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Four Essays on

Financial Stability and the Housing Market

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To my parents and
Alexandra.

Chapter 1

Introduction

The adverse macroeconomic consequences of the Great Recession in 2009 spread well beyond the United States, highlighting the importance of financial stability and the housing market for real economic activity. Moreover, the vicious bank-sovereign cycle and the resulting sovereign-debt crisis of 2010-2012 posed a big threat to the survival of the Economic and Monetary Union (EMU) as a whole. While there is widespread consensus about the underlying causes of these crises, policy makers are still debating about what can be done to prevent future crises and, especially in the Euro area, deeply disagree on the direction of reforms. After all, most regulatory measures face not only the trade-off between financial resilience versus efficiency but also the fundamental choice between rule or discretion based interventions (Bénassy-Quéré et al., 2018).

In response to the Great Recession, the last decade has seen a significant track record of the introduction of financial sector regulations at various levels. At the international stage, the Financial Stability Board (FSB) coordinates a comprehensive financial reform program that the G20 launched in 2009 to achieve the following goals: (i) end the too-big-to-fail distortions, (ii) strengthen financial resilience, (iii) establish a central clearing framework for derivatives markets, and (iv) effectively supervise and regulate the shadow banking system (FSB, 2017). Moreover, the newly enacted international supervisory architecture was accompanied by the implementation of macroprudential instruments which intend to (i) reduce excessive credit growth and indebtedness, (ii) smooth maturity mismatches and market liquidity, (iii) bring down overly risk concentration and (iv) get rid of the moral hazard problem (ESRB, 2014). Broadly speaking, there are two types of macroprudential policies. First, bank-specific Basel III instruments (e.g., leverage ratios, systemic risk buffers or anti-cyclical capital buffers) try to prop up the capitalization base of financial institutions. Second, loan-specific or borrower-specific instruments (e.g., loan-to-value ratios, debt-to-income or debt-service-to-income ratios) aim to tame the credit risk that originates from the borrower side. Recent literature has shown that these tools were largely successful in cushioning mortgage and household credit growth as one major factor in explaining recent crises (Akinci and Olmstead-Rumsey, forthcoming; Cerutti et al., 2017; Claessens et al., 2013; Mian and Sufi, 2009). At the European level, policy makers substantially reduced regulatory fragmentation in banking markets by enacting harmonized supervisory rules, a bail-in and resolution framework and a yet unfinished depository insurance schemes as main pillars of the European Banking Union (Wyplosz, 2016).

Despite the substantial progress that these regulatory interventions have achieved, they have not come far enough due to the following main shortcomings in the current institutional architecture. First, the credibility of the new bail-in regime has already been put to a test in June 2017 by the heterogeneous treatment of two prominent banks. Junior bondholders of the Spanish Banco Popular Espanol were bailed in by experiencing massive haircuts and on the contrary the distressed Italian bank Banca Monte dei Paschi di Siena received a state bailout in the very same month. Whereas the Italian decision to opt-out from the bail-in regime is de-jure compliant with the Bank Recovery Resolution Directive, it certainly raises concerns whether multiple (inter)national regulatory agencies and national governments are still able to protect their banking systems at the expense of overall financial stability (Koetter et al., 2017).

Second, the regulatory constraints and costs that macroprudential interventions might impose on banks, might incentivise them to engage in regulatory arbitrage by shifting risky financial transactions into the unregulated (shadow) banking sector. While traditional commercial banks in the US contracted lending activity due to increased capital and regulatory constraints, the market shares of shadow banks nearly doubled in relation to total mortgage origination between 2007-2015 and these banks also dominate the riskier borrower segment (Buchak et al., 2017). Also the FSB and the European Systemic Risk Board (ESRB) devoted their attention to the growing importance of shadow banks such as money market funds, investment funds and special purpose entities (SVR, 2017). The current strategy, data availability and tools of macroprudential policy are explicitly underdeveloped for addressing the risk in the shadow banking system and thereby fail to achieve the above mentioned prudential goals (ESRB, 2014).

The main contribution of this thesis is to complement the debate on the shortcomings in the current regulatory financial architecture by highlighting four risk-mechanisms that have been insufficiently discussed in both policy and academic circles. The second chapter investigates whether the *spatial dimension of systemic risk* is important to consider when supervision is shifted from national to supranational authorities such as the Single Supervisory Mechanism of the European Banking Union. The third chapter analyzes whether the *complexity of a banking system* is related to it's risk taking behavior, an observation which is necessary for understanding the regulation of more and more complex banks expanding for example into the shadow banking sector. The fourth chapter introduces the concept of "*Granularity*" to investigate how the presence of big banks in the regulated and unregulated US mortgage market can not only dampen risk diversification but also cause house price and employment fluctuations, even in absence of conventional risk-channels like contagion or too-interconnected-to-fail effects. The last chapter investigates the *political risk-channel* and documents that soft political power expands access to mortgage credit for their constituents, especially for minority households.

In Chapter 2 we empirically investigate the spatial dimension of systemic risk supervision in the banking system of the Euro area.[1] First, we ask whether a bank's contribution to systemic risk differs at the national as opposed to the Euro-area level? Second, do the drivers of systemic risk differ at these two spatial dimensions? Using stock market and bank balance sheet data for 80 Euro area listed banks, we follow Brownlees and Engle (2017) to calculate the systemic risk measure – SRISK – and differentiate a bank's contribution to systemic risk at the national versus the Euro-area level. We find that banks' systemic risk contributions differ at the national level compared to the Euro-area level across banks and over time. Addressing the second research question, we find that larger and more profitable banks have, on average, contributed more to systemic risk. While the qualitative determinants of systemic risk are similar at the national and Euro-area level, the quantitative importance of some determinants differs. For example, banks with a higher loan share contribute less to systemic risk, but the effect is stronger at the national level compared to the Euro-area level.

With regard to the European Baning Union, these research questions are highly policy relevant since macroprudential power in the EU is located at different spatial dimensions: both at the national and the supranational level. While macroprudential policy is mainly a national responsibility, the European Central Bank (ECB) can impose stricter capital requirements on banks in the event of a threat to systemic stability that is not addressed by national policies.

In Chapter 3, we analyze the relatively unexplored relationship between banks' complexity on banks' idiosyncratic and systemic riskiness during the financial crisis.[2] We construct a novel dataset and follow Cetorelli and Goldberg (2014) to compute bank-level measures of business and geographical complexity. Intuitively, a bank is more complex if it has more subsidiaries across different business types or countries/regions. Descriptive statistics

[1] Chapter 2 is based on a Bundesbank Discussion paper that is co-authored with Claudia Buch and Lena Tonzer (Buch et al., 2017).

[2] Chapter 3 is based on a published paper in *Economics Letters* that is co-authored with Talina Sondershaus and Lena Tonzer (Krause et al., 2017).

reveal that banks increased their number of non-bank subsidiaries. Our regression results show that higher geographical complexity and a higher share of foreign subsidiaries is positively related with banks' idiosyncratic and systemic riskiness. In contrast, a higher share of non-bank subsidiaries has stabilizing effects.

Given that interconnected and complex banking markets can either dampen or propagate financial shocks, analyzing the effects of bank complexity on financial risk is important for policy makers who intend to regulate a credit intermediation chain that gets ever more complex.

In Chapter 4, we investigate the role of market concentration in the regulated and the shadow US banking market for the propagation of idiosyncratic bank shocks and their effect on macroeconomic performance.[3] Building on the concept of "Granularity" (Gabaix, 2011), we ask whether the existence of few large and dominating mortgage lenders dampens risk-diversification effects. More specific, when market concentration is high, idiosyncratic shocks that hit the largest players in the market cannot be canceled out by the shocks of other mortgage lenders and might affect macro outcomes. First, we show that US mortgage markets at the level of Metropolitan Statistical Areas (MSA) are indeed highly concentrated. Second, we find that idiosyncratic shocks to newly issued mortgages at the bank level have positive and significant effects on house price growth at the MSA level. Third, these shocks are also positively linked to real variables like job creation or firm growth. And fourth, granularity in the shadow banking system has a stronger effect on house price growth than for the traditional deposit-taking institutions.

The focus of Chapter 4 on bank size and market concentration is also omnipresent in policy and academic debates because bail out expectations invite especially large banks to imprudent risk-taking behavior that can destabilize the whole financial system (Admati and Hellwig, 2013). The research question in Chapter 4 is relevant because it shows that the mere presence of big

[3]Chapter 4 is based on a IWH Discussion paper that is co-authored with Franziska Bremus and Felix Noth (Bremus et al., 2017).

banks can not only dampen risk diversification effects but also impact the real economy even in the absence of a financial crisis, contagion or spillover effects.

The last Chapter 5 shifts the focus to the impact of local political leadership on mortgage access in the United States. I use a regression discontinuity design (RD) to analyze 312 interracial elections in US cities in order to estimate causal effects of an African-American mayor on mortgage access and home ownership transition of African-American households. First, I find tentative evidence for an electoral mortgage cycle in US cities that elected an Africa-American mayor for the first time and show that the number of accepted mortgage applications from black applicants increase by 10% in the post election period. Second, my causal RD estimates document that a black mayor increases mortgage acceptance rates for African-American debtors by 3 to 9 percentage points in the short and long term. And third, while there are no effects on mortgage acceptance rates and debt-to-income ratios for black borrowers in the bottom of the income distribution, I find marginally significant effects on mortgage acceptance rates for high income black applicants.

The research question posed in the last chapter highlights that regulatory power can take various forms. For example, macroprudential policy such as debt-to-income ratios is a form of hard political power enacted by legislative acts to curtail household leverage. On the contrary, US city mayorship represents a form of soft political power that is able to increase credit access for their constituents. While this finding might be beneficial for historically disadvantaged groups with difficulties accessing mortgage markets, it also shows that politicians giving access to easy credit might have a role in the housing boom-bust cycle, no matter what the consequences to the economy's long term health (Ferreira et al., 2016).

Chapter 2

Drivers of Systemic Risk: Do National and European Perspectives Differ?

Abstract: *Since the establishment of the Banking Union, the European Central Bank can impose stricter regulations than the national regulator if systemic risks are not adequately addressed. We ask whether the drivers of systemic risk differ when applying a national versus a European perspective. We find that systemic risk increased during the financial crisis. An exploration of the drivers of systemic risk shows that banks' contribution to systemic risk is positively related to size and profitability but negatively to the loan share. The qualitative determinants of systemic risk are similar at the national and Euro-area level, whereas the quantitative importance differs.*[*]

2.1 Introduction

Systemic risk can create negative externalities for the financial system which individual banks do not internalize.[1] If banks experience a negative shock to capital, they curb their lending or sell assets. In responding to such an individual capital shortage, banks may fail to anticipate that other banks may have capital shortages, too. This may aggravate the response to the initial shock. Systemic risk thus leads to an aggregate shortage of capital

[*]This chapter is co-authored with *Claudia Buch*, Deutsche Bundesbank and Lena Tonzer from the Halle Institute for Economic Research, Member of the Leibniz Association. Contact: *claudia.buch@bundesbank.de*, *lena.tonzer@iwh-halle.de*. A version of this chapter has been published in the Bundesbank-Discussion Papers Series as Buch, Claudia M.; Krause, Thomas and Tonzer, Lena (2017): Drivers of Systemic Risk: Do National and European Perspectives Differ? Bundesbank Discussion Papers, No 09/2017, Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main.

[1]"Systemic" risk is not synonymous with "systematic" risk (Hansen, 2013). The latter is defined as macroeconomic or aggregate risks that cannot be diversified away. It is also known as market, non-diversifiable, or beta risk.

in the financial sector (Acharya and Steffen, 2012; Acharya et al., 2017). The externality that generates systemic risk is the propensity of a financial institution to be undercapitalized when the whole system is undercapitalized. It is the task of macroprudential supervision to internalize systemic risk by supervising financial institutions and, if needed, by imposing appropriate capital buffers on banks..

In this paper, we address two issues. First, what is a bank's contribution to systemic risk at the national as opposed to the Euro-area level? Second, do the drivers of systemic risk differ at the national and the Euro-area level? Understanding whether the assessment of systemic risk by national supervisors may differ from that by supranational supervisors and analyzing the factors driving systemic risk at different regional levels is important in Europe. Here, national supervisors are responsible for macroprudential oversight and for imposing macroprudential regulations. But, under the supranational Single Supervisory Mechanism (SSM), the ECB can impose stricter regulations than the national regulator if the ECB identifies systemic risks that are not adequately addressed by the macroprudential regulator at the national level.

Despite a large and growing literature on systemic risk in banking, most previous studies do not take into account potential differences in contributions to systemic risk at the national and Euro-area level. Prima facie, banks which are important and thus "systemic" for the national financial system may be less "systemic" for the European financial system simply because the relevant market is larger. But market share is not the only driver of systemic risk. The correlation of risks across banks, the exposure of banks to macroeconomic shocks, and the degree of interconnectedness of financial institutions are likewise drivers of systemic risk. If the impact of negative externalities caused by a bank at home differs from the contribution to systemic risk abroad, a national regulator might fail to take this cross-border externality into account. To the best of our knowledge, no comparative analysis of the drivers of systemic risk at the national level and those at the supranational, Euro-area level has been conducted before.

We combine stock market data for Euro-area banks with balance sheet data. Overall, our dataset consists of 80 Euro-area banks listed on the stock market and covers the years 2005-2013. To measure the systemic risk emerging from a specific bank and the underlying drivers, we proceed in two steps. First, we follow Brownlees and Engle, 2017 and calculate a systemic risk measure - SRISK - which captures a bank's contribution to an aggregate capital shortfall. SRISK is calculated based on stock market data. We differentiate between a bank's contribution to an undercapitalization of the financial system at the national versus the Euro-area level. This reveals whether supervisors assess banks' systemic risk differently, depending on their regional perspective, while using the same systemic risk measure.

Second, we analyze the determinants of systemic risk. Given that not all explanatory variables of interest are available for all banks, we analyze the determinants of systemic risk for 75 out of 80 banks. Finding that the drivers of systemic risk at the national level differ from those at the Euro-area level might have implications for the incentive of regulators to impose macroprudential rules and for the level at which banks should be supervised. Both of these are beyond the scope of the present analysis, however. Hence, our analysis reveals whether levels and drivers of measures of systemic risk derived from stock market data depend on the regional perspective taken.[2]

Our analysis is linked to three strands of literature. A first set of studies measures systemic risk empirically. The SRISK measure comes up in several previous studies. The study closest to ours is (Benoit, 2014), who extends the SRISK measure to distinguish the contribution to systemic risk at different levels - supranational or national. While the absolute values of SRISK can vary substantially across different regional levels, the ranking of banks according to SRISK is very similar for different levels. We apply the SRISK measure to all Euro-area banks that are listed on the stock market, including SSM-supervised banks. Similar to (Benoit, 2014), we compute the contributions of these banks to systemic risk at the national and the Euro-area

[2] We do not discuss whether national and supranational supervisors' objectives may differ. Also, our analysis does not extend to possible effects and resulting trade-offs of allocating supervision from the national to the supranational level.

level. We find that, on average, the values obtained for SRISK for the banks included in this study are similar at the national level and at the Euro-area level. However, at the level of the individual bank, we do find heterogeneity across banks and over time.

A measure of systemic risk which has been used as an alternative to SRISK is the ΔCoVaR by (Adrian and Brunnermeier, 2016). Conditional value at risk (CoVaR) is defined as the financial system's Value-at-Risk conditional on the state of a particular financial institution. An institution's contribution to systemic risk is then the difference between the CoVaR with the financial institution being in distress, and the CoVaR with the financial institution being at its median state. The reason we prefer SRISK over ΔCoVaR is that the former has frequently been used in related studies (Benoit, 2014; Bierth et al., 2015; Bostandzic and Weiß, 2013; Laeven et al., 2016). This ensures comparability to our results. Another advantage is that SRISK can be easily calculated at the regional level. While this also holds true for the distress, and the CoVaR with the financial institution being at its median state. The reason we prefer SRISK over ΔCoVaR, the derived values are more difficult to compare across regions (Benoit, 2014).

A second strand of literature analyzes why some banks are more systemically important than others. We contribute to this literature by analyzing the drivers behind banks' contribution to systemic risk at different regional levels. Previous evidence on the determinants of banks' contributions to regional systemic risk is scarce. Closest to our paper is the work by Weiß et al., 2014, who analyze the determinants of banks' contributions to global and local systemic risk during several historical financial crises using an event study approach. They find that bank-specific determinants of systemic risk are neither persistent across time nor across different regional levels. Our paper departs from their study in two dimensions. First, we rely on SRISK as a multidimensional measure of systemic risk, whereas Weiß et al., 2014 use tail measures of interconnectedness such as the marginal expected shortfall and lower tail dependence. Second, our focus is on a sample of publicly listed banks in the Euro area, which allows analyzing whether determinants of systemic risk differ depending on whether we take a national or a European perspective.

De Jonghe (2010) also studies the effect of bank-specific characteristics on systemic risk using tail betas, which is the probability of a sizeable decline in a bank's stock price if the stock market crashes. His main focus is on the effect of "revenue diversity", resulting from a diversified portfolio, on systemic stability. The effect of the share of non-interest income on systemic risk is assessed in De Jonghe et al., 2015. They find that non-interest income increases systemic risk measured by the marginal expected shortfall, but that the effect is weaker for larger banks. Our results show that higher non-interest income relates positively to systemic risk for the smaller banks, with the effect reversing itself for larger banks.

Laeven et al. (2016) regress measures of idiosyncratic risk (stock returns) and of systemic risk (SRISK) of banks during the crisis on pre-crisis bank characteristics. They find that larger banks contribute more to systemic risk if they have low capital and liquidity ratios and if they have complex and more market-based business models. We add to this literature by distinguishing between different regional levels when analyzing systemic risk and by placing a specific focus on the Euro area. For the sample of Euro-area banks, we confirm their finding that larger banks are more systemically important. We also document that banks with a more traditional business model captured by a higher loan share contribute less to systemic risk.

A third set of previous studies analyzes the costs and benefits of allocating regulatory or supervisory powers to the supranational level from a theoretical point of view (Calzolari et al., 2017; Carletti et al., 2017; Dell'Ariccia and Marquez, 2006; Kahn and Santos, 2005; Morrison and White, 2009; Vives, 2001). Regulation at the supranational level is more likely to internalize cross-country interdependencies (Beck et al., 2013). Dell'Ariccia and Marquez (2006), for instance, show that a supranational regulator is more likely to take into account beneficial effects of higher capital requirements on the stability of banks in other countries. However, regulation becomes less flexible if uniform regulatory standards apply across countries. This might be costly if banking systems are heterogeneous across countries.[3]

Empirical studies show that a national approach to supervision and regulation might lead to distortions. Agarwal et al. (2014a), for instance, exploit the fact that supervision of US commercial banks alternates between the state and federal regulator. They find that federal regulators tend to be less lenient.[4] Beck et al. (2013) analyze regulators' incentives to intervene in distressed banks depending on their type of cross-border activities. They show that the larger the share of foreign deposits and assets and the lower the share of foreign equity, the later national regulators step in. This supports the theoretical prediction that national regulators are less likely to internalize costs or benefits arising abroad.

In this paper, we are not only interested in possible differences in viewpoints between national and international supervisors arising from the measurement of banks' systemic risk, but also seek to assess whether drivers of systemic risk differ across regional levels. As regards the relevance of size, our study shows that larger banks contribute more to systemic risk than smaller banks, and this result holds irrespective of the regional level considered. "Size" is thus an important variable to identify global systemically important financial institutions (G-SIFIs). However, there are additional bank-level factors which are related to banks' contribution to systemic risk. More profitable banks, banks with a lower share of loans to total assets and thus a less "traditional" business model, contribute more to systemic risk. Given that one key criterion for a SSM-supervised bank is bank size, we analyze whether other drivers of risk differ between smaller and larger banks. Conditioning on bank size, we find that banks with higher profitability and a higher share of non-performing loans contribute more to systemic risk the larger they are. Moreover, the effect of the share of non-interest income

[3] Further theoretical studies include Colliard (2015), who compares the effects of local versus centralized supervision. Effects of supranational versus national bank resolution on contagion and market discipline are studied by Górnicka and Zoican (2016).

[4] Behn et al. (2015) use data for German banks to show that bailout decisions can be determined by the institutional design. Local supervisors are less likely to bail out banks before elections, and banks perform worse if local politicians intervene rather than the savings bank association, which is the head organization of the German savings banks. This suggests that increasing the distance between banks and supervisors can improve the decision-making process.

reverses: while smaller banks with a higher share of non-interest income contribute more to systemic risk, the effect turns negative for larger banks.

In qualitative terms, the determinants of systemic risk that we find are similar at the national and the Euro-area level. This is likely to reduce discrepancies between national and supranational supervisors, align incentives, and contribute to financial stability. Carletti et al. (2017) study agency problems that can occur between local and centralized supervisors if decision-making power is shifted to the centralized supervisor while local supervisors remain responsible for collecting information on banks' soundness. Their model shows that local supervisors reduce their efforts to collect information if the discrepancy in the objective functions of different supervisors is large. However, in quantitative terms, we find that the relevance of some determinants of systemic risk differ across regional levels. A high share of loans in total assets, for example, tends to lower systemic risk, but this effect is stronger at the national than at the Euro-area level.

The paper is structured as follows. In Section 2, we describe the institutional background for macroprudential supervision and regulation in the Euro area. In Section 3, we explain the definition and measurement of systemic risk using the SRISK concept. In Section 4, we present our data, capturing possible determinants of systemic risk, and in Section 5, we show regression results relating systemic risk to these determinants. Section 6 concludes.

2.2 Institutional Background

Macroprudential supervision and regulation is a relatively new policy field. In Europe, the legislation establishing the European Systemic Risk Board (ESRB) came into force in 2010. It is based on a recommendation of the de Larosière report of the year 2009 to establish a European body with a mandate to oversee risks in the financial system as a whole.[5] The ESRB has no direct regulatory power, but it can issue warnings and recommendation

[5]See `ec.Europa.eu/finance/general-policy/docs/de_larosiere_report_en.pdf`

to national regulators or to other authorities. An ESRB recommendation issued in the year 2011 requires EU member states to establish or designate an authority entrusted with the conduct of macroprudential policy. In addition, the new EU-wide prudential requirements for credit institutions (CRD IV/CRR) require member states to create an authority which can take measures to mitigate systemic risk posing a threat to financial stability *at the national level*.[6]

Upon the entry into force of the European Banking Union in November 2014, the Single Supervisory Mechanism (SSM) gave the ECB the right to impose stricter regulations than the national authorities if the ECB identifies systemic risks which are not adequately addressed by the national regulator. Note that the ECB's ability to tighten national regulation is restricted to those instruments available under the Capital Requirements Regulation and Capital Requirements Directive (CRR/CRD IV). There is, hence, shared responsibility between the national and supranational supervisor as concerns macroprudential policies. This division of power between the national and the Euro-area level may have implications for the stringency of macroprudential regulation. On the one hand, regulatory forbearance and "inaction bias" may be more pronounced at the national level if political considerations influence decision-making. On the other hand, European supervisors may fail to act if systemic risk is deemed to be contained to national financial markets. Our paper contributes to the discussion on whether the assessment of systemic risk can be expected to differ between the national and the European level.

Furthermore, with the establishment of the SSM, the ECB directly supervises the largest 120 Euro-area banks, representing almost 82% of total banking assets in the Euro area. Designation of financial institutions to be supervised by the SSM is based on a definition of systemic risk. The ECB uses the following criteria to define a systemically important financial institution:

[6]For details, see the ESRB recommendation of April 4, 2013, on intermediate objectives and instruments of macroprudential policy, ESRB/2013/1.

(i) total assets (size),

(ii) importance of the bank for the (national) economy,

(iii) significance of cross-border activities, and

(iv) requested ESM/EFSF financial assistance.[7]

One goal of our empirical model is to analyze whether these factors are related to the systemic risk of individual banks. Other pieces of legislation likewise include assumptions on the drivers of systemic risk. The Basel Committee on Banking Supervision (BCBS, 2013), for instance, proposes measuring the systemic importance of financial institutions based on five equally-weighted criteria: size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity. Each of these five criteria (excluding size) is composed of various sub-indicators which again receive equal weights. For example, the measure "cross-jurisdictional activity" considers cross-jurisdictional claims and cross-jurisdictional liabilities. This measure was adopted by the Financial Stability Board (FSB) to identify G-SIFIs.

One advantage of the existing regulatory classification is that it is based on indicators which do not fluctuate widely over time. Basing the designation of systemically important financial institutions on market-based indicators like SRISK or ΔCoVaR which vary over time, would not be very practical. At the same time, it is important for regulators to know whether these indicators would yield assessments of the systemic importance of financial institutions that are similar to those provided by more structural indicators.

2.3 Defining and Measuring Systemic Risk

Defining and measuring systemic risk is a core component of our paper. In this section, we introduce our main measure - the expected shortfall of capital of a financial institution during a crisis situation - and we discuss why this measure might differ at the national and the Euro-area level.

[7]For an online reference, see `http://www.ecb.Europa.eu/ssm/html/index.en.html`

2.3.1 Marginal Expected Shortfall and Systemic Risk

We follow Brownlees and Engle (2017) and define systemic risk as a bank's expected capital shortfall if it only occurs whenever the rest of the financial sector is undercapitalized. The capital shortfall of an individual bank, given that the whole financial system experiences a capital shortfall, is a measure of the bank's contribution to systemic risk. The market-based systemic risk measure SRISK thus reflects a bank's contribution to systemic risk by describing the expected capital need, conditional on a systemic event:

$$SRISK_{it} = E_t \left(Capital\ Shortfall_{it+h} | R_{mt+1:t+h} < C \right), \tag{2.1}$$

where $R_{mt+1:t+h}$ is a multi-period market return between period $t+1$ and $t+h$. C is an extreme threshold loss. Hence ,$SRISK_{it}$, which gives the expected capital shortfall, depends on the systemic event $\{R_{mt+1:t+h} < C\}$. Applying this definition of systemic risk requires assumptions on the systemic event and on a bank's capital shortfall. To interpret SRISK in an meaningful way and to capture the capital shortfall of an institution conditional on a systemic event, the amount by which the market index falls has to be large enough and the period during which it falls has to be long enough (Brownlees and Engle, 2017). Previous work assumes that a financial system is in a crisis whenever the market index falls by 40% over the next six months (Acharya et al., 2012). So the extreme threshold loss is set to -40%. However, even if these parameters are modified, Brownlees and Engle (2017) show that SRISK provides similar rankings of banks at the top positions.

Equation 2.1 shows that SRISK is based on the accuracy with which market participants anticipate the capital need of an individual bank in times of crisis. Any mechanism that might lead to an under- or overestimation of risk would affect the accuracy of this proxy for systemic risk. Similar problems apply to alternative measures of systemic risk based on market data such as ΔCoVaR models. Given that our focus is on differences in banks' contribution to systemic risk at the national and at the Euro-area level, the possible mispricing of risk would be problematic if the degree of mispricing were to vary across regions. In robustness tests, we control for periods in which countries introduced short-sale bans as this might impact pricing in markets and thus SRISK. Yet our main conclusions remain robust. A financial institution experiences a capital shortfall if the value of its equity capital drops below a given fraction k of its total (i.e. non-risk weighted), “stressed” assets: $Capital\ Shortfall_{it+h} = k(Assets_{it+h} - Equity_{it+h})$. k is the microprudential minimum capital requirement for each institution to maintain a given percentage of its assets as equity capital. Substituting this into equation 2.1 gives:

$$\begin{aligned} SRISK_{it} &= E_t\left(Capital\ Shortfall_{it+h}|R_{mt+1:t+h} < C\right) \\ &= E_t\left(k(Assets_{it+h}) - Equity_{it+h}|R_{mt+1:t+h} < C\right) \\ &= E_t\left(k(Debt_{it+h} + Equity_{it+h}) - Equity_{it+h}|R_{mt+1:t+h} < C\right) \\ &= kE_t(Debt_{it+h}|R_{mt+1:t+h} < C) - (1-k)E_t(Equity_{it+h}|R_{mt+1:t+h} < C) \end{aligned}$$

Assuming that there is sufficient equity capital to cover potential losses (hence no bail-in of creditors is needed in case of distress), the book value of debt will be relatively constant. So $Debt_{it+h}$ cannot be renegotiated in the midst of a financial crisis, and the expression $E_t\left(Debt_{it+h}|R_{mt+1:t+h} < C\right)$ simplifies to $E_t\left(Debt_{it+h}|R_{mt+1:t+h} < C\right) = Debt_{it}$:

$$\begin{aligned} SRISK_{it} &= kDebt_{it} - (1-k)E_t(Equity_{it+h}|R_{mt+1:t+h} < C) \\ &= kD_{it} - (1-k)E_t(E_{it+h}|R_{mt+1:t+h} < C), \end{aligned} \tag{2.2}$$

where D_{it} is the book value of total liabilities and E_{it+h} is the expected market value of equity between the period $t+1$ and $t+h$ conditional on the multi-period market return. However, in the event of a crisis, equity owners will have to absorb losses. The sensitivity of a bank’s equity conditional upon a (future) crisis of the financial system is captured by the long-run marginal expected shortfall, $LRMES_{it}$, such that $LRMES_{it} = E_t(R_{it+1:t+h}|R_{mt+1:t+h} < C)$. $LRMES_{it}$ can be interpreted as the bank’s expected loss per Euro conditional on a particular market index falling by more than the threshold loss, $C = -40\%$, at a time horizon of six-months. Hence, $(1 - LRMES_{it})$ represents the devaluation of the market value of equity after a shock has hit the system.[8] Equation 2.2 can be written as:

$$\begin{aligned} SRISK_{it} &= kD_{it} - (1-k)(1 - LRMES_{it}E_{it}) \\ &= E_{it}\left[kL_{it} + (1-k)LRMES_{it} - 1\right],, \end{aligned} \quad (2.3)$$

where L_{it} is the leverage ratio $D_{it} + E_{it}/E_{it}$. Hence, the systemic risk of a financial institution is higher the higher its leverage, the higher its expected equity loss given a market downturn (higher tail dependence), and the larger the bank. Note that SRISK may become negative if a bank has a low degree of leverage and/or a low marginal expected shortfall. SRISK delivers a clearly interpretable unit of measurement: the amount of capital needed to fulfill capital requirements after an adverse shock. The higher a bank's capital shortfall, the higher the probability that a bank will be distressed. If the entire sector is in distress and exhibits an aggregate capital shortage, banks find it hard to collectively improve their balance sheets. This generates negative externalities to the rest of the economy. Note also that a higher prudential capital ratio expressed by k implies that banks would need a larger amount of capital to maintain operations during crisis times, which, in turn, causes an increase in the capital shortfall. In sum, SRISK is the difference between a bank's required capital and the available capital, conditional on a substantial decline in the overall market. Banks with the largest shortfall contribute most to the system's aggregate capital shortfall. Banks with a capital shortfall are vulnerable to runs, forcing them to liquidate long-term assets. This might fuel downward asset price spirals and destabilize the financial system. There is, thus, an important distinction between an institution's failure in normal times, without an aggregate capital

[8] In line with Acharya et al. (2012), we proxy the LRMES using the marginal expected shortfall (MES) measure, where $LRMES_{it} \cong 1 - exp(18 * MES_{it})$. MES is defined as the one-day expected equity loss per dollar invested in a bank if the respective market index declines by more than its 5% VaR. To calculate MES, we follow Brownlees and Engle (2017) and opt for the GJR-GARCH volatility model and the standard DCC correlation model. The estimation period for MES is 2000-2015. Technical details of MES estimation can be found in the appendices of the two referenced papers.

shortage, and a bank's failure when the whole system is undercapitalized. Only the latter displays a key feature of systemic risk, which SRISK captures. In this sense, Acharya et al. (2017) provide a theoretical model in which negative externalities arise due to a capital shortfall at one firm conditional on situations in which the whole financial system is undercapitalized.

2.3.2 National versus European Perspectives

Generally, a bank's contribution to systemic risk depends on its market share, the degree of diversification, and its exposure to market risk at home and abroad (Acharya et al., 2017). A priori, one might expect SRISK to be higher for the national market than for the Euro-area market. In the extreme case of a monopolistic domestic bank without foreign operations, the capital of this bank would move one-to-one with the capital of the domestic banking system. The smaller the domestic market share of the bank is and the more the bank diversifies its activities away from the domestic market, the weaker the link will be between bank i and the national banking market. This suggests that it is not clear a priori that SRISK is necessarily higher if the national market rather than the Euro-area market is taken as a benchmark. As we are interested in comparing the contribution to systemic risk of a bank at the national (N) and at the Euro-area level (EA), we follow Benoit (2014) and distinguish two measures of systemic risk:

$$SRISK_{it}^{EA} = kD_{it} - (1-k)(1 - LRMES_{it}^{EA})E_{it}, \tag{2.4}$$

$$SRISK_{it}^{N} = kD_{it} - (1-k)(1 - LRMES_{it}^{N})E_{it}, , \tag{2.5}$$

Because there is nothing that a priori prevents $LRMES$ with respect to the home market from being smaller or larger than $LRMES$ with respect to the Euro-area market, the difference between the two measures of systemic risk may be positive or negative:

$$\begin{aligned} \Delta SRISK_{it} &= SRISK_{it}^{EA} - SRISK_{it}^{N} \\ &= (1-k)(LRMES_{it}^{EA} - LRMES_{it}^{N})E_{it} \end{aligned} \tag{2.6}$$

This difference reveals in which market a downturn induces a higher capital shortfall, and it proxies at which level the bank is contributing more to systemic risk. If $\Delta SRISK_{it} < 0$ the bank exhibits a *national effect*, i.e., the bank's ability to absorb losses is smaller during a decline in the domestic market than during a decline in the Euro-area market. If national SRISK is smaller than Euro-area SRISK ($\Delta SRISK_{it} > 0$) , a Euro-area effect prevails: a bank contributes more to a decline in the capitalization of the European banking sector than to a decline in the capitalization of the national banking sector, given that there is a capital shortfall in the system. In this case, the national supervisor may have insufficient incentives to internalize the contribution of banks' to systemic risk at the Euro-area level. This could be one reason for inaction bias at the national level when it comes to the activation of macroprudential policies aimed at strengthening the resilience of banks.[9]

2.3.3 Data Sources

SRISK is calculated based on daily stock market data which are publicly available. This facilitates comparability across studies but restricts our analysis to publicly listed banks. For many European banking systems, the number of banks for which we can calculate SRISK covers only a relatively small share of the market. The German banking market, for instance, is dominated by relatively small savings and cooperative banks as well as their central institutions. Nevertheless, in the context of recent regulatory changes, discussions have focused on the surveillance of large and systemically important banks. Also, publicly listed banks accounted for more than 80% of the total capital shortfall reported in the ECB's comprehensive assessment (Acharya and Steffen, 2014).

To calculate SRISK, we consult data provided by Datastream. The SRISK of bank i consists of three data components: the book value of total

[9] One potential caveat is that the national stock market index is driven by developments at the national but also at the Euro-area level. This would imply that SRISK at the national level is also driven by Euro-area factors. To check whether this affects our results, we conduct robustness tests, in which we extract Euro-area factors from the national stock market index.

liabilities, the market value of equity, and the long-run marginal expected shortfall ($LRMES$). While 110 banks were listed in the Euro area as of January 2014, Datastream provides only yearly data on the book value of total liabilities and the daily market value of equity measured as shares outstanding times share price for 97 banks. 7 banks with poor trading frequency are dropped because the GJR-GARCH model, which underlies the estimation of $LRMES$, could not estimate time-varying volatilities due to insufficient fluctuation and/or zeros in the stock price data. Further, we drop 10 institutions with a market capitalization of less than 100 million Euros as of 31 December 2007. For the remaining 80 banks, we calculate SRISK. To correct for outliers, we winsorize the series obtained for a bank's SRISK at the 1st and 99th percentile.

Finally, we match those banks for which we have calculated SRISK to balance sheet and income statement data from Bankscope by using te ISIN number. While we can match 80 banks, the regression analysis is based on 75 banks in 15 Euro-area countries due to missing values in Bankscope. Given that Bankscope data are available at annual frequency, for most of our analysis, we use the annual average of a bank's SRISK.[10] The list of banks included in our sample can be found in the supplementary material. Only a fraction of the 128 banks which participated in the ECB's comprehensive assessment (henceforth: "SSM banks") are publicly listed and remain in our sample such that we can compute SRISK for 44 SSM banks.

$LRMES$ gives the sensitivity of a bank's equity return to a shock to the market. It is based on the bank's stock price and the Euro-area or the national market index. To compute SRISK at the Euro-area level, we make use of the Euro STOXX Total Market Index (TMI), which represents a broad coverage of Euro-area companies. For the national level, we make use of STOXX Country Total Market Indices (TMI). These indices have two advantages. First, they are available for all Euro-area countries. Second, they allow us to take into consideration financial and real sector developments.

[10] In robustness tests, we also calculate the median of the daily values by bank to aggregate the SRISK series to the annual frequency.

Our approach is similar to Acharya and Steffen (2012) and Laeven et al. (2016), who use the S&P 500 index and not an index specific to the banking sector for the market return.[11]

Summary statistics of the daily stock market data used for the calculation of SRISK can be found in Table 1, which covers the national returns, the return of the Euro STOXX Total Market Index, and the average across the returns of all banks in the sample. We observe that mean values are, on average, close to zero. The standard deviation is smaller in relative terms for the Euro-area stock return compared to most of the national stock returns, suggesting diversification opportunities.

2.3.4 Descriptive Statistics

Table 2.2 shows summary statistics for SRISK at the national and the Euro-area level. Panel (a) uses daily data, while Panel (b) uses annual data. On average, SRISK at the Euro-area level is close to SRISK at the national level. In order to check whether the averages cloud relevant patterns of heterogeneity across countries or across time, Table 2.3 shows the number of banks for which the difference between SRISK at the Euro-area level and SRISK at the national level is positive. Based on daily data, we first calculate the difference of a bank's SRISK between the two levels. We then average this difference for each bank by year. Based on these averaged differences, we count the number of banks per country for which the difference is greater than zero, i.e. the average contribution to systemic risk measured by SRISK is higher at the Euro-area level.

– Insert Table 2.2 here –

Table 2.3 reveals a considerable degree of cross-country heterogeneity. One the one hand, there are countries like Germany where the majority of banks have a positive difference, i.e. a higher level of SRISK at the Euro-area

[11]In robustness tests, we use an index related to the banking sector instead of a broad market index. SRISK tends to show higher values if this banking sector index is used. This arises due to a higher correlation of individual bank indices with the banking sector index at the country level.

level. One the other hand, the number of banks with a positive difference is small in countries such as Greece. Even within some countries, there is heterogeneity across time. In France, for example, the number of banks with a Euro-area effect increases in the crisis period.

– Insert Table 2.3 here –

Figure 2.1 plots SRISK, averaged across all listed banks in the 15 Euro-area countries. It shows that national and Euro-area SRISK increased substantially in 2007. On average, the contribution of listed banks to systemic risk during times of systemic distress has thus increased. These patterns are very similar when considering the national and the Euro-area level while the time series of $\Delta SRISK$ shows that the contribution of banks to systemic risk has, on average, been higher at the national level than at the Euro-area level. At the disaggregated level, there is heterogeneity across countries and over time as shown in Table 2.3, which is not reflected in these simple averages. Also, it is to consider that even if there is a co-movement among the two measures, they can differ in their levels. Given that we denote SRISK in billion Euros, differences in the level can correspond to significant amounts.[12]

– Insert Figure 2.1 here –

2.4 Measuring Drivers of Systemic Risk

The systemic importance of banks might increase in their size, their risk, their degree of interconnectedness, and their exposure to macroeconomic risks (Cai et al., 2016; Laeven et al., 2016). In addition, structural characteristics of banking systems may affect the systemic importance of banks across countries. Next, we describe how we measure potential bank-level drivers of systemic risk.

[12]The similar pattern of national and Euro-area SRISK can be due to the national stock market index being driven by developments at the Euro-area level. To account for this, we conduct robustness tests, in which we extract Euro-area factors from the national stock market index.

2.4.1 Bank-Level Determinants of Systemic Risk

Banks' balance sheet and income statement data are taken from Bankscope. Given that the market data from Datastream are based on consolidated balance sheets, we resort to consolidated statements from Bankscope if available. The data appendix provides more detailed information on the variables used, and summary statistics are provided in Table 2.4. To correct the data for implausible values, we exclude observations for which total assets are missing. We drop observations if assets, equity, or loans are negative. We do the same if the variables expressed as percentages such as the liquidity ratio are negative or exceed 100%. We keep only banks with at least three consecutive observations. To correct for outliers, we winsorize the explanatory bank-level variables at the 1st and 99th percentile.

– Insert Table 2.4 here –

One key driver of systemic risk is bank size, which we measure through (log) total assets. Shocks to large banks can affect aggregate outcomes simply because of granularity effects (Bremus et al., 2013). But large banks can also benefit from a "too-big-to-fail" subsidy which might affect their risk-taking behavior (IMF, 2014). Furthermore, the business models of larger banks differ from those of smaller banks (Laeven et al., 2016). They tend to be more complex in their organizational structure and to be more involved in market-based activities. All these features imply that large banks are systemically more important; hence we expect a positive effect of bank size. To capture the relative importance of a bank for the domestic economy, in robustness tests, we include a bank's total assets in % of GDP.

To capture characteristics of banks' business models, we include the ratio of loans to total assets as well as the share of non-interest income in total income. Previous studies show that banks which are more involved in non-traditional activities have a higher exposure to (systemic) risk (Brunnermeier et al., 2012; Demirgüç-Kunt and Huizinga, 2010). From a theoretical point of view, the impact of banks' business models on systemic risk is not obvious ex ante. Whereas a more diversified portfolio which combines loans and other securitized assets can reduce banks' idiosyncratic risk of failure, market-based activities are often more volatile and thus more risky. For example, De Jonghe (2010) shows that non-interest generating activities increase banks' systemic risk exposure. De Young and Torna (2013) find for a sample of US banks that fee-based non-traditional activities lowered the risk of failure during the recent crisis, whereas asset-based non-traditional activities increased it.

