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

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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. Our analysis refers to banks that provide loans in counties where the Community Reinvestment Act (CRA) applies. We find that on average TARP banks provide loans in more distressed counties than the other banks. Moreover, TARP banks show larger size and they provide larger amount of loans than the rest of the banks. These patterns characterize the entire period analysed, even if the differences among the bank groups increase over time. Exploiting the panel dimension of the dataset, we find that the TARP banks provide on average 12% higher loans origination than the other banks. Moreover, by defining a bank geographical coverage indicator, we show how that previous results depend on this feature: TARP is effective only for banks with high geographical coverage. Finally, by distinguishing between economically sound and economically distressed counties, we show that the results are partially driven by a demand side effect. Several robustness tests confirm the main results.

Keywords TARP, Solvency Risk, Liquidity Risk, Financial Crisis
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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 not 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 provided by banks that are located in counties where the Community Reinvestment Act (CRA) applies. 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 2006 to 2010, data are annually based. We distinguish banks depending on their participation to the TARP program. Comparing the groups of banks before the beginning of the crisis (2006), TARP banks are on average larger than the rest of the banks and they provide more new loans. Finally, they are more likely to provide loans in counties with high poverty and high unemployment than the other banks. These differences persist and become larger once the program is finished.

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[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 and the county socio-economic features have been obtained from the Federal Financial Institutions Examination Council (FFIEC) websites.

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, we define as high geographical coverage if a bank 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 0.55 decimal degrees[3]. 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 of the TARP program to ensure its effectiveness.

The results 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, it follows that it is the quality of the counties and not the TARP program that drives the results. In order to control for this potential issue, we add to the baseline model two dummy variables capturing poverty an unemployment problems characterizing each county. Poverty captures chronic features of the county while unemployment reflects how well the economy performs in the given country. Poverty and unemployment capture long run and transitory features of the counties, respectively. The results highlight that the TARP program is effective in counties suffering from unemployment issues, while its effect is not statistical significant in counties affected by poverty problems.

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;

[3]The distance in geographic coordinates of 0.55 translates into 40 to 50 kilometre, depending on the latitude.

- TARP is effective for banks investing in counties suffering from high unemployment;

- TARP is not effective for banks investing in counties suffering from high poverty.

These results are robust to the dependent variable employed, to the geographical coverage definition employed, to the measures of distressed counties used 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, less related with our study, 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 has 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 loan origination to small businesses. In this way, we can assess the effectiveness of the TARP program on a relevant fraction of the US economy as previously mentioned. 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. The selection issue has been fixed by using two approaches. First, we run a matching exercise, so that we are able to focus only on banks that are similar in all the features considered, but the participation to the TARP program. Alternatively, we run the baseline regressions excluding counties without TARP banks or with only TARP banks. The findings of previous contribution 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. We fix this point by creating three alternative measures of geographical coverage and including 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 controlled for. In order to deal with this potential issue, we take explicitly into account the socio-economic features of the counties where banks invest. 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. Within TARP, there are Bank Support Programs ($250.46 billion), Credit Market Programs ($26.52 billion), Housing Programs ($45.60 billion) and Other Programs ($147.53 billion)[5]. Our analysis focuses on the Bank Support Programs. Among these programs we can distinguishing between the 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 direct 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 received 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 Report). 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 2006: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 U.S. Treasury.

Finally, information about bank loan provision at county level, and the socio-economic

[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.

conditions of the low and moderate income neighbourhoods where banks provide loans have been downloaded from the CRA website. Data are recorded yearly and the period considered goes from 2006 to 2010. The sources employed to generate the dataset are provided in Table 11 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 forth quarter of each year: the sample period goes from 2006 to 2010. From the TARP dataset 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: commercial banks and Bank Holding Companies (BHC). Our analysis is led at commercial 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 reports 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 only banks that provide loans in low- and moderate-income neighbourhoods. Therefore, the majority of the depository institutions included in the Call Reports is dropped.

After merging and filtering procedures, in 2006, the final dataset contains 751 banks, and of those 226 received financial sustain through the TARP program. Overall, banks provide loans in 2620 counties, while the TARP banks provide loans in 2049 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 includes around 10

[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.

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 sizes 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 the 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, there is the information about those zones defined as distressed non-metropolitan middle-income. More precisely, $POVERTY$ takes value one if a county has a poverty rate of 20 percent or more and zero otherwise; $UNEMPLOYMENT$ is a dummy variable and takes value one if in a particular county the unemployment rate is at least 1.5 times the national average, and zero otherwise. These thresholds are defined by the FFIEC[9]. A detailed list of the original names of the series employed in this paper, their definitions and their labels is provided in Table 11 in the Appendix.

