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Working Paper Series

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Working Paper Series No. 38

SAFE | Sustainable Architecture for Finance in Europe
A cooperation of the Center for Financial Studies and Goethe University Frankfurt

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Non-Technical Summary

In the course of the recent financial crisis and the ongoing sovereign debt crisis, understanding the design and consequences of deposit insurance schemes has anew become an important policy issue. Deposit insurance is a corner stone of many banking systems worldwide because it helps protect small savers and prevent bank runs. However, it also gives banks incentives for excessive risk-taking because, first, it weakens the market discipline carried out by creditors, and second, mispricings of the deposit insurance premium, which come from the regulators' limited ability to assess risks and to charge risk-adjusted premiums, make higher risk-taking attractive for shareholders. Whether deposit insurance impacted banks' risk-taking in the U.S. during the recent financial crisis is not yet explored. The effect of deposit insurance may be complementary to other important aspects of the financial crisis, such as the effect of bank CEO incentives, bank equity, and government bailout policies on banks' risk-taking.

This paper explores how a bank's amount of insured deposits affects its stability and lending decisions during the recent financial crisis. We use variation introduced by the U.S. *Emergency Economic Stabilization Act* in October 2008, which increased the deposit insurance coverage from $100,000 to $250,000 per depositor and bank. This change increased the total sum of insured deposits in the U.S. from roughly $4,800 billion to roughly $5,300 billion. Importantly for our analysis, banks were affected differently. For some banks, this event significantly increased the amount of insured deposits ("affected banks"). For other banks, it only had a minor effect ("unaffected banks").

Our empirical analysis shows that an increase in the amount of insured deposits causes the affected banks to become more risky relative to the unaffected banks. This result is reflected in estimations for two alternative risk measures, banks' predicted probabilities of default and banks' z-scores (a measure for a bank's ability to absorb losses by its capital), and is robust for alternative model specifications and the consideration of newly introduced transaction account guarantees in October 2008. Further, our analysis shows that affected banks increase their investments in commercial real estate loans, which is considered a particularly risky loan category, relative to unaffected banks after the regulatory change. This presumably contributes to a relatively lower asset quality of affected banks following the increase of insured deposits, as reflected in a significantly higher ratio of non-performing loans to total assets of this loan category. In an extension of our analysis, we find that increased risk-taking is specifically exercised by affected banks that are relatively low capitalized, and not by relatively high capitalized banks.

Our results point to unintended consequences of a central and controversial part of bank regulation. Notably, affected banks with high capital levels do not become more risky. These results should be considered for ongoing reforms of the banking sector.

How do insured deposits affect bank risk? Evidence from the 2008 Emergency Economic Stabilization Act*

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October 2014

Abstract

This paper tests whether an increase in insured deposits causes banks to become more risky. We use variation introduced by the U.S. *Emergency Economic Stabilization Act* in October 2008, which increased the deposit insurance coverage from \$100,000 to \$250,000 per depositor and bank. For some banks, the amount of insured deposits increased significantly; for others, it was a minor change. Our analysis shows that the more affected banks increase their investments in risky commercial real estate loans and become more risky relative to unaffected banks following the change. This effect is most distinct for affected banks that are low capitalized.

Keywords: financial crisis, deposit insurance, bank regulation

JEL Classification: G21, G28

*We thank Allen Berger, Martin Brown, Falko Fecht, Filippo Ippolito, Michael Koetter, Jan Pieter Krahnen, Simon Kwan, Karen K. Lewis, Andrea Schertler, Reinhard H. Schmidt, Isabel Schnabel, Stefan Straetmans, Johannes Tischer, Razvan Vlahu and the participants at the 2012 Research Seminar in Riezlern, the 2013 Research Workshop in Financial Economics in Mainz, the 2013 Financial Intermediation Research Society meeting in Dubrovnik, the 2013 European Finance Association meeting in Cambridge, the 2013 GEABA meeting in Magdeburg, the 2014 Bundesbank/DIW/ESMT/CfS conference on Achieving Sustainable Financial Stability in Berlin and the 2014 CEPR conference on Financial Stability and Regulation in Barcelona for valuable comments and suggestions.

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1 Introduction

In the course of the recent financial crisis and the ongoing sovereign debt crisis, understanding the design and consequences of deposit insurance schemes has anew become an important policy issue. Deposit insurance is a corner stone of many banking systems worldwide because it helps protect small savers and prevent bank runs. However, it also gives banks incentives for excessive risk-taking because, first, it weakens the market discipline carried out by creditors, and second, mispricings of the deposit insurance premium, which come from the regulators' limited ability to assess risks and to charge risk-adjusted premiums, make higher risk-taking attractive for shareholders. The empirical evidence whether deposit insurance leads to more bank risk-taking is mixed, but most studies indicate that the existence of a deposit insurance scheme increases risk-taking and the likelihood of banking crises (e.g., Demirgüç-Kunt and Detragiache, 2002). Whether deposit insurance impacted banks' risk-taking in the U.S. during the recent financial crisis is not yet explored. The effect of deposit insurance may be complementary to other important aspects of the financial crisis which are explored by the literature, such as the effect of bank CEO incentives (Fahlenbrach and Stulz, 2011), bank equity (Berger and Bouwman, 2013), and government bailout policies (Gropp et al., 2011; Dam and Koetter, 2012; Black and Hazelwood, 2012; Duchin and Sosyura, 2012) on banks' risk-taking.

This paper explores how a bank's amount of insured deposits affects its stability and lending decisions during the recent financial crisis. The main challenge for such an empirical test is an identification problem. The banks with more insured deposits might be the ones that take more risks, or, the more risky banks might be the ones that make more efforts to attract deposits and, thus, have more insured deposits. To circumvent this problem, we use variation introduced by the U.S. *Emergency Economic Stabilization Act* in October 2008, which increased the deposit insurance coverage from \$100,000 to \$250,000 per depositor and bank. This change increased the total sum of insured deposits in the U.S. from roughly \$4,800 billion to roughly \$5,300 billion. Importantly for our identification strategy, banks were affected differently. For some banks, this event significantly increased the amount of insured deposits ("affected banks"). For other banks, it only had a minor effect ("unaffected banks").

Using the affected banks as the treatment group and the unaffected banks as the control group, we employ a difference-in-difference estimation technique conditional on propensity score matching. Through the matching procedure we make sure that both groups of banks are similar before the event and thereby that our results do not reflect systematic differences between both groups.

Our empirical analysis shows that an increase in the amount of insured deposits causes the affected banks to become more risky relative to the unaffected banks. This result is reflected in estimations for two alternative risk measures, banks' predicted probabilities of default and banks' z-scores,[1] and is robust for alternative model specifications and the consideration of newly introduced transaction account guarantees in October 2008. Further, our analysis shows that affected banks increase their investments in commercial real estate loans, which is considered a particularly risky loan category, relative to unaffected banks after the regulatory change. This presumably contributes to a relatively lower asset quality of affected banks following the increase of insured deposits, as reflected in a significantly higher ratio of non-performing loans to total assets of this loan category. Thereby, the study provides empirical evidence on unintended consequences of an important and controversial part of bank regulation.

Our study also provides evidence on a related policy topic: the role of bank capital. In an extension of our analysis, we find that increased risk-taking is specifically exercised by affected banks that are relatively low capitalized, and not by relatively high capitalized banks. This result suggests that stricter capital requirements may be an appropriate policy measure to mitigate risk-shifting incentives deriving from deposit insurance.[2]

Fig. 1 presents illustrative evidence on our main results. The upper left graph shows predicted probabilities of default that we estimate with a probability model. Each value represents the average probability that an affected bank or an unaffected bank defaults in one of the following four quarters. Affected banks show on average higher predicted probabilities

[1] We use banks' z-scores as a measure for bank risk following Laeven and Levine (2009). The z-score is defined as the sum of a bank's return on assets and its capital ratio, standardized by the volatility of the bank's return on assets. Thus it measures a bank's ability to absorb losses by its bank capital. A lower z-score indicates lower bank stability and, accordingly, higher bank risk.

[2] Note that our identification focusses on changes in insured deposits and not on differences in bank capital. Therefore, our study provides only indirect evidence on the role of bank capital for risk-taking.

of default than unaffected banks following the regulatory change at the beginning of the fourth quarter of 2008. The upper right graph shows banks' z-scores, which are relatively lower for affected banks after the event (indicating higher bank risk). The lower left graph shows the ratio of real estate commercial loans to assets. The relatively higher ratios for affected banks after the regulatory change indicate that affected banks invested relatively more in this risky loan category. Finally, the lower right graph represents banks' ratios of non-performing real estate commercial loans to assets. It shows that this loan category contributed to relatively higher problem loans of affected banks after the regulatory change. In summary, the graphs of Fig. 1 provide a first indication that affected banks become riskier relative to the unaffected banks following the increase of insured deposits as induced by the *Emergency Economic Stabilization Act*.

[Fig. 1 about here]

In addition to the effect of the regulatory change in October 2008 on bank risks, there were other important direct and indirect effects of this change for the banking system and the economy. Notably, the change occurred at a time when many banks suffered from liquidity shortages in the interbank market and the risk of a panic among depositors and bank runs became apparent. As stated by FDIC Chairman Bair, the increase in deposit insurance coverage "should go far to help consumers maintain confidence in the banking system and the marketplace".[3] Further, a higher risk-taking of banks, e.g., through an increased supply of relatively risky commercial real estate loans, may also have positive effects on the overall economy during a crisis period. Note that a comprehensive economic analysis is beyond the scope of this paper, and our analysis does not assess whether deposit insurance is a meaningful policy tool. This paper focusses on banks' risk-taking, which is one important aspect of bank regulation and the recent financial crisis.

Our study adds to the large literature that examines the effect of insured deposits on bank risk and banking system stability. Important theoretical contributions include Merton (1977) and Diamond and Dybvig (1983).[4] Previous empirical studies for the U.S. typically

[3] Source: FDIC press release, October 7, 2008.

[4] More broadly related to the effects of deposit insurance are the seminal papers by Diamond (1984) and

use historical data from the first half of the 20th century or data on specific bank types. For example, Wheelock (1992) and Wheelock and Wilson (1995) examine the voluntary membership in the Kansas state insurance system during the 1920s and find that insured banks were more likely to fail than non-insured banks. Grossman (1992) finds that newly insured thrifts in Milwaukee and Chicago during the 1930s at first undertook less risk than their uninsured counterparts, possibly because of initial exams by the deposit insurance authorities, but they gradually undertook more risk and surpassed the level of risk of their uninsured counterparts after five years. Karels and McClatchey (1999) analyse the adoption of federal deposit insurance for U.S. credit unions in the 1970s, and find no evidence that it increased the risk-taking of these institutions. Hovakimian and Kane (2000) assess how reforms in deposit insurance affect bank risk-taking decisions using a sample of 123 listed U.S. banks during the period 1985 to 1994. Using an option model, they show that deposit insurance aggravates risk-shifting despite capital regulation. Ioannidou and Penas (2010) find that after the introduction of deposit insurance in Bolivia in December 2001, banks issued more risky loans relative to the previous time period.

Most of the more recent empirical literature conducts cross-country studies to examine how the existence of explicit deposit insurance affects the stability of a country's banking system. For example, Demirgüç-Kunt and Detragiache (2002) show for a sample of 61 countries around the world that during the 1980s and 1990s the existence of deposit insurance had an adverse impact on bank stability. Laeven (2002) analyzes how deposit insurance and governance structures affect banks' risk-taking decisions for a sample of 144 listed banks worldwide during the period 1991 to 1998. He finds that the implicit cost of deposit insurance has some power in predicting bank failures. Gropp and Vesala (2004) find in a cross-country study for 15 European countries that during the 1990s explicit deposit insurance reduces the risk-taking of banks, because deposit insurance serves as a commitment device to limit public guarantees,

Gorton and Pennacchi (1990) that study the function of financial institutions to create liquid assets for uninformed customers. In a recent theoretical paper, Morrison and White (2011) find that socially too few deposits are made in equilibrium because of market failures, and that deposit insurance should be funded out of general taxation to improve welfare. Despite the large literature, they argue that "our understanding of the design and consequences of deposit insurance schemes is in its infancy" (p. 3400). Allen et al. (2013) analyze a model where both panic and fundamental runs are possible. They find that blanket guarantees are optimal if the government's budget is large, and limited guarantees are optimal if the government's budget is tight. A study by Danisewicz et al. (2014) on U.S. banks during the period 1983 to 1993 suggests that priority for depositors in the resolution process could improve the soundness of the banking system. See Allen et al. (2011) for a review of the theory of deposit insurance.

and consequently induces market monitoring through non-deposit creditors. Anginer et al. (2014) show for a sample of 96 countries worldwide that explicit deposit insurance leads to more bank risk and higher systemic fragility during the non-crisis period 2004 to 2006, while it leads to less bank risk and higher systemic stability during the crisis period 2007 to 2009.[5]

Our approach is a significant extension of the existing empirical literature, that typically focuses on historical data for smaller subsamples of (listed) U.S. banks or cross-country data. Our study provides within-country evidence for over 1,300 FDIC insured U.S. commercial banks. Compared to studies that use cross-country variation in deposit insurance schemes, we are able to restrict our study to U.S. banks because the regulatory change of insured deposits did not, in practice, affect all banks equally. This allows us to identify how affected banks change their risk-taking and lending decisions as a consequence of the event compared to unaffected banks within a homogeneous macroeconomic area. Both perspectives, the cross-country perspective from the existing literature and the within-country perspective in our study, provide important insights and complement each other.[6]

Further, we provide new evidence on determinants of banks' risk-taking during the recent financial crisis. We demonstrate that the increase in insured deposits in October 2008, which presumably had beneficial short-term effects to calm banking markets, led to increased risk-taking of affected banks and contributed to bank fragility in the wake of the financial crisis. This finding adds to the long-standing as well as the more recent assessments of several researchers that the U.S. deposit insurance should be revised (e.g., Berlin et al., 1991; Calomiris, 1999; Pennacchi, 2006, 2009).

Our analysis is also related to the extensive literature on determinants of bank failures and bank risk-taking. For example, Furlong and Keeley (1989) and Berger and Bouwman (2013) provide evidence that bank capital affects bank risk-taking. Based on this literature, we control for well known risk factors such as equity, non-performing loans, profitability,

[5]For an overview on deposit insurance schemes around the world, see Demirgüç-Kunt et al. (2008).