The choice of the business model also determines the profitability of a bank, which we capture through its return on assets (RoA). The effect of RoA on systemic risk is not clear cut a priori. RoA can serve as a crude proxy for the market power of banks. The link between market power and bank risk-taking, in turn, is ambiguous. Many cross-country studies report a negative relationship between banks' market power and risk (Ariss 2010, Beck 2008, Schaeck et al. 2009). This negative relationship is in line with Allen and Gale (2004) and Martinez-Miera and Repullo (2010), who argue theoretically that less intense competition increases banks' margins and buffers against loan losses. However, banks with a high degree of market power may also inflict excessively high funding costs on corporate customers, ultimately leading to higher credit risk and bank instability (Boyd and De Nicoló, 2005).

As a proxy for the failure risk of banks, we include the share of non-performing loans (NPL) in total loans. If the whole financial system is in distress and liquidity is scarce, banks with a high share of non-performing loans are likely to become distressed. For instance, if banks are forced to write down non-performing assets held at market prices, these fire sales can cause a further decline in prices. This can affect other banks with common exposures in case they also have to write down their respective assets (Allen and Gale, 2012).[13]

We also include a measure of liquidity risk. To capture liquidity risk stemming from the liability side of banks' balance sheets, we include the ratio of short-term deposits to total deposits. A high share can fuel unsound

[13]Studies that analyze the relationship between asset commonality and systemic risk empirically include Blei and Ergashev (2014) and Lehar (2005).

expansions of banks' balance sheets and the buildup of systemic risks (Perotti and Suarez, 2009; Song Shin, 2010). In the run-up to the recent crisis, for instance, banks' reliance on short-term debt led to an increase in leverage. This mechanism broke down as soon as banks encountered difficulties rolling over short-term debt to finance long-term assets due to freezes of the interbank market (Gale and Yorulmazer, 2013). In robustness tests, we control for liquidity risk related to the structure of banks' assets and maturity mismatch. The former is measured as the ratio of liquid assets to total assets.[14] Maturity mismatch is defined as short-term debt relative to liquid assets. A high ratio of short-term deposits to liquid assets can reduce flexibility and result in losses if banks are forced to liquidate assets prematurely to meet unexpected demand for liquidity on the part of depositors (Allen and Gale, 2000; Cifuentes et al., 2005).

Banks' capitalization can reflect their ability to withstand losses. However, given that capitalization is strongly related to our dependent variable that measures the capital shortfall during a systemic event, we only control for the equity ratio in robustness tests. Banks with a higher equity ratio have a larger buffer if negative shocks occur and shareholders have more incentives to monitor banks if a larger share of their capital is at stake. Thus, a higher equity ratio is expected to reduce banks' systemic risk.

Banks that have a larger contribution to systemic risk at the Euro-area compared to the national level and vice versa might differ in their balance sheet characteristics. Thus, in Table 2.5, we show summary statistics for the bank-level variables from Bankscope for the subsample of observations for which $\Delta SRISK$ is smaller than zero (Columns 1-2), i.e. SRISK measured at the Euro-area level is smaller than SRISK measured at the national level, and the subsample for which is larger than zero (Columns 3-4). After testing whether the means between those subsamples are significantly different, we find that banks that have a higher SRISK at the Euro-area level have, for example, a lower equity ratio, a lower loan share and a lower return on

[14]Liquid assets relative to total assets are included only in robustness tests given that they are highly correlated with the loan share.

assets ratio. Interestingly, those banks that have a higher SRISK at the national level tend to have, on average, a greater relevance for the domestic economy in terms of the bank assets-to-GDP ratio, though the means are not significantly different between the two groups. In the following regression analysis, we will examine whether these determinants matter differently for systemic risk depending on the considered regional level.

– Insert Table 2.5 here –

We also relate SRISK to information about the complexity of banks' (international) activities. The more complex the international organization of a bank, the more difficult it will be to restructure and possibly resolve in times of distress. This, in turn, may create bailout expectations. In fact, the classification of banks as G-SIFIs by the FSB has increased the implicit state subsidies enjoyed by these banks (SVR, 2014). Implicit subsidies may be particularly relevant for large banks, given that no effective regime for the resolution of large, internationally active banks was in place during the time period of our study. Even though the international reform agenda is moving in the right direction, bank resolution is still largely uncharted territory. We thus control for the assignment of the G-SIFI status by the FSB by creating a dummy which equals one for the years in which a bank was considered a G-SIFI and zero otherwise. Furthermore, we construct a dummy variable for SSM banks that equals one if a bank took part in the ECB's first comprehensive assessment as announced in 2013 and zero otherwise.

Also, we capture the degree of complexity of international banks by drawing on data provided by the Bankscope Ownership Module. This data source contains information on banks' subsidiaries and allows two measures of a bank's degree of internationalization to be calculated, whereas we consider only banks' subsidiaries for which the headquarters is the direct (level one) and ultimate (at least 50%) owner. First, we calculate the share of foreign subsidiaries in total subsidiaries. To differentiate between banks with a high share of foreign subsidiaries, we create a dummy that is one if this share is larger than the sample average. Banks with a higher share of foreign subsidiaries might be more difficult to resolve as different national authorities have to coordinate their actions and distribute the losses. Second, geographical complexity (or diversification) is measured as a normalized Herfindahl index (HHI) across the different regions in which a bank's domestic and foreign subsidiaries are located (Cetorelli et al., 2014). It is defined such that higher values indicate a higher degree of complexity, i.e. the bank has subsidiaries equally distributed across many different countries. Banks with a higher degree of geographical complexity might have more diversification opportunities and be able to buffer country-specific shocks. We again determine an indicator variable that is one if a bank has a high geographical HHI (above the sample average) and zero otherwise.

Following the criteria chosen by the ECB to determine whether a bank should be supervised by the SSM, we also control for financial assistance. To do so, we draw on the European Commission's State Aid Register (EC, 2015). We create a dummy which equals one if the bank has received state aid and zero otherwise. More specifically, whenever a bank in our sample appears as a case in the State Aid Register, we assign a value of one to the state aid dummy at the time when the decision about the state aid request was made.

In Table 2.6, we show the average values of SRISK for subsamples of banks. We differentiate between banks that have received state aid at time t, have been assigned the G-SIFI status at time t, and SSM banks. On average, SRISK is higher for banks classified as G-SIFIs compared to those banks which have not been assigned G-SIFI status. Average values are also larger for banks which have received state aid or are supervised by the SSM. This points toward the fact that ECB criteria such as financial assistance indeed matter for systemic risk, and also that established classifications for whether a bank is systemically important such as G-SIFI status correlate with our measure for systemic risk.

– Insert Table 2.6 here –

2.4.2 Country-Level Determinants of Systemic Risk

To control for the general macroeconomic environment, we include in our regression model a country's annual GDP growth and the inflation rate. In robustness tests, we add further macro controls. We include a country's government debt relative to GDP and the ratio of domestic credit to GDP. Higher public debt positions might reflect unsustainable fiscal policies, and higher private credit-to-GDP ratios might capture higher levels of financial development but can also be related to unsound expansion in the financial sector.

In line with the ECB's criteria for determining whether a bank falls under the SSM, we also look at banks' international activities. Unfortunately, bank-level data on banks' cross-border activities is not publicly available. We thus resort to aggregate data on banks' cross-border activities from the Consolidated Banking Statistics of the Bank for International Settlements to measure the importance of cross-border activities. To obtain at least a proxy for banks' degree of internationalization, we use data from the Bankscope Ownership Module as described above. This allows us to control for a bank's ratio of foreign subsidiaries to total subsidiaries as well as the spread of subsidiaries across geographical regions.

Finally, we control for economic health and competitiveness by including a country's current account (in % of GDP). The sustainability of the banking system as a whole is captured by including the aggregate capital to assets ratio.

2.5 Main Results

2.5.1 The Empirical Model

With measures of systemic risk and data on potential drivers of such risk at hand, we can now turn to our second research question: What are the determinants of banks' contribution to systemic risk at the national level compared to the Euro-area level? And do the drivers of systemic risk differ at the national level and at the Euro-area level? We estimate an empirical model similar to Laeven et al. (2016) and Laeven et al. (2014), explaining SRISK derived from equations 2.4 - 2.5 by bank-level variables:

$$\begin{aligned} SRISK^R_{ijt} &= \alpha_i + \gamma_t + \beta_1 \Delta GDP_{jt} + \beta_2 Inf_{jt} \\ &\quad + \beta_3 X_{ijt-1} + \beta_4 G - SIFI_{ijt} + \beta_5 StateAid_{ijt} + \epsilon_{ijt} \end{aligned} \tag{2.7}$$

Our panel consists of i = 1,..., 75 banks across j = 1,..., 15 countries and t = 2005,..., 2013 years, where R denotes the level at which systemic risk is measured, that is Euro-area (EA) or national (N). We account for bank-invariant characteristics by including bank fixed effects α_i. Common macroeconomic developments are captured through year fixed effects (γ_i). To account for time-varying developments at the country level, we include GDP growth and the inflation rate.[15]

Time-varying, bank-specific factors are captured by X_{ijt-1} . These include proxies for bank size (log of total assets), the business model (loan share, share of non-interest income), profitability (RoA), the quality of loans (share of non-performing loans), liquidity risk (share of short-term debt). In addition, we include a G-SIFI dummy ($G-SIFI_{ijt}$), which is equal to one if a bank is assigned G-SIFI status at time t and zero otherwise, and a dummy for $StateAid_{ijt}$, which equals one if a bank received state aid in a particular year and zero otherwise. Standard errors are clustered at the level of the individual bank.[16] To compare whether the impact of a given variable differs from a national or European viewpoint, we additionally run seemingly unrelated regressions based on our estimation sample with (i) $SRISK^{EA}$ and (ii) $SRISK^N$ as the dependent variables. We then conduct Chi-squared tests of equality of coefficients resulting from these regressions. In the regression tables, we report the difference in coefficients joint with the statistical

[15] We control for alternative country-level drivers of systemic risk in robustness tests.

[16] We have also conducted regressions with two-way clustering to control for serial correlation across time for one bank and serial correlation across banks for one year. Results can be obtained upon request.

significance of these tests.

2.5.2 Baseline Regression Results

In Table 2.7, we regress SRISK measured at different regional levels on bank-level variables capturing possible drivers of risk. Columns 1-3 show results for the full sample of banks over the period 2005-2013. Columns 4-6 focus on the crisis period (2007-2012). This takes into account that the outbreak of the financial crisis represents a structural break in financial markets and was accompanied by changes in the regulatory framework. This, in turn, might impact the relevance of some drivers of systemic risk.

– Insert Table 2.7 here –

For the full sample, we find a positive and significant relationship between bank size and systemic risk. This finding is not very surprising, given that large banks are typically considered to be more systemically important than smaller banks. It also confirms previous research (Laeven et al., 2016; Laeven et al., 2014). The effect of bank size becomes more pronounced during crisis times (Columns 4-5). For both samples, we find that size matters significantly more for the national contribution to systemic risk (Columns 3 and 6). Our proxy for bank size - the log of total assets - does not answer the question as to through which channel large banks become systemically important. Large banks, for instance, are more active internationally than smaller banks, and they operate with more complex business models. In Section 2.5.3, we will thus include interactions between size and other bank-level explanatory variables to learn more about the specific links between size and systemic risk.

Two additional variables, the G-SIFI dummy and the dummy for state aid, capture the impact of bank size and show, at the same time, the role of regulatory policy. The correlation between the dummy indicating whether a bank has received state aid and systemic risk is positive and highly significant. This is not surprising because rescue measures were targeted at the larger banks in financial distress. However, given that the proxy for bank size does not lose significance when we include the dummy for state aid, this suggests that additional information is included in the later variable. The G-SIFI dummy becomes significant only for the crisis sample. This might go back to the fact that banks received G-SIFI status only from 2011 onwards, which, in this reduced sample, gives the variable higher explanatory power.

We measure the retail orientation of a bank using the loan share and the share of non-interest income in total income. The link between a bank's business model and its contribution to systemic risk is not clear-cut. On the one hand, banks with a high share of loans in total assets have a lower degree of systemic risk, and this effect is more pronounced for the crisis period. The point estimate (in absolute terms) is higher for SRISK at the national market. The difference in the point estimates is also statistically significant as shown by the result of the Chi-squared test for equality of coefficients in Column 3.[17] On the other hand, banks with a higher share of non-interest income contribute (weakly) less to systemic risk during crisis times. Overall, these findings caution against jumping to conclusions regarding the superiority of specific business models when it comes to the contribution to systemic risk.

Another variable which has a quite robust and significant correlation with systemic risk is bank profitability. More profitable banks have a higher level of systemic risk. This effect does not differ much across regional levels. One explanation for this positive correlation could be that banks' returns are used to calculate both, RoA and SRISK. However, we derive our explanatory variable for profitability from annual balance sheet data whereas SRISK is calculated from daily stock market data. This should weaken concerns that the correlation between SRISK and profitability is spurious. In robustness tests, we exclude profitability (Table B.III) from the set of explanatory variables, and the main results are unchanged.

The non-performing loan ratio has a positive sign - banks with a higher share of bad loans in their balance sheet contribute more to systemic risk.

[17]E.g. an increase of the loan share by one standard deviation relates to a Euro-area (national) SRISK reduced by 2.87 (2.98) billion Euros.

While the coefficient is not significant itself, the result in Columns 3 and 6 implies that the effect is stronger at the Euro-area level. Our proxy for banks' exposure to liquidity risk is insignificant in both samples. This holds for the short-term debt ratio as well as for the liquid assets to total assets ratio (Table B.III). One channel through which an aggregate shortage of capital in the banking system could affect individual banks is their ability to liquidate assets prematurely. Therefore, one would expect liquidity risk to matter. Our results suggest, instead, that systemic risk is driven mostly by the profitability of a bank and the structure of its assets.

2.5.3 Interactions with Size Measures

Size is an important factor affecting banks' contribution to systemic risk (Laeven et al., 2016). Some reform proposals thus go so far as to impose outright restrictions on bank size (Johnson and Kwak, 2010). However, bank size might be a proxy for other factors that affect banks' contribution to systemic risk, such as the degree of internationalization or the degree of interconnectedness. Also, size is an important criterion of whether a bank is supervised by the SSM. Hence, our sample of SSM banks includes mostly large banks, and a supervisor might need to know which criteria besides size matter for banks' contribution to systemic risk.

In order to analyze whether the determinants of systemic risk are different for large and small banks, Table 2.8 includes interactions of bank-level variables and bank size measured by the log of total assets (Columns 1-2) as well as the dummy that indicates whether a bank is supervised by the SSM (Columns 4-5). Large banks may, for instance, rely more on short-term financing, which exposes them to rollover risk if liquidity shocks occur. Large banks might also find it easier to diversify and invest in non-traditional activities like trading. These, in turn, could affect banks' contribution to systemic risk (Gennaioli et al., 2013).

– Insert Table 2.8 here –

The first result is that, when including interaction terms with log of total assets, the remaining variables by and large retain their signs. Statistical significance increases. Also, we find that a higher share of non-performing loans is positively and significantly related to SRISK. The share of non-interest income gains in significance. Turning to the significance of the interaction terms, we find that the negative impact of non-interest income on systemic risk, the positive impact of profitability, and the positive effects of non-performing loans seem to be stronger for the larger banks.

To obtain a more comprehensive view on the relationship between size and bank-level determinants of systemic risk, we plot average marginal effects of the different explanatory variables conditional on bank size (Figures 2.2 - 2.3). These plots show how the economic importance of each of the drivers of systemic risk varies with bank size. The plots confirm the results of the point estimates: the share of loans in total assets is highly significant and negative for a bank of average size. The sign of the non-interest income even reverses itself: it is positive for smaller banks but turns negative when bank size increases. This illustrates the fact that determinants of systemic risk are not homogeneous across banks but can differ for small and large banks. The marginal effects of the return on assets ratio and the non-performing loans ratio are significantly positive for larger banks, and they increase with size.

– Insert Figures 2.2 and 2.3 here –

Regarding the interaction of the SSM dummy with bank-level variables, our results suggest that bank size and the loan share are significantly related to SRISK for non-SSM banks (Table 2.8, Columns 4-5). Banks that are supervised by the SSM contribute differently to systemic risk: the interaction term is significantly negative for the share of non-interest income, and significantly positive for profitability and the share of non-performing loans.[18]

[18]Note that a dummy for the establishment of the SSM is not included because it is captured by bank fixed effects.

In sum, we find no qualitative differences in the drivers of systemic risk whether we take a national or European perspective. However, the quantitative magnitudes are significantly different for some variables like the loan share or profitability. For example, at the national level, systemic risk decreases by more compared to the Euro-area level if banks have a higher loans share, and this effect is stronger for larger banks (Column 3). This suggests that a more traditional business model as captured by a higher loan share is likely to generate a buffer against systemic shocks. Yet, the economic magnitudes of the effects differ between the national and the European level. The reason for that might be that banks that operate more at the supranational level are more engaged in wholesale activities.

2.5.4 Interactions with Internationalization Measures

Another dimension of systemic risk is a bank's degree of internationalization. A priori, the effect of financial integration on systemic risk is not obvious. One the one hand, more international links among banks can be a source of systemic risk if they facilitate the spillover of shocks. One the other hand, well-distributed international exposures can serve as buffers against domestic shocks and offer diversification opportunities. Also, Hale and Obstfeld (2016) show that greater financial integration in the Euro area fostered the build-up of large current account imbalances in the peripheral countries. To obtain some insights into the effects at work, we interact the bank-level determinants of systemic risk with indicator variables for (i) banks' share of foreign subsidiaries and (ii) banks' degree of diversification regarding the distribution of subsidiaries across different regions.[19]

Results are shown in Table 2.9. For the average bank, we find that a higher share of foreign subsidiaries relates positively to banks' contribution to systemic risk (Columns 1-2). The relationship becomes stronger for banks with a higher share of non-interest income and more profitable banks. In contrast, a higher degree of geographical diversification shows a negative sign but does not have a significant effect for the average bank (Columns 4-5).

[19]See the appendix B.I or section 2.4.1 for a detailed description of these variables.

The reduction of systemic risk due to diversification is more pronounced for banks with a higher share of non-interest income. This again points in the direction that the negative correlation of non-interest income with systemic risk is attributable to diversification opportunities.

– Insert Table 2.9 here –

2.5.5 Robustness Tests

We test the robustness of our results by changing the sample, including additional bank-level variables, controlling for short-sale bans and modifying the way in which SRISK has been calculated. These tests are conducted in six steps and for reasons of space all Tables R1-R6 can be found in the supplementary material.

First, we restrict the sample to cover only banks that are supervised by the SSM (Table B.II). In line with the results in Table 2.8 where we interacted bank-level variables with the SSM dummy, we find that bank size is to a minor extent associated with SRISK. This can go back to the fact that the sample of SSM banks is a rather homogeneous sample in terms of bank size, i.e. only large banks are included, causing bank size to lose explanatory power. For this sample, size has a stronger qualitative effect for banks' contribution to systemic risk at the national level.

Regarding the other bank-level variables, we confirm that systemic risk decreases in the share of loans on banks' balance sheets and increases in the degree of profitability. In this reduced sample, significance tends to be stronger. As already indicated by the significant results for the interaction terms of the bank-level variables and the SSM dummy (Table 2.8, Columns 4-5), for the sample of SSM banks, we find that the ratio of non-interest income to total income and the share of non-performing loans correlate significantly with banks' systemic risk. As observed in Table 2.7, the G-SIFI dummy only becomes significant during the crisis period.[20]

[20] We have also conducted robustness tests restricting the sample to developed countries following the "MSCI Global Investable Market Indices Methodology" as of 2013. Excluding Cyprus, Malta, Slovakia and Slovenia, results remain robust for the crisis sample.

Second, we vary bank-level determinants of systemic risk (Table B.III). We exclude the variable return on assets which might be correlated with a bank's stock market returns and thus SRISK (Columns 1-2) and include the equity ratio (Columns 3-4). We confirm the results for bank size, the loan share, and the state aid dummy if we exclude the return on assets. Including the equity ratio affects the significance of bank size, which might be due to multicollinearity. The other variables remain significant while the equity ratio itself is significant with a negative sign, suggesting that banks' contribution to systemic risk decreases as the capital buffer increases.

In Columns 5-6, we include the ratio of short-term debt to liquid assets to capture a bank's maturity mismatch. The higher the short-term debt is relative to liquid assets, the more difficult it is to meet unexpected withdrawals of short-term deposits. The ratio of short-term debt to total liabilities is excluded as the two variables are both composed of the short-term debt position. As expected, banks with a higher reliance on short-term funding but lower amounts of liquid assets, have a higher contribution to systemic risk.

In Columns 7-8, we include the market-to-book value of equity, whereas higher values indicate that the market has a positive assessment of the bank's performance. However, this variable has no significant coefficient. To test whether we also observe a positive effect if we control for a bank's relative importance for the economy, we include a bank's total assets to GDP (in %) instead of the log of total assets (Columns 9-10). The significant and positive coefficient reflects the fact that the relative importance of a bank for the economy, too, relates to banks' contribution to systemic risk. Our final control variable is the ratio of liquid assets to total assets which we include instead of the loan share (Columns 11-12). However, this dimension of liquidity does not seem to play a relevant role within our regression sample.

Third, we include other macro controls (Table B.IV). Our main result for the positive relationship of bank size, a lower loan share and higher profitability with systemic risk remain mostly robust. As regards the additional

Coefficients partially lose significance for the full sample period, most likely due to reduced sample size.

control variables, banks contribute more to systemic risk if the economy is highly leveraged, i.e. when public debt or domestic credit are high.

Fourth, we change the way the SRISK measure is calculated (Table B.V). In Columns 1-2, we take the log of SRISK to account for skewness in the distribution. In Columns 3-4, we do not base the calculation of SRISK on the market index but exchange it by a stock price index related to the banking sector. In Columns 5-6, we do not take the mean across daily SRISK values to aggregate to the annual level, but we take the median to reduce the effect of outliers. In Columns 7-8, we set the prudential capital ratio to 5.5 (Acharya and Steffen, 2012). In general, our results remain robust for bank size, the loan share, and the state aid dummy. The coefficient of return on assets partly loses in significance while keeping its positive sign.

Fifth, we account for the fact that, during the financial crisis, several countries introduced short-sale bans. This could result in mispricing and thus introduce distortions in the calculation of SRISK. According to Beber and Pagano (2013), there are ten countries in our sample which introduced such bans in the years 2008-2009.[21] This should reduce concerns about confounding factors in the pricing of financial stocks at different points in time for different countries. Also, we average the daily SRISK series to aggregate it to the yearly frequency. This helps further reduce confounding pricing factors that prevail only in the short run.

To verify whether the introduction of short-sale bans affects our regression results, we include a dummy variable that takes a value of one for the period 2008-2009 and the countries that introduced a short-sale ban. The results remain in general robust (Table B.VI). Only the coefficient of the non-interest income for the crisis sample loses significance. The short-sell ban variable itself has a positive and significant coefficient. This suggests that banks' systemic riskiness has been at higher levels during periods, in which a country maintained a short-sell ban.

[21] Austria, Belgium, France Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain introduced short-sale bans in September or October 2008 for around 234 to 277 days.

Finally, we account for the fact that Euro-area stock market indices can be driven by national developments, but more importantly, that national stock market indices can be driven by Euro-area developments. Euro-area and national stock market indices are used to calculate SRISK at the Euro-area and national level, respectively. Hence, this can imply that the systemic risk measure at the two regional levels are not completely separable and contain partly the same information. Thus, we conduct an additional set of robustness tests, which are shown in Table B.VII and briefly summarized below. For more details on data and estimations regarding this part of the robustness tests, please see Appendix B.IV in the supplementary material.

For comparison, the first two columns of Table R6 show the result of our baseline model where the dependent variable is either SRISK at the Euro-area level (Column 1) or SRISK at the national level (Column 2). In Column 3, we compute banks' SRISK at the Euro-area level but use MSCI stock market indices for the Euro area, which exclude the national index from the respective banks' country of location. This reduces national influences from the Euro-area index. For comparison, we repeat the analysis using the MSCI national stock market index to compute banks' SRISK at the national level (Column 4).

To further address this concern, we extract Euro-area developments from national stock returns to improve upon the measurement of banks' systemic risk at the national level. We make use of a principal component analysis to generate a Euro-area factor that is common to all sample countries. This common factor is used to extract Euro-area developments from national stock market returns by means of a regression analysis. The residuals of this regression analysis, which reflect developments that can not be explained by Euro-area factors, are used for the calculation of banks' SRISK at the national level. Columns 5 and 6 show results derived from two different ways of generating the Euro-area factor.

In sum, our results remain robust across the different specifications. This holds for sign and significance of the coefficients. The non-interest income variable now also turns significant, which has been previously observed only for the crisis sample. However, bank size captured by the log of total assets loses significance. Part of this result might be explained by the G-SIFI dummy becoming significant in Columns 3-6.[22]

2.6 Conclusion

The establishment of the European Banking Union shifted the regulation and supervision of systemically important banks to the Euro-area level. The ECB-based, centralized Single Supervisory Mechanism (SSM) is designed to apply uniform microprudential rules across countries. While national supervisors are mainly in charge of macroprudential policies, the SSM has the power to tighten certain national macroprudential policies. Whether or not it is in the interest of the European supervisor to overrule national macroprudential authorities depends, inter alia, on their assessment of systemic risk. In this paper, we analyze whether the drivers of systemic risk differ depending on whether regulators adopt a national or a European perspective.

We use a measure of systemic risk - SRISK - that was proposed by Brownlees and Engle (2017). SRISK measures the marginal contribution of a bank to an aggregate shortfall of capital in the banking system. We calculate this measure for about 80 publicly listed European banks. Our sample spans the years 2005-2013. We distinguish between the contribution of banks to a shortfall of capital at the national and at the Euro-area level. The two measures of systemic risk can differ because banks have different market shares at home and abroad or because they have different degrees of diversification and thus different return correlations. We then analyze the determinants of systemic risk at the national and at the Euro-area level. Our research delivers three main findings.

First, on average, banks' contribution to systemic risk at the national level is slightly higher than that at the Euro-area level. This suggests that most banks have stronger links with national than Euro-area stock markets. Based on this assessment, a national supervisor would be more likely than

[22]For brevity, we only report results for the full sample. Conclusions are qualitatively the same for the crisis sample and can be obtained upon request.

a supranational supervisor to consider a bank to be systemically relevant. However, this does not hold for all banks and countries in the sample. Especially large and internationally active banks with, presumably, a higher exposure to other Euro-area countries are likely to contribute more to systemic risk at the Euro-area level. As regards time trends, systemic risk increased during the recent financial crisis.

Second, we analyze the determinants of banks' contribution to systemic risk. Systemic risk increases in bank size and in bank profitability. There is no direct link between the reliance of banks on more traditional activities and the degree of systemic importance: banks with a high share of loans are less systemically important, yet the same holds for banks with a high share of non-interest income in total revenue. These results are stronger for the larger banks in the sample. We do not find a significant relationship between liquidity risk on the asset or the liability side of the balance sheet and systemic risk.

Third, the main qualitative results hold irrespective of the regional level considered. This might suggest that there is no trade-off in assigning macro-prudential oversight to the national level versus the Euro-area level as concerns the micro-level determinants of bank risk. But while the determinants do not change with the regional level, banks' contribution to systemic risk can still differ in magnitude. Our results show that there can be specific features which explain why banks' contribution to systemic risk at the national level is different from that at the Euro-area level. The mitigating impact of the loan share on systemic risk, for instance, is stronger at the national level than at the Euro-area level.

Our results have a couple of interesting implications for the regulatory debate. The fact that the qualitative determinants of systemic risk differ little between regulatory levels implies that incentives for information collection should be largely aligned. The reason is that national and supranational supervisors might want to gather information on the same variables driving banks' systemic riskiness. At the same time, this does not mean that incentives for regulatory intervention might be aligned as well. The political economy of interventions may well differ across regional levels, but an analysis of a potential “inaction bias” would require taking a look at actual supervisory action. However, analyzing actual regulatory action is beyond the scope of the present study. Also, our results suggest that some drivers of systemic risk, such as bank profitability, are not included in the standard classification schemes for significant institutions and should thus be subject to additional surveillance.

Tables and Figures

Table 2.1: Summary Statistics for Stock Market Data.

		Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
Austria	DS Bank index	2,347	-0.00011	0.024	-0.13	7.89	-0.14	0.14
	STOXX index	2,301	0.00002	0.017	-0.15	21.66	-0.17	0.17
Belgium	DS Bank index	2,347	-0.00055	0.029	-0.42	11.3	-0.25	0.19
	STOXX index	2,301	-0.00001	0.013	-1.23	17.8	-0.16	0.09
Cyprus	DS Bank index	2,347	-0.0011	0.027	0.22	6.79	-0.12	0.16
	STOXX index	2,299	-0.0006	0.025	-0.28	10.23	-0.24	0.16
Finland	DS Bank index	2,347	0.00033	0.023	0.08	11.22	-0.18	0.2
	STOXX index	2,301	0.00006	0.018	0.1	23.81	-0.19	0.19
France	DS Bank index	2,347	-0.00015	0.025	0.31	9.61	-0.13	0.18
	STOXX index	2,301	0.00011	0.015	-0.03	16.68	-0.15	0.13
Germany	DS Bank index	2,347	-0.00028	0.022	-0.05	12.97	-0.16	0.16
	DS Bank index	2,301	0.00024	0.016	0.03	42.04	-0.2	0.19
Greece	STOXX index	2,347	-0.00142	0.034	0.35	8.66	-0.16	0.22
	DS Bank index	2,301	-0.0005	0.021	0.11	7.13	-0.1	0.15
Ireland	STOXX index	2,347	-0.00152	0.048	-1.44	35.8	-0.75	0.3
	DS Bank index	2,301	-0.00014	0.016	-0.4	8.13	-0.11	0.09
Italy	STOXX index	2,347	-0.00041	0.022	-0.1	7.54	-0.12	0.16
	DS Bank index	2,301	-0.0002	0.016	-0.04	10.62	-0.12	0.11
Malta	STOXX index	2,347	0.0001	0.011	0.17	16.25	-0.09	0.1
	DS Bank index	2,299	0.00008	0.013	0.17	21.92	-0.11	0.13
Netherlands	STOXX index	2,347	-0.00125	0.035	-22.79	845.05	-1.3	0.15
	DS Bank index	2,301	0.00014	0.014	-0.13	24.33	-0.14	0.14
Portugal	DS Bank index	2,347	-0.00066	0.021	0.09	8.21	-0.12	0.13
	STOXX index	2,301	-0.00017	0.013	-0.07	10.89	-0.1	0.1
Slovakia	DS Bank index	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	STOXX index	2,299	-0.00002	0.025	-0.66	16.58	-0.29	0.15
Slovenia	DS Bank index	2,347	-0.00243	0.027	-2.88	37.88	-0.33	0.19
	STOXX index	2,299	-0.00015	0.012	-0.6	11.78	-0.1	0.09
Spain	DS Bank index	2,347	-0.00014	0.021	0.49	12.14	-0.14	0.19
	STOXX index	2,301	-0.00001	0.016	0.16	9.41	-0.1	0.14
Euro Area	DS Bank index	2,347	0.00011	0.013	-0.14	10.38	-0.08	0.09
	STOXX index	2,347	-0.00032	0.023	0.15	8.32	-0.11	0.18
Banks' Stock Returns		178,346	-0.00056	0.03	-1.25	131.11	-1.54	1.07
Banks' Market Values		175,422	8.13	15.18	2.79	10.94	0.02	98.58
Banks' Total Liabilities		179,676	192.02	385.78	2.84	11.02	0.06	2,162.04

Notes: This table shows summary statistics for the daily stock market data (excluding weekend days). The national indices (STOXX and DS Bank index), the Euro-area index (STOXX and DS Bank index) and individual banks' stock returns cover the period 1/1/2005-12/31/2013. The stock returns of the 80 banks are taken from consolidated accounts. Both the returns of the market indices and banks' stock returns are calculated as first log differences. Banks' market values and total liabilities are in billion Euros. For more details on data sources, see the description in the Data Appendix.

TABLE 2.2: Summary Statistics for SRISK.

a) Daily	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
SRISK (Euro area, Market Index)	177,563	10.75	25.55	3.26	14.23	-36.96	171.03
SRISK (National, Market Index)	174,066	11.01	25.66	3.23	13.99	-39.93	170.48
SRISK (Difference, Market Index)	174,066	-0.25	0.88	-10.02	490.67	-49.8	18.81
SRISK (Euro area, Bank Index)	177,563	10.78	25.6	3.26	14.23	-36.66	170.93
SRISK (National, Bank Index)	175,216	11.25	25.87	3.24	14.1	-34.2	171.64
SRISK (Difference, Bank Index)	175,216	-0.33	1.22	4.89	80.01	-16.34	28.86
b) Yearly	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
SRISK (Euro area, Market Index)	687	10.66	25.34	3.27	14.23	-17.48	158.21
SRISK (National, Market Index)	687	10.91	25.46	3.23	13.96	-20.15	157.77
SRISK (Difference, Market Index)	687	-0.25	0.62	-2.93	16.4	-4.5	2.76
SRISK (Euro area, Bank Index)	687	10.68	25.4	3.27	14.22	-17.61	157.87
SRISK (National, Bank Index)	678	11.15	25.67	3.24	14.11	-15.84	160.15
SRISK (Difference, Bank Index)	678	-0.33	1.08	3.63	44.03	-5.39	11.54

Notes: This table shows summary statistics for the systemic risk measure SRISK. The sample comprises 80 banks listed on the stock market in the Euro area and the period 1/1/2005-12/31/2013. SRISK is calculated from stock market data and expressed in billion Euros. We proceed like Brownlees and Engle (2017) to calculate a bank's marginal contribution to systemic risk when there is an aggregate capital shortfall in the national, respectively Euro-area market (Section 3). The calculation makes use of either the market index or the bank index. Panel (a) is based on daily data; Panel (b) provides summary statistics for SRISK averaged to yearly frequency.

TABLE 2.3: Summary Statistics for the Difference Between Euro-Area and National SRISK.

	Number of Banks Per Year with $\Delta SRISK_{it} > 0$									Total Nr. of Banks
	2005	2006	2007	2008	2009	2010	2011	2012	2013	at Time t
Austria	1	0	0	0	0	0	2	2	1	5
Belgium	0	0	0	0	0	2	2	2	2	2
Cyprus	0	0	0	0	0	0	0	0	0	2
Finland	2	1	3	2	2	1	2	2	1	3
France	5	6	4	6	12	10	13	10	10	17
Germany	5	5	6	6	5	6	6	5	5	6
Greece	0	0	0	0	0	0	0	0	0	6
Ireland	2	0	0	0	0	0	2	2	1	2
Italy	3	1	1	0	0	2	2	0	1	18
Malta	0	0	0	0	0	0	0	0	0	3
Netherlands	2	2	1	1	1	2	2	1	1	2
Portugal	0	0	0	0	0	0	0	0	0	3
Slovakia	0	0	0	0	0	0	0	0	0	1
Slovenia	2	2	1	0	0	0	0	0	2	2
Spain	3	3	2	2	2	2	1	1	0	8
Total	25	20	18	17	22	25	32	25	24	80

Notes: This table shows the number of banks for which the average difference between $SRISK_{it}^{EA}$ and $SRISK_{it}^{N}$ is greater than zero. The sample comprises 80 publicly listed banks in the Euro area over the period 2005-2013. In a first step, we calculate the difference between $SRISK_{it}^{EA}$, measured at the Euro-area level, and $SRISK_{it}^{N}$, measured at the national level, based on daily data for each bank. In a second step, we average this difference for each bank by year. Based on these average differences, we count the number of banks per country and year for which the difference is greater than zero, i.e. the average contribution to systemic risk measured by SRISK is higher at the Euro-area level. The last column shows the total number of banks in our sample.

TABLE 2.4: Summary Statistics for the Bank-Level Variables.

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
Equity ratio (%)	430	6.55	3.11	2.17	12.7	1.45	24.6
Liquid assets (%)	430	17.11	10.23	1.31	5.25	2.51	61.56
Loan share (%)	430	62.21	17.13	-1.08	3.95	3.94	88.57
Market to book value (%)	415	1.19	0.78	0.99	3.51	0.06	3.84
Maturity mismatch (%)	430	0.01	0.05	8.14	68.62	0	0.48
Non-interest income (%)	430	21.14	8.87	2.06	13.45	3.73	78.44
Non-performing loans (NPL) (%)	430	5.24	4.26	1.56	5.96	0.41	25.45
RoA (%)	430	0.58	0.94	-2.63	17.12	-5.98	2.36
Short-term debt (%)	430	20.11	14.14	1.3	5.29	0.57	73.48
Total assets (log, k USD)	430	18.07	1.93	-0.09	2.38	13.39	21.66
Total assets to GDP (%)	430	34.28	45.95	2.02	7.28	0.03	231.58

Notes: This table shows summary statistics for the explanatory variables. The sample is based on all Euro-area banks listed on the stock market which appear in our benchmark regression sample and covers the period 2005-2013. Equity ratio is the equity to total assets ratio (in %). Liquid assets is the share of liquid assets in total assets (in %). Loan share gives the ratio of total loans to total assets (in %). Market to book value denotes the market to book value of equity. Maturity mismatch reflects the ratio of short-term deposits to liquid assets (in %). Non-interest income is measured relative to total income (in %). NPL is defined as impaired loans over gross loans (in %). RoA is the ratio of operating profits to total assets (in %). Short-term debt indicates the ratio of short-term debt to total liabilities (in %). Total assets denote the logarithm of bank assets in thousands of USD. Total assets to GDP is the ratio of a bank's total assets to the country's GDP (in %). For more details, see the description in the Data Appendix.

Table 2.5: Difference in Means of Bank-Level Variables by ΔSRISK.

	$\Delta SRISK_{it} < 0$		$\Delta SRISK_{it} > 0$		T-test of equal means		
	Obs.	Mean	Obs.	Mean	ΔMean	t-value	p-value
Equity ratio (%)	341	6.71	89	5.96	0.75	2.02	0.04
Liquid assets (%)	341	16.51	89	19.41	-2.9	-2.39	0.02
Loan share (%)	341	63.7	89	56.53	7.17	3.56	0
Market to book value (%)	329	1.28	86	0.88	0.4	4.3	0
Maturity mismatch (%)	341	0.01	89	0	0.01	1.2	0.23
Non-interest income (%)	341	20.92	89	21.98	-1.06	-1	0.32
Non-performing loans (NPL) (%)	341	5.44	89	4.49	0.95	1.87	0.06
RoA (%)	341	0.63	89	0.36	0.27	2.46	0.01
Short-term debt (%)	341	17.79	89	29.03	-11.24	-7.04	0
Total assets (log, k USD)	341	18.01	89	18.3	-0.29	-1.28	0.2
Total assets to GDP (%)	341	35.33	89	30.25	5.08	0.93	0.35

Notes: This table shows mean values for the explanatory variables for the subsample of observations for which $\Delta SRISK_{it} < 0$ and $\Delta SRISK_{it} > 0$, respectively. The last three columns show the difference in means, as well as the t-value and p-value derived from testing whether the means differ significantly between those two subsamples. The sample is based on all publicly listed Euro-area banks which appear in our benchmark regression sample and covers the period 2005-2013. Equity ratio is the equity to total assets ratio (in %). Liquid assets is the share of liquid assets in total assets (in %). Loan share gives the ratio of total loans to total assets (in %). Market to book value denotes the market to book value of equity. Maturity mismatch reflects the ratio of short-term deposits to liquid assets (in %). Non-interest income is measured relative to total income (in %). NPL is defined as the fraction of impaired loans relative to gross loans (in %). RoA is the ratio of operating profits to total assets (in %). Short-term debt indicates the ratio of short-term debt to total liabilities (in %). Total assets denote the logarithm of bank assets in thousands of USD. Total assets to GDP is the ratio of a bank's total assets to the country's GDP (in %). For more details, see the description in the Data Appendix.

Table 2.6: Systemic Risk, State Aid, and Complexity.

	State aid		G-SIFI		SSM	
	Yes	No	Yes	No	Yes	No
SRISK (Euro area)	35.76	11.96	79.43	9.32	17.19	3.84
SRISK (National)	35.79	12.3	80.44	9.6	17.64	3.88

Notes: This table shows mean values for SRISK (yearly, bn Euros) at the Euro-area and national level for the period 2005-2013. The first two columns show results for the subsample of banks for which the state aid dummy equaled one at a specific date and for the observations for which the state aid dummy was zero. Column (3) shows results for the subsample of banks for which the G-SIFI dummy equaled one at a specific date and for the observations for which the G-SIFI dummy was zero (Column (4)). Columns (5) and (6) compare banks which were required to participate in the comprehensive assessment of the ECB, "SSM banks", with non-SSM banks. For more details, see the description in the Data Appendix.

