – outlier robust



This figure reports the current customer deposits of alternative and conventional banks in an outlier-robust modification of the above figure. It reports the median customer deposits of a dataset that is restricted to banks that are available in the data set from 2002–2012 and not involved in large mergers since the outbreak of the crisis.

3.6.4 Regression results

Table 3.6: Regression results. Comparing the riskiness of conventional and alternative banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alternative bank dummy	14.72**	10.79*	14.51**	18.49***	17.82***	14.78**	14.56**
	[6.06]	[6.19]	[6.06]	[5.89]	[5.96]	[6.07]	[6.07]
Bank size	6.44***	8.08***	6.16***	5.95***	5.79***	5.79***	5.42***
	[1.62]	[1.75]	[1.63]	[1.36]	[1.37]	[1.54]	[1.55]
Loans / Assets	0.33***	0.26**	-0.12	0.49***	-0.10	0.33***	-0.16
	[0.09]	[0.11]	[0.20]	[0.09]	[0.19]	[0.09]	[0.20]
Customer deposits / Assets	0.44***	0.57***	0.54***	0.45***	0.56***	0.43***	0.53***
	[0.11]	[0.14]	[0.11]	[0.09]	[0.09]	[0.11]	[0.11]
Income diversity	-0.77***	-0.72***	-0.78***	-0.73***	-0.75***	-0.80***	-0.81***
	[0.12]	[0.12]	[0.12]	[0.11]	[0.11]	[0.11]	[0.11]
Cost / Income		-0.00					
		[0.03]					
Loan deposit ratio			0.37**		0.45***		0.40***
			[0.15]		[0.15]		[0.15]
Constant	-22.91	-39.26**	-26.99*	0.71	-4.46	-20.48	-25.01
	[14.41]	[16.92]	[14.27]	[11.08]	[10.83]	[17.32]	[17.15]
Bank type dummies	YES	YES	YES	YES	YES	YES	YES
Country dummies	YES	YES	YES	NO	NO	YES	YES
Year dummies	NO	NO	NO	NO	NO	YES	YES
Observations	1,584	1,484	1,584	1,584	1,584	1,584	1,584
R^2	0.16	0.15	0.16	0.12	0.12	0.16	0.16

This table reports the OLS regression estimates of equation 3.2. The dependent variable is the z-score. Robust standard errors are in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Regression results. Robustness of calculation of z-score and modified z-scores

z-score type	(1) expected ROA	(2) Downward I (Abs.)	(3) Downward. II (Squrd.)	(4) winsor
Alternative bank dummy	12.79*	30.00***	29.66***	10.40**
	[6.83]	[8.87]	[7.32]	[5.01]
Bank size	7.62***	8.01***	6.62***	4.85***
	[1.84]	[2.04]	[1.70]	[1.29]
Loans / Assets	0.31***	0.54***	0.36***	0.38***
	[0.10]	[0.12]	[0.10]	[0.08]
Customer dep. / Assets	0.47***	0.69***	0.58***	0.36***
	[0.12]	[0.13]	[0.11]	[0.09]
Income diversity	-0.83***	-0.86***	-0.69***	-0.71***
	[0.13]	[0.14]	[0.12]	[0.09]
Constant	-27.32*	-47.31***	-36.81**	-12.64
	[16.39]	[18.29]	[15.24]	[11.80]
Bank type dummies	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES
Observations	1,332	1,584	1,584	1,584
R^2	0.16	0.19	0.19	0.18

This table reports the OLS regression estimates of equation 3.2. The dependent variable is the z-score in different specifications as detailed in the header. Column (1) uses the expected ROA in the calculation of the z-score. Columns (2) and (3) use downward volatility measures rather than overall volatility measures in the calculation of the z-score. Column (2) uses the absolute downward deviations and column (3) the squared downward deviations of the ROA, following Hesse and Čihak (2007). Column (4) reports results using a z-score that is winsorized at the 1% and 99% level. Robust standard errors are in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Regression results. Use of robust and quantile regression methods.

Regression method	(1) robust	(2) robust	(3) median	(4) median
Alternative bank dummy	3.38*	5.74***	6.97***	8.93***
	[2.02]	[2.16]	[2.59]	[3.18]
Bank size	-0.81	0.17	-1.25*	-0.81
	[0.58]	[0.54]	[0.74]	[0.80]
Loans / Assets	0.35***	0.44***	0.45***	0.43***
	[0.04]	[0.04]	[0.06]	[0.06]
Customer deposits / Assets	-0.06	-0.05	-0.06	-0.03
	[0.05]	[0.05]	[0.06]	[0.07]
Income diversity	-0.40***	-0.31***	-0.33***	-0.29***
	[0.04]	[0.05]	[0.06]	[0.07]
Constant	35.38***	32.61***	31.46***	33.11***
	[7.00]	[6.44]	[8.98]	[9.47]
Bank type dummies	YES	YES	YES	YES
Country dummies	YES	NO	YES	NO
Observations	1,584	1,584	1,584	1,584
R^2	0.36	0.21		

This table reports regression estimates of equation 3.2 using robust and quantile regression methods. The dependent variable is the z-score. Columns (1) and (2) report results using an estimation technique robust to outliers in the data (see Hamilton, 2012 for a description). Columns (3) and (4) report median least squares regressions. Standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 3.9: Regression results. Bank-specific variables lagged by one year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alternative bank dummy	13.92**	10.41	13.70**	17.67***	16.87***	13.90**	13.66**
	[6.46]	[6.58]	[6.47]	[6.22]	[6.31]	[6.47]	[6.48]
L. Bank size	7.35***	8.74***	7.08***	6.63***	6.50***	6.69***	6.29***
	[1.73]	[1.88]	[1.74]	[1.46]	[1.47]	[1.65]	[1.65]
L.Loans / Assets	0.31***	0.24**	-0.17	0.47***	-0.17	0.31***	-0.22
	[0.10]	[0.11]	[0.22]	[0.09]	[0.22]	[0.10]	[0.23]
L.Customer dep. / Assets	0.46***	0.59***	0.55***	0.45***	0.57***	0.45***	0.55***
	[0.12]	[0.15]	[0.12]	[0.10]	[0.10]	[0.12]	[0.12]
L.Income diversity	-0.79***	-0.73***	-0.81***	-0.77***	-0.79***	-0.82***	-0.84***
	[0.12]	[0.12]	[0.12]	[0.11]	[0.11]	[0.12]	[0.12]
L.Cost / Income		0.00					
		[0.04]					
L.Loan deposit ratio			0.39**		0.49***		0.44**
			[0.17]		[0.17]		[0.17]
Constant	-27.77*	-43.46**	-31.78**	-0.36	-5.55	-26.82	-31.39*
	[15.61]	[18.46]	[15.53]	[11.75]	[11.47]	[18.09]	[18.10]
Bank type dummies	YES	YES	YES	YES	YES	YES	YES
Country dummies	YES	YES	YES	NO	NO	YES	YES
Year dummies	NO	NO	NO	NO	NO	YES	YES
Observations	1,455	1,366	1,455	1,455	1,455	1,455	1,455
R^2	0.16	0.15	0.16	0.12	0.12	0.16	0.16

This table reports the OLS regression estimates of equation 3.2 which is modified by lagging all bank-specific explanatory variables by one year to mitigate potential issues of endogeneity. The dependent variable is the z-score. Robust standard errors are in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 3.10: Regression results. Addition of interaction terms of alternative bank status and bank-level control variables.

Regression method	(1) OLS	(2) OLS	(3) robust	(4) robust
Alternative Bank Dummy	13.89**	9.92*	14.40***	14.74***
	[5.76]	[5.71]	[2.21]	[2.24]
Bank size	7.22***	4.87***	-1.03*	-1.22**
	[1.73]	[1.36]	[0.57]	[0.61]
Alt.*Bank size		11.76**		1.40
		[4.75]		[1.07]
Loans / Assets	0.27***	0.31***	0.22***	0.23***
	[0.09]	[0.09]	[0.05]	[0.05]
Alt.*Loans / Assets	0.24	0.21	0.50***	0.51***
	[0.24]	[0.25]	[0.09]	[0.09]
Customer deposits / Assets	0.25***	0.22**	-0.03	-0.03
	[0.09]	[0.09]	[0.05]	[0.05]
Alt.*Customer deposits / Assets	1.87***	2.20***	0.21	0.26*
	[0.42]	[0.51]	[0.14]	[0.14]
Income diversity	-0.92***	-0.90***	-0.56***	-0.56***
	[0.09]	[0.08]	[0.05]	[0.05]
Alt.*Income diversity	1.37***	1.35***	1.02***	1.03***
	[0.49]	[0.48]	[0.12]	[0.12]
Constant	46.59***	46.80***	32.63***	32.64***
	[4.11]	[4.12]	[3.45]	[3.46]
Bank type dummies	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES
Observations	1,584	1,584	1,584	1,584
R^2	0.17	0.18	0.40	0.40

This table reports the regression estimates of equation 3.3 using OLS (columns 1 and 2) and robust regression methods (columns 3 and 4). The dependent variable is the z-score. Robust standard errors are in brackets for OLS regressions. Standard errors are in brackets for robust regressions. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1 All bank control and interacted variables are demeaned for ease of interpretation (See Balli and Sørensen, 2013; Brambor et al., 2006).

