TARP Effect on Bank Lending Behaviour: Evidence from the last Financial Crisis.*

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First Version: **June 2012**
This Version: **March 2013**

Abstract

Using a unique dataset based on US commercial banks, we assess the impact of the Troubled Asset Relief Program (TARP) on small business loan origination. We find that on average TARP banks show larger size and they provide larger amounts of loans than the rest of the banks. These patterns characterise the entire period analysed. Moreover, TARP banks exhibit lower levels of Tier 1 capital ratio in 2005 and less non-performing loans. This pattern is reverted in 2010. Exploiting the panel dimension of the dataset, we find that the TARP banks provide on average 12% higher loan origination than the other banks. Furthermore, by defining a bank geographical coverage indicator, we show how that previous result depends on this feature: TARP is effective only for banks with high geographical coverage. Finally, by taking into account socio-economic features at a county level (unemployment, poverty and median income), we show that the results are partially driven by a demand side effect. Several robustness tests confirm the main results.

Keywords TARP, Financial Crisis, Loan provision
JEL Classification C23, E58, G21, G28

*The authors are grateful to seminar participants at HEC Lausanne for useful comments.

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1 Introduction

"*TARP was an abysmal failure on those very important goals the reason why they got that money to give to the banks in the first place....[TARP] did help prevent financial Armageddon, but there's a reason why Congress required and Treasury promised TARP would do a lot more.*" **Neil M. Barofsky**, Former TARP Inspector General.

"*If the alternative was indeed the abyss, TARP was clearly an unqualified success: we have escaped the abyss.*" **Luigi Zingales**, Economist.

"*The program was essential to averting a second Great Depression, stabilizing a collapsing financial system, protecting the savings of Americans and restoring the flow of credit that is the oxygen of the economy. And it helped achieve all...[TARP was] the most effective government program in recent history.*" **Timothy Geithner**, Treasury Secretary.

These three opinions about the effectiveness of the TARP program highlight the disagreement about the results of the largest rescue plan ever promoted by the US Treasury. This asymmetry in judging the success of the TARP program is partially due to the ambiguity and the conflict related to its goals. Through the TARP program the US Treasury intended to help banks to improve their balance sheets and therefore to increase the robustness of the financial system. Furthermore, banks that benefited from the TARP program were asked to keep providing credit to firms, small businesses and households. Potentially, the achievement of these two goals is in conflict: if banks keep on providing loans to distressed businesses, it is likely to observe an increase in banks non-performing loans, which might further weaken the banking system. The current debate on the TARP program discusses the potential cost for the US taxpayer, but also in this case there is no consensus on the results. Veronesi and Zingales (2010) find that TARP increased the value of banks' financial claims by $130 billion. However, the majority of the gain goes to the bondholders of banks while the cost is incurred by the US taxpayers. By contrast, the Treasury Secretary, Timothy Geithner, stresses the fact that "...taxpayers are likely to receive an impressive return (totalling tens of billions) on the investments made under the TARP outside the housing market."[1].

In the public debate as well as in the literature less importance has been given to the aspect referring to the TARP program and its goals. In particular, in the literature there is a lack about the effect of the TARP program on bank lending activity to small businesses. According to a report of the US Small Business Administration (Kobe, 2012), in 2008 small businesses (businesses with less than 500 employees) account for 46 percent of total non-farm GDP and about 50 percent in total non-farm employment. Moreover, as claimed by Berger and Udell (2002) "Small firms are [...] vulnerable because of their dependence on financial institutions for external funding. These firms simply do not have access to public capital markets." This fact is confirmed from data collected by the Federal Reserve Board (2003), where 87 percent of small firms report that their lender is a bank.

In this paper we fill the gap in the literature by assessing the impact of the TARP program on small business loan origination. We achieve our goal by creating a unique dataset based on banks balance sheet, TARP program participation, loan origination to small businesses and county socio-economic features[2]. The period taken into account goes from 2005 to 2010, data are annually based. We distinguish banks depending on their participation to the TARP program. Comparing the groups of banks in 2005, TARP banks provide on average larger amount of new loan, show lower level of capital buffers and smaller level of non performing loans than the rest of the banks. Finally, they are more likely to provide loans in counties that suffer from poverty and unemployment. In 2010, once the program is over, TARP banks still provide more new loans, and they are more likely to be located in country with poverty and unemployment problems, but they also show a higher level of capital buffer and non

[1] Timothy Geithner, The Washington Post, 10.10.2010.

[2] The banks balance sheet data have been obtained from the Call reports. The information about TARP program participation has been downloaded from the US Treasury, while loan origination to small businesses have been obtained from the Federal Financial Institutions Examination Council (FFIEC) websites and finally the county socio-economic features have been downloaded from the U.S. Census Bureau and the Bureau of Labor Statistics.

performing loans than the rest of the banks. These differences may shed lights on the way banks employed TARP sustain aside from keep on financing small businesses: increasing their buffers and lending to lower quality borrowers.

Exploiting the panel dimension of our dataset, we find that TARP banks increase loan origination compared to the rest of the banks. This effect is statistical as well as economical significant: a TARP bank increases loan origination by about 12% in the years after receiving TARP equity. Previous results could be driven by some specific feature of the banks, in particular referring to the geographical coverage that each bank serves. For this reason, we construct three alternative measures of geographical coverage. In particular, a bank shows high geographical coverage if it provides loans in more than one US state, or provides loans in more than 5 counties, or if the average distance between all served counties exceeds 60 kilometres[3]. The geographical coverage can be interpreted by using a signalling extraction theory: counties where banks invest are hit by shocks, banks receive signals about the shocks, the precision of the signal increases the larger is the number of counties where the bank provides loans. Alternatively, it can be explained by using a diversification argument, so that banks that follow the well-known saying to "not put all the eggs in the same basket" are minimizing the risk of being hit by a shock. To support our intuition, the difference between the maximum and minimum median income of the counties where a bank provides loans is computed. This measure is higher, the larger the geographical coverage. The results show that the TARP is effective only for banks with high geographical coverage. We can conclude that bank geographical coverage is a complement to the TARP program to ensure its effectiveness.

The findings instead of being purely related to the TARP effect on banks loan activity, could be driven by a demand side effect: if TARP banks are located in sounder counties, with a high demand for loans, it follows that our results capture the fact that the supply of

[3]The thresholds refer to the median values of the number of counties served by a bank, and the average distance of the counties where banks provide loans.

loans meets the demand and it does not refer to a pure TARP effect. Therefore, it is the quality of the counties and not the TARP program that would drive the results. Besides including county fixed effects, we also add to the baseline model two variables capturing poverty and unemployment characterising each county. Poverty captures persistent economic problems, while unemployment reflects more temporary economic issues, due to the fact it is strongly related with the business cycle. The results highlight that higher levels of unemployment and/or poverty decrease loan provision. However, the interaction between TARP and Poverty is not significant, while this is the case for the interactive dummy TARP × UNEMPLOYMENT. Therefore it seems that TARP program is effective in counties suffering from temporary but not more persistent economic problems. When computing the total effect of the TARP program we find that the results are not driven by the so-called demand side effect.

In sum, the main results of our contribution are the following:

- TARP positively affects small business loan originations;
- TARP is effective only for banks with higher geographical coverage;
- TARP effect is not driven by the demand side effect;
- TARP is effective for banks investing in counties suffering from unemployment;
- TARP is not effective for banks investing in counties suffering from poverty.

These results are robust to the dependent variable, the geographical coverage definition employed and the sample period employed, to the inclusion in the econometric model of economic distress indicators, and to the potential selection issue.

In the literature there are several contributions related to our study, which assess different aspects of the TARP program. Taliaferro (2009) finds that TARP banks exhibit higher commitments (that is opportunities for new lending), are more exposed to troubled loan classes and show higher leverage and expected costs of regulatory downgrades. Moreover, by using an event study approach supported by an econometric analysis he finds that of each dollar of new government equity provided trough the TARP, on average thirteen cents are employed to expand loans and sixty cents are used to increase capital ratios. The corollary is that TARP was not effective in helping banks in their task of providing loans to households and small business. These results are partially in line with those of Li (2011). On the one hand, by focusing on banks with Tier 1 capital ratios below the median, Li finds that TARP sustain helped banks in increasing loan supply by an annualized rate of 6.43%. This increase in loan supply was not to the detriment of the quality of the loans. On the other hand, Li shows that of each dollar provided to the banks trough the TARP program one-third has been used to finance new loans, and two-third to restructure their balance sheets. Black and Hazelwood (2012) assess the effect of the TARP program on bank risk-taking behaviour. Specifically, they focus on the risk rating of banks' commercial loans. By distinguishing between big and small banks they find that TARP sustain increases risk taking behaviour for big banks while the relation goes into the other direction in case of small banks. These findings are confirmed when spreads instead of risk ratings are employed.

Other contributions focus on the determinants of the TARP participation as in Bayazitova and Shivdasani (2011); the relevance of the political connection in the likelihood of obtaining the financial sustain as documented by Duchin and Sosyura (2012); the reaction of the stock market to banks' participation to the TARP program as in Ng et al. (2011); the effective cost of the TARP program as analysed by Veronesi and Zingales (2011); and finally on the key features explaining banks' early exit from the TARP program as discussed by Wilson and Wu (2010).

This paper shows several novelties with respect to previous contributions on the same topic. This is the first study exploiting the CRA dataset. On the one hand, this allows us to focus on loan origination to small businesses, representing, as previously mentioned a relevant fraction of the US economy. On the other hand, using the CRA dataset and exploiting the bank-county dimension, we are able to mitigate, at least partially, the selection issue that characterises TARP-like programs. We adopt two approaches to control for the selection bias. First, we use propensity score matching to match TARP and NO TARP banks. Second, we run the baseline regressions excluding counties without TARP banks or with only TARP banks. The findings of previous contributions can be partially biased because the distinction between banks with high and low geographical coverage is not taken into account. This features could be of relevance in the practice of providing loans due to signalling extraction or to diversification investment strategy. To address this question we create three alternative measures of geographical coverage and include it in the main specification. Another source that can bias the results of previous studies refers to the fact that the demand side effect has not been taken into account. In order to deal with this potential issue, we explicitly include in the specification the socio-economic features of the counties where banks invest. Finally, previous contributions do not control for the fact that TARP banks already before the beginning of the program provide more new loans than the rest of the banks, therefore, the results obtained would not be ascribed to the TARP program, but to the fact that *per se* TARP banks provide more loans. We control this potential issue in two different ways. First, we lead a placebo experiment by running a "false" TARP program for the period 2002-2007, by distinguishing banks according to their "true" participation to the TARP program. The other approach to fix this issue refers to matching TARP banks with the other banks, using loan provision in 2005. Therefore, the sub sample generated includes banks that are different only with respect to the participation to the TARP program. The differences between our results and those of previous studies can be due to the dataset employed (CRA vs Call reports), the type of loans analysed (origination vs outstanding) or, as documented below, to the type of aggregation employed (bank-county level vs bank level).