3.4 Mains facts

3.4.1 Descriptive statistics

In Table 3, for each of the variables, we report the number of observations, banks and counties when this is possible, the mean, the standard deviation, and the 10^{th}, 50^{th} and the 90^{th} percentiles. Variables are measured in 2006, before the beginning of the crisis. 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 the other two loan types. Moreover, $LOAN$ 0 show the lowest level of spread around the average, and finally, for the first tenth percentile of bank-pairs, median and large loan types are absent, indicating that banks focuses 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 (2006) and AFTER (2010) periods. Then, we test whether the unconditional averages differ across the TARP and NO TARP banks and across the before and the after periods. We run the following regression, excluding from the specification additional explanatory variables:

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

[9] For further information: http://www.ffiec.gov/geocode/help3.aspx

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

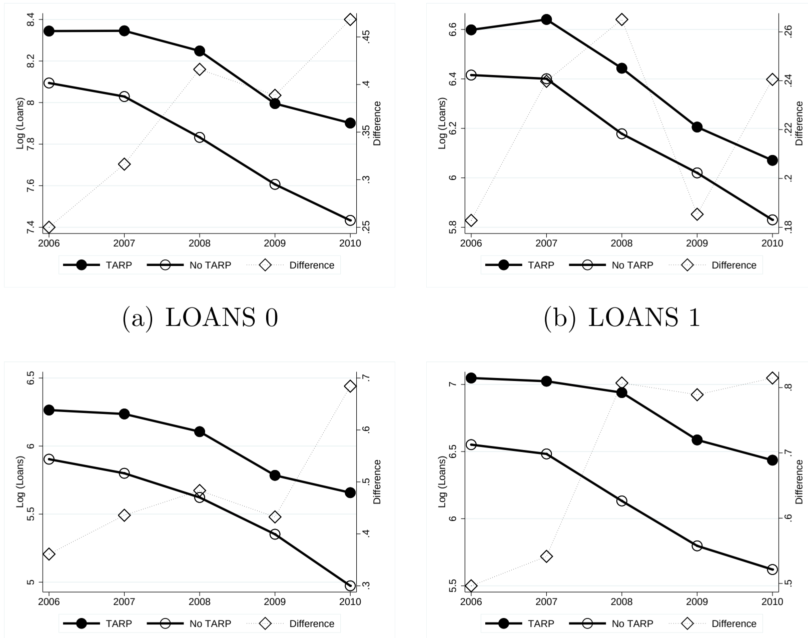
Table 1: Different cases

	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 difference 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. In Table 1 this effect is captured by β_3. The results are reported in Table 5 in the Appendix. Having a closer look at the differences across groups, columns (1) and (2), the findings suggest that TARP banks provide on average more loans, independently of the loan size and period. This is also true AFTER. If we look at the changes within groups, columns (3) and (4), the results highlight that both groups of banks decrease their loans over time. Finally, and most importantly, the difference between groups increases once the program is over. From this analysis, we can conclude that the TARP program alleviated the drop in loan provision.

Previous findings are supported by the graphs showed in Figure 1. For the different measures of loan origination, we document the per-quarter averages distinguishing between bank

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 (full circles) and NO TARP (empty circles) banks (left hand scale). The difference is also shown (diamonds, right hand scale). Aggregation by giving each bank-county observation the same weight.

groups (TARP vs NO TARP)[10]. Moreover, for each measure we also provide the evolution of the differences between the loans provided by the two groups. The pattern is increasing over time, even if the difference temporary decreases during 2008 and 2009. The drop is more or less important depending on the type of loans considered.

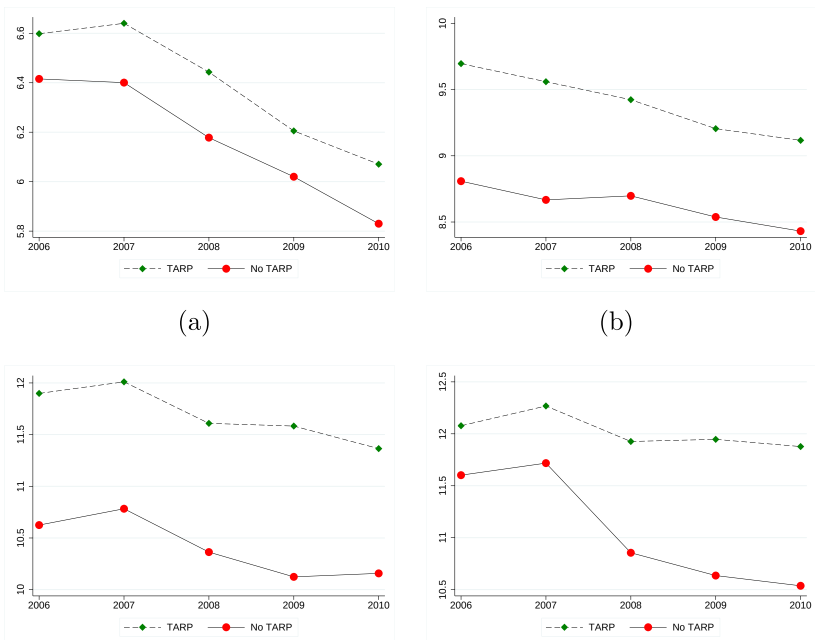
3.4.3 Aggregation

In the previous subsection we mentioned that in the aggregation process each observation received the same weight. However, depending on the type of aggregation process is employed, different results are obtained. In Figure 2 we document for *LOANS* 1 the results of the aggregation procedure using different approaches[11]. In Panel (a), the aggregation has been

[10]Each observation receives the same weight in the aggregation process.
[11]Using the other measures we obtain the same results.

done at bank-county level, and each observation receives the same weight. In Panels (b), (c) and (d) the aggregation is at bank level[12]. Panel (b) shows the result when using equal-weight (for each bank) approach, while Panels (c) and (d) weights each bank by the number of counties where a bank provides loans (extensive margin) and the total loans provided by each bank (intensive margin).