[6]Note that the literature on deposit insurance also examines how bank runs may develop (see, e.g., Iyer and Puri, 2012; Kiss et al., 2012; Brown et al., 2013) and how or whether depositors discipline banks (see, e.g., Berger and Turk-Ariss, 2014; Iyer et al., 2013). Calomiris and Wilson (2004) study the disciplinary role of depositors for New York City banks during the 1920s and 1930s. They find evidence for a trade-off between low-asset risk and high capital of banks because depositors have preferences for low-risk deposits and may withdraw their deposits if they fear high default risk. In this study we do not examine these aspects, but focus on banks' risk-taking decisions following an increase in insured deposits.

liquidity and commercial real estate loans, which are largely incorporated in the CAMELS ratings of the Federal Deposit Insurance Corporation (see, e.g., Wheelock and Wilson, 2000; Cole and White, 2010).[7]

The paper proceeds as follows. Section 2 describes aspects of the U.S. *Emergency Economic Stabilization Act* of October 2008 that are in particular relevant for banks' insured deposits. Section 3 presents our identification strategy, the data and summary statistics. Section 4 explains the empirical model and shows the main estimation results. Section 5 and Section 6 extend the analysis by exploring the role of transaction account guarantees and the role of bank capitalization for the effect of insured deposits on bank risk, respectively. Finally, Section 7 concludes.

2 The Emergency Economic Stabilization Act of October 2008

The *Emergency Economic Stabilization Act* was a reaction to the financial crisis of 2007 and 2008, which is considered the worst such crisis since the Great Depression. It was signed into law on October 3, 2008. The rationale of the act was to restore consumer confidence in the banking system and financial markets.

Central to the act is the Troubled Asset Relief Program (TARP) that allowed the Treasury Department to spend $700 billion to support troubled institutions (Shah, 2009).[8] Part of the TARP is the Capital Purchase Program (CPP), which enabled the government to purchase equity directly from troubled institutions. The act also initiated further stabilizing actions, e.g., allowing the Fed to pay higher interest rates on banks' deposits held as reserve requirements, or foreclosure avoidance and homeowner assistance with regard to mortgage payments (see, e.g., Nothwehr, 2008).

Importantly for our study, Section 136 of the *Emergency Economic Stabilization Act* provided a piece of reform that affected deposit insurance: It raised insured deposits per account from $100,000 to $250,000, effective October 3, 2008. Though initially temporarily until De-

[7]The study by Berger and Bouwman (2013) provides a recent overview on this field of the literature.
[8]The amount was later reduced to $475 billion under the Dodd-Franck Act of 2010.

cember 31, 2009, the increase of insured deposits was prolonged through January 1, 2014 on May 20, 2009 by the *Helping Families Save Their Homes Act*. Finally, the introduction of the *Dodd-Frank Act*, signed into law on July 21, 2010, made the temporary increase in insured deposits permanent.

3 Identification strategy and data

To assess how an increase in insured deposits affects banks' risk-taking, we have to consider potential parallel macroeconomic and industry-wide factors that affect all banks, independently of the regulatory change. It would be misleading to simply test how (or whether) banks adapt their risk-taking after the regulatory change. Rather, we need to explore how affected banks adapt their risk-taking relative to the risk-taking of a counter-factual that is similar to the affected banks. We therefore construct a group that includes the affected banks, i.e., the treatment group, and a group that includes banks representing the counter-factual behavior, i.e., the control group. The identification of the treatment group and the control group is the main challenge of our study. In particular, we need to make sure that banks in both groups are similar before the event. We proceed in using a difference-in-difference estimation technique with time and bank fixed effects conditional on a matched sample of banks.

Our identification strategy is based on variation introduced by the regulatory change and as such the intensity of banks being *effectively* affected by the change in the deposit insurance scheme initiated through the *Emergency Economic Stabilization Act* of October 2008. In particular, we observe that some banks reported relatively large increases in their insured deposits following the regulatory change, while other banks reported relatively low increases. As discussed in more detail in Subsection 3.2, we classify the former banks as affected banks, which form our preliminary treatment group, and we classify the latter banks as unaffected banks, which form our preliminary control group.

It is important for our identification strategy to recognize that the external variation which determines the selection of banks into both groups is not purely random. The affected banks are those with relatively many deposit accounts above $100,000, while the unaffected banks are those with relatively few such accounts. We need to make sure that this difference between banks in both groups does not create a selection bias for our estimation results. In principle, the following could be relevant for our estimations: First, the difference between banks may be uncorrelated with the dependent variables we are interested in. In this case, we would get unbiased estimation results. Second, the difference between banks may have a *static level effect* on the dependent variables we are interested in. For example, banks in the treatment group and control group have different business models, such that banks in the treatment group are systematically more likely to fail by certain percentage points relative to banks in the control group. In this case, a difference-in-difference estimation technique also provides unbiased estimation results because it explores how differences between both groups change after an event, not the different levels itself. Furthermore, bank fixed effects in our estimation account for potential static differences between banks. Third, the difference between banks may have a *dynamic effect* on the dependent variables we are interested in. For example, banks in the treatment group are systematically more risk loving during recessions and more risk averse during booms relative to banks in the control group. In this case, we are limited in controlling for this bias in our estimation model. To rule out this problem, we restrict our sample to banks in the treatment group and banks in the control group that are similar over the business cycle. Accordingly, we reduce our treatment group and control group to a matched sample of affected banks and unaffected banks that shows similar characteristics for many variables and over time.

In the following subsections, we first describe the data used in this study (Subsection 3.1). We then describe in more detail our definition of affected and unaffected banks (3.2). Next, we explain how we construct a matched sample of banks (3.3). The subsequent subsections provide the summary statistics (3.4) and further evidence on the similarity of treatment and control group over the business cycle (3.5).

3.1 Data

Our main analyses cover the period ±8 quarters around the introduction of the *Emergency Economic Stabilization Act* at the beginning of Q4 2008, i.e., the period from Q4 2006 to Q3 2010. The data come from the Federal Deposit Insurance Corporation (FDIC), the U.S. Department of the Treasury and the Federal Reserve Bank of St. Louis. In particular, we use quarterly data on U.S. banks from the *FDIC Statistics on Depository Institutions* and the *FDIC Uniform Bank Performance Reports*, which include detailed balance sheet, income statement and deposits data for all FDIC-insured banks in the United States. We use information on bank failures in the period 2000 to 2012 from the *FDIC Failed Bank List* to estimate probabilities of default. Further, we use data on which banks opted out of the *Transaction Account Guarantee Program* from the FDIC website[9] and data on which banks received TARP from the *TARP Investment Program Transaction Reports*, which are available on the website of the U.S. Department of the Treasury. Finally, to control for regional real estate prices, we use the Case-Shiller-Index which is available from the *Federal Reserve Economic Data* database of the Federal Reserve Bank of St. Louis. A description of the variables used in this study is provided in Table 1.

We restrict our sample to 7,137 commercial banks that existed at the end of the third quarter of 2008. We do not consider savings and loan associations or thrifts because they may differ in their business models. Further, we exclude 822 banks that received TARP for their institution or bank holding company because capital injections through this program may bias our main risk proxies, estimated probabilities of default and z-scores, and may affect the risk-taking incentives of these banks. We also exclude 826 banks that decided to opt out of the *Transaction Account Guarantee Program* in 2008 because the decision to opt out may be based on certain bank characteristics that bias our results. This results in a total of 5,489

[9] Transaction accounts provide frequent access to funds, e.g., through ATM and debit cards, cheques and electronic funds transfers, and are commonly used to meet payroll and other business transaction purposes. The *Transaction Account Guarantee Program* became effective on October 14, 2008, about two weeks after the *2008 Emergency Economic Stabilization Act*, and was part of the FDIC's *Temporary Liquidity Guarantee Program*, which sought to strengthen confidence and to encourage liquidity in the banking system. It provided full coverage to noninterest-bearing transaction accounts on a non-mandatory basis, allowing banks to opt out of the program. Following some temporary extensions of the program and the provisions of the Dodd-Frank Act of 2010, which made the guarantees mandatory for all banks, the unlimited coverage expired for all banks on December 31, 2012. For further details, see, e.g., FDIC (2010, 2013).

banks. Furthermore, we want to exclude biases from newly founded or converted banks and therefore require banks' existence as a commercial bank three years before the *Emergency Economic Stabilization Act* was enacted. This leaves us with 5,128 banks. Previous studies that also use the FDIC data point out that some of the data are erroneous and that it includes banks that are very small or not commercial banks in the common sense. Therefore, similar to Berger and Bouwman (2009), we exclude banks that (1) hold gross total assets below $25 million; (2) have no commercial real estate or commercial and industry loans outstanding; (3) hold consumer loans exceeding 50% of gross total assets; (4) have unused commitments exceeding four times gross total assets; (5) are similar to a thrift (residential real estate loans or commercial, construction & development real estate loans exceed 50% of gross total loans), or (6) have domestic deposits below 10% of total assets. Accordingly, we are left with 3,854 banks. As described in the following subsection, we need to observe the amount of banks' insured deposits in the third quarter of 2009 for our identification strategy.[10] Our sample therefore only includes banks that did not fail before the third quarter of 2009, which results in a sample of 3,749 banks. Further, our identification strategy only considers banks in the top quartile (treatment group) or lowest quartile (control group) of reported changes in insured deposits. This cuts our sample in half to a total of 1,874 banks. Finally, as described in Subsection 3.3, we apply propensity score matching and require that banks in the treatment group and control group have very similar characteristics before the regulatory change. After matching, the final data set includes 1,342 banks, of which 671 constitute our treatment group (affected banks) and 671 constitute our control group (unaffected banks).

While our main difference-in-difference estimations cover the period from Q2 2006 to Q2 2011, we also use data of the period Q1 2000 to Q4 2012 to estimate probabilities of default for each bank and quarter. For this extended period, our estimation includes on average 7,000 commercial banks per quarter and a total of 382,370 bank-quarter observations.

[10]The third quarter of 2009 is the first quarter that banks reported their insured deposits based on the new $250,000 limit.

3.2 Definition of affected and unaffected banks

3.2.1 Basic procedure

We define our treatment and control group based on the change in insured deposits initiated through the *Emergency Economic Stabilization Act* of October 3, 2008 and test whether this increase altered risk-taking of affected banks relative to unaffected banks. According to previous theoretical and empirical research, a higher ratio of insured deposits to assets may weaken market discipline and lead to moral hazard and excessive risk-taking (see, e.g., Merton, 1977; Demirgüç-Kunt and Detragiache, 2002).

We construct the sample of affected and unaffected banks in two steps. First, we calculate the difference between the original ratio of insured deposits to asset (based on the $100,000 limit) and the new ratio of insured deposits to assets (based on the $250,000 limit) at the end of Q3 2008, which was three days before the regulatory change was adopted and became effective.[11] Second, we assign banks to the treatment group ("affected") if this difference is in the top quartile of the sample. Banks that exhibit a difference in the lowest quartile belong to the control group ("unaffected"). Intuitively, affected banks have relatively more customers in their portfolio with deposits exceeding $100,000 to the act taking effect.

The upper left graph of Fig. 2 shows average ratios of insured deposits to assets for all banks before and after the *Emergency Economic Stabilization Act* was introduced, and the upper right graph shows these average ratios separately for affected banks (solid line) and unaffected banks (dashed line). By construction we see a sharp change for the affected banks relative to the group that we consider unaffected by the event. Further, we observe that average values of the ratio of insured deposits to assets between affected and unaffected banks converges during the two years following the regulatory change.[12] The lower left graph shows that the average ratio of total deposits to assets for all banks has not changed much following the regulatory change, and the lower right graph shows that these average ratios

[11] As discussed in more detail in the next subsection, banks continued to report insured deposits based on the old $100,000 limit until Q3 2009, and we therefore need to approximate the amounts of insured deposits held by banks based on the new $250,000 limit in Q3 2008.

[12] Interestingly, as Fig. 1 in the introduction shows, we find a similar pattern for bank variables that reflect bank risk.

are not significantly different between the treatment group and the control group.

[Fig. 2 about here]

3.2.2 Approximation of insured deposits in Q3 2008

Following the increase in insured deposits through the Emergency Economic Stabilization Act on October 3, 2008, which was effective immediately, banks were required to continue reporting based on the old \$100,000 limit until the Q3 2009 reporting period. Hence, the new amount of insured deposits to assets (based on the \$250,000 limit) is not directly reported by banks for Q3 2008 (three days before the act). We therefore need to approximate the new amount of insured deposits at the end of Q3 2008 for each bank.

Baseline approximation. For our baseline approximation of insured deposits based on the new \$250,000 limit in Q3 2008, we proceed in two steps. First, we calculate the ratio of insured deposits to total domestic deposits in Q3 2009 for all banks. We make the assumption that this reported ratio is representative for a bank's ratio in Q3 2008. Second, we approximate each bank's new amount of insured deposits as of Q3 2008 by multiplying this ratio and the bank's reported amount of domestic deposits in Q3 2008. The ratios of insured deposits to assets for Q4 2008 to Q2 2009, as shown in Fig. 2 (a) and (b), are based on the same approximation.

Note that this approximation may create a bias if the ratio of insured deposits to total domestic deposits based on the new \$250,000 limit is not constant but changes between Q3 2008 and Q3 2009. For example, if banks experience relatively high inflows of insured deposits and relatively low inflows (or outflows) of uninsured deposits during this period, this leads to a relatively higher ratio of insured deposits to total domestic deposits in Q3 2009, and to an upward bias of our approximated ratio of insured deposits to assets in Q3 2008. We cannot observe whether this ratio actually changes for the banks in our sample, otherwise, we would not have to approximate the ratio of Q3 2008 insured deposits to assets in the first place. What we can observe is that the ratio of total deposits to total assets increases on average by 0.52% for the banks in our treatment group and on average by 1.96% for the banks in our control group between Q3 2008 and Q3 2009. Further, the ratio of insured deposits to total assets based on the old $100,000 limit increases on average by 2.87% and decreases on average by 2.23% for the banks in our treatment and control group, respectively, between Q3 2008 and Q2 2009. Practically, it is not possible to disentangle whether such differences already result from the regulatory change, or whether such differences are based on other determinants. To make sure that our results are not biased, we take three measures. First, as already mentioned, we restrict our sample to banks with a relatively high or a relatively low increase in insured deposits to assets in Q3 2008. Second, we provide evidence that an alternative approximation strategy yields very similar results. Finally, we provide evidence that banks' efforts to attract new deposits by offering higher interest rates do not differ between both groups during the period Q3 2008 to Q3 2009.