Table 3.11: Regression results. Robustness. Comparing different regression datasets and matching methods

Dataset	(1) 1997 - 2011	(2) balanced	(3) no exact	(4) 6 matches	(5) 3 matches	(6) bias adj.	(7) inv. var	(8) ordering	(9) match in 2007
Alternative bank dummy	15.25**	18.59**	13.55**	22.85***	15.38**	13.67**	11.20*	13.61**	14.89**
	[6.18]	[8.11]	[5.99]	[5.84]	[6.27]	[6.06]	[6.42]	[6.06]	[5.80]
Bank size	6.31***	9.80***	5.30***	3.58***	10.05***	5.20***	3.52*	5.02***	5.54***
	[1.63]	[3.34]	[1.65]	[1.22]	[1.94]	[1.63]	[1.86]	[1.63]	[1.58]
Loans / Assets	0.33***	0.31***	0.34***	0.30***	0.25**	0.35***	0.20*	0.35***	0.12
	[0.09]	[0.10]	[0.10]	[0.06]	[0.11]	[0.09]	[0.11]	[0.09]	[0.10]
Customer deposits / Assets	0.43***	0.43***	0.40***	0.36***	0.43***	0.40***	0.48***	0.41***	0.25**
	[0.11]	[0.12]	[0.11]	[0.08]	[0.13]	[0.11]	[0.11]	[0.11]	[0.10]
Income diversity	-0.74***	-0.66***	-0.84***	-0.72***	-0.72***	-0.83***	-0.76***	-0.82***	-0.89***
	[0.11]	[0.18]	[0.12]	[0.09]	[0.13]	[0.12]	[0.12]	[0.12]	[0.13]
Constant	-23.79	-49.64*	-12.11	2.17	-47.63***	-10.70	-1.42	-10.77	11.08
	[15.16]	[25.49]	[13.97]	[10.28]	[17.09]	[14.45]	[17.38]	[14.45]	[11.83]
Bank type dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,467	1,203	1,580	2,184	1,335	1,585	1,620	1,594	1,638
R^2	0.16	0.13	0.16	0.16	0.16	0.16	0.13	0.16	0.16

The table reports robustness tests of the regression results of equation 3.2 using different modifications of the data set in each column as detailed in the data appendix. The dependent variable is the z-score. OLS regression with robust standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 3.12: Regression results. Alternative banks in the global financial crisis.

	(1)	(2)	(3)	(4)	(5)	(6)
Crisis measure	None	None	Crisis Intensity	Crisis Intensity	Crisis Dummy	Crisis Dummy
Alternative bank dummy	-1.00	-0.73	-1.64**	-1.43**	-1.69**	-1.49**
	[0.67]	[0.63]	[0.68]	[0.66]	[0.69]	[0.69]
Crisis intensity			-0.27*	-0.33*		
			[0.15]	[0.17]		
Int. Crisis Intensity* Alt. Bank			1.12**	1.20*		
			[0.52]	[0.62]		
Crisis Dummy					-0.73	-0.92
					[0.70]	[0.74]
Int. Crisis Dummy*Alt.Bank					3.69**	3.86*
					[1.76]	[2.01]
Bank size	-2.57***	-1.74***	-2.62***	-1.77***	-2.61***	-1.75***
	[0.44]	[0.29]	[0.44]	[0.29]	[0.44]	[0.29]
Loans / Assets	-0.13***	-0.10***	-0.13***	-0.10***	-0.13***	-0.11***
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Customer deposits / Assets	-0.02	-0.06**	-0.02	-0.06**	-0.02	-0.06**
	[0.02]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]
Income diversity	0.01	0.02	0.02	0.02	0.02	0.02
	[0.02]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]
Constant	43.86***	39.83***	44.02***	39.90***	44.22***	40.08***
	[4.02]	[4.12]	[4.02]	[4.11]	[4.05]	[4.16]
Bank type dummies	YES	YES	YES	YES	YES	YES
Country dummies	YES	NO	YES	NO	YES	NO
Observations	522	522	522	522	522	522
R^2	0.39	0.30	0.40	0.31	0.39	0.31

This table reports the regression estimates of equation 3.2 in columns (1) and (2). Columns (3-6) report regression estimates of equation 3.4 which includes a measure of economic crisis as detailed in the header. The dependent variable is the Regulatory Capital Ratio. OLS regression with robust standard errors in brackets. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Chapter 4

Riskiness of ethical and social banks in the United States

4.1 Introduction

Since the outbreak of the global financial crisis, social and ethical forms of banking have experienced growth in total assets as well as in interest from the general public. The second paper of this dissertation presents a new database on alternative banks, that is banks that pursue ethical, social, sustainable, environmental or other "added social value" goals as a core part of their business strategy. It also presents results on the stability of alternative banks in EU and OECD countries excluding the United States. This companion paper extends the analysis to the riskiness of alternative banks in the United States. In the interest of comparability, the methodology in the previous paper is followed as far as possible.

From a theoretical perspective, alternative banks could be more or less risky than conventional banks. On the one hand, alternative banks could be less risky as they are generally risk-averse, focused on the real economy and tend to avoid speculative activities. On the other hand, alternative banks could be more risky, if, for example, they generate less profits that can be used to re-build capital buffers after crisis events or they may be exposed to higher credit default risk if the "worthy causes" among their borrowers are not financially sound.

The main result of this paper is that in contrast to the previous paper, alternative banks in the United States are significantly less stable than their conventional counterparts. This result is obtained for different risk measures and is robust to different estimation methods and data specifications. This result is probably due to the close relationship of alternative banks in the United States to Community Development Financial Institutions (CDFIs), a group of banks that specialize in economically disadvantaged customers.

The remainder of this paper is organized as follows. Section 2 introduces the special features of alternative banks in the United States and especially CDFI banks and discusses how these special features impact the riskiness of alternative banks in the United States. Section 3 describes the data and the matching of the conventional bank control group. Section 4 presents regression results on bank stability in the United States and robustness tests. Section 5 concludes. An appendix contains methodological details.

4.2 Social and ethical forms of banking in the United States

The overview of social and ethical banks developed in the previous paper contains 15 banks in the United States, which were not part of the analysis. This was partly due to lack of data and partly due to theoretical considerations. The database used in the previous paper was limited to the larger banks in each country while social and ethical banks are comparatively small. Also, as banks in the United States were at the epicenter of the financial crisis, they might not be comparable to alternative banks overall.

This paper fills this gap by using regulatory data available from the FDIC that contains balance sheet and income statement data on all banks in the United States. However, out of those 15 alternative banks only nine have enough observations available for an analysis of their riskiness, as some merged, and others were only recently founded. As inference based on nine banks of interest is of limited reliability, I repeat the analysis with two different groups of banks, which resemble the group of interest in many aspects. In this section, I develop multiple arguments that show that these additional groups of banks are very similar to the "core" alternative banks, which are dubbed social and ethical banks for the remainder of the paper. These banks can therefore be used to demonstrate the robustness of the results. For a general introduction to social and ethical banking as well as for general methodological details, reference is made to the aforementioned paper.

CDFIs

The first additional group are banks that are certified as Community Development Financial Institutions (CDFI). While CDFIs can also be loan funds, thrifts, credit unions or venture funds, this analysis focuses on commercial banks among CDFIs. There were in total 62 CDFI banks in the U.S. in 2009 of which 52 can be used for the analysis.

CDFI banks are normal, commercial banks that must fulfill a set of criteria in order to be certified by the CDFI fund, which is operated by the U.S. Department of Treasury. Among the most important criteria for certification are that a bank has to have a "primary mission of promoting community development" in economically distressed communities, a focus on "an investment area or targeted population" and the bank has to offer additional services, such as credit counseling (Swack et al., 2012). As certified CDFIs, banks then can apply for financial award assistance from the fund (Lowry, 2012). As the CDFI fund was founded in 1994 this analysis also starts in 1994.

Over 75% (or seven out of nine) of the social and ethical banks which are included in the analysis are, at the same time, certified CDFIs. This high degree of overlap between the two groups of banks is a first, strong indicator of their similarity. Second, both groups are mission-driven financial institutions. In the literature on social and ethical banking, social banks are defined as banks that aim "to have a positive impact on people, the environment and culture" (Weber and Remer, 2011, p.2) or as banks that have a dual bottom line, that is, they strive for economic *and* social profitability at the same time (San-Jose et al., 2011). CDFIs are described in the literature as having a "primary mission of improving economic conditions for low-income individuals and communities" (Benjamin et al., 2004) and CDFI banks report as main facets of their mission-oriented work "lending to previously excluded borrowers, such as women, minorities, and low-income individuals", "lending to underserved groups" and "environmental lending, such as loans for clean energy and sustainable agriculture" (NCIF, 2012, p.9). Similarly to social and ethical banks, CDFI banks face the challenge to "balance their social mission with profitability" (Fairchild and Jia, 2014, p.9). The fact that CDFIs have to be certified ensures that their mission of community development is more than a marketing phrase.

Third, social and ethical banks and CDFI banks are of remarkably similar size. The median social and ethical bank studied in this paper has a balance sheet of 127 million USD in 2006, while the CDFI banks in the study have a median balance sheet size of 131 million USD.