Figure 2: Per-quarter-group, averages



(a) (b)

(c) (d)

Notes: Per-quarter averages of loan origination ($LOANS$ 1) for TARP and NO TARP banks, using different aggregation approaches. Panel (a): bank-county level, equal weight. Panel (b): bank level, weighted equally. Panel (c): bank level, weighted by number of counties. Panel (d): bank level, weighted by $LOANS$ 0.

Focusing on Panels (c) and (d) the clear common pattern refers to the important drop on average loans provision for the NO TARP banks in 2007, at the beginning of the crisis[13]. 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

[12]In this case, we first sum loan origination for each bank in all counties, and then average across banks.

[13]Although there does not exist an official beginning of the crisis, many use August 9^{th} 2007, when BNP Paribas announced that it was not able to value the holdings of three investment funds.

both groups of banks, but we do not observe the drastic contraction experienced by the NO TARP banks, as shown 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.

3.4.4 Who invests where

In the perspective of controlling for the demand side effect, it is of interest analysing in which counties the two groups of banks provide loans. For each bank we compute the fraction of counties where the bank invests that are "distressed"[14]. Then, we average these values by bank groups and over time. The results are reported in Figure 3. Independently from the socio-economic distress indicator employed, on average TARP banks are more likely to provide loans in more distressed counties than the NO TARP banks. Moreover, the gap between the two groups increases over time.

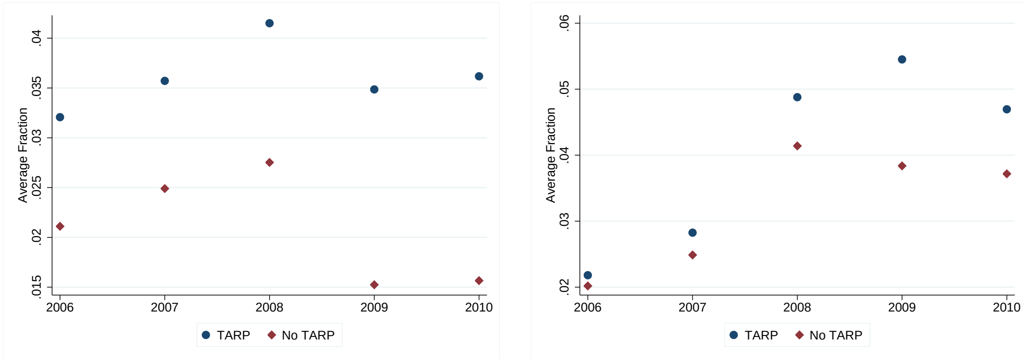
This can be due to the following reasons:

- TARP banks decided to invest in more distressed counties;
- NO TARP banks disinvest from distressed counties;
- Counties that before were not distressed turn out to be distressed and this happens more frequently in counties where TARP banks provide loans.

Focusing on the unemployment indicator, 135 counties improved their condition from 2006 to 2010: in the 65 percent of the cases (88 counties) these are counties where TARP

[14]We adopt the FFIEC's definition, where a county is distressed if unemployment is 1.5 times higher than the national average or if the level of poverty exceeds 20 percent.

Figure 3: Average fraction of distressed counties where banks provide loans



(a) Unemployment (b) Poverty

Notes: For TARP and NO TARP banks we report the average fraction of counties with high unemployment, Panel (a), and high level of poverty, Panel (b), over the total number of counties where banks invest.

banks provide loans. In the same period, 132 counties worsened their economic condition. In the 66 percent of the cases (87 counties) these are counties where TARP banks provide loans. Moreover, there are also counties that temporary changed their conditions. More precisely, 18 counties in 2006 were in a distressed situation, they improved their condition, but in 2010 they were again in a distressed situation. TARP banks provided loans in 12 out of 18 of these counties. Finally, 67 counties worsened their economic conditions before going back to their original situation. TARP banks are located in 39 out of 67 of these counties. When using the poverty indicator, similar patterns are found, as highlighted by Table 2. It follows that the third hypothesis is the weakest among those listed above, it is more likely that the patters documented in Figure 3 depend only on the first two hypotheses.

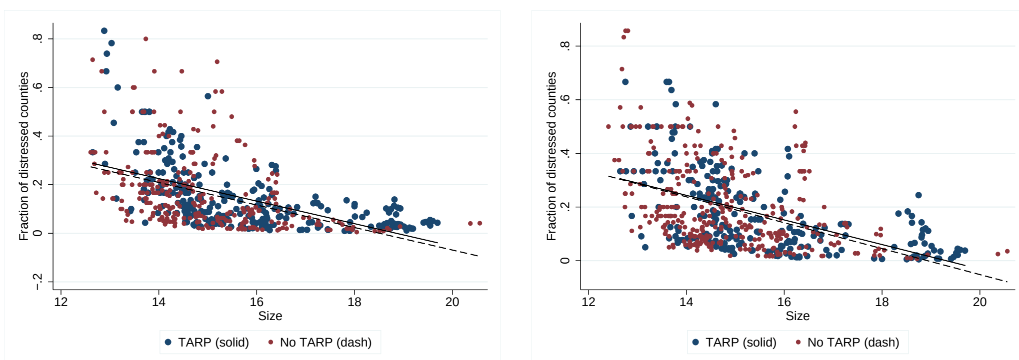
Table 2: Different cases

	Unemployment			Poverty		
Cases	Total	TARP	Fraction	Total	TARP	Fraction
Improving	135	88	.65	7	2	.285
Worsening	132	87	.66	259	141	.54
Unchanged (bad)	18	12	.66	4	0	0
Unchanged (good)	67	39	.54	75	39	.52