Sample restrictions. We only consider banks in our regressions with differences between the original ratio of insured deposits to asset (based on a $100,000 limit) and the new ratio of insured deposits to assets (based on a $250,000 limit) at the end of Q3 2008 in the top quartile or bottom quartile of the sample. Banks in the top quartile of the sample, which represent our treatment group, show differences of 10.5% or more. Banks in the bottom quartile of the sample, which represent our control group, show differences of 4.8% or less. This "buffer zone" between 4.8% and 10.5% makes it unlikely that a bank's varying ratio during the period Q3 2008 to Q3 2009 causes a change for the bank from treatment group to control group, or vice versa.

Estimation of deposits. For robustness, we use regression analysis to estimate the banks' amounts of insured deposits in Q3 2008 based on the new $250,000 limit. In particular, we use the banks' amounts of insured deposits to assets ($DEPI$) from the first four quarters when banks reported insured deposits based on the new $250,000 limit, i.e., Q3 2009 to Q2 2010, as dependent variable in the following OLS regression:

$$\mathrm{DEPI}_{it} = \nu_i + \sum_{j=1}^{6} \beta_j \mathrm{DEPS}_{jit} + \epsilon_{it}. \tag{1}$$

The explanatory variables DEPS_{jit} for each bank i and quarter t provide information about the mix of banks' deposits: (1) deposits of individuals, partnerships and corporations to assets; (2) deposits of the U.S. Government to assets; (3) deposits of states and political subdivisions in the U.S. to assets; (4) deposits of commercial banks and other depository institutions in the U.S. to assets; (5) deposits of banks in foreign countries to assets; and (6) deposits of foreign governments and official institutions to assets. We also include bank fixed effects (ν_i). We find that this regression explains the amount of insured deposits during the period Q3 2009 to Q2 2010 very well with an adjusted $R2$ of 0.95. These determinants should also be highly relevant for banks' amounts of insured deposits based on the new $250,000 limit during the previous quarters, and they are also reported by banks for Q3 2008. Accordingly, we use the coefficients from this regression to estimate banks' amounts of insured deposits to assets based on the new $250,000 limit for Q3 2008.

Importantly, we find that using the estimated amounts for our identification instead of using the amounts from the baseline approximation yields very similar results for our main analysis in Sections 4 and 6. Further, we see that the resulting classifications of banks into banks in the top quartile or lowest quartile of differences in ratios of insured deposits in Q3 2008 are largely comparable. In particular, 75.6% of our preliminary sample of 3,749 banks are classified the same (top quartile, lowest quartile or "buffer zone" with the two middle quartiles), 23.9% fall within the buffer zone with the one or with the other approximation,[13] and only 0.6% of banks change groups (from top quartile to the lowest quartile, or vice versa).

Evidence on banks' interest rates on deposits. Recent research points out that some banks attracted deposits by offering higher interest rates during the recent financial crisis (Acharya and Mora, 2014). We explore this aspect to rule out that differences in this regard between both groups of banks during the period Q3 2008 to Q3 2009 bias our identification of affected and unaffected banks. Fig. 3 illustrates the development of the average interest rates that banks offer to their clients to attract deposits, as reflected in banks' reported funding costs of deposits.[14] The left graph shows average interest rates of total interest bearing deposits

[13] Different classifications that affect only the "buffer zone" are not of concern. This includes banks that are slightly above the 75% threshold for one approximation and slightly below the 75% threshold for the other approximation.

[14] Source: *FDIC Uniform Bank Performance Reports.*

for affected banks and for unaffected banks, and the right graph shows respective average interest rates of large time deposits over $100,000. Large time deposits were fully uninsured until Q3 2008 and partly uninsured (over $250,000) afterwards. The figure shows that these average interest rates of both groups developed similarily before and after the regulatory change. Further, unreported regressions confirm that there are no significant differences in this regard between both groups of banks. Hence, our evidence makes it unlikely that our identification is biased by banks that were more active in acquiring new deposits during the period Q3 2008 to Q3 2009 which is relevant for our identification.

[Fig. 3 about here]

3.3 Matching estimation

To further disentangle the treatment effect from a potential selection bias, we first estimate a logit model that explains the probability that a bank is materially affected by the legislative change. The propensity score matching helps us to construct similar samples based on bank-specific characteristics before the event. In particular, we match banks based on key characteristics that determine bank stability following Wheelock and Wilson (2000) and Cole and White (2010). These characteristics are similar to the determinants of the FDIC's CAMELS ratings and reflect banks' capital adequacy, liquidity, earnings, asset quality and loan composition.

We estimate the model using average data per bank for the period from Q4 2006 to Q3 2008, i.e., the two years before the act was introduced. In particular, we estimate the following matching equation:

$$\begin{aligned}\text{Affected}_i =& \beta_0 + \beta_1 EQ_i + \beta_2 TA_i + \beta_3 LIQU_i + \beta_4 ROA_i \\ &+ \beta_5 NPL_i + \beta_6 ORE_i + \beta_7 IENC_i + \beta_8 LOANS_i + \beta_9 CI_i + \\ &+ \beta_{10} RECD_i + \beta_{11} RECO_i + \beta_{12} REMF_i + \beta_{13} RESF_i + \epsilon_i.\end{aligned} \tag{2}$$

The explanatory variables in this equation are: total equity to assets (EQ), bank size represented by the natural logarithm of assets (TA), liquidity measured as cash and U.S. Treasury securities standardized by assets ($LIQU$), net income before taxes to assets (ROA), non-performing loans to assets (NPL)[15], other real estate owned to assets (ORE), income earned, not collected on loans to assets ($IENC$), total loans to assets ($LOANS$), commercial and industry loans to assets (CI), real estate construction and development loans to assets ($RECD$), real estate commercial loans to assets ($RECO$), real estate multi family loans to assets ($REMF$), and real estate single family loans to assets ($RESF$).

We use the nearest neighbor matching procedure (on a one-to-one basis), which selects the banks closest in terms of their propensity scores. We conduct the analysis without replacement, which means that a neighbor can only be used once. We require common support and impose a tolerance level of 1%, the so-called caliper. The caliper is equivalent to choosing an individual from the comparison group as a matching partner for a treated individual that lies within the caliper (propensity range) and is closest in terms of propensity score.

3.4 Summary statistics

Mean values, median values and standard deviations of our main variables and further bank characteristics are presented in Table 2 for the two year period before the regulatory change, i.e., from Q4 2006 to Q3 2008. The table differentiates between affected and unaffected banks in order to compare characteristics of both samples before the event. Since our difference-in-difference estimation is based on a matched sample, which uses affected banks as the treatment group and unaffected banks as the control group, we technically insure that banks in both groups have similar characteristics.

Additionally, as suggested by Imbens and Wooldridge (2009), Table 2 also reports normalized differences to compare both groups with respect to important bank characteristics. Normalized differences are a scale-free measure of the difference in distributions, and calculated as "the difference in averages by treatment status, scaled by the square root of the sum

[15] We define non-performing loans as assets past due 30-89 days and still accruing interest, assets past due 90 days and still accruing interest, plus non-accrual assets.

of the variances" (Imbens and Wooldridge, 2009, p. 24):

$$ND = \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{SD_1^2 + SD_0^2}}, \tag{3}$$

where $\bar{X}_1$ and $\bar{X}_0$ represent the mean values of the group of affected banks and unaffected banks, respectively, and SD_1^2 and SD_0^2 represent the respective variances. As a rule of thumb, groups are regarded as sufficiently equal and adequate for linear regression methods if normalized differences are generally in the range of ±0.25.[16]

Overall we find that both groups are very similar before the event. This includes characteristics regarding size (log of total assets), capital adequacy (equity, total risk-based capital), funding composition (total liabilities to total assets), asset composition (total loans, real estate loans, consumer loans, commercial and industrial loans), asset quality (loan loss provisions, charge-offs, other real estate owned, non-performing loans), the Case-Shiller index and default risk (probability of default, z-score). The banks' exposures to subcategories of real estate loans (commercial, construction and development, single and multifamily real estate loans), which proved to be especially important for bank risk during the recent financial crisis (see, e.g., Cole and White, 2010), are also very similar. All characteristics show normalized differences well below ±0.25. Normalized differences above ±0.25 are only evident for the share of insured deposits to assets (or total deposits), which we use for identifying the treatment and the control group.

In summary, Table 2 shows that dividing the sample in affected and unaffected banks by the change in insured deposits leaves us with two sub-samples that resemble very similar characteristics before the event. The descriptive statistics show that our identification procedure is appropriate and that our results are unlikely to be disturbed by differences in groups.

[Table 2 about here]

[16]Note the difference with the t-statistics, which is sensitive to the sample size and which tests whether there is a significant difference in means, not, as normalized differences, whether linear regression methods tend to be sensitive to the specification.

3.5 Similarity of treatment and control group over the business cycle

In this section we provide further evidence that our results are not driven by *dynamic effects* resulting from differences between the treatment group and the control group over the business cycle. As such, we inspect whether the trend of the probability of default and the z-score is parallel for both groups. Additionally, we observe whether normalized differences of various other bank variables are within the required range for each quarter since the year 2000.

3.5.1 Parallel trend assumption

To adequately employ a difference-in-difference estimation technique, we have to guarantee, that the parallel trend assumption is satisfied. As such, we have to make sure that the development of our main risk proxies, the probability of default and the *z-score*, follow a similar trend for the treatment group and the control group before the event. Analogous to previous studies we graphically inspect the trend of the mean values of these measures for both groups, as shown in Fig. 1 (a) and (b), and we confirm that the parallel-trend assumption holds.

The parallel trend assumption also holds for many other variables until Q3 2008, the event quarter. Illustrative evidence is provided in Fig. 4 for total loans to assets (a), real estate loans to assets (b), return over assets (c) and non-performing loans to assets (d).

[Fig. 4 about here]

3.5.2 Normalized differences quarter by quarter

We also want to make sure that affected banks and unaffected banks are similar not only on average throughout the two years before the event, as reported in Table 2, but also for each quarter since 2000. We therefore calculate normalized differences for key variables for each quarter since 2000.

In unreported results we observe that the values of the normalized differences of all variables (other than total deposits to assets and insured deposits to assets) are between ±0.25 before the regulatory change in Q4 2008 for each quarter since 2000, which means that both groups are sufficiently equal and generally adequate for our linear regression method (Imbens and Wooldridge, 2009). Thereby, concerns are alleviated that banks' characteristics differed for banks in the treatment and control group over the business cycle before the event.

4 Empirical model and main results

4.1 Baseline estimation

By applying a conditional difference-in-difference estimation technique, which is equivalent to a matching of groups procedure before estimating the treatment effect, we estimate whether higher risk-taking by banks is systematic and can be attributed to the change in regulation. Formally, we estimate the following equation with a fixed effects OLS model:

$$\mathrm{Risk}_{it} = \nu_i + \beta_1 \mathrm{Event}_t + \beta_2(\mathrm{Event}_t \times \mathrm{Affected}_i) + \beta_3 CSI_{\gamma t} + \tau_t + \epsilon_{it}. \tag{4}$$

The short-hand $Risk_{it}$ is a proxy for bank risk of bank i at time t. The different measures that we use for $Risk_{it}$ are common in the literature and explained in more detail in the following subsection. Our event window is the fourth quarter of 2008. Accordingly, the variable $Event_t$ is a time dummy with a value of zero for all quarters before the *Emergency Economic Stabilization Act* was introduced ($t <$ Q4 2008) and a value of one for all quarters after the event ($t >$ Q4 2008). The variable $Affected_i$ is a dummy variable of bank i that is one if the bank experienced a sharp increase in insured deposits per customer (belongs to the top 25% quantile) and thus belongs to the treatment group, and zero otherwise (belongs to the bottom 25% quantile). Hence, the interaction term $Event_t \times Affected_i$ is one for affected banks after the event, and zero otherwise. The corresponding coefficient β_2 is our main interest. It captures the average effect of the introduction of the act on the bank risk of affected banks. As a macroeconomic control variable, we consider regional real estate prices on state level, as reflected in the Case-Shiller-Index, $CSI_{\gamma t}$, for each bank at quarter t with a headquarter in state γ. Further, we are concerned that unobserved differences between banks might influence our results. Thus, we include fixed effects ν_i for each bank i. The variable τ_t represents quarterly time fixed effects. Finally, ϵ_{it} is the idiosyncratic error term. To account for heterogeneity among banks, we use clustered standard errors at the bank level. For robustness, we reestimate our baseline estimation without bank fixed effects. The variable $Affected_i$ that otherwise interferes with bank fixed effects then enters the equation.

4.2 Results for banks' predicted probabilities of default

First, we use banks' predicted probabilities of default as a proxy for bank risk, $Risk_{it}$. We thereby provide evidence whether the predicted probabilities of default of affected banks increase significantly relative to unaffected banks after the regulatory increase of insured deposits in the fourth quarter of 2008. Because banks' predicted probabilities of default are not directly observable, we follow three steps: First, we run a probability model with historical bank failures to explore how different bank characteristics determine a bank's probability of default. Second, we use these regression results to calculate predicted probabilities of default for all banks in our sample. Finally, we use the predicted probability of default as dependent variable in Eq. (4).

Our probability model is based on a sample of all U.S. commercial banks registered at the FDIC in the period of 2000-2012, i.e., a total of about 7,000 banks on average per quarter, of which 416 banks failed during this period. See Figure 5 for the time distribution of these bank failures. In particular, we estimate the following linear probability model:

$$\begin{aligned} \text{Failure}_{it} = {} & \nu_i + \beta_1 EQ_i + \beta_2 TA_i + \beta_3 LIQU_i + \beta_4 ROA_i \\ & + \beta_5 NPL_i + \beta_6 ORE_i + \beta_7 IENC_i + \beta_8 LOANS_i + \beta_9 CI_i + \\ & + \beta_{10} RECD_i + \beta_{11} RECO_i + \beta_{12} REMF_i + \beta_{13} RESF_i + \tau_\gamma + \epsilon_{it}. \end{aligned} \tag{5}$$

The variable $Failure_{it}$ is a binary variable, which we assign a value of one for the last four quarters before a bank failed, and a value of zero otherwise. The explanatory variables are the same as the ones we use for the propensity score matching in the previous section and based on Wheelock and Wilson (2000). The variables ν_i and τ_γ represent bank fixed effects and quarterly time fixed effects, respectively.[17]

[Fig. 5 about here]

Next, we calculate the predicted probability of default for each bank and quarter. According to the specification of the linear probability model in Eq. 5, the values indicate a bank's probability to fail during one of the following four quarters. See Figure 1 (a) for the development of the mean predicted probability of default for the groups of affected and unaffected banks, and Table 2 for related summary statistics.