Fourth, just as ethical and social banks have been experiencing rapid growth in the aftermath of the financial crisis (Benedikter, 2011) the total assets of CDFI banks as well have grown at higher rates than those of conventional banks. Swack et al. (2012) find that the median annualized asset growth rate of CDFIs was 7.9% between 2006–2010 while conventional banks of similar size grew by 0.63%. As a last example, finding and retaining qualified staff can also be an issue for CDFIs (Swack et al., 2012) as it can be for social and ethical banks (von Passavant, 2011). In sum, considering that social and ethical banks as well as CDFIs occupy closely related market niches, their risk profile should be quite similar.

While both groups of banks account for only a tiny fraction of the banking market, there are 52 CDFI banks suitable for an analysis. This allows to confirm results of social and ethical banks using a much larger sample. While, to the best of my knowledge, no studies on the riskiness of social and ethical banks in the United States exist, the performance of CDFIs has been the subject of previous evaluations conducted for the CDFI fund. While Fairchild and Jia (2014) find that CDFI banks do not have a higher probability of failure than traditional institutions of a roughly similar size, Swack et al. (2012) conclude that CDFI banks experience higher loan-losses and have higher operating expenses than traditional banks.

Although CDFI banks and social and ethical banks appear to be quite similar, some distinctions between the two groups should be made. The mission of CDFI banks is community development. They are therefore very focused in terms of geography and activities. Social and ethical banks in general can pursue all kinds of banking activities as long as it meets their standards of accountability. Also, CDFI banks are certified by a government entity and may receive additional funds for their activities, which social and ethical banks in general do not.

New CDFIs

The second additional group of similar banks is made up by banks that were not yet certified as CDFIs during the time of the analysis, but became certified CDFIs during the year 2010. This group of banks is called "New CDFIs" in this paper. It contains 27 banks of which 26 were used for analysis in this paper.

This high number of banks that became newly certified as CDFIs during 2010 was driven by the Community Development Capital Initiative by the U.S. Department of Treasury (NCIF, 2010). This initiative, as part of the financial crisis recovery measures, offered additional capital to certified CDFIs, which was to be used primarily for community development and small business lending. As the conditions for capital availability were comparatively generous, banks that were not yet certified CDFIs but could easily fulfill the criteria were incited to become certified (NCIF, 2010). As the certification process is described as "demanding" and "onerous", not every institution that would qualify had previously chosen to undergo the process (Rosenthal, 2012).

As noted above, banks that are certified as CDFIs can receive financial support from the CDFI Fund. Although only 3% of the capital under management of depository CDFIs (among them banks) comes from government sources (Weech, 2009; Bershadker et al., 2007), this form of government support may increase the stability of banks certified as CDFIs. Extending the analysis to banks that do not receive this support, but, in all likelihood, serve the same disadvantaged groups as the CDFI banks, provides a control for the support that these banks receive.

Riskiness of social and ethical banks in the United States

When looking at social and ethical banks in the United States, several points emerge in which they may differ from social and ethical banks in other OECD and EU countries. First, the overwhelming majority of alternative banks in the United States has a localized geographical focus. Judging from their mission statements, many see themselves serving a specific region or community. This is observed to a lesser degree for social and ethical banks in other developed countries. This regional focus is probably driven by the large size of the United States, historically restrictive geographical regulation for bank activities (Berger et al., 1995) and the overlap with CDFI banking designation, which mandates a community focus. In terms of risk profile, higher geographical concentration risks may emerge as a consequence.

A second source of higher concentration risk, at least for social and ethical banks that are also certified as CDFIs, may be lack of sectoral diversification in lending portfolios. Salin et al. (2008) find that many CDFIs "specialize in particular types of lending". Especially, real estate lending is a traditional focus of CDFI activity (Benjamin et al., 2004). As a consequence, this lack of diversification of activities among social and ethical banks and CDFIs in the United States may have an impact on their risk profile in comparison with social and ethical banks in other OECD and EU countries and therefore merits a separate analysis.

While the previous paper also analyzed the performance of social and ethical banks during the financial crisis, this is not repeated in the special case of the United States. In the financial crisis, CDFIs have also been affected by the economic downturn in the communities which they serve (Bernanke, 2009). The effects of the financial crisis are not easily distinguished from the effect of the Community Development Capital Initiative, which is why a separate analysis of performance of social and ethical banks during the crisis is not conducted here.

4.3 Data and Methodology

4.3.1 Data and matching methodology

Data on bank balance sheets, income and regulatory capital is obtained from the quarterly Reports of Condition & Income, which are made available by the FDIC. The time frame studied is chosen to avoid any obscuring effects. The analysis starts in 1994, as the CDFI Fund, which certifies CDFIs, was founded in 1994. The analysis ends in 2009 to exclude the effects of the U.S. Department of Treasury's Community Development Capital Initiative, that gave additional funding to certified CDFIs (NCIF, 2010).

First, an initial cleaning of the dataset is performed to ensure that banks that are not suitable for matching are excluded from the set of potential matches. For example, only banks with the designation "no special analysis" are included in the control group, which excludes, among others, bridge entities, cash management banks, banks not subject to reserve requirements, depository trust companies, banks that primarily provide credit cards and other special cases. Then, the alternative banks are matched to similar conventional banks using nearest neighbor matching. The banks are matched based on characteristics that are chosen to be important for the behavior and stability of the bank and the business environment the bank acts in but at the same time these characteristics should not be overly influenced by the status of the bank as being an alternative bank. The three groups of banks (social and ethical, CDFIs and New CDFIs) are matched separately, so that three regression datasets are constructed.

As CDFIs are mostly active in economically disadvantaged areas and specifically lend to low-income and minority borrowers (Swack et al., 2014), it is important to match the social and ethical banks and CDFI banks with conventional banks that are active in a similarly challenging business environment. Matching is therefore done based on bank size, which has been shown to affect capital, risk and lending strategies in banking (Berger and Black, 2011; Demsetz and Strahan, 1997) as well as the per capita personal income of the county in which the bank is headquartered in.

Per capita personal income should capture the economic affluence of the county that the bank is located in. As the banks of interest are small banks, with few or no branches, the location of their headquarters can be taken as the location of their activities. In the case of this dataset, the median population of a county in 2009 was around 31.000. This includes only counties in which a bank was headquartered. The control for economic conditions at the location of the bank via personal income is therefore done on a relatively granular level. However, individual counties may be significantly larger than the median, which can impact the quality of the match. I also considered directly matching banks on county basis, similarly to the matching on country basis in the previous paper. This was not possible as multiple counties were the headquarters of only the social or ethical bank in question, so that no match existed. As in the first paper on alternative banks, banks are matched in the year 2006 in order of them to be unaffected by the outbreak of the financial crisis in summer 2007.

4.3.2 Descriptive statistics

Figure 4.1 in the appendix shows the amount of total assets of the social and ethical banks and the matched conventional banks over time. Figures 4.2 and 4.3 show the same for the group of CDFI banks and the "New CDFIs". As banks are matched for size as well as for personal income in their county of origin, average size in 2006 is not necessarily the same for the banks of interest as for the traditional banks. The development of total assets since 2007 shows a slightly larger growth of total assets of social and ethical banks and of CDFI banks in comparison to traditional banks, as described in Swack et al. (2012).

Table 4.2 provides summary statistics for the matched sample. It also compares the averages of the matched banks and the social and ethical banks and reports results from a significance test of sample means. Based on a simple comparison of means, social and ethical banks have slightly lower loan over asset ratios. Their demand deposit ratios are higher than that of conventional banks which indicates that they may be more rooted in the real economy. Holdings of securities are higher which may be a measure of precaution against illiquidity. Interestingly, the importance of real estate lending and residential real estate lending on their balance sheet is even slightly lower than that of conventional banks. Table 4.3 shows the same ratios for CDFI banks. Social and ethical banks and CDFI banks share their relatively high holdings of demand deposits. The other balance sheet and performance indicators are also reasonably similar, although not identical. One exception is that CDFI banks have higher cost to income ratios than social and ethical banks. Table 4.4 contains summary statistics for "New CDFIs" which are again reasonably similar to the social and ethical banks.

4.4 Regressions and results

4.4.1 Baseline regression

The following regressions evaluate the riskiness of alternative banks in comparison with conventional banks.

$$RISK_{i,t} = \alpha + \beta_1\, Alt.\, Bank_i + \beta_2 S_i + \beta_3\, B_{i,t-4} + \sum \gamma_t\, Q_t + \sum_{j=1}^{3} \delta_j D_j + \epsilon_{i,t} \tag{4.1}$$

The dependent variable is the bank risk of bank i in quarter t. The effect of being an alternative bank (or not) is captured in the regression with the dummy variable "Alt. Bank" that equals one if the bank is an alternative bank and zero if it is a conventional bank. In the main regressions of interest "Alt. Bank" stands for the social and ethical banks. In the supplementary analysis it is replaced with the CDFI banks and the "New CDFI" banks which are used to confirm the robustness of results. Bank size (S) is approximated by log of total assets. B is a vector of bank specific control variables that are in large part identical to the previous paper. In the baseline specification, it includes the loan to asset ratio, the income diversity to control for the (lack of) diversification of activities in social and ethical banks and the ratio of demand deposits to total assets. As demand deposits are obtained from checking accounts, they can be taken as an indicator for core customers (DeYoung and Hasan, 1998). Bank control variables are lagged by one year to mitigate concerns of endogeneity. Other control variables are added in robustness checks.