2 TARP and Community Reinvestment Act

2.1 The main features of the TARP

The TARP program has been launched by the US Treasury in 2008 after the collapse of Lehman Brothers. With available funds of $700 billion[4], the TARP program was the largest program ever promoted by the US Government. TARP consists of Bank Support Programs ($250.46 billion), Credit Market Programs ($26.52 billion), Housing Programs ($45.60 billion) and Other Programs ($147.53 billion)[5]. The program of interest are the Bank Support Programs, which can divided into Target Investment Program –which was exclusively addressed to Citigroup and Bank of America–, the Capital Purchase Program (CPP), and the Community Development Capital Initiative (CDCI). Our analysis focuses on the CPP.

The CPP was a voluntary program directed to financial institutions in a broad sense. The program was created in October 2008. The amount of capital provided through this program was about $205 billion. 707 institutions benefited from the program funds. The CPP mechanism to inject capital was based on purchases of senior preferred stock and warrants exercisable for common stock with a promised dividend of 5% for the first 5 years and 9% thereafter. Under the CPP, institutions could receive an amount included between 1% and 3% of their risk weighted assets. The aims of the CPP were to provide the financial institution with capital, to restore confidence in the banking sector, and to sustain financial institutions to keep financing firms, small businesses and households. Only solvent institutions were eligible for CPP.

[4] Only around $420.12 billion were effectively used.

[5] Other programs include the sustain for American International Group (AIG) and the auto-mobile sector.

2.2 What is the Community Reinvestment Act?

The Community Reinvesting Act has been approved by the US Congress in 1977 with the aim "to encourage depository institutions to help meet the credit needs of the communities in which they operate, including low- and moderate-income neighbourhoods, consistent with safe and sound operations"[6]. The law was introduced to counteract discriminatory loan practices, commonly referred to "redlining", where loan providers used to mark in red the borders of specific areas they did not intend to serve with any type of loans (see for instance Figure 5 in the Appendix).

3 Data and descriptive analysis

3.1 The dataset

The dataset employed in this paper is the result of several merging processes. Data concerning financial institutions balance sheets[7] is obtained from the Report of Condition and Income (generally referred to as Call Reports). We accessed the Call Report data through the Federal Reserve of Chicago website. The frequency of the data is quarterly. The period considered goes from 2005:Q1 to 2010:Q4.

Data referring to the TARP program is publicly available, and can be downloaded from the US Treasury website. The period considered goes from the end of October 2008, when TARP program started operating, to April 2012, when the majority of the banks returned their preferred stock obligations or they bought back their warrants owned by the US Treasury.

The information about bank loan provision at county level has been downloaded from the CRA website, while the poverty and the unemployment rates have been obtained from

[6]http://www.bos.frb.org/commdev/regulatory-resources/cra/cra.pdf

[7]Call Report data suffer from the so-called "window dressing" effect. Specifically, the day before the report, banks adopt a virtuous behaviour so that their balance sheets look particularly good on the day of the report. Unfortunately, we cannot control for this issue.

the US Census Bureau and the Bureau of Labor Statistics, respectively. Data are recorded yearly and the period considered goes from 2005 to 2010. The sources employed to generate the dataset are provided in Table 13 of the Appendix.

3.2 Combining Call Reports, TARP and CRA datasets

Due to the different frequency of the datasets, we focus on annual data. When the frequency is quarterly, we measured the series in the fourth quarter of each year: the sample period goes from 2005 to 2010. We drop the nine banks that have been forced to participate to the TARP program[8]. There are two types of institutions that benefited from the TARP program: individual banks and Bank Holding Companies (BHC). Our analysis is led at bank level. As a consequence, we map each commercial bank with its own BHC. Therefore, for each depository institution included in our final dataset, we can assess whether it benefited (directly or indirectly) from the TARP program. From the original Call Report dataset, we drop all foreign banking organizations (FBOs) and banks that report capital ratios smaller than 6% (the minimum requirement), since these banks were not eligible for TARP. The CRA dataset contains information about banks that are subject to the reporting requirements[9] and that provide small business loans. Therefore, the majority of the depository institutions included in the Call Reports is dropped.

After the above-mentioned merging and filtering procedures, in 2005, the final dataset contains 794 banks, and of those 213 received financial sustain through the TARP program. Overall, banks provide loans in 2634 counties, while the TARP banks provide loans in 2026 counties. In 2010, the dataset counts 635 banks that provide loans in 2650 counties. Of these banks 255 received the TARP sustain and they provide loans in 2113 counties. Our dataset

[8]These institutions are Citigroup, Wells Fargo, JPMorgan, Bank of America, Goldman Sachs, Morgan Stanley, State Street, Bank of New York Mellon, and Merrill Lynch.

[9]"All institutions regulated by the Office of the Comptroller of the Currency, Federal Reserve System, Federal Deposit Insurance Corporation, and the Office of Thrift Supervision that meet the asset size threshold are subject to data collection and reporting requirements.", http://www.ffiec.gov/cra/reporter10.htm

includes around 10 percent of institutions that hand in Call Reports, and around 50 percent of all TARP banks. It is a panel of banks tracked for five years.

3.3 Description of the variables

The baseline measure of loan origination to small businesses is $LOANS$ 0. It is defined as the log of one plus the sum of total loan origination. Loan origination can be classified by size. We define $LOANS$ 1 (loan size between 0 and \$100k), $LOANS$ 2 (loan size between \$100k and \$250k) and $LOANS$ 3 (loan size between \$250k and \$1m) as the log of one plus loan origination of the respective size. These variables are on a bank-county level.

The majority of the variables included in our dataset, due to its nature, are bank-specific. $TOTLOANS$ is the ratio of total loans over total assets. $RELOANS$ is the ratio of real estate loans over total loans. $SIZE$ is the log of one plus the total assets of the banks (both on and off balance sheet items), while NPL is defined as the ratio of non-performing loans over total loans. $CAPRATIO$ is defined as Tier 1 (core) capital divided by adjusted total assets. Following Goetz and Gozzi (2011), we also include $TOT.\ UNCOMM.$ and $NOCORE\ PA$. These variables are defined as the fraction of total unused loan commitments over total assets (on and off balance sheet items) and as the sum of total time deposits of at least \$100k, foreign office deposits, insured brokered deposits issued in denominations of less than \$100k, securities sold under agreements to repurchase, federal funds purchased, and other borrowed money over total assets, respectively. Finally, we also consider a set of variables that refer to the socio-economic features of the counties included in the CRA dataset. In particular, we obtained the series about poverty, county median income and unemployment from the US Census Bureau and the Bureau of Labour Statistics, respectively. More precisely, $POVERTY$ is defined as the estimated percentage of people of all ages in poverty; MED_INC is the estimated of median household income, while $UNEMPLOYMENT$ is defined as the ratio of people who do not have a job, have actively looked for work in the prior 4 weeks, and are currently available for work over total labour force[10]. A detailed list of the original names of the series employed in this paper, their definitions and their labels is provided in Table 13 in the Appendix.

3.4 Main facts

3.4.1 Descriptive statistics

In Table 3, for each of the variable, we report the number of observations, banks and counties when this is possible, the mean, the standard deviation, and the 10th, 50th and the 90th percentiles. All variables are measured in 2005. In Table 4, we report the correlations between the variables. In both tables, the analysis referring to the different loan variables is at bank-county level, while for the rest of the variables a bank level perspective has been employed. Focusing on the loan variables, from Table 3, it follows that on average $LOANS\ 2$ are lower than the other two loan types. Moreover, $LOAN\ 0$ show the lowest level of dispersion around the average, and finally, the 10th percentile of bank-pairs of $LOANS\ 2$ and $LOANS\ 3$ are nil, indicating that banks focus more on small size loans.

3.4.2 Unconditional average differences

We divide the banks in two groups (TARP and NO TARP) depending on whether they received TARP sustain and define BEFORE (2005) and AFTER (2010) periods. Then, we test whether the unconditional averages differ across groups and across periods. We run the following regression, excluding any additional explanatory variables:

$$Y_{s,t} = \alpha + \beta_1 time_t + \beta_2 TARP_s + \beta_3 TARP_s \times time_t + \epsilon_{s,t} \tag{1}$$

In Equation (1) the variable of interest, $Y_{s,t}$, is regressed on a constant, a *time* dummy

[10]For further information about the definitions: http://www.census.gov/did/www/saipe/ and http://www.bls.gov/cps/tables.htm

variable that captures the time dimension ($time$ takes value one in the AFTER period, zero otherwise); a $TARP$ dummy variable ($TARP$ takes value one if a bank has received TARP sustain, zero otherwise) and an interactive dummy variable, $TARP \times time$, capturing the difference in difference. Table 1 provides a quick view of the possible combinations.

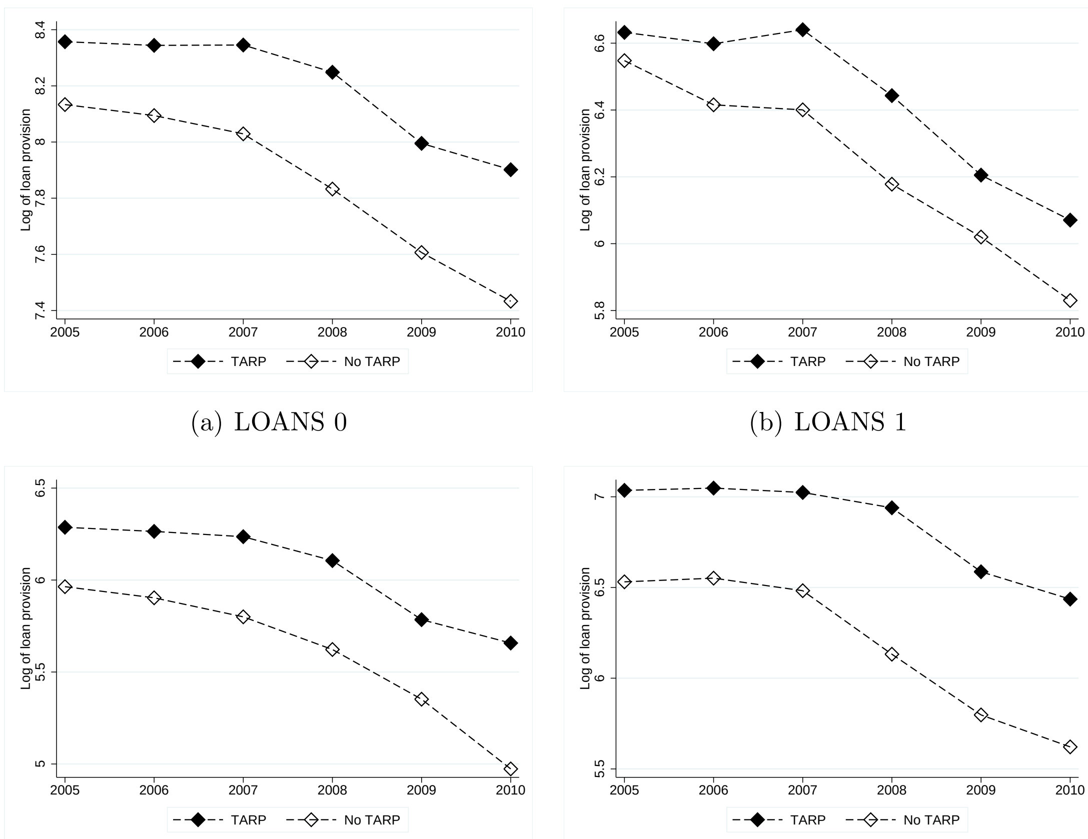
Table 1: Different cases

	TARP	NO TARP	Diff.
After	$\alpha + \beta_1 + \beta_2 + \beta_3$	$\alpha + \beta_1$	$\beta_2 + \beta_3$
Before	$\alpha + \beta_2$	α	β_2
Diff.	$\beta_1 + \beta_3$	β_1	β_3