Finally, we estimate Equation (4) for the sample of affected banks (treatment group) and unaffected banks (control group), using the predicted probability of default of each bank and quarter as dependent variable, Risk_{it}. The interaction term *Affected*×*Event* measures the average difference in banks' default probabilities between affected and unaffected banks after the event relative to the period before the event. In particular the interaction term in Table 3 indicates whether affected banks become riskier (higher default probability) or less risky (lower default probability) after the event relative to the group of unaffected banks.

Table 3 shows results for four different specifications of Eq. (4). Each column of Table 3 includes quarterly time fixed effects and standard errors (in parentheses) that are clustered on the bank level. The first column presents results for an OLS regression with bank and time fixed effects, using ± 8 quarters around the event. It shows a positive and significant interaction effect that indicates that banks more affected by the raise in insured deposits have higher probabilities of default after the event relative to the control group. This effect is economically highly significant. The point estimate of 0.0031 indicates that, in expectation,

[17] We use a linear probability model instead of a nonlinear probability model because we want to include bank and time fixed effects in our model. Thus, we can correctly address that bank failures may be explained by bank- and time-specific factors that are not captured by our explanatory variables. With a nonlinear probability model, the introduction of many dummy variables leads to i) practical problems because the presence of many dummy variables makes the estimation much more difficult, and ii) the so-called incidental parameters problem (see, e.g., Greene et al., 2002; Fernández-Val, 2009). According to Fernández-Val (2009), the incidental parameters problem "arises because the unobserved individual characteristics are replaced by inconsistent sample estimates, which, in turn, bias estimates of model parameters." We are aware that using a linear model to predict bank failures comes with the problem that we do not capture the shape of the distribution of bank failures correctly, and we may predict probabilities of default of less than 0% or above 100%. However, we weight this bias less severe than the potential problem from neglecting fixed bank and time effects or the potential incidental parameters problem.

about 3 out of 1,000 affected banks *additionally* get into default per year compared to the unaffected banks. In relation to a mean predicted probability of default of unaffected banks during the two years after the event of 0.011, i.e., 11 out of 1,000 expected bank defaults, this is an important effect.

This results is corroborated by the following two columns. In Column (2) we rerun the estimation without bank fixed effects, and find largely unchanged results. In Column (3) we include again bank fixed effects and additionally some covariates that are regarded important for determining bank risk-taking during the recent financial crisis: bank size, equity and investments in real estate loan categories (see, e.g., Cole and White, 2010). Given that unlimited coverage of noninterest-bearing transaction accounts was introduced through the *Transaction Account Guarantee Program* around the same time as the increase for insured deposits, we additionally control for noninterest-bearing transaction accounts in Column (3). Because this amount is not precisely reported by banks for our sample period, we use the ratio of total transaction account assets to assets (TRA) as a proxy that we include as additional control variable in the model.[18] For all specifications, the effect is robust and the coefficients of the interaction terms are largely unchanged.

This evidence supports results from the literature that investigates the effects of deposit insurance schemes on bank stability on a cross-country base, and also finds detrimental effects (e.g., Demirgüç-Kunt and Detragiache, 2002). The recent study by Anginer et al. (2014) is more positive on deposit insurance, as it finds that explicit deposit insurance increases bank stability during crisis times for a sample of banks in 96 countries around the world (but explicit deposit insurance also decreases bank stability in non-crisis times).

For the U.S., a country where explicit deposit insurance has existed since the 1930s, we provide new evidence that the increase in deposit insurance has led to higher risk of affected banks. A possible explanation is that more guarantees such as the increase in deposit insurance coverage decrease market discipline, consequently opening the door for more risk-taking by banks.

[18]We explore potential simultaneous effects of the increase in insured deposits and the introduction of transaction account guarantees on bank risk in more detail in Section 5, using a specification with additional interaction terms.

[Table 3 about here]

4.3 Results for banks' z-scores

As a second risk measure that is commonly used in the literature, we use the bank z-score, which measures a bank's ability to absorb losses by its equity (see, e.g., Laeven and Levine, 2009). The z-score of bank i at time t is defined as the natural logarithm of the sum of a bank's return on assets, ROA_{it}, and its core capital to assets ratio, CAP_{it}, standardized by the volatility of bank's return on assets, $SD(ROA)_{it}$, i.e.,

$$\text{z-score}_{it} = log\left(\frac{ROA_{it} + CAP_{it}}{SD(ROA)_{it}}\right). \tag{6}$$

A larger z-score value is associated with a more stable bank. Note that ROA_{it} and CAP_{it} reflect book values as reported by the banks. Market values would only be available for a much smaller sample of banks. Technically, we calculate $SD(ROA)_{it}$ as the 12 quarter rolling standard deviation of return on assets for each bank and quarter. The definition of the z-score comprises the natural logarithm because the measure is otherwise highly skewed.

Regression results for different specifications of Eq. (4), using the banks' z-scores as the dependent variable, are provided in Columns (4) to (6) of Table 3. In Column (4) we measure the effect of the change in the deposit insurance scheme on the banks' z-scores including bank fixed effects and time fixed effects. We observe a negative and significant coefficient of the interaction term, which indicates that affected banks become riskier after the event relative to the control group. Hence, the raise in insured deposits from \$100,000 to \$250,000 in Q4 2008 has a destabilizing effect on banks that "benefited" from this act. The point estimate of -0.0925 shows that this effect is also economically relevant. As we are estimating a log-linear model (the left-hand side represents the logarithm of banks' z-scores), the interaction term (which is zero or one) shows that the ratio $\frac{ROA_{it}+CAP_{it}}{SD(ROA)_{it}}$ decreases by 9.25% for banks in the treatment group relative to banks in the control group after the regulatory change in Q4 2008. The additional columns of Table 3 show that this result is robust for model specifications without bank fixed effects (Column (5)) and with bank fixed effects and further control variables (Column (6)). Importantly, estimation results using banks' probabilities of default or banks' z-scores as dependent variables yield consistent results.

Table 4 shows regression results using the banks' z-score components as the dependent variable: the banks' core capital to assets ratios (CAP), the banks' returns over assets (ROA), and the volatility of banks' returns over assets (SD(ROA)). In this table, as well as in all following tables, we report results for our baseline specification of Eq. (4), which includes bank fixed effects and time fixed effects and uses data for the period $\pm$ 8 quarters around the event. First, we find that relatively lower z-scores of affected banks are unlikely to come from lower core capital to assets ratios of affected banks. As shown in Column (2), this ratio shows a non-significant coefficient for the interaction term. Further, as shown in Column (3) and in Column (4), our results indicate that z-scores of affected banks after the regulatory change are driven by a significant decline in the banks' returns over assets and a significantly higher volatility of their returns over assets relative to unaffected banks after the event, respectively.

Given that these banks take more risks after the introduction of the regulatory change, one is likely to expect higher profits for these banks. In the following subsection we will show that affected banks accumulate a larger amount of non-performing real estate commercial loans after the regulatory change, which is presumably one important factor for a decline in profits.

[Table 4 about here]

4.4 Risk channels

In this section we explore *how* affected banks become more risky relative to unaffected banks after the introduction of the *Emergency Economic Stabilization Act* in October 2008. In particular, we investigate whether the portfolio composition of affected banks and unaffected banks developed differently and whether this led to different ratios of problem loans to assets after the regulatory change.

Portfolio composition. First, as shown in Panel A of Table 5, we estimate effects on banks' total loans to assets (LOANS), cash to assets (CASH), government securities to assets

(GOV), non-government securities to assets (NGOV), trading assets to assets (TRADE), and other assets to assets (OTHER). We find a significant and positive interaction term only for total loans to assets (+0.73 percentage points), which indicates that affected banks change their portfolio composition after the regulatory change.[19]

Next, we take a closer look at the different loan categories: consumer loans to assets (CON), commercial and industrial loans to assets (CI), and real estate loans to assets (RE). The latter include real estate construction and development loans to assets (RECD), real estate commercial loans to assets (RECO), multifamily residential real estate loans to assets (REMF) and single family residential real estate loans to assets (RESF). As shown in Panel B of Table 5, we find that the share of consumer loans (CON) and the share of commercial and industrial loans (CI) do not develop differently for affected and unaffected banks after the regulatory change, as indicated by insignificant interaction coefficients (see Column (1) and Column (2), respectively), while the share of real estate loans shows a positive and significant interaction coefficient (+0.89 percentage points). This indicates that affected banks shift their asset holdings into real estate loans relative to the unaffected banks. Zooming into the different real estate loan subcategories, we find that this effect is due to a higher share of real estate commercial loans (+0.47 percentage points). Commercial real estate loans have always been regarded as very risky and contributed to bank failures during the recent financial crisis (see, e.g., Cole and White, 2010). Real estate construction and development loans, which are also considered very risky, however, show insignificant interaction coefficients.

In summary, the results for the different loan categories provide evidence that investment decisions of affected banks after the increase in insured deposits through the *Emergency Economic Stabilization Act* of October 2008 induced affected banks to shift towards a more risky portfolio composition relative to unaffected banks.

[Table 5 about here]

Problem loans. The previous results indicate that the observed higher risk of affected banks relative to the control group after the regulatory change may come from a relatively

[19] Note that this development is illustrated in Fig. 4 (a).

higher share of commercial real estate loans. Next, we explore whether these loans in fact resulted in more problem loans of affected banks and therefore consider alternative periods after the regulatory change. Inspecting Fig. 1 (d) we expect that there is no significant effect for the first one or two year after the regulatory change but potentially a significant effect after three or four years.

First, we run the regression for a one year period (± 4 quarters) around the event, and we find no significant effect, as shown in Column (1) of Table 6. There is also no significant effect for the two year period around the event (Column (2)). The effect becomes significant for the period two and three years (Column (3)) and three and four years (Column (4)) after the event.

[Table 6 about here]

In light of this result, the question arises why probabilities of default and z-scores of affected banks already deteriorate during the two year period after the regulatory change, while problem loans only materialize three to four years after the regulatory change. An obvious explanation is that probabilities of default, that reflect defaults in the next four quarters, pick up changes in banks' risk relatively early.[20] The effect on the z-scores of affected banks seems to materialize about one year after the regulatory change, as indicated by Fig. 1 (b). This may be due to higher loan loss provisions and subsequently lower and more volatile returns. From a timing perspective, banks form provisions for loans before these loans actually become non-performing if banks correctly anticipate the future and make provisions accordingly.

4.5 Robustness tests

In the previous sections we provide results for difference-in-difference regressions using Eq. (4) and thereby show that affected banks become riskier after the raise in insured deposits relative to the control group of unaffected banks, measured as relatively higher predicted probabilities

[20]Note that the prediction equation of probabilits of default includes covariates such as the ratio of real estate loans to assets, as shown in Eq. 5.

of default and relatively lower z-scores. We find robust results for several alternative model specifications. The following two paragraphs provide further robustness by checking other econometric issues of our regression design.

Cross-section results. To guarantee that the results are not driven by serial correlation, a typical problem with difference-in-difference estimation, Bertrand et al. (2004) suggest ignoring the time structure of the data. Therefore, we average the data before and after the event and rerun the estimation for this collapsed sample. In unreported results, we find that our findings are not driven by serial correlation and observe coefficient of similar magnitude and significance.

Time-placebo estimation. We also want to be sure that our results are not driven by time trends unrelated to the change in insured deposits. Therefore, we conduct a placebo estimation in which we shift the event to Q3 2005. We then rerun our estimation for observations ±8 quarters before and after this "2005 pseudo event". In unreported results we do not find an effect for the 2005 pseudo event in any of our baseline specifications. This finding supports our assumption that our results are not driven by factors unrelated to increase in deposit insurance per customer.

5 The role of transaction account guarantees

In this section, we explore potential simultaneous effects of the increase in deposit insurance coverage and the introduction of unlimited coverage of noninterest-bearing transaction accounts as part of the *Temporary Liquidity Program.* As described in Section 3.1, transaction account guarantees became effective on October 14, 2008, about two weeks after the increase in deposit insurance coverage. It is therefore of interest to explore whether both measures had similar effects on bank risk-taking.

One may expect that the effect of increased deposit insurance coverage and the effect of new transaction account guarantees on bank risk-taking are similar because both measures safeguard investors against potential losses. Hence, these investors may not monitor bank risk and may not exert market discipline on banks, which may induce higher risk-taking of banks. However, there are also important differences between both measures: First, in contrast to funds from insured depositors, funds from transaction account holders are presumably relatively sensitive to potential bank defaults even if they are fully guaranteed. The reason is that short-term disruptions of payment transactions during a bank default can have very adverse consequences for individuals and businesses. At worst, an individual or business may not be able to meet its payment obligations and become insolvent if its bank defaults. As stated by the FDIC (2014) in its information for depositors, creditors, and borrowers:

> When the failed bank's deposits are assumed by an open bank, some or all of the offices typically reopen the next business day and there is usually no interruption in the processing of checks drawn on the failed bank. ... In a payoff, however, any outstanding transactions or checks presented after the bank has closed cannot be paid or charged against the account. ... [It is the customer's] responsibility to make other funds available to creditors who receive checks that were returned and did not clear [the customer's] deposit account because of the bank closing.

Second, while the increase in insured deposit coverage became permanent, transaction account guarantees expired at the end of 2012. This may have been anticipated by banks and affected their behavior. Summing up, these arguments suggest that new transaction account guarantees had a different effect on bank risk-taking than increased deposit insurance coverage following their implementations in October 2008.