The regression also includes time fixed effects (Q) and a set of seasonal dummies (D). The inclusion of bank fixed effects is not possible as the status of being an alternative bank is also fixed over time. That is why the regression is implemented using pooled ordinary least squares (OLS) following Čihak and Hesse (2010). The robustness section also presents results obtained with different regression methods that are more robust to outliers.

Tables 4.6 and 4.7 present results for the baseline specification in columns (1) to (3) for social and ethical banks. The better data availability on regulatory capital and loan performance in Call report data makes it possible to use a series of risk measures which are explained in detail in the appendix. Table 4.6 presents results using the regulatory capital adequacy ratio, leverage and z-score as risk measures. Social and ethical banks have significantly lower regulatory capital adequacy and higher leverage ratios than their matched conventional counterparts. Regulatory capital ratios are on average 0.01 lower for social and ethical in comparison to conventional banks. At average regulatory capital ratios of 0.16, this is a moderate, but meaningful difference from the perspective of bank stability. The same holds true for leverage. Somewhat surprisingly, the z-scores of social and ethical banks do not differ significantly from conventional banks.

Table 4.7 shows the results for risk measures based on loan performance, that is for problem loans, loan not accruing and loan loss provisions (LLP). In all cases, the risk measures point towards a higher risk of the loan portfolio of social and ethical banks. Again, differences are not large, but meaningful from a perspective of risk. While the average percentage of problem loans in the loan portfolio is 1.41% for all observations in the sample, social and ethical banks have a ratio of problem loans that is 0.6% higher than that of conventional banks.

4.4.2 Robustness checks

The validity of results is checked in a series of robustness tests. Columns (4) to (6) in tables 4.6 and 4.7 repeat the regressions using the dataset on CDFI banks. All risk measures retain their sign and their significance. The coefficient values also remain in the same order of magnitude. Additionally, CDFIs display significantly lower z-scores than their conventional counterparts and can therefore be considered more risky in that regard. The validity of the results for the relatively small sample of social and ethical banks is therefore confirmed by similar findings for the larger sample of CDFI banks.

The results for the third group of banks, the “New CDFIs” can be found in columns (7) to (9) in tables 4.6 and 4.7. Again, all risk measures including the z-score retain their sign and their significance. Coefficient values tend to be a little bit smaller than for social and ethical banks and CDFIs. This is not surprising, given that this group was not yet certified as CDFIs. It is therefore reasonable that they should be somewhat more similar to their conventional control group. However, given that this group is only made up out of 28 banks, the results should not be overly interpreted by themselves, but rather taken as confirmation of the results on social and ethical banks.

Table 4.8 shows that the results are robust to the exact specification choice of the z-score. Z-score type (I) includes the expected return on assets, while z-score types (II) and (III) only consider downward deviations of the return on assets. Z-score type (IV) is winsorized at the 1% and 99% level to mitigate the effect of outliers. These modifications leave the main results unchanged for all three groups of banks.

Tables 4.9 and 4.10 repeat the main regressions using two different estimation methods that are particularly robust to outliers. As least squares regression methods are especially vulnerable to outliers, in the case of relatively small datasets the possibility exists that individual banks may be driving the results. Table 4.9 therefore repeats the regression using an outlier-robust estimator that assigns lower weights to outliers in the data (Hamilton, 2012) while table 4.10 presents results from a median least squares regression. The main results are very robust to these alternative regression techniques.

One point to mention is that results in the previous paper and in this companion paper partially rely on different risk measures. The previous paper uses the z-score as the main risk measure, which is found to be significantly higher in alternative banks. In this paper, the difference in z-score is not statistically significant in all regression methods and datasets. Therefore, especially the fact that the z-score is significantly negative for social and ethical banks in the outlier-robust estimation method presented in table 4.9 is reassuring.

In table 4.11 the analysis ends in 2006 rather than in 2009 to ensure that the results are not driven by the outbreak of the financial crisis. Signs and significance of the risk measures remain unchanged. However, the coefficients of risk measures based on loan portfolio quality are lower, suggesting that social and ethical banks, many of which particularly serve to economically disadvantaged areas and persons, were especially affected by the financial crisis.

In unreported regressions additional explanatory variables that might affect the riskiness of social and ethical banks are added. The fraction of real estate holdings on the balance sheet as well as the fraction of residential real estate holdings on the balance sheet are introduced as a control variable due to the nature of the financial crisis that started in 2007, as well as the historical focus of CDFIs on housing finance (Benjamin et al., 2004). Also, as CDFIs have been found to display higher operating expenses (Swack et al., 2012), the cost to income ratio is included. Other control variables are a liquidity measure as well as membership in a bank holding company. Again, these additional control variables leave main results unchanged. Lastly, the main regression results are not affected by the use of annual data instead of quarterly data.

4.5 Conclusion

This paper compared the riskiness of social and ethical banks in the United States with similar, traditional banks. In contrast to findings in the previous paper, social and ethical banks in the United States are found to be more risky than similar conventional banks. This result is somewhat surprising, but confirmed with a series of robustness tests and additional datasets making use of CDFI banks, which are similar to social and ethical banks in many respects.

As a matter of fact, the difference in stability of social and ethical banks in the United States from social and ethical banks in other OECD and EU countries could potentially be explained with the high degree of overlap between CDFI banks and social and ethical banks in the United States. CDFI banks have the mission of community development and are obliged to focus their lending on economically disadvantaged lenders and communities. Social and ethical banks in general are able to greatly diversify their banking activities. However, this is only a hypothesis and a closer analysis of balance sheet structure and geographical diversification of social and ethical banks in the United States and other countries could be an avenue for future research.

Another possible explanation for the higher risk of banks certified as CDFIs may be found in Benjamin et al. (2004). The authors describe that CDFI banks were active in providing housing finance and would take the riskiest part of the financing in order to entice conventional lenders to finance the rest. With the benefit of hindsight, it is easy to conclude that this involvement of CDFIs in the United States housing market made them very vulnerable. This confirms that a separate analysis of social and ethical banks in the United States is necessary and provides additional insight.

This analysis ends in 2009, as the effects of the Community Development Capital Initiative by the U.S. Department of Treasury, which was part of the financial crisis countermeasures, would obscure the crisis impact. Since new social and ethical banks have been founded after the financial crisis, an extension of the analysis to a time after the crisis would also be possible.

4.6 Appendix to chapter 4

4.6.1 Data sources

For methodological details, reference is made to the appendix in the previous paper. The main differences are due to the fact that this paper focuses on one country only, and the different availability of balance sheet data in the United States. The alternative banks are matched to conventional banks that closely resemble them in basic characteristics using nearest neighbor matching. The banks are matched based on characteristics that are chosen to be important for the behavior and stability of the bank and the business environment the bank acts in but at the same time these characteristics should not be overly influenced by the status of the bank as being an alternative bank. Matching is therefore done based on bank size and the personal income in the county that the bank is headquartered in. Banks are only considered for matching if a full set of data is available during the years 2006 to 2009. As all social and ethical banks are chartered as commercial banks no matching by bank specialization is necessary or possible.

CDFI list

For the purpose of this study, I obtained lists of certified CDFIs from the Annual Reports by the National Community Investment Fund (NCIF, 2009, 2010).

Personal income data

Personal income is defined as all income from all sources. Data on personal income is obtained from the Bureau of Economic Analysis. It is available for the roughly 3000 counties or county-equivalents (e.g. parishes or boroughs) in the United States. In a very limited number of cases, banks could not be matched with personal income data in their county (for example, due to counties having been merged or restructured). This affects less than 0.5% of the banks in the potential control group, which are then discarded. No observations among social and ethical banks as well as CDFIs are discarded due to lack of personal income data.

4.6.2 Data description and summary statistics

Table 4.1: Variable overview and definitions

Variable	Calculation	Description / Source
Risk measures and components thereof		
z-score	$= \frac{ROA_{i,t}+CAR_{i,t}}{SDROA_i}$	Call report data
z-score (Expected ROA)	$= \frac{\frac{1}{3}*(ROA_{i,t}+ROA_{i,t-1}ROA_{i,t-2})+CAR_{i,t}}{SDROA_i}$	Call report data
Downward z-score (I)	as standard z-score, but with downward absolute volatility of return on assets	specification following Hesse and Čihak (2007)
Downward z-score (II)	as standard z-score, but with downward squared volatility of return on assets	specification following Hesse and Čihak (2007)
Capital Adequacy	Regulatory capital / risk-weighted assets	Regulatory Capital Adequacy Ratio
Leverage	$rcfd2170/rcfd3210$	Total assets / total equity capital
Problem loans	$\frac{rcfd1407+rcfd1403}{rcfd1400}$	Loans late and loans not accruing over total loans
Loans not accruing	$rcfd1403/rcfd1400$	Total loans not accruing over total loans
LLP	$riad4230/rcfd1400$	Loan loss provisions
Control variables		
Alternative bank indicator	1 for alternative banks, 0 for conventional banks	Source: own research
Bank size	$log(rcfd2170)$	Log of total assets
Demand deposit ratio	$rcfd2210/rcfd2170$	Demand Deposits / Assets
Loans / Assets	$rcfd1400/rcfd2170$	Total loans and leases over Total assets
Income diversity	$= 1 - \lvert\frac{Net\,interest\,income - other\,operating\,income}{Total\,Operating\,Income}\rvert$	specification following Laeven and Levine (2007)
Real estate holdings	$rcfd1410/rcfd2170$	real estate loans over total assets
Cost to income ratio	$riad4130/riad4340$	(Interest + Non-interest expense)/ Net income

To allow for correct interpretation, ratios relying on income data in numerator and denominator are set missing if the banks' income is negative.