We are interested in testing average differences within group across time and within time across groups. By fixing the bank group (TARP or NO TARP) we assess whether there are on average differences within the group and across periods. Instead, by fixing the time dimension (AFTER or BEFORE) we test whether there are on average differences across groups and within periods. Finally, taking the difference of the difference, we assess whether there are statistical significant differences across groups and across periods. As can be seen in Table 1, this effect is captured by β_3. The results are reported in Table 5 in the Appendix. It turns out that TARP banks provide more new loans. This is always true, regardless of the period (columns 1 and 2), and the type of loans. Moreover, both groups of banks decrease their loan provision between 2005 and 2010, but TARP banks do less (columns 3 and 4). As a consequence, the difference of the difference is positive and statistically significant for all loan types (column 5). A second finding refers to the level of $CAPRATIO$: in 2005 (column 1), TARP banks show lower level of capital buffer compared to the rest of the bank. All banks, over time, increase their capital buffer but TARP banks do more (columns 3 and 4). It follows that the difference of the difference is positive and statistically significant (column 5). Finally, looking at the non performing loans, the results highlight that in 2005 TARP banks show a lower level of non performing loans compared to the rest of the banks (column

1). Over time, both groups of banks are subject to higher non-performing loans, but TARP banks experience a higher expansion (columns 3 and 4). It follows that the difference of the difference is positive and statistically significant (column 5). From the previous analysis we can infer three main conclusions: TARP program alleviates the drop in loans; TARP banks use the financial sustain, at least partially, to increase their capital buffer; the borrowers' quality of the TARP banks decreases over time faster than that of the rest of the banks.

Figure 1: Per-quarter-group, averages



(a) LOANS 0

(b) LOANS 1

(c) LOANS 2

(d) LOANS 3

Notes: Per-quarter average loan origination to small businesses for TARP and NO TARP banks. Aggregation by giving each bank-county observation the same weight.

The results from the unconditional averages tests are confirmed by a visual counterpart (see Figure 1). For the different measures of loan origination, we document the per-quarter averages distinguishing between bank groups (TARP vs NO TARP)[11].

3.4.3 Aggregation

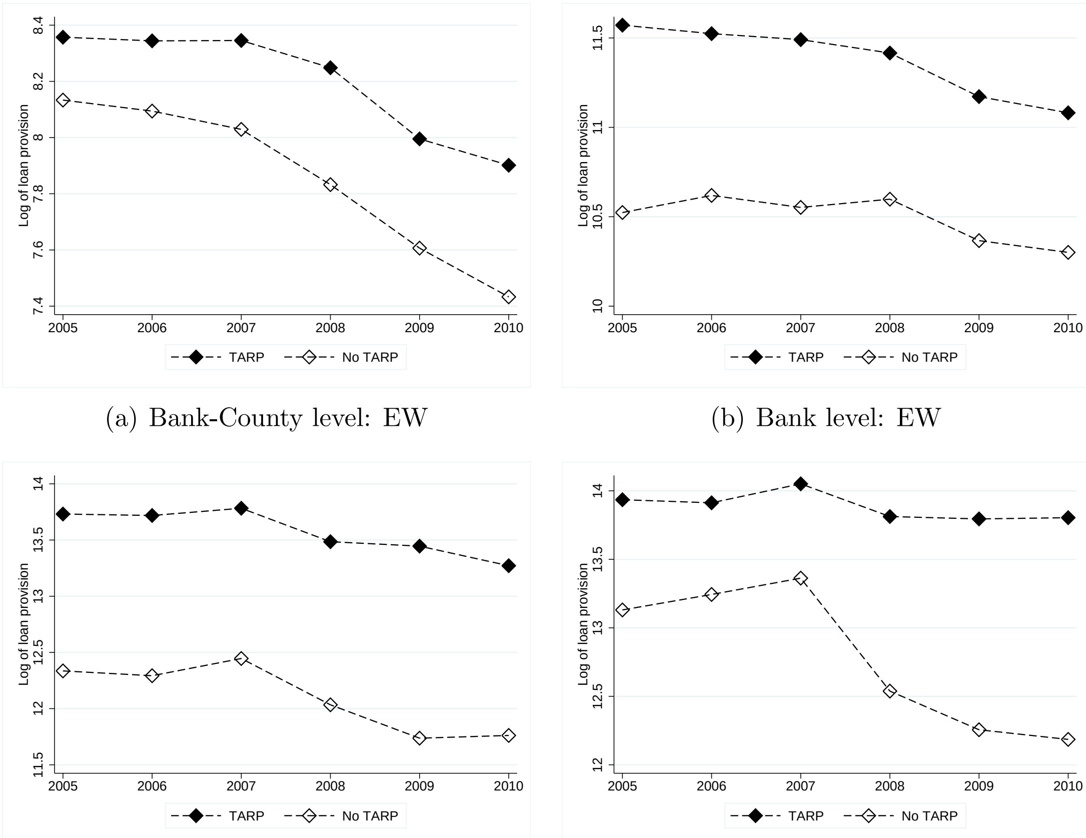
In the previous subsection we mentioned that in the aggregation process each observation received the same weight. However, depending on the weighting used to aggregate, different results are obtained. In Figure 2 we document for $LOANS$ 0 the results of the aggregation procedure using different approaches[12]. In Panel (a), the aggregation has been done at bank-county level, and each observation receives the same weight. In Panels (b), (c) and (d) the aggregation is at bank level. In this case, we first sum loan origination by bank across counties, and second compute the average across banks by year. Panel (b) shows the result when using equal-weight (for each bank) approach, while Panels (c) and (d) the weights are based on the number of counties where a bank provides loans (extensive margin) and the total loans provided by each bank (intensive margin).

Focusing on Panels (c) and (d) the clear common pattern refers to the important drop on average loans provision for the NO TARP banks from 2007 to 2008. These banks drastically reduce their lending activity in CRA counties. Also TARP banks show a drop in loan provision but it is of smaller magnitude. If we compare Panels (c) and (d) with Panel (b), the results differ: in the latter case, there is a drop in lending activity for TARP banks but not for the rest of the banks. This is not the case in Panels (c) and (d). On the one hand, NO TARP banks provide, on average, loans in more counties and they supply a larger amount of loans than TARP banks. On the other hand, they are also the banks that cut loan provision more. These effects are not captured if we ascribe equal weights to all the banks. If instead, the extensive and the intensive margin are taken into account these differences arise and the different patterns of the two groups of banks in loan provision are clearer.

[11] Each observation receives the same weight in the aggregation process.

[12] Using the other measures we obtain the same results.

Figure 2: Per-quarter-group, averages



(a) Bank-County level: EW

(b) Bank level: EW

(c) Bank level: CW

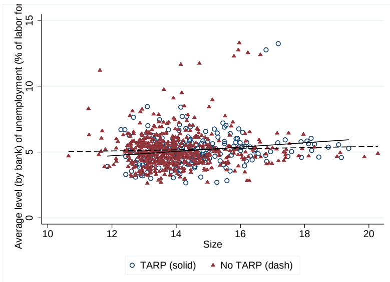
(d) Bank level: LW

Notes: Per-quarter averages of loan origination ($LOANS\,0$) for TARP and NO TARP banks, using different aggregation approaches. EW: equal weighted; CW: weighted by number of counties; LW: weighted by $LOANS\,0$.

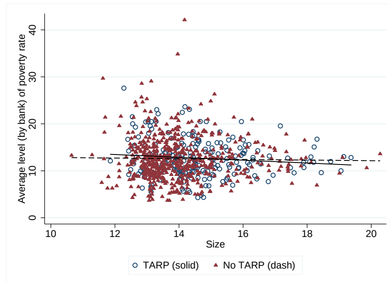
3.4.4 County socio-economic features

The importance of leading the analysis at county-level can also be motivated by the uneven density of banks across counties (see Figure 6), which may reflect an unequal distribution of business opportunities. These differences could drive our results. Therefore, it is of relevance to conduct an accurate analysis of the relationship between bank investment strategies and county features. In the perspective, by bank and year, we compute the average unemployment rate, the poverty rate and the average median income of the counties where the bank has loan activity. We are interested in assessing the relationship between these indicators and bank size. As documented in Figure 3, there are no substantial differences across the two groups of banks. This is true independently from the period considered. In particular, the results suggest that the average level of unemployment and poverty rates of the counties where a bank provides loans is weakly positively correlated with its size. A positive relationship for the two groups of banks characterises the relationship between the average median income of the countries where a bank has a lending activity and its size. This relationship disappears in 2010. It follows that bank size is not the main determinant in bank investment decision.