In the following, we analyze jointly the effect of both measures on bank risk-taking. In particular, we use the sample from our previous regressions of 1,342 banks and introduce a new dummy variable, TAG, that separates between banks that were relatively strongly affected by the new transaction account guarantees or relatively unaffected. Accordingly, the variable TAG has a value of 1 if a bank's ratio of noninterest-bearing transaction account assets above the deposit insurance limit of \$250,000 over assets is in the top quartile of the sample in Q4 2008, and a value of 0 if the bank's ratio is in the bottom quartile of the sample in Q4 2008.[21] This results in a new subsample of 671 banks.[22] Formally, we estimate the following equation with a fixed effects OLS model:

$$\begin{aligned}\text{Risk}_{it} = \nu_i + \beta_1 \text{Event}_t + \beta_2(\text{Event}_t \times \text{Affected}_i) + \beta_3(\text{Event}_t \times \text{TAG}_i) \\ + \beta_4(\text{Event}_t \times \text{Affected}_i \times \text{TAG}_i) + \beta_5 CSI_{\gamma t} + \tau_t + \epsilon_{it}.\end{aligned} \tag{7}$$

The equation extents Eq. (4) by the interaction terms *Event* × *TAG* and *Event* × *Affected* × *TAG*. As before, we run the regressions using banks' probabilities of default and bank's z-scores as dependent variables for three specifications: (1) with bank fixed effects as represented in Eq. (7); (2) without bank fixed effects; and (3) with bank fixed effects and some covariates that are common in the literature.[23]

As shown in Table 7, we find that the coefficients of the interaction term *Event* × *Affected* remain significantly positive for predicted probabilities of default and significantly negative for z-scores. The coefficients are even higher than in the baseline regressions without TAG (see Table 3). Hence, the results qualitatively confirm our earlier results that banks affected by the raise in insured deposits become significantly riskier following the introduction of increased deposit insurance coverage. Concerning the effect of new transaction account guarantees in October 2008, we observe that all regressions show insignificant coefficients for the interaction term *Event* × *TAG*, which means that there is no effect of this measure on banks' probabilities of default or z-scores for the group of banks that were relatively unaffected by the increase in deposit insurance coverage (Affected=0). Further, the triple interaction term *Event* × *Affected* × *TAG* indicates whether the effect of newly insured deposits (*Event* × *Affected*) is different for the groups of banks with low or high ratios of newly guaranteed

[21] We refer to this ratio in our variables description in Table 1 as TA250. Banks were required to report this data in Q4 2008 and the subsequent quarters. Note that the variable TA250 reflects the amount of new transaction account guarantees more precisely than the variable TRA, which we used before as control variable in the regressions of Table 3. However, TA250 cannot be used as control variable in Table 3 because it is not available before Q4 2008.

[22] We only consider the top and bottom 25% of the sample to be consistent with the construction of our dummy variable *Affected*, which separates banks that experience a high (top 25%) or low (bottom 25%) increase in insured deposits following the policy change.

[23] Compared to the previous regressions with bank covariates, we exclude the ratio of total transaction account assets to assets (TRA) from the covariates because banks' amounts of transaction account assets are already reflected in the TAG dummy variable. Nevertheless, our results are the same if we also include TRA in the regressions.

transaction account assets (TAG=0 or TAG=1, respectively).[24] We find that the coefficients are insignificant when using probabilities of default as dependent variable and significantly positive when using z-scores as dependent variable. Hence, we find partial evidence that the effect of increased deposit insurance on bank risk-taking also depends on banks' exposure to noninterest-bearing transaction account assets. Finally, the very bottom rows of Table 7 contrast the interaction effect *Event* $\times$ *Affected* on bank risk-taking for the groups with low or high ratios of newly guaranteed transaction account assets (TAG=0 or TAG=1, respectively). For the group with TAG=0, this effect is just the interaction effect *Event* $\times$ *Affected* from the regressions above. For the group with TAG=1, this effect is the sum of the interaction effects *Event* $\times$ *Affected* and *Event* $\times$ *Affected* $\times$ *TAG* from the regressions above.[25] The rows show a positive and significant effect of an increase in insured deposits on bank risk-taking for the group with relatively low ratios of noninterest-bearing transaction accounts over assets (TAG=0), but not for the group with relatively high ratios (TAG=1). However, as shown by the statistics of the triple interaction term from the regressions above, the effect is statistically different for both groups only when the z-score is used as dependent variable.

[Table 7 about here]

Summing up, the analysis in this section provides three main insights: First, for the group of banks that had relatively low ratios of newly guaranteed transaction account assets over assets when the regulatory changes were implemented in October 2008, we find that the increase in insured deposit coverage causes banks to become more risky, which confirms our earlier results from the baseline regressions in Table 3. Second, we find no evidence that the transaction account guarantee program causes banks to become more risky. Third, our evidence even points to less risk-taking of banks with relatively high ratios of guaranteed transaction account assets over assets following the increase in deposit insurance coverage. The likely explanation for these results is that transaction account holders are relatively

[24] Note that, likewise, the triple interaction term indicates whether the effect of newly guaranteed transaction account assets (Event $\times$ TAG) is different for the groups of banks with low or high ratios of newly insured deposits (Affected=0 or Affected=1, respectively).

[25] Technically, we therefore estimate a variant of Equation (7), where we interact *Event* and *Event* $\times$ *Affected* with the dummy variable *TAG*: $\text{Risk}_{it} = \nu_i + [\beta_1 \text{Event}_t + \beta_2(\text{Event}_t \times \text{Affected}_i)] \times \text{TAG}_i + \beta_3 CSI_{\gamma t} + \tau_t + \epsilon_{it}$.

sensitive to bank risk, even if their funds are fully guaranteed, because, with or without guarantees, a bank default could have very adverse effects on their ability to meet financial obligations.

6 The role of bank capitalization

In the subsequent analysis, we explore whether the effect of increased deposit insurance coverage on banks' risk-taking is different for banks that vary in their capitalization before the regulatory change. Several studies show that bank capital matters for risk-taking of banks. For example, Furlong and Keeley (1989) find that incentives to increase risk decline when capital increases. Berger and Bouwman (2013) show that banks with higher capital monitor more carefully and invest in safer assets, which enhances the performance of these banks during crises. Thus, bank capital may also affect how banks adjust their risk-taking following the regulatory change.[26]

We define a bank to be "low capitalized", if a bank's total risk-based capital ratio is in the bottom quartile of the sample as of Q3 2008 (below 11.8%), to be "medium-capitalized" if it is in the second or third quartile (between 11.8% and 17.1%), and "high capitalized" if its in the top quartile (above 17.1%). Then, we rerun our baseline regressions of Eq. (4) for these three subsamples of banks.

First, using probabilities of default as dependent variable, we find a significant interaction coefficient for the group of low-capitalized banks of 0.0089 and an insignificant interaction coefficient for the groups of medium-capitalized or high-capitalized banks, as shown in Panel A of Table 8. The Wald-Test reveals that the interaction coefficient of low-capitalized banks

[26] In unreported results, we also explore the effect of bank size on our baseline results. Following a common classification in the literature (see, e.g., Berger and Bouwman, 2013), we classify small banks, medium banks and large banks as those with total assets below \$1 billion, exceeding \$1 billion and up to \$3 billion, and exceeding \$3 billion, respectively. For our sample, this creates subgroups with 1245, 71 and 26 banks, respectively. We find that our baseline result, i.e., relatively higher probabilities of default and lower z-scores of affected banks after the regulatory change, is robust for the group of small banks. We do not find a significant effect for the group of medium-sized banks or large banks. An economic explanation could be that medium and large banks are "too big to fail" and therefore benefit from public guarantees anyway, irrespective of the amount of insured deposits. Thus, an increase in insured deposits has no effect on the risk-taking of these banks. From an econometric perspective, note that the subgroups of medium-sized and large banks are relatively small, i.e., 71 and 26 banks, respectively, and therefore might lack explanatory power in the regressions.

is significantly higher than the interaction coefficients of both other subgroups.

Estimation results using the z-score as dependent variable are shown in Panel B of Table 8. We again find a significant effect for the group of low capitalized banks, which is also significantly different from the insignificant effect for high capitalized banks. The interaction coefficient for the group of medium-capitalized banks is also significant and significantly different from the interaction coefficient of high-capitalized banks.

[Table 8 about here]

Estimation results from Table 8 are illustrated in Fig. 6. The left graph shows the interaction coefficients for estimations with probabilities of default as dependent variables for the three different subgroups. The vertical lines show the 95% confidence interval of the interaction coefficients of each subgroup. The dashed horizontal line shows the interaction coefficient of the full sample, which is 0.0030. As reflected in the estimation results and illustrated in this graph, the effect of the regulatory change on the probabilities of default of affected banks relative to unaffected banks decreases in bank capitalization. The right graph shows the interaction coefficients for estimations with z-scores as dependent variables. The interaction coefficient of the full sample is -0.0925 and shown as a dashed line. Here, the effect on the z-score increases in bank capitalization, which again reflects that the effect on bank risk decreases in bank capitalization.

[Fig. 6 about here]

In summary, our results provide conclusive evidence that the risk-taking effect of the regulatory change is most distinct for affected banks that are low capitalized and not significant for affected banks that are high capitalized. Hence, the effect of insured deposits on bank risk-taking is not uniform for different banks. This result complements findings from Laeven and Levine (2009) who explore the role of corporate governance and show that the effect of deposit insurance on risk-taking depends on whether the bank has a large and powerful equity holder.

Our results may have important consequences for banking regulation. Stricter capital requirements seem to be an appropriate policy measure to balance risk-taking incentives of banks.[27] While this relation is known for a long time – or at least has been suspected – our evidence from the financial crisis episode shows that the pre-crisis capital levels were not sufficiently high to mitigate risk-taking incentives that result from increased deposit insurance coverage.

7 Conclusion

Deposit insurance has long been regarded a source of moral hazard that potentially increases banks' risk-taking. Nevertheless, at the peak of the financial crisis when the fear of bank runs and market disruptions was imminent, the U.S. policymakers decided to increase the deposit insurance from \$100,000 to \$250,000 per depositor and bank, which increased the total amount of insured deposits in the U.S. by roughly \$500 billion. This paper analyzes the consequences of this regulatory change, and thereby provides the first empirical assessment of the impact of insured deposits on banks' risk-taking for a large sample of banks within a major economy. Our results add to the existing literature that provides empirical evidence mainly based on cross-country studies.

We find that banks materially affected by the regulatory change, measured as the change in the ratio of insured deposits to assets, become more risky after the regulatory change relative to the unaffected banks. This result is robust for different risk proxies, alternative model specifications and consideration of the contemporaneous introduction of transaction account guarantees. We observe that affected banks invest relatively more in risky commercial real estate loans. These loans perform relatively poorly after the regulatory change in Q4 2008, measured as a higher ratio of non-performing loans to assets, and significantly deteriorate the stability of affected banks. In an extension of our analysis, we find that the higher risk-taking is in particular exercised by affected banks that are low capitalized and not by affected banks that are high capitalized.

[27]Note that we do not directly test a causal relation from bank capital on risk-taking in the face of deposit insurance changes. Therefore, further research on this relation is needed.

In addition to the effect of the regulatory change on banks' risk-taking, there were other important effects on the banking system and the overall economy, which we do not consider in our analysis. Potentially, the regulatory change helped to restore confidence and to avoid a panic among depositors. Hence, our analysis does not assess whether deposit insurance is a meaningful policy tool during a financial crisis. However, our results point to unintended consequences of a central and controversial part of bank regulation. Notably, affected banks with high capital levels do not become more risky. Given the renewed attention and importance of deposit insurance schemes in light of the financial and sovereign debt crisis, these results should be considered for ongoing reforms of the banking sector.

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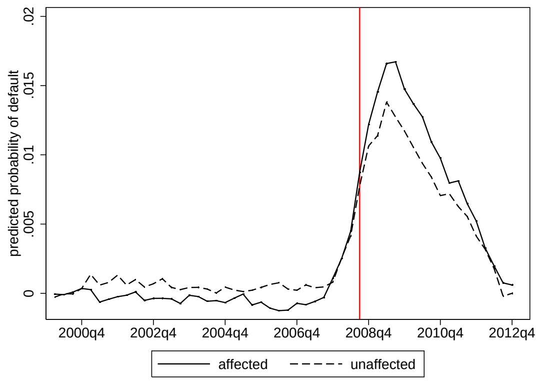
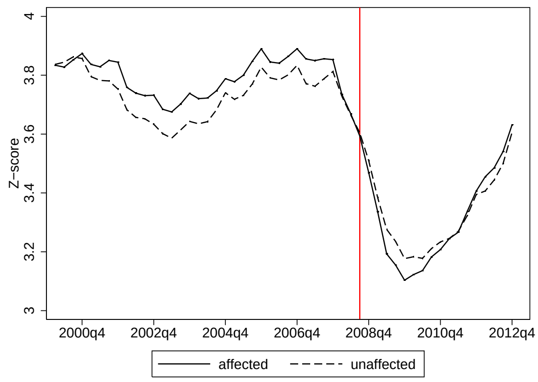
A Figures

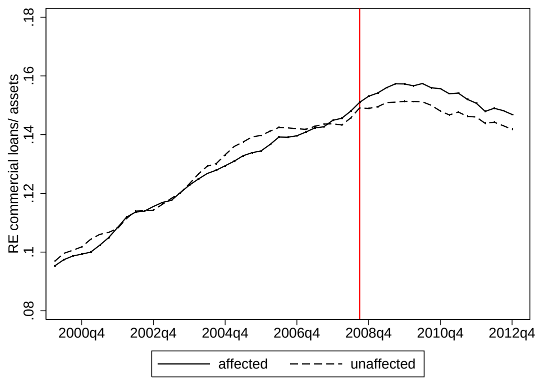
Figure 1: Illustrative evidence



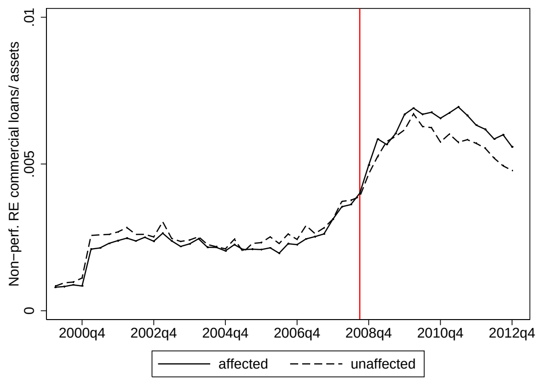
(a) Predicted probability of default



(b) Z-score



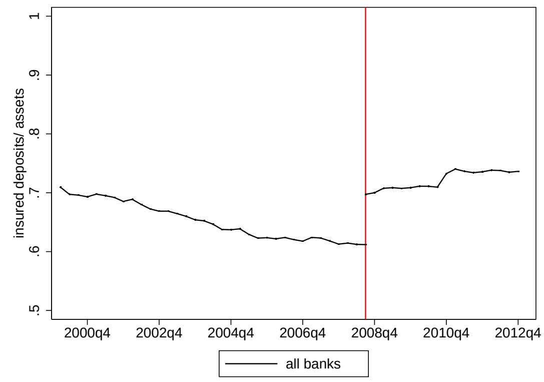
(c) Real estate commercial loans to assets



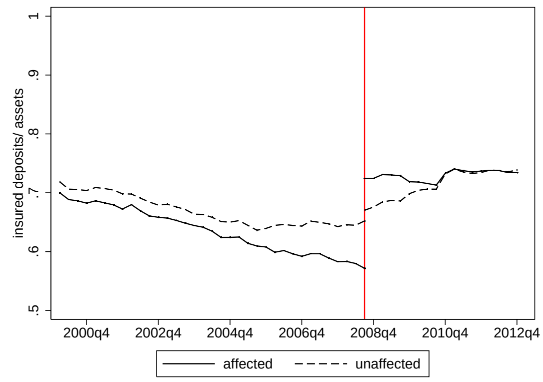
(d) Non-perf. real estate commercial loans to assets

The upper left graph shows banks' predicted probabilities of defaults. The mean values for affected banks and unaffected banks are represented by a solid and dotted line, respectively (each group comprises a total of 671 banks). The upper right graph shows banks' z-scores, where a lower value represents a more risky bank. The lower left graph shows banks' ratios of real estate commercial loans to assets. The lower right graph shows banks' ratios of non-performing real estate commercial loans to assets. All graphs reflect quarterly values for the period 2000 to 2012. The solid vertical lines show the end of the third quarter of 2008, three days before the *Emergency Economic Stabilization Act* was introduced.

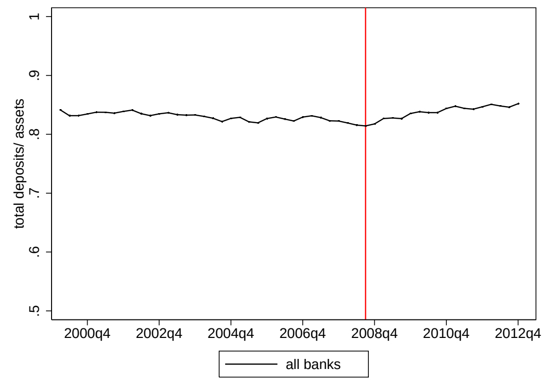
Figure 2: Volume of insured deposits and total deposits



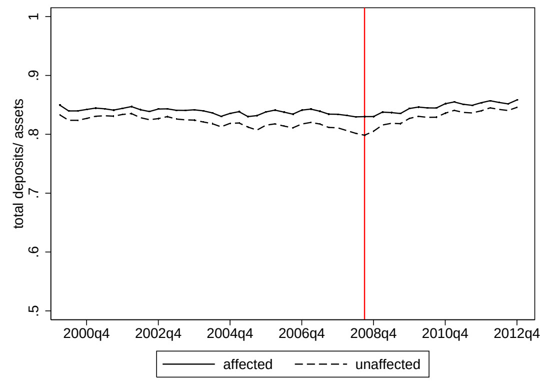
(a) Insured deposits to assets: all banks



(b) Insured deposits to assets by treatment status



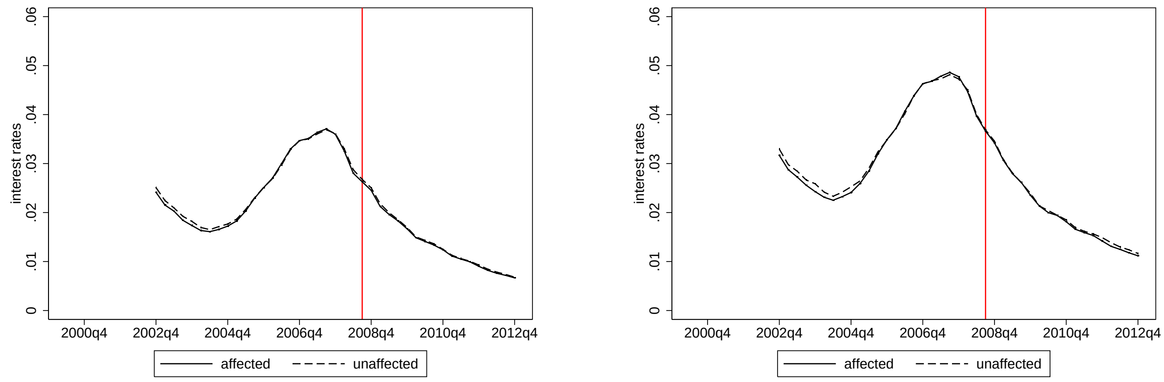
(c) Total deposits to assets: all banks



(d) Total deposits to assets by treatment status

The figure shows the development of the mean values of the ratio of *insured deposits to assets* for all banks (a) and by treatment status (b), and the development of the mean values of the ratio of *total deposits to assets* for all banks (c) and by treatment status (d). The solid vertical lines show the end of the third quarter of 2008, three days before the *Emergency Economic Stabilization Act* was introduced. In Graph (b) and Graph (d), the mean values of affected banks are represented by a solid line, and the mean values of unaffected banks are represented by a dashed line.

Figure 3: Interest rates of deposits

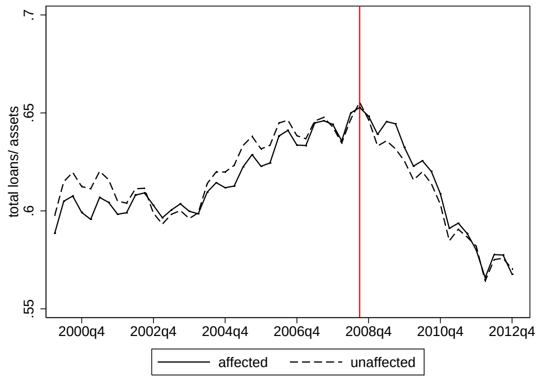


(a) Interest rates of total interest bearing deposits

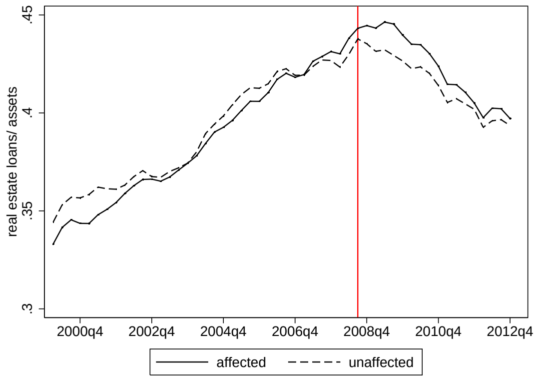
(b) Interest rates of large time deposits (over $100.000)

The figure shows the development of interest rates of total interest bearing deposits (a) and large time deposits over $100.000 (b) for the groups of affected banks and unaffected banks. The data is available since Q4 2002. We drop all observations with obvious outliers (interest rates below 0% or above 20%). The solid vertical lines show the end of the third quarter of 2008, three days before the *Emergency Economic Stabilization Act* was introduced.

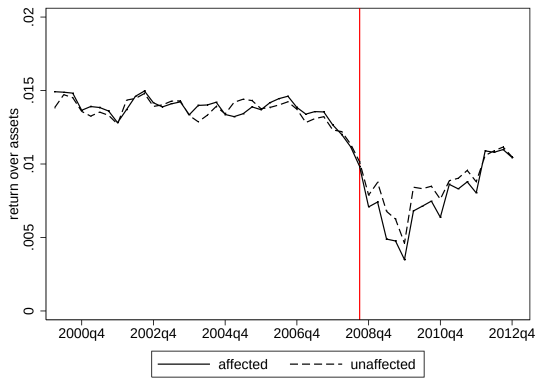
Figure 4: Selected bank characteristics over time



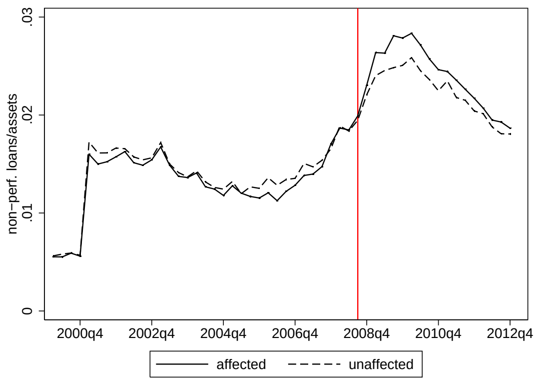
(a) Total loans to assets (LOANS)



(b) Real estate loans to assets (RE)



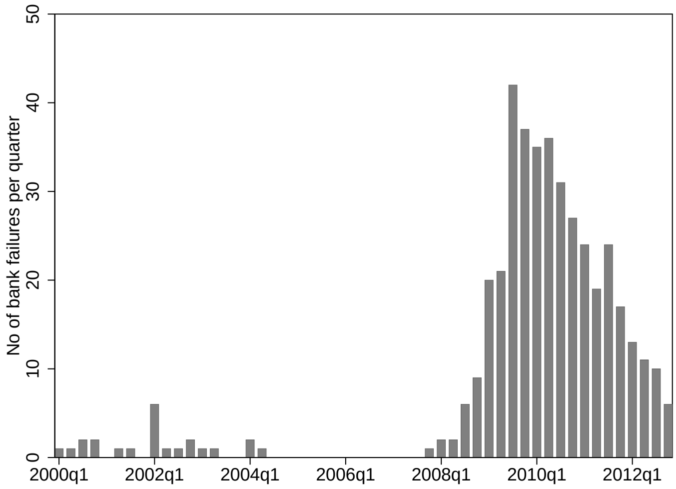
(c) Return to assets (ROA)



(d) Non-performing loans to assets (NPL)

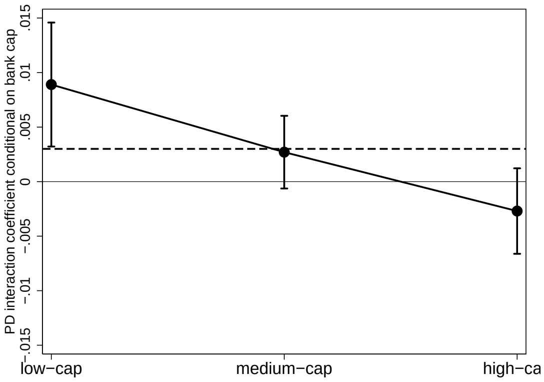
The figure shows the development of the mean values of selected variables for the period 2000 to 2012. The mean values for affected and for unaffected banks are represented by a solid line and a dashed line, respectively. The solid vertical lines show the end of the third quarter of 2008, three days before the *Emergency Economic Stabilization Act* was introduced.

Figure 5: Number of bank failures per quarter from 2000 to 2012

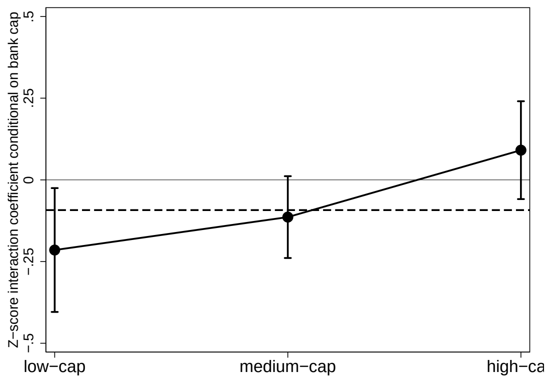


The figure shows the number of commercial bank failures per quarter from 2000 to 2012 based on the *FDIC Failed Bank List*.

Figure 6: Effect of increased deposits on bank risk conditional on bank capitalization



(a) Predicted probability of default



(b) Z-score

The figure illustrates the interaction coefficients from Table 8, which reflect the effect of increased deposits on bank risk, separately for low-capitalized banks, medium capitalized banks and high-capitalized banks. The left and right graphs relate to regressions using predicted probabilities of default and z-scores as dependent variables, respectively. The vertical lines show the 95% confidence interval of the interaction coefficients of each subgroup. The dashed horizontal line shows the interaction coefficient of the full sample.

B Tables

Table 1: Variables description

Notes: The source for all FDIC variables below as well as their descriptions is the *FDIC Statistics on Depository Institutions*, unless otherwise stated. For more details, refer to http://www2.fdic.gov/SDI/main.asp. If not otherwise stated, all variables are standardized by total assets. For the income and expenses variables, indicated with an asterix (*), we first calculate quarterly values based on the aggregated values provided by the FDIC database and then annualize these values by multiplying quarterly values by four.

FDIC variables		
Variable name	Calculation by FDIC codes	Description
ALLOW	lnatres/asset	**Loan loss allowances to assets:** This includes total allowances held by banks that are adequate to absorb estimated credit losses associated with its loan and lease portfolio.
ANIEXP	ideoth/asset2*	**Additional noninterest expense to assets:** This includes all other operating expenses of the institution. These may consist of net (gains) or losses on other real estate owned, loans sales, fixed assets sales, amortization of intangible assets, or other itemized expenses.
ASSET	asset	**Total assets:** This comprises the sum of all assets owned by the institution including cash, loans, securities, bank premises and other assets. It does not include off-balance-sheet accounts.
ASSET2	asset2	**Average quarterly assets.**
CAP	rbc1aaj	**Core capital ratio.** This includes Tier 1 (core) capital as a percent of average total assets minus ineligible intangibles.
CASH	chbal/asset	**Cash to assets:** This includes all cash and balances due from depository institutions.
CHOFF	ntlnls/asset	**Net charge-offs to assets:** This includes total loans and leases charged-off (removed from balance sheet because of uncollectibility), less amounts recovered on loans and leases previously charged-off.
CI	lnci/asset	**Commercial and industrial loans to assets:** This excludes all loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions and lease financing receivables.
CON	lncon/asset	**Consumer loans to assets:** This includes loans to individuals for household, family, and other personal expenditures including outstanding credit-card balances and other secured and unsecured consumer loans.
DEP	dep/asset	**Total deposits to assets:** This is the sum of all deposits including demand deposits, money market deposits, other savings deposits, time deposits and deposits in foreign offices.
DEPI	depins/asset	**Insured deposits to assets:** This is the estimated amount of FDIC insured deposits in domestic offices and in insured branches of Puerto Rico and US territories and possessions.
EQ	eqv	**Total bank equity to assets:** This includes preferred and common stock, surplus and undivided profits.
GOV	scus/asset	**Government securities to assets.**
IENC	oaienc/asset2*	**Income earned not collected on loans to assets:** This is loan income earned but not collected which is also included in other assets.
IEXP	eintexp/asset2*	**Total interest expense to assets**.
IINC	intinc/asset2*	**Total interest income to assets**.
IRTD	ubpre701	**Interest rates of total deposits:** This data comes from the *FDIC Uniform Bank Performance Reports.*
IRLD	ubpre704	**Interest rates of large time deposits (over $100,000:** This data comes from the *FDIC Uniform Bank Performance Reports.*
LIAB	liab/asset	**Total liabilities to assets:** This includes deposits and other borrowings, subordinated notes and debentures, limited-life preferred stock and related surplus, trading account liabilities and mortgage indebtedness.
LIQU	(chbal+scust)/asset	**Liquidity to assets:** This includes a bank's total cash and balances due from depository institutions (chbal) and its total U.S. Treasury securities.
LOANS	lnlsnet/asset	**Total loans to assets:** This includes total loans and lease financing receivables minus unearned income and loan loss allowances.
NIINC	nonii/asset2*	**Total noninterest income to assets.**
NIEXP	nonix/asset2*	**Total noninterest expense to assets.**
NGOV	(sc-scus)/asset	**Non-government securities to assets**.

Table 1: Variable description (continued)

FDIC variables		
Variable name	Calculation by FDIC codes	Description
NPLR	(p3asset+p9asset+naasset)/ asset	**Non-performing loans to assets**. This includes total assets past due 30-90 days and still accruing interest (p3asset), total assets past due 90 or more days and still accruing interest (p9asset), and total assets which are no longer accruing interest (naasset).
NPL-RECO	(p9renres+p3renres+narenres)/ asset	**Non-performing real estate commercial loans to assets**.
OA	(frepo+bkprem+ore +intan+idoa)/asset	**Other assets to assets:** This is the sum of federal funds sold and reverse repurchases, bank premises and fixed assets, goodwill and other intangibles, and all other assets.
OL	(tradel+idoliab)/asset	**Other liabilities to assets:** This is the sum of trading liabilities and all other liabilities.
ORE	ore/asset	**Other real estate owned to assets:** This includes direct and indirect investments in real estate. The amount is reflected net of valuation allowances.
OREL	ore/lnre	**Other real estate owned over real estate loans**.
PROV	elnatr/asset2*	**Provision for loans to assets:** This comprise the amount needed to make the allowance for loan and lease losses adequate to absorb expected loan and lease losses.
RBC	rbcrwaj	**Total risk-based capital ratio:** This is total risk based capital as a share of risk-weighted assets.
RE	lnre/asset	**Real estate loans to assets:** These are loans secured primarily by real estate, whether originated by the bank or purchased.
RECD	lnrecons/asset	**Real estate construction and development loans to assets:** This includes construction and land development loans secured by real estate held in domestic offices. This item includes loans for all property types under construction, as well as loans for land acquisition and development.
RECO	lnrenres/asset	**Real estate commercial loans to assets:** This includes all nonresidential loans primarily secured by real estate.
REMF	lnremult/asset	**Multifamily real estate loans to assets:** This includes multifamily (5 or more) residential property loans secured by real estate held in domestic offices.
RESF	lnreres/asset	**Single family real estate loans to assets:** This includes total loans secured by 1-4 family residential properties (including revolving and open-end loans) held in domestic offices.
ROA	roaptx	**Return over assets (pre-tax):** This is the annualized pre-tax net income as a percent of average assets.
SEC	sc/asset	**Securities to assets:** This includes total securities.
SUB	subnd/asset	**Subordinated debt to assets.**
WHOF	(frepp+idobrmtg)/asset	**Wholesale funding to assets:** This includes federal funds purchased and repurchase agreements, and other borrowed funds.
TA	log(asset)	**Log of assets:** The natural logarithm of total assets.
TRA	trn/asset	**Total transaction account assets to assets**.
TRADE	trade/asset	**Trading account assets to assets**.

Further variables	
Variable name	Description
Affected	**Affected:** This is a binary variable with a value of one if the bank experiences a change in the ratio of insured deposits to assets following the regulatory change in the top quartile of all banks in the sample, and zero if the change is in the lowest quartile. See Section 3.2 for details.
CSI	**Case-Shiller index:** This index reflects regional estate prices. We use it on state level. Our source for this index is the Federal Reserve Bank of St. Louis.
Failure	**Failure:** This is a binary variable with a value of one for the last four quarters before a bank failed according to the *FDIC Failed Bank list*, and a value of zero otherwise.
SD(ROA)	**Standard deviation of return over assets:**We calculate the standard deviation of return over assets for each bank and quarter over 12 rolling quarters.
PD	**Probability of default:** We estimated the probability of default for each bank and quarter via a probability model based on bank failures between 1993 and 2012, as described in Section 4.2.
TA250	**Newly guaranteed transaction account assets:** Ratio of noninterest-bearing transaction account assets of more than $250,000 (RCONG167) over assets. Source: Call report data provided by the *Federal Reserve Bank of Chicago* (www.chicagofed.org) as part of its *Commercial Bank Data*.
TAG	**TAG:** This is a binary variable with a value of 1 if the bank's ratio of noninterest-bearing transaction account assets above the deposit insurance limit of $250,000 over assets (TA250) is in the top quartile of the sample in Q4 2008, and a value of 0 if the bank's ratio is in the lowest quartile of the sample in Q4 2008. See Section 5 for details.
Z-score	**Z-score:** We calculate the z-score for each bank and quarter as the natural logarithm of the sum of a bank's return on assets and its core capital ratio, standardized by the standard deviation of the bank's return on assets, as described in Section 4.3.

Table 2: Descriptive statistics and group comparison

This table reports descriptive statistics for various bank characteristics for the period two years prior to the economic stabilization act that took effect in Q4 2008 (Q4 2006 - Q3 2008). We report all statistics separately for the group of affected banks and the group of unaffected banks. Banks are assigned to the group of affected banks (treatment group) if the change of insured deposits over deposits in the top quartile of the sample. Banks that exhibit a change in the ratio of insured deposits over deposits in the lowest quartile belong to the group of unaffected banks (control group). The last column shows the normalized differences (ND) according to Imbens and Wooldridge (2009), which compares differences between affected and unaffected banks. As a rule of thumb, values between ±0.25 indicate that groups are sufficiently equal and adequate for linear regression methods. An asterix (*) indicates that a variable is used for matching and for estimating probabilities of default. Abbreviations used in this paper are in parentheses. A detailed description of all variables is given in Table 1.

		Affected			Unaffected		
	Mean	Median	SD	Mean	Median	SD	ND
General bank characteristics							
Asset (in US$ millions)	350	143	1,712	505	120	2,003	-0.0588
Log of assets (TA)*	11.9840	11.8716	0.9992	11.9454	11.6988	1.2036	0.0246
Total risk-based capital ratio (RBC)	0.1596	0.1404	0.0610	0.1574	0.1408	0.0562	0.0275
Funding composition							
Equity/assets (EQ)*	0.1029	0.0958	0.0300	0.1042	0.0978	0.0289	-0.0297
Core capital/assets (CAP)	0.1015	0.0937	0.0298	0.1008	0.0928	0.0271	0.0176
Liabilities/assets (LIAB)	0.8971	0.9042	0.0300	0.8958	0.9022	0.0289	0.0297
Deposits/assets (DEP)	0.8354	0.8478	0.0610	0.8106	0.8308	0.0913	0.2263
Insured deposits/assets (DEPI)	0.5865	0.6052	0.1163	0.6472	0.6750	0.1379	-0.3362
Transaction account assets/assets (TRA)	0.2153	0.2103	0.1111	0.2065	0.2045	0.1034	0.0581
Portfolio composition							
Liquidity (LIQU)*	0.0471	0.0340	0.0452	0.0471	0.0338	0.0458	0.0000
Cash/assets (CASH)	0.0426	0.0321	0.0396	0.0423	0.0320	0.0393	0.0058
Government securities/assets (GOV)	0.1733	0.1484	0.1233	0.1717	0.1493	0.1171	0.0096
Non-government securities/assets (NOGV)	0.0594	0.0477	0.0566	0.0615	0.0483	0.0611	-0.0260
Allowances/assets (ALLOW)	0.0082	0.0077	0.0036	0.0084	0.0079	0.0037	-0.0390
Trading account assets/assets (TRADE)	0.0007	0.0000	0.0062	0.0010	0.0000	0.0088	-0.0222
Other assets/assets (OA)	0.0897	0.0769	0.0540	0.0884	0.0773	0.0544	0.0163
Total Loans/assets (LOANS)*	0.6425	0.6643	0.1483	0.6435	0.6575	0.1452	-0.0048
Consumer loans/assets (CON)	0.0503	0.0390	0.0474	0.0492	0.0394	0.0400	0.0188
Comm. and ind. loans/assets (CI)*	0.1013	0.0898	0.0608	0.1052	0.0896	0.0698	-0.0424
Real estate loans/assets (RE)	0.4295	0.4409	0.1546	0.4259	0.4332	0.1495	0.0166
RE con. & dev. loans/assets (RECD)*	0.0611	0.0436	0.0596	0.0612	0.0417	0.0611	-0.0008
RE commercial loans/assets (RECO)*	0.1444	0.1354	0.0855	0.1440	0.1349	0.0851	0.0030
RE multifamily loans/asset (REMF)*	0.0112	0.0041	0.0207	0.0113	0.0052	0.0183	-0.0056
RE single-family loans/assets (RESF)*	0.1651	0.1597	0.0908	0.1595	0.1538	0.0880	0.0436
Portfolio quality							
Non-performing loans/assets (NPL)*	0.0162	0.0117	0.0160	0.0165	0.0127	0.0153	-0.0140
Non-performing RECO (NPL-RECO)	0.0030	0.0010	0.0051	0.0032	0.0011	0.0052	-0.0198
Other real estate owned/assets (ORE)*	0.0020	0.0001	0.0053	0.0020	0.0002	0.0042	-0.0021
Inc. earned, not coll./assets (IENC)*	0.0081	0.0070	0.0039	0.0082	0.0073	0.0036	-0.0111
Charge-offs/assets (CHOFF)	0.0009	0.0003	0.0023	0.0009	0.0003	0.0026	-0.0084
Income and expenses							
ROA*	0.0125	0.0133	0.0092	0.0124	0.0129	0.0100	0.0106
SD(ROA)	0.0034	0.0023	0.0036	0.0036	0.0024	0.0045	-0.0403
Interest income/assets (IINC)	0.0158	0.0158	0.0024	0.0159	0.0157	0.0028	-0.0033
Interest expenses/assets (IEXP)	0.0065	0.0066	0.0018	0.0066	0.0066	0.0018	-0.0440
Loan loss provisions/ assets (PROV)	0.0007	0.0003	0.0017	0.0006	0.0002	0.0018	0.0186
Noninterest income/assets (NIINC)	0.0020	0.0017	0.0015	0.0023	0.0018	0.0045	-0.0768
Noninterest expenses/assets (NIEXP)	0.0077	0.0074	0.0026	0.0080	0.0076	0.0043	-0.0607
Add. Noninterest exp./assets (ANIEXP)	0.0023	0.0022	0.0013	0.0025	0.0022	0.0020	-0.0748
Regional macro variables							
Case-Shiller index (CSI)	314	297	96	310	297	86	0.0320
Estimated/ calculated risk proxies							
Probability of default (PD)	0.0018	-0.0028	0.0200	0.0021	-0.0018	0.0190	-0.0117
Z-score	3.7869	3.8591	0.7655	3.7454	3.8244	0.7958	0.0376
No. of banks	671			671			

Table 3: Baseline results: Probability of default and z-score

This table shows results for regressions of Eq. (4) with banks' quarterly *probabilities of default* and *z-scores* as the dependent variables.
Event is a dummy variable that is zero for the pre-event period and one for the post-event period, where the event is the signing into law of the *Emergency Economic Stabilization Act* at the beginning of Q4 2008. *Affected* is a dummy variable that is one for banks affected by the event (the change of insured deposits following the event is in the top quartile) and zero for banks unaffected by the event (the change is in the lowest quartile). *Event×Affected* is the respective interaction term. *CSI* reflects the Case-Shiller index on state level, which we include to control for regional differences in real estate prices.
All columns show OLS regression results for a period of two years (±8 quarters) around the event. The first column presents results for a regression with bank fixed effects. The second column presents results for a regression without bank fixed effects. The third column shows results for a regression with bank fixed effects and other bank control variables: *log of total assets (TA)*, *equity to assets (EQ)*, *real estate construction and development loans to assets (RECD)*, *real estate commercial loans to assets (RECO)*, *multifamily real estate loans to assets (REMF)*, *single family real estate loans to assets (RESF)* and *transaction account assets to assets (TRA)*. Columns (4) to (6) correspond to the specifications of Columns (1) to (3), using banks' z-scores as dependent variables.
All regressions include quarterly time fixed effects. We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables is given in Table 1.

	(1) PD	(2) PD	(3) PD	(4) Z-score	(5) Z-score	(6) Z-score
Event	-0.0019*	0.0000	0.0009	-0.3280***	-0.5934***	-0.3856***
	(0.0010)	(0.0010)	(0.0012)	(0.0336)	(0.0361)	(0.0379)
Affected		-0.0004			0.0455	
		(0.0009)			(0.0375)	
Event × Affected	0.0030**	0.0033***	0.0030**	-0.0925**	-0.1015**	-0.0919**
	(0.0013)	(0.0013)	(0.0012)	(0.0447)	(0.0438)	(0.0413)
CSI	-0.0002***	0.0000***	-0.0001***	0.0043***	-0.0011***	0.0024***
	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0003)	(0.0008)
SIZE			-0.0233***			0.6637***
			(0.0045)			(0.1455)
EQ			-0.3571***			13.6681***
			(0.0436)			(1.2168)
RECD			-0.0580***			3.3338***
			(0.0220)			(0.5534)
RECO			-0.0351**			0.1693
			(0.0144)			(0.4686)
REMF			0.0013			0.9163
			(0.0594)			(1.6467)
RESF			0.0086			-0.3281
			(0.0159)			(0.5298)
TRA			-0.0063			0.0480
			(0.0070)			(0.2480)
Constant	0.0669***	0.0025	0.3776***	2.3094***	4.1288***	-6.6799***
	(0.0081)	(0.0020)	(0.0580)	(0.2418)	(0.0816)	(1.8264)
Bank FE	YES	NO	YES	YES	NO	YES
Time FE	YES	YES	YES	YES	YES	YES
No. of banks	1342	1342	1342	1342	1342	1342
No. of obs.	21365	21365	21365	21272	21272	21272
Adj. R2	0.6622	0.0475	0.6933	0.6575	0.0980	0.6968

Table 4: Z-score components

This table shows results for regressions of Eq. (4) with banks' *z-scores* and their components – the return on assets, the volatility of return on assets and the equity-to-asset ratio – as the dependent variable.
Event is a dummy variable that is zero for the pre-event period and one for the post-event period, where the event is the signing into law of the *Emergency Economic Stabilization Act* at the beginning of Q4 2008. *Affected* is a dummy variable that is one for banks affected by the event (the change of insured deposits following the event is in the top quartile) and zero for banks unaffected by the event (the change is in the lowest quartile). *Event*×*Affected* is the respective interaction term. *CSI* reflects the Case-Shiller index on state level, which we include to control for regional differences in real estate prices.
All columns show OL regression results for a period of two years (±8 quarters) around the event and include quarterly time fixed effects. We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables is given in Table 1.

	(1) Z-score	(2) CAP	(3) ROA	(4) SD(ROA)
Event	-0.3280***	-0.0013**	-0.0007	0.0015***
	(0.0336)	(0.0007)	(0.0005)	(0.0002)
Event × Affected	-0.0925**	-0.0004	-0.0013**	0.0006**
	(0.0447)	(0.0009)	(0.0006)	(0.0003)
CSI	0.0043***	0.0001***	0.0001***	-0.0000**
	(0.0008)	(0.0000)	(0.0000)	(0.0000)
Constant	2.3094***	0.0729***	-0.0130***	0.0087***
	(0.2418)	(0.0068)	(0.0034)	(0.0019)
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of banks	1342	1342	1342	1342
No. of obs.	21272	21365	21365	21272
Adj. R2	0.6575	0.8209	0.5092	0.5725

Table 5: Portfolio composition

Panel A of this table shows results for for regressions of Eq. (4) with the ratios of *total loans to assets* (LOANS), *cash to assets* (CASH), *government securities to assets* (GOV), *non-government securities to assets* (NGOV), *trading account assets to assets* (TRADE), and *other assets to assets* (OA) as dependent variables.
Panel B shows results for the ratios of *commercial and industrial loans to assets (CI)*, *consumer loans to assets (CON)*, *real estate loans to assets (RE)*, *real estate construction and development loans to assets (RECD)*, *real estate commercial loans to assets (RECO)*, *real estate multi family loans to assets (REMF)*, and *real estate single family loans to assets (RESF)* as dependent variables.
Event is a dummy variable that is zero for the pre-event period and one for the post-event period, where the event is the signing into law of the *Emergency Economic Stabilization Act* at the beginning of Q4 2008. *Affected* is a dummy variable that is one for banks affected by the event (the change of insured deposits following the event is in the top quartile) and zero for banks unaffected by the event (the change is in the lowest quartile). *Event*×*Affected* is the respective interaction term. *CSI* reflects the Case-Shiller index on state level, which we include to control for regional differences in real estate prices.
All columns show OLS regression results for a period of two years (±8 quarters) around the event and include quarterly time fixed effects. We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables is given in Table 1.

Panel A: asset classes							
	(1) LOANS	(2) CASH	(3) GOV	(4) NGOV	(5) TRADE	(6) OA	
Event	-0.0393***	0.0350***	-0.0105***	0.0149***	0.0001	-0.0001	
	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.8625)	(0.9564)	
Event × Affected	0.0073**	0.0016	-0.0044	-0.0025	0.0002	-0.0022	
	(0.0321)	(0.5057)	(0.1904)	(0.2370)	(0.5377)	(0.2939)	
CSI	0.0001***	-0.0001***	-0.0001**	0.0001***	0.0000	0.0000	
	(0.0060)	(0.0002)	(0.0257)	(0.0030)	(0.1193)	(0.8695)	
Constant	0.6002***	0.0864***	0.1997***	0.0364***	-0.0034	0.0807***	
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.1686)	(0.0000)	
Bank FE	YES	YES	YES	YES	YES	YES	
Time FE	YES	YES	YES	YES	YES	YES	
No. of banks	1342	1342	1342	1342	1342	1342	
No. of obs.	21365	21365	21365	21365	21365	21365	
Adj. R2	0.8993	0.6248	0.8654	0.8385	0.4103	0.5462	
Panel B: loan categories							
	(1) CI	(2) CON	(3) RE	(4) RECD	(5) RECO	(6) REMF	(7) RESF
Event	-0.0129***	-0.0076***	-0.0164***	-0.0174***	0.0003	0.0014***	-0.0025**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8555)	(0.0004)	(0.0497)
Event × Affected	0.0015	-0.0009	0.0089***	0.0011	0.0047**	0.0003	0.0026
	(0.3479)	(0.3862)	(0.0036)	(0.4996)	(0.0119)	(0.4741)	(0.1064)
CSI	0.0001**	-0.0000	0.0001	0.0002***	-0.0001***	0.0000	-0.0000
	(0.0244)	(0.8441)	(0.2282)	(0.0000)	(0.0004)	(0.5185)	(0.9591)
Constant	0.0832***	0.0483***	0.4197***	0.0128	0.1842***	0.0097**	0.1683***
	(0.0000)	(0.0000)	(0.0000)	(0.2090)	(0.0000)	(0.0123)	(0.0000)
Bank FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
No. of banks	1342	1342	1342	1342	1342	1342	1342
No. of observations	21365	21365	21365	21365	21365	21365	21365
Adj. R2	0.8762	0.9193	0.9320	0.8616	0.9203	0.8989	0.9486

Table 6: Non-performing real estate commercial loans

This table shows results for regressions of Eq. (4) with *non-performing real estate commercial loans to assets* (NPL-RECO) as dependent variables. The alternative specifications vary in the sample period around the event. The first column uses one year around the event (± 4 quarters). The second column uses two years around the event (± 8 quarters). The third column uses two years before and the second and third year after the event (-8 quarters and +5 to +12 quarters). The fourth column uses two years before and the third and fourth year after the event (-8 quarters and +9 to +16 quarters).
Event is a dummy variable that is zero for the pre-event period and one for the post-event period, where the event is the signing into law of the *Emergency Economic Stabilization Act* at the beginning of Q4 2008. *Affected* is a dummy variable that is one for banks affected by the event (the change of insured deposits following the event is in the top quartile) and zero for banks unaffected by the event (the change is in the lowest quartile). *Event×Affected* is the respective interaction term. *CSI* reflects the Case-Shiller index on state level, which we include to control for regional differences in real estate prices.
All regressions include quarterly time fixed effects. We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables is given in Table 1.

	(1) NPL-RECO Year 1	(2) NPL-RECO Year 1/2	(3) NPL-RECO Year 2/3	(4) NPL-RECO Year 3/4
Event	0.0014***	0.0019***	0.0010***	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Event × Affected	0.0002	0.0004	0.0007*	0.0009**
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
CSI	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0187***	0.0181***	0.0184***	0.0165***
	(0.0028)	(0.0023)	(0.0019)	(0.0016)
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of banks	1342	1342	1342	1342
No. of obs.	10736	21365	21059	20727
Adj. R2	0.5608	0.4800	0.4693	0.4645

Table 7: The relevance of transaction account guarantees

This table shows results for regressions of Eq. (7) with banks' quarterly *probabilities of default* and *z-scores* as the dependent variables. *Event* is a dummy variable that is zero for the pre-event period and one for the post-event period, where the event is the signing into law of the *Emergency Economic Stabilization Act*, and, simultaneously, the introduction of the *Transaction Account Guarantee Program* at the beginning of Q4 2008. *Affected* is a dummy variable that is one for banks materially affected by the increase in insured deposit coverage (the change of insured deposits following the event is in the top quartile) and zero for banks unaffected by the event (the change is in the lowest quartile). *TAG* is a dummy variable that is one for banks materially affected by the new transaction account guarantees (the ratio of newly guaranteed transaction account assets over assets in Q4 2008 is in the top quartile) and zero for banks unaffected by the event (the ratio is in the lowest quartile). *Event* × *Affected*, *Event* × *TAG*, *Affected* × *TAG* and *Event* × *Affected* × *TAG* are the respective interaction terms. *CSI* reflects the Case-Shiller index on state level, which we include to control for regional differences in real estate prices.
All columns show OLS regression results for a period of two years (±8 quarters) around the event. The first column presents results for a regression with bank fixed effects. The second column presents results for a regression without bank fixed effects. The third column shows results for a regression with bank fixed effects and other bank control variables, as also used and described in Table 3. Columns (4) to (6) correspond to the specifications of Columns (1) to (3), using banks' z-scores as dependent variables. The bottom rows of this table contrast the interaction effect *Event* × *Affected* on bank risk-taking for the groups with TAG=0 and TAG=1, i.e, the effect *Event* × *Affected* and the effect (*Event* × *Affected*) + (*Event* × *Affected* × *TAG*) from the regressions above.
All regressions include quarterly time fixed effects. We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables is given in Table 1.

	(1) PD	(2) PD	(3) PD	(4) Z-SCORE	(5) Z-SCORE	(6) Z-SCORE
Event	-0.0007	0.0008	0.0019	-0.2714***	-0.5321***	-0.3003***
	(0.0019)	(0.0018)	(0.0018)	(0.0604)	(0.0627)	(0.0611)
Affected		-0.0000			0.1366*	
		(0.0019)			(0.0763)	
Event × Affected	0.0062**	0.0054*	0.0060**	-0.2976***	-0.2758***	-0.2963***
	(0.0029)	(0.0029)	(0.0027)	(0.0933)	(0.0899)	(0.0873)
TAGP		-0.0042**			0.1212	
		(0.0019)			(0.0802)	
Event × TAG	-0.0031	-0.0034	-0.0031	-0.0984	-0.0802	-0.0987
	(0.0024)	(0.0023)	(0.0022)	(0.0833)	(0.0804)	(0.0776)
Affected × TAG		-0.0028			-0.1125	
		(0.0027)			(0.1051)	
Event × Affected × TAG	-0.0052	-0.0029	-0.0039	0.4120***	0.3429***	0.3655***
	(0.0037)	(0.0037)	(0.0035)	(0.1233)	(0.1218)	(0.1157)
CSI	-0.0002***	0.0000**	-0.0001***	0.0037***	-0.0009***	0.0023**
	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0003)	(0.0010)
SIZE			-0.0231***			0.5784***
			(0.0057)			(0.1762)
EQ			-0.3077***			10.8448***
			(0.0563)			(1.6343)
RECD			-0.0463			3.4014***
			(0.0328)			(0.7646)
RECO			-0.0213			-0.4300
			(0.0173)			(0.5950)
REMF			0.0737			-1.1616
			(0.0743)			(2.2683)
RESF			0.0028			-0.4848
			(0.0253)			(0.7847)
Constant	0.0624***	0.0061**	0.3635***	2.4298***	3.9619***	-5.2277**
	(0.0095)	(0.0027)	(0.0726)	(0.3086)	(0.1182)	(2.2364)
Bank FE	YES	NO	YES	YES	NO	YES
Time FE	YES	YES	YES	YES	YES	YES
No. of banks	671	671	671	671	671	671
No. of obs.	10668	10668	10668	10603	10603	10603
Adj. R2	0.6630	0.0651	0.6898	0.6585	0.1019	0.6909
"Event × Affected" for TAG=0	0.0062**	0.0054*	0.0060**	-0.2976***	-0.2758***	-0.2963***
	(0.0029)	(0.0029)	(0.0027)	(0.0933)	(0.0899)	(0.0873)
"Event × Affected" for TAG=1	0.0010	0.0025	0.0021	0.1145	0.0670	0.0692
	(0.0022)	(0.0023)	(0.0021)	(0.0812)	(0.0823)	(0.0758)

Table 8: The relevance of bank capitalization

This table shows results for regressions of Eq. (4) with banks' *probability of default* (Panel A) and banks' *z-scores* (Panel B) as the dependent variables for various subsamples of banks. The first column restates results for the full sample. The second, third and fourth columns divide banks in low-capitalized banks (bottom quartile), medium-capitalized banks (second and third quartile) and high-capitalized banks (top quartile) according to their total risk-based capital ratio (RBC) in Q3 2008.
Event is a dummy variable that is zero for the pre-event period and one for the post-event period, where the event is the signing into law of the *Emergency Economic Stabilization Act* at the beginning of Q4 2008. *Affected* is a dummy variable that is one for banks affected by the event (the change of insured deposits following the event is in the top quartile) and zero for banks unaffected by the event (the change is in the lowest quartile). *Event×Affected* is the respective interaction term. *CSI* reflects the Case-Shiller index on state level, which we include to control for regional differences in real estate prices.
All columns show OLS regression results for a period of two years (±8 quarters) around the event and include quarterly time fixed effects. We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables is given in Table 1.
The last two rows of each panel show differences between interaction coefficients of different subsamples and whether they are significantly different from each other.

Panel A (dependent variable: PD)				
	(1) All	(2) Low-cap	(3) Medium-cap	(4) High-cap
Event	-0.0019*	0.0025	-0.0034**	-0.0021
	(0.0010)	(0.0023)	(0.0013)	(0.0017)
Event × Affected	0.0030**	0.0089***	0.0027	-0.0027
	(0.0013)	(0.0029)	(0.0017)	(0.0020)
CSI	-0.0002***	-0.0002***	-0.0002***	-0.0001***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Constant	0.0669***	0.0776***	0.0622***	0.0477***
	(0.0081)	(0.0180)	(0.0097)	(0.0154)
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of banks	1342	342	670	330
No. of obs.	21365	5407	10696	5262
Adj. R2	0.6622	0.6736	0.6690	0.6627
Diff. (2) vs. (3)		0.0062*		
Diff. (2) vs. (4)		0.0116***		
Diff. (3) vs. (4)			0.0054**	

Panel B (dependent variable: Z-score)				
	(1) All	(2) Low-cap	(3) Medium-cap	(4) High-cap
Event	-0.3280***	-0.3928***	-0.3058***	-0.3300***
	(0.0336)	(0.0705)	(0.0475)	(0.0618)
Event × Affected	-0.0925**	-0.2147**	-0.1139*	0.0909
	(0.0447)	(0.0967)	(0.0639)	(0.0764)
CSI	0.0043***	0.0040**	0.0049***	0.0020
	(0.0008)	(0.0016)	(0.0010)	(0.0015)
Constant	2.3094***	2.0697***	2.1083***	3.3493***
	(0.2418)	(0.4976)	(0.3047)	(0.4379)
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of banks	1342	342	670	330
No. of obs.	21272	5379	10647	5246
Adj. R2	0.6575	0.6564	0.6292	0.6648
Diff. (2) vs. (3)		-0.1008		
Diff. (2) vs. (4)		-0.3055**		
Diff. (3) vs. (4)			-0.2048**	

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