Table 4.2: Summary statistics for regression dataset of social and ethical banks and matched conventional banks

	N	Mean	Standard deviation	Min	Max	Mean conv. banks	Mean alt. banks	p-value
Total assets (Million USD)	2,247	258.68	432.59	2.09	2,691.62	256.00	269.41	0.59
Loans / Assets	2,247	65.60	16.43	0.02	96.90	66.32	62.71	0.00
Cost / Income	1,952	12.14	54.22	0.88	1,560.25	12.42	10.98	0.47
Income diversity	2,247	23.83	20.08	0.00	100.00	23.96	23.32	0.46
Demand deposit ratio	2,247	13.48	9.40	0.00	59.43	12.87	15.89	0.00
Loans / Deposits	2,245	79.34	21.37	0.10	206.76	80.05	76.47	0.00
Securities / Assets (%)	2,247	21.48	15.28	0.00	92.02	20.49	25.48	0.00
Real estate loans /total assets	2,247	0.46	0.17	0.00	0.88	0.46	0.44	0.01
Residential real estate loans /total assets	2,247	0.16	0.13	0.00	0.83	0.17	0.14	0.00
Regulatory capital adequacy	1,491	0.17	0.14	0.05	2.44	0.17	0.15	0.02
Leverage	2,247	10.34	2.99	1.00	61.92	10.11	11.24	0.00
z-score	2,247	16.32	10.91	-4.29	69.66	16.36	16.14	0.71
z-score (expected ROA)	2,207	16.06	10.63	-0.24	66.54	16.08	15.98	0.85
Downward z-score (I)	2,247	19.10	14.89	-5.90	90.52	18.98	19.59	0.42
Downward z-score (II)	2,247	13.47	10.75	-2.56	65.84	13.44	13.59	0.76
Problem loans (%)	2,247	1.41	2.12	0.00	22.61	1.33	1.73	0.00
Loans not accruing (%)	2,247	1.13	1.92	0.00	21.41	1.05	1.45	0.00
Loan loss provisions (%)	2,247	0.35	0.73	-1.37	11.83	0.31	0.50	0.00

The p-values reported stem from a t-test of equality of the means of conventional banks and alternative banks. The test allows for the variance to be different between the banking types.

Table 4.3: Summary statistics for regression dataset of CDFI banks and matched conventional banks

	N	Mean	Standard deviation	Min	Max	Mean conv. banks	Mean alt. banks	p-value
Total assets (Million USD)	12,823	152.44	225.31	2.09	2,691.62	152.03	153.80	0.72
Loans / Assets	12,823	61.44	15.88	0.02	104.33	61.79	60.28	0.00
Cost / Income	11,204	12.69	77.27	0.19	3,477.00	11.74	16.26	0.01
Income diversity	12,823	22.36	16.12	0.00	100.00	20.10	29.75	0.00
Demand deposit ratio	12,823	13.28	7.27	0.00	59.43	12.93	14.42	0.00
Loans / Deposits	12,821	74.19	56.37	0.10	3,996.53	75.10	71.23	0.00
Securities / Assets (%)	12,823	24.66	15.06	0.00	92.02	24.74	24.39	0.25
Real estate loans /total assets	12,823	0.41	0.18	0.00	0.89	0.40	0.41	0.00
Residential real estate loans /total assets	12,823	0.16	0.12	0.00	0.83	0.16	0.15	0.00
Regulatory capital adequacy	8,121	0.18	0.17	0.03	6.26	0.19	0.15	0.00
Leverage	12,823	10.40	3.20	1.00	80.97	10.04	11.54	0.00
z-score	12,823	18.81	13.95	-4.29	124.43	20.74	12.51	0.00
z-score (expected ROA)	12,647	18.68	13.82	-1.88	93.42	20.60	12.41	0.00
Downward z-score (I)	12,823	23.69	18.72	-5.90	161.99	26.12	15.76	0.00
Downward z-score (II)	12,823	17.17	14.41	-2.56	116.85	19.00	11.18	0.00
Problem loans (%)	12,823	1.48	2.16	0.00	30.39	1.21	2.34	0.00
Loans not accruing (%)	12,823	1.08	1.81	0.00	28.39	0.85	1.83	0.00
Loan loss provisions (%)	12,823	0.35	0.83	-5.95	22.73	0.32	0.44	0.00

The p-values reported stem from a t-test of equality of the means of conventional banks and CDFI banks. The test allows for the variance to be different between the banking types.

Table 4.4: Summary statistics for regression dataset of New CDFI banks and matched conventional banks

	N	Mean	Standard deviation	Min	Max	Mean conv. banks	Mean alt. banks	p-value
Total assets (Million USD)	7,033	177.72	211.57	4.36	2,154.80	162.06	245.36	0.00
Loans / Assets	7,033	60.51	15.68	0.34	97.21	59.58	64.54	0.00
Cost / Income	6,517	8.46	85.34	1.07	6,248.00	8.30	9.17	0.54
Income diversity	7,033	20.50	11.34	0.00	99.99	20.10	22.24	0.00
Demand deposit ratio	7,033	12.05	5.41	0.17	38.72	12.28	11.10	0.00
Loans / Deposits	7,033	72.59	20.15	1.60	259.91	71.19	78.62	0.00
Securities / Assets (%)	7,033	27.32	15.35	0.00	88.41	28.33	22.98	0.00
Real estate loans /total assets	7,033	0.40	0.17	0.00	0.95	0.40	0.43	0.00
Residential real estate loans /total assets	7,033	0.18	0.10	0.00	0.54	0.18	0.17	0.00
Regulatory capital adequacy	4,258	0.18	0.15	0.07	3.57	0.18	0.16	0.00
Leverage	7,033	10.21	2.69	1.10	37.32	10.10	10.69	0.00
z-score	7,033	22.46	13.03	-1.00	68.00	23.92	16.11	0.00
z-score (expected ROA)	6,985	22.44	13.03	-0.78	67.41	23.93	16.00	0.00
Downward z-score (I)	7,033	28.19	17.86	-0.73	93.80	29.95	20.61	0.00
Downward z-score (II)	7,033	20.19	13.94	-0.54	73.52	21.46	14.73	0.00
Problem loans (%)	7,033	1.25	1.69	0.00	23.58	1.20	1.47	0.00
Loans not accruing (%)	7,033	0.90	1.47	0.00	18.39	0.87	1.06	0.00
Loan loss provisions (%)	7,033	0.26	0.59	-12.35	8.99	0.23	0.37	0.00

The p-values reported stem from a t-test of equality of the means of conventional banks and New CDFI banks. The test allows for the variance to be different between the banking types.

Table 4.5: Correlation table of bank risk measures and control variables

	Size	Loans / Assets	Demand deposit ratio	Income diversity	Capital Adequacy	Leverage	z-score	Problem Loans	Loans Not Accruing	LLP
Size	1									
Loans / Assets	0.26	1								
Demand deposit ratio	-0.16	-0.14	1							
Income diversity	0.03	-0.03	0.36	1						
Capital adequacy	-0.26	-0.40	-0.037	-0.09	1					
Leverage	0.05	0.06	0.15	0.13	-0.43	1				
z-score	0.09	-0.24	-0.06	-0.15	0.23	-0.33	1			
Problem loans	0.018	0.014	-0.016	0.11	-0.072	0.17	-0.19	1		
Loans Not Accruing	0.05	0.05	-0.02	0.10	-0.07	0.16	-0.18	0.93	1	
LLP	0.018	0.045	-0.08	0.08	0.09	0.02	-0.17	0.32	0.30	1