TABLE 2.7: Determinants of Systemic Risk - Bank-Level Variables.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			Crisis sample		
	SRISK EA	SRISK NAT	ΔCoefficient	SRISK EA	SRISK NAT	ΔCoefficient
GDP growth$_t$	-0.146	-0.158	0.012	-0.235	-0.246	0.011
	(0.218)	(0.224)		(0.169)	(0.175)	
Inflation rate$_t$	-0.860	-0.880	0.020	-0.367	-0.378	0.011
	(0.531)	(0.541)		(0.352)	(0.355)	
Log assets$_{t-1}$	8.616**	9.165**	-0.548**	11.688***	12.406***	-0.718*
	(3.414)	(3.478)		(4.164)	(4.327)	
Loan share$_{t-1}$	-2.877*	-2.983*	0.106*	-3.373**	-3.451**	0.078
	(1.500)	(1.524)		(1.605)	(1.648)	
Non-interest income$_{t-1}$	-1.040	-1.032	-0.008	-0.991*	-0.996*	0.005
	(0.736)	(0.740)		(0.587)	(0.591)	
RoA$_{t-1}$	0.994*	1.041*	-0.046	0.896**	0.930**	-0.034
	(0.570)	(0.601)		(0.414)	(0.438)	
NPL$_{t-1}$	0.876	0.785	0.091**	0.264	0.120	0.144**
	(0.644)	(0.668)		(0.810)	(0.850)	
Short-term debt$_{t-1}$	-0.493	-0.553	0.060	-0.939	-1.009	0.070
	(0.776)	(0.796)		(0.976)	(1.004)	
G-SIFI$_t$	5.624	5.598	0.026	7.898***	7.733**	0.165
	(3.955)	(3.984)		(2.965)	(3.033)	
State aid$_t$	4.776***	4.789***	-0.012	5.002***	5.045**	-0.043
	(1.675)	(1.751)		(1.863)	(1.944)	
Observations	430	430	-	328	328	-
R^2	0.336	0.330	-	0.414	0.406	-
Number of banks	75	75	-	66	66	-

Notes: This table reports fixed effects regressions for the full sample (2005-2013) and the crisis sample (2007-2012) that are based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros). In Columns (1) and (4), the reference level is the Euro area and in Columns (2) and (5), the national level. In Columns (3) and (6), the difference in coefficients joint with the significance level of Chi-squared tests for equality of coefficients resulting from seemingly unrelated regressions are reported. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %). These bank-level variables are lagged by one period and standardized. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2.8: Determinants of Systemic Risk - Interaction with Size Measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Interactions with log assets			Interactions with SSM status		
	SRISK EA	SRISK NAT	ΔCoefficient	SRISK EA	SRISK NAT	ΔCoefficient
GDP growth$_t$	-0.188	-0.196	0.008	-0.082	-0.095	0.013
	(0.209)	(0.216)		(0.202)	(0.208)	
Inflation rate$_t$	-1.097*	-1.115*	0.018	-0.872	-0.903	0.031
	(0.553)	(0.562)		(0.547)	(0.553)	
Log assets$_{t-1}$	10.495***	10.932***	-0.437*	11.170***	11.766***	-0.596**
	(3.661)	(3.747)		(3.500)	(3.533)	
Loan share$_{t-1}$	-2.761**	-2.914**	0.153***	-2.966**	-2.947**	-0.019
	(1.330)	(1.351)		(1.186)	(1.195)	
Non-interest income$_{t-1}$	-1.866**	-1.879**	0.013	0.653	0.651	0.002
	(0.897)	(0.904)		(0.492)	(0.498)	
RoA$_{t-1}$	2.021**	2.124**	-0.103***	-0.333	-0.346	0.013
	(0.960)	(0.987)		(0.216)	(0.215)	
NPL$_{t-1}$	1.741**	1.678**	0.063*	-0.704	-0.766	0.062*
	(0.759)	(0.768)		(0.634)	(0.643)	
Short-term debt$_{t-1}$	0.731	0.698	0.033	0.328	0.287	0.041
	(0.989)	(1.012)		(0.663)	(0.667)	
G-SIFI$_t$	5.054	5.090	-0.035	4.946	4.928	0.018
	(3.561)	(3.568)		(3.838)	(3.862)	
State aid$_t$	4.909***	4.982***	-0.073	5.380***	5.431***	-0.051
	(1.321)	(1.398)		(1.499)	(1.580)	
Interactions between the explanatory variables and log assets/SSM status						
Interaction with Loan share$_{t-1}$	-0.851	-0.960	0.109***	-0.152	-0.344	0.192**
	(1.461)	(1.460)		(1.701)	(1.702)	
Interaction with Non-interest income$_{t-1}$	-2.693***	-2.707***	0.014	-3.237***	-3.236***	-0.000
	(0.715)	(0.714)		(1.150)	(1.152)	
Interaction with RoA$_{t-1}$	1.340**	1.393**	-0.052**	2.778**	2.908**	-0.130***
	(0.556)	(0.568)		(1.115)	(1.151)	
Interaction with NPL$_{t-1}$	1.443**	1.408**	0.035	2.663***	2.646***	0.017
	(0.602)	(0.618)		(0.902)	(0.906)	
Interaction with Short-term debt$_{t-1}$	-0.361	-0.363	0.002	-0.475	-0.477	0.002
	(0.983)	(1.010)		(1.319)	(1.348)	
Observations	430	430	-	430	430	-
R^2	0.407	0.401	-	0.360	0.354	-
Number of banks	75	75	-	75	75	-

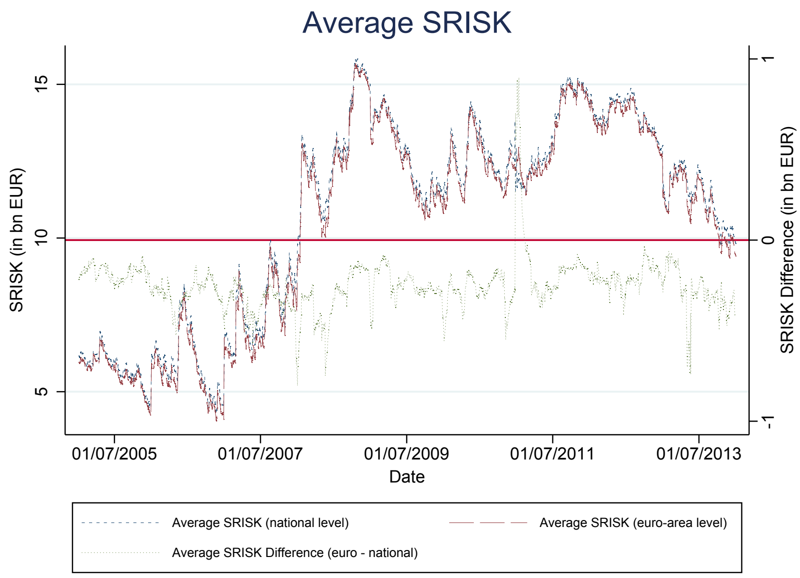
Notes: This table reports fixed effects regressions for the full sample (2005-2013) that is based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros). In Columns (1) and (4), the reference level is the Euro area and in Columns (2) and (5), the national level. In Columns (3) and (6), the difference in coefficients joint with the significance level of Chi-squared tests for equality of coefficients resulting from seemingly unrelated regressions are reported. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables (lagged by one period and standardized): log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %), and their interactions with bank size measured by log of total assets (Columns 1-2) or a dummy that equals one if the bank is supervised by the SSM and zero otherwise (Columns 4-5). G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2.9: Determinants of Systemic Risk - Interaction with Internationalization Measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Interaction with foreign subsidiaries			Interactions with HHI geo		
	SRISK EA	SRISK NAT	ΔCoefficient	SRISK EA	SRISK NAT	ΔCoefficient
GDP growth$_t$	-0.088	-0.099	0.011	-0.135	-0.147	0.012
	(0.208)	(0.215)		(0.217)	(0.225)	
Inflation rate$_t$	-0.816	-0.839	0.023	-0.865	-0.888	0.023
	(0.560)	(0.569)		(0.577)	(0.588)	
Log assets$_{t-1}$	6.418*	6.983**	-0.565**	9.312***	9.499***	-0.187
	(3.360)	(3.440)		(3.505)	(3.504)	
Loan share$_{t-1}$	-3.053*	-3.204*	0.151***	-2.776**	-2.870**	0.094*
	(1.625)	(1.650)		(1.306)	(1.332)	
Non-interest income$_{t-1}$	-2.215*	-2.189*	-0.025	-0.296	-0.293	-0.003
	(1.121)	(1.128)		(0.491)	(0.490)	
RoA$_{t-1}$	-0.286	-0.253	-0.033	1.109*	1.146*	-0.036
	(0.664)	(0.670)		(0.601)	(0.621)	
NPL$_{t-1}$	1.032	0.945	0.087***	1.161*	1.111*	0.050*
	(0.677)	(0.683)		(0.658)	(0.664)	
Short-term debt$_{t-1}$	-0.389	-0.472	0.083	-0.208	-0.257	0.049
	(1.244)	(1.275)		(0.693)	(0.698)	
Internationalization$_t$	1.945**	1.934**	0.011	-0.521	-0.262	-0.259***
	(0.940)	(0.930)		(1.338)	(1.305)	
G-SIFI$_t$	5.517	5.487	0.030	5.736	5.735	0.001
	(3.831)	(3.856)		(3.869)	(3.885)	
State aid$_t$	4.168**	4.197**	-0.028	4.747***	4.769***	-0.022
	(1.833)	(1.910)		(1.608)	(1.689)	
Interactions between the explanatory variables and foreign subsidiaries/HHI geo dummy						
Interaction with Log assets$_{t-1}$	1.039	1.036	0.003	-1.311	-1.163	-0.148**
	(1.068)	(1.058)		(1.378)	(1.336)	
Interaction with Loan share$_{t-1}$	-0.602	-0.497	-0.105***	-0.528	-0.700	0.172***
	(0.826)	(0.827)		(1.540)	(1.532)	
Interaction with	2.281**	2.252**	0.029	-1.778**	-1.762*	-0.016
Non-interest income$_{t-1}$	(0.899)	(0.904)		(0.888)	(0.892)	
Interaction with RoA$_{t-1}$	1.855*	1.920*	-0.064	-0.277	-0.237	-0.040
	(1.012)	(1.049)		(0.648)	(0.667)	
Interaction with NPL$_{t-1}$	0.059	0.072	-0.013	-0.747	-0.839	0.092**
	(0.738)	(0.742)		(0.716)	(0.740)	
Interaction with Short-term debt$_{t-1}$	0.084	0.149	-0.065	-0.257	-0.314	0.057
	(1.179)	(1.190)		(0.958)	(0.978)	
Observations	420	420	-	420	420	-
R^2	0.373	0.367	-	0.354	0.348	-
Number of banks	74	74	-	74	74	-

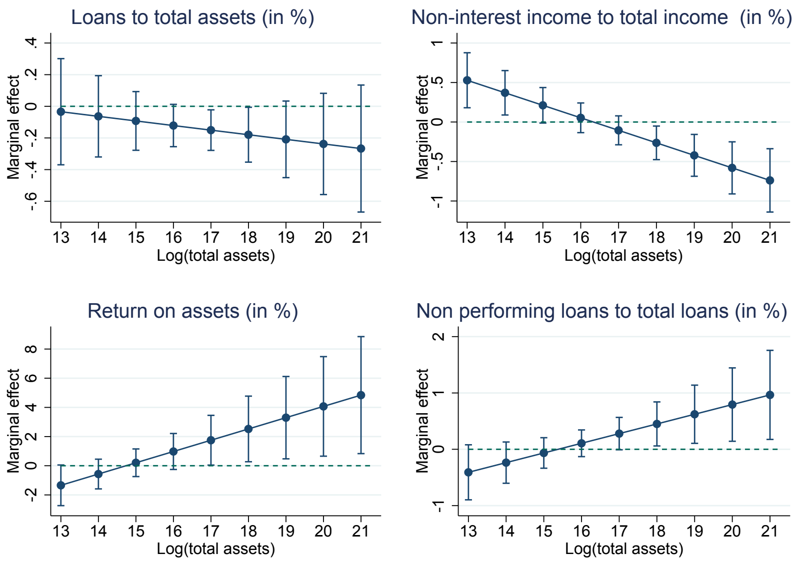
Notes: This table reports fixed effects regressions for the full sample (2005-2013) that is based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros). In Columns (1) and (4), the reference level is the Euro area and in Columns (2) and (5), the national level. In Columns (3) and (6), the difference in coefficients joint with the significance level of Chi-squared tests for equality of coefficients resulting from seemingly unrelated regressions are reported. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables (lagged by one period and standardized): log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %), and their interactions with the internationalization variable. In Columns (1)-(2), internationalization is captured by a foreign subsidiaries dummy that is one if a bank's share of foreign subsidiaries to total subsidiaries lies above the sample average and zero otherwise. In Columns (4)-(5), internationalization is captured by a dummy that is one if the HHI geographical is larger than the sample average and zero otherwise. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 2.1: Average Systemic Risk over Time.



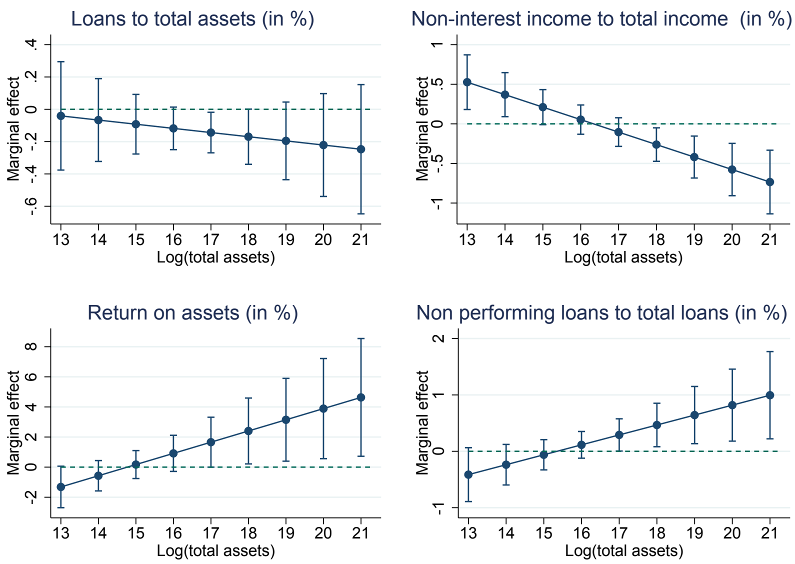
Notes: This figure shows the evolution of the average systemic risk measure SRISK at the national and Euro-area level. The sample comprises 80 banks listed on the stock market in the Euro area during the period 2005-2013. SRISK is derived from banks' stock market data and average across all banks in the sample. We depict the Euro-area SRISK (red, long-dashed line; left axis), the national SRISK (blue, dashed line; left axis) and the difference between the two (green, dotted line; right axis).

Figure 2.2: Average Marginal Effects Conditional on Bank Size - National SRISK.



Notes: The graphs below show the average marginal effects of loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %) on SRISK (national) and conditional on bank size measured by the log of total assets. The estimated marginal effects are denoted by dots enclosed by 95% confidence bands. .

Figure 2.3: Average Marginal Effects Conditional on Bank Size - Euro-Area SRISK.



Notes: The graphs below show the average marginal effects of loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %) on SRISK (Euro area) and conditional on bank size measured by the log of total assets. The estimated marginal effects are denoted by dots enclosed by 95% confidence bands.

Appendix B

B.I Data Appendix

To measure a bank's contribution to systemic risk, we calculate the SRISK measure, which is derived from data obtained from Datastream. In order to analyze the determinants of banks' contribution to systemic risk, we rely on various data sources. Balance sheet data are taken from Bankscope. We complement the dataset by information on ownership obtained from the Bankscope Ownership Module, state aid data from the European Commission, and country-level controls provided by the International Monetary Fund (IMF), the World Bank, and the Bank for International Settlements (BIS).

Bank-Level Data

Equity ratio: We use the equity to total assets ratio (in %), Bankscope.

Liquid assets: The liquidity ratio (in %) is defined as the ratio of banks' liquid assets to total assets, Bankscope.

Loan share: The variable loan share is defined as the ratio of total loans to total assets (in %), Bankscope.

Market to book value: The market to book value of equity is calculated from Datastream/ Worldscope and defined as the market value of the ordinary (common) equity divided by the balance sheet value of the ordinary (common) equity in the company.

Maturity mismatch: Maturity mismatch is defined as the ratio of short-term deposits to liquid assets (in %), Bankscope.

Non-interest income: We use non-interest income relative to total income (gross interest income and non-interest income) (in %), Bankscope.

Non-performing loans (NPL): The NPL ratio is defined as impaired loans over gross loans (in %), Bankscope.

Return on assets (RoA): RoA is the ratio of operating profits to total assets (in %), Bankscope.

Short-term debt: To measure banks' reliance on short-term funding, we use the sum of deposits from banks, repos and cash collateral, plus other deposits and short-term borrowing over total liabilities (in %), Bankscope.

Total assets: We use the logarithm of banks' total assets (in thousands of USD, %), Bankscope.

Total assets to GDP: To capture a bank's relative importance for the domestic economy, we calculate the ratio of a bank's total assets to a country's gross domestic product (in %), Bankscope, IMF.

Internationalization: We use the Bankscope Ownership Module to obtain information on a bank's degree of internationalization. The ownership data give information about banks' subsidiaries, their type, and the country in which they are located. We only keep level one subsidiaries that are owned by more than 50% by the parent bank because we have this information for all years. These data are used to calculate two measures:

First, we derive a normalized Herfindahl index (HHI) capturing geographical complexity (or diversification) following Cetorelli and Goldberg (2014). The HHI is defined as follows:

$HHI_i = \frac{R}{R-1}\left(1 - \sum_{i=1}^{R}(\frac{count^i}{totalcount})^2\right)$ where R is the number of geographical regions in which banks' subsidiaries are located. The regions encompass the Euro area, the UK, Japan, South Korea, China, Canada, the USA, Taiwan, Middle East, other Americas, other Europe, Eastern Europe, other Asia, other. The HHI is defined between zero, lowest complexity, and one, highest complexity. Based on this HHI, we create a dummy which equals one if the bank's geographical complexity exceeds the sample average, and zero otherwise.

Second, we calculate a bank's share of foreign subsidiaries to total subsidiaries (in %). We then define a foreign subsidiaries dummy variable that equals one if a bank has a share of foreign subsidiaries that is larger than the sample average, and zero otherwise.

SSM bank: We create a dummy which equals one throughout the sample period if a bank was required to participate in the comprehensive assessment conducted by the ECB together with national authorities in the context of the establishment of the Single Supervisory Mechanism (SSM), and zero otherwise. See ECB (2013). Note: Comprehensive Assessment. `http://www.ecb.Europa.eu/press/pr/date/2013/html/pr131023.en.html`

G-SIFI: We create a dummy which equals one if a bank was assigned the status of global systemically important financial institution (G-SIFI) by the Financial Stability Board for a given year and zero otherwise.

State aid: We make use of the State Aid Register provided by the European Commission, which gives information on support measures like recapitalization or the provision of guarantees for individual banks. If a bank is listed as a case and received any kind of state aid, we assign a value of one at the decision date of the support measure, and zero otherwise.

Data Used to Calculate Systemic Risk (SRISK)

Book value of total liabilities: Total liabilities represent all short and long-term obligations expected to be satisfied by the company (Datastream/Worldscope). The book value of liabilities includes, but is not restricted to: Current Liabilities, Long Term Debt, Provision for Risk and Charges (non-U.S. corporations), Deferred taxes, Deferred income, Other liabilities, Deferred tax liability in untaxed reserves (non-U.S. corporations), Unrealized gain/loss on marketable securities (insurance companies), Pension/Post retirement benefits, Securities purchased under resale agreements (banks). The book value of liabilities excludes: Minority Interest, Preferred stock equity, Common stock equity, Non-equity reserves.

Market index: We use the Euro STOXX Total Market Index (TMI). This index is a regional subset of the STOXX Europe TMI Index which covers approximately 95% of the free float market capitalization of Europe = 552 constituents. With a variable number of components, the Euro STOXX TMI Index represents a broad coverage of Euro-area companies. The index comprises Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Malta, the Netherlands, Portugal, Slovenia and Spain. The Euro STOXX TMI comprises large, mid and small-capitalization indices: the Euro STOXX TMI Large Index, the Euro STOXX TMI Mid Index and the Euro STOXX TMI Small Index (www.STOXX.com). Index returns are calculated as 1 day change with natural logs.

Bank index: We use the Datastream Bank Index (DS-Banks). Indices are calculated on a representative list of stocks for each market and bank indices are market value weighted. The sample covers a minimum of 75-80% of total bank market capitalization. The index is available for Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Malta, the Netherlands, Portugal, Slovenia, Spain, and the EMU market. Index returns are calculated as 1 day change with natural logs.

Market value of equity: Market value is the share price multiplied by the number of ordinary shares in issue. The amount in issue is updated whenever new tranches of stock are issued or after a capital change. For companies with more than one class of equity capital, the market value is expressed according to the individual issue (Datastream/Worldscope).

National market indices: For the national stock index, we use the STOXX Country Total Market Indices (TMI) representing the relevant country as a whole. It covers approximately 95% of the free float market capitalization of companies in the represented country, with a variable number of components (www.STOXX.com). Index returns are calculated as 1 day change with natural logs.

Stock prices: Stock prices of market listed banks (Datastream/Worldscope). Stock returns are calculated as 1 day change with natural logs.

Country-Level Variables

Bank capital: Aggregate bank capital to assets (in %) is obtained from the World Bank.

Cross-border exposures: To capture banks' foreign activities, we use cross-border assets of banking systems (in % of GDP) from the Consolidated Banking Statistics of the BIS. Cross-border assets of banking systems are provided by the BIS at the quarterly level and we use end-of-year values to aggregate them to the annual frequency. These data are only available at the country level.

Current account: The current account (CA) in % of GDP is taken from the

IMF.

Domestic credit: Domestic credit by private sector banks (in % of GDP) is obtained from The World Bank.

GDP growth: We use the percentage change in a country's gross domestic product as obtained from the IMF.

Government debt: Central government debt (in % of GDP) is obtained from The World Bank.

Inflation: We use the percentage change in average consumer prices as obtained from the IMF.

B.II List of Banks

TABLE B.I: List of Banks.

Name of Bank	Country
Bank für Tirol und Vorarlberg AG-BTV (3 Banken Gruppe)	AUSTRIA
BKS Bank AG	AUSTRIA
Erste Group Bank AG	AUSTRIA
Oberbank AG	AUSTRIA
Raiffeisen Bank International AG	AUSTRIA
Dexia SA	BELGIUM
KBC Groep NV/ KBC Groupe SA-KBC Group	BELGIUM
Bank of Cyprus Public Company Limited-Bank of Cyprus Group	CYPRUS
Hellenic Bank Public Company Limited	CYPRUS
Aktia Bank Plc	FINLAND
Alandsbanken Abp-Bank of Aland Plc	FINLAND
Pohjola Bank plc-Pohjola Pankki Oyj	FINLAND
Banque de la Réunion SA	FRANCE
BNP Paribas	FRANCE
C.R. de Crédit Agricole Mutuel Atlantique Vendée SC-Crédit Agricole Atlantique Vendée	FRANCE
C.R. de Crédit Agricole Mutuel Brie Picardie SC-Crédit Agricole Brie Picardie	FRANCE
C.R. de Crédit Agricole Mutuel de la Touraine et du Poitou SC-Crédit Agricole de la Touraine et du Poitou	FRANCE
C.R. de Crédit Agricole Mutuel de l'Ille-et-Vilaine SA-Crédit Agricole de l'Ille-et-Vilaine	FRANCE
C.R. de Crédit Agricole Mutuel de Normandie-Seine	FRANCE
C.R. de Crédit Agricole Mutuel de Paris et d'Ile-de-France SC-Crédit Agricole d'Ile-de-France	FRANCE
C.R. de Crédit Agricole Mutuel du Languedoc SC	FRANCE
C.R. de Crédit Agricole mutuel du Morbihan SC-Crédit Agricole du Morbihan	FRANCE
C.R. de Crédit Agricole Mutuel Nord de France SC-Crédit Agricole Nord de France	FRANCE
C.R. de Crédit Agricole Mutuel Sud Rhône-Alpes SC-Crédit Agricole Sud Rhône Alpes	FRANCE
C.R. de Crédit Agricole Mutuel Toulouse 31 SC-Crédit Agricole Mutuel Toulouse 31 CCI	FRANCE
Crédit Agricole S.A.	FRANCE
Crédit Industriel et Commercial SA - CIC	FRANCE
Natixis SA	FRANCE
Société Générale SA	FRANCE
Commerzbank AG	GERMANY
Deutsche Bank AG	GERMANY
Deutsche Postbank AG	GERMANY
IKB Deutsche Industriebank AG	GERMANY
Oldenburgische Landesbank - OLB	GERMANY
Quirin Bank AG	GERMANY
Alpha Bank AE	GREECE
Attica Bank SA-Bank of Attica SA	GREECE
Eurobank Ergasias SA	GREECE
General Bank of Greece SA	GREECE
National Bank of Greece SA	GREECE
Piraeus Bank SA	GREECE
Allied Irish Banks plc	IRELAND
Bank of Ireland-Governor and Company of the Bank of Ireland	IRELAND
Banca Carige SpA	ITALY
Banca Finnat Euramerica SpA	ITALY
Banca Monte dei Paschi di Siena SpA-Gruppo Monte dei Paschi di Siena	ITALY
Banca Piccolo Credito Valtellinese-Credito Valtellinese Soc Coop	ITALY
Banca Popolare dell'Emilia Romagna	ITALY
Banca Popolare dell'Etruria e del Lazio Soc. coop.	ITALY
Banca Popolare di Milano SCaRL	ITALY
Banca Popolare di Sondrio Societa Cooperativa per Azioni	ITALY
Banca Popolare di Spoleto SpA	ITALY
Banca Profilo SpA	ITALY
Banco di Desio e della Brianza SpA-Banco Desio	ITALY
Banco di Sardegna SpA	ITALY
Banco Popolare - Società Cooperativa-Banco Popolare	ITALY
Credito Emiliano SpA-CREDEM	ITALY
Intesa Sanpaolo	ITALY
Mediobanca SpA-MEDIOBANCA - Banca di Credito Finanziario Società per Azioni	ITALY
UniCredit SpA	ITALY
Unione di Banche Italiane Scpa-UBI Banca	ITALY
Bank of Valletta Plc	MALTA
HSBC Bank Malta Plc	MALTA
Lombard Bank (Malta) Plc	MALTA
ING Groep NV	NETHERLANDS
Van Lanschot NV	NETHERLANDS
Banco BPI SA	PORTUGAL
Banco Comercial Português, SA-Millennium bcp	PORTUGAL
Banco Espirito Santo SA	PORTUGAL
Vseobecna Uverova Banka a.s.	SLOVAKIA
Abanka Vipa dd	SLOVENIA
Nova Kreditna Banka Maribor d.d.	SLOVENIA
Banco Bilbao Vizcaya Argentaria SA	SPAIN
Banco de Sabadell SA	SPAIN
Banco Popular Espanol SA	SPAIN
Banco Santander SA	SPAIN
Bankia, SA	SPAIN
Bankinter SA	SPAIN
Caixabank, S.A.	SPAIN
Liberbank SA	SPAIN

Notes: The following list contains all banks included in our sample. While 110 banks were listed in the Euro area as of January 2014, Datastream provides only yearly data on the book value of total liabilities and the daily market value of equity measured as shares outstanding times share price for 97 banks. 7 banks with poor trading frequency are dropped because the GJR-GARCH model could not estimate time-varying volatilities due to insufficient fluctuation in the stock market data. Further, we drop 10 institutions with a market capitalization of less than 100 million Euros as of 31 December 2007. For the remaining 80 banks, we calculate SRISK and match Bankscope by using the ISIN number.

B.III Robustness - Tables and figures

TABLE B.II: Sample of SSM Banks.

	(1)	(2)	(3)	(4)	(5)	(6)
	SSM sample			SSM crisis sample		
	SRISK EA	SRISK NAT	ΔCoefficient	SRISK EA	SRISK NAT	ΔCoefficient
GDP growth$_t$	-0.116	-0.132	0.016	-0.259	-0.271	0.012
	(0.252)	(0.260)		(0.198)	(0.204)	
Inflation rate$_t$	-0.986	-1.028	0.042	-0.450	-0.484	0.034
	(0.669)	(0.676)		(0.460)	(0.460)	
Log assets$_{t-1}$	9.677	10.597*	-0.920***	11.543	12.767*	-1.224*
	(5.884)	(5.892)		(7.189)	(7.338)	
Loan share$_{t-1}$	-4.698**	-4.849**	0.151**	-4.948**	-5.091**	0.143
	(2.215)	(2.249)		(2.247)	(2.302)	
Non-interest income$_{t-1}$	-2.235*	-2.256*	0.021	-1.740*	-1.787*	0.047
	(1.312)	(1.319)		(0.976)	(0.985)	
RoA$_{t-1}$	2.711**	2.830**	-0.119***	2.219***	2.323***	-0.104***
	(1.124)	(1.155)		(0.790)	(0.810)	
NPL$_{t-1}$	2.105**	2.006**	0.099**	0.921	0.764	0.157**
	(0.890)	(0.900)		(1.042)	(1.071)	
Short-term debt$_{t-1}$	-0.252	-0.292	0.040	-0.712	-0.749	0.037
	(1.274)	(1.306)		(1.410)	(1.455)	
G-SIFI$_t$	4.814	4.778	0.036	6.851**	6.670**	0.181
	(3.783)	(3.817)		(2.891)	(2.965)	
State aid$_t$	5.059***	5.116***	-0.056	4.743**	4.829**	-0.085
	(1.664)	(1.739)		(1.840)	(1.924)	
Observations	292	292	-	226	226	-
R^2	0.398	0.392	-	0.468	0.461	-
Number of banks	44	44	-	41	41	-

Notes: This table reports fixed effects regressions for the sample of SSM banks and the period (2005-2013) as well as the crisis period (2007-2012) based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros). In Columns (1) and (4), the reference level is the Euro area and in Columns (2) and (5), the national level. In Columns (3) and (6), the difference in coefficients joint with the significance level of Chi-squared tests for equality of coefficients resulting from seemingly unrelated regressions are reported. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %). These bank-level variables are lagged by one period and standardized. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.III: Alternative Micro-Level Variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	w/o RoA		Equity Ratio		Maturity Mismatch		Market to Book Value		Bank Size to GDP		Liquid Assets	
	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT
GDP growth$_t$	-0.143	-0.156	-0.205	-0.216	-0.125	-0.136	-0.135	-0.155	-0.113	-0.126	-0.115	-0.126
	(0.221)	(0.227)	(0.220)	(0.227)	(0.209)	(0.215)	(0.268)	(0.280)	(0.201)	(0.205)	(0.219)	(0.225)
Inflation rate$_t$	-0.872	-0.892	-0.859	-0.879	-0.912	-0.938*	-0.929	-0.961	-0.811	-0.829	-0.875	-0.895
	(0.535)	(0.544)	(0.541)	(0.551)	(0.551)	(0.562)	(0.577)	(0.594)	(0.517)	(0.527)	(0.556)	(0.565)
Log assets$_{t-1}$	10.134**	10.755**	5.426	6.021*	8.408**	8.916**	8.531**	9.158**			12.730***	13.432***
	(3.952)	(4.077)	(3.572)	(3.601)	(3.457)	(3.517)	(3.762)	(3.832)			(3.459)	(3.563)
Loan share$_{t-1}$	-2.585*	-2.678*	-2.662*	-2.771*	-2.842*	-2.942**	-3.054*	-3.159*	-2.863**	-2.992**		
	(1.460)	(1.482)	(1.484)	(1.509)	(1.443)	(1.465)	(1.589)	(1.622)	(1.417)	(1.439)		
Non-interest income$_{t-1}$	-0.688	-0.663	-0.964	-0.957	-1.118	-1.118	-0.888	-0.894	-1.284*	-1.285*	-1.090	-1.085
	(0.751)	(0.760)	(0.756)	(0.760)	(0.720)	(0.724)	(0.694)	(0.697)	(0.734)	(0.737)	(0.725)	(0.728)
RoA$_{t-1}$			1.112*	1.158*	1.432*	1.513*	0.964*	1.017*	1.169*	1.226*	0.936*	0.982*
			(0.615)	(0.648)	(0.737)	(0.773)	(0.568)	(0.599)	(0.599)	(0.633)	(0.539)	(0.569)
NPL$_{t-1}$	0.159	0.034	0.874	0.784	1.090*	1.013*	0.823	0.743	1.095	1.010	1.027	0.942
	(0.926)	(0.977)	(0.594)	(0.618)	(0.560)	(0.572)	(0.673)	(0.702)	(0.662)	(0.689)	(0.694)	(0.720)
Short-term debt$_{t-1}$	-0.476	-0.535	-0.751	-0.808			-0.731	-0.806	-0.402	-0.454	-0.218	-0.267
	(0.760)	(0.778)	(0.840)	(0.861)			(0.850)	(0.875)	(0.751)	(0.770)	(0.679)	(0.695)
G-SIFI$_t$	5.811	5.794	6.044	6.012	5.520	5.488	5.586	5.560	5.155	5.109	5.729	5.706
	(4.002)	(4.033)	(3.920)	(3.952)	(3.950)	(3.987)	(3.915)	(3.943)	(3.733)	(3.738)	(4.119)	(4.150)
State aid$_t$	4.404**	4.399**	4.205**	4.226**	4.845***	4.856***	4.235**	4.281**	4.536**	4.525**	5.164***	5.191***
	(1.832)	(1.912)	(1.742)	(1.813)	(1.706)	(1.782)	(1.726)	(1.800)	(1.868)	(1.952)	(1.610)	(1.683)
Bank-level control$_{t-1}$			-1.726*	-1.701*	1.186*	1.278*	-1.130	-1.048	6.484*	6.708*	0.703	0.736
			(0.981)	(1.000)	(0.705)	(0.742)	(0.884)	(0.923)	(3.323)	(3.510)	(0.764)	(0.767)
Observations	430	430	430	430	430	430	415	415	430	430	430	430
R^2	0.328	0.321	0.342	0.336	0.339	0.333	0.347	0.341	0.350	0.344	0.329	0.322
Number of banks	75	75	75	75	75	75	72	72	75	75	75	75

Notes: This table reports fixed effects regressions for the full sample (2005-2013) that is based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros) whereas the reference level is either the Euro-area or the national level as indicated at the top of each column. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), short-term debt to total liabilities (in %), equity to total assets (in %), maturity mismatch (in %), ratio of market to book value, total assets to GDP (in %), liquid asset to total assets (in %). These bank-level variables are lagged by one period and standardized. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE B.IV: Alternative Macro-Level Variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Government Debt		Domestic Credit		Cross-Border Exposures		Current Account		Capitalization	
	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT
GDP growth$_t$	-0.240	-0.254	-0.052	-0.063	-0.204	-0.208	-0.086	-0.095	-0.303	-0.309
	(0.255)	(0.263)	(0.236)	(0.242)	(0.307)	(0.315)	(0.194)	(0.198)	(0.188)	(0.195)
Inflation rate$_t$	-0.462	-0.479	-0.793	-0.811	-1.058	-1.069	-0.735	-0.747	-1.044*	-1.054*
	(0.584)	(0.604)	(0.528)	(0.538)	(0.740)	(0.761)	(0.477)	(0.481)	(0.591)	(0.605)
Log assets$_{t-1}$	8.049*	8.458**	7.884**	8.425**	9.319*	9.601**	8.855**	9.419***	10.095***	10.581***
	(4.110)	(4.140)	(3.428)	(3.470)	(4.683)	(4.742)	(3.460)	(3.514)	(3.285)	(3.308)
Loan share$_{t-1}$	-2.616*	-2.764*	-3.168**	-3.277**	-2.650	-2.789	-2.662**	-2.755**	-1.929	-2.026
	(1.468)	(1.495)	(1.549)	(1.569)	(1.662)	(1.684)	(1.335)	(1.351)	(1.276)	(1.297)
Non-interest income$_{t-1}$	-1.212	-1.197	-1.026	-1.018	-1.074	-1.065	-1.072	-1.065	-0.768	-0.762
	(0.840)	(0.847)	(0.722)	(0.726)	(0.869)	(0.869)	(0.729)	(0.732)	(0.596)	(0.597)
RoA$_{t-1}$	1.180*	1.231*	0.910*	0.957*	0.946	0.991	1.064*	1.116*	0.910	0.961
	(0.591)	(0.623)	(0.512)	(0.542)	(0.582)	(0.609)	(0.609)	(0.642)	(0.569)	(0.600)
NPL$_{t-1}$	0.524	0.367	0.785	0.693	0.587	0.472	0.926	0.838	1.033	0.932
	(1.002)	(1.047)	(0.644)	(0.671)	(0.851)	(0.876)	(0.683)	(0.710)	(0.754)	(0.780)
Short-term debt$_{t-1}$	-0.998	-1.076	-0.614	-0.676	-0.572	-0.616	-0.477	-0.536	-0.856	-0.907
	(1.264)	(1.303)	(0.768)	(0.788)	(0.804)	(0.821)	(0.766)	(0.785)	(0.706)	(0.729)
G-SIFI$_t$	10.399***	10.279***	5.607	5.581	5.363	5.337	5.638	5.614	4.041	4.025
	(3.415)	(3.519)	(3.952)	(3.986)	(3.931)	(3.948)	(3.936)	(3.962)	(3.547)	(3.600)
State aid$_t$	6.387**	6.371**	4.855***	4.868***	4.527***	4.553**	4.800***	4.814***	4.949***	4.974***
	(2.709)	(2.801)	(1.658)	(1.733)	(1.659)	(1.740)	(1.673)	(1.749)	(1.772)	(1.849)
Country control$_t$	0.025*	0.026*	0.028*	0.028*	0.002	0.004	0.118	0.125	-0.568	-0.622
	(0.013)	(0.013)	(0.015)	(0.015)	(0.018)	(0.018)	(0.165)	(0.169)	(0.656)	(0.681)
Observations	357	357	430	430	378	378	430	430	413	413
R^2	0.443	0.433	0.340	0.334	0.355	0.350	0.338	0.332	0.329	0.324
Number of banks	64	64	75	75	67	67	75	75	75	75

Notes: This table reports fixed effects regressions for the full sample (2005-2013) that is based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros) whereas the reference level is either the Euro-area or the national level as indicated at the top of each column. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %). These bank-level variables are lagged by one period and standardized. Additional control variables at the country-level include government debt relative to GDP (in %), domestic credit to GDP (in %), cross-border exposures of the country's banking system to GDP (in %), current account to GDP (in %), the banking system's aggregate bank capital to assets ratio (in %). G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.V: Alternative SRISK Calculation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(SRISK)		SRISK (Bank index)		SRISK (Median)		SRISK (k=5.5)	
	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT
GDP growth$_t$	-0.018*	-0.018*	-0.170	-0.193	-0.139	-0.199	-0.120	
	(0.010)	(0.010)	(0.230)	(0.153)	(0.220)	(0.147)	(0.189)	(0.195)
Inflation rate$_t$	-0.045**	-0.048**	-0.881	0.328	-0.817	0.321	-0.661	-0.681
	(0.022)	(0.023)	(0.544)	(0.202)	(0.549)	(0.206)	(0.454)	(0.463)
Log assets$_{t-1}$	0.733***	0.801***	8.671**	19.560***	8.072**	19.214***	4.297	4.854
	(0.178)	(0.235)	(3.480)	(3.886)	(3.422)	(3.811)	(3.219)	(3.241)
Loan share$_{t-1}$	-0.097*	-0.117*	-2.966*	-0.391	-2.970*	-0.442	-2.342*	-2.453*
	(0.050)	(0.060)	(1.539)	(1.096)	(1.504)	(1.083)	(1.287)	(1.308)
Non-interest income$_{t-1}$	-0.009	-0.010	-1.057	-1.215	-1.112	-1.487*	-1.052*	-1.044
	(0.018)	(0.020)	(0.750)	(0.815)	(0.768)	(0.822)	(0.630)	(0.635)
RoA$_{t-1}$	0.041	0.057	1.030*	0.647	1.010*	0.673	0.955*	1.004*
	(0.032)	(0.044)	(0.590)	(0.416)	(0.535)	(0.409)	(0.523)	(0.554)
NPL$_{t-1}$	-0.024	-0.065	0.911	0.612	0.978	0.735	0.747	0.654
	(0.061)	(0.090)	(0.638)	(0.474)	(0.658)	(0.485)	(0.617)	(0.643)
Short-term debt$_{t-1}$	-0.037	-0.042	-0.507	-1.095	-0.600	-1.206	-0.309	-0.370
	(0.023)	(0.026)	(0.807)	(0.848)	(0.777)	(0.854)	(0.678)	(0.696)
G-SIFI$_t$	0.107*	0.089	6.245	4.946	5.545	5.479	5.863*	5.837*
	(0.060)	(0.059)	(4.073)	(4.072)	(4.054)	(4.109)	(3.087)	(3.103)
State aid$_t$	0.141*	0.184*	4.907***	5.575***	5.401***	7.040***	5.051***	5.062***
	(0.073)	(0.109)	(1.791)	(1.115)	(1.892)	(1.696)	(1.789)	(1.869)
Observations	430	430	430	423	430	430	430	430
R^2	0.421	0.374	0.342	0.247	0.342	0.265	0.375	0.368
Number of banks	75	75	75	74	75	75	75	75

Notes: This table reports fixed effects regressions for the full sample (2005-2013) that is based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is log of SRISK (bn Euros) whereas we add a constant to avoid negative values, Columns (1)-(2), a bank's SRISK based on the aggregate bank index, Columns (3)-(4), SRISK derived from taking the median across the daily data, Columns (5)-(6), and SRISK when setting the prudential capital ratio to 5.5, Columns (7)-(8). The reference level is either the Euro-area or the national level as indicated at the top of each column. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %). These bank-level variables are lagged by one period and standardized. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.VI: Short-Sell Ban.