Notes: Periods taken into account: 2006 and 2010. Improving(Worsening), refers to counties that improved(worsened) their socio-economic condition with respect to the unemployment or poverty point of view. Unchanged refers to counties that temporary changed their socio-economic status.

Until now we just classified the banks depending on their TARP participation, disregarding other potential determinants that can drive the county investment decisions of the banks. In Figure 4 we document the relation between the bank size and the type of counties (distressed or not) where banks provide their loans, distinguishing also by TARP and NO TARP banks. The graph highlights that the larger the size of the bank the more likely is that the bank invests in economic sound counties (in percentage term). This result is potentially related to the banks geographical coverage: it could be that smaller (with respect to size) banks have a smaller geographical coverage and they are locally based. Therefore, for these banks it is more likely to invest in counties with the same socio-economic features. Finally, the graphs also show that for a given bank size, TARP banks are more likely to provide loans in more distressed counties.

Figure 4: Fraction of distressed counties and banks size



(a) Unemployment (b) Poverty

Notes: For TARP and NO TARP banks we report the scatter plot between the fraction of counties with unemployment, graph (a), and poverty problems, graph (b), over the total number of counties where banks invest and banks size. Period: 2006-2010. The dash and solid lines refer to the fitted values obtained by running the regressions of the fraction of distressed counties explained by a constant, the size of the bank and an error term, for the TARP and NO TARP groups respectively.

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[15]. 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 the 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

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

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[16] $TARP \times SIZE$ and $TARP \times CAPRATIO$. Looking 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[17], 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 can 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

[16]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.

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

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[18]: assume that each county included in the dataset can be potentially hit by a negative economic shock. This shock can be short or more 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 it receives from the shock. Therefore, banks with a higher geographical coverage have better signals, and therefore they can better distinguish about the nature of the shock. Alternatively, we can interpret bank geographical coverage as a proxy for bank diversification: banks that show high geographical coverage are more likely to be located also in economically sounder counties. As a consequence they ask for TARP sustain due to the fact they provide loans in distressed counties, but they use these funds to expand the loan activity in the healthy ones.

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[19];
- if the average distance between all the counties where the bank provides loans is larger than 0.55 decimal degrees[20].

[18] See for instance Chamley (2004).

[19] The threshold refers to the average number of counties where a bank provides loans.

[20] The threshold refers to the average value of the average distance of the counties where the banks provide

According to the three definitions, the dataset contains 29%, 43% and 49% of banks with high geographical coverage, respectively[21]. Moreover, among the high geographical coverage there are 42%, 43% and 61% of TARP banks, respectively. Based on these alternative measures we test our second hypothesis:

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

To test our second hypothesis we run two separate regressions by distinguishing between low and high geographical coverage. The results, as 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). Therefore, it follows that the fact of having a high geographical coverage is a complementarity feature that banks need in order to make the TARP program effective.

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 are driven by the socio-economic features of the counties where TARP banks are located. Specifically, it could be that TARP banks are located in economically sounder counties. In order to control for this potential issue we add to equation(2) four additional variables: $POVERTY$, $UNEMPLOYMENT$[22] 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

loans.

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

[22] $POVERTY$ takes value one if a county j in specific year t has a poverty rate of 20 percent or more and zero otherwise. $UNEMPLOYMENT$ takes value one if a particular county j in a specific year t shows an unemployment rate of at least 1.5 times the national average, and zero otherwise.

frictions. 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 a external financial sustain. In this context, even if banks benefit from the TARP program, and therefore potentially have additional resources to invest, banks do not find any type of demand for loans. It follows that the TARP program is not effective. The findings reported in Table 8 confirm our intuitions: the baseline results are not driven by the demand side effect in counties that suffer of unemployment, while it seems that the results suffer of a demand side effect in counties affected by poverty issues.

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 2006 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 38422 observations, 411 banks, and 2577 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 39934 observations, 926 banks, and 1727 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[23]: 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 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 effectiveness of the TARP program, and in particular of the CPP program that had as target the banking sector. Our analysis focus on banks that provide loans in counties that are in low- and moderate-income neighbourhoods according to the definition provided by CRA. From a general point of view, our findings highlight that TARP program was effective. 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 banks loan activity.

[23]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.

Moreover, the results also document the importance of banks geographical coverage[24] in the effectiveness of the TARP program. We find that the TARP program is effective only 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 of cyclical economic problems. It 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 U.S. 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

[24] 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.