4.6.3 Figures and regression results

Figure 4.1: Total assets of social and ethical and matched conventional banks

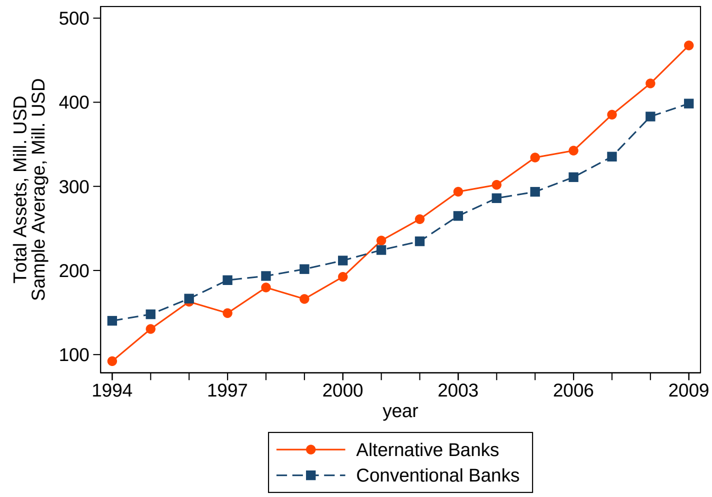


Figure 4.2: Total assets of CDFIs and matched conventional banks

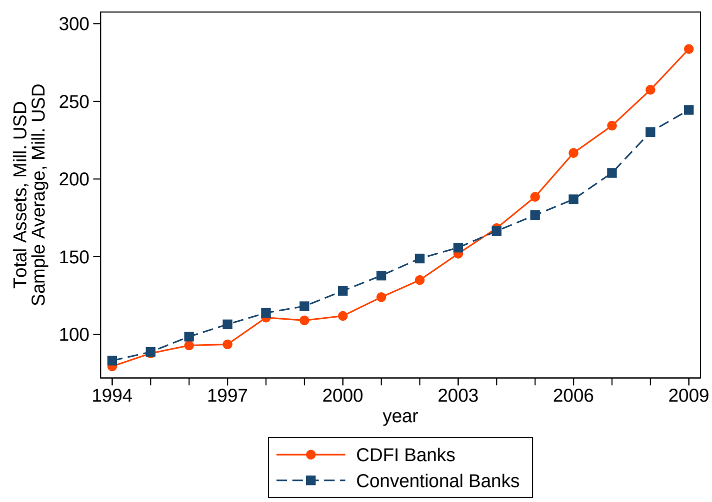


Figure 4.3: Total assets of new CDFIs and matched conventional banks

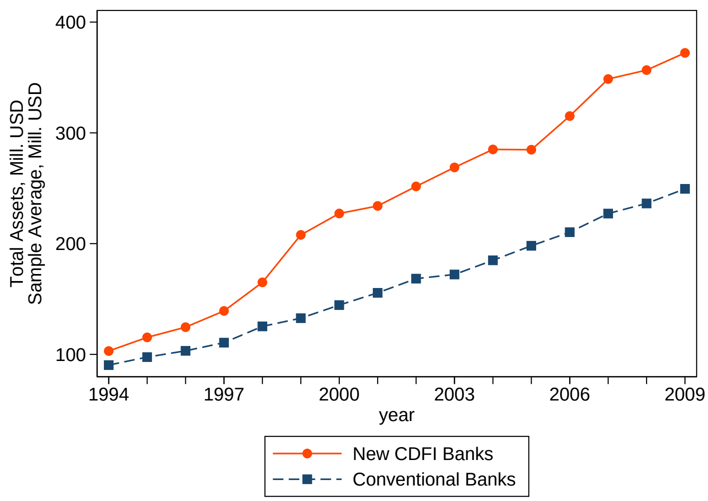


Table 4.6: Regression results. Comparing the riskiness of alternative and conventional banks in terms of regulatory capital adequacy, leverage and z-score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Matched data set	Social & ethical			CDFIs			New CDFIs		
Risk measure	Capital adequacy	Leverage	z-score	Capital adequacy	Leverage	z-score	Capital adequacy	Leverage	z-score
Alternative bank dummy	-0.01***	1.41***	-0.04						
	[0.00]	[0.18]	[0.66]						
CDFI				-0.02***	1.38***	-7.46***			
				[0.00]	[0.07]	[0.23]			
New CDFI							-0.01***	0.46***	-7.23***
							[0.00]	[0.08]	[0.34]
Bank size	-0.01***	0.63***	2.00***	-0.02***	0.57***	1.97***	-0.01***	0.34***	2.92***
	[0.00]	[0.08]	[0.17]	[0.00]	[0.04]	[0.12]	[0.00]	[0.04]	[0.16]
Loans / Assets (L4)	-0.00***	0.05***	-0.13***	-0.00***	0.03***	-0.20***	-0.00***	0.04***	-0.19***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]
Demand Dep. Ratio (L4)	0.00***	-0.04***	-0.11***	-0.00***	0.05***	0.02	-0.00***	0.05***	0.09***
	[0.00]	[0.01]	[0.02]	[0.00]	[0.00]	[0.02]	[0.00]	[0.01]	[0.03]
Income diversity (L4)	0.00	0.02***	-0.01	-0.00*	0.01***	-0.09***	-0.00***	0.03***	-0.15***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]
Constant	0.45***	1.10	5.16*	0.54***	1.58***	13.22***	0.48***	3.44***	3.55
	[0.02]	[1.03]	[3.07]	[0.04]	[0.47]	[1.82]	[0.02]	[0.59]	[2.35]
Observations	1,447	2,072	2,072	7,946	11,870	11,870	4,192	6,546	6,546
R^2	0.41	0.20	0.10	0.30	0.13	0.13	0.49	0.15	0.14

This table reports the OLS regression estimates of equation 4.1. The dependent variable is one of the risk measures as detailed in the header. Robust standard errors are in brackets. All regressions include a set of seasonal and time dummies which are not shown for brevity. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 4.7: Regression results - Comparing the riskiness alternative and conventional banks in terms of credit risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Matched data set	Social & ethical			CDFIs			New CDFIs		
Risk measure	Problem loans	Loans not accruing	LLP	Problem loans	Loans not accruing	LLP	Problem loans	Loans not accruing	LLP
Alternative bank dummy	0.60***	0.59***	0.20***						
	[0.10]	[0.10]	[0.04]						
CDFI				1.10***	1.00***	0.06***			
				[0.05]	[0.05]	[0.02]			
New CDFI							0.26***	0.18***	0.10***
							[0.06]	[0.05]	[0.02]
Bank size	0.33***	0.19***	-0.04***	-0.07***	-0.05**	-0.01	-0.35***	-0.27***	-0.01
	[0.04]	[0.03]	[0.01]	[0.03]	[0.02]	[0.01]	[0.03]	[0.02]	[0.01]
Loans / Assets (L4)	0.00*	0.01***	-0.00**	0.00***	0.01***	0.00	0.01***	0.01***	0.00***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Demand Deposit Ratio (L4)	-0.03***	-0.02***	-0.01***	-0.03***	-0.02***	-0.02***	-0.02***	-0.02***	-0.00***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Income diversity (L4)	0.00*	0.00*	-0.00**	0.02***	0.01***	0.01***	0.00	0.00*	0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Constant	-1.90***	-1.13**	0.75***	2.03***	0.93***	0.24***	4.64***	3.34***	0.03
	[0.73]	[0.56]	[0.16]	[0.33]	[0.27]	[0.08]	[0.38]	[0.32]	[0.13]
Observations	2,072	2,072	2,072	11,870	11,870	11,870	6,546	6,546	6,546
R^2	0.30	0.31	0.31	0.15	0.17	0.17	0.13	0.15	0.16

This table reports the OLS regression estimates of equation 4.1. The dependent variable is one of the loan risk measures as detailed in the header. Robust standard errors are in brackets. All regressions include a set of seasonal and time dummies which are not shown for brevity. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 4.8: Regression results. Robustness to the calculation of z-score and modified z-scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Matched data set	Social & ethical				CDFIs				New CDFIs			
z-score variant	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
Alt. bank dummy	-0.04	0.82	0.20	0.01								
	[0.66]	[0.85]	[0.59]	[0.66]								
CDFI in 12-2009					-7.46***	-9.73***	-7.40***	-7.36***				
					[0.23]	[0.32]	[0.25]	[0.23]				
New CDFI									-7.23***	-8.30***	-5.93***	-7.19***
									[0.34]	[0.47]	[0.38]	[0.34]
Bank size	2.03***	3.36***	2.15***	2.01***	1.99***	1.90***	1.32***	1.98***	2.92***	3.81***	2.94***	2.94***
	[0.17]	[0.22]	[0.17]	[0.17]	[0.12]	[0.17]	[0.13]	[0.12]	[0.16]	[0.23]	[0.18]	[0.16]
Loans / Assets (L4)	-0.13***	-0.21***	-0.15***	-0.13***	-0.20***	-0.29***	-0.21***	-0.19***	-0.19***	-0.29***	-0.23***	-0.19***
	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]
Dem. Depos. (L4)	-0.11***	-0.18***	-0.11***	-0.11***	0.02	0.01	0.01	0.02	0.08***	0.08**	0.02	0.09***
	[0.02]	[0.03]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.04]	[0.03]	[0.03]
Inc. diversity (L4)	-0.01	0.01	0.01	-0.01	-0.09***	-0.10***	-0.07***	-0.09***	-0.15***	-0.22***	-0.17***	-0.14***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]
Constant	4.61	-1.35	1.13	4.93	12.79***	25.53***	19.17***	12.60***	3.38	6.42**	4.24*	2.84
	[3.09]	[4.17]	[3.07]	[3.06]	[1.82]	[2.52]	[1.97]	[1.78]	[2.34]	[3.20]	[2.51]	[2.31]
Observations	2,072	2,072	2,072	2,072	11,870	11,870	11,870	11,870	6,544	6,546	6,546	6,546
R^2	0.10	0.13	0.11	0.10	0.13	0.13	0.12	0.13	0.14	0.13	0.13	0.14