	(1)	(2)	(3)	(4)
	Full sample		Crisis sample	
	SRISK EA	SRISK NAT	SRISK EA	SRISK NAT
GDP growth$_t$	-0.150	-0.162	-0.240	-0.252
	(0.216)	(0.222)	(0.165)	(0.170)
Inflation rate$_t$	-0.712	-0.729	-0.210	-0.218
	(0.544)	(0.555)	(0.364)	(0.369)
Log assets$_{t-1}$	8.017**	8.553**	10.723**	11.425***
	(3.442)	(3.494)	(4.138)	(4.288)
Loan share$_{t-1}$	-3.052*	-3.162**	-3.579**	-3.661**
	(1.532)	(1.555)	(1.644)	(1.683)
Non-interest income$_{t-1}$	-0.967	-0.957	-0.919	-0.923
	(0.731)	(0.734)	(0.586)	(0.590)
RoA$_{t-1}$	1.018*	1.066*	0.933**	0.968**
	(0.567)	(0.597)	(0.418)	(0.442)
NPL$_{t-1}$	0.884	0.793	0.290	0.146
	(0.645)	(0.669)	(0.813)	(0.852)
Short-term debt$_{t-1}$	-0.462	-0.522	-0.924	-0.995
	(0.771)	(0.792)	(0.968)	(0.997)
G-SIFI$_t$	5.790	5.768	8.083***	7.921**
	(3.959)	(3.985)	(2.953)	(3.018)
State aid$_t$	4.818***	4.831***	5.045***	5.089***
	(1.632)	(1.707)	(1.826)	(1.905)
Short-sale bant	1.802*	1.841*	1.569*	1.594*
	(0.986)	(1.006)	(0.843)	(0.854)
Observations	430	430	328	328
R^2	0.338	0.332	0.417	0.408
Number of banks	75	75	66	66

Notes: This table reports fixed effects regressions for the full sample (2005-2013) and the crisis sample (2007-2012) that are based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros). In Columns (1) and (3), the reference level is the Euro area and in Columns (2) and (4), the national level. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %). These bank-level variables are lagged by one period and standardized. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. Short-sale ban is a dummy variable that takes a value of one for the years in which a country maintained a short-sell ban and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.VII: Orthogonalized Stock Market Indices.

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline		EA index excl. Nat.		National index excl. EA	
	$SRISK^{EA}$	$SRISK^{NAT}$	$SRISK^{EA}_{MSCIexcl.NAT}$	$SRISK^{NAT}_{MSCI}$	$SRISK^{NAT}_{Excl.EA}$	$SRISK^{NAT}_{Excl.EA}$
GDP growth$_t$	-0.146	-0.158	-0.133	-0.142	-0.122	-0.112
	(0.218)	(0.224)	(0.192)	(0.198)	(0.208)	(0.210)
Inflation rate$_t$	-0.860	-0.880	-0.667	-0.690	-0.569	-0.328
	(0.531)	(0.541)	(0.452)	(0.460)	(0.475)	(0.492)
Log assets$_{t-1}$	8.616**	9.165**	4.447	5.479	4.146	3.690
	(3.414)	(3.478)	(3.237)	(3.348)	(3.462)	(3.804)
Loan share$_{t-1}$	-2.877*	-2.983*	-2.369*	-2.503*	-2.737*	-2.712**
	(1.500)	(1.524)	(1.286)	(1.297)	(1.382)	(1.284)
Non-interest income$_{t-1}$	-1.040	-1.032	-1.048*	-1.023	-1.129*	-1.120*
	(0.736)	(0.740)	(0.625)	(0.630)	(0.629)	(0.617)
RoA$_{t-1}$	0.994*	1.041*	0.978*	1.085*	1.147*	1.257*
	(0.570)	(0.601)	(0.538)	(0.614)	(0.624)	(0.690)
NPL$_{t-1}$	0.876	0.785	0.718	0.524	0.583	0.664
	(0.644)	(0.668)	(0.631)	(0.738)	(0.715)	(0.795)
Short-term debt$_{t-1}$	-0.493	-0.553	-0.326	-0.398	-0.427	-0.601
	(0.776)	(0.796)	(0.681)	(0.696)	(0.733)	(0.683)
G-SIFI$_t$	5.624	5.598	6.043*	5.950*	7.685**	11.267***
	(3.955)	(3.984)	(3.104)	(3.098)	(3.241)	(3.265)
State aid$_t$	4.776***	4.789***	5.020***	5.014***	5.621***	6.313***
	(1.675)	(1.751)	(1.763)	(1.796)	(2.122)	(2.334)
Observations	430	430	430	430	430	430
R^2	0.336	0.330	0.378	0.366	0.388	0.423
Number of banks	75	75	75	75	75	75

Notes: This table reports fixed effects regressions for the full sample (2005-2013) that are based on yearly data of publicly listed banks in Euro-area countries. The dependent variable is SRISK (bn Euros). Columns (1)-(2) refer to our baseline model whereas in Column (1) the reference level is the Euro area and in Column (2) the national level. In Column (3), SRISK is calculated using the EMU MSCI index excluding the national index. In Column (4), SRISK is calculated using the MSCI national index. In Column (5), SRISK is calculated using the national stock return orthogonalized to the first factor derived from Euro-area series by means of a principal component analysis. In Column (6), SRISK is calculated using the national stock return orthogonalized to the first factor derived from national stock returns of Euro-area member states by means of a principal component analysis. For more details see Appendix B. The explanatory variables include GDP growth and the inflation rate as well as bank-level variables: log of total assets, loans to total assets (in %), non-interest income to total income (in %), return on assets (in %), non-performing loans to total loans (in %), and short-term debt to total liabilities (in %). These bank-level variables are lagged by one period and standardized. G-SIFI denotes a dummy which equals one if the bank was classified as a global systemically important bank by the Financial Stability Board and zero otherwise. State aid denotes a dummy which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. Short-sale ban is a dummy variable that takes a value of one for the years in which a country maintained a short-sell ban and zero otherwise. The regressions take into account bank and year fixed effects. Standard errors are clustered by individual bank and depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

B.IV Orthogonalization - Data and Estimation Approach

This appendix contains additional information regarding the robustness tests presented in Table B.VII. Underlying data and pre-estimations conducted before calculating the SRISK measure are explained.

MSCI Stock Market Data

For our main analysis, we make use of Eurostoxx data to obtain national and Euro-area stock market indices. The reason is that, from this data source, we obtain stock market data defined in the same way for a large set of countries, which ensures comparability. In robustness tests (Table B.VII, Columns 3 and 4), we make instead use of MSCI stock market indices as provided by Datastream. This has the advantage that we obtain a national series for each country but also a Euro-area series for each country excluding the respective country. We can hence calculate SRISK at the Euro-area level based on the Euro-area stock market index excluding national influences. The disadvantage is that data series are not available for all countries, such that we report these results in the robustness section.

Principal Component Analysis

Additionally, we want to extract Euro-area factors from the national stock market data. To do so, we proceed as follows. First, we make use of a principal component analysis to generate a common "Euro-area" factor. The Euro-area factor is calculated in two ways:

In a first approach, we use standardized daily series of Euro-area and global variables to generate a factor representing Euro-area and global developments. The variables include changes in the (i) Thomson Reuters Euro Government Benchmark Bid Yield 10 Years (Euro), (ii) Standard and Poor's 500 Composite index, and (iii) STOXX Europe 600 Euro equity index. From these series, we extract the first principal component, which is assumed to reflect a common, Euro-area factor. A scree plot of eigenvalues after factor confirms that there is one major factor as well as the Kaiser-Meyer-Olkin measure confirms that the sample is well-chosen.

In a second approach, we take the daily national stock market indices of the countries included in our sample being early members of the European monetary union. One reason for this choice of countries is data coverage. But more importantly, this choice increases homogeneity in the sample and, consequently, facilitates the extraction of a Euro-area factor.[23] We use the standardized national stock market return series, and also for these series, we extract the first principal component, which is assumed to reflect a common, Euro-area factor. Again the relevant tests confirm that there is a major common factor driving these series.

Second, having generated these Euro-area factors, we orthogonalize national stock market returns with respect to Euro-area developments. This is done by regressing them on one of these previously generated Euro-area factors. Finally, the residuals of these regressions are used as a proxy for national stock returns excluding Euro-area factors in the calculation of banks' SRISK at the national level. This should, as a result, give a cleaner measure to simulate shocks emerging in national market, which are then used for the calculation of banks' national SRISK.

Results of the regressions with SRISK at the national level, which is calculated based on national stock market returns being orthogonal to a Euro-area factor, are shown in Table B.VII. In Column 5, the Euro-area factor derived from aggregate Euro-area and global series has been used. In Column 6, the Euro-area factor derived from stock market returns of Euro-area countries has been used.

[23]Hence, Cyprus, Malta, Slovenia and Slovakia are excluded from the calculation of the Euro-area factor.

Chapter 3

Complexity and Bank Risk during the Financial Crisis

Abstract: *We construct a novel dataset to measure banks' complexity and relate it to banks' riskiness. The sample covers stock listed Euro-area banks from 2007 to 2014. Bank stability is significantly affected by complexity, whereas the direction of the effect differs across complexity measures.*[*]

3.1 Introduction

Over recent years, the European banking system has become more financially integrated and expanded its business activities toward securitization or the insurance sector (Cetorelli et al., 2014; Poszar et al., 2010). This has increased banks' complexity. Complexity can dampen the impact of shocks emerging in one country or business sector. However, shocks can be propagated in interlinked and complex systems. This might have adverse consequences for bank stability. Also, supervision and regulation, as well as the resolution of complex banks become more difficult.

Despite the relevance of the topic, there exists limited empirical research on the relationship between bank complexity and financial stability.[1] We use a novel dataset on parent banks' subsidiary structure to determine four

[*]This paper is co-authored with *Lena Tonzer*, Martin Luther University Halle-Wittenberg and Halle Institute for Economic Research, and *Talina Sondershaus*, Halle Institute for Economic Research. Contact: *talina.sondershaus@iwh-halle.de*, *lena.tonzer@iwh-halle.de*. A version of this chapter has been published in *Economics Letters* as: Krause, Thomas; Sondershaus, Talina and Tonzer, Lena (2017): Complexity and bank risk during the financial crisis. *Economics Letters*, 150, 118–121.

[1]Higher complexity can simultaneously imply a higher degree of diversification. We use the term complexity throughout the paper.

proxies for banks' complexity and relate them to bank risk. The dataset covers stock listed banks in the Euro area for the period 2007-2014. Following Cetorelli and Goldberg (2014), we compute parent banks' business and geographical complexity. Hence, complexity is conceptually defined by the variety of business types and geographical regions of banks' subsidiaries: banks are more complex if they have subsidiaries across different business types/ regions. We extend the set of complexity measures to cover the share of non-bank/ foreign subsidiaries because these are useful complements in explaining key dynamics in the before mentioned measures.[2] The results show that banks have increased their number of subsidiaries. However, this has not necessarily translated into higher complexity. The effect of complexity on bank stability depends on the choice of the complexity measure.

Cetorelli and Goldberg (2014) calculate complexity measures for the year 2012 and show that banks' degree of complexity varies across countries and institutions; a common feature is a concentration of subsidiaries in the home country of the parent bank. We extend this literature by computing complexity measures over time and relate them to bank stability. Gong et al. (2015) show that effective capital ratios of US banks are lower than reported ones if minority-owned subsidiaries would be consolidated. Undercapitalization increases bank risk, suggesting that banks arbitrage regulation. Cetorelli and Goldberg (2016) take the perspective of foreign branches in the US being part of a larger, global conglomerate. They find that the more complex the conglomerate, the lower is the lending sensitivity of branches to funding shocks. Liu et al. (2015), based on a sample of US bank holding companies, show that higher complexity increases banks' stability. This is in contrast to our results and might be driven by a different sample composition and calculation of complexity.

[2]A more detailed survey about the concept of complexity is provided by Carmassi and Herring (2014).

3.2 Bank Complexity

The analysis is based on a sample of 80 stock listed banks in the Euro area over 2007-2014.[3] For these banks, we have obtained data from the Bankscope Ownership Module containing information on banks' domestic and foreign subsidiaries like their business area, location, and percentage of ownership. We only consider majority-owned (>50%) subsidiaries that are directly owned by the parent bank. We compute four complexity measures:

- **Business complexity** is a normalized Herfindahl index (*HHI*) depending on the number of subsidiaries by business types relative to the total number of subsidiaries: $HHI_{it} = \frac{T}{T-1}\left(1 - \sum_{\tau=1}^{T}\left(\frac{count^{it\tau}}{totalcount^{it}}\right)^2\right)$ with T being the number of subsidiary types. The index is defined between zero and one, higher values reflect a higher degree of complexity. Subsidiary types include banks, insurance companies, mutual and pension funds, other financial subsidiaries, non-financial subsidiaries (Cetorelli and Goldberg 2014). A more complex subsidiary network might entail economies of scale and buffer against the occurrence of losses in one sector. However, transaction and monitoring costs can increase, which might incentivize banks to take more risks.

- **Geographical complexity** is a normalized HHI depending on the number of subsidiaries by region relative to the total number of subsidiaries: $HHI_{it} = \frac{R}{R-1}\left(1 - \sum_{r=1}^{R}\left(\frac{count^{itr}}{totalcount^{it}}\right)^2\right)$ with R being the number of geographical regions. Higher values indicate a higher degree of complexity in the sense that the parent bank's subsidiaries are equally distributed across various regions. Regions include the Euro area, the UK, Japan, South Korea, China, Canada, the USA, Taiwan, Middle East, other Americas, other Europe, Eastern Europe, other Asia, other. Higher geographical complexity can help withstand local shocks but it can also increase agency problems and exposure to global

[3]Details on the sample composition are available in Table A1 in the supplementary appendix.

shock spillovers. This would result into increased risk-taking before a crisis and higher vulnerability during a crisis.

- **Non-bank subsidiaries** is the ratio of a parent bank's non-bank subsidiaries to total subsidiaries. Non-bank subsidiaries can be used to become active in other activities than the traditional financial intermediation process such as securitization.

- **Foreign subsidiaries** is the ratio of a parent bank's foreign subsidiaries to total subsidiaries. A larger share of foreign subsidiaries contains possibilities for regulatory arbitrage -in general, subsidiaries fall under the regulation of their host country- and cause coordination problems among regulators from different countries in case a bank has to be resolved.

Figure 3.1 shows that banks have increased their number of subsidiaries (like in Carmassi and Herring 2014). However, this has not resulted in an increase of all complexity measures (Figure 3.2). Business and geographical complexity, and the share of foreign subsidiaries have declined. The reason for this downward trend is that banks have extended the ownership of non-bank/ local subsidiaries relatively more than the one of bank/ foreign subsidiaries. This implies a higher degree of concentration in one sector/ region and thus a decline in the HHIs.

– Insert Figures 3.1 and 3.2 here –

3.3 Main Results

3.3.1 Zscore

To evaluate the relationship between banks' complexity and riskiness during the recent crisis period, we estimate the following model:

$$Zscore_{ij,average08-10} = \alpha + \beta_1 X_{ij,2007} + \beta_2 Country_{j,2007} + \beta_3 Complex_{ij,2007} + \epsilon_{ij} \tag{3.1}$$

where $Zscore_{ij,average08-10}$ is the average Zscore for bank i located in country j during the financial crisis period from 2008 to 2010. To ensure linearity, the Zscore is defined as $Zscore_{ij} = \log(1 + \widehat{Zscore}_{ij})$, whereas higher values indicate higher stability.[4]

We add pre-crisis values of bank-level controls ($X_{ij,2007}$) obtained from Bankscope including the log of total assets, the CAMEL variables (Cole and White, 2012), and a complexity measure ($Complex_{ij,2007}$).[5] At the country-level ($Country_{j,2007}$), we control for GDP growth and inflation, and an indicator variable for the GIIPS countries (Greece, Ireland, Italy, Portugal, Spain). This estimation approach reduces simultaneity concerns (Laeven et al., 2016).

The results in Table 3.1 show that two of the four complexity measures have a significant coefficient. Higher geographical complexity and a higher share of foreign subsidiaries before the crisis can be associated with higher bank risk (or a lower Zscore) during the crisis. Hence, negative effects due to higher monitoring costs and agency problems, as well as global shock spillovers during the recent crisis significantly outweigh positive effects going back to being diversified across regions. Business complexity and the share of non-bank subsidiaries remain insignificant suggesting that diversification advantages are equalized by disadvantages arising from specialization losses. Our results remain robust differentiating by crisis period, whereas

[4] $\widehat{Zscore}_{ij}$ is calculated as $\frac{\mu_{RoA,i}+equ_{it}}{\sigma_{RoA,i}}$, with $\mu_{RoA,i}$ being the mean and $\sigma_{RoA,i}$ being the standard deviation of return on assets over 2007-2014, equ_{it} denotes the equity to assets ratio (Lepetit and Strobel, 2013). The pattern of the $Zscore$ is depicted in Figure 3.2.

[5] We exclude the equity ratio and return on assets because they are part of our dependent variable. To correct for outliers, we keep only observations with non-missing assets. We drop observations with negative values for assets, equity, or loans, and if ratios take implausible values (e.g. greater than 100%). All CAMEL variables are winsorized at the top and bottom percentile. For summary statistics, see the supplementary appendix (Tables A2-A4).

geographical complexity shows a stronger effect during the financial crisis compared to the sovereign debt crisis.[6]

– Insert Table 3.1 here –

3.3.2 State Aid

Alternatively, we test whether bank complexity affected the probability to be in the need of state aid during 2008-2014 (Cole and White, 2012; Shaffer, 2012). The state aid indicator is a more precise signal that a bank had serious problems:

$$\begin{aligned} Stateaid_{ij,t} = \alpha + \beta_1 X_{ij,t-1} + \beta_2 Country_{j,t} \\ + \beta_3 Complex_{ij,t-1} + \theta_t + \epsilon_{ij,t} \end{aligned} \quad (3.2)$$

where the dependent variable is a dummy equaling one if bank i has received state aid in period t, e.g. recapitalization or asset guarantees, and zero otherwise. Information on state aid requests comes from the *State Aid Register* of the European Commission. The explanatory variables are defined as above. Global developments are captured by time fixed effects θ_t.

In Table 3.2, it can be seen that higher geographical complexity and a higher share of foreign subsidiaries increase the probability of a state aid request. This finding is consistent with the previous results and most prevalent during the sovereign debt crisis period. From a supervisory perspective, this implies that coordinated actions across national borders can help detect problems at international banks earlier and intervene before a bank requests state aid. A higher share of non-bank subsidiaries significantly reduces the probability of state aid. This suggests risk-sharing possibilities: shocks in the financial system can be mitigated by being active in other sectors; internal cross-funding possibilities within a bank holding company including different subsidiaries types can reduce liquidity strains during crisis times.

[6]See Table A7. Our results remain also robust for a set of robustness tests like running univariate or panel regressions as well as using a systemic risk measure as dependent variable (see supplementary appendix, Tables A5-A9).

– Insert Table 3.2 here –

3.4 Conclusion

The recent financial crisis has brought the issue of bank complexity on the agenda of policymakers. We find that banks have steadily increased their number of (non-bank) subsidiaries. However, this has not necessarily translated into higher complexity regarding the diversification of subsidiaries across regions and business types. When evaluating the relationship between bank complexity and stability, the results show a heterogeneous picture. Higher geographical complexity and a higher share of foreign subsidiaries increase banks' riskiness. In contrast, a higher share of non-bank subsidiaries has stabilizing effects. This advises against the use of a single complexity measure.

Tables and Figures

Table 3.1: Regression Results - Zscore.

	(1)	(2)	(3)	(4)
Log assets_{2007}	0.027	0.121	0.02	0.096
	-0.065	-0.09	-0.066	-0.087
NPL_{2007}	-0.08	-0.084**	-0.076	-0.075*
	-0.049	-0.04	-0.047	-0.042
Cost-to-income2007	0.002	0.006	0.002	0.005
	-0.01	-0.009	-0.011	-0.008
Liquid assets_{2007}	-0.005	-0.002	-0.008	-0.005
	-0.01	-0.009	-0.011	-0.01
GDP_{2007}	0.038	0.03	0.02	0.017
	-0.137	-0.132	-0.153	-0.135
Inflation_{2007}	-0.870***	-0.725***	-0.895***	-0.784***
	-0.264	-0.233	-0.266	-0.257
GIIPS Country_{2007}	0.259	0.238	0.227	0.181
	-0.423	-0.43	-0.435	-0.417
HHI Business_{2007}	-0.206			
	-0.511			
HHI Geo_{2007}		-1.057**		
		-0.442		
Ratio Nonbanks_{2007}			0.221	
			-0.485	
Ratio Foreign_{2007}				-0.853*
				-0.487
Observations	54	54	54	54
R^2	0.316	0.371	0.316	0.356

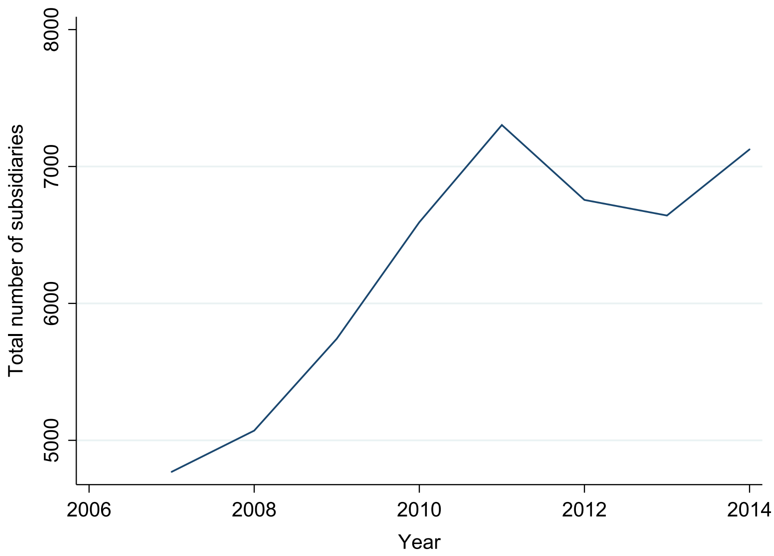
Notes: This table reports cross-sectional regressions. The dependent variable is a bank's average Zscore over 2008-2010. Robust standard errors are depicted in parentheses. The p-values are: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3.2: Regression Results - State Aid.

	(1)	(2)	(3)	(4)
HHI Business$_{t-1}$	0.788			
	(1.614)			
HHI Geo$_{t-1}$		3.452***		
		(1.14)		
Ratio Nonbanks$_{t-1}$			-3.738***	
			(1.189)	
Ratio Foreign$_{t-1}$				2.505**
				(1.01)
Controls	Yes	Yes	Yes	Yes
Observations	399	400	399	400
# Banks	75	75	75	75

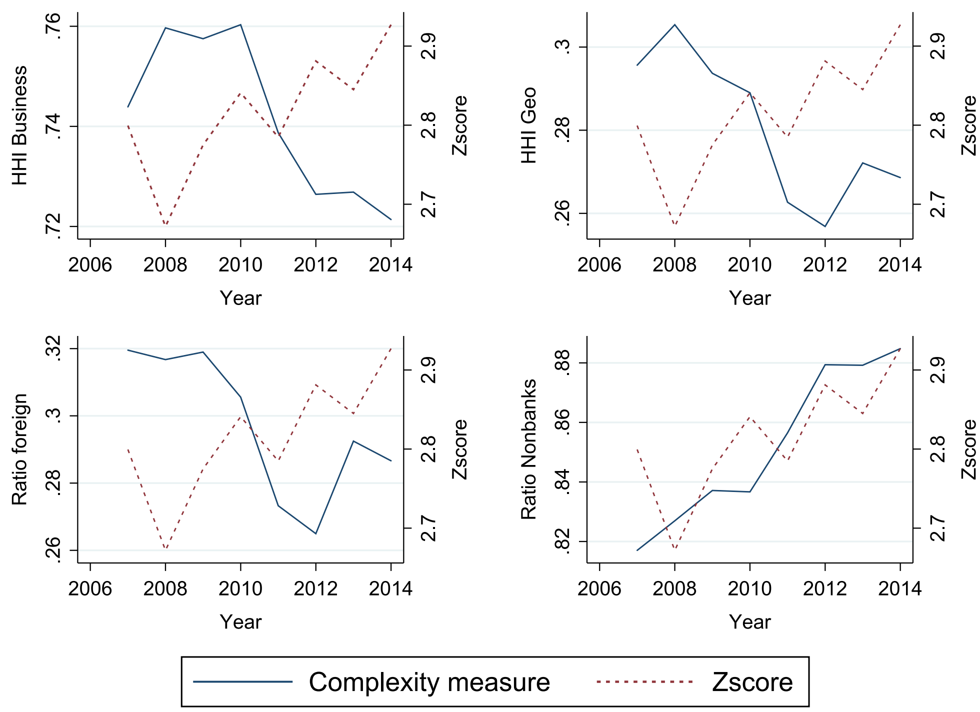
Notes: This table reports probit regressions. The dependent variable equals one if the bank received state aid and zero otherwise. Standard errors clustered at the bank level are depicted in parentheses. The p-values are: *** p<0.01, ** p<0.05, * p<0.1.

Figure 3.1: Number of Banks' Subsidiaries.



Notes: This graph shows the number of majority-owned subsidiaries by parent banks.

Figure 3.2: Complexity and Zscore.



Notes: This graph shows the average pattern of a complexity measure (left axis; blue solid line) and the Zscore (right axis; red dotted line).

Appendix B

B.I Sample Composition

The following list in Table B.I contains information on the sample composition. The first column contains the names of the banks included in the sample. The second column indicates the bank type. The status information in the third column shows that there is no bank that died within our sample period.[7] The fourth column lists the country in which the bank is located. The last column shows the average weight of each bank's capitalization to the total capitalization of all banks in the respective country over the period 2007-2014. Except for Slovakia, the banks included in our sample cover on average more than 85% of total market capitalization.[8] As of July 2014, 111 banks were stock listed in the Euro area according to Datastream. To correct the sample from outliers, we drop banks with insufficient variation in the stock market data and institutions with a market capitalization of less than 100 million Euros as of 31 December 2007. Finally, we drop banks that could not be matched to Bankscope. For the remaining 80 banks, we can thus ensure to have sufficient variation in the data to obtain reasonable estimates of ΔCoVaR. We match stock market data of these 80 banks to balance sheet information provided by Bankscope by using the ISIN number. For this final sample of banks, we have obtained information from the Bankscope Ownership Module on banks' domestic and foreign subsidiaries over the period 2007-2014. This allows the calculation of complexity measures. The number of banks included in the regressions can be smaller than 80 due to missing values for explanatory variables.

[7] Although POHJOLA PANKKI A bank died on October 1st 2014, we still have non-missing values of the variables in 2014.

[8] The aggregated sum of market capitalization across all banks in one country can be slightly larger than 100% in selected cases due to taking average values across the whole period.

Table B.I: Sample Composition.

Name of Bank	**Type**	**Status**	**Country**	**Market Value (avg.)**
BK.FUR TIROL UND VBG.	Equity	Active	Austria	2.59%
BKS BANK	Equity	Active	Austria	3.11%
ERSTE GROUP BANK	Equity	Active	Austria	52.36%
OBERBANK	Equity	Active	Austria	6.93%
RAIFFEISEN BANK INTL.	Equity	Active	Austria	34.77%
DEXIA	Equity	Active	Belgium	18.94%
KBC GROUP	Equity	Active	Belgium	66.43%
BANK OF CYPRUS	Equity	Active	Cyprus	79.64%
HELLENIC BANK	Equity	Active	Cyprus	16.25%
COMMERZBANK	Equity	Active	Germany	19.73%
DEUTSCHE BANK	Equity	Active	Germany	63.39%
DEUTSCHE POSTBANK	Equity	Dead (23/12/15)	Germany	11.86%
IKB DEUTSCHE INDSTRBK.	Equity	Active	Germany	1.20%
OLDENBURGISCHE LB.	Equity	Active	Germany	1.74%
QUIRIN BANK	Equity	Active	Germany	0.14%
BANCO DE SABADELL	Equity	Active	Spain	4.09%
BANCO POPULAR ESPANOL	Equity	Active	Spain	4.83%
BANCO SANTANDER	Equity	Active	Spain	47.65%
LIBERBANK	Equity	Active	Spain	0.69%
BANKIA	Equity	Active	Spain	5.66%
BANKINTER 'R'	Equity	Active	Spain	2.14%
BBV.ARGENTARIA	Equity	Active	Spain	28.55%
CAIXABANK	Equity	Active	Spain	9.73%
AKTIA 'A'	Equity	Active	Finland	11.50%
ALANDSBANKEN 'A'	Equity	Active	Finland	4.68%
POHJOLA PANKKI A	Equity	Dead (01/10/14)	Finland	86.70%
BANQUE REUNION	Equity	Dead (07/05/15)	France	0.13%
BNP PARIBAS	Equity	Active	France	44.38%
CIC 'A'	Equity	Active	France	4.07%
CR.AGR.SUD RHONE ALPES	GDR	Active	France	0.07%
CR.AGRICOLE MORBIHAN	Equity	Active	France	0.06%
CRCAM ATLANTIQUE VENDEE	Equity	Active	France	0.07%
CREDIT AGRICOLE BRIE PICARDIE	Equity	Active	France	0.25%
CRCAM ILLE-VIL.CCI	Equity	Active	France	0.09%
CRCAM LANGUED CCI	Equity	Active	France	0.07%
CRCAM NORD DE FRANCE CCI	Equity	Active	France	0.22%
CRCAM NORMANDIE SEINE	GDR	Active	France	0.06%
CREDIT AGR.ILE DE FRANCE	Equity	Active	France	0.42%
CREDIT AGR.TOULOUSE	Equity	Active	France	0.07%
CREDIT AGR.TOURAINE	Equity	Active	France	0.05%
CREDIT AGRICOLE	Equity	Active	France	18.94%
NATIXIS	Equity	Active	France	8.37%
SOCIETE GENERALE	Equity	Active	France	22.17%
ALPHA BANK	Equity	Active	Greece	20.75%
ATTICA BANK	Equity	Active	Greece	1.47%
BANK OF PIRAEUS	Equity	Active	Greece	15.39%
EUROBANK ERGASIAS	Equity	Active	Greece	15.47%
GENERAL BANK OF GREECE	Equity	Active	Greece	1.39%
NATIONAL BK.OF GREECE	Equity	Active	Greece	41.43%
ALLIED IRISH BANKS	Equity	Active	Ireland	67.78%
BANK OF IRELAND	Equity	Active	Ireland	32.22%
BANCA CARIGE	Equity	Active	Italy	2.40%
BANCA FINNAT EURAMERICA	Equity	Active	Italy	0.18%
BANCA MONTE DEI PASCHI	Equity	Active	Italy	5.10%
BANCA POPOLARE DI MILANO	Equity	Active	Italy	1.95%
BANCA PPO.ETRURIA LAZIO	Equity	Active	Italy	0.23%
BANCA PROFILO	Equity	Active	Italy	0.24%
BANCA PPO.DI SONDRIO	Equity	Active	Italy	1.97%
BANCA PPO.DI SPOLETO	Equity	Active	Italy	0.10%
BANCA PPO.EMILIA ROMAGNA	Equity	Active	Italy	2.51%
BANCO DI SARDEGNA RSP	Equity	Active	Italy	0.07%
BANCO POPOLARE	Equity	Active	Italy	3.76%
BNC.DI DESIO E DELB.	Equity	Active	Italy	0.44%
CREDITO EMILIANO	Equity	Active	Italy	1.72%
BCA.PICCOLO CDT.VALTELL	Equity	Active	Italy	0.90%
INTESA SANPAOLO	Equity	Active	Italy	32.50%
MEDIOBANCA BC.FIN	Equity	Active	Italy	6.91%
UNIONE DI BANCHE ITALIAN	Equity	Active	Italy	5.40%
UNICREDIT	Equity	Active	Italy	33.30%
BANK OF VALLETTA	Equity	Active	Malta	38.60%
HSBC BANK MALTA	Equity	Active	Malta	47.59%
LOMBARD BANK	Equity	Active	Malta	5.11%
ING GROEP	Equity	Active	Netherlands	97.10%
VAN LANSCHOT	Equity	Active	Netherlands	2.90%
BANCO BPI	Equity	Active	Portugal	19.24%
BANCO COMR.PORTUGUES 'R'	Equity	Active	Portugal	37.91%
BANCO ESPIRITO SANTO DEAD	Equity	Dead (03/02/16)	Portugal	42.54%
VSEOBECNA UVEROVA BANKA	Equity	Active	Slovakia	24.93%
ABANKA VIPA	Equity	Active	Slovenia	36.70%
NOVA KREDITNA BANKA MARIBOR	Equity	Active	Slovenia	63.30%

B.II Tables and Figures

Table B.II: Summary Statistics - Full Sample.

VARIABLES	N	mean	sd	skewness	kurtosis	min	max
Dependent variables							
Zscore	608	2.82	1.07	0.18	2.43	0.25	5.11
Stateaid	610	0.05	0.21	4.34	19.83	0	1
ΔCoVaR	601	0.01	0.01	0.62	3.02	0	0.05
Complexity measures							
HHI Business	587	0.74	0.24	-1.82	5.84	0	0.99
HHI Geo	589	0.28	0.27	0.41	1.78	0	0.85
Ratio Nonbanks	587	0.85	0.16	-1.4	5.7	0	1
Ratio Foreign	589	0.3	0.26	0.5	2.26	0	1
Bank-level controls							
Log assets	610	17.8	1.97	0.07	2.46	13.28	21.66
Equity	610	7.34	3.5	1.28	6.73	1.45	24.6
NPL	520	7.94	8.32	2.24	8.29	0.41	42.58
Cost-to-income	579	60.93	12.01	0.6	3.11	36.73	96.01
RoA	610	0.3	1.26	-2.69	12.65	-5.98	2.36
Liquid assets	610	15.22	11.64	1.71	6.09	2.51	61.56
Macroeconomic variables							
Inflation	610	1.85	1.29	-0.11	2.88	-1.71	5.65
GDP	610	0.03	2.7	-0.59	3.74	-8.86	10.68

Notes: This table shows summary statistics for the dependent variables Zscore, Stateaid and ΔCoVaR, bank-level control variables, as well as macroeconomic control variables. The sample consists of 80 banks listed on the stock market in the Euro area and covers the years 2007-2014. Zscore is the log of the Zscore calculated as in Lepetit and Strobel (2013). Stateaid denotes a dummy, which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. ΔCoVaR is calculated following Benoit et al. (2016) and market data are obtained from Datastream. HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, Ratio Nonbanks gives the number of nonbank subsidiaries over the total number of subsidiaries, and Ratio Foreign is the number of subsidiaries that are located in a different country than the bank holding company over the total number of subsidiaries. Due to lack of information on subsidiary type for the year 2011, we take the average of the preceding and succeeding year for the HHI Business and the Ratio Nonbanks. Log assets denotes the logarithm of bank assets in thousands of USD. Equity is the equity to total assets ratio (in %). In order to measure asset quality, NPL is used which is defined as the fraction of impaired loans relative to gross loans (in %). Cost-to-income is a measurement of the management quality defined as the cost to income ratio (in %). Earnings are measured by the return on assets (RoA) which is the ratio of operating profits to total assets (in %). Liquid assets is the share of liquid assets in total assets (in %). The inflation rate (in %) and GDP growth (in %) of the bank holding company's country of location are used as macroeconomic controls.

Table B.III: Summary Statistics - Regression Sample.

VARIABLES	N	mean	sd	skewness	kurtosis	min	max
Dependent variable							
Zscore	74	2.72	1.07	0.24	2.39	0.56	4.94
Complexity measures							
HHI Business	70	0.74	0.26	-1.77	5.42	0	0.99
HHI Geo	70	0.3	0.28	0.31	1.6	0	0.8
Ratio Nonbanks	70	0.82	0.21	-1.91	7.61	0	1
Ratio Foreign	70	0.32	0.27	0.47	2.24	0	1
Bank-level controls							
Log assets	74	17.82	1.98	0.16	2.42	13.28	21.66
Cost-to-income	73	57.1	9.98	0.71	5.08	36.73	96.01
NPL	57	3.22	2.86	2	8.32	0.41	15.27
Equity	74	7.71	3.98	1.4	6.11	2.04	24.6
RoA	74	1.06	0.66	-1.75	10.64	-2.24	2.36
Liquid assets	74	19.25	13.36	1.57	5.36	2.51	61.56
Macroeconomic variables							
Inflation	74	2.12	0.56	0.31	3.5	0.7	3.61
GDP	74	3.08	1.55	1.94	9.59	1.47	10.68

Notes: This table shows summary statistics for the dependent variable Zscore, bank-level control variables, as well as macroeconomic control variables. The sample consists of 74 banks listed on the stock market in the Euro area. Explanatory variables are from the year 2007. Zscore (in logs) is calculated as in Lepetit and Strobel (2013) and averaged across the crisis years 2008-2010. HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, Ratio Nonbanks gives the number of nonbank subsidiaries over the total number of subsidiaries, and Ratio Foreign is the number of subsidiaries that are located in a different country than the bank holding company over the total number of subsidiaries. Log assets denotes the logarithm of bank assets in thousands of USD. Equity is the equity to total assets ratio (in %). In order to measure asset quality, NPL is used which is defined as the fraction of impaired loans relative to gross loans (in %). Cost-to-income is a measurement of the management quality defined as the cost to income ratio (in %). Earnings are measured by the return on assets (RoA) which is the ratio of operating profits to total assets (in %). Liquid assets is the share of liquid assets in total assets (in %). The inflation rate (in %) and GDP growth (in %) of the bank holding company's country of location are used as macroeconomic controls.

TABLE B.IV: Correlations.

	Zscore	Stateaid	ΔCoVaR	HHI Business	HHI Geo	Ratio Nonbanks	Ratio Foreign	Log Assets	Equity	NPL	Cost-to-income	RoA	Liquid assets
Zscore	1												
Stateaid	-0.2	1											
ΔCoVaR	-0.35	0.06	1										
HHI Business	-0.43	0.11	0.53	1									
HHI Geo	-0.33	0.2	0.51	0.52	1								
Ratio Nonbanks	0.24	-0.01	-0.26	-0.31	-0.22	1							
Ratio Foreign	-0.31	0.19	0.44	0.4	0.87	-0.15	1						
Log assets	-0.05	0.16	0.52	0.53	0.66	-0.22	0.58	1					
Equity	0.41	-0.2	-0.29	-0.52	-0.48	0.15	-0.42	-0.56	1				
NPL	-0.37	0.25	-0.06	-0.05	-0.11	-0.03	-0.05	-0.12	0	1			
Cost-to-income	-0.25	0.12	-0.08	0.15	0.13	-0.18	0.1	0.06	-0.27	0.21	1		
RoA	0.41	-0.28	0.05	-0.13	-0.1	0.08	-0.14	-0.03	0.25	-0.7	-0.51	1	
Liquid assets	-0.13	-0.09	0.06	0.15	0.26	-0.01	0.2	0.1	-0.12	-0.2	0.16	-0.02	1

Notes: This table shows pairwise correlations between the dependent and explanatory variables at the bank level for the period 2007-2014. The Zscore (in log) is calculated as in Lepetit and Strobel (2013). The dummy Stateaid equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. $\Delta CoVaR$ is calculated following Benoit et al. (2016) and market data are obtained from Datastream. Bank-level data on complexity are obtained from the Bankscope Ownership Module: HHI Business, indicating diversification of banks across different business activities, HHI Geo indicating diversification of banks across geographical regions, number of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the number of subsidiaries that are located in a different country than the bank holding company over the total number of subsidiaries (Ratio Foreign). Further bank characteristics are obtained from Bankscope and comprise: Log assets denotes the logarithm of bank assets in thousands of USD. Equity is the equity to total assets ratio (in %). In order to measure asset quality, NPL is used, which is defined as the fraction of impaired loans relative to gross loans (in %). Cost-to-income is a measurement of the management defined as the cost to income ratio (in %). Earnings are measured by the return on assets (RoA), which is the ratio of operating profits to total assets (in %). Liquid assets is the share of liquid assets in total assets (in %).

Table B.V: Univariate Cross-Sectional Regression Results - Zscore.