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 2006 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, and it is effective only in counties which are in sound economical conditions, and those that show a level of unemployment that is less than 1.5 times the national average, while it is not effective in counties that show level of poverty exceeds 20 percent. 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 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 in counties where the CRA applies. 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.

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Appendices

A Tables

Table 3: Descriptive Statistics

	Obs.	Banks	Counties	mean	p10	p50	p90	sd
LOANS 0	10021	751	2620	8.218	5.733	8.368	10.490	1.875
LOANS 1	10021	751	2620	6.506	4.111	6.781	8.789	2.091
LOANS 2	10021	751	2620	6.082	.000	6.798	8.904	2.870
LOANS 3	10021	751	2620	6.797	.000	7.728	10.001	3.360
CAPRATIO	751	751		8.825	6.760	8.380	11.090	3.046
SIZE	751	751		14.252	12.811	14.035	16.042	1.383
TOT UNCOMM	751	751		.200	.078	.169	.298	.286
NO CORE PA	751	751		.261	.120	.247	.415	.123
TOT LOANS	751	751		.650	.468	.678	.798	.139
RELOANS	751	751		.745	.545	.767	.931	.158
NPL	751	751		.015	.004	.011	.029	.013

Notes: The descriptive statistics referring the different types of loans are bank-county based. The rest of the descriptive statistics are bank-based. The results refer to 2006. At bank-county level there are 10021 observations, 751 banks and 2620 counties. At bank level there are 751 observations that correspond also to the number of banks.

Table 4: Correlations

	LOANS 0	LOANS 1	LOANS 2	LOANS 3			
LOANS 0	1						
LOANS 1	.800***	1					
LOANS 2	.831***	.698***	1				
LOANS 3	.879***	.598***	.657***	1			
	CAPRATIO	SIZE	TOT UNCOMM	NO CORE PA	TOT LOANS	RELOANS	NPL
CAPRATIO	1						
SIZE	-.109**	1					
TOT UNCOMM	.526***	.150***	1				
NO CORE PA	-.0202	.0734*	.00933	1			
TOT LOANS	.0693	-.110**	.0621	.213***	1		
RELOANS	-.0622	-.337***	-.342***	.0637	.149***	1	
NPL	.180***	-.00667	.0666	.227***	-.0163	-.0182	1

Notes: *** $= p < .001$, ** $= p < .01$, * $= p < .05$. The correlations referring the different types of loans are bank-county based. The correlations between the other variables are bank-based. The correlations are measured in 2006.

Table 5: Averages diff in diff (Unconditional)

Variable	Before	After	No TARP	TARP	Diff in Diff
	(1)	(2)	(3)	(4)	(5)
LOANS 0	.250***	.468***	-.661***	-.443***	.218***
	(.037)	(.039)	(.041)	(.035)	(.054)
LOANS 1	.183***	.241***	-.585***	-.528***	.058
	(.042)	(.042)	(.045)	(.038)	(.059)
LOANS 2	.361***	.684***	-.930***	-.607***	.323***
	(.057)	(.062)	(.064)	(.055)	(.084)
LOANS 3	.496***	.815***	-.930***	-.612***	.318***
	(.067)	(.072)	(.074)	(.065)	(.098)
Obs./Bank-County	10021	9970	6617	6922	13539
Banks	751	635	670	226	896
CAPRATIO	-.603***	-.128	.041	.516***	.475*
	(.186)	(.184)	(.200)	(.169)	(.262)
SIZE	.630***	.784***	.069	.222*	.154
	(.114)	(.107)	(.080)	(.135)	(.156)
TOT UNCOMM	.030*	.012*	-.073***	-.090***	-.017
	(.018)	(.006)	(.015)	(.011)	(.019)
NO CORE PA	.016*	-.004	-.018**	-.039***	-.021
	(.009)	(.009)	(.008)	(.010)	(.013)
TOT LOANS	.056***	.037***	-.023***	-.042***	-.018
	(.010)	(.009)	(.009)	(.010)	(.013)
RELOANS	-.031***	-.015	.012	.028**	.016
	(.012)	(.012)	(.010)	(.013)	(.017)
NPL	-.002***	.010***	.034***	.046***	.013***
	(.001)	(.004)	(.002)	(.003)	(.004)
Obs./Banks	751	635	670	226	896

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. The statistics referring the different types are bank-county based. The rest of the statistics are bank-based. The before period is 2006, 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 1+2+3	LOANS 1+2+3	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)	(5)
TARP	.120**	.281	.352	.741	.137
	(.053)	(.388)	(.491)	(.642)	(.624)
TARP × Size		-.005	-.015	-.028	.006
		(.019)	(.025)	(.033)	(.029)
TARP × Tier 1 ratio		-.008	-.000	-.019	-.008
		(.021)	(.024)	(.031)	(.034)
Size	.350***	.353***	.390**	.456**	.529***
	(.116)	(.117)	(.156)	(.185)	(.175)
Total Uncomm.	.243***	.236***	.200	.284**	.409**
	(.078)	(.077)	(.141)	(.112)	(.168)
Non-Core Fin.	.752**	.755**	.614	.504	1.385**
	(.369)	(.370)	(.456)	(.620)	(.554)
Tier 1 Ratio	-.012	-.009	-.023	-.004	-.008
	(.014)	(.015)	(.022)	(.018)	(.021)
Total Loans	.191	.198	.144	.426	.385
	(.352)	(.359)	(.393)	(.504)	(.616)
Real Est. Loans	.051	.037	.638	.065	-.460
	(.521)	(.518)	(.515)	(.780)	(.837)
Non-Perf. Loans	-2.548***	-2.535***	-1.253*	-2.998***	-5.063***
	(.632)	(.635)	(.711)	(.993)	(1.262)
Marginal effect TARP	.120	.129	.127	.170	.163
p-value	.0230	.00570	.0101	.0276	.0702
Obs.	50367	50367	50367	50367	50367
Banks	944	944	944	944	944
County	2793	2793	2793	2793	2793