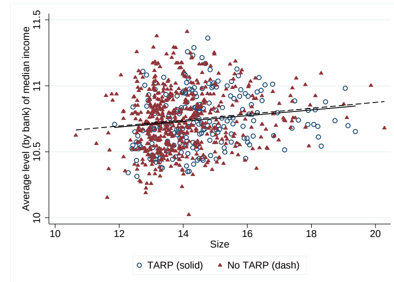
Figure 3: Scatter plot of average level of different socio-economic indicators of counties where banks provide loans and bank size



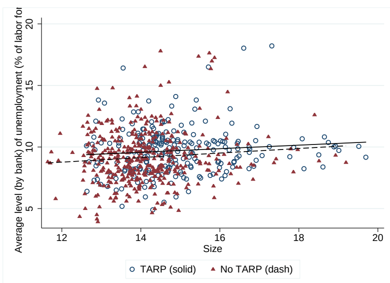
(a) Unemployment, 2005



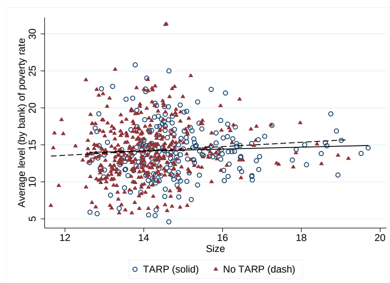
(b) Poverty, 2005



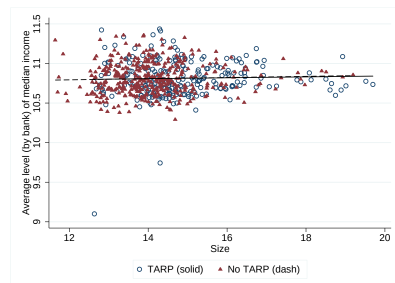
(c) Median income, 2005



(d) Unemployment, 2010



(e) Poverty, 2010

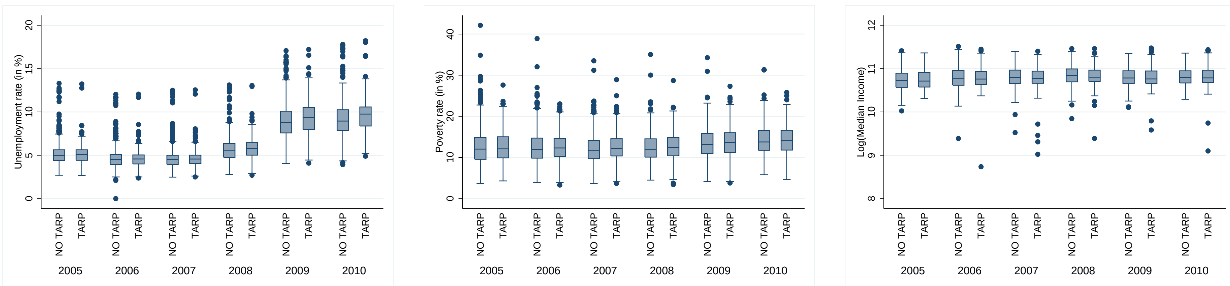


(f) Median income, 2010

*Notes:*For TARP and NO TARP banks we report the scatter plot between average values of unemployment rate, poverty rate, average median income of counties where a bank provides loans and its size for the years 2005 and 2010. The solid and dash lines refer to the fitted values for the TARP and NO TARP groups, respectively.

Furthermore, in Figure 4 we show the boxplots for the unemployment rate, poverty rate and log median income of the counties where the TARP and NO TARP banks invest. The figures document that there is no difference in the median between TARP and NO TARP in these measures for the entire period studied. These results indicate that the so-called demand side effect is not a driver in determining our results. Nevertheless, there may be interesting explanatory power in these measures which we discuss in subsection 5.3.

Figure 4: Boxplots for different socio-economic indicators of the counties where TARP and NO TARP bank provide loans



(a) Unemployment (b) Poverty (c) Median income

Notes: For TARP and NO TARP banks we report the evolution over time of the unemployment rate, poverty rate and median income of the counties where these groups of banks invest.

4 Econometric strategy

We estimate a panel regression based on the following specification:

$$\begin{aligned} LOAN_{i,j,t} =\ & \beta_1\, TARP_{i,t} + \beta_2\, TARP \times SIZE_{i,t} + \beta_3\, TARP \times CAPRATIO_{i,t} + \\ & \beta_4\, SIZE_{i,t} + \beta_5\, NPL_{i,t} + \beta_6\, TOTLOANS_{i,t} + \beta_7\, RELOANS_{i,t} + \beta_8\, CAPRATIO_{i,t} + \\ & \beta_9\, NOCORE\_PA_{i,t} + \beta_{10}\, TOT\_UNCOMM_{i,t} + \alpha_i + \gamma_j + \delta_t + \xi_{i,j,t} \end{aligned} \tag{2}$$

The dependent variable is total loan origination to small businesses provided in year (t) by bank (i) in county (j). We include bank, county, and year fixed effects (α_i, γ_j, and δ_t, respectively). The inclusion of $SIZE$ has the aim to control for the size of the bank in the lending activity: larger banks could provide more loans because of their size. NPL captures potential pressures on bank lending activity due to non-performing loans. TOT $LOANS$ captures the overall loan activity of the bank. $RELOANS$ has been taken into account to control for the bank exposure in the real estate market. The $CAPRATIO$ is added to measure the potential impact of bank soundness on bank loan provision. Finally, TOT $UNCOMM$ and $NOCORE$ PA capture, respectively, the potential liquidity risk, and the bank's financing sources (in particular for wholesale funding) effect on the dependent variable. The inclusion of this set of variables is in line with previous contributions in the same field[13]. Finally, the effect of the TARP program on loan origination is captured by $TARP$, which takes value one from the moment the bank benefited from the TARP program and zero otherwise. In the main specification, we also include two other variables. On the one hand, the interaction of TARP with $SIZE$ ($TARP \times SIZE$) captures a size effect: as documented by Li (2011), TARP sustain has been given above all to small banks (excluding the 9 banks that have been forced to participate to the TARP). Including this variable we control for this potential effect. On the other hand, the interaction term of TARP with $CAPRATIO$ ($TARP \times CAPRATIO$) aims to control for the capitalization effect: less well capitalized banks might use TARP funds to increase their capital buffer instead of providing loans. In all estimations we cluster standard errors by bank.

5 Hypotheses and Results

5.1 TARP effect on bank loans

Equation (2) allows us to test the hypothesis whether the TARP program has an impact on loan provision. Specifically, our hypothesis is that:

H1: Banks that benefited from the TARP program provide more loans than the other banks.

The results reported in columns (1) and (2) of Table 6 confirm *H1*. In particular, as shown in column (1), TARP program increases bank loan origination by 12%. In column (2) we add the interaction terms[14] $TARP \times SIZE$ and $TARP \times CAPRATIO$. Looking

[13] See for instance, Goetz and Gozzi (2010).

[14] When computing the marginal effect of the TARP program we measure SIZE and CAPRATIO at the average values of the TARP banks for the period included between 2007 and 2010.

at the marginal effect of TARP program on loan provision it follows that the results do not change. From this first analysis we can conclude that the TARP program achieved its goal to help banks in financing small businesses and households. The results can be justified by using a simple banking model[15], where banks have capital ratios targets to meet in each period. If a bank incurs losses (possibly due to loan write-downs), its equity is lowered and the bank has to act to re-establish the desired capital ratio. It can either increase equity or cut the asset side. Peek and Rosengren (1991) show that, above all during a crisis, the first possibility is more expensive. Therefore, the easiest thing to do is to reduce the asset side. If banks are provided with new equity, they can increase the capital ratio without cutting credit. According to our results, this is exactly what the TARP program did.

5.2 TARP program and banks geographical coverage

It could be that previous results are driven by some features of the banks. In particular, a key role in the effectiveness of the TARP program could be played by banks geographical coverage. The argument behind the above intuition refers to a signal extraction theory[16]: assume that each county included in the dataset can be potentially hit by a negative economic shock. This shock can be more or less persistent. Ex-ante, banks do not know about the type of shock they observe. They receive a signal of the shock from each county where they provide loans. The larger the number of counties where a bank invests, the higher is the quality of the signal received. Therefore, banks with a higher geographical coverage have better signals, and hence they can better distinguish the nature of the shock. Alternatively, we can interpret banks geographical coverage as a proxy for bank diversification. Banks know that the counties where they invest can be hit by economic shocks that are at least partially idiosyncratic. In order to minimize the risk of a shock, banks apply the rule of "not putting

[15] See for instance Shrieves and Dahl (1992), Jacques and Nigro (1997), Aggarwal and Jacques (2001), Jokipii and Milne (2010).

[16] See for instance Chamley (2004).

all the eggs in the same basket". As a consequence banks with high geographical coverage may supply a larger level of loans because their risk associated to the economic shock is lower.

In order to measure banks geographical coverage we construct three alternative measures. According to our definitions, a bank shows high geographical coverage if:

- it provides loans in more than one US state;
- if it provides loans in more than 5 counties[17];
- if the average distance between all the counties where the bank provides loans is larger than 60 kilometres[18].

According to the three definitions, the dataset contains 28%, 41% and 47% of banks with high geographical coverage, respectively[19]. Moreover, among the high geographical coverage there are 39%, 36% and 33% of TARP banks, respectively. Based on these alternative measures we test the following hypothesis:

H2: TARP program is effective only for banks with high geographical coverage.

The results, reported in Table 7, show that independently from the measure employed the TARP program is effective for banks with high geographical coverage, columns (2), (4) and (6), while its effect is not statistical significant for low geographical coverage banks, columns (1), (3) and (5).

The idea behind the geographical coverage hypothesis is that by increasing their geographical coverage, banks can exploit a certain degree of heterogeneity at county level to obtain better signals about a shock or to implement more effective diversification policies. To support our intuition, we define a measure of county heterogeneity that is reflected by

[17]The threshold refers to the median number of counties where a bank provides loans in 2005.

[18]The threshold refers to the median value of the average distance of the counties where the banks provide loans in 2005.

[19]Banks can enter in both groups due to the fact that the geographical coverage is a bank feature that changes across years.

bank investment strategy. More precisely, we compute the difference between the maximum and the minimum measure of the median income of the counties where each bank invests (Δmax-min), and then we compare the average values for low and high geographical coverage. The banks with high geographical coverage show a higher average value. As documented in Table 2, for each measure of geographical coverage the difference between groups is positive and statistically significant, confirming indirectly our intuition: banks with high geographical coverage invest in more heterogeneous counties (based on median income). This implies that, in case of a shock, high coverage banks can potentially receive more informative signals or the risk of being affected by the shock is smaller due to a diversified strategy.

Table 2: Heterogeneity across counties in median income, 2005

Geographical coverage:	Crossstate			No. of counties			Avg. distance		
	0	1	Δ	≤ 5	> 5	Δ	≤ 0.55	> 0.55	Δ
Δmax-min	0.275	0.679	0.404***	0.183	0.641	0.458***	0.203	0.550	0.346***
	(0.267)	(0.320)	(0.025)	(0.215)	(0.274)	(0.018)	(0.264)	(0.300)	(0.020)
Obs.	586	586	784	452	332	784	390	394	784

Notes: For each measure of geographical coverage we test whether the max-min difference of the median income of the counties where banks invest is statistically significant.

5.3 Demand side effect

Until now we did not explicitly control for demand side effect. It could be that our findings do not depend on the TARP effect, but instead they are driven by the socio-economic features of the counties where TARP banks are located. Specifically, TARP banks could be located in economically sounder counties. In order to control for this potential issue we add to Equation (2) four additional variables: $POVERTY$, $UNEMPLOYMENT$ and the interactions with the TARP program dummy variable: $TARP \times POV$ and $TARP \times UNEMP$. The two socio-economic variables capture different issues: $POVERTY$ captures chronic economic problems, while $UNEMPLOYMENT$ is more related to temporary economic frictions[20]

[20] A way to check this intuition is to calculate at county level the standard deviation of the two variables assessing economic distress and then to compute their average values. Unemployment shows higher variability than poverty (.98 versus .74) , confirming our intuition.

Our third hypothesis takes the following form:

H3: TARP program is effective if a county has temporary economic troubles, while it is not effective in counties with permanent economic issues.

The idea behind *H3* is that in case of negative shocks hitting the economy, firms reduce the number of employees or are forced to close. This leads to an increase in unemployment, captured by the $UNEMPLOYMENT$ indicator. In this circumstance, TARP sustain is effective, because it can provide banks with additional credit that can be employed to keep on financing productivity activities. On the other hand, high poverty reflects more persistent characteristics of a county, which are unlikely to change in case of an external financial sustain. In this context, even if banks benefit from the TARP program, and therefore potentially have additional resources to invest, they do not find any type of demand for loans. It follows that, in this context, the TARP program is not effective. The findings reported in Table 8 confirm our intuitions: unemployment and poverty negatively impact the provision of new loans. Moreover, the TARP program is effective in context afflicted by temporary economic problems, but it is useless in counties that suffer from more persistent economic issues. When computing the total effect of the TARP program we find that the results referring to LOANS 0 and LOANS 1 do not suffer from demand side effect. The effect of the TARP program disappears if LOANS 2 and LOANS 3 are considered.

6 Robustness

6.1 Participation effect

The selection process of the TARP program contains three steps. Firstly, banks opt to ask for TARP sustain. Secondly, the US Treasury certifies the eligibility of the bank. Thirdly, once banks have received the confirmation of being eligible by the Treasury, they either accept or refuse the financial help. As Taliaferro (2009) points out, the Treasury rejected less than 16% of the institutions that applied for the TARP program, therefore the main concerns about the selection issues refer to the first degree of selection. The selection or participation effect might bias our results. More precisely, it could be that what drives the results is not the TARP program but the features (not controlled) of the banks that affected banks decision about the participation to the TARP program. From a general point of view, we drop from the sample those banks that in some period of the sample taken into account exhibited capital ratio smaller than the minimum amount of capital (6%) required by the Fed. Moreover, we also exclude from the sample those banks that have been forced by the Treasury to participate to the TARP program. We control for the selection effect also in an explicit way, by using two alternative approaches. In the first one we run a run a matching exercise. More precisely, using 2005 data, we match TARP and NO TARP banks, taking five neighbours, with respect to the following variables: $SIZE$, $CAPRATIO$, TOT_UNCOMM, $NOCORE\_PA$, TOT_LOANS $REALOANS$, NPL, $POVERTY$ and $UNEMPLOYMENT$. In this way, we generate a sub-sample of 44923 observations, 405 banks, and 2589 counties. Alternatively, we only include observations of counties where the fraction of TARP banks over all banks is strictly between zero and one (which we call 'dropping extreme cases'). This ensures that in every county there is at least one No TARP bank, and at least one TARP bank. The sub-sample generate using this strategy counts for 48069 observations, 1023 banks, and 1801 counties.

The results reported in Table 9 in the Appendix show that the matching exercises and the 'dropping extreme cases' approach lead to similar results: even when controlling for the potential selection effect, the TARP program is effective in sustaining banks in their lending activity. For the total level of loans at the origination the results do not change: the estimated coefficient is still statistical significant and positive.

6.2 Loan size

As described in Section 3, the CRA dataset provides data about loans distinguishing by small, medium and large loans. We test our results by exploiting this information. In particular, we test our hypothesis by using as dependent variables LOANS 1, LOANS 2 and LOANS 3. As reported in Table 6, columns (3), (4) and (5) the result about the TARP effect does not change when different loan sizes are employed. The results are also confirmed when using a matched sample (see Table 9, columns (2), (3) and (4)). When using an alternative approach to control for the selection issue, as documented in Table 6, columns (6) to (8), the results hold for LOAN 1, while the coefficient of the TARP dummy is not statistically significant in case of LOAN 2 and LOAN 3. When we look at the geographical coverage and the demand side effect hypotheses similar results are found[21]: there exists a geographical coverage effect for $LOAN$ 1, while no effect is measured when using $LOAN$ 2 and $LOAN$ 3 (see Table 10); TARP is effective in counties with high unemployment but not with high poverty in case of LOAN 1, while the findings seem driven by a demand side effect when considering the other loan sizes. (see Table 8).

6.3 Loan provision

As documented in subsection (3.3) TARP banks provide more loans than the other banks independently from the period analysed. It could be that the results obtained are not related to the TARP program but they can be ascribe to this features of the TARP banks. In order to control for this potential issue, we adopt two alternative strategies.

[21]The results referring to the geographical hypothesis are not shown to save some space and are available upon request. Results about the demand side hypothesis are reported in Table 8 in the Appendix.

6.3.1 Placebo experiment

The first strategy consists in running a "placebo" experiment. More precisely, we consider from 2001 to 2007, prior to the crisis and the policy action. We still distinguishing between TARP banks and NO TARP banks, but we fictionally assume that the TARP participation took place four years earlier. Accordingly, a bank that participated to the true TARP program in 2009, participates to the placebo TARP program in 2005. We run the baseline regressions by using the placebo-sample. If our results are not driven by the fact that TARP banks per se provide more loans, we should find the TARP effect is statistically not significant, or better that the sign is negative. The results of the placebo experiment, reported in Table 11 confirm our intuition. In all the cases the TARP effect is always negative, and it is statistically significant for the total amount of loans provided. It follows that our results are not driven by the fact that TARP banks they always provide a larger level of loans than the rest of the banks.

6.3.2 Matching exercise

The second strategy adopted is based on propensity score matching. More precisely, we match TARP banks with the others based on their loan provision types, size and capratio measured in 2005. In this way, we consider only banks that ex-ante show similar features but the participation to the TARP program. In the matched sample there are 594 banks (TARP and NO TARP) and 2744 counties. The results of the baseline regression estimated using the matched sample are reported in Table 11. The results show that the TARP effect is still positive and statistical significant for all loan types. These results, together with those referring to the placebo experiment suggest that our results are driven by the TARP program and not by the loan provision features that distinguish the TARP banks form the others during the period analysed.

6.4 TARP amount

In the baseline analysis we do not control for the size of the sustain received by each bank in the context of the TARP program. Since most TARP funds have been provided to bank holding companies (BHC), we do not know exactly the amount received by each bank. We assume that each bank of a BHC receives TARP funds proportionally to its total assets over BHC total assets[22]. We call this new variable $TARPAmount/TotalAssets$, which is bank specific and time variant. We modify the baseline model by replacing the TARP dummy by the new variable. The results, reported in Table 12, show that a 1 percentage point increase in TARP leads to a 4 percent increase in total loan origination. It follows that the participation as well as the amount received play a crucial role in the loan provision process.

6.5 Discussion

The debate about the effectiveness of the TARP program is a hot topic among academics and politicians. As mentioned at the beginning of this paper, there is no consensus about it, and this is probably due to the fact that the opinion changes depending on the point of view adopted for the analysis. In this contribution we focus on the effect of the TARP program, and in particular of the CPP program, on loan origination. Our analysis focuses on banks that provide loans to small business, as reported in the CRA. From a general point of view, our findings highlight that the TARP program did increase loan origination. TARP banks provide on average 12 percent more loans than the rest of the bank. From this perspective the US Treasury through the CPP program avoided a stronger contraction in bank loan activity.

Moreover, the results also document the importance of banks geographical coverage[23] in the effectiveness of the TARP program. We find that the TARP program is effective only

[22]This measure is potentially biased, since we only take into account subsidiaries of a BHC which are in our dataset.

[23]We employ three different measures of geographical coverage, based on the number of US states, the number of counties or the average distance between all the counties where a bank provide loans.

for banks with high geographical coverage. This result can be interpreted using a signalling extraction or a diversification strategy argument. Therefore, the policy advice that follows from our finding is that TARP-like programs have to be addressed to financial institutions that are able to better interpret the shocks that hit the economic system, or that have the possibility to adopt diversification investment strategies. Furthermore, from these results it also follows that, in normal times, the practice of the banks of investing in a large number of counties, should be promoted.

Finally, our results highlight that the TARP program was effective when banks were investing in counties that were not in an economic distressed situation, or in those counties that suffer from cyclical economic problems. The TARP program is not effective in those cases where banks invest in counties with persistent economic problems. The policy implication that follows is that TARP-like programs are more effective to contrast temporary distressed situations. In contrast, in order to solve or reduce chronic episodes of economic distress the policy maker should put in place alternative measures, which do not must necessary be implemented through the banking system.

7 Conclusion

According to a report of the US Small Business Administration (Kobe, 2012), in 2008 Small Businesses (businesses with less than 500 employees) account for 46 percent of total non-farm GDP and about 50 percent in total non-farm employment. Moreover, as claimed by Berger and Udell (2002) "Small firms are [...] vulnerable because of their dependence on financial institutions for external funding. These firms simply do not have access to public capital markets." This fact is confirmed from data collected by the Federal Reserve Board (2003), where 87 percent of small firms report that their lender is a bank. From the above figures it is clear that sustaining small businesses is a national issue and it is crucial for the entire US economy. During the last financial crisis, the US Treasury launched the Capital Purchase Program (CPP) in the framework of the Troubled Asset Relief Program (TARP) in order to help banks in their lending activity to support small businesses and households. Contrasting opinions characterize the debate about the TARP program. This is due to the multiple aspects that refer to this program. In this paper we assessed whether the TARP program through the CPP achieved the goal of helping banks in sustaining loan activity to firms and small businesses. We used a unique dataset obtained by merging information of bank balance sheets (Call Reports, Fed of Chicago), TARP participation (US Treasury) and loan origination (Federal Financial Institutions Examination Council, FFIEC) to small businesses. We consider an annual dataset from 2005 to 2010 with observations for each bank-county pair. Using a panel data approach (fixed effects, standard errors clustered by banks), our results highlight that TARP banks provide on average 12% higher loan origination than the other banks. Moreover, the TARP program is effective only for banks with high geographical coverage. Moreover, poverty and unemployment are detrimental for loan provision. In particular, TARP is still effective in counties affected by unemployment issues, while this is not the case if the bank that received the TARP sustain is located in counties suffering from poverty issues. When computing the total TARP effect we find that the results are not driven by a demand side effect. Several robustness checks confirm the main results. In particular, we control for the selection issue as well as for the dependent variable employed., This paper contributes to filling the gap in the literature about the TARP program effectiveness. In particular, our results shed light on the effectiveness of the TARP program on a specific group of banks, those that provide loans to small businesses. The findings show that the TARP program was effective, but at the same time we provide evidence that this is true only for a particular type of banks (those with high geographical coverage) and that in some cases, when the county suffer of poverty issues the TARP program is no more effective.

References

[1] A. N. Berger and G. F. Udell, "Small business credit availability and relationship lending: The importance of bank organisational structure," *The Economic Journal*, vol. 112, no. 477, 2002.

[2] K. Kobe, "Small business GDP: Update 2002–2010," tech. rep., U.S. Small Business Administration, 2012.

[3] The Federal Reserve Board, "2003 survey of small business finances," 2003.

[4] R. Aggarwal and K. T. Jacques, "The impact of FDICIA and prompt corrective action on bank capital and risk: Estimates using a simultaneous equations model," *Journal of Banking & Finance*, vol. 25, pp. 1139–1160, June 2001.

[5] D. Bayazitova and A. Shivdasani, "Assessing TARP," *Review of Financial Studies*, vol. 25, no. 2, pp. 377–407, 2012.

[6] C. P. Chamley, *Rational Herds*. Cambridge University Press, 2004.

[7] J. C. Gozzi and M. Goetz, "Liquidity shocks, local banks, and economic activity: Evidence from the 2007-2009 crisis," *mimeo*, 2010.

[8] K. Jacques and P. Nigro, "Risk-based capital, portfolio risk, and bank capital: A simultaneous equations approach," *Journal of Economics and Business*, vol. 49, no. 6, pp. 533–547, 1997.

[9] T. Jokipii and A. Milne, "Bank capital buffer and risk adjustment decisions," *Journal of Financial Stability*, vol. 7, pp. 165–178, August 2011.

[10] L. Li, "TARP funds distribution and bank loan supply," tech. rep., Boston College, 2011.

[11] J. Peek and E. Rosengren, "The capital crunch: neither a borrower nor a lender be," Working Papers 91-4, Federal Reserve Bank of Boston, 1991.

[12] R. E. Shrieves and D. Dahl, "The relationship between risk and capital in commercial banks," *Journal of Banking & Finance*, vol. 16, pp. 439–457, April 1992.

[13] R. Taliaferro, "How do banks use bailout money? optimal capital structure, new equity, and the TARP," tech. rep., Harvard Business School, Finance Unit, 2009.

[14] L. Wilson and Y. W. Wu, "Escaping TARP," *Journal of Financial Stability*, vol. 8, no. 1, pp. 32 – 42, 2012.

[15] F. P. V. Jeffrey Ng and R. W. Moerman, "The impact of TARP's capital purchase program on the stock market valuation of participating banks," Research Paper No. 10-10, Chicago Booth, 2012.

Appendices

A Tables

Table 3: Descriptive Statistics

Variable	mean	sd	p10	p50	p90
LOANS 0	8.236	1.866	5.787	8.375	10.52
LOANS 1	6.587	2.053	4.234	6.836	8.843
LOANS 2	6.112	2.856	0	6.815	8.925
LOANS 3	6.763	3.384	0	7.717	10.01
CAPRATIO	8.817	2.578	6.710	8.365	11.20
SIZE	14.17	1.381	12.81	13.92	16.05
TOTAL UNCOMM	.201	.283	.0775	.167	.299
NO CORE PA	.255	.127	.114	.242	.410
TOTAL LOANS	.641	.137	.467	.667	.789
RELOANS	.733	.168	.511	.757	.925
NPL	.0132	.0122	.00230	.0104	.0267

Notes: The descriptive statistics referring the different types of loans are bank-county based. The rest of the descriptive statistics refer to the bank level. The results refer to 2005. At bank-county level there are 10047 observations, 794 banks and 2634 counties. At bank level there are 794 observations that correspond also to the number of banks.

Table 4: Correlations

Variables	LOANS 0	LOANS 1	LOANS 2	LOANS 3			
LOANS 0	1						
LOANS 1	.805***	1					
LOANS 2	.833***	.690***	1				
LOANS 3	.876***	.605***	.668***	1			
	CAPRATIO	SIZE	TOTAL UNCOMM	NO CORE PA	TOTAL LOANS	RELOANS	NPL
CAPRATIO	1						
SIZE	-.173***	1					
TOTAL UNCOMM	.153***	.175***	1				
NO CORE PA	-.0405	.0643	.122***	1			
TOTAL LOANS	-.0303	-.156***	.0266	.153***	1		
RELOANS	-.0162	-.299***	-.351***	-.00225	.228***	1	
NPL	.189***	.00578	.000579	.128***	.0438	-.0924**	1

Notes: $*** = p < .001$, $** = p < .01$, $* = p < .05$. The correlations referring the different types of loans are bank-county level based. The correlations between the other variables are bank level based. The correlations are measured in 2005.

Table 5: Averages diff in diff (Unconditional)

Variable	Before	After	No TARP	TARP	Diff in Diff
LOANS 0	0.224***	0.468***	-0.700***	-0.456***	0.245***
	(0.037)	(0.039)	(0.040)	(0.036)	(0.054)
LOANS 1	0.084**	0.241***	-0.718***	-0.562***	0.156***
	(0.041)	(0.042)	(0.044)	(0.039)	(0.058)
LOANS 2	0.323***	0.684***	-0.991***	-0.629***	0.362***
	(0.057)	(0.062)	(0.062)	(0.056)	(0.084)
LOANS 3	0.504***	0.815***	-0.910***	-0.600***	0.310***
	(0.067)	(0.072)	(0.073)	(0.066)	(0.098)
CAPRATIO	-0.456***	0.238***	0.696***	1.390***	0.694***
	(0.031)	(0.039)	(0.040)	(0.029)	(0.050)
SIZE	1.256***	1.497***	-0.159***	0.082**	0.241***
	(0.040)	(0.037)	(0.039)	(0.038)	(0.054)
TOTAL UNCOMM	0.070***	0.055***	-0.055***	-0.070***	-0.015***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)
NO CORE PA	-0.011***	-0.024***	-0.042***	-0.055***	-0.013***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
TOTAL LOANS	0.015***	0.018***	-0.011***	-0.008***	0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
RELOANS	-0.053***	-0.035***	0.014***	0.032***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
NPL	0.000*	0.007***	0.039***	0.046***	0.007***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)

Notes: *** $= p < .001$, ** $= p < .01$, * $= p < .05$. The statistics referring the different types are bank-county level based. The rest of the statistics are bank level based. The before period is 2005, the after period is 2010. TARP stays for the group of banks that received the financial sustain through the TARP program, while NO TARP includes the rest of the banks.

Table 6: Baseline

Dependent variable:	LOANS 0	LOANS 0	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)	(5)
TARP	.100*	.420	.569	.383	.199
	(.054)	(.435)	(.506)	(.336)	(.354)
TARP × Size		-.014	-.029	-.014	-.005
		(.019)	(.025)	(.016)	(.016)
TARP × Capratio		-.011	-.001	-.013	-.006
		(.022)	(.023)	(.016)	(.017)
Size	.365***	.370***	.350**	.273***	.239**
	(.114)	(.115)	(.136)	(.094)	(.097)
Total Uncomm.	.234***	.228**	.131	.140	.474*
	(.090)	(.090)	(.112)	(.181)	(.282)
Non-Core Fin.	.825**	.814**	.702**	.549**	.676***
	(.325)	(.322)	(.343)	(.243)	(.249)
Capratio	-.010	-.006	-.017	-.000	-.003
	(.013)	(.014)	(.022)	(.011)	(.009)
Total Loans	.184	.200	.153	.535**	.588**
	(.326)	(.335)	(.329)	(.251)	(.281)
Real Est. Loans	-.139	-.168	.184	-.014	-.182
	(.424)	(.420)	(.439)	(.323)	(.299)
Non-Perf. Loans	-2.412***	-2.384***	-1.129**	-1.384***	-1.970***
	(.590)	(.592)	(.524)	(.415)	(.450)
Marginal effect TARP	.100	.127	.135	.0664	.0776
p-value	.0647	.0101	.00280	.0811	.0829
Obs.	60411	60411	58193	50013	48723
Banks	1048	1048	1032	1031	1034
County	2812	2812	2805	2684	2599

Notes: *** $= p < .001$, ** $= p < .01$, * $= p < .05$. Column (1) does not include the interaction terms between TARP and SIZE and TARP and Capratio. The other columns include these two additional variables. Columns (1) and (2) refer to the total loans at the origination, while columns (3), (4) and (5) refer to the different type of loans: $\leq$ 100k, $\leq$ 250k and $\leq$ 1m.

Table 7: Geographical coverage

Dependent variable:	Total Small Business Loans Originations 1+2+3					
Geographical coverage:	Crossstate		No. of counties		Avg. distance	
	0	1	≤ 5	> 5	≤ 0.55	> 0.55
	(1)	(2)	(3)	(4)	(5)	(6)
TARP	-.563	.307	.953	.385	.531	.375
	(.701)	(.580)	(.809)	(.486)	(.719)	(.494)
TARP × Size	.032	-.006	-.051	-.011	-.011	-.013
	(.044)	(.025)	(.055)	(.021)	(.051)	(.022)
TARP × Capratio	.019	-.012	-.031	-.009	-.034	-.007
	(.031)	(.027)	(.023)	(.024)	(.036)	(.025)
Size	.775***	.318***	.438***	.367***	.789***	.332***
	(.164)	(.122)	(.116)	(.119)	(.244)	(.117)
Total Uncomm.	.348***	-.273	.266***	.114	.304***	.036
	(.057)	(.630)	(.035)	(.572)	(.073)	(.397)
Non-Core Fin.	.472	.966*	.248	.825**	.661	.822**
	(.348)	(.511)	(.236)	(.367)	(.491)	(.405)
Capratio	.014	-.023	.008	-.009	-.003	-.009
	(.016)	(.021)	(.008)	(.019)	(.018)	(.019)
Total Loans	.188	.355	1.469***	.002	.602	.219
	(.423)	(.488)	(.268)	(.401)	(.440)	(.403)
Real Est. Loans	-1.121	.148	-.195	-.127	-.407	-.111
	(.737)	(.539)	(.379)	(.455)	(.817)	(.484)
Non-Perf. Loans	-1.874**	-2.737***	-1.995***	-2.379***	-2.264*	-2.506***
	(.868)	(.866)	(.627)	(.712)	(1.295)	(.702)
Marginal effect TARP	.0450	.118	-.0222	.140	.0935	.122
p-value	.516	.0824	.636	.0118	.304	.0338
Obs.	16742	43669	5833	54578	8089	52322
Banks	836	326	687	480	630	550
County	1927	2635	999	2791	1009	2792

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. The results refer only to total loans. Findings about the other measures of loan provisions are available under request. Three different measures of geographical coverage have been employed: findings reported in columns (1) and (2) refer to the cross-state definition; results in columns (3) and (4) are based on the number of counties where a bank invests; finally, estimates reported in columns (5) and (6) refer to the average distance between counties where a bank invests.

Table 8: Demand side effect

Type of sample:	Unmatched				Matched			
Dependent variable:	LOANS 0	LOANS 1	LOANS 2	LOANS 3	LOANS 0	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP	.391	.566	.424	.164	.348	.754	.489	.117
	(.452)	(.524)	(.343)	(.348)	(.469)	(.628)	(.350)	(.352)
TARP × Size	-.015	-.027	-.015	-.006	-.010	-.034	-.014	.001
	(.021)	(.025)	(.017)	(.017)	(.020)	(.030)	(.016)	(.017)
TARP × Capratio	-.010	.002	-.016	-.012	-.006	-.003	-.021	-.014
	(.023)	(.025)	(.016)	(.017)	(.026)	(.032)	(.019)	(.019)
TARP × UNEMPL	.017*	.008	.012*	.021***	.016	.005	.012	.022***
	(.009)	(.008)	(.007)	(.006)	(.011)	(.009)	(.008)	(.007)
TARP × POVERTY	-.009**	-.009**	-.007**	-.005*	-.010***	-.008**	-.008***	-.006**
	(.004)	(.004)	(.003)	(.003)	(.004)	(.004)	(.003)	(.003)
UNEMPLOYMENT	-.020*	-.016	-.013*	-.028***	-.021	-.016	-.014	-.028**
	(.012)	(.010)	(.008)	(.009)	(.014)	(.012)	(.009)	(.011)
POVERTY	-.005	-.001	-.003	-.005	-.004	-.003	-.003	-.004
	(.003)	(.004)	(.003)	(.004)	(.004)	(.005)	(.004)	(.004)
Size	.329***	.342**	.247***	.220**	.366***	.433***	.269***	.218**
	(.112)	(.139)	(.093)	(.098)	(.124)	(.159)	(.103)	(.106)
Total Uncomm.	.212**	.118	.122	.467*	.174	-.085	.235	.472
	(.087)	(.117)	(.180)	(.276)	(.423)	(.513)	(.296)	(.319)
Non-Core Fin.	.737**	.735*	.512**	.590**	.964**	1.153**	.602*	.798**
	(.370)	(.386)	(.257)	(.263)	(.414)	(.490)	(.318)	(.311)
Capratio	-.007	-.019	.001	-.001	-.011	-.014	.006	-.001
	(.014)	(.023)	(.012)	(.010)	(.021)	(.034)	(.017)	(.014)
Total Loans	.391	.095	.593**	.596*	-.004	-.114	.338	.294
	(.349)	(.371)	(.266)	(.306)	(.475)	(.492)	(.360)	(.398)
Real Est. Loans	-.024	.118	-.070	-.213	-.022	.455	.108	-.160
	(.421)	(.490)	(.325)	(.313)	(.505)	(.665)	(.390)	(.353)
Non-Perf. Loans	-2.160***	-1.414**	-1.290***	-1.752***	-2.026**	-1.315	-1.221**	-1.889***
	(.667)	(.659)	(.439)	(.519)	(.895)	(.890)	(.597)	(.713)
Marginal effect TARP	.0906	.124	.0534	.0550	.118	.149	.0726	.0826
p-value	.0549	.00624	.165	.206	.0469	.00669	.142	.151
Obs.	57497	55580	48054	46872	46601	45431	39268	38446
Banks	1038	1022	1021	1024	404	404	402	400
County	2725	2718	2599	2514	2492	2484	2378	2316

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. Columns (1) to (4) report the results for the unmatched sample. Columns (5) to (8) refer instead to the matched sample.

Table 9: Participation effect and H1

Method:	Matching				Dropping extreme cases			
Dependent variable:	LOANS 0	LOANS 1	LOANS 2	LOANS 3	LOANS 0	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP	.420	.798	.466	.173	.280	.807	.287	-.029
	(.453)	(.623)	(.345)	(.359)	(.436)	(.625)	(.348)	(.356)
TARP × Size	-.012	-.038	-.015	.000	-.004	-.040	-.008	.005
	(.019)	(.030)	(.016)	(.016)	(.019)	(.034)	(.016)	(.017)
TARP × Capratio	-.011	-.009	-.019	-.010	-.014	-.008	-.011	.003
	(.025)	(.030)	(.018)	(.019)	(.022)	(.025)	(.017)	(.017)
Size	.384***	.431***	.275***	.223**	.437***	.467***	.323***	.266**
	(.129)	(.159)	(.105)	(.105)	(.123)	(.161)	(.097)	(.104)
Total Uncomm.	.199	.011	.241	.496	.276***	.188**	.151	.550*
	(.431)	(.517)	(.295)	(.325)	(.085)	(.092)	(.184)	(.295)
Non-Core Fin.	.958**	1.077**	.596*	.806***	.658**	.696*	.496**	.539**
	(.394)	(.488)	(.313)	(.302)	(.310)	(.380)	(.250)	(.260)
Capratio	-.008	-.009	.005	-.002	-.010	-.013	-.005	-.008
	(.021)	(.034)	(.016)	(.013)	(.014)	(.022)	(.012)	(.010)
Total Loans	-.102	-.081	.343	.335	.176	.133	.465*	.567**
	(.475)	(.465)	(.345)	(.377)	(.324)	(.314)	(.252)	(.280)
Real Est. Loans	-.260	.482	-.004	-.222	-.201	.273	-.045	-.209
	(.504)	(.636)	(.386)	(.344)	(.426)	(.497)	(.324)	(.297)
Non-Perf. Loans	-2.232***	-.879	-1.471***	-1.993***	-2.549***	-.957*	-1.505***	-2.037***
	(.724)	(.749)	(.553)	(.640)	(.608)	(.546)	(.433)	(.462)
Marginal effect TARP	.141	.155	.0822	.0954	.108	.142	.0723	.0769
p-value	.0240	.00542	.0949	.108	.0426	.00438	.0784	.117
Obs.	48079	46799	40341	39484	49419	47514	41903	41582
Banks	407	407	405	404	1023	1009	1006	1005
County	2579	2571	2462	2401	1801	1801	1781	1764

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. In columns from (1)-(4), we replicate *H1* estimations using a matched sample. In columns from (5)-(8), we replicate *H1* estimations dropping from the sample the counties where there are only TARP banks, and those where there are only NO TARP banks.

Table 10: Participation effect and H2

Dependent variable:	Total Small Business Loans Originations 1+2+3					
Geographical coverage:	Crossstate		No. of counties		Avg. distance	
	0	1	≤ 5	> 5	≤ 0.55	> 0.55
	(1)	(2)	(3)	(4)	(5)	(6)
TARP	-.180	.261	1.036	.434	.629	.376
	(.862)	(.583)	(1.045)	(.500)	(1.002)	(.505)
TARP × Size	.012	-.004	-.063	-.012	-.015	-.012
	(.055)	(.024)	(.068)	(.021)	(.064)	(.022)
TARP × Capratio	-.001	-.007	-.017	-.012	-.050	-.006
	(.038)	(.029)	(.027)	(.027)	(.042)	(.027)
Size	.790***	.357**	.280	.377***	.670***	.369***
	(.191)	(.137)	(.170)	(.133)	(.196)	(.132)
Total Uncomm.	.637*	.071	.551*	.235	.488	.181
	(.328)	(.752)	(.283)	(.664)	(.451)	(.461)
Non-Core Fin.	-.114	1.193**	.335	1.008**	.339	1.002**
	(.357)	(.548)	(.344)	(.423)	(.449)	(.437)
Capratio	.044*	-.029	-.001	-.006	.001	-.010
	(.026)	(.026)	(.020)	(.023)	(.018)	(.024)
Total Loans	-.162	.058	.850*	-.216	.035	-.085
	(.598)	(.609)	(.507)	(.530)	(.642)	(.504)
Real Est. Loans	-2.580***	.186	-.946*	-.234	-1.147	-.179
	(.844)	(.605)	(.511)	(.532)	(1.004)	(.557)
Non-Perf. Loans	-1.618	-2.463**	-2.491**	-2.138***	-3.337*	-2.271***
	(1.204)	(1.046)	(1.027)	(.778)	(1.730)	(.832)
Marginal effect TARP	-.0168	.143	.0154	.140	-.00224	.146
p-value	.816	.0780	.843	.0383	.980	.0303
Obs.	8938	39142	2137	45943	3139	44941
Banks	286	182	194	269	185	285
County	1410	2425	451	2567	581	2571

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. Participation effect controlled by using a matched sample. The results refer only to total loans. Findings about the other measures of loan provisions are available under request. Three different measures of geographical coverage have been employed: findings reported in columns (1)-(2) refer to the cross-state definition; results in columns (3)-(4) are based on the number of counties where a bank invests; finally, estimates reported in columns (5)-(6) refer to the average distance between counties where a bank invests.

Table 11: Placebo effect and Matching

Type of strategy:	Placebo					Matched				
Dependent variable:	LOANS 0	LOANS 0	LOANS 1	LOANS 2	LOANS 3	LOANS 0	LOANS 0	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TARP	-.088*	1.516***	1.959***	1.853***	2.418***	.111**	.441	.774	.430	.130
	(.051)	(.466)	(.630)	(.636)	(.633)	(.056)	(.439)	(.591)	(.332)	(.346)
TARP × Size		-.066***	-.089**	-.081***	-.097***		-.015	-.041	-.015	-.000
		(.024)	(.036)	(.028)	(.030)		(.019)	(.030)	(.016)	(.016)
TARP × Capratio		-.064**	-.072*	-.074*	-.108***		-.008	-.002	-.014	-.005
		(.029)	(.039)	(.041)	(.037)		(.023)	(.026)	(.017)	(.018)
Size	.377***	.418***	.388***	.559***	.562***	.375***	.379***	.390***	.283***	.237**
	(.100)	(.084)	(.117)	(.126)	(.117)	(.118)	(.118)	(.148)	(.097)	(.099)
Total Uncomm.	.227	.297*	.120	.646*	.409	.267	.260	.077	.158	.452
	(.157)	(.168)	(.222)	(.377)	(.264)	(.285)	(.282)	(.370)	(.192)	(.289)
Non-Core Fin.	-.190	-.241	.040	-.466	-.481	.866**	.844**	.876**	.562**	.716***
	(.334)	(.291)	(.373)	(.478)	(.528)	(.343)	(.339)	(.409)	(.260)	(.266)
Capratio	-.020	-.005	-.018	-.011	.009	-.012	-.009	-.013	.000	-.007
	(.019)	(.011)	(.020)	(.023)	(.019)	(.016)	(.017)	(.026)	(.013)	(.011)
Total Loans	.721***	.712***	.999***	.219	1.245***	.061	.081	.109	.462*	.540*
	(.277)	(.257)	(.382)	(.429)	(.444)	(.362)	(.369)	(.371)	(.279)	(.305)
Real Est. Loans	-.407	-.376	-.256	-.682*	-.247	-.091	-.132	.390	.109	-.152
	(.326)	(.289)	(.428)	(.400)	(.514)	(.451)	(.446)	(.525)	(.342)	(.305)
Non-Perf. Loans	-1.321	-1.091	3.199	-2.475	-3.830	-2.302***	-2.274***	-1.004*	-1.442***	-2.067***
	(1.178)	(1.064)	(2.109)	(1.787)	(2.428)	(.642)	(.644)	(.591)	(.460)	(.488)
Marginal Effect TARP	-.0882	.0396	.0817	.0786	.125	.111	.144	.145	.0797	.0815
p-value	.0859	.349	.163	.246	.115	.0468	.00687	.00273	.0503	.0877
Obs.	56371	56371	56371	56371	56371	57003	57003	55025	47232	46158
Banks	985	985	985	985	985	587	587	584	586	585
County	2752	2752	2752	2752	2752	2725	2725	2715	2597	2522