	(1)	(2)	(3)	(4)	(5)
HHI Business_{2007}	-1.691***				-1.473***
	(0.586)				(0.454)
HHI Geo_{2007}		-1.311***			-0.942
		(0.385)			(0.657)
Ratio Nonbanks_{2007}			1.062**		1.116**
			(0.463)		(0.542)
Ratio Foreign_{2007}				-0.986**	0.409
				(0.463)	(0.769)
Constant	3.976***	3.106***	1.850***	3.033***	3.050***
	(0.488)	(0.187)	(0.324)	(0.204)	(0.497)
Observations	70	70	70	70	70
R-squared	0.165	0.119	0.044	0.063	0.250

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries. The dependent variable is a bank's average Zscore over the years 2008-2010. The complexity measures are from the year 2007 and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE B.VI: Cross-Sectional Regression Results by Year - Zscore (HHI Business).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.046	0.136**	0.081	0.108**	0.128**	0.097**	0.083*
	(0.08)	(0.063)	(0.061)	(0.05)	(0.056)	(0.042)	(0.042)
NPL$_{t-1}$	-0.049	-0.102*	-0.074*	-0.065**	-0.104***	-0.087***	-0.056***
	(0.059)	(0.053)	(0.037)	(0.027)	(0.02)	(0.018)	(0.01)
Cost-to-income$_{t-1}$	-0.005	0.007	-0.015*	-0.003	-0.009	-0.019***	-0.018***
	(0.015)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
Liquid assets$_{t-1}$	0.007	0.028*	-0.002	-0.007	-0.017**	-0.018**	-0.023***
	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.009)	(0.007)
GDPt	0.207	0.126*	0.184**	0.158***	0.190**	0.024	-0.062
	(0.139)	(0.069)	(0.079)	(0.042)	(0.071)	(0.059)	(0.055)
Inflation$_t$	-0.432**	0.333**	0.071	0.431**	0.474**	-0.035	-0.069
	(0.188)	(0.158)	(0.174)	(0.172)	(0.2)	(0.189)	(0.145)
GIIPS Country$_t$	0.432	0.205	0.136	0.137	0.188	-0.396**	-0.645***
	(0.4)	(0.266)	(0.262)	(0.201)	(0.193)	(0.198)	(0.215)
HHI Business$_{t-1}$	-0.855	-2.159	-1.333	-1.943**	-1.414**	-1.349***	-0.744*
	(0.566)	(1.285)	(0.896)	(0.76)	(0.566)	(0.482)	(0.435)
Constant	3.719*	1.594	3.075**	1.418	1.963	4.678***	4.558***
	(1.993)	(1.389)	(1.448)	(1.176)	(1.423)	(0.824)	(0.68)
Observations	54	52	55	55	50	62	69
R-squared	0.194	0.335	0.344	0.607	0.657	0.678	0.722

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is the HHI Business indicating diversification of banks across different business activities. Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE B.VII: Cross-Sectional Regression Results by Year - Zscore (HHI Geo).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.204**	0.172***	0.102	0.116**	0.084	0.120**	0.096**
	(0.098)	(0.061)	(0.067)	(0.053)	(0.052)	(0.048)	(0.046)
NPL$_{t-1}$	-0.047	-0.100**	-0.073**	-0.075**	-0.112***	-0.096***	-0.058***
	(0.041)	(0.044)	(0.031)	(0.029)	(0.018)	(0.017)	(0.008)
Cost-to-income$_{t-1}$	0.002	0.006	-0.016*	-0.003	-0.007	-0.014**	-0.017***
	(0.011)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)
Liquid assets$_{t-1}$	0.009	0.027**	0.004	0	-0.012	-0.018*	-0.020***
	(0.012)	(0.011)	(0.014)	(0.01)	(0.01)	(0.009)	(0.008)
GDPt	0.240**	0.162**	0.121	0.138***	0.218***	0.052	-0.05
	(0.118)	(0.07)	(0.098)	(0.044)	(0.068)	(0.066)	(0.049)
Inflation$_t$	-0.480***	0.272*	-0.016	0.32	0.216	-0.178	-0.158
	(0.152)	(0.143)	(0.195)	(0.215)	(0.207)	(0.16)	(0.142)
GIIPS Country$_t$	0.536	0.059	-0.022	-0.033	0.165	-0.611***	-0.766***
	(0.38)	(0.26)	(0.29)	(0.241)	(0.191)	(0.195)	(0.189)
HHI Geo$_{t-1}$	-1.928***	-1.469***	-0.953	-1.175**	-0.803*	-1.216***	-0.790**
	(0.451)	(0.464)	(0.599)	(0.441)	(0.437)	(0.432)	(0.338)
Constant	0.478	-0.014	2.196	0.507	2.483*	3.664***	3.960***
	(2.366)	(1.285)	(1.514)	(1.585)	(1.413)	(0.976)	(0.813)
Observations	54	52	55	55	51	62	69
R-squared	0.364	0.397	0.339	0.552	0.622	0.684	0.725

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is HHI Geo indicating diversification of banks across geographical regions. Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE B.VIII: Cross-Sectional Regression Results by Year - Zscore (Ratio Nonbanks).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.007	0.072	0.009	0.013	0.021	0.019	0.051
	(0.08)	(0.056)	(0.05)	(0.042)	(0.043)	(0.041)	(0.04)
NPL$_{t-1}$	-0.056	-0.097*	-0.064**	-0.064*	-0.110***	-0.089***	-0.056***
	(0.059)	(0.052)	(0.03)	(0.033)	(0.021)	(0.019)	(0.009)
Cost-to-income$_{t-1}$	-0.001	0.005	-0.018**	-0.005	-0.009	-0.017**	-0.021***
	(0.015)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)
Liquid assets$_{t-1}$	0.008	0.032**	0.001	-0.01	-0.022**	-0.026***	-0.024***
	(0.015)	(0.014)	(0.016)	(0.011)	(0.009)	(0.009)	(0.008)
GDPt	0.219	0.089	0.183**	0.181***	0.263***	0.092	-0.064
	(0.15)	(0.069)	(0.078)	(0.045)	(0.069)	(0.067)	(0.059)
Inflation$_t$	-0.391*	0.276*	0.027	0.292	0.255	-0.185	-0.023
	(0.203)	(0.16)	(0.177)	(0.231)	(0.223)	(0.203)	(0.152)
GIIPS Country$_t$	0.361	0.032	-0.003	0.028	0.224	-0.607***	-0.651***
	(0.45)	(0.28)	(0.285)	(0.257)	(0.197)	(0.216)	(0.24)
Ratio Nonbanks$_{t-1}$	-0.832	-0.634	-0.486	0.143	-0.181	-0.064	0.832
	(0.553)	(0.551)	(0.523)	(0.572)	(0.484)	(0.613)	(0.714)
Constant	4.054*	1.465	3.920***	2.055	3.778**	5.497***	3.987***
	(2.08)	(1.163)	(1.385)	(1.645)	(1.682)	(1.109)	(0.959)
Observations	54	52	55	55	50	62	69
R-squared	0.199	0.299	0.314	0.512	0.606	0.634	0.712

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks). Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE B.IX: Cross-Sectional Regression Results by Year - Zscore (Ratio Foreign).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.134	0.162***	0.083	0.092*	0.07	0.124**	0.066
	(0.106)	(0.053)	(0.056)	(0.054)	(0.058)	(0.048)	(0.046)
NPL$_{t-1}$	-0.036	-0.090**	-0.049	-0.057*	-0.108***	-0.090***	-0.057***
	(0.047)	(0.038)	(0.03)	(0.033)	(0.018)	(0.015)	(0.009)
Cost-to-income$_{t-1}$	0	0.005	-0.017*	-0.005	-0.007	-0.016**	-0.018***
	(0.012)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)
Liquid assets$_{t-1}$	0.006	0.026**	0.007	-0.001	-0.014	-0.018**	-0.024***
	(0.014)	(0.01)	(0.013)	(0.011)	(0.01)	(0.009)	(0.007)
GDPt	0.189	0.155**	0.094	0.143***	0.212***	0.038	-0.048
	(0.129)	(0.063)	(0.1)	(0.048)	(0.066)	(0.066)	(0.052)
Inflation$_t$	-0.409**	0.267*	-0.068	0.339	0.153	-0.159	-0.132
	(0.178)	(0.151)	(0.209)	(0.208)	(0.212)	(0.156)	(0.14)
GIIPS Country$_t$	0.329	-0.035	-0.167	-0.115	0.11	-0.712***	-0.813***
	(0.385)	(0.242)	(0.29)	(0.238)	(0.171)	(0.188)	(0.193)
Ratio Foreign$_{t-1}$	-1.258**	-1.738***	-1.173**	-1.064**	-0.843	-1.392***	-0.446
	(0.563)	(0.5)	(0.502)	(0.473)	(0.556)	(0.47)	(0.363)
Constant	1.546	0.37	2.744*	0.893	3.017*	3.713***	4.522***
	(2.443)	(1.167)	(1.481)	(1.527)	(1.515)	(0.959)	(0.806)
Observations	54	52	55	55	51	62	69
R-squared	0.256	0.444	0.378	0.545	0.622	0.689	0.711

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.X: Different Crisis Periods - Zscore.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log assets$_{2007}$	0.019	0.115	0.012	0.088	0.072	0.159*	0.061	0.137
	(0.066)	(0.09)	(0.067)	(0.088)	(0.064)	(0.092)	(0.065)	(0.087)
NPL$_{2007}$	-0.08	-0.084**	-0.076	-0.075*	-0.078	-0.082*	-0.073	-0.072
	(0.049)	(0.04)	(0.047)	(0.042)	(0.051)	(0.043)	(0.048)	(0.045)
Cost-to-income$_{2007}$	0.002	0.006	0.002	0.004	0.009	0.012	0.009	0.011
	(0.01)	(0.009)	(0.011)	(0.008)	(0.01)	(0.009)	(0.01)	(0.009)
Liquid assets$_{2007}$	-0.008	-0.004	-0.01	-0.007	-0.003	0	-0.006	-0.003
	(0.01)	(0.01)	(0.012)	(0.01)	(0.01)	(0.009)	(0.011)	(0.009)
GDP$_{2007}$	0.025	0.017	0.007	0.004	0.105	0.095	0.082	0.081
	(0.142)	(0.136)	(0.158)	(0.14)	(0.115)	(0.112)	(0.135)	(0.115)
Inflation$_{2007}$	-0.866***	-0.721***	-0.892***	-0.781***	-0.932***	-0.795***	-0.965***	-0.848***
	(0.272)	(0.24)	(0.275)	(0.265)	(0.234)	(0.21)	(0.232)	(0.231)
GIIPS Country$_{2007}$	0.244	0.222	0.211	0.165	0.356	0.322	0.309	0.264
	(0.428)	(0.434)	(0.439)	(0.421)	(0.401)	(0.416)	(0.418)	(0.4)
HHI Business$_{2007}$	-0.214				-0.319			
	(0.504)				(0.586)			
HHI Geo$_{2007}$		-1.067**				-1.026**		
		(0.443)				(0.479)		
Ratio Nonbanks$_{2007}$			0.216				0.27	
			(0.487)				(0.474)	
Ratio Foreign$_{2007}$				-0.854*				-0.865*
				(0.493)				(0.488)
Constant	4.192**	2.106	4.147**	2.837	2.695	0.694	2.641*	1.327
	(1.646)	(2.139)	(1.584)	(2.016)	(1.63)	(2.176)	(1.557)	(2.038)
Observations	54	54	54	54	54	54	54	54
R-squared	0.311	0.367	0.311	0.351	0.334	0.379	0.333	0.369

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries. The dependent variable in columns (1)-(4) is a bank's average Zscore over 2008 and 2009. The dependent variable in columns (5)-(8) is a bank's average Zscore over 2010, 2011 and 2012. Explanatory variables as of the year 2007 include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location as of the year 2007 include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures are from the year 2007 and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.XI: Panel Regression Results - Zscore.

	(1)	(2)	(3)	(4)
Log assets$_{t-1}$	-0.621***	-0.605***	-0.597***	-0.573***
	(0.149)	(0.14)	(0.123)	(0.125)
NPL$_{t-1}$	-0.003	-0.003	-0.003	-0.004
	(0.005)	(0.005)	(0.004)	(0.004)
Cost-to-income$_{t-1}$	0	0	0	0
	(0.002)	(0.002)	(0.001)	(0.001)
Liquid assets $_{t-1}$	0.003	0.002	0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.004)
GDP$_t$	0.030***	0.029***	0.023**	0.023**
	(0.009)	(0.01)	(0.009)	(0.009)
Inflation$_t$	0.021	0.016	0.009	0.004
	(0.019)	(0.02)	(0.017)	(0.017)
Crisis (0/1)	-0.389***	-0.347***	0.211***	0.228***
	(0.089)	(0.088)	(0.056)	(0.053)
HHI Business$_{t-1}$	-0.066*			
	(0.035)			
Crisis (0/1)*HHI Business$_{t-1}$	0.007			
	(0.03)			
HHI Geo$_{t-1}$		-0.007		
		(0.051)		
Crisis (0/1)*HHI Geo$_{t-1}$		-0.057**		
		(0.024)		
Ratio Nonbanks$_{t-1}$			0.019	
			(0.023)	
Crisis (0/1)*Ratio Nonbanks$_{t-1}$			-0.070***	
			(0.022)	
Ratio Foreign$_{t-1}$				0.017
				(0.032)
Crisis (0/1)*Ratio Foreign$_{t-1}$				-0.048**
				(0.022)
Constant	14.056***	13.764***	13.229***	12.792***
	(2.745)	(2.576)	(2.25)	(2.27)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	397	398	443	444
R-squared	0.347	0.354	0.349	0.326
Number of banks	75	75	75	75

Notes: This table reports fixed effects regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a bank's Zscore (in logs). Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures are standardized and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. The complexity measures are interacted with the dummy variable Crisis (0/1), which equals one in the years 2008, 2009 and 2010, and zero otherwise. The regressions take into account bank and year fixed effects. Cluster-robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.XII: Regression Results - ΔCoVaR.

	(1)	(2)	(3)	(4)
Log $assets_{2007}$	0.002***	0.002***	0.003***	0.002***
	0.	(0.001)	0.	(0.001)
$Equity_{2007}$	0	0	0	0
	0.	0.	0.	0.
NPL_{2007}	0.001	0.001*	0.001	0.001*
	(0.001)	0	(0.001)	0
Cost-to-$income_{2007}$	0	0	0	0
	0	0	0	0
RoA_{2007}	0.003	0.006**	0.006*	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Liquid $assets_{2007}$	0	0	0	0
	0	0	0	0
GDP_{2007}	0	0	-0.001	0
	(0.001)	(0.001)	(0.001)	(0.001)
$Inflation_{2007}$	0.004	0.003	0.004	0.003
	(0.003)	(0.002)	(0.002)	(0.002)
GIIPS $Country_{2007}$	0.003	0.004	0.004	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)
HHI $Business_{2007}$	0.008			
	(0.006)			
HHI Geo_{2007}		0.012***		
		(0.004)		
Ratio $Nonbanks_{2007}$			0.007	
			(0.004)	
Ratio $Foreign_{2007}$				0.013***
				(0.004)
Constant	-0.046***	-0.03	-0.059***	-0.029
	(0.016)	(0.019)	(0.017)	(0.018)
Observations	54	54	54	54
R-squared	0.582	0.641	0.58	0.682

Notes: This table reports cross section regressions that are based on yearly data of stock listed banks of Euro area countries. The dependent variable is a bank's average ΔCoVaR over the years 2008-2010. Explanatory variables are from the year 2007 and include bank-level controls: Log assets is the log of total assets, equity is the ratio of equity to total assets (in %), NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), return on assets (RoA, in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures are also from year the 2007 and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.XIII: Regression Results - State aid.

	(1)	(2)	(3)	(4)
Log assets$_{t-1}$	0.513**	0.316	0.632**	0.427*
	(0.257)	(0.238)	(0.311)	(0.245)
Equity$_{t-1}$	-0.297***	-0.297***	-0.350***	-0.291***
	(0.112)	(0.109)	(0.105)	(0.101)
NPL$_{t-1}$	0.135***	0.143***	0.149***	0.128***
	(0.046)	(0.036)	(0.051)	(0.033)
Cost-to-income$_{t-1}$	-0.009	-0.015	-0.011	-0.009
	(0.02)	(0.019)	(0.022)	(0.02)
RoA$_{t-1}$	-0.21	-0.342	-0.311	-0.207
	(0.211)	(0.218)	(0.238)	(0.214)
Liquid assets$_{t-1}$	-0.103**	-0.112**	-0.119**	-0.116**
	(0.049)	(0.05)	(0.053)	(0.052)
GDP$_t$	0.138	0.145	0.166	0.166
	(0.105)	(0.104)	(0.115)	(0.108)
Inflation$_t$	-1.021**	-0.794**	-1.161***	-0.927**
	(0.402)	(0.348)	(0.395)	(0.376)
GIIPS Country$_t$	-1.083	-0.943	-1.386**	-0.86
	(0.693)	(0.605)	(0.707)	(0.602)
HHI Business$_{t-1}$	0.788			
	(1.614)			
HHI Geo$_{t-1}$		3.452***		
		(1.14)		
Ratio Nonbanks$_{t-1}$			-3.738***	
			(1.189)	
Ratio Foreign$_{t-1}$				2.505**
				(1.01)
Constant	-5.543	-2.791	-9.044	-9.528*
	(5.777)	(5.027)	(6.127)	(5.175)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	399	400	399	400
Number of banks	75	75	75	75

Notes: This table reports random effects probit regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a dummy for state aid, which equals one if the bank received state aid that year following the State Aid Register of the European Commission, and zero otherwise. Explanatory variables include bank-level controls: Log assets is the log of total assets, equity is the ratio of equity to total assets (in %), NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), return on assets (RoA, in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures comprise: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. Regressions include time fixed effects. Standard errors clustered at the bank level are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE B.XIV: Different Crisis Periods - State aid.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log assets$_{t-1}$	0.496*	0.324	0.705**	0.431*	0.506*	0.312	0.638**	0.432*
	(0.26)	(0.241)	(0.349)	(0.239)	(0.259)	(0.237)	(0.319)	(0.255)
Equity$_{t-1}$	-0.292***	-0.343***	-0.404***	-0.314***	-0.298***	-0.287***	-0.352***	-0.299***
	(0.109)	(0.113)	(0.103)	(0.102)	(0.113)	(0.108)	(0.105)	(0.1)
NPL$_{t-1}$	0.136***	0.162***	0.159***	0.130***	0.133***	0.139***	0.151***	0.136***
	(0.046)	(0.04)	(0.054)	(0.033)	(0.045)	(0.035)	(0.052)	(0.037)
Cost-to-income$_{t-1}$	-0.01	-0.025	-0.01	-0.015	-0.009	-0.015	-0.011	-0.008
	(0.02)	(0.019)	(0.023)	(0.018)	(0.021)	(0.019)	(0.022)	(0.02)
RoA$_{t-1}$	-0.217	-0.454*	-0.271	-0.241	-0.221	-0.365	-0.306	-0.179
	(0.21)	(0.238)	(0.243)	(0.208)	(0.225)	(0.235)	(0.239)	(0.209)
Liquid assets$_{t-1}$	-0.100**	-0.112**	-0.128**	-0.114**	-0.101**	-0.113**	-0.121**	-0.115**
	(0.049)	(0.05)	(0.059)	(0.052)	(0.05)	(0.049)	(0.054)	(0.052)
GIIPS Country$_t$	-1.047	-0.838	-1.425*	-0.776	-1.047	-0.971	-1.403*	-0.811
	(0.699)	(0.619)	(0.8)	(0.586)	(0.701)	(0.611)	(0.719)	(0.598)
GDP$_t$	0.151	0.196**	0.144	0.192**	0.141	0.136	0.168	0.158
	(0.108)	(0.098)	(0.128)	(0.097)	(0.105)	(0.1)	(0.115)	(0.112)
Inflation$_t$	-0.996***	-0.699**	-1.241***	-0.860**	-1.022**	-0.810**	-1.160***	-0.901**
	(0.384)	(0.342)	(0.431)	(0.352)	(0.397)	(0.342)	(0.399)	(0.365)
HHI Business$_{t-1}$	0.335				0.093			
	(0.458)				(0.439)			
Crisis(0/1)*HHI Business$_{t-1}$	-0.432				0.523			
	(0.604)				(0.638)			
HHI Geo$_{t-1}$		1.234***				0.876**		
		(0.299)				(0.348)		
Crisis(0/1)*HHI Geo$_{t-1}$		-1.036***				0.237		
		(0.335)				(0.393)		
Ratio Nonbanks$_{t-1}$			-0.311				-0.659***	
			(0.259)				(0.221)	
Crisis(0/1)*Ratio Nonbanks$_{t-1}$			-0.670*				0.124	
			(0.362)				(0.237)	
Ratio Foreign$_{t-1}$				0.749***				0.727**
				(0.244)				(0.294)
Crisis(0/1)*Ratio Foreign$_{t-1}$				-0.422				-0.348
				(0.328)				(0.297)
Constant	-4.561	-0.845	-13.405*	-8.560*	-4.798	-1.664	-12.330*	-9.158*
	(5.221)	(5.184)	(7.)	(5.08)	(5.163)	(5.051)	(6.618)	(5.437)
ME complexity, crisis=1	**-0.004**	**0.006**	**-0.040*** **	**0.013**	**0.03**	**0.051** **	**-0.022** **	**0.015** **
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	399	400	399	400	399	400	399	400
Number of banks	75	75	75	75	75	75	75	75

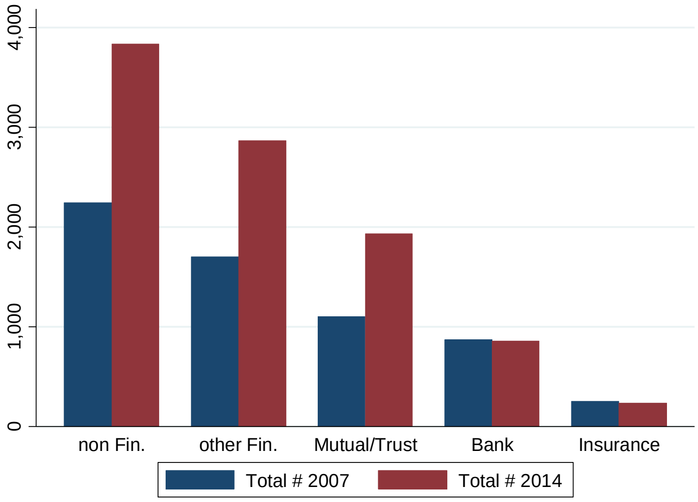
Notes: This table reports random effects probit regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a dummy for state aid, which equals one if the bank received state aid that year following the State Aid Register of the European Commission, and zero otherwise. In columns (1)-(4), the complexity measures are interacted with the dummy variable Crisis (0/1), which equals one in the years 2008 and 2009 and zero otherwise. In columns (5)-(8), the dummy variable Crisis (0/1) equals one in the years 2010, 2011 and 2012 and zero otherwise. Marginal effects (ME) for the complexity measures in case of crisis are reported below. Explanatory variables are defined as before. The complexity measures comprise: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. Regressions include time fixed effects. Standard errors clustered at the bank level are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

TABLE B.XV: Regression Results - State Aid and Restructuring Power.

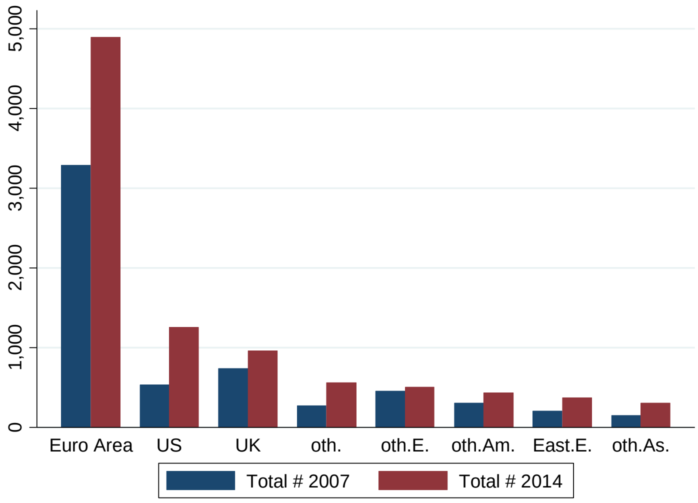
	(1)	(2)	(3)	(4)
Log assets$_{t-1}$	0.472**	0.251	0.597**	0.384
	(0.232)	(0.223)	(0.298)	(0.238)
Equity$_{t-1}$	-0.253**	-0.268**	-0.329***	-0.263***
	(0.103)	(0.106)	(0.103)	(0.1)
NPL$_{t-1}$	0.135***	0.146***	0.150***	0.128***
	(0.047)	(0.04)	(0.055)	(0.036)
Cost-to-income$_{t-1}$	-0.002	-0.005	-0.003	0
	(0.019)	(0.018)	(0.021)	(0.019)
RoA$_{t-1}$	-0.14	-0.264	-0.218	-0.117
	(0.195)	(0.201)	(0.214)	(0.188)
Liquid assets$_{t-1}$	-0.107**	-0.117**	-0.123**	-0.121**
	(0.048)	(0.05)	(0.055)	(0.053)
GIIPS Country$_t$	-1.135*	-0.969*	-1.358*	-0.861
	(0.673)	(0.575)	(0.702)	(0.584)
GDP$_t$	0.149	0.187*	0.182	0.200*
	(0.11)	(0.106)	(0.122)	(0.113)
Inflation$_t$	-0.845*	-0.458	-0.991**	-0.667
	(0.494)	(0.406)	(0.488)	(0.438)
Restructuring Power$_t$	-0.061	-0.153	-0.077	-0.112
	(0.143)	(0.112)	(0.127)	(0.105)
HHI Business$_{t-1}$	1.78			
	(2.033)			
HHI Geo$_{t-1}$		3.884***		
		(1.272)		
Ratio Nonbanks$_{t-1}$			-3.524***	
			(1.14)	
Ratio Foreign$_{t-1}$				2.662**
				(1.05)
Constant	-6.568	-3.227	-8.902	-9.189*
	(5.843)	(5.043)	(5.919)	(5.292)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	393	394	393	394
Number of banks	75	75	75	75

Notes: This table reports random effects probit regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a dummy for state aid, which equals one if the bank received state aid that year following the State Aid Register of the European Commission, and zero otherwise. Explanatory variables include bank-level controls: Log assets is the log of total assets, equity is the ratio of equity to total assets (in %), NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), return on assets (RoA, in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. We include Restructuring Power provided by the World Bank Surveys on Bank Regulation to control for cross-country heterogeneity of regulation. The complexity measures comprise: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. Regressions include time fixed effects. Standard errors clustered at the bank level are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

FIGURE B.I: Complexity measures decomposed 2007 versus 2014.



Notes: This graph shows the number of subsidiaries by type for the years 2007 and 2014.



Notes: This graph shows the number of subsidiaries by region for the years 2007 and 2014.

Chapter 4

Lender-Specific Mortgage Supply Shocks and Macroeconomic Performance in the US

Abstract: *This paper highlights the importance of market concentration both in the regulated and unregulated US mortgage market for the propagation of idiosyncratic mortgage supply shocks to the macroeconomy. Based on micro-level data from the Home Mortgage Disclosure Act for the 1990-2014 period, our results suggest that lender-specific mortgage supply shocks affect house price and employment dynamics at the regional level. The larger the idiosyncratic shocks to newly issued mortgages, the stronger are house price growth and job creation. We show that the positive link between idiosyncratic mortgage shocks and regional housing and labor market outcomes is economically meaningful and robust to alternative specifications.*[*]

4.1 Introduction

Building on the concept of granularity (Gabaix, 2011), this paper investigates the role of micro-level mortgage supply shocks for aggregate house price and employment dynamics across US regions. The idea is that *lender-specific* shocks to mortgage origination can impact macroeconomic variables if concentration in the mortgage market is very high. If a few large mortgage lenders dominate the market, diversification effects are dampened, such that idiosyncratic lending shocks can lead to movements in aggregate mortgage supply, house prices, and real economic activity.

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Indeed, mortgage market concentration in general has increased substantially since the 1990s. While the top 1% of all US lenders supplied half the mortgages in 1991, they accounted for almost 80% of total mortgages in 2007. Also, the market share of shadow banks within the mortgage market significantly increased. While the share of overall mortgage originations by non-bank lenders has nearly doubled between 2007-2015, it has increased even more in the riskier borrower segment (Buchak et al., 2017). Figure 4.1 illustrates that mortgage lending accounts for an increasing fraction of the overall credit business: while mortgages made up for less than one quarter of total loans in the US at the beginning of the 1990s, the ratio of mortgages to total loans has significantly increased during the run-up to the financial crisis. In 2010, it stood at roughly 45%. Regarding the macroeconomic consequences of these developments, besides the fact that the American housing market was at the center of the last financial crisis, the literature shows that mortgage lending is an important driver of macroeconomic vulnerabilities (Jorda et al., 2016).[1]

Previous literature has shown that *aggregate* mortgage supply shocks explain a significant portion of house price movements (Favara and Imbs, 2015) and employment(Di Maggio and Kermani, 2017) via changes in housing net worth and hence aggregate demand (Mian et al., 2013; Mian and Sufi, 2014b). We contribute to this strand of literature in two distinct ways. First, our analysis extends the literature by shifting the focus towards lender-specific, granular effects. Given that risk at the level of individual financial institutions can harm aggregate economic stability, this paper asks whether *idiosyncratic* changes in the mortgage supply of large lenders impact house price growth and real economic performance as measured, e.g., by job creation. It thus aims at shedding light on how sensitive the US economy reacts to idiosyncratic credit supply shocks at the level of large mortgage lending

[1]Overall, concentration in the US banking sector has continued to rise after the financial crisis, e.g. due to takeovers of ailing competitors by the largest American banks. Banking sector concentration has thus been a topic of increasing general interest. According to https://politicsofpoverty.oxfamamerica.org/2016/01/too-big-to-fail-and-only-getting-bigger/, while accounting for about ten percent of total bank assets in the beginning of the 1990s, the biggest five American banks own nearly half of total bank assets in the US today.

institutions – a question that is of utmost importance given that US mortgages are the world's largest asset class (Economist 2016). Second, given the importance of the shadow banking sector for financial supervisors and politicians who face the challenge to make the financial system resilient, we are the first to investigate granular effects in this segment of the mortgage market.

We analyze the nexus of lender-specific mortgage supply shocks, house price and employment dynamics in US regions in two steps. First, we examine if the degree of concentration in the market for newly issued mortgages is high enough for granular effects on regional variables to emerge. Technically speaking, we have to test whether the distribution of mortgages follows a fat-tailed power law. Second, we investigate whether and how lender-specific mortgage supply shocks drive house price movements and real economic activity at the regional level.

At first glance, idiosyncratic shocks should not matter for aggregate outcomes. Bank-specific events, including financial innovations, fine payments, computer glitches, and unexpected managerial decisions, should not have any far-reaching power beyond the micro-level in an economy with a large number of firms and banks, like the United States. If firm sizes were normally distributed, the law of large numbers would smooth out the impact of idiosyncratic shocks, ultimately showing negligible effects on aggregate variables. However, if markets are highly concentrated, as they are in manufacturing Di Giovanni et al., 2011 and especially in banking Bremus et al., 2013, such diversification effects are dampened. Gabaix (2011) demonstrates, both theoretically and empirically, that a fat-tailed power law distribution of firm sizes implies a significant role of idiosyncratic, firm-level shocks for aggregate volatility. Intuitively, idiosyncratic fluctuations of the sales of Nokia cannot be easily counteracted by other firms, exposing Finland's economic activity to the fates of one big market player. Gabaix (2011) labels this phenomenon as "Granularity" and presents evidence that firm-specific shocks hitting the largest manufacturing firms in the US explain one-third of aggregate output fluctuations.

We apply the the concept of granularity to the US mortgage market. Analyzing the impact of mortgage market concentration and idiosyncratic mortgage supply shocks is important, because even if (large) banks have been regulated more strictly since the financial crisis, non-bank mortgage lenders that are less regulated have increasingly gained market share during the last years (Buchak et al., 2017).[2] An analysis of mortgage market concentration and shocks originating from large mortgage lenders is thus important to inform the regulatory debate on both micro- and macroprudential approaches.

Our analysis yields four key findings. First, we provide evidence that the mortgage market is highly concentrated at the level of US Metropolitan Statistical Areas (MSAs). Estimations of the power law coefficient of the regional distributions of new mortgages show that mortgage size follows a power-law with a fat right tail in all MSAs. Thereby, we can show that the necessary condition for granular effects to emerge from the mortgage market is fulfilled at our level of analysis, the MSA-level.

Second, our estimation results reveal a positive and statistically significant link between idiosyncratic shocks to newly issued mortgages and house price growth. These findings are in line with previous results from the granularity-literature (Amiti and Weinstein, forthcoming), and confirm that credit shocks at the micro-level can translate into aggregate movements. The larger that the shocks to mortgage lending at the level of lenders are, the greater is house price growth. Hence, the presence of large mortgage lenders amplifies the effects of idiosyncratic mortgage supply shocks compared to less concentrated markets.

Third, we present evidence that idiosyncratic mortgage supply shocks have macroeconomic effects beyond the housing market. Supply shocks originating from large mortgage lenders are not only positively linked to house price growth, but also to real economic variables like firm growth or

[2]In 2011, half of all new mortgages where issued by the three largest US banks (JPMorgan Chase, Bank of America, Wells Fargo). In 2016, this share declined to about 20%, and at the same time, six out of the top ten mortgage lenders where non-banks (Washington Post, February 23, 2017).

job creation. Hence, the presence of large mortgage lenders and increasing concentration in the mortgage market affects macroeconomic performance.

And fourth, we show that granular effects from non-bank mortgage lenders on house price growth are economically stronger than the effects originating from traditional deposit-taking institutions. However, these shocks do not translate to the real economy. Idiosyncratic mortgage supply shocks from the non-bank mortgage lenders do not show a statistically significant impact on aggregate employment in US regions.

Our identification strategy rests on two features. First, micro-level data from the Home Mortgage Disclosure Act (HMDA) on mortgage applications enable us to employ information on newly issued mortgages, whereas the bank balance sheet data used in several previous studies just provide outstanding stocks of loans, from which newly issued loans can only be proxied. Second, the HMDA data allow for assigning mortgages to the region they are supplied to, such that lender-specific shocks can be precisely linked to the region they affect. We aggregate each lender's mortgage supply at the level of MSAs. Since the financial institutions in our sample lend to multiple regions, we can follow the identification strategy by Khwaja and Mian (2008) to reduce concerns that our shock measure is plagued by regional demand factors. Thus, we can significantly increase the internal validity of the estimation of granular effects from the financial sector.

To put the contribution of our results into perspective, note that standard asset pricing literature suggests that house prices should equal the sum of expected income payoffs from renting a house Allen and Gale, 2007. Hence, the price of housing assets should depend only on their expected return, regardless of how the asset purchase is financed.[3] Yet, recent literature underlines that cheaper credit is one of the main factors driving house price increases: In a theoretical paper, Justiniano et al. (2015) show that empirical features of the housing boom can be best explained by looser lending constraints in the mortgage market, not by borrowing constraints. Empirical evidence by

[3]Kindleberger (1978) was the first to challenge that view and argue that the ability to borrow money impacts asset prices.

Adelino et al. (2012) reveals that easier credit supply positively affects house prices. Mian and Sufi (2009) show that securitization led to an extension in subprime mortgages and, finally, to increased house price growth over the 2002-2005 period. In a similar vein, Di Maggio and Kermani (2017) find that US counties with greater mortgage origination have seen higher house price increases in booms, and steeper house price reductions during busts. Based on US branching deregulation as an instrument for credit growth, empirical findings by Favara and Imbs (2015) support that access to credit is an important driver of house prices - both in statistical and economical senses.

– Insert Figure 4.1 here –

Regarding the macroeconomic consequences of movements in mortgage supply and house prices, based on historical credit data, Jorda et al. (2016) highlight that the importance of mortgage credit in financial sector activity has significantly increased over time, so that banks and households have levered up substantially. They identify mortgage booms as one important reason for financial as well as real fluctuations. Loutskina and Strahan (2015) show that financial integration within the US has led to a closer link between house price developments and the real economy. The amplified effect of collateral shocks on the real economy has increased macroeconomic volatility. According to the household balance sheet view of Mian and Sufi (2014a), macroeconomic performance in the US crucially depends on household debt dynamics. The evolution of household debt, in turn, is linked to house prices: the larger the growth in house prices, and hence in home equity, the more that leverage builds up in the household sector, such that default risk rises. In case of a sudden drop in house prices, households have to deleverage, which depresses private consumption and, hence, aggregate demand. Thus, linkages between the credit market and house prices appear to be a crucial determinant of macroeconomic performance. Consequently, our question of whether idiosyncratic mortgage supply shocks matter for house price developments and real economic activity in concentrated mortgage markets is important for the regulatory debate over micro- and macroprudential policies.

Our study is most closely related to the literature on granular origins of aggregate fluctuations in the banking sector. Blank et al. (2009) were the first to measure granular effects from banking to investigate how bank concentration affects the stability of the German banking system. Using a panel of Eastern European countries, Buch and Neugebauer (2011) find significant effects of idiosyncratic shocks to large banks on the real economy. Using a linked bank-firm level data set, Amiti and Weinstein (forthcoming) demonstrate that idiosyncratic credit supply shocks explain about 40% of aggregate loan and investment fluctuations in Japan. Bremus et al. (2013) provide a general equilibrium model of granular effects from the credit market and find empirical support that bank-specific credit shocks affect the macroeconomy in a large set of countries.

For the large and well diversified US economy, the evidence on granular effects from the financial sector is so far very limited. One exception is the study by Landier et al. (2017), who demonstrate that - due to high concentration and hence granular effects - financial integration is an important driver of the increased synchronization of house prices across US states. We add to this literature by studying how market structure in the US mortgage market affects macroeconomic performance in terms of regional house prices and employment.

The following section presents the data and our empirical methodology. Section 4.3 discusses the estimation results, while Section 4.4 concludes.

4.2 Data and Methodology

In order to test whether lender-specific mortgage supply shocks affect house price movements at the regional level, we proceed in three steps. First, we calculate idiosyncratic shocks to mortgage supply. Second, a measure of granular effects from the regional mortgage market is constructed using lenders' regional mortgage market shares. We then regress our macroeconomic variables of interest (house prices and labor market outcomes) on this measure of granular effects.

Table 4.1 provides detailed information about our data and variable definitions.

– Insert Table 4.1 here –

4.2.1 Mortgage Market Data

To measure idiosyncratic mortgage supply shocks, we rely on HMDA data. This data set provides annual information on every newly issued mortgage loan from individual mortgage lenders to individual households. To determine whether institutions are serving the housing finance needs of their local communities, the Home Mortgage Disclosure Act from 1975 requires approximately 80% of all mortgage lending institutions nationwide to disclose information about the geographic location and other characteristics of the mortgage loans they originate, like the year of application, the dollar amount of the loan, and the application outcome. Most depository institutions (commercial banks, savings associations, and credit unions) with home or branch offices in an MSA are required to report. The only exemptions are small institutions with assets of less than $35 million for the 2006 reporting year, lenders not in the home-lending business, or those that have offices exclusively in rural areas (non-MSAs). Non-depository consumer- and mortgage-finance companies do have to report if they originate one hundred or more home purchase or home refinancing loans per year covered. Our sample includes both depository and non-depository institutions covered by the HMDA.

The HMDA data have two important advantages over bank balance sheet data that is typically used in the granularity-literature. First, they provide information about newly issued mortgages (a flow variable). In contrast, balance sheet data provide information about the stock of credits only, such that newly issued credit can only be proxied by looking at credit growth.

And second, the HMDA data allow for assigning mortgages to the regions where they are supplied, something bank balance sheet data does not permit.

Our regression sample covers annual information on mortgages for 345 MSAs from 1990 through 2014. More than thirty lenders are active per year in each MSA included in the sample (Table 4.2). Exploiting the HMDA data set, we aggregate all accepted mortgage loans for each lending institution[4] according to the location of the purchased property, namely by MSA. In the baseline scenario we include all lenders, i.e. both depository and non-depository institutions and in section 4.2.6 we distinguish effects of granularity by bank type. We keep all loan purpose types (home purchase, home improvement and refinancing loans), all lien types and all owner-occupancy types. The reason for this non-restrictive loan selection is that we are interested in lending supply shocks, independent of loan types. Also, since most loan type indicators are available as of 2004 only, any removal of certain loan types would lead to incomparability with past sample years.

4.2.2 Granular Effects from the Mortgage Market

Intuitively, the idea behind granular effects from the mortgage market is that idiosyncratic shocks matter for aggregate house prices and real economic activity if concentration is high enough. If the market shares of the players in the credit market are relatively equal, then idiosyncratic shocks cancel out across a large number of lenders. Yet, when concentration is high, such that the largest players dominate the market, they can contribute to aggregate movements in house prices and the real economy.[5]

Following the exposition by Landier et al. (2017), we posit that mortgage origination of a given lender b in region m can be decomposed into a lender-specific lending shock, $\epsilon_{bm,t}$, and a common shock, ζ_t. Mortgage growth at the level of the lender can then be expressed as

$$\frac{\Delta L_{bm,t}}{L_{bm,t-1}} = \zeta_t + \epsilon_{bm,t} \,. \tag{4.1}$$

[4]We treat every combination of respondent ID and agency code as distinct lending institution.

[5]For a theoretical derivation of granular effects, see Gabaix (2011), Section 2.3.

The idiosyncratic shock $\epsilon_{bm,t}$ can be interpreted as a shock to a lender's loan origination policy, e.g. due to unexpected managerial decisions, or as a lender-specific funding shock that translates into a change in mortgage origination.

Based on findings from previous literature (Adelino et al., 2012; Favara and Imbs, 2015; Amiti and Weinstein, forthcoming), we hypothesize that macroeconomic outcomes in region m are affected by credit supply, so that

$$\frac{\Delta Y_{m,t}}{Y_{m,t-1}} = \mu \frac{\Delta L_{m,t}}{L_{m,t-1}} + \eta_{m,t} \tag{4.2}$$

where $L_{m,t} = \sum_1^B L_{bm,t}$ is the aggregate volume of mortgage loans in region m at time t, $Y_{m,t}$ denotes regional housing and labor market variables like house prices or job creation, and $\eta_{m,t}$ is a fundamental macroeconomic shock to $Y_{m,t}$.

Combining the two equations above yields

$$\frac{\Delta Y_{m,t}}{Y_{m,t-1}} = \mu \left[\zeta_t + \sum_1^B \epsilon_{bm,t} \left(\frac{L_{bm,t-1}}{L_{m,t-1}} \right) \right] + \eta_{m,t}. \tag{4.3}$$

Equation (4.3) reveals that the growth rate of the aggregate variable Y_t depends (i) on the common credit shocks ζ_t, (ii) the idiosyncratic mortgage supply shock, $\epsilon_{bm,t}$, weighted by lender b's market share in region m, $L_{bm,t-1}/L_{m,t-1}$, and (iii) on the fundamental shock to the macroeconomic variable considered $\eta_{m,t}$. While Favara and Imbs (2015) have focused on the identification of a causal link between house price growth and a common, exogenous mortgage supply shock ζ_t, the goal in this paper is to investigate how idiosyncratic mortgage supply shocks $\epsilon_{bm,t}$ that originate from the business of large mortgage lenders affect the housing market and ultimately the real economy.

Concentration in mortgage origination. Before testing whether lender-specific mortgage supply shocks affect house price growth in US regions, we have to check whether the necessary condition for granular effects from the mortgage market is fulfilled. To that goal, the dispersion of the distribution of newly issued mortgages has to be high enough, such that idiosyncratic shocks do not cancel out across a large number of mortgage suppliers. A first look at the data reveals that US mortgage origination is indeed dominated by large lenders. Figure 4.2 reports mortgage origination activity of the largest institutions as a fraction of total mortgage origination. Mortgage origination of the top 1% of institutions is almost 80% of overall lending in 2007. The top 0.1% of lenders still account for more than 40% of total mortgage activity in 2010, thus hinting at a high degree of mortgage market concentration.

– Insert Figure 4.2 here –

Since granular effects can emerge only if mortgage origination is extremely concentrated, we must test whether the distribution of newly issued mortgages follows a fat-tailed power law (Gabaix (2011), Proposition 2).

This is the case if the power law coefficient of the distribution is less than one in absolute value.

Following Gabaix and Ibragimov (2011), we estimate the dispersion parameter of the size distribution of newly issued mortgages for each MSA using the following regression equation

$$ln(\mathrm{Rank}_{bm} - 0.5) = \alpha + \beta ln(\mathrm{NL}_{bm}) + \epsilon_{bm} \,, \tag{4.4}$$

where $Rank_{bm}$ is the rank of lender b's newly issued mortgages in MSA m, and NL_{bm} is the corresponding volume of newly issued mortgages. β is the power law coefficient, i.e., the parameter of interest here.

– Insert Figure 4.3 here –

Figure 4.3 illustrates the estimation results. It plots the histograms of the estimated power law coefficients across MSAs for each year between 1990 and 2014. All coefficients are significant at the one percent level.[6] The figure reveals that all estimates are below one (also in absolute values),

[6] The numerical estimation results are available from the authors upon request.

meaning that the distribution of newly issued mortgages is indeed extremely dispersed with infinite variance. Thus, the distribution of new mortgages follows a fat-tailed power law in all MSAs in our sample, such that the necessary condition for granular effects from the mortgage market is fulfilled. Thereby, idiosyncratic shocks can play a role for house price growth given that concentration in mortgage origination is high enough for large lenders to affect the economy.

Measuring mortgage supply shocks. To identify the idiosyncratic mortgage supply shocks, we take a similar approach to that of Greenstone et al. (2014) and regress the natural logarithm of the volume of newly issued mortgage credits of lender b in MSA m at time t on a set of lender-, time-, and MSA-fixed effects

$$ln(NL_{bmt}) = \alpha_b + \beta_t + \gamma_m + \delta_{mt} + \epsilon_{bmt} \, . \tag{4.5}$$

The goal is to purge lender b's new mortgages extended to MSA m from all macroeconomic and common mortgage market factors. Extracting the residual from this specification yields the lender-specific mortgage supply shock at the MSA-level that is exogenous to local mortgage demand and other common credit disturbances: While α_b purges newly issued mortgages from all time-invariant characteristics of lender b, like its general business model, β_t controls for all time-varying factors that affect all MSAs, like common changes in credit, general funding conditions, and economic growth. To control for mortgage demand effects, we apply the approach proposed by Khwaja and Mian (2008) and define a mortgage loan as a lender-MSA pair. Since every MSA borrows from multiple institutions, including an MSA-fixed effect accounts for time-invariant differences in demand by the same MSA across the different suppliers of credit. In addition, the combined MSA-and-year fixed effects, δ_{mt}, account for time-varying credit demand changes across regions. Thus, our shock measure is purged from MSA-specific demand changes.

– Insert Table 4.2 here –

The first panel of Table 4.2 presents summary statistics for the mortgage origination shock ϵ_{bmt}. It reveals that even if the sample mean of lender-specific mortgage supply shocks is zero, the measure takes on negative and positive values with a standard deviation of 1.7. As shown by Equation (4.5), positive values present positive deviations of newly issued mortgages (by lender b to MSA m in year t) from the conditional mean due to lender-specific events like unexpected managerial decisions on credit supply. Negative values reflect negative deviations in mortgage origination, e.g., due to idiosyncratic funding shortages.

Granularity in regional mortgage markets. To compute a measure of granular effects from the mortgage market at the MSA-level, the *Banking Granular Residual* (BGR), we weigh the idiosyncratic mortgage shocks from the previous section with the respective market share of each mortgage lender in an MSA. According to theoretical considerations for non-financial (Gabaix, 2011) and financial firms (Bremus et al., 2013) and following the econometric approach by Greenstone et al. (2014) and Mondragon (2015), we aggregate these weighted shocks, in our case at the MSA level

$$BGR_{mt} = \sum_{b=1}^{B} \frac{\mathrm{NL}_{bm,t-1}}{\mathrm{NL}_{m,t-1}} \epsilon_{bmt} , \tag{4.6}$$

where $NL_{bm,t-1}/NL_{m,t-1}$ is the lagged market share in mortgage origination of lender b in MSA m, and ϵ_{bmt} is the contemporaneous regional mortgage supply shock of lender b. This yields our measure of granular effects from the mortgage market at the MSA level, which is available at annual frequency for the period 1990-2014. The higher concentration in an MSA or the larger mortgage supply shocks, the larger the value of the BGR becomes.

According to the concept of granularity, we expect the effect of the BGR on aggregate house price growth and real economic activity to be positive.

If concentration in mortgage origination is high enough, the higher lender-specific shocks or concentration are - and thus the larger the *BGR* - the stronger should be the link to these macroeconomic variables.

– Insert Figure 4.4 here –

To visualize the regional differences of the *BGR*, the top panel of Figure 4.4 plots the average *BGR*s for MSAs in the US between 1994-2014. Even if the BGR can take on negative and positive values in individual years (see Table 4.2), on average, we observe positive values for our measure of mortgage supply shocks at the MSA-level. If any, we find a weak geographical pattern in our measure of micro-level mortgage supply shocks – high values of the *BGR* (dark colors) tend to be more frequent in the Eastern MSAs. We find very high values for the *BGR* for MSAs in Illinois (e.g., Champaign-Urbana, Kankakee, Rockford, and Springfield) and New York (e.g., Buffalo-Cheektowaga-Niagara Falls, Ithaca or Rochester), while MSAs in Nevada (Carson City), Utah (St. George), Delaware (Dover and Salisbury), and California (e.g., El Centro, Hanford-Corcoran, Madera and Merced) are at the bottom of the range.

4.2.3 Macroeconomic Outcomes and Control Variables

Our first dependent variable of interest, house price growth, is computed based on the Freddie Mac House Price Index (FMHPI), which is available for 367 MSAs over the 1975 to 2015 period. The FMHPI is based on an ever expanding database of loans purchased by Freddie Mac or Fannie Mae. It is constructed using a repeat-transactions methodology, which is an increasingly common practice in housing research Bollerslev et al., 2016. The FMHPI index is estimated with data including transactions on one-family and townhome properties serving as collateral on loans originated between January 1, 1975 and the end of the most recent index month. Given that the original data are published at monthly frequency, we take the median to get to annual frequency.[7]

[7] Taking the mean of monthly house prices does not change our results qualitatively or quantitatively. If anything, it only increases the significance of our results.

The bottom panel of Figure 4.4 shows average house price growth for MSAs in our sample between 1994 and 2014. From this graphical inspection there is even less of an indication of a pattern for house price growth across the US than for the *BGR*s (see top panel of Figure 4.4). In terms of house price growth, we find that the top three MSAs are in North Carolina (Asheville), Texas (Austin-Round Rock), and Oregon (Bend-Redmond) while MSAs with the lowest house price growth in our sample are in Michigan (Ann Arbor), Massachusetts (Barnstable Town), and Connecticut (Bridgeport-Stamford-Norwalk).

The second set of dependent variables, namely job creation, firm and establishment growth at the MSA-level, come from the Business Dynamic Statistics (BDS) from the US Census Bureau. They are available for 333 MSAs. More detailed information is provided in Table 4.1.

A set of control variables at the MSA-level is included in the regression model for house price growth presented below. Following Favara and Imbs (2015), we include per capita personal income growth and population growth, as well as the first lags of all controls. These data are available for 382 MSAs from the Bureau of Economic Analysis (BEA). Information on housing supply elasticities for each MSA is available from Saiz (2010). The elasticities are based on the amount of land that can be developed in each MSAs. This is motivated by the observation that most regions where housing supply is inelastic are strongly land-constrained for topographic reasons.

4.2.4 Idiosyncratic Mortgage Supply Shocks and House Price Movements

We now turn to the link between idiosyncratic mortgage supply shocks and house price growth at the MSA-level. In order to analyze whether micro-level mortgage supply shocks have aggregate effects on house prices in US regions, we run the following regression model

$$\widehat{HP}_{mt} = \lambda_m + \gamma_t + \beta BGR_{mt} + \Gamma X_{mt} + \epsilon_{mt} \ , \tag{4.7}$$

where standard errors are clustered at the MSA level. $\widehat{HP}_{mt}$ is annual house price growth computed by the log-difference of the house price index described above. To control for region-specific differences in house prices as well as common time trends that affect house prices in all MSAs, a set of regional (λ_m) and time fixed effects (γ_t) is included in each regression. BGR_{mt} is the banking granular residual, and X_{mt} includes a set of the time-varying MSA-specific control variables. It is well known that house prices display considerable geographic heterogeneity in the US Ferreira and Gyourko, 2011. Such heterogeneity can arise from the demand side of the market, simply because income, demographic factors, and amenities are geographically heterogeneous (Lamont and Stein, 1999; Gyourko et al., 2013; Glaeser and Gyourko, 2007; Glaeser et al., 2008; Favara and Song, 2014). We follow Favara and Imbs (2015) and include per capita personal income growth and population growth here.

Yet, house price developments across regions can also be the result of differences in housing supply elasticities, for instance because of local costs, land use regulation, or geographical restrictions Gyourko and Saiz, 2006; Gyourko et al., 2008; Saiz, 2010. To investigate how housing supply elasticities affect the link between idiosyncratic mortgage supply shocks and house price growth, we include an interaction term between the BGR and the housing supply elasticity at the regional level, HSE_m, such that the regression model becomes

$$\widehat{HP}_{mt} = \lambda_m + \gamma_t + \beta_1 BGR_{mt} + \beta_2 BGR_{mt} \times HSE_m + \Gamma X_{mt} + \epsilon_{mt} \,. \quad (4.8)$$

Note that the individual effect of the housing supply elasticity is absorbed by the MSA-fixed effects λ_m, given that our elasticity measure is time-invariant. Based on the analysis of Favara and Imbs (2015), the idea is that changes in mortgage supply impact housing demand, which in turn affects house prices - and this the more so the lower is the elasticity of housing supply. Put differently, the more limited is the reaction of housing supply to changes in demand, the stronger the adjustment in prices should be. Hence, we expect

β_2 to be negative.

4.2.5 Idiosyncratic Mortgage Supply Shocks and Labor Market Outcomes

In order to analyze whether micro-level mortgage supply shocks have aggregate implications also beyond the housing market, we run the following regression model

$$\begin{aligned} Y_{mt} = \lambda_m + \gamma_t + \beta_1 BGR_{mt} + \beta_2 \widehat{HP}_{mt} \\ + \beta_3 \widehat{HP}_{mt} \times BGR_{mt} + \Gamma X_{mt} + \epsilon_{mt}, \end{aligned} \tag{4.9}$$

where standard errors are clustered at the MSA level. Y_{mt} is annual job creation, annual firm growth or annual establishment growth. To control for regional differences in labor market outcomes as well as common time trends that affect all MSA's labor markets, a set of regional (λ_m) and time fixed effects (γ_t) is included in each regression. BGR_{mt} is the banking granular residual, and X_{mt} includes a set of time-varying MSA-specific control variables. We include the same control variables as in the baseline regression (Equation (4.8)).[8]

Following the reasoning by Mian and Sufi (2014b) and Di Maggio and Kermani (2017), increased mortgage supply fosters house prices, thereby increasing households' housing wealth, so that their balance sheets improve. This leads to a rise in consumer demand and finally in employment. We thus expect a positive direct link between the BGR and real economic outcomes, in line with previous findings for other countries (Amiti and Weinstein, forthcoming; Bremus et al., 2013; Buch and Goldberg, 2017). In addition, the coefficient on the interaction term, β_3 in Eq.(4.9), is expected to be positive. The stronger house price growth (e.g. in response to mortgage supply shocks that increase housing demand), the more pronounced should be the effect of (idiosyncratic) mortgage supply shocks on the real economy. This

[8] The labor market variables are available for only 333 MSAs. In unreported regressions, we confirm that our baseline results for the housing market do not change when restricting the sample to the same 333 MSAs.

hypothesis is in line with the amplification mechanism between borrowing constraints and asset prices in the model developed by Kiyotaki and Moore (1997).[9]

4.2.6 Granular Effects from Non-Bank Mortgage Lenders

The market share of shadow banks[10] almost doubled from 2007-2015, and these less regulated financial institutions gained even more weight in lending activity to less creditworthy borrowers by increasing their market share from 45% to 75% over the same period Buchak et al., 2017. The growing importance of this less regulated market segment obviously raises concerns about financial stability. In order to investigate whether idiosyncratic shocks at the level of shadow banks have macroeconomic effects, we estimate the following regression model

$$Y_{mt} = \lambda_m + \gamma_t + \beta_1 BGR_{mt}^{shadow} + \beta_2 BGR_{mt}^{bank} + \Gamma X_{mt} + \epsilon_{mt} \ , \qquad (4.10)$$

where standard errors are clustered at the MSA level. As in the regression models discussed above, Y_{mt} is house price growth, annual job creation, annual firm growth or annual establishment growth. To control for regional differences in labor market outcomes as well as common time trends that affect labor markets in all MSAs, a set of regional (λ_m) and time fixed effects (γ_t) is included in each regression. BGR_{mt}^{shadow} is the banking granular residual based only on non-depository mortgage lenders, whereas BGR_{mt}^{bank} is the banking granular residual including only depository mortgage lenders, and X_{mt} includes a set of time-varying MSA-specific control variables. We include the same control variables as in the baseline regression (Equation

[9] In their model, small shocks can result in large swings in asset prices and real economic activity, as durable assets - like buildings - serve as collateral for loans. If collateral value decreases, credit-constrained firms are forced to reduce (residential) investment. For markets to clear, house prices have to fall which, in turn, tightens credit limits. Persistence and amplification reinforce each other, and real economic activity decreases. Hence, the model predicts a negative link between (tighter) borrowing constraints and real economic activity.

[10] By shadow banks we mean non-bank lenders without access to deposit funding or more general according to Adrian and Brunnermeier (2016) as a "web of specialized financial institutions that conduct credit, maturity, and liquidity transformation without direct, explicit access to public backstops." In the data we identify them with the HMDA lender file by Robert Avery.

(4.8)). In line with the previous rationale for why there might be a positive link between the *BGR* and macroeconomic outcomes, we also hypothesize the same positive link between granular effects from non-bank mortgage lenders and aggregate outcomes. Yet, the strength of the economic impact may differ between the regulated and the less regulated lenders.

4.3 Main Results

4.3.1 Effects on House Price Growth

Table 4.3 provides our baseline regression results. It reveals that lender-specific shocks at the MSA-level, as measured by the *BGR*, are positively linked to house price growth. In Column (1) we find a positive and statistically significant effect of the *BGR* on house price growth, meaning that positive innovations to mortgage origination at the level of individual large mortgage lenders lead to stronger house price growth. Vice versa, negative lender-specific mortgage supply shocks dampen house price growth. Thus, our results provide evidence for granular effects from the US mortgage lending sector on the regional housing market. The more concentrated mortgage origination is, the easier do lender-specific shocks spread across the housing market.

All control variables have the expected positive effects on house price growth: the higher income and population growth is in an MSA, the higher is the demand for housing, and the higher rents tend to be. This, in turn, fosters house price growth.

Quantitatively, the estimated coefficient in column (1) reveals that an increase in the *BGR* by one standard deviation (0.7) leads to an increase in MSA-level house price growth by 0.7 percentage points. Put differently, variation in lender-specific mortgage supply explains 11% of the variation in house price growth at the MSA-level.[11] Regarding the economic significance

[11] This quantification is based on the normalized beta-coefficient that is obtained by multiplying the estimated coefficient of interest with the standard deviation of the corresponding regressor (here: the *BGR*) and dividing by the standard deviation of the dependent variable (house price growth).

of the control variables, contemporaneous population growth explains about 20% of house price growth at the MSA-level, while the normalized beta-coefficient of income growth amounts to 0.27.

Overall, column (1) supports the expectation that idiosyncratic changes in mortgage lending positively affect house price growth at the MSA-level both in terms of statistical and economic significance. Hence, given that concentration in mortgage origination is very high, meaning that a few lenders dominate the market, we conclude that idiosyncratic shocks to mortgage supply have aggregate effects at the housing market.

– Insert Table 4.3 here –

The elasticity of housing supply. Having established a positive link between micro-level mortgage shocks and regional house price growth on average, following the literature (Gyourko and Saiz, 2006; Gyourko et al., 2008; Saiz, 2010), we now investigate how the housing supply elasticity affects the relation between idiosyncratic mortgage supply shocks and house prices at the MSA level. By analyzing the effect of housing elasticity on our previous findings, we aim at verifying our hypothesis above, namely that the relation between mortgage supply shocks originating from large lenders and house prices works through an increase in housing demand.

Based on a standard supply-demand schedule, we expect the effect of lender-specific mortgage supply shocks to have more pronounced effects on house prices the less elastic is housing supply. To test this hypothesis, column (2) of Table 4.3 provides regression results for Equation (4.8). It shows, first, that the BGR retains its positive and statistically significant effect on house price growth. Second, the interaction effect with the housing supply elasticity is negative, as expected, and statistically significant, thus indicating that granular effects from the mortgage market on house prices are weaker the more elastic housing supply becomes.[12]

[12]Note that the housing supply elasticity measure is available for only 252 MSAs. Unreported results of the baseline specifications remain quantitatively and qualitatively unchanged when restricting the sample to 252 MSAs.

Figure 4.5 illustrates the marginal effect of the *BGR* on house price growth, conditional on the elasticity of housing supply (based on Table 4.3, column (2)). It reveals that idiosyncratic mortgage supply shocks affect house price growth only if housing supply is relatively inelastic, for example in regions in which supply extension is geographically limited, like in the Rocky Mountains. In contrast, in regions in which supply can react more easily to changes in housing demand, price changes resulting from idiosyncratic mortgage supply shocks are weaker and eventually disappear. Regarding the distribution of the elasticity of housing supply, the graph reveals that the BGR has a statistically significant effect on house prices for a large majority of the observed elasticities – the effect turns statistically insignificant only in the few regions with the largest elasticities of housing supply.

– Insert Figure 4.5 here –

The financial crisis of 2007-09. Column (3) of Table 4.3 investigates how the financial crisis of 2007-09 impacts our baseline results. To alleviate concerns about crisis-driven effects, we augment Equation (4.7) to include a crisis dummy that equals one for the years 2007 to 2009 and zero otherwise, as well as its interaction with the *BGR*. The results in column (3) highlight that the crisis dummy has a negative and statistically significant effect on house price growth, which is not surprising as house prices have been depressed during the crisis years. However, the granular effect from the mortgage market, as measured by the *BGR*, remains intact. Furthermore, interacting the crisis dummy with the *BGR* reveals stronger granular effects from the mortgage market on house price growth during the crisis. That is, lender-specific mortgage supply shocks affect house price dynamics even more in times of distress.

Market concentration. As pointed out above, granular effects should be more pronounced in areas with a higher market concentration, which we investigate by expanding Equation (4.7) with a Herfindahl-Hirschman index (HHI) and its interaction with the *BGR*. The HHI is based on the volume of newly issued mortgages and therefore captures concentration in mortgage origination. Indeed, column (4) of Table 4.3 indicates that MSAs with higher mortgage market concentration show a closer link between the *BGR* and house price changes. Figure 4.6 displays the marginal effect of the *BGR* on house price growth conditional on the mortgage market HHI. In accordance with column (4) of Table 4.3, the marginal effect of the *BGR* on house price growth becomes stronger with increasing mortgage market concentration. Hence, our results seem to point in the same direction as recent findings by Akins et al. (2016) who show that US states that have less competitive banking markets experienced – among others – a much higher growth in house prices before the crisis of 2007-09.

– Insert Figure 4.6 here –

Asymmetric effects of mortgage market granularity. Column (5) of Table 4.3 shows that house price growth responds asymmetrically to high and low values of the BGR. We follow Guerrieri and Iacoviello (2017) and include a MSA-specific dummy variable[13] equaling one in times of above-trend *BGR* and zero in times of below-trend *BGR* and interact with the *BGR*:

$$\begin{aligned}\widehat{HP}_{mt} = \lambda_m + \gamma_t + \beta_{high} A_{mt} BGR_{mt} + \\ + \beta_{low}(1 - A_{mt}) BGR_{mt} + \Gamma X_{mt} + \epsilon_{mt},\end{aligned} \tag{4.11}$$

The results reveal that the link between the BGR and house price growth is stronger for high values of the BGR compared to below-average values.

Further robustness tests. Our results are robust against further sanity checks. The effect of the *BGR* presented in column (1) of Table 4.3 remains intact for different shock specifications of Equation (4.5). As shown in the second column of Table 4.4, we find a positive and significant effect

[13]The definition of high versus low *BGR* times is based on a regression of the *BGR* on a linear time trend separately estimated for each MSA. Above-trend values depict high *BGR* times and below-trend values as low *BGR*.

of the *BGR* on house price growth. The most parsimonious measure of the *BGR* (column (2)) is based on a shock specification that includes only year, MSA and year-MSA fixed effects. It indicates the largest effect of all different specifications of the *BGR*. This is plausible since the variation in mortgage lending driven by (time-invariant and -variant) heterogeneity at the level of mortgage lenders is contained in the shocks. Column (3) of Table 4.4 shows an insignificant effect of the *BGR* on house prices based on a lavish shock specification: lender, MSA, time, lender-time and MSA-time fixed effects. Taking a closer look at the shocks ϵ_{bmt} from the baseline specification, these shocks are a combination of lender-time effects, time-invariant lender-MSA effects and lender-MSA-time shocks. When including lender-time fixed effects in Eq. (4.5) as is done for the results in column (3) of Table 4.4, all lender-year variation in mortgage origination is eliminated from our shocks. Consequently, these regressions show that the link between our baseline measure of mortgage supply shocks and house price growth is mainly due to lender-year shock, i.e. shocks to mortgage origination policy at the level of the lender (common across all MSAs the lender operates in).

– Insert Table 4.4 here –

In addition, the positive link between the *BGR* and house price growth remains significant if we exclude all control variables or fixed effects from Equation (4.7). As shown in Table C.I, the positive and significant effect of the *BGR* on house price growth is more pronounced when we use no other time- and MSA-varying control variables but MSA and time fixed effects (columns (7) and (5)). If we include both sets of fixed effects separately and add the other control variables (columns (4) and (6)), we even find a smaller effect of the *BGR* than in our baseline regression with the full set of controls. This may provide evidence that the effects in our sample are affected differently by region and time fixed effects, thus making the fully-specified model that we estimate via Equation (4.7) most credible.

– Insert Table C.I here –

4.3.2 Real Effects

Table 4.5 shows how the *BGR* affects real economic activity as measured by job creation, firm and establishment growth. For all three variables, the link with granular effects from the mortgage market is statistically significant at least at the 5%-level. Compared to the more direct effects on house price growth, the normalized beta-coefficients of the *BGR* are smaller though. They range between 0.03 and 0.06, i.e. 3% of the variation in job creation can be attributed to the *BGR* in Table 4.5, while the latter accounts for about 6% of the variation in establishment growth (columns 1 - 3).

Regarding the interactions between house price growth and the *BGR*, our results support the hypothesis made above, namely that stronger house price growth coincides with a tighter link between mortgage market granularity and real economic outcomes.

Overall, our results are in line with both theory and empirical research. Theoretical papers (Gabaix, 2011; Bremus et al., 2013) predict a role of idiosyncratic shocks for aggregate outcomes if market concentration is high. The empirical literature confirms a positive relationship between idiosyncratic, lender-specific, shocks and aggregate outcomes. Amiti and Weinstein (forthcoming) demonstrate a significant role of granular shocks to the banking system for the macroeconomy in Japan. In their case, granular effects from banking explain roughly 40% of the variation in aggregate investment. Buch and Neugebauer (2011) also find a positive impact of the *BGR* on short run GDP growth, explaining 16% of the short run, cyclical variation in per capita GDP growth within a given country. Buch and Goldberg (2017) establish that 5-16% of the variation in GDP per capita growth in a panel of 79 countries can be attributed to bank-specific shocks to asset growth due to granular effects. Keeping in mind that the mortgage business is a subcomponent of total credit, and that the US economy is highly diversified our findings thus seem plausible in comparison to the size of the estimated effects in the studies discussed above.

Granular effects from non-bank mortgage lenders. Table 4.6 reports the disaggregated effects of the shadow banking granular residual and the depository banking granular residual on house price growth and employment variables. Column (1) shows statistically significant effects of both BGRs on house price growth. As an F-test with a test statistic of 1.14 reveals that these two coefficients are statistically *not* different from each other, the shadow BGR has the larger point estimate than the depository BGR. In terms of economic significance, the variation in depository banking granularity explains 6% of the variation in house price growth while the variation in shadow bank granularity explains 9% of house price growth variation. For the labor market variables, however, idiosyncratic shocks from the shadow banking sector do not seem to matter.

4.4 Conclusion

This paper highlights the importance of mortgage market concentration for the propagation of idiosyncratic events at the level of mortgage lenders and their effect on house price growth and real economic activity. Our analysis of granular effects from the US mortgage market yields three main findings. First, mortgage origination at the MSA-level is highly concentrated. The distribution of newly issued mortgages follows a fat-tailed power law, meaning that a small number of players dominate mortgage origination. Second, idiosyncratic mortgage supply shocks are a driver of house price growth. The larger the increase in mortgage supply due to lender-specific events is, the faster house prices grow. These results are robust to several alternative model specifications. Third, granular effects from the mortgage market are not limited to the housing market, but affect real outcomes like job creation and firm growth as well. Fourth, shadow bank granularity has a larger effect on house price growth than granularity in the traditional banking system does. Yet, these effects do not seem to propagate to the real economy.

The results are important for informing the debate on the treatment of large financial institutions, since they stress that lender-specific shocks like financial innovations or unexpected managerial decisions happening to mortgage lenders with large market shares have implications beyond the micro-level. The higher mortgage market concentration, the easier do micro-level events spread across housing markets and finally to the real economy. In addition to indicators like mortgage growth and loan-to-value ratios, macro-prudential regulation should take market shares and mortgage market concentration into account when analyzing macroeconomic stability. Moreover, given the recent rise in non-bank mortgage lender's role in the US mortgage market, in order to reduce idiosyncratic mortgage supply shocks (or: idiosyncratic risk), the differential regulatory treatment of banks and non-bank lenders should be harmonized, and shadow banks should come more into the focus of mortgage market regulation.

Tables and Figures

TABLE 4.1: Variable Descriptions.

Variable Name	Description	Source
	Micro variables at the bank level	
Accepted mortg. volume	Newly originated loan amount in thousands of dollars. Loan purpose includes home purchase loans, home improvement loans and refinancing loans for all property types: 1-4 family houses, manufacturing houses and multifamily houses. Accepted loan amounts at the bank-household level are aggregated at the bank-MSA level.	HMDA
Idiosyncratic shock	We regress the log of accepted mortgage volume on bank fixed effects, time fixed effects, MSA fixed effects and MSA-time fixed effects. The residual from this regression is the idiosyncratic shock.	HMDA
	Macro variables at the MSA-level	
House price index	The monthly Freddie Mac House Price Index (FMHPI) captures prices of one-family and townhome properties according to the repeat transactions methodology. It is based on loans purchased either by Freddie Mac or Fannie Mae. We convert the monthly index to annual frequency by calculating the median.	Freddie Mac
Banking Granular Residual (BGR)	The idiosyncratic shock is weighted by the market share of the respective bank. The market share is originated mortgage volume of the bank relative to total mortgage volume in the MSA the bank is located. Summing up all these weighted shocks across banks in a given MSA m in year t yields the $BGR_{m,t}$	HMDA
Depository BGR	Calculation as above except we exclusively consider depository institutions which we identify by the HMDA lender file from Robert B. Avery.	HMDA
Shadow BGR	Calculation as with the conventional BGR except we exclusively consider non-depository institutions which we identify by the HMDA lender file from Robert B. Avery. Basically, shadow banks comprise all non-depository that do not take deposits and this makes them exempt from a large amount of regulatory oversight (Buchak et al., 2017)	HMDA
Herfindahl Index	Sum of squared market shares based on accepted mortgage loan volume.	HMDA
Income per capita growth	Growth (% change from preceding period) of per capita personal income, in current dollars (not adjusted for inflation).	BEA
Population growth	Population growth (% change from preceding period) based on Census Bureau population estimates.	BEA
Housing supply elasticity	Topographic measure of developable land elasticities, by MSA. For example, regions where housing supply is inelastic are strongly land-constrained for topographic reasons.	Saiz (2010)
Firm growth	First log difference multiplied by 100 based on the number of firms in a MSA. A firm with establishments in multiple MSA's is counted multiple times, once in each MSA, irrespective of the portion of the firm residing in that MSA.	BDS
Establishment growth	Establishment growth is the first log difference multiplied by 100 based on the number of establishments in a MSA. Establishment is s simple count of the number establishments in a MSA.	BDS
Job creation	Count of all jobs created within MSA over the last 12 months.	BDS

TABLE 4.2: Summary Statistics for the Regression Sample.

	Obs.	Mean	SD	Skewness	Kurtosis	Min	Max
HMDA Data - bank level variables							
Idiosyncratic shock	2,537,640	0.00	1.72	0.10	3.63	-11.49	8.65
Accepted mortgages ($ mill.)	2,538,943	22.62	198.43	52.05	4988.40	0.00	35,677.24
Number of banks per MSA		430.73	221.83	0.89	3.42	31	1,246
HMDA Data - MSA-level variables							
Banking Granular Residual (*BGR*)	6,932	1.93	0.71	0.20	3.97	-1.55	5.33
BGR (Depository Institutions)	6,882	2.11	0.82	0.41	3.52	-0.68	5.81
BGR (Shadow Banks)	6,571	1.35	0.78	-0.45	5.14	3.03	4.20
Herfindahl index (Accepted mortgages)	6,932	4.28	2.91	7.93	155.52	1.03	85.48
BEA/BDS - MSA-level variables							
House price index (% change)	6,932	2.46	6.25	-0.92	11.32	-53.41	34.07
Income per capita (% change)	6,932	3.55	2.87	-0.22	10.93	-21.80	33.70
Income (% change)	6,932	4.61	3.16	-0.08	7.63	-19.50	35.70
Population (% change)	6,932	1.03	1.14	-1.12	45.27	-25.00	8.10
Housing supply elasticity (%)	4,940	2.67	1.45	2.05	11.34	0.67	12.15
Firm growth	6,741	0.57	1.92	-0.22	6.06	-17.32	12.59
Establishment growth	6,741	0.77	1.84	-0.15	5.72	-15.55	12.78
Job creation	6,741	30.04	49.21	3.83	21.58	1.43	466.07

Table 4.3: Lender-Specific Mortgage Supply Shocks and House Price Growth.

	House price growth				
	(1)	(2)	(3)	(4)	(5)
Banking Granular Residual	1.049***	1.669***	0.842***	0.692***	
	(0.138)	(0.283)	(0.144)	(0.203)	
Income (p.c.) growth	0.610***	0.635***	0.618***	0.609***	0.610***
	(0.047)	(0.055)	(0.047)	(0.047)	(0.047)
Lagged income (p.c.) growth	0.477***	0.524***	0.472***	0.477***	0.479***
	(0.035)	(0.042)	(0.035)	(0.035)	(0.035)
Population growth	1.206***	1.199***	1.204***	1.204***	1.207***
	(0.210)	(0.278)	(0.211)	(0.210)	(0.212)
Lagged population growth	0.953***	0.984***	0.964***	0.953***	0.945***
	(0.087)	(0.107)	(0.089)	(0.087)	(0.087)
Crisis dummy			-7.514***		
			(1.227)		
BGR x Crisis dummy			2.387***		
			(0.692)		
BGR x Housing supply elasticity		-0.206***			
		(0.062)			
Herfindahl				-13.799*	
				(7.347)	
BGR x Herfindahl				6.314**	
				(2.821)	
Banking Granular Residual (low)					0.596***
					(0.169)
Banking Granular Residual (high)					0.863***
					(0.139)
P-value coef. equality					0.000
MSA fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	6,932	5,347	6,932	6,932	6,932
R-squared	0.580	0.580	0.585	0.581	0.581
Number of MSAs	345	252	345	345	345

Notes: This table reports fixed effects regressions of the log change in house price index on the Banking Granular Residual (*BGR*). Column (1) is the baseline scenario with the following explanatory variables: the current and lagged log change in MSAs income per capita and population. Column (2) interacts the *BGR* with the housing supply elasticity by Saiz (2010). Column (3) introduces a crisis dummy that equals one for the period 2007-2009 and zero otherwise, plus an interaction with the *BGR*. Column (4) contains a MSA-level Herfindahl-Hirschman Index based on the volume of newly issued mortgage loans, both as single regressor and as an interaction term with the *BGR*. Column (5) implements asymmetric granular effects with an indicator variable that one for high values of the *BGR* and 0 for low values of *BGR*. Granularity is high if it is above a linear time trend separately estimated for each MSA for the 1990-2014 period. P-value coef. equality displays the p-value of the test for differences in the coefficients of BGR (high) versus BGR (low). The sample of column (1) to (5) includes all US metropolitan statistical areas for which mortgage and house price data is available for the period 1990-2014. All regressions include MSA and year fixed effects. Standard errors are robust to heteroskedasticity and are clustered at the MSA-level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.4: Robustness regarding Different Shock Specifications.

	House price growth		
	(1)	(2)	(3)
Banking Granular Residual 1	1.049***		
	(0.138)		
Banking Granular Residual 2		0.356***	
		(0.116)	
Banking Granular Residual 3			1.650***
			(0.169)
Income (p.c.) growth	0.610***	0.616***	0.616***
	(0.047)	(0.047)	(0.046)
Lagged income (p.c.) growth	0.477***	0.483***	0.479***
	(0.035)	(0.035)	(0.034)
Population growth	1.206***	1.207***	1.194***
	(0.210)	(0.210)	(0.208)
Lagged population growth	0.953***	0.953***	0.932***
	(0.087)	(0.088)	(0.089)
MSA fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes
Observations	6,932	6,932	6,932
R-squared	0.580	0.576	0.585
Number of MSAs	345	345	345

Notes: This table presents fixed effects regressions of the log change in house price index on different specifications of the Banking Granular Residual (BGR). Regressors are the current and lagged log change in MSAs income per capita and population. Column (1) repeats our baseline regression based on Equation 4.5. The $BGR2$ is based on shocks including only year, MSA and year-MSA fixed effects. For computing $BGR3$, idiosyncratic shocks are measured with bank, MSA, time, bank-time and MSA-time fixed effects. The sample includes all US MSAs for which mortgage and house price data are available for the period 1990-2014. Also, regional and time fixed effects are incrementally included. Robust standard errors are given in parentheses and clustered at the MSA-level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 4.5: Lender-Specific Mortgage Supply Shocks and Real Effects.

	Firm growth (1)	Establishment growth (2)	Job creation (3)	Firm growth (4)	Establishment growth (5)	Job creation (6)
Banking Granular Residual	0.139***	0.167***	2.127***	0.101**	0.136***	1.228**
	(0.040)	(0.039)	(0.572)	(0.041)	(0.040)	(0.491)
Income (p.c.) growth	0.053***	0.052***	0.145***	0.051***	0.050***	0.107***
	(0.010)	(0.008)	(0.038)	(0.010)	(0.008)	(0.036)
Lagged income (p.c.) growth	0.072***	0.074***	0.500***	0.069***	0.072***	0.427***
	(0.010)	(0.009)	(0.100)	(0.010)	(0.009)	(0.091)
Population growth	0.541***	0.515***	0.305	0.538***	0.512***	0.224
	(0.088)	(0.079)	(0.220)	(0.089)	(0.080)	(0.233)
Lagged population growth	0.059	0.092*	0.526*	0.054	0.088*	0.411
	(0.061)	(0.052)	(0.293)	(0.061)	(0.052)	(0.295)
House price growth	0.073***	0.065***	0.116***	0.049***	0.045***	-0.456***
	(0.007)	(0.007)	(0.039)	(0.011)	(0.010)	(0.082)
House price growth * BGR				0.017***	0.014***	0.409***
				(0.006)	(0.005)	(0.063)
MSA fixed effects						
Year fixed effects						
Observations	6,707	6,707	6,707	6,707	6,707	6,707
R-squared	0.652	0.653	0.192	0.653	0.654	0.226
Number of msa	333	333	333	333	333	333

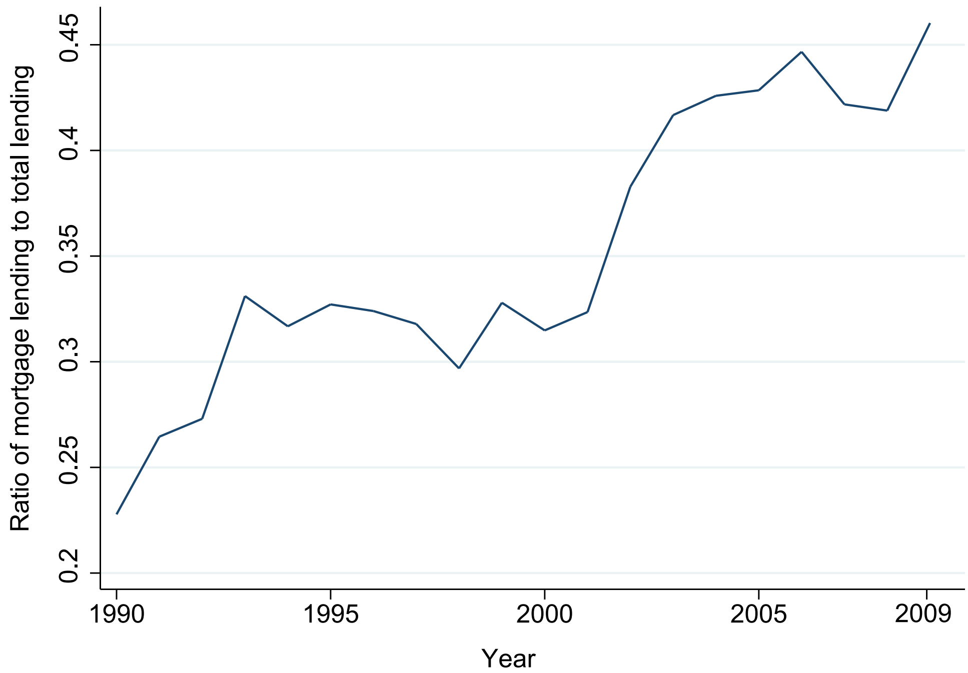
Notes: This table shows the panel regression of real sector variables on the Banking Granular Residual (*BGR*). Job Creation is defined as count of all jobs created within MSA over the last 12 months. Firm growth is the first log difference multiplied by 100 based on the number of firms in a MSA. A firm with establishments in multiple MSA's is counted multiple times, once in each MSA, irrespective of the portion of the firm residing in that MSA. Establishment growth is the first log difference multiplied by 100 based on the number of establishments in a MSA. Establishment is s simple count of the number establishments in a MSA. The sample includes all US metropolitan statistical areas for which mortgage and house price data is available for the period 1990-2014. Also regional and time fixed effects are included. Robust standard errors in parentheses and clustered at MSA-level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 4.6: Granularity in Shadow Banking and Real Effects.

	House price growth (1)	Firm growth (2)	Establishment growth (3)	Job creation (4)
BGR (Depository Institutions)	0.493***	0.174***	0.188***	1.978***
	(0.149)	(0.043)	(0.041)	(0.544)
BGR (Shadow Banks)	0.710***	0.005	0.009	0.475
	(0.119)	(0.027)	(0.025)	(0.355)
Income (p.c.) growth	0.639***	0.049***	0.048***	0.153***
	(0.048)	(0.010)	(0.008)	(0.039)
Lagged income (p.c.) growth	0.493***	0.068***	0.070***	0.519***
	(0.036)	(0.010)	(0.009)	(0.104)
Population growth	1.272***	0.557***	0.532***	0.328
	(0.232)	(0.089)	(0.080)	(0.242)
Lagged population growth	0.997***	0.048	0.084	0.709**
	(0.092)	(0.062)	(0.052)	(0.349)
House price growth		0.074***	0.065***	0.100***
		(0.007)	(0.007)	(0.038)
MSA fixed effects				
Year fixed effects				
Observations	6,932	6,344	6,344	6,344
R-squared	0.587	0.656	0.656	0.215
Number of msa	345	333	333	333

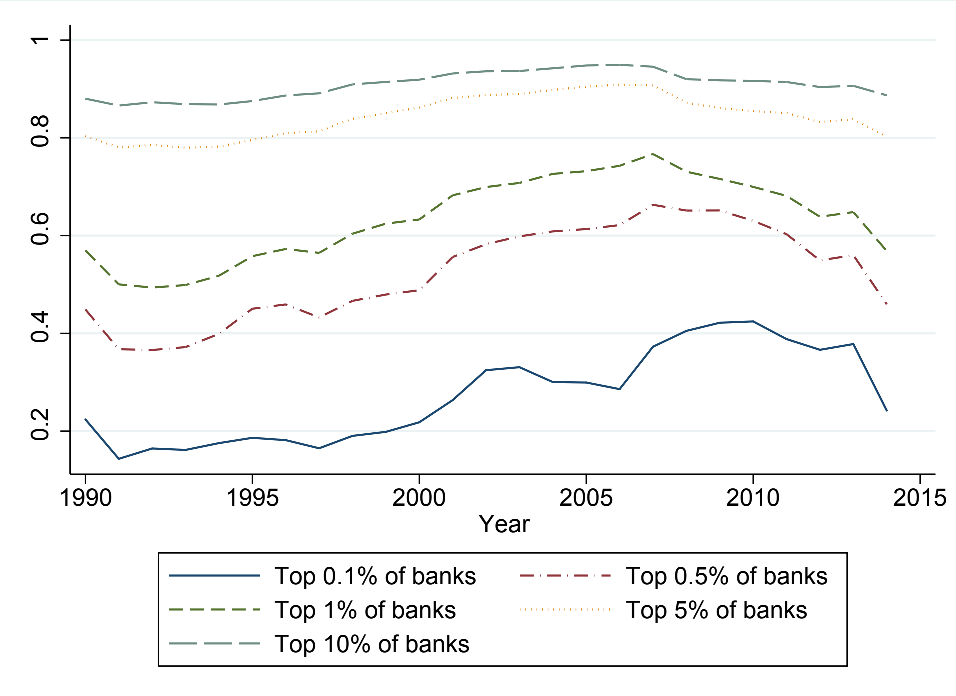
Notes: This table shows the panel regression of house price growth and real sector variables on the Banking Granular Residual based on depository institutions *BGR (Depository Institutions)* and on non-depository institutions *BGR (Shadow Banks)*. The former is defined as banks with access to deposit funding and the latter as non-banks without access to deposit funding. Both bank types are identified with the HMDA lender by Robert B. Avery. House price growth is the annual log change in house price index. Job creation is defined as count of all jobs created within MSA over the last 12 months. Firm growth is the first log difference multiplied by 100 based on the number of firms in a MSA. A firm with establishments in multiple MSA's is counted multiple times, once in each MSA, irrespective of the portion of the firm residing in that MSA. Establishment growth is the first log difference multiplied by 100 based on the number of establishments in a MSA. Establishment is s simple count of the number establishments in a MSA. The sample includes all US metropolitan statistical areas for which mortgage and house price data is available for the period 1990-2014. Also regional and time fixed effects are incrementally included. Robust standard errors in parentheses and clustered at MSA-level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

FIGURE 4.1: US Mortgage Loans to Total Loans.



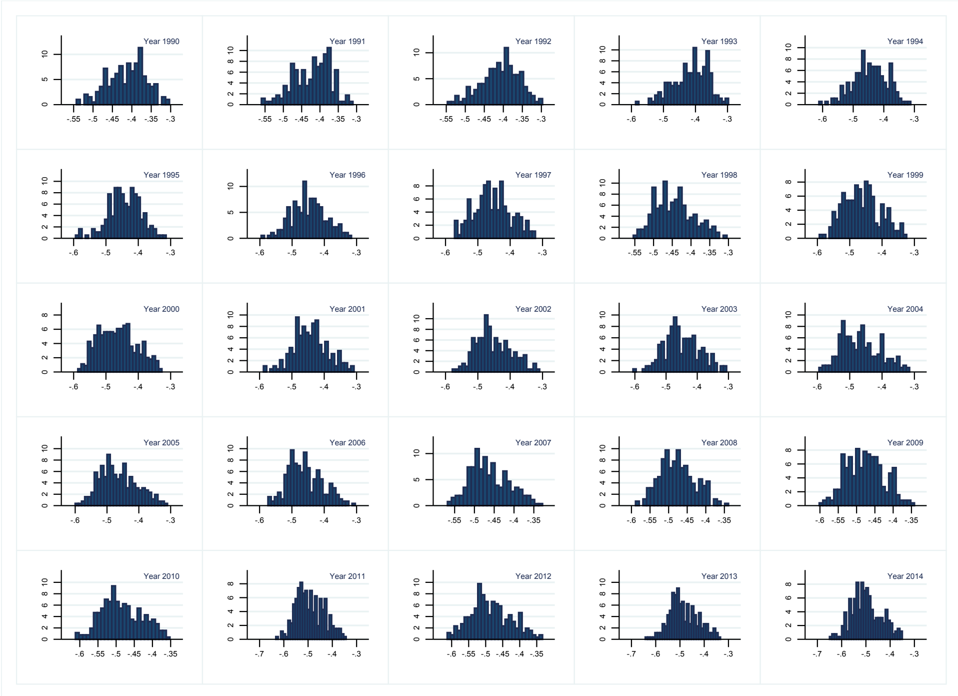
Notes: This figure plots the ratio of mortgages to total loans for the period 1990-2009. Mortgages are defined as the total stock of 1-4 family and 5+ (multifamily) real estate mortgages. Total loans are measured as aggregate gross book value of total loans (before deduction of valuation reserves). The Call Reports data cover all banks regulated by the FRS, FDIC, and the OCC.

FIGURE 4.2: Mortgage Lending of the Largest Banks to Total Mortgage Lending.



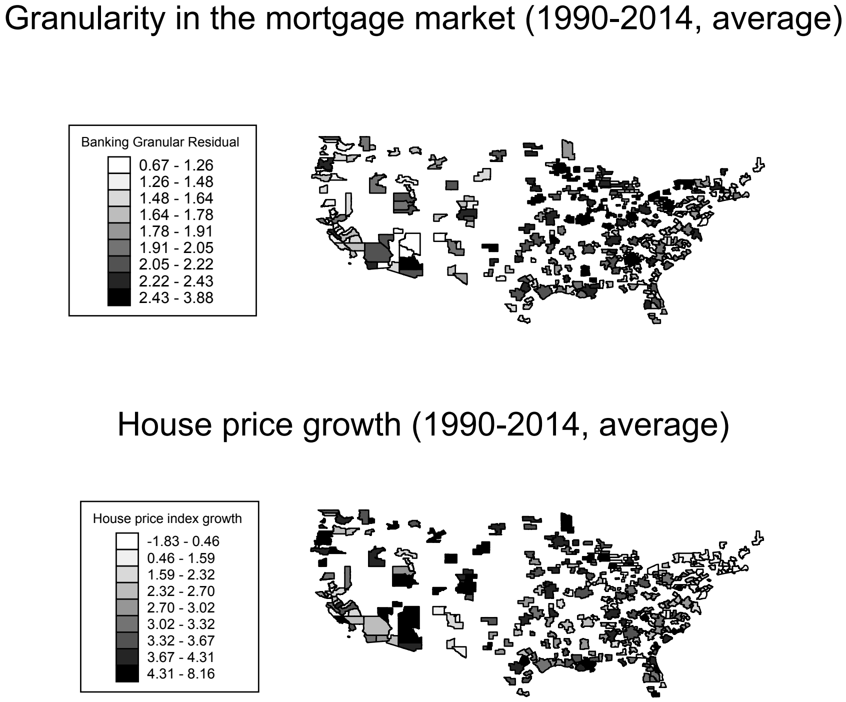
Notes: This figure illustrates the sum of newly issued mortgages for the top 0.1%, 0.5%, 1%, 5% and 10% of banks aggregated at the US level, as a fraction of total newly issued mortgages of all banks over the period 1990-2014. The total average number of banks each year is 7900 comprising both depository and non-depository institutions. The average number of banks in the top 10% is 800. The HMDA data cover 80% of bank home lending activity nationwide.

FIGURE 4.3: Histogram of Estimated Power Law Coefficients of the Mortgage Size Distribution.



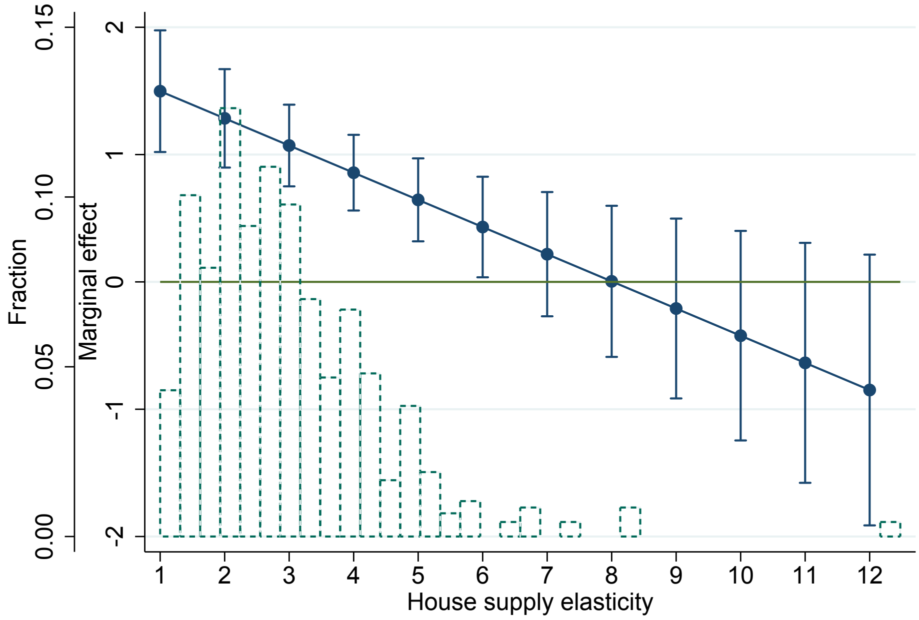
Notes: This graph shows the histogram of power law coefficients of the distribution of newly issued mortgages loans per MSA for each year. Following Gabaix and Ibragimov (2011), for each of the 256 MSAs that enter the baseline regression, we regress the log of banks' rank (based on newly issued mortgages) on the log of their newly issued mortgages. The resulting coefficient indicates whether the bank size distribution in each MSA market follows a fat-tailed power law. This is the case if the absolute value is below one.

FIGURE 4.4: Regional Variation in Mortgage Market Granularity and House Price Growth.



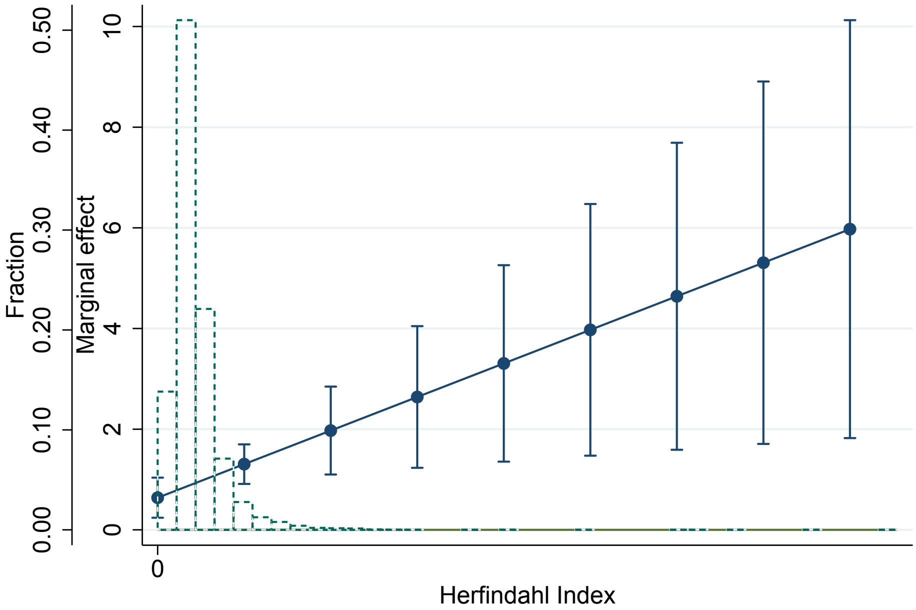
Notes: This figure depicts the averaged Banking Granular Residual (upper subgraph) over the period 1990-2014 across all 345 MSAs in our sample and the average house price index growth (lower subgraph) over the same period for all MSAs in the sample.

FIGURE 4.5: Marginal Effects of the *BGR* depending on Housing Supply Elasticity.



Notes: This graph shows the average marginal effect of the Banking Granular Residual on house price growth conditional on Saiz's Index of Housing Supply Elasticity Saiz, 2010. The estimated marginal effects are denoted by dots enclosed by 95% confidence bands. The second Y-axis depicts the distribution of the housing supply elasticity measure. The graph is based on specification (2) of Table 4.3.

FIGURE 4.6: Marginal Effects of the *BGR* depending on Mortgage Market Concentration



Notes: This graph shows the average marginal effect of the Banking Granular Residual on house price growth conditional on mortgage market concentration. The concentration measure is constructed by a Herfindahl index (HHI) based on newly issued mortgage loans. Higher values of the HHI indicate greater concentration. The estimated marginal effects are denoted by dots enclosed by 95% confidence bands. The second Y-axis depicts the distribution of the HHI. The graph is based on specification (4) of Table 4.3.

Appendix C

C.I Robustness

TABLE C.I: Robustness Regarding Controls

	House price growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Banking Granular Residual	1.159***	0.767***	0.774***	0.666***	1.447***	0.789***	1.508***	1.049***
	(0.116)	(0.089)	(0.100)	(0.088)	(0.162)	(0.126)	(0.162)	(0.138)
Income (p.c.) growth		0.615***		0.576***		0.604***		0.610***
		(0.038)		(0.043)		(0.039)		(0.047)
Lagged income (p.c.) growth		0.394***		0.502***		0.359***		0.477***
		(0.019)		(0.032)		(0.021)		(0.035)
Population growth		0.827***		0.578***		1.270***		1.206***
		(0.216)		(0.120)		(0.288)		(0.210)
Lagged population growth		0.092		0.393***		0.488***		0.953***
		(0.197)		(0.114)		(0.161)		(0.087)
MSA fixed effects	no	no	yes	yes	no	no	yes	yes
Year fixed effects	no	no	no	no	yes	yes	yes	yes
Observations	6,932	6,932	6,932	6,932	6,932	6,932	6,932	6,932
R-squared	0.017	0.177	0.462	0.561	0.016	0.176	0.468	0.580
Number of MSAs	345	345	345	345	345	345	345	345

Notes: This table shows the panel regression of the log change in house price index on the Banking Granular Residual (*BGR*). Uneven number columns report univariate regression with the *BGR* as regressor and incremental inclusion of fixed (regional and time) effects. Even number columns report multivariate regressions with the BGR as the main variable of interest and the following covariates: the current and lagged log change in MSAs income per capita and population. The sample includes all US metropolitan statistical areas for which mortgage and house price data is available for the period 1990-2014. Also regional and time fixed effects are incrementally included. Robust standard errors in parentheses and clustered at MSA-level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 5

African-American Mayors, Home Ownership and Mortgage Lending

Abstract: *This paper analyzes the short and long run consequences of electing a black mayor for mortgage access and home ownership transition of black households. For identification, I use a regression discontinuity design to analyze US mayoral elections between 1990 and 2016. Exploiting rich micro data on mortgage applications and originations from the Home Mortgage Disclosure Act, I find that mortgage acceptances increase by 11 percentage points for black applicants relative to total mortgage applications after black mayors took office. These findings are stronger for mortgage applicants in the upper part of the income distribution. Black political leadership also increases debt-to-income ratios for higher income households.*

5.1 Introduction

For most households, home ownership is one of the largest financial commitments and purchase decisions. Owning a home can not only insure against income risk but has also important socio-economic consequences such as being located in areas with less crime or better school systems (Glaeser and Sacerdote, 1999). Home ownership is also an important tool for wealth accumulation and upward mobility. Consequently, any policy that attempts to reduce wealth disparities has to understand the reasons for home ownership differences across individuals. Charles and Hurst (2002) emphasize one particular type of wealth disparity by documenting that white renters are much more likely to become home owners than black renters. Two frictions in the mortgage market are responsible for this observation. First, black mortgage applications were 73% more likely to be rejected than white mortgage applications even after controlling for credit score proxies and demographics. Second, black renters exhibit a 20 percentage points lower likelihood to initiate a mortgage application in the first place than white renters.[1] I contribute to the literature by addressing these two frictions in the US mortgage market and explore whether local political leadership is able to generate a favorable environment for financial commitment, mortgage access and home ownership.

This paper analyzes the short and long run effects of local black political leadership on both mortgage access and home ownership transition of black households between 1990 and 2016. To address endogeneity of political leadership, I employ a static and dynamic regression discontinuity (RD) design to analyze interracial elections in US cities. This strategy compares housing market outcomes in US cities where a black candidate barely won a mayoral election with housing market outcomes in cities where a black candidate barely lost.

The RD design takes advantage of three main datasets. First, I complement existing records on mayoral elections with information on the name, party affiliation, vote return and the race for each of the top two mayoral candidates. This results in a total dataset consisting of 1,083 mayoral elections between 1990-2016 in 905 US cities. Second, loan-level application data from the Home Mortgage Disclosure Act (HMDA) contain rich borrower information on the applicant's income, sex, loan amount, location of the house, whether the loan volume was accepted or denied and most importantly the race of the applicant. Additionally, the HMDA data structure allows me to disentangle loan supply from loan demand by using multiple bank-city lending relationships to exploit a within city lending comparison that absorbs city-specific credit demand changes. Third, the Panel Study of Income Dynamics (PSID) is a Longitudinal survey of US families and tracks

[1] Black households might be discouraged to apply due to systematic racial differences in e.g. down payment constraints, uncertainty about income streams or demographic status and supply-side borrowing constraints. See Charles and Hurst (2002) for a well structured description on why home ownership constraints might differ by race.

home ownership transitions of households, housing wealth and mortgage applications over time.

Before turning to causal effects, I first show the existence of an electoral mortgage cycle for US cities that elected an African-American mayor for the very first time. Raw bank-level correlations demonstrate not only that the number of accepted mortgage applications from black applicants increase between 10 to 19% in the post-election period but also that the black-white acceptance differential increases by 3% one year after the election. Static RD estimates confirm this tentative evidence with a positive treatment effect of 11 percentage points increase of black mortgage acceptance rates in the year after black mayors took office. The dynamic RD design indicates long run effects on black mortgage acceptance rates that are most pronounced around four to six years after a black mayor gets elected. Interestingly, these long-run effects are significant around the transition between mayoral term periods and might indicate re-election effects. I find that banks accept more mortgage applications from black borrowers in the upper part of the income distribution while no significant treatment effects can be found in the lower part of the income distribution. Also, black debt-to-income ratios increase for the higher income groups. Evidence on local political leadership affecting home ownership transitions is still to be done as soon as the PSID data access is available.

Establishing a channel to rationalize these findings is challenging. Given that US cities have always been confronted with racial discrimination in housing markets (Appel and Nickerson, 2016), a black mayor should be more concerned about housing conditions for the black population than a white mayor. As a result one might expect newly elected black mayors to prioritize the elimination of such frictions in *direct* and *indirect* ways. One possibility is that black incumbency leads to a perception change since it provides concrete information that disproves the fears and expectations of many white residents and also loan officers. Because it is very hard to provide empirical evidence for this explanation, I concentrate on channels where data availability is given. The first African-American mayor of Atlanta, Maynard Jackson, pressured white-run banks to appoint black individuals as executives and used deposits of city money to exert pressure on these financial institutions (Bayor, 2001). In a first step, I examine this narrative evidence by collecting bank-level data on city deposits to investigate such a *political-pressure* channel. Second, I exploit the Census Building Permits Survey data at the city level between 1988-2010 to analyze whether the results might be driven by housing supply expansion. Third, FDIC Data on minority bank ownership and bank types will give insight into the *proximity channel*: a mayor's soft power and leverage on banks is higher if a depository institution is owned by a peer or if it is a community bank. Finally, data on (CRA) bank examinations will enable me to investigate the *reputation channel*: assuming that banks are concerned about their reputation, I hypothesize that discriminating banks would act against their prior as soon as a black politician got elected.

The first strand of literature on economic effects of local political leadership has concentrated exclusively on "aggregate" city policy outcomes such as public spending, employment, education or crime rates (Ferreira and Gyourko, 2009; Ferreira and Gyourko, 2014; Hopkins and McCabe, 2012; Meyersson, 2014). The second strand of literature focuses on the impact of hard political power, such as US federal laws or regulations, on mortgage lending outcomes. Despite numerous efforts of legislative acts[2] to expand credit access and reduce discrimination in the mortgage market, evidence on the success of these government actions is mixed (Agarwal et al., 2014a; Agarwal et al., 2016b; Agarwal et al., 2017; Bayer et al., 2017; Munnell et al., 1996). This paper is mostly related to the third strand of literature on the nexus between soft political power and the mortgage market. Akey et al. (2017) show that ascension to the chairmanship of US Senate committee is associated with a large reduction in the availability of consumer credit in the ascending Senator's state. Antoniades and Calomiris (2016) exploit the US presidential election in 2008 to show that voters punish Presidential

[2] See for example the Fair Housing Act of 1968, the Equal Credit Opportunity Act of 1974, the Community Reinvestment Act of 1977 or the Home Mortgage Disclosure Act of 1975.

candidates for local mortgage supply contractions but do not reward them for local mortgage supply expansions. Chavaz and Rose (2016) demonstrate that receivers of the 2008 liquidity assistance program TARP increased bank lending by 23% to 60% more in areas located inside their home representative's district than elsewhere. I contribute to this third strand of literature in two distinct ways. First, no attention has been paid to political influence on bank lending at the very local level: city mayorships. This is an important angle since political power might be most effective in municipal environments where spatial proximity between politicians and banks is closest. Second, no understanding has been established on whether and how politicians have an impact on mortgage access and home ownership transitions of minority groups. Since historically disadvantaged groups face higher uncertainty, especially in the context of long-lasting and large financial commitments, it is of relevance if political leadership can create a comfort zone for their voters.

This paper reveals important implications. First, political participation matters. Since hard political power is only partially effective in reducing mortgage market frictions (e.g. Agarwal et al., 2014a; Agarwal et al., 2016b; Agarwal et al., 2017; Bayer et al., 2017; Munnell et al., 1996), I show that soft political power can be a complementary tool for alleviating these market imperfections. From a policy perspective, this means that the mortgage market can be a useful wealth accumulation tool given certain constraints for politicians to redistribute wealth and income at the local level. Second, the evidence for political influence on easy credit might assign politicians a role in the housing boom-bust cycle.

The paper is structured as follows. Section 5.2 describes the three main datasets, explains the RD design and tests for the validity of the research design. Section 5.3 presents the results for the electoral mortgage cycle, the short run static RD effects and the dynamic RD effects in the long run. Section 5.4 concludes.

5.2 Data and Empirical Strategy

5.2.1 Data Description

Electoral data. Data on mayoral elections come from two main sources: Ferreira and Gyourko (2009) and Vogl (2014). Merging these two datasets and hand-collecting[3] missing information on the race of the top two candidates leads to a final dataset on 7,000 mayoral elections in over 1,000 US cities between 1950 and 2017. It contains information on the name, vote share, party affiliation and the race of winner and runner-up candidate. Two data constraints reduce the number of observations: (i) the outcome variable (mortgage access) is only available from 1990 onwards until 2016 and (ii) the RD design requires to analyze only interracial elections[4], i.e. a black candidate runs against a white candidate. This produces a regression sample with 312 interracial elections that enters the RD estimation. Table 5.1 shows summary statistics for all elections between 1990 and 2016.

– Insert Table 5.1 here –

Mortgage data. Data on mortgage originations and applications come from the Home Mortgage Disclosure Act (HMDA). It provides loan-level information on the year of the application, the dollar amount of the loan and the decision of the bank (denial or acceptance of the loan). Normalizing accepted loan volumes by the total mortgage flow (accepted plus declined loan applications) is one way to "control" for loan demand (Loutskina and Strahan, 2009). A rich set of applicant information like income, race, ethnicity and the location of the property at the census tract level allow me not only to track each mortgage application at the city level but also to distinguish between minority versus non-minority loan applications. The main outcome variables are defined as follows:

[3]See Appendix D.I for details.

[4]The motivation behind this constraint is to compare cities where black mayors barely won with cities where black mayors barely lost. As a consequence, the RD design disregards all elections where the mayor and the runner-up have the same race.

- $Acceptance\ rate^b = \frac{Accepted\ Mortgages^b}{Accepted\ Mortgages^b + Declined\ Mortgages^b}$ (volume and number),
- $Approval\ differential = \frac{Acceptance\ rate^b}{Acceptance\ rate^w}$ (volume and number)

where superscript b stands for African-American applicants and w denotes white (non-Hispanic) applicant. Acceptance rates are defined as accepted mortgages (in terms of loan volume or number of loan applications) divided by total mortgages (volume/number) which is the sum of accepted and declined mortgage applications. Approval differentials are calculated as the ratio of black acceptance rate to white acceptance rate and are interpreted as percentage point differential between black and white approval rates. Mortgage volume corresponds to dollar amounts of mortgage lending.

Home ownership data. Data on home ownership transition come from the Panel Study of Income Dynamics (PSID). The PSID is an extensive household survey that tracks families over time and records demographic information (e.g. age, race, family composition, education) and, most importantly, housing information (paid rents, housing values, outstanding mortgage payments, mortgage rates and when the mortgage was acquired). Unfortunately, the data is not available yet since the geographic identifier information for US cities is restricted data use and subject to an application process which I am currently involved.

5.2.2 Bank Level Evidence for Electoral Mortgage Cycles

As the first African-American mayor of Atlanta, Maynard Jackson defeated his main competitor Sam Massel in the 1973 mayoral election. Despite a contentious electoral campaign where the incumbent mayor Sam Massel used the "Atlanta, Too Young to Die" slogan to suggest that a black mayor would mean the end of the city Atlanta, Maynard Jackson won the election with a majority of 68%. As Bayor (2001) documents, Atlanta always has been a city where business leaders from banking, utility, insurance, law and real estate companies ran city hall. Such a white business-oriented power structure had not only conflicting interests with the priorities of black communities but also saw affirmative action in minority hiring and promotion as subordinate priority. In the first year of mayor Jackson, he appointed twelve whites and fifteen black to head city departments and agencies. Even more important for this paper, he pressured white-run banks to appoint black as executives and used deposits of city money to exert pressure on banks. In an interview Maynard Jackson stated equal opportunity as motivation for "moving a half-million account out of a bank that would not comply with the city policy to a bank that had come in on the twenty-ninth day of a thirty-day ultimatum" (Bayor, 2001). This anecdotal evidence is just one example of how banks and local politicians interact.

Ex ante, I would hypothesize that the effects of black political leadership on bank lending is most pronounced for the cases where African-American mayors get elected for the first time. In order to test this hypothesis, I pick only elections where a black candidate won the mayoral election for the first time. This leaves me with 46 elections[5] in 46 cities between 1990 and 2015 that are merged with the HMDA dataset. I run the following simple panel regression:

$$M^{b,w}_{i,c,t} = \beta_1 black_{c,t} + \alpha_i + \kappa_c + \gamma_t + \epsilon_{i,c,t}, \tag{5.1}$$

where $M_{b,c,t}$ is the log of number of mortgage applications (accepted, accepted plus declined) from African-American applicants (b) or non-Hispanic white applicants (w) for bank i in city c in year t. $black_{c,t}$ is the election dummy variable equal to one in the year where the first black mayor won and zero for all other years. α_i, κ_c and γ_t are bank, city and time fixed effects. To analyze an electoral mortgage cycle I follow Englmaier and Stowasser (2017) and replace the election indicator $black_{c,t}$ with pre- and post-election dummies $black_{c,t-\tau}$, where $\tau = (-1, 0, 1, 2, 3)$. Since the banks in our sample

[5]See appendix D.II for details.

lend to multiple cities[6], we can follow the identification strategy by Khwaja and Mian (2008) to reduce concerns that our shock measure is plagued by regional demand factors that could affect both the election probability of the black candidate and mortgage outcomes.

The purpose of investigating raw correlations between black political leadership and mortgage lending outcomes is to get tentative evidence and a first impression. Obviously, correlation is not causation. Table D.II shows the sample composition of cities and the corresponding vote characteristics. Apparently, some cities elected their first black mayor with a substantial majority which can be driven by e.g. unobserved demographic characteristics that affect both the victory of the black candidate and housing outcomes. In order to tackle such an omitted variable bias and other endogeneity types, the next section presents the methodological setup for causal treatment effects of black political leadership on mortgage access.

5.2.3 The RD Design

Since black mayorships are not randomly assigned to US cities, identifying the causal effect of black political leadership is complicated by endogeneity. Comparing housing market outcomes in black governed cities with housing market outcomes in white governed cities is biased because e.g. demographic developments, that are unobserved by the researcher, can both lead to the black candidate's victory but also to higher mortgage demand. Cities with high support for a black mayor might be systematically different from cities where black communities are not that strong resulting in white mayorship. According to Lee (2008) and Lee and Lemieux (2010), narrowly decided interracial elections provide quasi-random variation in election winners because which race wins is likely to be determined by pure chance as long as contestants cannot systematically manipulate the election outcome.

[6]On average, each bank operates in 13 cities.

The conventional RD design embodies the reasoning above by assigning the treatment (black mayorship) deterministically to those units whose running variable (vote share) is above the cutoff 50% while leaving units with vote share below the cutoff as untreated. Black candidates with a vote share below the cut-off (50%) are assigned to the control group (white mayoralty). In the context of interracial elections, the RD design holds constant the conditions that give rise to black mayoralties and thereby reduces omitted variable bias (OVB). Think of it as proxying an experiment whereby cities that pick their mayors in very close elections are close to be randomly assigned. Moreover, the granularity of the bank-level data allows me to improve the RD internal validity even further via quasi-counterfactual lending conditions: since the majority of banks in the sample lend to multiple cities at the same time, I can compare how lending of the same bank reacts to a close victory of a black candidate relative to a narrow defeat.

Short run effects. The short run effects of black political leadership on housing market outcomes is estimated as follows:

$$M_{c,t+1} = \beta_0 + \theta_1 black_{c,t} + P(\beta, bvote_{c,t}) + \epsilon_{c,t} \tag{5.2}$$

where $M_{c,t+1}$ represents the housing market outcome in city c in the year after the mayoral election $t+1$. $black_{c,t}$ is a dummy variable with value one indicating whether the black candidate won the mayoral election t in city c and zero if the black candidate lost the mayor's race. The running variable $bvote_{c,t}$ is the vote share of the black candidate and defined as the number of votes received by the black candidate divided by the sum of all votes. P stands for an n-order polynomial in the vote share to control for different functional forms (linear, quadratic and cubic). In order to increase the precision of the estimator of the RD treatment effect (Calonico et al., 2017), I additionally include predetermined control variables that come from the US

Census.[7] $\epsilon_{c,t}$ is an idiosyncratic error term.

Long run effects. Given that the effects of a black mayor might operate through intermediate variables[8] and occur slowly with unknown lags, I follow Cellini et al. (2010) to estimate dynamic "treatment-on-the-treated" (TOT)[9] effects in the presence of dynamics in the assignment of treatment. For each electoral (c,t) combination, I pool observations from two years before through six years after the election to estimate the following "intent-to-treatment" (ITT)[10] effects. Intuitively, ITT investigates housing market outcomes in cities where the black candidate won or lost a specific initial electoral (c,t) combination controlling for the black vote share in this election but not for any subsequent years or other control variables:

$$M_{c,t,\tau} = \theta_{\tau}^{ITT} black_{c,t} + P(\beta_{\tau}, bvote_{c,t}) + \alpha_{\tau} + \kappa_{t} + \gamma_{ct} + \epsilon_{c,t,\tau} \tag{5.3}$$

where $M_{c,t,\tau}$ represents the housing market outcome in city c in the election year t and the number of years elapsed between the election date and the date the outcome was measured τ. $black_{c,t}$ is a dummy variable equal to one if city c elected a black mayor in year t and zero if the black candidate lost the election or if there was no election. The running variable $bvote_{c,t}$ is the vote share of the black candidate and defined as described above. P stands for an n-order polynomial in the vote share to control for different functional forms (linear, quadratic and cubic). I also include year fixed effects (FE) (κ_t), years relative to the election FE (α_τ) and election FE (γ_{ct}).

[7]Covariates come from the US Census and contain log(population), % of black households, median household income, home ownership rate, house value, poverty rate, % black owner occupied housing units and whether the mayor in the previous period was black.

[8]Imagine that a narrowly electoral defeat of a black candidate might increase the probability of the same or different candidate winning the next time.

[9]Measures the effect of an black candidate that has actually been elected.

[10]This is a reduced form IV approach where the black mayoralty is instrumented with the black candidate being "eligible" to get elected and the ITT measures the effect of a black candidate that might get elected. Originally proposed by Cellini et al. (2010), the dynamic RD design is also adapted by Ferreira and Gyourko (2014) in the context ITT effects of female mayors on city outcomes.

$\epsilon_{c,t}$ is an idiosyncratic error term.

In order to estimate changes in housing market outcomes due to he cumulative sequence of black city leaders, I use the estimated coefficients θ_τ^{ITT} and recursively solve for the dynamic TOT effects using the following equation

$$\theta_\tau^{TOT} = \theta_\tau^{ITT} - \sum_{h=1}^{\tau} \pi_h \theta_{\tau-h}^{TOT} \tag{5.4}$$

and all available years to permit even longer lags.[11] The delta method delivers the standard errors. Unfortunately, the dynamic TOT effects become very imprecise at long horizons. In the vein of Cellini et al. (2010), I improve precision of lagged election effects by estimating the “one-step-estimator” in a conventional panel where observations are uniquely identified by city c and time t. Housing market outcomes in year t depend on the full history of elected black city leaders. The panel estimation looks as follows:

$$M_{c,t} = \sum_{\tau=0}^{\bar{\tau}} \Big(black_{c,t-\tau}\theta_\tau^{TOT} + m_{c,t-\tau}\alpha_\tau + P(\beta_\tau, bvote_{c,t-\tau}) \Big) + \gamma_c + \kappa_t + \epsilon_{c,t}. \tag{5.5}$$

Notation is the same as above except one additional indicator $m_{c,t-\tau}$ for a black candidate’s victory in year $t-\tau$ and a city fixed effect γ_c. Also, Equation (5.5) controls for the history of vote shares. Standard errors are clustered at the city level.

5.2.4 Sample Representativeness

Table 5.2 shows some key city characteristics of the election sample. Column (1) shows descriptive stats for US cities above 25,000 inhabitants as of the year 2000, the threshold of cities I focus at. Apparently, interracial elections take place disproportionately in the southern region of the US and in large cities. Also, the fraction of African-American people living in these cities

[11] See Cellini et al. (2010) for details.

is higher compared to cities in the first column. The over-representation of the sample in the southern part of the United States might also explain the lower median family income and house prices.

– Insert Table 5.2 here –

5.2.5 Internal Validity

Density of the running variable. A standard validity check in the RD literature is to test for discontinuity of the assignment variable at the cut-off (Imbens and Lemieux, 2008). Intuitively, a discontinuous jump of the vote shares around 50% might indicate that certain candidates might have systematic advantage or differential resources to influence the outcome and self-select into treatment. This endogenous sorting around the threshold would be a serious threat to internal validity. As Vogl (2014) notes, the RD setting on black political leadership is especially vulnerable to this assumption. He shows that black candidates might disproportionally have control over the outcomes of close elections since they mobilize large groups of previously unregistered and unincorporated electorates. However, this setting does not suffer from endogenous sorting around the cut-off for two reasons. First, there is no statistically significant discontinuous jump of the assignment variable as indicated in figure 5.1 plots the density of the assignment variable via a histogram (upper sub-graph) and a local density plot (bottom sub-graph). In addition, the statistical manipulation test by Cattaneo et al. (2017) based on local polynomial density estimation technique yields a p-value of 0.39. Therefore, it fails to reject the null hypothesis of no difference in the density of treated and control observations at the cut-off. Second, since the sample period does not start until 1990, issues like voter suppression and voter mobilization during the rise of black mayors do not play such a big role anymore due to an assimilation process. The more time passed by since the Civil Rights Movement the less African-Americans were excluded from political life in their local communities and the less important an untapped pool of eligible voters play. Subfigure (a) also indicates a balanced distribution of treated and non-treated observations around the cut-off. More in detail, 151 non-treated cities are located left to the cut-off and 169 treated black mayor cities are located right to the cut-off.

– Insert Figure 5.1 here –

Differences in pre-election trends. Due to the panel structure of the dataset, I am able to check for pre-election trends in the outcome variable, a feature which most of conventional RD designs are not able to test. Technically, if the RD design really incorporates random variation in black political leadership, then the election outcome should by definition not have any explanatory power for predicting pre-election housing market outcomes. Table 5.3 shows the corresponding results for regressing pre-election mortgage outcomes on a dummy variable of whether the black candidate won or lost the election. Columns (1) and (2) only uses observations one year before the election includes year fixed effects. Already this most parsimonious specification shows no difference in pre-election outcomes and including cubic vote shares in Column (2) does not alter the result. Columns (3) and (4) use the pooled observation ITT setting as in Equation (5.3) and reports the coefficients θ_{-1}. Irrespective of adding election fixed effects γ_{ct} in Column (4), there are no pre-election outcome differences except in the black-white approval differential (volume). These differences in trends between cities that elect and fail to elect a black mayor do vanish if pre-election growth rates are investigated. Columns (5) to (7) regress the annual growth rate of the mortgage outcome variables between year $t-2$ and $t-1$ on year fixed effects and the indicator for whether the black candidate won or lost the mayoral election. Column (6) also contains cubic vote shares. Also here there is no indication for pretreatment trends in the outcome variable, validating the randomness of the treatment variable Lee and Lemieux, 2010.

– Insert Table 5.3 here –

5.3 Main Results

5.3.1 Electoral Mortgage Cycle of First Black Mayors

I begin with showing the effects of black political leadership in cities where black mayors got elected for the very first time on mortgage outcomes based on bank panel regressions.[12] Figure 5.2 plots the electoral mortgage cycle effects based on the β coefficients of pre- and post-election indicators in Equation 5.1. The dots are OLS point estimates with 90% confidence intervals. The first two subgraphs (a) and (b) provide evidence for a significant correlation between black political leadership and mortgage lending. While there are no effects in the election year, banks not only receive 9-17% higher number of total mortgage applications from black applicants but also lend out 10-19% higher number of mortgages in the post-election period after the first black mayor took office. Subgraph (c) analyzes the effects on the black-white acceptance differential and indicate that banks accept more applications from African-American households relative to white applicants in the first year after the focal election. To address the issue of differences in application propensities between black and white households raised by Charles and Hurst (2002), I proxy differential latent mortgage demand by constructing the variable black-white denial differential. Although none of the pre- and post-election indicators have a significant effect on the number of black declined mortgage application relative to white declined mortgage applications, the point estimates turn positive from the second year after the election. This might be an indication for black households applying relatively more than white households after first black mayors enter city government.

– Insert Figure 5.2 here –

5.3.2 Short Run Effects of Black Political Leadership

In contrast to the previous analysis, this section switches aggregation levels by moving from the bank level to the city level. It shows the estimation

[12] See appendix D.II for details on the sample composition.

results for the short term effects of black political leadership based on Equation 5.2. The static RD design is implemented by using the "rdrobust" STATA package according to Cattaneo et al. (2016). Table 5.4 presents the cross-sectional regression results of the baseline scenario. The first column depicts the unconditional mean[13] of the outcome variables and its standard deviation in brackets. The dependent variables are mortgage acceptance rates and approval differentials in the year after the election. While most of the coefficients have a positive sign, significance differs across specifications. Column (6) includes a linear vote share and a black mayor dummy variable as the only regressors and can be interpreted as a slightly modified difference in means t-test. It shows no significant impact of a black mayor on mortgage outcomes. While adding covariates in Column (5) does not alter the results, additionally including polynomial vote shares in Column (4) and (3) increases not only the point estimates substantially but also establishes statistical significance. According to Column (4), black political leadership increase mortgage acceptance rates one year after the mayoral election between 11 and 13 percentage points and this effect is statistical significant at 1 percent. Column (2) is the specification of interest including higher order polynomials of the vote share, control variables and a lagged outcome variable. The latter is included to reduce sampling variance in case the dependent variable is very persistent over time. Coefficients of the specification in Column (2) suggest that black mayors still increase black acceptance rates but with lower statistical significance at the 5 percent level for mortgage volumes. As mentioned above, the RD literature includes lagged outcome variables as regressors only if the dependent variable is very persistent over time. Unreported graphs show that average acceptance rates do fluctuate substantially over time and are therefore not very persistent. However, since there is no general quantitative definition or measure on when a variable is persistent, I prefer the conservative specification in Column (2).

[13] Note that the relatively high acceptance rates for black mortgage applications is due to HMDA data filtering. Keeping only home purchase loans and dropping home refinance or home improvements increases the mean of acceptance rates substantially as documented by Avery (2008). The same intuition applies to keeping only conventional and Federal Housing Administration (FHA) insured loans.

Based on this coefficient, the RD estimate displays a 11.2 percentage point treatment effect on mortgage acceptance rates for black applicants one year after the election. In terms of economic significance, a 11 percent increase in mortgage acceptance rates corresponds to a 12 percent increase relative to the mean.

– Insert Table 5.4 here –

5.3.3 Long Run Effects of Black Political Leadership

Given that the effects of political leadership might occur with unknown lags or operate through electoral defeats that increase chances of winning the next time, Table 5.5 presents the results for the dynamic effects of black political leadership on mortgage access. Panel (a) presents the θ coefficients of the ITT effects for mortgage acceptance rates and approval differential based on Equation 5.3 for a six year post-election period. Whereas black mayors have no significant effects in the first three years, they begin to become significant in the fourth and fifth year even though with low significance. The dynamic RD estimates display between 3.2 and 6.2 percentage point treatment effects on mortgage acceptance rates. In contrast to the static RD setup, the approval differential here is significantly affected by black political leadership already in the second year after the election and even more in the fourth year of the post-election period. Panel (b) shows the coefficients of the TOT effects which a larger in size and more persistent. As discussed in Section 5.2.3, this is plausible since TOT effects capture the dynamic nature of the treatment. The one-step estimator shows even marginal significance in the first year and sixth year of the post-election period. But the most obvious overlap among all specifications is that significance appears to be most pronounced in the fourth and fifth year after the focal election. One possible reason for these dynamics could be re-election effects, since almost all municipal legislation periods last 4 years and most mayors govern US cities over multiple terms.

– Insert Table 5.5 here –

Figures 5.3 and 5.4 plots the point estimates and the corresponding 90% confidence bands of the TOT effects for the black mortgage acceptance rate that correspond to panel (b) in Table 5.5. As already previously discussed black mayors have significant effects in years 4,5 and 6.

– Insert Figures 5.3 and 5.4 here –

5.3.4 Black Mayor Effects for Different Income Groups

This section analyzes potential heterogeneities underlying my results. Given that the two frictions mentioned by Charles and Hurst (2002), the negative treatment by banks and different application propensities across races, might affect low-income group blacks more than high-income group households, I hypothesize that black political leadership has differential effects depending on the income distribution. Fortunately, the HMDA data also contain information on the applicants income allowing me to differentiate the same mortgage outcomes as described in Section 5.2.1 by income quartiles. Figure 5.5 shows the effects of black political leadership on mortgage acceptance rates by income group. While the bottom income quartile shows insignificant effects, the upper income groups gain higher mortgage access yet with marginal significance mostly in year 4 and 5 of the post-election period.

– Insert Figure 5.5 here –

Another interesting question is also whether applicants receive larger mortgage loans relative to their income. For each accepted mortgage application by income group, I divide the mortgage loan volume by the gross annual income of the applicant use an average at the bank-year-city-level to proxy debt-to-income ratios for different income groups in the respective city. These debt-to-income ratios are used as dependent variable for the dynamic RD design to find out whether the riskiness of loans changes after black mayors took office. According to Figure 5.6 this seems to be marginally the case for the above median income group applicants and therefore indicate that the riskiness of the mortgage portfolio is not increasing, at least not for low net worth households.

– Insert Figure 5.6 here –

5.3.5 Channels of Black Leadership Effects

The following section describes possible channels through which the effects might operate.

Political Pressure Channel. Following the narrative on how the first black mayor, Maynard Jackson, of Atlanta used city deposits to pressure white run banks to appoint black bank executives, I collect bank-level data on city deposits to investigate the narrative *political-pressure* channel.

Housing supply. The first exercise plans to use data from the Building Permits Survey by the US Census Bureau to find out whether effects are driven by an expansion in housing supply. A mayor has several opportunities to preserve and expand housing supply at the municipal level. Almost every city has a budget for housing programs that are collected both from local and federal sources that can be effectively used to increase housing housing supply expansion. Besides that, the municipal leaders can more or less intensify already active policies like inclusionary zoning, the tenant opportunity to purchase act, local rent supplement program or property tax credits as the example of Washington DC shows (Tatian, 2014). The dataset provides monthly information on the number of new housing units authorized by building permits at the city level from 1988-2015. Unfortunately, information on building permits are not broken down by race.

Proximity channels. To investigate whether political factors might drive the results, I run the regression discontinuity design only for a subsample of mortgage lending by community banks. According to the FDIC, community banks have total assets less than $1 billion, are associated with basic banking functions of deposit gathering and lending, operate withing a fairly circumscribed geographic area and engage in relationship banking. Assuming that the proximity between a mayor and a community bank is closer compared to other bank types, I expect the effect of black mayoralty to be stronger in this subsample.

Exploiting FDIC data on minority depository institutions will enable me to test whether black-owned banks react more strongly than other banks to the African-American city leader. The implicit assumption behind this hypothesis is that the proximity between bankers and politicians is closer the more they belong to the same peer group. In such an environment I would expect the black mayor to have a higher ability to influence the banks' lending policies.

Collecting information on the location of the mayor's office or where the mayor was born/raised could provide insight into a third political economy channel. Given that local politicians would favor their home districts and constituents more than the distant ones, I would expect that mayors can differentially exert influence on home-district banks. This investigation goes into the direction of Chavaz and Rose (2016) who document the existence of a "home-district effect" where banks channeled government subsidies for bank lending into areas of their home-representative's congressional district.

Reputation channel. Using data on CRA[14] examinations might provide insights into the reputation channel. Assuming that banks are concerned about their reputation, I hypothesize that discriminating banks would act against their prior as soon as the first black politician got elected. More specific, financial institutions that received a lot of consumer complaints and thereby didn't comply to standards of the Community Reinvestment Act (CRA) such as discriminatory or other illegal credit practices might tend to act less discriminatory after black mayors got elected.

[14]The Community Reinvestment Act (CRA) intends to encourage banks to help meet the credit needs of especially low- and moderate-income communities. The banks' track record is regularly evaluated by the corresponding supervisory agencies via CRA examinations.

5.4 Conclusion

This paper identifies effects of black political leadership on mortgage access and home ownership transition of African-American households. I implement a static and dynamic regression discontinuity design to investigate 312 interracial elections in 122 US cities between 1990 and 2016. Overall, the findings suggest significant effects on mortgage acceptance outcomes along several dimensions. First, raw bank-level correlations reveal significant electoral mortgage cycle effects for US cities that elect an African-American mayor for the very first time. More specific, I find that first black mayors lead to an increase of accepted mortgage volume to black applicants by 9-17% in the post-election period. Second, a static and dynamic regression discontinuity design strengthens the internal validity of this tentative result by showing positive and significant treatment effects of black mayors on mortgage access in the short and in the long run. Mortgage acceptance rates increase by 12 percent one year after the election. The long run effects are marginally significant mostly in the fourth and fifth year since the focal election. Third, I find that these results are more pronounced for black applicants in the upper part of the income distribution and that debt-to-income ratios for the same people increase relative to applicants in the bottom part of the income distribution. While the current version of the paper is silent about the mechanism driving these results, it proposes four potential channels and leaves them for future empirical work: *political pressure* channel, *housing supply* channel, *social proximity* channel and the *reputation* channel.

This paper reveals important implications. First, political participation matters. Since hard political power is only partially effective in reducing mortgage market frictions such as discriminatory lending practices or differential application propensities by race (Agarwal et al., 2014b; Agarwal et al., 2016b; Agarwal et al., 2016a; Bayer et al., 2017; Munnell et al., 1996), I indicate that soft political power at the local level can be an effective tool for alleviating such market imperfections. Second, it also indicates that politicians might have had a role in fueling the housing boom-bust cycle by increasing mortgage access to minority groups (Ferreira et al., 2016).

However, some limitations underlie the findings of this study. As most RD settings with high internal validity, this setup has limited external validity since it focuses on a narrow sample of interracial elections that are overrepresented in the southern region of the US. Furthermore, this paper can neither claim that politicians reduce discrimination in the housing finance market nor do they lead to more risky mortgage lending. After all, the limitations of a study can represent fruitful avenues for future research.

Tables and Figures

Table 5.1: Mayoral Elections by Year.

Year	Number of elections (1)	White-White elections (2)	Black-Black elections (3)	Black-White elections (4)	Black mayors (5)
1990	16	6	2	8	6
1991	57	40	3	14	12
1992	18	16	0	2	1
1993	55	37	3	15	11
1994	25	14	1	10	7
1995	57	38	2	17	11
1996	21	17	0	4	3
1997	56	34	4	18	14
1998	21	11	4	6	7
1999	67	40	4	23	15
2000	28	19	0	9	3
2001	62	33	7	22	20
2002	28	20	5	3	6
2003	74	52	4	18	16
2004	31	21	2	8	6
2005	62	38	7	17	16
2006	34	24	2	8	6
2007	62	35	9	18	18
2008	33	25	1	7	7
2009	62	32	9	21	17
2010	22	11	5	6	9
2011	52	28	9	15	19
2012	18	10	1	7	6
2013	42	23	5	14	12
2014	16	8	4	4	7
2015	47	26	8	13	12
2016	17	11	1	5	4
$\sum$	1,083	669	102	312	271

Notes: This table shows election characteristics based on elections with non-missing vote shares and race information.

TABLE 5.2: Sample Representativeness.

	US cities with > 25,000	Election sample	Interracial elections
	(1)	(2)	(3)
Number of cities	1,492	905	122
Population	88,782	108,590	353,565
	(268,261)	(341,703)	(797,459)
% west	29.22	28.51	12.30
% midwest	23.93	32.27	27.87
% south	30.70	24.75	44.26
% northeast	16.15	14.48	15.57
% white	73.33	72.58	51.84
	(19.38)	(20.45)	(17.79)
% black	12.35	13.13	35.11
	(16.73)	(17.85)	(19.95)
% college degree	4.69	4.42	3.91
	(1.34)	(1.32)	(1.15)
Median family income	55,343	50,746	43,189
	(18,823)	(16,591)	(10,195)
Median house value	152,427	135,099	111,307
	(100,659)	(87,492)	(61,945)

Notes: This table shows mean city characteristics (standard deviation in brackets) for different city categories. Column (1) depicts US cities with more than 25,000 people as of year 2000. Column (2) shows cities where I was able to gather and complement election information necessary for the RD design. The last column presents cities that have interracial elections between 1990 and 2016 that enter the baseline regression.

Table 5.3: Differences in Pre-Election Trends.

	Year before election				Growth rate before election		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acceptance rates							
Black (volume)	-0.79	-0.39	-1.06	-0.09	-0.36	0.44	0.36
	(0.949)	(1.976)	(1.835)	(1.864)	(0.85)	(1.682)	(1.584)
Black (number)	-0.92	-0.61	-1.27	-0.54	-0.67	0.15	0.20
	(0.948)	(1.942)	(1.863)	(1.952)	(0.856)	(1.684)	(1.701)
Approval differentials							
Black to white (volume)	-0.85	-2.37	-2.82*	-3.02*	0.08	-2.10	-1.76
	(0.83)	(1.664)	(1.485)	(1.493)	(0.856)	(1.713)	(1.558)
Black to white (number)	-0.51	-1.10	-1.72	-1.75	0.17	-1.68	-1.70
	(0.723)	(1.279)	(1.186)	(1.411)	(0.862)	(1.77)	(1.693)
Observations	304	304	2,552	2,552	291	291	2,237
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic in vote share	No	Yes	Yes	Yes	No	Yes	Yes
Sample pools relative years	No	No	Yes	Yes	No	No	Yes
Election FE	No	No	No	Yes	No	No	No

Notes: Column (1) to (7) reports estimated effects of the black winner dummy variable on pre-election mortgage outcomes. Each entry represents a separate regression for each of the outcome variables. The first four columns depict outcomes in levels one year before the election. Columns (5) to (7) analyze the annual growth rate of mortgage outcomes from t-2 to t-1. Columns (3), (4) and (7) uses the pooled observation ITT setting with keeping two years before through six years after the election for each electoral (c,t) combination including high order polynomial of the vote share, year and relative year fixed effects. Column (4) additionally adds election fixed effects. The amount of observations varies for each outcome variable: Robust standard errors (in parentheses) are clustered at the city level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5.4: Short Run Effects of Black Mayors on Mortgage Outcomes.

		Static Regression Discontinuity design				
	Average (stdev)		Bias corrected			
	(1)	(2)	(3)	(4)	(5)	(6)
Acceptance rates						
Black (volume)	91.59	11.189**	13.983***	7.364**	2.089	0.438
	(7.87)	(5.504)	(5.416)	(3.621)	(2.439)	(2.687)
Black (number)	90.60	8.227*	11.483**	5.717*	1.091	-1.126
	(8.34)	(4.578)	(4.539)	(3.361)	(2.344)	(2.640)
Approval differentials						
Black to white (volume)	96.68	1.000	2.883	0.686	-0.894	-0.736
	(5.27)	(3.058)	(3.202)	(2.331)	(1.569)	(1.651)
Black to white (number)	96.52	0.473	2.652	0.120	-1.150	-0.989
	(5.78)	(2.777)	(3.169)	(2.306)	(1.616)	(1.677)
Covariates		Yes	Yes	Yes	Yes	No
Linear vote share		Yes	Yes	Yes	Yes	Yes
Quadratic vote share		Yes	Yes	Yes	No	No
Cubic vote share		Yes	Yes	No	No	No
Outcome at t-1		Yes	No	No	No	No

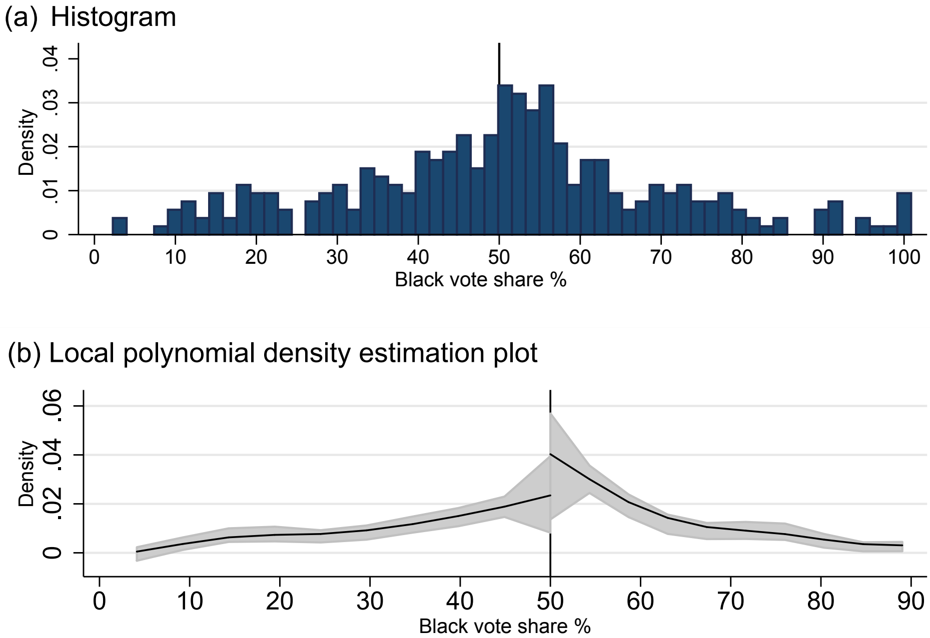
Notes: Column (1) shows the mean and standard deviation (in brackets) of the mortgage outcome variable. Acceptance rates are defined as the ratio of accepted mortgages of black applicants to total black mortgage applications (both in mortgage volume or number). The outcome approval differential is defined as the ratio of black acceptance rate to white acceptance rate. Columns (2) to (6) report RD coefficients ,θ, based on Equation (5.3) for each outcome variable. The discontinuity is defined as black candidates winning the election if the vote share is greater than 50%. Column (6) displays the parsimonious RD specification including linear vote share without covariates. Column (5) inserts covariates while Column (4) and Column (3) additionally include a quadratic and cubic vote share, respectively. Column (1) comes with the lagged outcome variable on the right hand side of Equation (5.3). Covariates come from the US Census and contain log(population), % of black households, median household income, home ownership rate, house value, poverty rate, % black owner occupied housing units and whether the mayor in the previous period was black. Bias-corrected standard errors are given in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 5.5: Long Run Effects of Black Mayors on Mortgage Outcomes.

	+1 year	+2 years	+ 3 years	+ 4 years	+ 5 years	+ 6 years
	(1)	(2)	(3)	(4)	(5)	(6)
	(a) ITT					
Acceptance rates						
Black (vol.)	1.67	1.59	0.47	3.24*	3.95**	1.71
	(1.786)	(1.743)	(1.737)	(1.727)	(1.643)	(1.431)
Black (nr.)	0.68	1.75	0.05	3.26*	4.06**	2.05
	(1.846)	(1.887)	(1.615)	(1.842)	(1.577)	(1.507)
Approval differential						
Black to white (vol.)	0.76	1.69	1.01	2.25*	1.43	1.27
	(1.111)	(1.604)	(1.423)	(1.333)	(1.398)	(1.194)
Black to white (nr.)	-0.35	2.62*	0.77	2.98**	0.67	0.36
	(1.176)	(1.557)	(1.245)	(1.388)	(1.292)	(1.090)
	(b) TOT					
Acceptance rates						
Black (vol.)	2.73	2.46	1.22	4.21**	4.39**	2.06
	(1.725)	(1.869)	(1.764)	(2.004)	(1.714)	(1.528)
Black (nr.)	1.73	2.53	0.65	3.98*	4.41**	2.24
	(1.847)	(1.989)	(1.814)	(2.135)	(1.734)	(1.807)
Approval differential						
Black to white (vol.)	1.07	2.25	1.62	2.84**	1.66	1.07
	(1.069)	(1.565)	(1.407)	(1.353)	(1.332)	(1.071)
Black to white (nr.)	0.08	3.21**	1.45	3.47**	0.97	0.13
	(1.179)	(1.567)	(1.268)	(1.432)	(1.374)	(1.119)
	(c) One-step estimate					
Acceptance rates						
Black (vol.)	3.19*	3.02	2.06	4.64**	6.24***	3.46*
	(1.812)	(2.003)	(1.933)	(2.182)	(2.038)	(1.921)
Black (nr.)	2.15	3.22	1.49	4.40*	6.09***	3.29
	(1.876)	(2.189)	(2.056)	(2.357)	(2.112)	(2.096)
Approval differential						
Black to white (vol.)	1.17	2.48	1.65	2.48	2.49	2.15
	(1.163)	(1.659)	(1.378)	(1.550)	(1.566)	(1.361)
Black to white (nr.)	0.07	3.71**	1.28	3.44**	1.56	1.10
	(1.199)	(1.680)	(1.308)	(1.502)	(1.581)	(1.325)

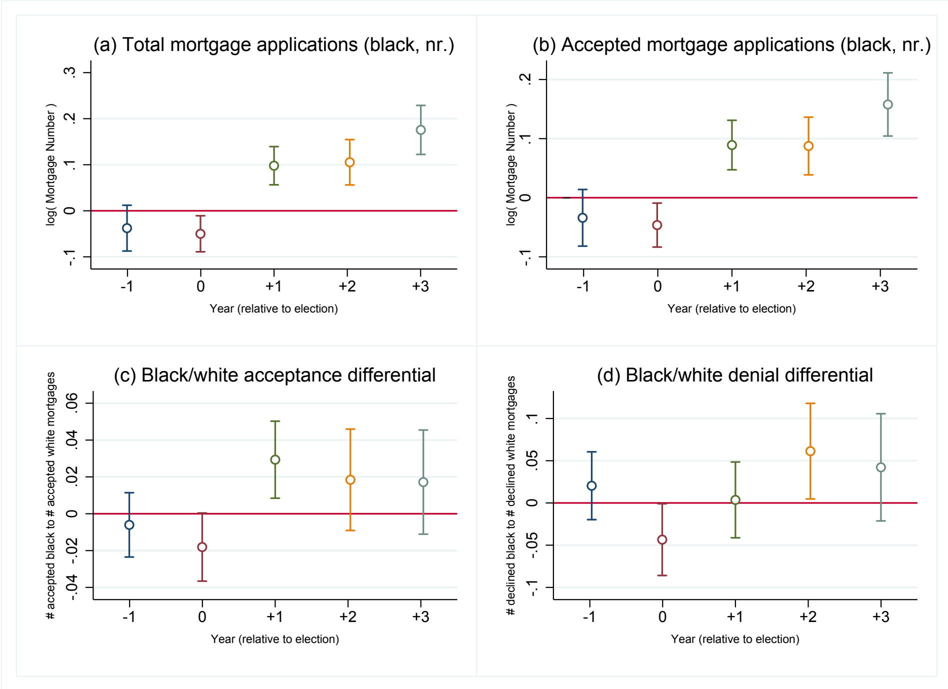
Notes: Panel (a) and (b) show the "intent-to-treat" (ITT) and the "treatment-on-the-treated" (TOT) effects as described in subsection 5.2.3 with each row representing a separate regression of the mortgage outcome variables on the election indicator, polynomials of the vote share, year fixed effects (FE), years relative to the election FE and election FE. The pooled sample consists of two years before through six years after the election for each electoral (c,t) combination and gives 2,504 observations. Each entry represents the coefficient of the indicator for black candidate winning or losing the electoral race. Entries in Panel (b) are coefficients obtained by the recursive equation $\theta_\tau^{TOT} = \theta_\tau^{ITT} - \sum_{h=1}^{\tau} \pi_h \theta_{\tau-h}^{TOT}$ using all available observations and not only the relative year -2 through 6. This results in 8,384 observations. Panel (c) utilize the conventional (c, t) panel structure additionally includes an indicator for a black candidate's victory in year $t-\tau$ and city FE. Standard errors (in parentheses) are clustered at the city level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

FIGURE 5.1: Manipulation Test.



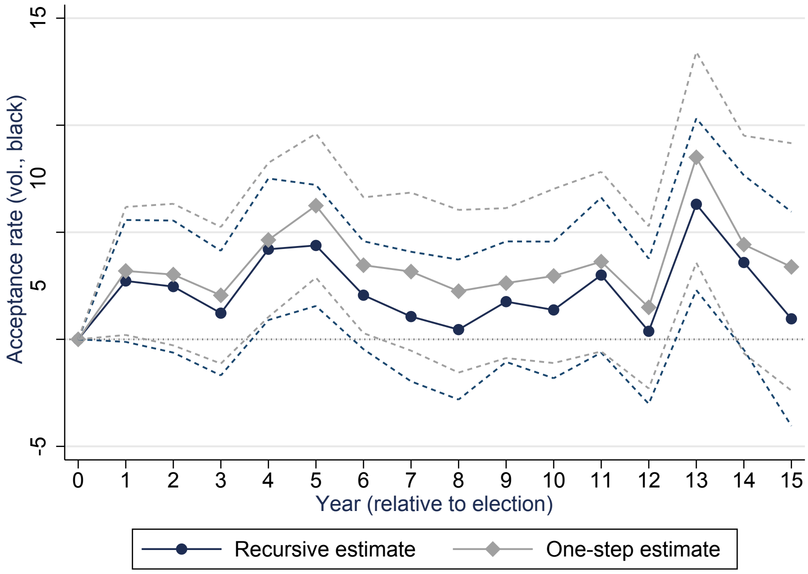
Notes: This graph shows the distribution of the assignment variable for the interracial elections. The assignment variable is the vote share of the black candidate with the cut-off being 50%. Subgraph (a) displays the histrogram of the black vote share. Subgraph (b) reports a local polynomial density plot of the black vote share with 95% confidence intervals to show whether there is a discontinuity at the winner threshold. Vertical lines in both subgraphs denote the 50% cut-off.

FIGURE 5.2: Effects of First Black Mayors on Mortgage Lending.



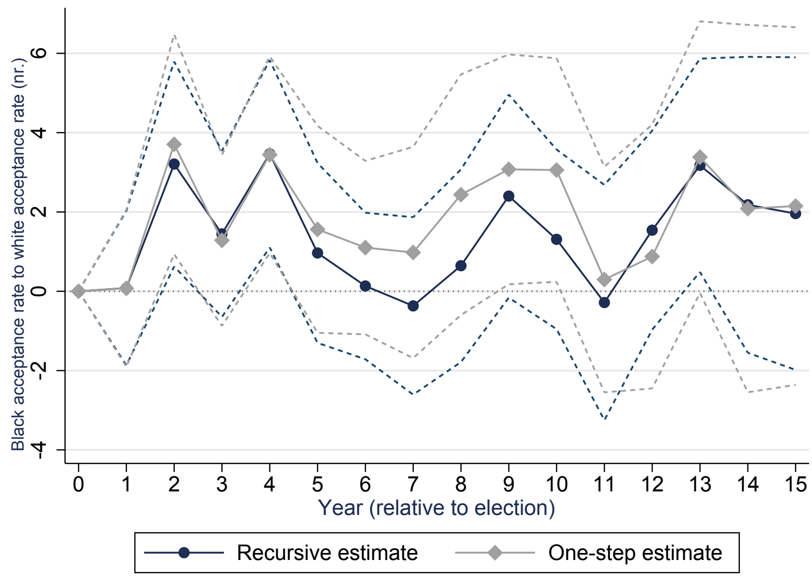
Notes: This graph shows the electoral mortgage cycle effects for first-time African American winners of mayoral elections between 1990 and 2015. Each dot represents the point estimate based on a bank panel regression of mortgage outcomes on the pre- or post-election indicator $black_{c,t-\tau}$ and bank-, city,- and time fixed effects separately estimated for $\tau = -1, 0, 1, 2, 3$. The total number of observations is 78,946 with 4,203 banks. Standard errors are clustered at the city level.

FIGURE 5.3: Long Run Effects – Mortgage Acceptance Ratio.



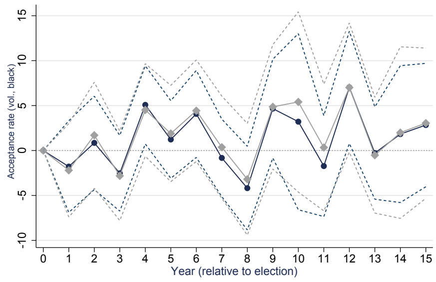
Notes: This graph plots the coefficients and 90% confidence intervals for the treatment-on-the-treated (TOT) effects. The outcome variable is mortgage acceptance rate calculated as accepted mortgage volume to total mortgage volueme for black applicants. The recursive estimate is based on Equation (5.4) and the one-step estimate is based on Equation (5.5). Confidence Intervals are based on standard errors clustered at the city level.

FIGURE 5.4: Long Run Effects – Black/White Approval Differential.

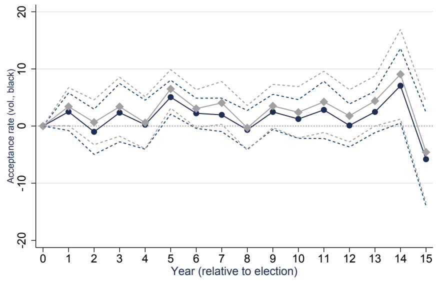


Notes: This graph plots the coefficients and 90% confidence intervals for the treatment-on-the-treated (TOT) effects. The outcome variable black-white approval differential is calcluated as the ratio of black acceptance rate divided by white acceptance rate. The recursive estimate is based on 5.4refeq:recursive) and the one-step estimate is based on Equation (5.5). Confidence Intervals are based on standard errors clustered at the city level.

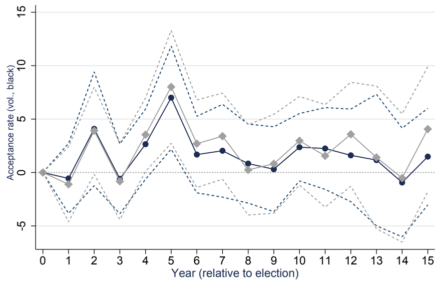
Figure 5.5: Black Mayor Effects on Mortgage Acceptance Rates by Income Group.



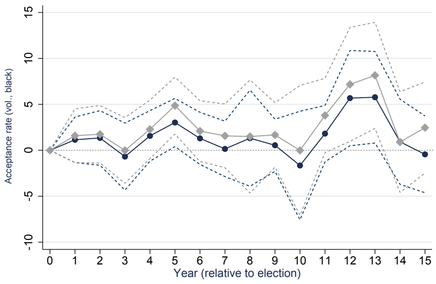
Income Group 1



Income Group 2



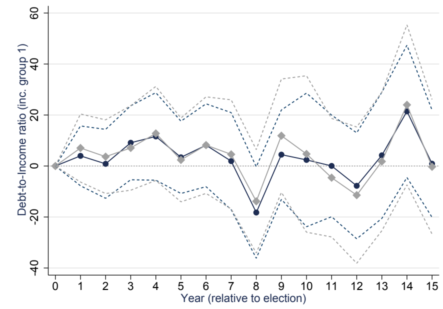
Income Group 3



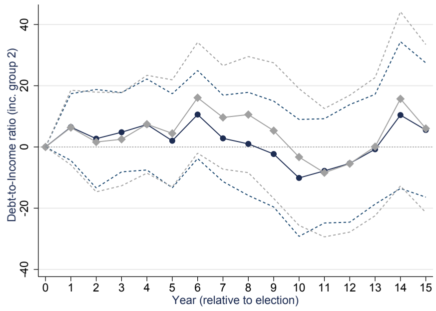
Income Group 4

Notes: This graph plots the coefficients and 90% confidence intervals for the treatment-on-the-treated (TOT) effects. The outcome variable is mortgage acceptance rate calculated as accepted mortgage volume to total mortgage volueme for black applicants by income group. Applicant's income is used to divide all loan applications for each bank into four income groups and calculate respective mortgage acceptance rates. The recursive estimate is based on Equation (5.4) and the one-step estimate is based on Equation (5.5). Confidence Intervals are based on standard errors clustered at the city level.

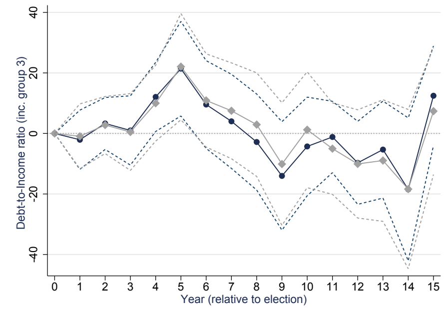
Figure 5.6: Black Mayor Effects on Debt-to-Income Ratios by Income Group.



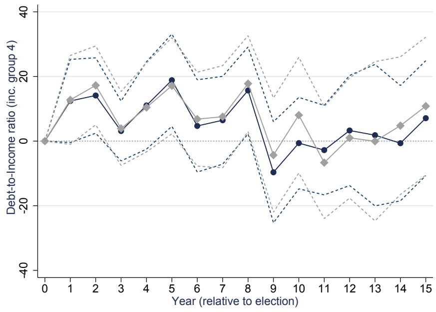
Income Group 1



Income Group 2



Income Group 3



Income Group 4

Notes: This graph plots the coefficients and 90% confidence intervals for the treatment-on-the-treated (TOT) effects. The outcome variable is mortgage acceptance rate calculated as accepted mortgage volume to total mortgage volueme for black applicants by income group. Applicant's income is used to divide all loan applications for each bank into four income groups and calculate respective debt-to-income ratios. The denominator is measured as yearly income at the time the household applied for a loan and the numerator is total mortgage volume accepted. The recursive estimate is based on Equation (5.4) and the one-step estimate is based on Equation (5.5). Confidence Intervals are based on standard errors clustered at the city level.

Appendix D

D.I Appendix A: Data

This paper merges different datasets with information on mayoral elections, mortgage application data and home ownership data. The following section describes the data sources and data preparation in detail.

Mayoral elections. For the regression discontinuity design to work, I need year and city of the election, vote shares of the mayor and the runner-up candidate and their races. These information come from three data sources: Ferreira and Gyourko (2009), Vogl (2014) and own hand-collection. Ferreira and Gyourko (2009) sent surveys to all US cities with more than 25,000 inhabitants as of the year 2000 and received the date of the election, the name of the mayor and the runner-up, vote totals for each candidate, type of election and some additional information for 2,000 mayoral elections in 413 cities between 1950 and 2000. Unfortunately, this dataset does not contain information on the race of the top two candidates. Vogl (2014) collects 1,196 elections between 1965 - 2010 with information on names, vote counts and the race for the top-two candidates. Given that the mortgage data start in 1990 and I can only exploit interracial elections, I increase the amount of observations by complementing these two datasets. Sources of my manual search, especially for the race information, include the following:

- www.ourcampaigns.com
- Wall Street Journal Online, Washington Post Online
- Nexis®
- EBSCO - Academic Search Premier
- Bayor (2001)
- Black Elected Officials - A National Roster 1990, 1991, 1993-1997 and 1999

Mortgage loans. Data on mortgage applications come from the Home Mortgage Disclosure Act (HMDA). This regulation was enacted in 1975 and requires approximately 80% of all mortgage lending institutions nationwide to disclose information on their mortgage lending activity Avery et al., 2007. It provides loan-level application data on rich borrower characteristics like applicant's income, race, sex, loan amount, location of the borrower's house and whether/why the loan application was denied or accepted. The granularity of the HMDA data enables to me to track each mortgage application at the census tract level. The geographic area of each city in the United States consists of several census tracts. Therefore, I collapse loan-level information at the city level for each banks that lend to borrowers who have their home property in the respective city. Since information on race and income of the borrower is only available from 1990 onwards, I have to restrict the sample period from 1990 to 2016 although electoral data start in 1950. I drop all loans if income or mortgage amount is zero or negative and keep loan applications where race contains values "Non-hispanic White" and "Black" or "African-American". I keep only "Conventional" and "FHA-insured" loans and drop "Veterans Administration", "Farm Service Agency" or "Rural Housing Service" loans. Since the paper focuses on home ownership decisions, I select only home purchase loans and disregard refinance and home improvement loans. I keep only owner-occupied loans. Keep banks which had at least one African-American loan application. Based on this filter, I calculate outcome variables (mortgage acceptance rates and approval differentials) at the bank-level and take the median over all banks in the respective city.

Home ownership transition. Data on home ownership transition come from the Panel Study of Income Dynamics (PSID) for which I am currently in the application process. The PSID is an extensive household survey that tracks families over time and records demographic information (e.g. age, race, family composition, education) and, most importantly, housing information (paid rents, housing values, outstanding mortgage payments, mortgage rates and when the mortgage was acquired).

D.II Appendix B: First Black Mayor Elections

Table D.I: Summary statistics - First Black Mayor Elections.

Year	City	State	Mayor name	Party	Gender	Vote share	City pop.	Black pop.(%)
1990	Irvington	New Jersey	Michael G. Steele	Democratic	male	n.a.	61,018	70%
1990	Trenton	New Jersey	Douglas Palmer	Democratic	male	51%	88,675	49%
1990	Washington	District of Columbia	Sharon Pratt Kelly	Democratic	female	86%	606,900	66%
1991	Denver	Colorado	Wellington Webb	Democratic	male	58%	467,610	13%
1991	Kansas City	Missouri	Emanuel Cleaver II	Democratic	male	55%	435,146	30%
1991	Memphis	Tennessee	Willie W. Herenton	Democratic	male	49%	610,337	55%
1992	Wilmington	Delaware	James H. Sills, Jr.	Democratic	male	91%	71,529	52%
1993	Minneapolis	Minnesota	Sharon Sayles Belton	Democratic	female	57%	368,383	13%
1993	Rochester	New York	William A. Johnson, Jr.	Democratic	male	71%	231,636	32%
1993	St. Louis	Missouri	Freeman Bosley, Jr.	Democratic	male	67%	396,685	48%
1995	Dallas	Texas	Ron Kirk	Democratic	male	62%	1,852,810	20%
1995	San Francisco	California	Willie Brown	Democratic	male	57%	723,959	11%
1996	Monroe	Louisiana	Abe Edward Pierce, III	Democratic	male	51%	52,573	61%
1996	Savannah	Georgia	Floyd Adams, Jr.	Democratic	male	n.a.	137,560	51%
1997	Arlington	Texas	Elzie Odom	n.a.	male	n.a.	332,969	14%
1997	Houston	Texas	Lee P. Brown	Democratic	male	53%	1,953,631	25%
1997	Jackson	Mississippi	Harvey Johnson, Jr.	Democratic	male	70%	184,256	71%
1999	Columbus	Ohio	Michael B. Coleman	Democratic	male	60%	711,470	24%
2001	Fayetteville	North Carolina	Marshall Pitts, Jr.	Democratic	male	56%	121,015	42%
2001	Hattiesburg	Mississippi	Johnny DuPree	Democratic	male	53%	44,779	47%
2001	Southfield	Michigan	Brenda L. Lawrence	Democratic	female	53%	78,296	54%
2001	Toledo	Ohio	Jack Ford	Democratic	male	n.a.	313,619	24%
2003	Alexandria	Virginia	William D. Euille	Democratic	male	52%	128,283	23%
2003	Miami Gardens	Florida	Shirley Gibson	Democratic	female	n.a.	107,167	76%
2003	Palm Springs	California	Ron Oden	Democratic	male	51%	42,807	4%
2003	San Ramon	California	H. Abram Wilson	Republican	male	n.a.	44,722	2%
2004	Albany	Georgia	Willie Adams, Jr	n.a.	male	62%	67,939	65%
2004	Baton Rouge	Louisiana	Kip Holden	Democratic	male	54%	227,818	50%
2004	Pine Bluff	Arkansas	Carl A. Redus, Jr.	Democratic	male	n.a.	55,085	66%
2005	Asheville	North Carolina	Terry M. Bellamy	Democratic	female	57%	68,889	18%
2005	Buffalo	New York	Byron Brown	Democratic	male	61%	292,648	37%
2005	Cincinnati	Ohio	Mark L. Mallory	Democratic	male	52%	331,285	43%
2005	Mobile	Alabama	Samual L. Jones	Democratic	male	56%	198,915	46%
2005	Youngstown	Ohio	Jay Williams	Democratic	male	52%	82,026	44%
2006	Shreveport	Louisiana	Cedric Glover	Democratic	male	54%	199,311	55%
2007	Greensboro	North Carolina	Yvonne Johnson	Democratic	female	57%	269,666	41%
2007	Mansfield	Ohio	Donald Culliver	Democratic	male	n.a.	47,821	22%
2007	Wichita	Kansas	Carl Brewer	Democratic	male	62%	382,368	12%
2008	Sacramento	California	Kevin Johnson	Democratic	male	57%	466,488	15%
2009	Freeport	New York	Andrew Hardwick	Democratic	male	n.a.	24,860	31%
2010	Columbia	South Carolina	Stephen K. Benjamin	Democratic	male	56%	129,272	30%
2011	Ithaca	New York	Svante Myrick	Democratic	male	54%	30,014	7%
2011	Jacksonville	Florida	Alvin Brown	Democratic	male	50%	821,784	31%
2012	Phenix City	Alabama	Eddie Lowe	n.a.	male	64%	32,822	47%
2014	Teaneck	New Jersey	Lizette Parker	Democratic	female	n.a.	39,776	28%
2015	San Antonio	Texas	Ivy Taylor	Democratic	female	52%	1,327,407	7%

Notes: This table lists all mayoral elections where African-American candidates won for the very first time in the a city. Data source is the same dataset as described in Appendix D.I

Chapter 6

Conclusion

The Great Recession and the European sovereign-debt crisis triggered substantial regulatory change in the international financial architecture. In order to increase the resilience of the banking sector, meaningful reforms such as enacting a European Banking Union or the implementation of macroprudential policies have been undertaken in many countries. While these efforts are a first step in the right direction, some regulatory reforms are still unfinished as well as it is to question whether the set of reforms is sufficient to make the system less vulnerable to severe crisis episodes. This thesis contributes to the current regulatory debate by providing four novel risk-mechanisms that are crucial for understanding recent developments in financial markets, the regulatory framework and their implications for financial stability.

Chapter 2 explores banks' contribution to systemic risk at the national as opposed to the Euro-area level. Also, we ask whether the drivers of systemic risk differ at the national and at the Euro-area level. We find that banks contributed not only differently to systemic risk at these regional levels but also that larger and more profitable banks have, on average, contributed more to systemic risk. While the qualitative determinants of systemic risk are similar at the national and Euro-area level, the quantitative importance of some determinants differs. These results have a couple of interesting policy implications. The fact that the qualitative determinants of systemic risk differ little between regulatory levels implies that incentives for information collection should be largely aligned. The reason is that national and supranational supervisors might want to gather information on the same variables driving banks' systemic riskiness. At the same time, this does not mean that incentives for regulatory intervention might be aligned as well. The political economy of interventions may well differ across regional levels, but an analysis of a potential "inaction bias" would require taking a look at actual supervisory action. However, analyzing actual regulatory action is beyond the scope of Chapter 2 and an interesting avenue for future research. Also, our results suggest that some drivers of systemic risk, such as bank profitability, are not included in the standard classification schemes for significant institutions and should thus be subject to additional surveillance.

Chapter 3 constructs a novel dataset on bank complexity to show that banks have increased their number of subsidiaries in different geographical regions or sectors over time and that banks' complexity is associated with higher bank risk during the financial crisis. Although these findings have no causal interpretation they nevertheless report important implications. Technological innovation and regulatory arbitrage induced banks to provide specialized financial services increasingly via non-bank entities and incorporating these complex entities as subsidiaries under common ownership and control (Cetorelli et al., 2014). Our results suggest that this growth process in shadow banking might be accompanied by more risk taking and that these bank-like intermediaries should therefore be subject to the same macroprudential standards as traditional banks. However, our paper also shows that any analysis of the link between bank complexity and financial stability should be done with multiple measures of bank complexity.

Chapter 4 shows that highly concentrated banking markets give a role for very specific bank events to propagate from the micro level to the macro level which ultimately affects the real economy. All in all, these findings are important for informing the regulatory debate on the treatment of large financial institutions, since these findings stress that lender-specific shocks like financial innovations or unexpected managerial decisions happening to mortgage lenders with large market shares have implications beyond the micro-level. The higher mortgage market concentration, the easier do micro-level events spread across housing markets and finally to the real economy. In addition to indicators like mortgage growth and loan-to-value ratios, macroprudential regulation should take market shares and mortgage market concentration into account when analyzing macroeconomic stability. Moreover, given the recent rise in shadow banks' role in the US mortgage market, in order to reduce idiosyncratic mortgage supply shocks (or: idiosyncratic risk), the differential regulatory treatment of banks and non-bank lenders should be harmonized.

Chapter 5 provides not only evidence on electoral mortgage cycle effects for US cities that elected their first black mayor but also that black political leadership increases mortgage acceptance rates for African-American households. These findings reveal important policy implications. First, political participation matters. Since hard political power is only partially effective in reducing mortgage market frictions such as discriminatory lending practices or differential application propensities by race (Agarwal et al., 2014b; Agarwal et al., 2016b; Agarwal et al., 2016a; Bayer et al., 2017; Munnell et al., 1996), I show that political leadership at the local level can be an effective tool for alleviating such market imperfections. Second, it shows that politicians might have had a role in fueling the housing boom-bust cycle, irrespective of the economy's long term health consequences (Ferreira et al., 2016).

In summary, this thesis provides important insights for the current debate about regulating the international financial architecture. A financial sector reform is successful if it's intended outcomes are achieved. However, the self-assessment by the FSB documents a mediocre track record in the last decade. While most countries implemented higher and better quality capital and liquidity buffers following Basel III, there remain two big challenges (FSB, 2017). First, capturing, regulating and supervising risks arising in the shadow banking sector is stuck at an relatively early stage. Second, global regulatory cooperation is in need of improvement. It is crucial not to underestimate the first challenge due to the risks that arise in the shadow banking system and the corresponding real effects. After all, monitoring is not the same as regulation and the resulting heterogeneous regulatory treatment of banks and shadow banks can have unintended consequences that undermine the intended targets of the whole G20 reform package. Also, the second challenge of lacking regulatory cooperation at the global level can be interpreted in the light of Chapter 2 and 5. The intertwining of banks and politicians make it hard for public interests, such as financial resilience, to emerge consistently and in cooperation across countries and beyond private interests. Furthermore, the spatial dimension of systemic risk implicitly shows that national supervisors might have incentives of being too lenient and less willing to cooperate if the negative cross-border externalities of domestic banks materialize at the international level (Wagner and Beck, 2017).

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