This table reports the OLS regression estimates of equation 4.1. The dependent variable is the z-score in four different variations as listed in the header. Z-score type (I) uses the expected ROA in the calculation of the z-score. Z-score types (II) and (III) use downward volatility measures rather than overall volatility measures in the calculation of the z-score. Type (II) uses the absolute downward deviations and type (III) the squared downward deviations of the ROA, following Hesse and Čihak (2007). Type (IV) reports results using a z-score that is winsorized at the 1% and 99% level, to ensure that results are not driven by outliers. All regressions include a set of seasonal and time dummies which are not shown for brevity. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Regression results. Use of an outlier-robust regression method

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Matched data set	Social & ethical			CDFIs			New CDFIs		
Risk measure	Capital adequacy	Leverage	z-score	Capital adequacy	Leverage	z-score	Capital adequacy	Leverage	z-score
Alternative bank dummy	-0.01***	1.30***	-1.79***						
	[0.00]	[0.13]	[0.38]						
CDFI				-0.02***	1.16***	-6.14***			
				[0.00]	[0.06]	[0.26]			
New CDFI							-0.01***	0.51***	-6.95***
							[0.00]	[0.08]	[0.41]
Bank size	-0.01***	0.49***	2.47***	-0.01***	0.57***	1.84***	-0.01***	0.38***	3.10***
	[0.00]	[0.05]	[0.16]	[0.00]	[0.03]	[0.13]	[0.00]	[0.03]	[0.18]
Loans / Assets (L4)	-0.00***	0.05***	-0.07***	-0.00***	0.04***	-0.14***	-0.00***	0.04***	-0.16***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]
Demand Deposit Ratio (L4)	0.00***	-0.04***	0.06***	-0.00	0.04***	0.04***	-0.00***	0.06***	0.10***
	[0.00]	[0.01]	[0.02]	[0.00]	[0.00]	[0.02]	[0.00]	[0.01]	[0.03]
Income diversity (L4)	0.00	0.02***	-0.03***	-0.00***	0.01***	-0.07***	-0.00***	0.03***	-0.15***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.02]
Constant	0.38***	2.75***	-7.19***	0.39***	1.30***	9.09***	0.42***	2.61***	-0.92
	[0.02]	[0.81]	[2.35]	[0.01]	[0.40]	[1.77]	[0.02]	[0.46]	[2.46]
Observations	1,447	2,072	2,072	7,946	11,870	11,870	4,192	6,546	6,546
R^2	0.53	0.20	0.16	0.36	0.14	0.12	0.50	0.16	0.12

This table reports regression estimates of equation 4.1 using an estimation technique robust to outliers in the data (see Hamilton, 2012 for a description). The dependent variable is one of the risk measures as detailed in the header. Standard errors are in brackets. All regressions include a set of seasonal and time dummies which are not shown for brevity. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 4.10: Regression results. Use of quantile regression methods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Matched data set	Social & ethical			CDFIs			New CDFIs		
Risk measure	Capital adequacy	Leverage	z-score	Capital adequacy	Leverage	z-score	Capital adequacy	Leverage	z-score
Alternative bank dummy	-0.01***	1.30***	0.89						
	[0.00]	[0.18]	[0.55]						
CDFI in 12-2009				-0.02***	1.18***	-7.63***			
				[0.00]	[0.08]	[0.28]			
New CDFI							-0.01***	0.50***	-4.91***
							[0.00]	[0.09]	[0.56]
Bank size	-0.01***	0.56***	2.46***	-0.01***	0.73***	1.69***	-0.01***	0.59***	4.08***
	[0.00]	[0.07]	[0.22]	[0.00]	[0.04]	[0.14]	[0.00]	[0.04]	[0.26]
Loans / Assets	-0.00***	0.06***	-0.10***	-0.00***	0.04***	-0.21***	-0.00***	0.04***	-0.15***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]
Demand Deposit Ratio	0.00***	-0.02*	-0.07**	-0.00***	0.06***	-0.00	-0.00***	0.08***	0.13***
	[0.00]	[0.01]	[0.03]	[0.00]	[0.00]	[0.02]	[0.00]	[0.01]	[0.04]
Income diversity	0.00	0.01***	-0.01	-0.00***	0.01***	-0.06***	-0.00***	0.03***	-0.18***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.02]
Constant	0.40***	1.48	-4.34	0.45***	-0.44	13.42***	0.46***	0.15	-13.02***
	[0.03]	[1.06]	[3.27]	[0.02]	[0.51]	[1.91]	[0.02]	[0.53]	[3.41]
Observations	1,491	2,247	2,247	8,121	12,823	12,823	4,258	7,033	7,033

This table reports regression estimates of equation 4.1 using median least squares regression to mitigate the effect of outliers in the data. The dependent variable is one of the risk measures as detailed in the header. Standard errors are in brackets. All regressions include a set of seasonal and time dummies which are not shown for brevity. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.11: Regression results. End of analysis in 2006

Matched data set	Social & ethical					
Risk measure	Capital adequacy	Leverage	z-score	Problem loans	Loans not accruing	LLP
Alternative bank dummy	-0.02***	1.54***	0.17	0.25***	0.24***	0.17***
	[0.00]	[0.15]	[0.77]	[0.07]	[0.07]	[0.03]
Bank size	-0.01***	0.50***	2.19***	0.30***	0.16***	-0.05***
	[0.00]	[0.07]	[0.19]	[0.03]	[0.02]	[0.01]
Loans / Assets (L4)	-0.00***	0.06***	-0.11***	0.00	0.00**	-0.00**
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
Demand Deposit Ratio (L4)	0.00***	-0.03***	-0.15***	-0.02***	-0.02***	-0.00**
	[0.00]	[0.01]	[0.03]	[0.00]	[0.00]	[0.00]
Income diversity (L4)	-0.00	0.01***	-0.02**	0.00***	0.00***	-0.00
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
Constant	0.46***	1.94**	2.70	-1.49**	-0.72	0.69***
	[0.03]	[0.97]	[3.28]	[0.66]	[0.48]	[0.13]
Observations	918	1,543	1,543	1,543	1,543	1,543
R^2	0.41	0.22	0.10	0.11	0.08	0.21

This table reports the OLS regression estimates of equation 4.1. The dependent variable is one of the risk measures as detailed in the header. This table repeats the regressions shown in tables 4.6 and 4.7 for social and ethical banks but end the analysis in 2006 instead of in 2009 to demonstrate that the results are not driven by the effects of the financial crisis. Robust standard errors are in brackets. All regressions include a set of seasonal and time dummies which are not shown for brevity. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Summary of key results

Paper 1

The first chapter of this thesis studies the effect of the stance of monetary policy on the riskiness of banks. If the stance of monetary policy is too loose in relation to the local economic conditions, the local banks' propensity to take on risks may increase. One key feature of this study is that it uses data on regional commercial banks in the United States from 1990 until the outbreak of the global financial crisis. Most existing studies relying on loan-level or bank-level data usually consider only one monetary area. Thus, all banks operate in the same interest rate environment and it is difficult to differentiate the risk that is taken on due to monetary policy from other factors influencing risk. I mitigate this problem by exploiting differences in economic condition in the various regions of the United States. In the econometric analysis, I estimate the effect of monetary policy on bank risk-taking using a dataset of over 2,000 U.S. commercial banks in 23 different Metropolitan Statistical Areas (MSAs). The stance of monetary policy is then evaluated in relation to the regional economic condition using Taylor-type monetary policy rules. As the Federal Reserve cannot react to diverging regional economic conditions, monetary policy is not endogenous for these small, regionally active banks.

The estimation results provide evidence in favor of a risk-taking channel of monetary policy. Comparatively loose monetary policy is associated with a lower capital asset ratio, higher balance sheet risk and higher use of non-traditional funding sources. Also, risk measures that capture the growth of credit and the expansion of risky assets on bank balance sheets display significant and positive coefficients. This indicates that banks do not only have higher levels of risk when interest rates are too low in comparison to regional economic surroundings, but they are actively engaged in risk-taking. Risk measures that rely on non-performing loans show the opposite effect. Here, if monetary policy is comparatively loose in a region, the economy is doing relatively well and there is a low ratio of troubled loans.

Bank liquidity seems to mitigate the effect of comparatively loose monetary policy on bank risk-taking and could be a protective or stabilizing factor. Robustness tests show that results do not significantly depend on the exact choice of the monetary policy rule.

Paper 2

The second paper introduces a new and comprehensive dataset on social and ethical banks in different EU and OECD countries and, to the best of my knowledge, is the first paper that studies social and ethical banking using a comprehensive set of banks. Using the newly assembled dataset, the paper studies whether social and ethical or "alternative" banks differ from conventional banks in terms of riskiness. Specifically, I compare the riskiness of social and ethical banks with an appropriately matched control group of conventional banks using mean comparison and panel regression techniques.

The main result is that social and ethical banks are significantly more stable (in terms of z-score) than their conventional counterparts. Social and ethical banks also have lower loan to asset ratios and higher customer deposit ratios than conventional banks. The results are robust to the use of different estimation methods that are especially robust to outliers. Results are also robust to different matching methods and data specifications and specifications of the z-score.

The performance of social and ethical banks during the global financial crisis is also explored. While there is no difference in z-scores, there are indications that social and ethical banks proved more resilient in terms of regulatory capital in times of crisis than conventional banks.