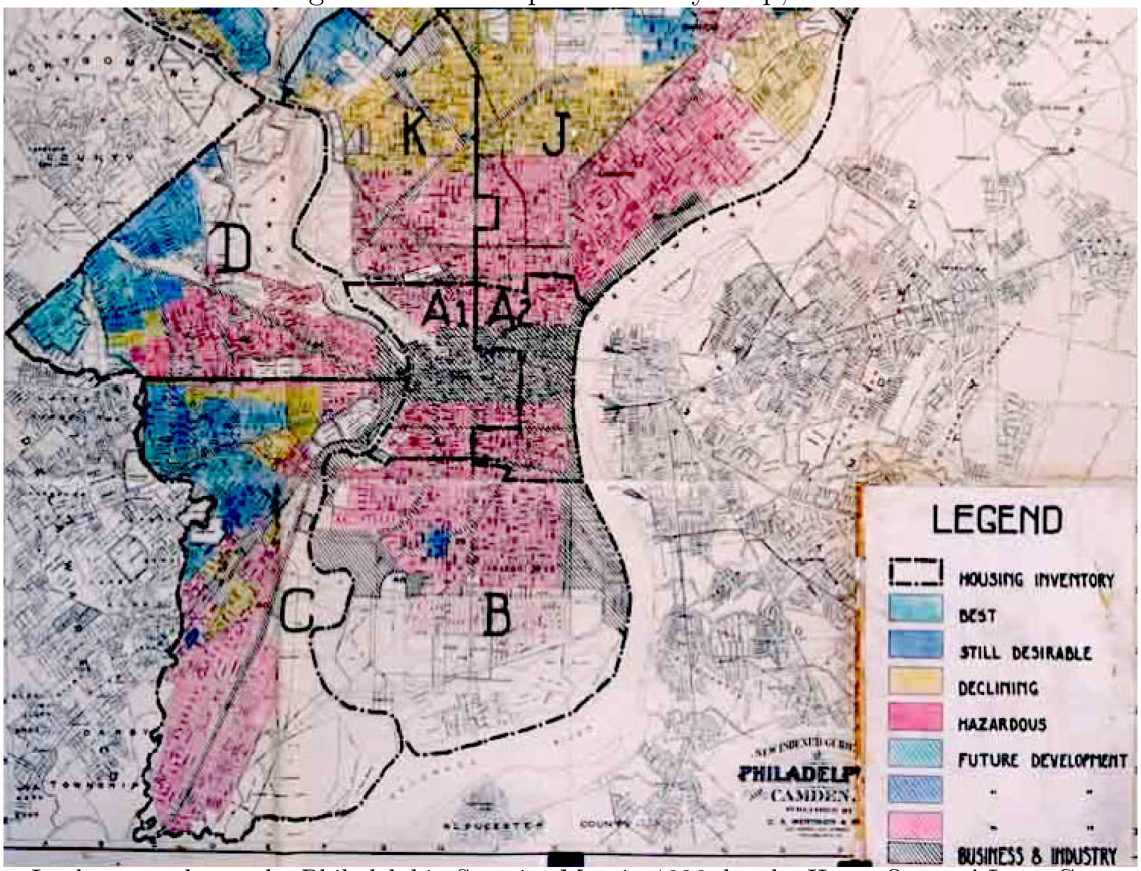
Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. Loan amount provision controlled by using two alternative strategies. Columns (1) to (5) report the results based on the placebo experiment. Columns (6) to (10) refer to the matching exercise. Columns (1) and (6) do not include the interaction terms between TARP and SIZE and TARP and CAPRATIO.

Table 12: Amount Effect

Dependent variable:	LOANS 0	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)
TARP Amount / Total Assets	3.968**	5.128**	1.461	2.288
	(1.915)	(2.138)	(1.484)	(1.878)
Size	.375***	.384***	.274***	.234**
	(.115)	(.145)	(.093)	(.097)
Total Uncomm.	.287***	.226*	.180	.474*
	(.095)	(.128)	(.184)	(.273)
Non-Core Fin.	.827***	.918**	.562**	.621**
	(.315)	(.429)	(.234)	(.246)
Tier 1 Ratio	-.009	-.019	-.004	-.004
	(.013)	(.018)	(.010)	(.009)
Total Loans	.119	.055	.461*	.536*
	(.338)	(.326)	(.258)	(.281)
Real Est. Loans	-.090	.459	.061	-.186
	(.426)	(.544)	(.324)	(.307)
Non-Perf. Loans	-2.391***	-1.311**	-1.393***	-1.937***
	(.589)	(.510)	(.415)	(.452)
Marginal effect TARP	3.968	5.128	1.461	2.288
p-value	.0385	.0166	.325	.223
Obs.	62021	59798	51438	50177
Banks	1048	1032	1031	1034
County	2812	2805	2684	2599

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. Columns (1) refers to total loans at the origination, while columns (2), (3), and (4) refer to the different type of loans: $\leq$ 100k, $\leq$ 250k and $\leq$ 1m.

Figure 5: Philadelphia Security Map, 1936

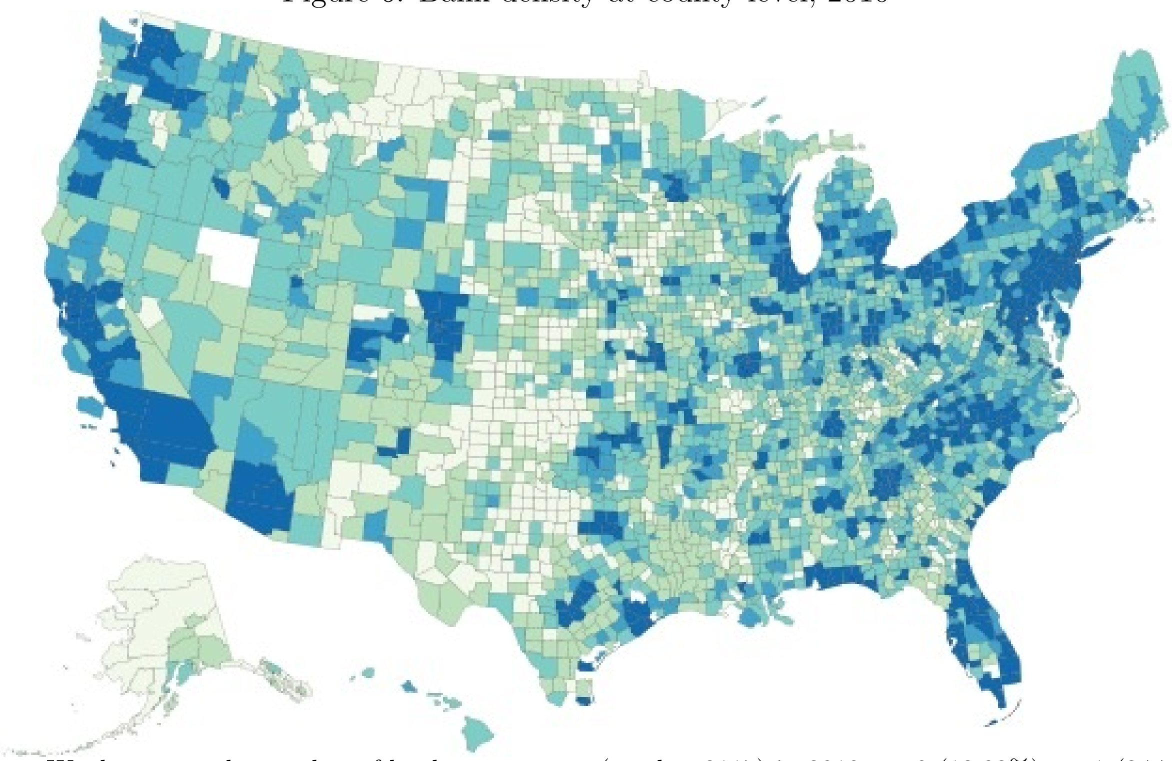


Notes: In the map above, the Philadelphia Security Map in 1936, by the Home Owners' Loan Corporation Philadelphia is reported. The different colours reflect the different riskiness in investing. The red colour refers to zones where investing is considered hazardous, see the legend. Source: Cartographic Modeling Lab, UPenn.

Table 13: Source and definition of the variables

Variable Label	Variable definition	Source
TARP	It takes value 1 if a bank received TARP sustain at least once, and 0 otherwise.	Federal Reserve Board
TARPDUMMY	It takes value 1 from the year (quarter) a bank received TARP sustain and zero before.	Federal Reserve Board
LAO_1	Loan Amount at Origination $\leq$ 100k	CRA
LAO_2	Loan Amount at Origination $\leq$ 250k	CRA
LAO_3	Loan Amount at Origination $\leq$ 1m	CRA
LAO_0	$LAO_1 + LAO_2 + LAO_3$	CRA
$LOANS_1$	log of (1 + LAO_1)	CRA
$LOANS_2$	log of (1 + LAO_2)	CRA
$LOANS_3$	log of (1 + LAO_3)	CRA
$LOANS_0$	log of (1 + LAO_0)	CRA
TOTAL ASSETS	On- and Off-Balance Sheet assets RCFDB696 + RCFDB697 + RCFDB698 + RCFDB699	U.S. Call Reports
SIZE	Log of 1+ banks total asset log(1 + TOTAL ASSETS)	U.S. Call Reports
$TLOANS\_PA$	Total loans and Leases, Gross over total assets RCFD1400/TOTAL ASSETS	U.S. Call Reports
RELOANS	Real Estate Loans over total loans RCFD1410/RCFD1400	U.S. Call Reports
CAPRATIO	Tier 1 (core) capital divided by adjusted total assets RCFD8274	U.S. Call Reports
NPL	Loans that are past due at least 30 days or are on non-accrual basis over total loans (RCFD1403 + RCFD1406 + RCFD1407)/RCFD1400	U.S. Call Reports
TOT_UNCOMM	fraction of total unused loan commitments over total assets RCFD3423/TOTAL ASSETS	U.S. Call Reports
$NOCORE\_PA$	fraction of total time deposits of at least $ 100000, foreign office deposits, insured brokered deposits issued in denominations of less than $ 100000, securities sold under agreements to repurchase, federal funds purchased, and other borrowed money over total assets (RCON2604 + RCFD3190 +RCON2343 + RCFDB993 + RCFDB995)/TOTAL ASSETS	U.S. Call Reports
POVERTY	estimated percentage of people of all ages in poverty	www.census.gov
MED INC	estimated of median household income	www.census.gov
UNEMPLOYMENT	ratio of people who do not have a job, have actively looked for work in the prior 4 weeks, and are currently available for work over total labour force	www.bls.gov

Figure 6: Bank density at county level, 2010



Notes: We document the number of banks per county (total = 3117) in 2010: x=0 (13.92%), x=1 (24.7%), 1<x=3 (30.41%), 3<x=5 (14.95%), x>5 (16.01%).