Notes: *** $= p < .001$, ** $= p < .01$, * $= p < .05$. Column (1) does not include the interaction terms between TARP and SIZE and TARP and CAP RATIO. 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:	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	-.453	.160	.716	.230	-.478	.118
	(.691)	(.534)	(.758)	(.433)	(.541)	(.424)
TARP × Size	.022	.002	-.036	-.003	.020	.005
	(.044)	(.024)	(.051)	(.021)	(.031)	(.020)
TARP × Tier 1 ratio	.020	-.008	-.031	-.005	.029	-.007
	(.029)	(.025)	(.022)	(.023)	(.031)	(.023)
Size	.939***	.270**	.430***	.352***	.573***	.345***
	(.204)	(.113)	(.135)	(.119)	(.152)	(.118)
Total Uncomm.	.346***	-.338	.258***	.062	.338***	-.139
	(.048)	(.633)	(.034)	(.584)	(.048)	(.557)
Non-Core Fin.	.560	.789	.186	.763*	.038	.778*
	(.398)	(.602)	(.263)	(.425)	(.368)	(.431)
Tier 1 Ratio	.019	-.028	.014	-.014	.001	-.015
	(.015)	(.021)	(.008)	(.020)	(.010)	(.019)
Total Loans	.216	.432	1.424***	-.011	1.598***	.033
	(.521)	(.475)	(.282)	(.436)	(.429)	(.433)
Real Est. Loans	-1.264	.540	.199	.048	-.368	.183
	(.838)	(.654)	(.430)	(.569)	(.510)	(.602)
Non-Perf. Loans	-1.589*	-3.277***	-2.240***	-2.570***	-2.063***	-2.942***
	(.955)	(.863)	(.720)	(.782)	(.667)	(.653)
Marginal effect TARP	.0383	.127	-.0463	.149	.0439	.127
p-value	.553	.0497	.311	.00424	.455	.0136
Obs.	13630	36737	4762	45605	5718	44649
Banks	731	308	592	448	540	514
County	1819	2623	901	2771	847	2758

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 1+2+3	LOANS 1	LOANS 2	LOANS 3	LOANS 1+2+3	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP (a)	.293	.359	.778	.174	.135	.256	.493	.088
	(.394)	(.496)	(.646)	(.628)	(.410)	(.559)	(.687)	(.636)
TARP × Size (b)	-.006	-.015	-.029	.005	-.000	-.009	-.016	.006
	(.019)	(.025)	(.033)	(.029)	(.020)	(.027)	(.036)	(.029)
TARP × Tier 1 ratio (c)	-.008	-.000	-.019	-.008	.005	.007	-.005	.014
	(.021)	(.024)	(.031)	(.034)	(.023)	(.030)	(.034)	(.035)
TARP × UNEMPL (d)	-.008	.007	-.259***	.008	-.010	.036	-.286***	.012
	(.041)	(.056)	(.091)	(.153)	(.042)	(.058)	(.096)	(.159)
TARP × POVERTY (e)	-.155**	-.118**	-.129	-.362**	-.137*	-.103	-.092	-.361*
	(.074)	(.060)	(.171)	(.177)	(.083)	(.069)	(.191)	(.189)
POVERTY	.009	.020	.002	.162	-.023	.001	-.110	.122
	(.042)	(.041)	(.099)	(.119)	(.057)	(.056)	(.126)	(.144)
UNEMPLOYMENT	-.031	-.085	-.105	.095	-.032	-.132**	-.100	.116
	(.039)	(.058)	(.089)	(.096)	(.043)	(.063)	(.097)	(.106)
Size	.353***	.391**	.457**	.531***	.315**	.308*	.389*	.564***
	(.117)	(.156)	(.185)	(.174)	(.127)	(.166)	(.210)	(.178)
Total Uncomm.	.237***	.201	.288***	.411**	-.206	-.607	-.394	-.141
	(.077)	(.141)	(.111)	(.168)	(.538)	(.729)	(.758)	(.899)
Non-Core Fin.	.756**	.613	.496	1.384**	.592	.615	.343	1.055
	(.370)	(.457)	(.619)	(.552)	(.494)	(.635)	(.827)	(.695)
Tier 1 Ratio	-.009	-.023	-.004	-.008	-.027	-.037	-.030	-.035
	(.015)	(.022)	(.018)	(.021)	(.020)	(.033)	(.023)	(.027)
Total Loans	.190	.140	.405	.369	.215	.273	.443	.365
	(.360)	(.394)	(.503)	(.618)	(.430)	(.504)	(.592)	(.712)
Real Est. Loans	.022	.628	.056	-.495	-.002	.832	.196	-.860
	(.517)	(.516)	(.775)	(.832)	(.543)	(.648)	(.872)	(.782)
Non-Perf. Loans	-2.516***	-1.233*	-2.959***	-5.025***	-2.989***	-2.367**	-4.076***	-5.841***
	(.633)	(.708)	(.990)	(1.257)	(.748)	(.939)	(1.201)	(1.551)
(a) + (b) + (c) = 0	.140	.135	.193	.188	.175	.183	.223	.290
p-value	.00362	.00686	.0153	.0423	.00319	.00246	.0251	.00896
(a) + (b) + (c) + (d) = 0	.132	.141	-.0661	.196	.165	.219	-.0631	.302
p-value	.0251	.0457	.556	.281	.0194	.00649	.624	.136
(a) + (b) + (c) + (e) = 0	-.0158	.0163	.0635	-.174	.0379	.0791	.131	-.0710
p-value	.835	.829	.708	.308	.665	.380	.499	.687
(a) + (b) + (c) + (d) + (e) = 0	-.0237	.0229	-.195	-.165	.0276	.116	-.155	-.0590
p-value	.773	.777	.271	.395	.775	.216	.433	.772
Obs.	50367	50367	50367	50367	38422	38422	38422	38422
Banks	944	944	944	944	411	411	411	411
County	2793	2793	2793	2793	2577	2577	2577	2577