Paper 3

The third paper is a companion paper to the second. It studies the riskiness of social and ethical banks in the United States, which had not been included in the second paper. Similarly to the second paper, it compares the riskiness of U.S. social and ethical banks with an appropriately matched control group of conventional banks using panel regression techniques.

In contrast to the second paper, I find that alternative banks in the United States are significantly more risky than their conventional counterparts. This result is somewhat surprising but holds for multiple risk measures and robustness tests. Social and ethical banks have significantly lower regulatory capital adequacy and higher leverage ratios than their matched conventional counterparts. Also, risk measures based on loan performance, for example problem loans, point towards a higher risk of the loan portfolio of social and ethical banks.

Results are also confirmed with a series of robustness tests using different regression methods that are more robust to outliers. Also, the analysis is repeated using two additional datasets that employ banks that are certified as Community Development Financial Institutions (CDFIs), which are similar to social and ethical banks in many respects, and yield very similar results.

The difference in riskiness of social and ethical banks in the United States from social and ethical banks in other OECD and EU countries could potentially be explained with the high degree of overlap between CDFI banks and social and ethical banks in the United States. CDFI banks have the mission of community development and are obliged to focus their lending on economically disadvantaged lenders and communities. They have a historical focus on real-estate lending. This can explain their higher riskiness in comparison to conventional banks. Social and ethical banks in general are able to greatly diversify their banking activities which may act as a stabilizing factor.

Zusammenfassung der Ergebnisse

Paper 1

Der erste Aufsatz untersucht die Auswirkungen der geldpolitischen Lage auf das Risiko von Banken. Wenn der geldpolitische Kurs der Zentralbank im Verhältnis zur lokalen wirtschaftlichen Lage zu locker ist, kann dies die Risikoneigung von Banken erhöhen. Eines der Hauptmerkmale dieser Studie ist, dass sie Daten von regionalen Geschäftsbanken von 1990 bis zum Ausbruch der weltweiten Finanzkrise nutzt. Die meisten existierenden Studien, die sich auf Daten auf Kreditebene oder Bankebene stützen, untersuchen nur ein Währungsgebiet. Da dann alle untersuchten Banken im selben Zinsumfeld operieren, ist es schwierig, das Risiko, das Banken wegen geldpolitischer Entscheidungen auf sich nehmen, von anderen Faktoren, die das Risiko von Banken beeinflussen können, zu unterscheiden. Dieses Problem umgehe ich, indem ich Unterschiede in der wirtschaftlichen Lage in den verschiedenen Regionen der Vereinigten Staaten nutze. In der ökonometrischen Analyse wird der Effekt von Geldpolitik auf die Risikoübernahme von Banken mit einem Datensatz von über 2.000 U.S.-Geschäftsbanken in 23 großstädtischen statistischen Erhebungsgebieten (Metropolitan Statistical Area) geschätzt. Der geldpolitische Kurs wird unter Verwendung einer geldpolitischen Regel des Taylor-Typs im Verhältnis zur regionalen wirtschaftlichen Lage evaluiert. Da die U.S.-Notenbank geldpolitisch nicht auf divergierende regionale Wirtschaftslagen reagieren kann, kann Geldpolitik für die untersuchten kleinen, regional aktiven Banken als nicht endogen angesehen werden.

Die Regressionsergebnisse liefern Anhaltspunkte, die für die Existenz eines Risikokanals der Geldpolitik sprechen. Vergleichsweise lockere Geldpolitik ist mit geringeren Eigenkapitalquoten, riskanteren Positionen in Bankbilanzen und stärkerer Verwendung von nicht-traditionellen Finanzierungsquellen assoziiert. Außerdem zeigen Risikomaße, die die Zunahme von Kreditvergabe und die Expansion von riskanten Positionen auf Bankbilanzen messen, signifikante und positive Koeffizienten. Dies deutet darauf hin, dass Banken nicht nur höhere Risikomaße aufweisen, wenn der Zinssatz im Vergleich zur regionalen wirtschaftlichen Lage zu niedrig ist, sondern, dass sie ihre Risikoübernahme aktiv steigern.

Risikomaße, die auf notleidenden Krediten basieren, zeigen den entgegengesetzten Effekt. Wenn Geldpolitik in einer Region vergleichsweise locker ist, geht es der lokalen Wirtschaft relativ gut, was sich in niedrigen Quoten von notleidenden Krediten niederschlägt.

Liquide Banken scheinen den Auswirkungen von verhältnismäßig lockerer Geldpolitik weniger ausgesetzt zu sein. Liquidität könnte also ein schützender oder stabilisierender Faktor für Banken sein. Ferner wird gezeigt, dass die Ergebnisse der Analyse robust gegenüber der Verwendung von unterschiedlichen geldpolitischen Regeln sind.

Paper 2

Der zweite Aufsatz stellt einen neuen und umfassenden Datensatz zu sozialen und ethischen Banken in verschiedenen EU- und OECD-Ländern vor und ist, nach meinem besten Wissen, der erste, der die Gruppe von sozialen und ethischen Banken an Hand eines umfassenden Datensatzes untersucht. Mit dem im Aufsatz vorgestellten Datensatz wird erforscht, ob sich soziale und ethische oder "alternative" Banken im Hinblick auf ihr Risiko von konventionellen Banken unterscheiden. Dafür wird das Risiko der sozialen und ethischen Banken mit einer angemessen ausgewählten ("gematchten") Kontrollgruppe von konventionellen Banken unter Verwendung von Mittelwertvergleichen und Panelregressionstechniken verglichen.

Als Hauptergebnis kann festgehalten werden, dass soziale und ethische Banken wesentlich stabiler als ihre konventionellen Pendants sind. Zentrales Risikomaß ist hier der z-score. Soziale und ethische Banken haben außerdem niedrigere Anteile an Krediten im Vergleich zu ihrer Bilanzsumme und höhere Anteile an Kundeneinlagen als konventionelle Banken. Die Ergebnisse sind robust bei der Verwendung von verschiedenen Regressionstechniken, die robust gegenüber Ausreißern in den Daten sind. Außerdem sind die Ergebnisse nicht abhängig von der Verwendung von verschiedenen Matching-Methoden, Spezifikationen des Datensatzes und Spezifikationen des z-scores.

Außerdem wird die Entwicklung von sozialen und ethischen Banken während der globalen Finanzkrise untersucht. Während sich keine Unterschiede im z-score zeigen, gibt es Hinweise darauf, dass die regulatorischen Eigenkapitalquoten von sozialen und ethischen Banken weniger von der globalen Finanzkrise beeinträchtigt wurden, als die von konventionellen Banken.

Paper 3

Der dritte Aufsatz ist eine Ergänzung des zweiten. Er untersucht das Risiko von sozialen und ethischen Banken in den Vereinigten Staaten, die im zweiten Aufsatz nicht enthalten sind. Hier vergleiche ich das Risiko von sozialen und ethischen Banken in den USA mit einer angemessen ausgewählten ("gematchten") Kontrollgruppe von konventionellen Banken unter Verwendung von Panelregressionstechniken.

Im Gegensatz zum vorherigen Aufsatz zeigt sich, dass alternative Banken in den Vereinigten Staaten riskanter als ihre konventionellen Pendants sind. Dieses Ergebnis ist zwar überraschend, kann aber für eine Reihe von verschiedenen Risikomaßen festgestellt werden. Soziale und ethische Banken haben signifikant niedrigere regulatorische Eigenkapitalquoten und höhere Verschuldungsquoten (leverage ratio) als ihnen entsprechende konventionelle Banken. Außerdem weisen Risikomaße, die auf der Qualität des Kreditportfolios beruhen, wie zum Beispiel notleidende Kredite, auf ein höheres Kreditrisiko im Kreditportfolio von sozialen und ethischen Banken hin.

Die Ergebnisse werden durch eine Reihe von Robustheitsuntersuchungen, wie durch die Verwendung von Regressionstechniken, die robust gegenüber Ausreißern im Datensatz sind, bestätigt. Außerdem wird die Analyse mit zwei weiteren Datensätzen von Banken, die als CDFIs (Finanzinstitute für lokale gesellschaftliche Entwicklung / Community Development Financial Institutions) zertifiziert sind, wiederholt. Diese Banken ähneln der Gruppe von sozialen und ethischen Banken in vielen Aspekten und die Analyse dieser Banken liefert ähnliche Ergebnisse.

Der Unterschied im Risikograd von sozialen und ethischen Banken in den Vereinigten Staaten und sozialen und ethischen Banken in anderen OECD- und EU-Ländern kann vermutlich mit der hohen Überschneidung von CDFIs mit sozialen und ethischen Banken in den Vereinigten Staaten erklärt werden. Da CDFI-Banken den Auftrag der gesellschaftlichen Entwicklung haben, sind sie verpflichtet, sich auf wirtschaftlich benachteiligte Kreditnehmer und soziale Gruppen zu spezialisieren. Außerdem sind sie traditionell im Bereich der Immobilienkreditfinanzierung aktiv. Dies kann ihr höheres Risiko im Vergleich zu konventionellen Banken erklären. Soziale und ethische Banken im Allgemeinen können dagegen ihre Aktivitäten besser diversifizieren, was stabilisierend wirken dürfte.

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