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. TARP marginal effect tests: (a) + (b) + (c) = 0 refers to counties that are not poor neither suffer of unemployment issues. (a) + (b) + (c) + (d) = 0 refers to counties that show unemployment problems but are not poor. (a) + (b) + (c) + (e) = 0 refers to counties that do not show unemployment problems but are poor. Finally, (a) + (b) + (c) + (d) + (e) = 0 refers to counties that do show unemployment problems and are poor.

Table 9: Participation effect and H1

Method:	Matching				Dropping extreme cases			
Dependent variable:	SBL 1+2+3	SBL 1	SBL 2	SBL 3	SBL 1+2+3	SBL 1	SBL 2	SBL 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP	.128	.256	.466	.062	.117	.183	.282	-.149
	(.405)	(.556)	(.684)	(.635)	(.393)	(.536)	(.608)	(.616)
TARP × Size	-.000	-.009	-.015	.006	.005	-.006	.000	.025
	(.020)	(.027)	(.036)	(.030)	(.019)	(.028)	(.031)	(.029)
TARP × Tier 1 ratio	.005	.007	-.005	.014	-.009	.003	-.019	-.010
	(.023)	(.030)	(.034)	(.035)	(.021)	(.024)	(.031)	(.035)
Size	.314**	.307*	.390*	.562***	.428***	.494***	.556***	.588***
	(.127)	(.165)	(.210)	(.180)	(.126)	(.167)	(.201)	(.192)
Total Uncomm.	-.213	-.612	-.428	-.151	.281***	.242*	.315***	.461***
	(.533)	(.727)	(.753)	(.892)	(.077)	(.136)	(.099)	(.135)
Non-Core Fin.	.589	.614	.350	1.044	.587*	.445	.299	1.193**
	(.495)	(.635)	(.829)	(.698)	(.355)	(.463)	(.597)	(.555)
Tier 1 Ratio	-.026	-.037	-.029	-.035	-.014	-.024	-.014	-.022
	(.020)	(.033)	(.023)	(.026)	(.014)	(.021)	(.020)	(.023)
Total Loans	.228	.277	.479	.392	.193	.153	.464	.271
	(.427)	(.502)	(.592)	(.706)	(.355)	(.391)	(.516)	(.629)
Real Est. Loans	.015	.842	.208	-.821	-.057	.616	-.309	-.504
	(.546)	(.648)	(.879)	(.789)	(.528)	(.514)	(.761)	(.882)
Non-Perf. Loans	-3.015***	-2.396**	-4.128***	-5.895***	-2.720***	-1.120	-2.927***	-5.748***
	(.751)	(.944)	(1.208)	(1.556)	(.670)	(.765)	(1.063)	(1.304)
Marginal effect TARP	.166	.178	.202	.268	.114	.120	.122	.131
p-value	.00421	.00304	.0374	.0128	.0242	.0287	.140	.168
Obs.	38422	38422	38422	38422	39934	39934	39934	39934
Banks	411	411	411	411	926	926	926	926
County	2577	2577	2577	2577	1727	1727	1727	1727

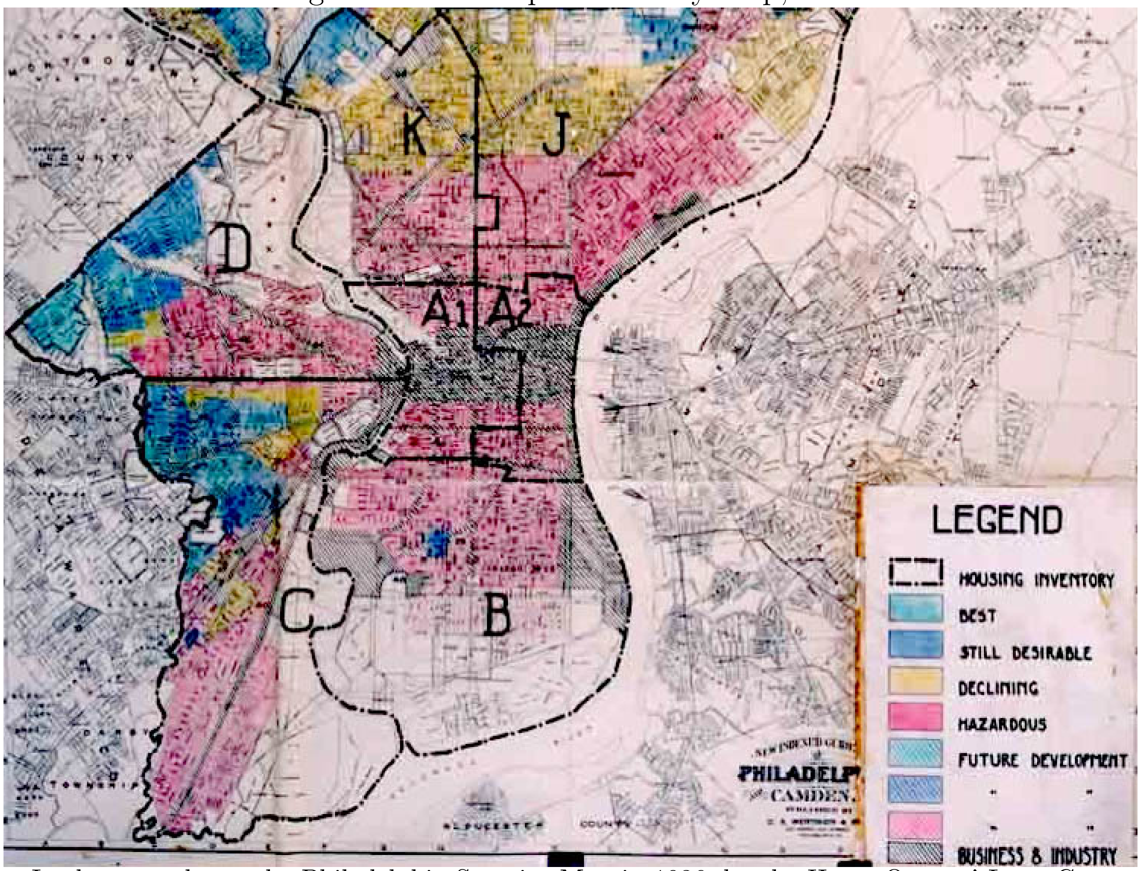
Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$. In columns from (1)-(4), we replicate *H1* estimations using a matched sample. In columns from (5)-(8), we replicate *H1* estimations dropping from the sample the counties where there are only TARP banks, and those where there are only NO TARP banks.

Table 10: Participation effect and H2

Dependent variable:	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	-.814	.144	.438	.159	-.724	.031
	(.673)	(.562)	(.794)	(.455)	(.571)	(.440)
TARP × Size	.039	.004	-.031	-.001	.025	.007
	(.044)	(.026)	(.053)	(.022)	(.030)	(.021)
TARP × Tier 1 ratio	.040	-.003	-.010	.004	.054	.001
	(.030)	(.027)	(.025)	(.025)	(.034)	(.024)
Size	.553***	.291*	.493**	.309**	.458***	.331**
	(.137)	(.150)	(.203)	(.130)	(.176)	(.135)
Total Uncomm.	.466	-.448	1.043**	-.324	.510	-.389
	(.447)	(.760)	(.408)	(.624)	(.411)	(.628)
Non-Core Fin.	.173	.749	-.053	.638	.305	.578
	(.394)	(.739)	(.328)	(.542)	(.493)	(.564)
Tier 1 Ratio	-.001	-.040	-.000	-.027	-.020	-.027
	(.027)	(.025)	(.024)	(.022)	(.025)	(.022)
Total Loans	-.085	.443	.988**	.148	1.525***	.076
	(.567)	(.583)	(.440)	(.468)	(.559)	(.475)
Real Est. Loans	-.657	.074	.159	-.049	-.422	-.004
	(.629)	(.763)	(.570)	(.582)	(.729)	(.636)
Non-Perf. Loans	-2.680**	-3.459***	-2.169**	-2.987***	-3.647***	-2.684***
	(1.115)	(1.107)	(.910)	(.811)	(1.213)	(.814)
Marginal effect TARP	.0775	.182	-.0790	.187	.0671	.154
p-value	.352	.0219	.168	.00284	.386	.0155
Obs.	7510	30912	1964	36458	3021	35401
Banks	286	180	197	265	194	275
County	1278	2461	453	2562	541	2544

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.

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 11: 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	It takes value 1 if a county, in a particular year, has a poverty rate of 20 percent or more, and 0 otherwise	CRA
UNEMPLOYMENT	It takes value 1 if a county, in a particular year, the unemployment rate is at least 1.5 times the national average, and 0 otherwise	CRA
POP_LOSS	It takes value 1 if a county, in a particular year, experiences a population loss of 5% or more in a five-year period preceding the most recent decennial census, and 0 otherwise	CRA

Notes: