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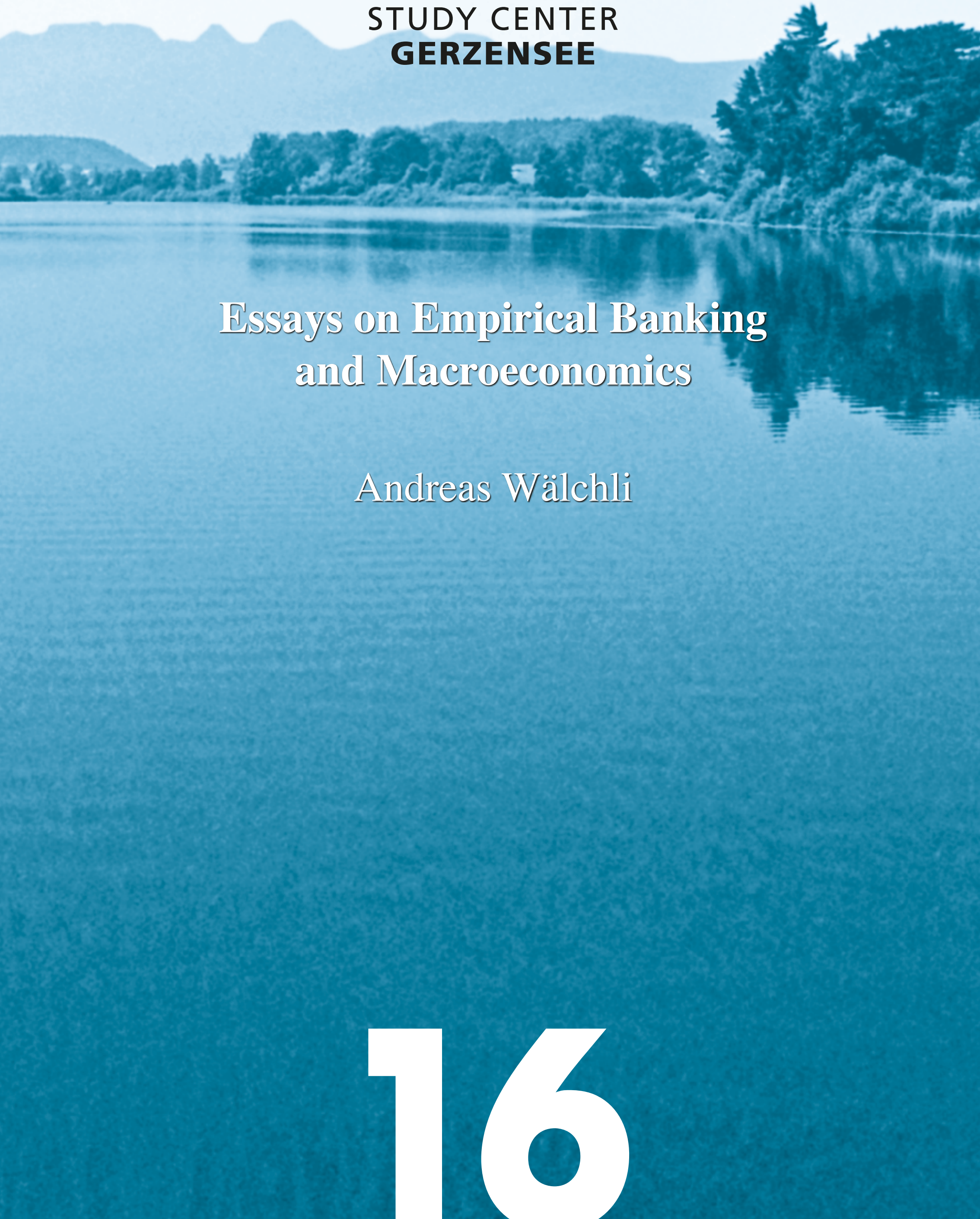

Essays on Empirical Banking and Macroeconomics

Andreas Wälchli

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Contents

Introduction

The recent global crisis from 2008–2012 did bring back the attention to the workings of financial systems and its various interactions with the economy as a whole. In fact, although the crisis started in the financial sector – more precisely, in the United States securitised mortgage market –, it had negative effects on growth and wealth on a global level. As a reaction to declining GDP, central banks loosened monetary policy to support the economy. The targets for short term nominal interest rates in the United States, the Euro Area and other major economies were lowered sharply. But as these proven methods were deemed insufficient, new policies were adopted. The success of these new and unconventional monetary and fiscal policies was however not granted.

The first two chapters of the thesis consider two out of the numerous new policy initiatives that were initiated during the recent crisis. These two chapters are empirical studies and analyse the effects of a particular policy on the financial system and the real economy. In the paper **"TAF Effect on Liquidity Risk Exposure"**, jointly written with Stefano Puddu from the University of Neuchatel, the Term Auction Facility (TAF) is the subject of study. The TAF was launched by the Federal Reserve in December 2007, and was tailored to provide short-term funding to banks. It is well known in the literature (Diamond and Dybvig, 1983, see e.g.) that the balance sheet of banks is prone to risks. While the assets of banks are usually long-term loans to its customers, the liability side are short-term deposits, which can be withdrawn within a short time. However, during the good times before the crisis, banks were not only using household deposits as short-term funding, but increasingly relied on short-term interbank debt.

When the housing bubble burst in 2007, the interbank market for short-term funding froze and left several banks with severe liquidity problems due to the maturity mismatch in their balance sheet. At the same time, those banks were reluctant to use the Federal Reserve's traditional channel of the discount window. It is because of this liquidity crisis that the Federal Reserve created the TAF and auctioned $3.81 trillion short-term debt between December 2007 and April 2010.

In the paper we construct a new dataset, which is a combination of balance sheet information and TAF participation data. In the first part, we compare the liquidity and liability features of US commercial banks according to whether they received credit from the TAF. The variables we use to measure liquidity risk are all closely related to the maturity mismatch in the balance sheet. Our main measure for liquidity risk is the (log) ratio of log of the short-term liabilities over short-term assets. (Assets and liabilities with a maturity less than one year are considered as short-term). The main result of the first part suggests that, on average, banks that benefited from the TAF exhibited higher ex ante levels of liquidity risk measures and illiquid collateral.

In the second part we assess the impact of the TAF on bank liquidity risk. The empirical strategy involves the estimation of a treatment-effects model, where the outcome equation and the participation equation are estimated jointly. To control for potential selection bias, we use the change in the US housing price index in the state where each bank was headquartered between 2002:Q1 and 2006:Q3 as an exclusion restriction. We find that TAF banks drastically reduce their funding liquidity risk positions in the periods after the first time they received the financial support. The reduction in liquidity exposure is statistically and economically significant. We also find that the larger the amount of reserves they received, the greater the impact.

Our study stresses the importance of banking liability term structure as a source of banking soundness. From this perspective, our contribution provides empirical justification to those arguments in favour of the introduction of liquidity risk measures in international financial regulations. In particular, the new measures, implemented in Basel III, such as the liquidity coverage ratio and the net stable funding ratio, go in the right direction of focusing on liquidity management for the proper functioning of the banking sector and financial markets.

The instability in the financial system did not only expose weak balance sheet fundamentals of banks. In fact, as banks tried to reduce their exposure, lending to households and businesses dropped. In the second chapter, **"TARP Effect on Bank Lending**

Behaviour: Evidence from the last Financial Crisis", co-authored with Stefano Puddu, we assess the question whether the government is capable to increase lending of the banking sector to the real sector.

After the collapse of Lehman Brothers, politicians in the United States were concerned about a credit crunch, that is a significant decrease in lending to households and businesses. As a result, the US Treasury launched in 2008 the Troubled Asset Relief Program (TARP). In total, $420 billion were effectively used under the TARP. The largest part of the funds were used for Bank Support Programs ($250.46 billion), and in particular for the Capital Purchase Program (CPP). Under the CPP, the US Treasury bought newly issued stocks and warrents of banks, therefore becoming a direct shareholder and increasing the equity of the banks. The aim of the CPP was to increase lending to the private sector, and in particular to small businesses. The paper estimates the effect of TARP participation on new loans provided to small businesses. Our study focuses on small businesses, because they account for a considerable amount of US GDP (about 50%) and employment (more than 50%). Also, small businesses are especially dependent on bank loans, because it is harder for them to raise money in the financial market.

We construct a unique data set, which combines balance sheet information of US commercial banks and loan origination data for these banks on a county level. Also, we extract the relevant information from publicly available data on TARP, to decide whether a bank has benefited from TARP. Overall, we have data for the period 2005–2010, covering nearly 800 banks that provided loans in more than 2500 counties. To control for a possible selection bias, we propose an identification strategy which exploits the ownership structure of bank holding companies. The result of the baseline specification suggest that TARP banks provide on average 19% higher loan originations compared to NO TARP banks. When we also take into account county-specific poverty and unemployment measures, we find that TARP is only effective in counties suffering from high unemployment.

Our policy conclusion from the second chapter is that governments are able to increase lending to small businesses. In light of the current economic situation in the Euro Area, European governments might find this result puzzling. However, while the US increased bank equity through TARP, the policies of the European Central Bank are aimed to provide sufficient lending facilities to the bank. The key difference between these two approaches are the fact that, *ceteris paribus*, the US policy decreases leverage, while the ECB policy increases leverage.

The third chapter is a theoretical contribution in the field of macroeconomics. In the paper **"Liquid Assets in a Cash-in-Advance Model"**, I analyse an extension to a well-known framework, the cash-in-advance (CIA) model. The CIA was first introduced by Lucas (1982) to study the determination of prices, interest rates, and exchange rates. In fact, Lucas was interested in the determination of nominal variables and to study the behaviour of nominal variables, one has to introduce money. But introducing money into a model with a representative household and a Walrasian auctioneer is tricky. Money – compared to other assets usually introduced in macro models– does not produce any real cash flows and neither is it possible to consume it. So if it does not yield any dividend, why is it valued and held in equilibrium by agents?

The CIA framework is useful because it models why money is valued in equilibrium. Lucas introduced in an otherwise standard real model an additional constraint. The CIA constraint requires that all consumption purchases have to paid with money. In this framework then, money is valuable because it is "liquid", where liquidity measures the ability to buy goods.

While the CIA framework usually imposes that only money can be used for purchases, I relief that strong assumption and allow that also a real asset provides some degree of liquidity. I then show how the static allocation in the model with the new CIA constraint changes. The main finding is that if the asset is also liquid, then the asset is valued more than what its real return would suggest. The difference between the effective value in the model and the fundamental value can be interpreted as the liquidity premium of the asset. I also calculate under which circumstances the liquidity premium is positive.

I also find that the mere fact of having a partially liquid asset does not affect the dynamic response of real and nominal variables to a productivity or a monetary shock. In particular, it remains true that money remains nearly neutral, even with the introduction of the partial liquidity of the real asset. The only exception is the fact that the nominal interest rate reacts much stronger to the shocks. One important finding is that a shock to the fraction of the asset that can be used to purchase consumption goods does have relatively large effects on the real variables. For future research, it would be interesting to measure empirically how much variability in real variables can be explained by a varying degree of liquidity.

Chapter 1

TAF Effect on Liquidity Risk Exposure

with **Stefano Puddu**, University of Neuchatel

Using a unique bank-level dataset, we compare the liquidity and liability features of US commercial banks according to whether they received credit from the Term Auction Facility (TAF) program during the recent financial crisis. Moreover, we identify bank features affecting the likelihood of receiving TAF support and assess the impact of the TAF program on bank liquidity risk. We control for potential selection bias by using the change in the US housing price index at state levels between 2002:Q1 and 2006:Q3 as an exclusion restriction. The results suggest that, on average, banks that benefited from the TAF program exhibited higher ex ante levels of liquidity risk measures and illiquid collateral. TAF banks drastically reduce their funding liquidity risk positions in the periods after the first time they received the financial support. These banks exhibited larger reductions in liquidity exposures and the larger the amount of reserves they received, the greater the impact. Finally, we find that TAF banks are more likely to be headquartered in US states that experienced sharper housing price appreciation before the beginning of the crisis. Several robustness checks confirm the main results.

1.1 Introduction

The bursting of the housing bubble in 2007 led to the most severe financial crisis since the Great Depression. As banks were forced to write down billions of dollars in bad loans, the interbank market for short-term funding froze, leaving several banks with severe liquidity problems. Although these banks were not able to roll over their short-term debt, they were also reluctant to use the Federal Reserve's traditional channel of the discount window (DW) credit programs. This aversion on the part of the banks was notably due to the fact that this strategy might have been interpreted by the market as a signal of being in financial trouble, which would intensify the pressure on the financial institution.

During the crisis the Federal Reserve carried out several extraordinary actions, including the creation of a number of new facilities. The Term Auction Facility (TAF) was based on auctioned short-term credit (with maturities between one and three months), with the general aim of supporting the financial sector and ensuring adequate access to liquidity for financial institutions. Among the programs promoted by the Federal Reserve, the TAF was the only that specifically addressed depository institutions. It was the most important with respect to the short-term credit provided and was available for the longest period. In fact, the Federal Reserve auctioned $3.81 trillion between December 2007 and April 2010 through TAF[1].

According to the Federal Reserve, "[the TAF program] could help ensure that liquidity provisions can be disseminated efficiently even when the unsecured interbank markets are under stress"[2]. The Federal Reserve, through the TAF program, was injecting liquidity into the market, effectively substituting for the interbank credit market and thus trying to affect liquidity risk and spreads in the money markets.

The actions undertaken by the Federal Reserve and the Treasury are known as unconventional monetary policy measures. Their effects must still be clearly assessed and

[1]After the collapse of Lehman Brothers in October 2008, the US Treasury launched the Troubled Assets Relief Program (TARP). The main differences between TAF and TARP lie in the goals of the programs (liquidity provision versus encouraging lending) and the instruments (short-term loans versus equity infusions).

[2]See http://www.federalreserve.gov/monetarypolicy/files/TAFfaqs.pdf.

defined. As claimed by Gertler (2010) "We need to develop models that can trace the effects of these policies on the economy in the same manner we can trace out the effects of interest rate policies." Our paper contributes to the current debate (e.g. Taylor, 2009, 2010, 2012) on the appropriateness and effectiveness of these extraordinary measures and aims to analyse the main determinants that affected decisions to participate in the TAF program, assess bank liability and liquidity features depending on their participation in the TAF program, and quantitatively measure the effect of the TAF program on liquidity risk.

Using a unique bank-level dataset, constructed by merging TAF program information with bank balance sheet data, we provide a complementary point of view to the existing TAF literature. Instead of relying on aggregate price measures that proxy liquidity risk (see e.g. Taylor and Williams, 2009; McAndrews et al., 2008; Wu, 2008; In et al., 2012; Sarkar and Shrader, 2010), our study emphasises the importance of a maturity mismatch between bank assets and liabilities. Our main measure for liquidity risk is the logarithm of the ratio of short-term liabilities to short-term assets.[3] This choice is consistent with the Basel Committee of Banking Supervision's definition of liquidity, that is "the ability to fund increases in assets and meet obligations as they come due". Due to the fact that the participation in the TAF program is not random, we control for the potential selection bias by employing a treatment effects model and use as exclusion restriction the change in the US housing price index at the state level from 2002:Q1 to 2006:Q3.[4] This approach to controlling the selection bias is novel in the TAF literature. The housing price index at the state level from 2002:Q1 to 2006:Q3 helps explain the probability of participation in the TAF program. This measure is a proxy for bank exposure to the local real estate bubble, and therefore indicates of how difficult it was for the bank to access the interbank credit market during the crisis due to the reluctance of other banks to lend to counterparts potentially under stress. We compare the liquidity and liability features

[3] Maturities of less than one year are defined as short-term.

[4] We choose these dates because 2002:Q1 marks the end of the recession following the dot-com bubble, while 2006:Q3 quarter is the fourth quarter before the beginning of the TAF program.

of banks that received TAF reserves with those that did not. We document the liquidity risk behaviour of banks that received the financial support before and after the period they received the TAF funds for the first time. Finally, we assess the impact of the TAF program on liquidity risk changes, measured by the difference of the liquidity risk before and after the TAF program.

Our main findings are the following:

- Banks that benefited from the TAF program exhibited ex ante higher levels of liquidity risk. High liquidity risk measures indicate that banks had more severe maturity mismatches and were therefore more exposed to the freezing of the interbank market since they were unable to roll over their short-term liabilities during the crisis. As a consequence, they were more likely to participate in the TAF program.

- Normalizing the first time when banks benefited from the TAF reserves, liquidity risk decreased in the following periods. During the period 2007:Q3–2010:Q3, all banks reduced liquidity risk, but TAF support implied a larger contraction. The larger the amount of reserves received, the bigger the reduction in liquidity risk. In other words, TAF banks were able to more quickly adjust the structure of their debt maturity. The TAF program provided banks with the extra time needed to improve their balance sheets.

- Banks headquartered in states that experienced a significant appreciation of housing prices between 2002:Q1 and 2006:Q3 were more likely to receive TAF support. These findings are consistent with Doms et al. (2007). The probability of participating in the TAF program also increases when a bank shows higher ex ante levels of liquidity risk and illiquid collateral, such as asset-backed securities (ABSs) and mortgage-backed securities (MBSs). These findings provide empirical support for Acharya et al. (2011).

Importantly, our findings highlight that banks that had significant liquidity mismatches and received TAF funds decreased liquidity risk faster than the rest of the banks.

They were thus able to alleviate their short-term financing exposure. The TAF program provided the depository institutions with liquidity during the liquidity distress, giving them the time to restructure the liability side of their balance sheets. In this sense, the Federal Reserve, through the TAF program, acted as a lender of last resort (LOLR), providing liquidity to distressed banks. From a policy-making perspective, our results strongly support the Federal Reserve's choice to intervene in the banking sector, through the implementation of extraordinary monetary measures, with the aim of providing depository institutions with liquidity (e.g. Rochet and Vives, 2004; Segura and Suarez, 2012) in the periods of financial distress.

Our main results are robust to several different tests. Since TAF loans are also short-term liabilities, our findings could be driven by an accounting effect. We avoid this issue by computing the change in liquidity risk between 2007:Q3 and 2010:Q3, after all the TAF loans were repaid.

The findings could be unrelated to the TAF program and, instead, driven by other measures promoted by the monetary authorities and operating at the same time as the TAF. We control for this issue by excluding from the dataset the banks that participated in the TARP program.

The results could also be driven by specific events that occurred during the period when the TAF was operating. In particular, the collapse of Lehman Brothers represents a tipping point in the context of the financial crisis that started in 2007. We control for this event in several ways. In particular, as suggested by Ivashina and Scharfstein (2010), we exclude from the dataset banks that had a large fraction of their credit lines co-syndicated with Lehman Brothers. We thus create a sub-sample of banks that received TAF funds for the first time before the collapse of Lehman Brothers. Finally, we study the behaviour of the average liquidity risk measures for the TAF banks after normalizing the first period when the banks received TAF support.

The TAF banks show higher levels of liquidity distress. This might imply that, in case of distress, they are forced to decrease their exposure faster than others. If this is true, our results are not capturing the TAF effect but, rather, they reflect a feature of the TAF banks. To control for this potential issue, we match TAF and NO TAF banks using liquidity risk indicators (short term liabilities to short term assets, short-term liabilities to total liabilities, short-term net liabilities, short-term liabilities to risk-free assets, short term liabilities and short term assets) measured in 2007:Q3.

Due to the sample's heterogeneous composition, which includes only a small fraction of TAF banks (3.49%), our results could reflect a sample feature instead of the effect of the TAF program. We control for this potential issue in different ways. On the one hand, we match TAF and NO TAF banks by using a set of control variables and the level of short term liabilities to short term assets measured in 2007:Q3. On the other hand, we run a bootstrap exercise. In each iteration, the sample includes all TAF banks and a randomly chosen subset of NO TAF banks, for a total of 1000 observations. We repeat the estimation 1000 times with different subsamples.

The results could also be driven by the sample period. To control for this potential issue we employ the difference in liquidity risk between 2006:Q3 and 2010:Q3 as dependent variable. We check whether our results hold for alternative measures of liquidity distress. In particular, we focus on short-term liabilities to total liabilities, short-term net liabilities, and short-term liabilities to risk-free assets.

A potential source of attenuation bias for our findings is the fact that, during the crisis, some banks were not allowed to fail, due to their systemic relevance. To control for this effect on the impact of the TAF program on liquidity risk, we focus on banks belonging to the 75th, 90th and 95th percentiles in terms of size.

It could be that banks participated in the TAF program because of solvency problems instead of maturity mismatches. We address this potential problem by focusing only on TAF banks with fundamentals[5] above larger the median of the fundamentals of the TAF banks that failed.

The results could be driven by the methodology employed. We provide evidence

[5]Fundamentals variables are capital buffer, portfolio risk, cash and short term liabilities over risk free assets

estimating the model using econometric techniques, such as ordinary least squares, two stage least squares and treatment effect model estimated in two-step.

Finally, we compute the impact of the TAF program looking at shorter horizons, in order to assess its short term effectiveness.

The literature reports mixed results on the effectiveness of the TAF program on liquidity risk, measured by the spread between the London Interbank Offered Rate (LIBOR) and the overnight indexed swap (OIS). Taylor and Williams (2009) and McAndrews et al. (2008) obtain different results from the same set of explanatory variables[6] but using as a dependent variable the level of liquidity risk and the first difference in liquidity risk, respectively. Specifically, the former study finds no impact of the TAF program, while the latter study finds the TAF program had a negative impact on the liquidity risk spread.

Wu (2008) expands the specification employed in previous contributions by adding a new set of explanatory variables and assuming that the TAF program had a permanent effect on LIBOR-OIS spreads. The author shows that the TAF program decreased liquidity risk spreads. However, these findings are subject to the criticisms of Taylor and Williams (2008), that the TAF program did not have a permanent effect on spreads.

In et al. (2012) distinguish between short and long-run TAF effects. They find that the LIBOR-OIS spread decreased when the TAF was announced, but the effect is not maintained over time. Moreover, according to their results, the TAF only affected three-month spreads. Sarkar and Shrader (2010) study the impact of TAF changes on three-month LIBOR-OIS spread changes by augmenting the specification employed in previous contributions on this topic. Their results show that changes in the TAF issuance volumes had a negative impact on the changes in the LIBOR-OIS spread. Moreover, the authors find that the spread changes depend on the amount of reserves provided.

Angelini et al. (2011) use the long-term interbank spread as dependent variable and distinguish between the period before and after the collapse of Lehman Brothers. They

[6]The variables included refer to the asset-backed commercial paper spread, the credit default swaps for major banks, the Tibor-Libor spread, the Libor-Repo spread, and a TAF dummy variable, which is one on each of the TAF bid submission dates and zero elsewhere.

identify the unconventional monetary policy measure by using a dummy variable that takes the value of one on the day of the announcement of the extraordinary measure and zero otherwise. The authors find that the monetary policy measures decreased the spread by about 10 to 15 basis points, but only after Lehman's collapse.

Contrary to our results, the findings of previous contributions are not robust to the dependent variable chosen, the specification employed, or the distinction between short- and long-run effects associated with the TAF program.

Our study contributes to the literature in a number of ways. We use a unique bank-level data set that allows us to analyse the effect of the TAF program on liquidity distress from the individual bank's perspective. Indeed, we focus on bank *funding liquidity* instead of *market liquidity*,[7] specifically focusing on the effect of the TAF program on bank quantities instead of on liquidity risk spreads. The micro-level data have the additional advantage of mitigating any potential aggregation effects. We also avoid the criticism related to using the LIBOR spread as a measure of liquidity risk. More precisely, Michaud and Upper (2008) show that prices were also impacted by factors other than liquidity risk such as uncertainty and the higher dispersion of credit quality. Moreover, as stressed by Drehmann and Nikolaou (2012) "The spread between interest rates in the interbank market and a risk free rate is purely a price measure and it does not reveal anything about market access, which maybe severely impaired during crisis, nor the volume of net-liquidity demand [...]". Finally, Abrantes-Metz et al. (2012) document the suspicion that the LIBOR was misreported by banks during the crisis such that its informative power was severely diminished.[8]

Since we exploit the cross section instead of the time series dimension, we do not incur the criticism of Taylor and Williams (2008) about the assumption of the long-run effect of the TAF program adopted by Wu (2008).

[7]For further details on funding versus market liquidity, see Brunnermeier and Pedersen (2009), Fontaine and Garcia (2012), and Allen et al. (2010).

[8]Generally, it is important to note that the LIBOR is not a market interest rate, but rather the average of the answers of large banks to the question, "At what rate could you borrow funds, were you to do so by asking for and then accepting interbank offers in a reasonable market size just prior to 11 a.m.?" (see http://www.bbalibor.com/bbalibor-explained/the-basics).

In our approach, we distinguish between banks that at some point received the reserves provided by the TAF program and the other banks and we also take into account the amount of funds received by each bank. This perspective raises the question whether we are able to distinguish between the treatment effects model of the program and the selection effect of the banks. We control for this potential source of bias by using a treatment model to estimate the model. The pre-crisis (2002:Q1–2006:Q3) percentage change in housing prices is the exogenous determinant of the probability of asking for TAF support. This variable affects bank participation in the program without affecting the variation of the liquidity risk measures during the period 2007:Q3–2010:Q3[9].

The rest of the paper is organized as follows. Section 2 discusses the TAF program. Section 3 discusses the data set, while Section 4 describes the econometric model. Section 5 discusses the results and Section 6 concludes the paper.

1.2 How the Term Auction Facility program works

According to the Federal Reserve's definition, "The TAF is a credit facility that allows a depository institution to place a bid for an advance from its local Federal Reserve Bank at an interest rate that is determined as the result of an auction".[10] The aim of the TAF was to compensate for the collapse of the short-term funding market by ensuring liquidity provisions when the inter-bank credit market was under stress.

All banks eligible for the discount window credit programs at the moment of the auction and during the term of the TAF loans were also eligible for participation in TAF.[11] The reserves provided in the TAF program had a maturity of 28 days or 84 days, and had to be fully collateralized. Banks were allowed to have more than one loan at the same time so facilities with different maturities could overlap. The information about banks bidding and receiving funds was private. For each auction the Federal Reserve

[9] This intuition is supported by the empirical evidence, see column (6) of Table 1.4 in Appendix C and by Figure 1.6.c.

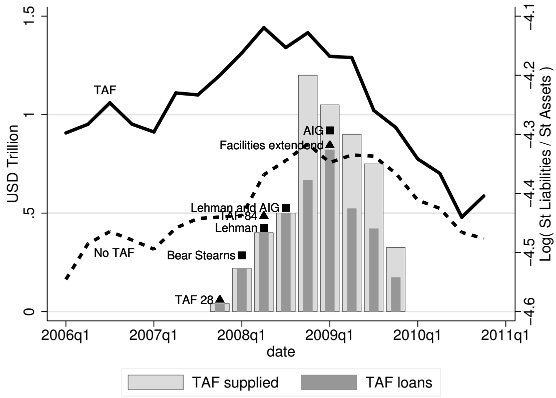
[10] See http://www.federalreserve.gov/monetarypolicy/taffaq.htm

[11] To be eligible, banks had to be "in sound financial condition". The soundness of a particular bank had to be certified by its local reserve bank and depended on solvency, liquidity, and profitability.

fixed the total amount to supply, the maximum amount an individual bank was allowed to obtain, and the minimum bid interest rate. For each auction, eligible banks had the possibility of making two rate amount offers. Specifically, the bid was characterized by the amount asked by the bank and a repayment interest rate. Bids were ordered according to the repayment interest rate bid. The Federal Reserve then began to accept bids, starting with the highest interest rate bids. It would continue to do so until the offered amount was reached; otherwise, all the bids were accepted. In the former case, the interest rate that had to be paid by all successful bidders was determined by the stop-out rate, that is, by the interest rate of the last accepted bid. If the supply exceeded the demand, the equilibrium interest rate would simply be equal to the minimum bid rate.

During the last financial crisis the normal instruments, such as the discount window credit programs, employed by the Federal Reserve to provide liquidity to depository institutions were less effective because of the so-called stigma effect. Depository institutions were concerned about the fact that the market would interpret benefiting from loans provided by the Federal Reserve by the normal discount window credit programs as a bad signal (stigma). Armantier et al. (2008) and Armantier et al. (2011) find that in the third quarter of 2008, banks preferred to pay, on average, at least 34 basis points more to borrow from the TAF program than from the DW. Ashcraft et al. (2010) confirm these findings. They show that after February 2008 depository institutions preferred to receive TAF support and pay a higher rate than to benefit from the discount window at a cheaper price. To avoid or minimize the stigma effect, the Federal Reserve decided to keep the information regarding the institutions that benefited from the loans in the TAF program framework confidential; at the same time, it adopted an auction mechanism to determine which institutions would obtain the reserves and to establish the repayment interest rate. An auction mechanism such as that described above has several important advantages in decreasing the potential stigma effect. First, the interest rate is determined through a market mechanism instead of being imposed by the authorities; second, banks approach the Federal Reserve collectively instead of individually.

Figure 1.1: TAF reserves, market events, policy measures and liquidity risk



Notes: The left-hand scale shows the reserves offered and effectively provided in the context of the TAF program. Moreover, the squares (triangles) refer to market (policy) events. The right-hand scale shows the average levels of short-term liabilities over short-term assets for the TAF and NO TAF bank groups.

Figure 1.1 shows the reserves supplied by the Federal Reserve and those effectively provided to the depository institutions each quarter under the TAF program (left-hand scale). The graph highlights that before the collapse of Lehman Brothers, the auctions were competitive. Following the Lehman Brothers collapse, this was no longer the case for the auctions: All depository institutions that asked for TAF facilities obtained them, since the Federal Reserve doubled the amounts supplied.

Figure 1.1 also reports several market events (squares) and policy measures related to the TAF program (triangles). The program was announced on December 12, 2007. The initial reserves had a maturity of 28 days. The amount provided was increased in the first quarter of 2008, after Fannie Mae and Freddie Mac requirements were eased to allow for increases in lending and Bear Stearns received emergency loans from the Federal Reserve. Reserves with longer maturities were established in 2008:Q2, after Lehman Brothers reported losses of $2.8bn. The amount of reserves provided kept rising after the Lehman Brothers bankruptcy and the downgrade of AIG debt. The maximum amount was supplied during 2009:Q1, when Fannie Mae and Freddie Mac reckoned a need for

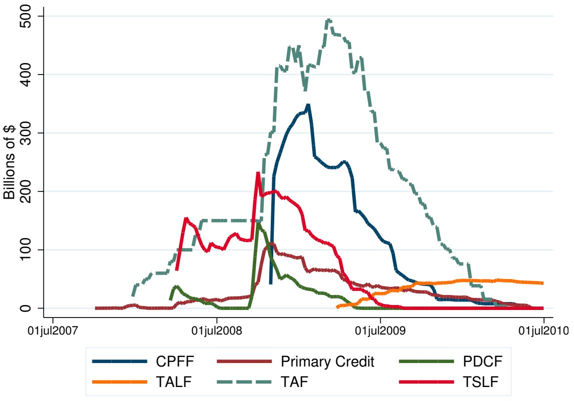
$51bn to continue operations and AIG announced large losses. From 2009:Q2 on, new facilities decreased to a level that persisted until March 8, 2010, when the last auction took place.

The graph (right-hand scale) also shows the average level of short-term liabilities over short-term assets for two groups of banks: TAF banks, that is, banks that received reserves at least once, and NO TAF banks, which did not. Before the beginning of the TAF program the two groups of banks showed similar (increasing) patterns, although TAF banks had higher levels of liquidity risk. Just after the collapse of Lehman Brothers, both groups started decreasing their liquidity exposure. However, the graph shows that TAF banks adjusted their exposure faster, to such an extent that these differences were no longer significant once the TAF program was over. These features of the series hold when the quartiles (25th, 50th, and 75th) of the series for the two groups of banks are compared, as highlighted in Figure 1.9, reported in Appendix D.

During the last financial crisis, apart from the TAF program, the Federal Reserve and the US Treasury put in place other facilities[12] for auctioning short-term credit, with the general aim of supporting the financial sector and ensuring adequate access to liquidity for financial institutions. Figure 1.2 shows the Federal Reserve's weekly outstanding lending to financial institutions through the different programs. The graph highlights the importance of the TAF program in the context of the measures launched by the Federal Reserve during the financial crisis, with respect to both the amounts employed and the duration of program operation.

[12]Appendix A discusses in detail the main features of the other programs launched by the Federal Reserve during this period to underline the common points and main differences.

Figure 1.2: Federal Reserve lending during the financial crisis



Notes: This figure shows the Federal Reserve's weekly outstanding lending to financial institutions through the different programs operating during the last financial crisis. Commercial Paper Funding Facility (CPFF), Term Asset-Backed Securities Loan Facility (TALF), Primary Dealer Credit Facility (PDCF), and Term Securities Lending Facility (TSLF).

1.3 Data and descriptive analysis

In this section we carry out a detailed analysis of the dataset employed in this study and summarise our main results.

1.3.1 Data

We create a unique dataset by merging several different sources. The data concerning bank balance sheets is a combination of the Report of Condition and Income (generally referred to as the Call Report) and the Uniform Bank Performance Report (UBPR). US banks are required to submit these reports to the Federal Financial Institutions Examination Council (FFIEC). The specific reporting requirements depend on the size of the bank and whether it has foreign offices. We accessed the Call Report data through the Federal Reserve of Chicago website and the UBPR data through the FFIEC website.[13] The

[13] A known issue of the Call Report data we cannot control for is the so-called window dressing effect: The day before the report, banks adopt virtuous behavior so that their balance sheets look particularly good on the day of the report.

period in question runs from 2006:Q3 to 2010:Q3. The data on the TAF auctions are from the Federal Reserve Board. The sample covers the period from 2007:Q4 to 2010:Q1. Although information regarding the TAF was kept private during the financial crisis, it had to be disclosed in December 2010, after Bloomberg won a federal lawsuit. Finally, the House Price Index (HPI) dataset was obtained from the Federal Housing Finance Agency website. The period covered is from 1991:Q1 to 2012:Q3 and the information is reported at the state level. We merged the datasets and transformed them into a cross-sectional dataset. The dependent variables are generated by taking the difference of the liquidity risk measures between 2007:Q3 and 2010:Q3, while the control variables are measured in 2007:Q3 and between 2002:Q1 and 2006:Q3, depending on the case.

Our final sample includes 7591 banks. Among them, 265 banks obtained TAF program reserves at least once. These banks represent approximately 3.49% of the banks in the sample.[14] We exclude all US branches of foreign banks and agencies of foreign banks from the final sample that were initially included in the TAF dataset because we have no comparable balance sheet data for these banks. Moreover, the sample includes failed, acquired, and surviving banks, so the results do not suffer from a survivorship bias.[15] Specifically, 804 banks disappeared (we consider them failed or acquired) before 2010:Q3. Among them, 27 obtained TAF program reserves.

1.3.2 Description of the variables

Since we are interested in the TAF program's effect on the change of banking funding liquidity risk, we distinguish between banks that obtained reserves through the TAF program at least once and those that did not. The dummy variable labelled TAF takes on the value of one if a bank received TAF reserves at least once and zero otherwise. We also focus on funds received by each bank through the TAF program. Specifically, we

[14] In the robustness checks, we control for the fact that the dataset is characterized by an uneven distribution of banks between the two groups.

[15] A survivor bias could arise if the sample included only surviving banks, disregarding those that failed or were acquired while the program was operated by the Federal Reserve. If this were the case, the results would not take into account the information associated with failed institutions, leading to biased results.

define $TAF\ AMOUNT\ 1$ as the log of one plus the overall amount of TAF funds received by each bank and $TAF\ AMOUNT\ 2$ as the log of one plus the ratio of the overall amount of TAF funds received by each bank and the total loans measured in 2007:Q3. Finally, $AVG\,TAF\ AMOUNT$ is defined as the log of one plus the ratio of the overall amount of TAF funds received by each bank to the corresponding number of times the bank received TAF reserves.[16]

In the baseline analysis, we approximate the liquidity risk of funding by the log of the short-term liabilities over short-term assets ($ST\,LIAB/ST\,ASS$). Larger values of this ratio imply a higher level of funding liquidity risk.

In the robustness checks we employ different measures of liquidity risk, such as the ratio of short-term liabilities to total liabilities ($ST\,LIAB/\,TLIAB$), the ratio of the log of short-term liabilities to risk-free assets ($ST\,LIAB/PF\,RISK\,0$), and the short-term net liabilities ($ST\,NET\,LIAB$). These proxies show how important short-term liabilities are with respect to different measures of liquid assets or with respect to the total volume of liabilities.

Control variables include bank liquidity capacity, portfolio composition, loan structure, loan losses, different types of collateral assets, capital capacity, profitability, and features of the US state where the bank has its headquarters. As a proxy for liquidity capacity, we employ two alternative measures: $LIQUIDITY$ is defined as the sum of total trading assets, total securities available for sale, and total securities held to maturity over total assets, while $CASH$ is determined by cash and balances due from depository institutions over total assets.

We also consider bank features regarding capital capacity and profitability as controls. Specifically, $CAPBUFFER$ is obtained by taking the difference between the tier 1 capital ratio and the minimum requirement established by the banking authorities,[17] return on

[16] The impact of the amounts received on liquidity risk should be studied at the margin. That is, by considering bank liquidity needs at the moment of receiving the funds. Unfortunately, the dataset precludes this type of analysis. In the cross-sectional context, we think that the alternative measures proposed above are the best approximation to capture the effect of TAF amounts on liquidity risk.

[17] In the period under analysis the minimum capital requirement was equal to 6%.

assets (ROA) is equal to the ratio of income before taxes and extraordinary items and other adjustments to total assets, $SIZE$ is measured by the log of total assets, the ratio of non-performing loans to total loans (NPL) is defined as loans past due at least 30 days or that are on a non-accrual basis, and provisions for non-performing loans ($PROV$) equal the ratio of loan loss provisions to total loans.

To account for the portfolio composition of bank assets, we calculate the ratio of risk-weighted assets to total assets ($PF\ RISK$).[18] This measure can be interpreted as a proxy for the portfolio risk: The higher this ratio, the higher the fraction of assets considered risky by the regulatory authorities. Another set of control variables includes the fraction of each asset risk category, according to Basel I.

For explanatory variables, we also take into account measures of bank loans. We consider total loans to total assets ($TLOANS$), as well as the ratio of different loan types over total loans. Specifically, we focus on commercial and industrial, real estate, individual, and agricultural loans ($CI\ LOANS$, $REST\ LOANS$, $INDIV\ LOANS$, and $AGRI\ LOANS$, respectively). The percentage variation of the housing price index during the crisis is included among the explanatory variables of the change in liquidity risk.

We add variables that serve as proxies for the amount of illiquid collateral. The quality of the collateral may have affected the likelihood of participation in the TAF program. More precisely, we take into account the Asset-Backed Securities and other types of Mortgage-Backed securities. They are defined as the ratio of asset-backed securities to total assets (ABS) and the ratio of other types of mortgage-backed securities to total assets ($MBS\ OTHER$). These measures assume that securities are held to maturity or are available-for-sale at their fair value. As a determinant of bank participation in the TAF program, we also include the percentage change in housing prices, at the US state level, during the period between the end of the dot-com bubble (2002:Q1) and the four

[18]The weights (0%, 20%, 50%, and 100%) are ascribed according to Basel I. On- and off-balance sheet items are summed when total assets are computed.

quarters before the beginning of the TAF program (2006:Q3). The value ascribed to each bank refers to that of the US state where the bank is headquartered. A detailed analysis of the sources and definitions of the variables are reported in Table 1.12 in Appendix C.

1.3.3 Descriptive statistics

Table 1.2 reports the descriptive statistics before (in 2007:Q3) and after (in 2010:Q3) the TAF program. Within each sub-period, we also provide separate descriptive statistics for the sub-sample of banks that received TAF support and for those that did not. With a focus on liquidity risk measures, the main findings highlight that before the beginning of the program (2007:Q3), TAF banks reported higher levels of funding liquidity risk than those of other banks (column [3] vs. column [1]) and that these differences decreased once the program is over (column [9] vs. column [7]). Liquidity risk volatility was higher for TAF banks than for the other banks. This is true for the two periods analysed. Focusing on the components of the baseline measure of liquidity risk,[19] we find TAF banks had larger values before and after they received TAF funds. Moreover, these banks increased short-term assets and decreased their exposure in short-term liabilities after the end of the program compared to before. Once the program was over, NO TAF banks experienced a decrease in $ST\ ASS$ and an increase in $ST\ LIAB$. The other relevant result is that although all banks lowered their funding liquidity exposure, TAF banks did so to a greater extent. The only measure that does not follow this pattern is $CASH$. Specifically, banks that did not receive reserves under the TAF program increased $CASH$ more than the other banks. A plausible explanation for this result is that NO TAF banks would have employed cash as a substitute for TAF reserves. To meet their liquidity needs, they would have increased their cash holdings, given that they chose not to benefit from alternative financial aid.

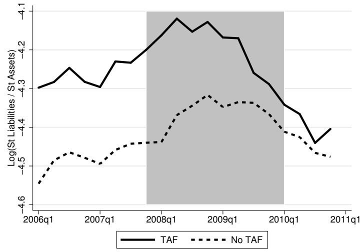
In Table 1.3, we test whether, on average, there exist differences within groups across time and within time across groups. The results confirm previous intuitions: Ex ante,

[19] Specifically, $ST\ LIAB$ and $ST\ ASS$ are defined as the log of short-term liabilities and the log of short-term assets, respectively.

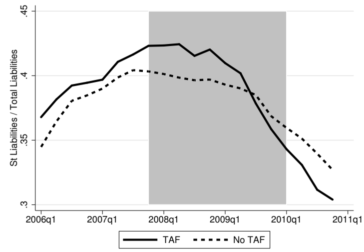
TAF banks exhibit higher levels of liquidity risk. Moreover, these differences decreased after the end of the program. Focusing on $ST\ LIAB$ and $ST\ ASS$, in both cases we find evidence that TAF banks compared to NO TAF banks show higher levels of the two variables both before and after they receive funds. Fixing the bank group, the results also highlight that there are no differences for the TAF banks across time, while NO TAF banks show a positive difference that is statistically significant. Finally, regarding liquidity measures, the results confirm that before and after the program TAF banks had less cash or liquidity than NO TAF banks, while the within-group analysis shows that only TAF banks experienced a significant increase in cash between the two periods.

The descriptive analysis highlights that both groups of banks adjusted the quantities that refer to liquidity risk, as indicated by liabilities and liquidity indicators. Moreover, in the majority of the cases, TAF banks changed these amounts more than the NO TAF banks. These changes also imply that the differences between the groups decreased or disappeared once the program was over. Previous patterns are illustrated in Figure 1.3. On average, bank liquidity risk levels between the groups were different just before the program began, while these differences decreased after the program ended. These results are confirmed by distinguishing bank quartiles (see Figure 1.9 in Appendix D).

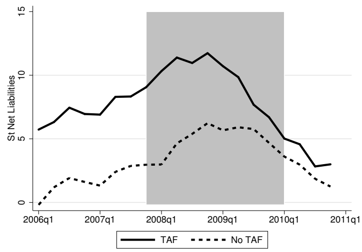
Figure 1.3: Bank average liquidity risk measures, by quarter



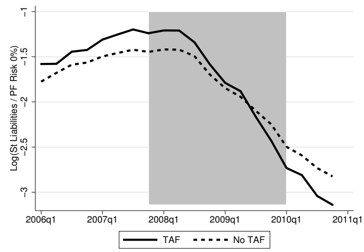
(a) ST Liabilities / ST Assets



(b) ST Liabilities / Total Liabilities



(c) ST Net Liabilities / Total Assets



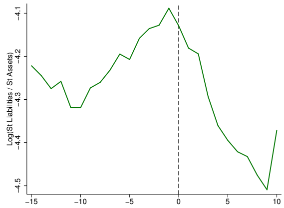
(d) ST Liabilities / PF Risk 0%

Notes: We document the average behaviour of the following measures of liquidity risk, distinguished by bank group (TAF and NO TAF): ST LIAB/ST ASS, ST LIAB/TLIAB, ST NET LIAB, and ST LIAB/PF RISK ZERO. The period during which the TAF program was operating is in gray.

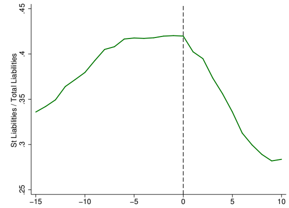
Figure 1.4 plots different measures of liquidity risk between 15 quarters before and 10 quarters after the first time banks received reserves under the TAF program. For all measures of liquidity risk, on average, the banks decreased their funding liquidity risk positions once they received the reserves. The graphical analysis suggests that the TAF program was effective and useful and that it especially improved the funding liquidity exposure of recipient banks.

One potential criticism could be that trends in previous graphs may be driven by the fact that banks received TAF support during a specific period. Therefore, if this is the case, it follows that what previous graphs are capturing does not refer to the effect of the TAF program but, rather, to other time-based events. Figure 1.5 shows the distribution of the quarters when banks received TAF support for the first time. The results highlight

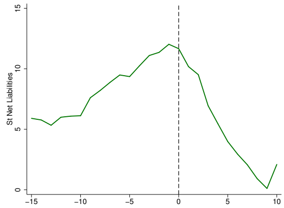
Figure 1.4: Average bank liquidity risk behaviour, by quarter



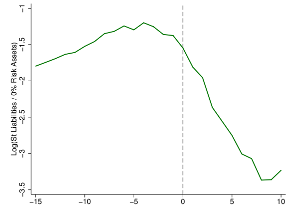
(a) ST Liabilities / ST Assets



(b) ST Liabilities / Total Liabilities



(c) ST Net Liabilities / Total Assets

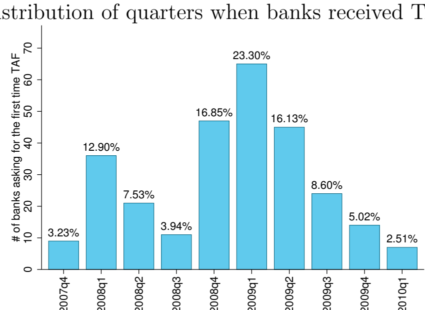


(d) ST Liabilities / PF Risk 0%

Notes: For TAF banks only, we document the average behaviour of the following measures of liquidity risk from 15 quarters before to 10 quarters after the first time the banks obtained reserves: ST LIAB/ST ASS, ST LIAB/TLIAB, ST NET LIAB, and ST LIAB/PF RISK ZERO.

that about 50% of the TAF banks received the support for the first time in the two quarters after the collapse of Lehman Brothers. The other 50% of the observations are spread around the rest of the quarters when the program was operating.

Figure 1.5: Distribution of quarters when banks received TAF support for the first time



Notes: This figure shows the distribution of the quarters when banks received TAF support for the first time. The vertical axis reports the frequencies. At the top of each bar is displayed the corresponding fraction of banks that received TAF support to the total number of TAF banks in a specific quarter.

To check whether the results summarized by Figure 1.4 are robust to this potential issue, we drop from the sample banks that received TAF support for the first time in the two quarters after the collapse of Lehman Brothers. The new findings reported in Figure 1.3 of the Appendix D do not change: The average liquidity risk per quarter decreases around the period zero. This is true for all the measures of liquidity risk employed.

1.4 Empirical strategy

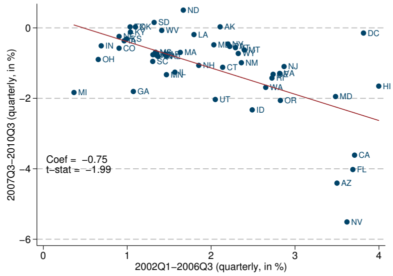
1.4.1 Selection

Participation in the TAF program was not random. Therefore, it is crucial to isolate the effect related to the voluntary choice of banks to ask for TAF funds, in order to assess the effect of the TAF program on the change in funding liquidity risk. We control for this selection issue by using the housing price index change at the US state level for the period 2002:Q1–2006:Q3 as an exogenous determinant of the probability to request TAF support.

More precisely, we claim that the 2002:Q1–2006:Q3 HPI percentage change is expected to positively affect participation in the TAF program. The reason is that US states that experienced a significant increase in housing prices for the period 2002:Q1–2006:Q3 were also those that, during the crisis, were hit by a relevant drop in housing prices (Figure 1.6.a) and a substantial increase in loan delinquency rates[20] (Figure 1.6.b). Therefore, banks headquartered in states where the HPI showed the patterns described above, were more likely to have suffered from the real estate collapse. These banks, in case of liquidity needs, could have found it more difficult to raise funds in the interbank credit market because of other banks' reluctance due to the risk related to the bursting of the real estate bubble. As a consequence, they should have been more likely to participate. It is important to note that the change in housing prices for the period 2002:Q1–2006:Q3 directly affects bank participation in the TAF program but does not affect bank strategy in changing liquidity risk during the period 2007:Q3–2010:Q3. Previous intuitions are supported by the results reported in column 6 of Table 1.4 and by Figure 1.6.c.

[20] The latter result is in line with those obtained by Doms et al. (2007).

Figure 1.6: Relation between changes in HPI and NPL before and during the crisis



(a)

(b)

(c)

Notes: In this figure, before the crisis (bc) is 2002:Q1–2006:Q3, and during the crisis (dc) is 2007:Q3–2010:Q3. Analysis at the state level (i). Figure 1.6.a: We document the relationship between the HPI percentage change before the crisis and that during the crisis. The line refers to the regression $\Delta\%HPI_{i,dc} = \alpha + \beta\Delta\%HPI_{i,bc} + \epsilon_i$. Figure 1.6.b: We document the relationship between the HPI percentage change before the crisis and the NPL percentage change during the crisis. The line refers to the regression $\Delta\%NPL_{i,dc} = \alpha + \beta\Delta\%HPI_{i,bc} + \epsilon_i$. Figure 1.6.c: We document the relationship between the HPI percentage change before the crisis and the change in liquidity risk ($ST\,LIAB/ST\,ASS$) during the crisis. The line refers to the regression $\Delta\%ST\,LIAB/ST\,ASS_{i,dc} = \alpha + \beta\Delta\%HPI_{i,bc} + \epsilon_i$.

Further information about the relationship between housing price changes and TAF participation is reported in Figure 1.11 of Appendix D. More precisely, for each US state, we report the percentage change in housing prices during the period 2002:Q1–2006:Q3 (green), the size (by asset value) of the banks whose headquarters lie in a specific state (blue pie), and the fraction (by asset value) of banks that received TAF support (red). This figure highlights how the fraction of TAF banks is larger in US states that experienced greater appreciation of the housing price during the period 2002:Q1–2006:Q3.

1.4.2 Econometric model

To assess the impact of the TAF program on bank liquidity risk, we use a treatment effects model with a binary endogenous explanatory variable. This type of model is estimated simultaneously using maximum likelihood (ML) to provide consistent, efficient, and asymptotically normal estimators under the assumption that the error terms follow a bivariate normal distribution.[21]

We are interested in fitting the treatment effects model:

$$\begin{aligned} \Delta\, STLIAB/STASS_i = {} & \alpha\, TAF_i + \beta_1\, LIQUIDITY_i + \beta_2\, CAPBUFFER_i + \beta_3\, ROA_i \\ & + \beta_4\, SIZE_i + \beta_5\, PFRISK\,0_i + \beta_6\, PFRISK\,20_i \\ & + \beta_7\, PFRISK50_i + \beta_8\, PFRISK100_i \\ & + \beta_9\, \Delta HPI_{i,\,2007:Q3-2010:Q3} + \xi_i \end{aligned} \tag{1.1}$$

$$TAF_i = \begin{cases} 1 & \text{if } TAF_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.2}$$

where the unobserved latent variable follows the specification below:

[21] We test joint normality following Lee (1984), Pagan and Vella (1989), Bera et al. (1984), and Gallant and Nychka (1987). The null hypothesis of joint normality is never rejected at a reasonable significance level. The results are available upon request.

$$TAF_i^* = \pi_0 + \pi_1\, ST\,LIAB/ST\,ASS_i + \pi_2\, CASH_i$$
$$+ \pi_3\, MBS\,OTHER_i + \pi_4\, ABS_i + \pi_5\, \Delta HPI_{i,\,2002:Q1-2006:Q3} + \nu_i \qquad (1.3)$$

In the outcome equation (1.1), the change of funding liquidity risk, $\Delta\ LIQ\,RISK$, depends on a set of explanatory variables and on TAF, a binary endogenous covariate that captures the TAF program's impact on the dependent variable. Moreover, in equation (1.3) the latent variable determines the values of the binary variable TAF, according to equation (1.2). Equations (1.2) and (1.3) represent the participation part of the model. The TAF dummy can be interpreted as a participation indicator: It equals one if bank i received the funds at least once, and zero otherwise.

Outcome equation

All the variables included in equation (1.1), except the change in housing price index, are measured in 2007:Q3, prior to the beginning of the program. The dependent variable in equation (1.1) refers to the change in funding liquidity risk between 2007:Q3 and 2010:Q3. Once the selection bias is controlled for, the TAF variable is expected to negatively affect the change in funding liquidity risk. If this is the case, the TAF program is effective in the sense that it allows banks in funding liquidity distress to adjust and improve their funding liquidity exposure.

Several additional controls are added to equation (1.1). More precisely, we focus on $LIQUIDITY$, the level of $CAPBUFFER$, the $SIZE$ of the banks, and the ROA. The variable $LIQUIDITY$ captures potential liquidity distress associated with bank liquidity needs. The higher the liquidity level, the smaller the change in funding liquidity risk. The inclusion of $CAPBUFFER$ is useful for assessing the impact of capital cushions on the level of liquidity risk. More precisely, higher capital buffer implies that banks are prone to adopt more aggressive investment strategies, so we expect that capital buffer positively affects the change of funding liquidity risk. We explicitly take into account the $SIZE$ of the banks, because banks of different sizes have different abilities to manage liquidity risk. In particular, big banks can more easily adjust funding liquidity mismatches, so $SIZE$ is expected to have a negative impact on the change in liquidity risk. Finally, return on assets is a measure of investment returns. A higher return on assets implies that some banks invest more efficiently and therefore may easily reduce their funding liquidity exposure. We assess the effects of portfolio composition on the change in funding liquidity risk by including in the baseline specification the different types of assets held by banks[22]. We do not have an a priori expected sign for the effect of this second set of explanatory variables on the change in funding liquidity risk. Finally, the specification is completed by including the change of the housing price index, ΔHPI, for the period when the program was operating. We expect that more important drops in housing price at the US state level during the period 2007:Q3–2010:Q3 positively increased bank liquidity distress.

The potential effect on liquidity risk of other Federal Reserve programs is not taken into account in the specifications. The reason is that the financial institutions that benefited from the other programs promoted by the Federal Reserve were not depository institutions.[23] The only programs directly affecting depository institutions are the primary, secondary, and seasonal credit discount window, but, as previously mentioned, during the crisis these programs were less effective due to the fact that depository institutions were concerned about the stigma effect. Accordingly, the TAF program effects captured in our analysis appear unlikely to have been driven by other programs not explicitly taken into account in the specifications. This view is also supported by the information highlighted by Figure 1.2, which plots the Federal Reserve's weekly outstanding lending to financial institutions through the different programs operating during the last financial crisis. This figure shows the relevant role played by the TAF program in terms of the amounts provided, as well as the length of the period when the program was operated by the Federal Reserve.

[22]The type of assets refers to their riskiness, consistent with Basel I.

[23]More details are provided in Appendix 1.A.

Participation equation

Equations (1.2) and (1.3) capture the probability of obtaining the reserves. As previously mentioned, the key variable included among the covariates to explain a bank's probability to request TAF support is the percentage change in the housing price index between 2002:Q1 and 2006:Q3. The impact of this variable on bank participation is expected to be positive. Moreover, we include funding liquidity risk, cash, and illiquid collateral assets such as ABSs and MBSs, all measured in 2007:Q3. We expect that banks with higher levels of funding liquidity risk were more likely to participate in the program. The level of cash is expected to negatively affect the probability of receiving funds because banks with sufficient levels of cash were better able to manage liquidity distress. Banks showing high levels of illiquid collateral, reflecting greater maturity mismatch, are expected to be more likely to have participated in the TAF program, as predicted by Acharya et al. (2011).[24] These banks were solvent, but temporarily illiquid, because they were unable to increase liquidity by selling some of their assets. Due to a lack of trust in the inter-bank credit market, these banks could not obtain liquidity from other banks, and only the Federal Reserve accepted their illiquid collateral assets in exchange for reserves.

1.5 Hypotheses and results

1.5.1 Participation effect on liquidity risk

Based on the findings of Section 1.3.3, our first hypothesis is that

H1: Banks that benefited from the TAF program decreased their liquidity risk exposures more quickly .

The results reported in Table 1.4 confirm our hypothesis. The TAF dummy is always

[24]In a model of debt capacity, under specific assumptions about the tenor of the debt (shorter than that of assets), the frequency (high) of rolling over the debt; the liquidation cost (small) in case of default, and the probability (low) of finding potential borrowers in the market without short-term debt finance issues, Acharya et al. (2011) find sufficient conditions for a market freeze. A market freeze is more likely for banks holding important amounts of ABSs, assets with little trading liquidity.

negative and statistically significant. This means that banks that received TAF reserves decreased funding liquidity exposure more quickly than those that did not. This effect is not only statistically significant but also economically substantial. Receiving TAF loans has an average extra effect on the quarterly growth rate of the funding liquidity exposure between -6.55 and -6.95 percentage points, depending on the case.[25] These results support the intuition that TAF reserves were crucial to reduce bank exposure and control for the funding liquidity risk of those banks with more severe maturity mismatches, which were most exposed to the freezing of the interbank market and unable to roll over their short-term liabilities during the crisis. This finding suggests that the TAF program provided banks with extra time to adjust the liability side of their balance sheets. A possible reason is that TAF banks might have considered themselves under scrutiny and might have reacted accordingly to look better when reassessed later on, although they were not subject to additional controls by the Federal Reserve.

The results hold regardless of the specification. More precisely, column (1) of Table 1.4 reports the results of the baseline model. In column (2) we replace the different risk type shares by the weighted asset risk $PF\,RISK$. In column (3) we use the different types of loans instead of banks assets classified by risk category. In column (4) we estimate a reduced form of the baseline specification by dropping the different types of assets, while in column (5) we augment the previous specification by adding $PROV$ and NPL to capture the impact of expected future and current distress due to bad loans on liquidity risk.

The findings also confirm our intuition about the impact of the covariates, included in the different specifications, on liquidity risk change. Finally, the λ parameter is never statistically different from zero. We can therefore conclude that our results do not suffer from selection bias.[26]

[25] To interpret the dependent variable as a quarterly growth rate we have to divide the estimated coefficient of the dummy variable TAF by 12, the number of quarters between 2007:Q3 and 2010:Q3.

[26] The null hypothesis is no selection bias. In all cases, we reject the null hypothesis at the 1% significance level (see the corresponding χ^2 statistics).

1.5.2 Effect of reserves amount on liquidity risk

Another element affecting the change in liquidity funding is the amount of reserves that banks received within the TAF program framework. We expect that the larger the support received (proportional to the bank's size), the greater the effect on decreasing liquidity risk exposure. More precisely, we propose the following hypothesis.

H2: The larger the amount of reserves received, the higher the impact of the TAF program on liquidity risk change.

We employ three different measures of the total amount of reserves received by each bank. Specifically, we focus on the amount received, $TAF\,AMOUNT\,1$; the amount received weighted by the level of total loans measured in 2007:Q3, $TAF\,AMOUNT\,2$; and the average amounts received by each bank, $AVG\,TAF\,AMOUNT$, that is, the total amount divided by the number of successful bids.

Due to the nature of these alternative measures, specifically that they are continuous and left censored at zero, we modify the econometric model described in Section 1.4.2. More precisely, equations (1.2) and (1.3) are estimated using a Tobit model instead of a probit model. The explanatory variables used do not change with respect to the baseline model.

The results, reported in Table 1.5, confirm our hypothesis. The findings highlight a negative relationship between the amount of reserves received and the adjustment of the funding liquidity risk. According to the results in column (1), a 1% increase in reserves received leads to a drop in the liquidity risk growth rate of 0.099%. The impact is reduced to about one-third if we focus on the fraction of amounts received with respect to the total loans the bank holds, as reported in column (2). Finally, as highlighted in column (3), an increase of 1% of the average amount of reserves received leads to a 0.147% decrease in the growth rate of the liquidity risk measure. This finding implies that the amount received through the TAF program matters in reducing exposure to liquidity risk. This holds regardless of the alternative measures of TAF benefits used, as documented by columns

(1) to (3). Moreover, we test whether the results hold when an alternative dependent variable is employed. As shown in columns (4) to (6), the findings do not depend on the proxy for liquidity risk.

1.5.3 HPI change and the probability of receiving TAF support

As thoroughly discussed in Section 1.4.1, we employ the change in housing price index between 2002:Q1 and 2006:Q3 at the US state level as an exclusion restriction in the first-stage regression. More precisely, US states that experienced a huge increase in HPI during the period 2002:Q1–2006:Q3 are also those that showed a drastic drop in the same variable during the period 2007:Q3–2010:Q3. These states particularly suffered from the bust of the real estate boom. This variable can explain the difficulties banks located in these US states had in accessing to the interbank credit market due to the reluctance of the other banks to lend. Accordingly, we propose the following hypothesis.

H3: Banks with headquarters in US states that experienced a larger appreciation in HPI during the period 2002:Q1–2006:Q3 are more likely to have received TAF funds.

The results support our hypothesis. As highlighted in Table 1.4, in the participation equation the change in HPI between 2002:Q2 and 2006:Q3 is always significant and positive. This result does not depend on the specification. In our opinion, this variable is crucial in fixing the selection effect, and therefore in isolating the effect of the TAF program. More precisely, the change in HPI from 2002:Q2 to 2006:Q3 affects the probability of receiving TAF support but does not directly affect the decision of the bank to decrease liquidity exposure during the period 2007:Q3–2010:Q3.

1.5.4 Illiquid collateral and the probability of receiving TAF support

The last hypothesis tested refers to the assessment of the impact of illiquid collateral on the probability of receiving TAF support. During the crisis, collateral such as MBSs or ABSs was revealed to be illiquid. Therefore, banks with important fractions of these types of collateral were more likely to be in need of liquidity. However, other banks were reluctant to lend them money because they thought that banks asking for funds were suffering from liquidity distress. Therefore, banks with higher fractions of MBSs and ABSs were more likely to have received TAF support. More precisely, we propose the following hypothesis.

H4: Banks with higher fractions of illiquid collateral such as MBSs and ABSs are more likely to have received TAF funds.

The results reported in Table 1.4, confirm our hypothesis. This holds regardless of the specification. The results support the theoretical model by Acharya et al. (2011). The findings hold in several robustness checks, as documented in Tables 1.8, 1.6, and 1.7.

1.5.5 Robustness

We perform several robustness tests and the results are reported in Tables 1.6 to 1.11.

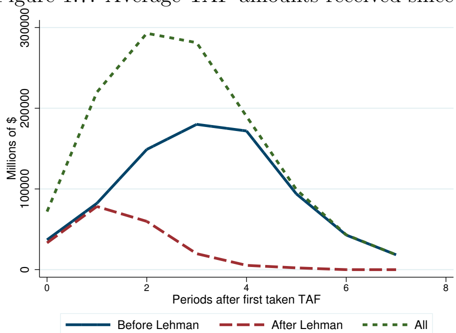
Competitive auctions and the pre-Lehman period

Our result could suffer from an omitted variable bias because other events occurred contemporaneously to the TAF program and were not explicitly taken into account.[27] One relevant episode was the failure of Lehman Brothers in 2008:Q3. We already controlled for the Lehman event by dropping all banks that had a large fraction of their credit lines co-syndicated with Lehman Brothers, as reported by Ivashina and Scharfstein (2010). For comparison reasons, the results of the baseline model are reported in column (1) of Table 1.6. Moreover, in column (2) we verify the results by limiting our sample to the pre-September 2008 TAF auctions. The results show that the TAF coefficient is statistically different from zero and has the expected negative sign. The results of the competitive auctions are consistent with the baseline findings in terms of the direction of the effect

[27] As previously discussed, we do not control for the effect of the other extraordinary programs promoted by the Federal Reserve since depository institutions were not eligible for those programs.

(negative) of the TAF program and with respect to the size of the effect (4.68 percentage points in the competitive auctions versus 6.55 percentage points for the overall sample). Despite these common elements, we can capture differences in the amounts received by the two groups of TAF banks, those that benefited from the program for the first time before Lehmans collapse and those that benefited from the program afterward. Figure 1.7 shows the average amounts of reserves received by all the banks, by banks that received the reserves for the first time before the collapse of Lehman Brothers, and by banks that received the reserves for the first time after the collapse of Lehman Brothers. The majority of the funds were ascribed to depository institutions that received the facilities for the first time before the collapse of Lehman Brothers. Moreover, for these banks, the maximum average amount received was obtained after three periods, and they benefited from the program for a longer period than the depository institutions that obtained the reserves for the first time after the collapse of Lehman Brothers.

Figure 1.7: Average TAF amounts received since the first time



Notes: This figure shows the average amounts of reserves received by all banks, by banks that received the reserves for the first time before the collapse of Lehman Brothers, and by banks that received the reserves for the first time after the collapse of Lehman Brothers.

Controlling for TARP

Another event that could affect our results is the Troubled Asset Relief Program (TARP)[28] promoted by the US Treasury in October 2008. Among the banks in our sample, only seven received both TAF reserves and equity through the TARP program. However, we found that 89 banks received TAF and participated in the TARP program through their bank holding companies. To control for the TARP effect on liquidity risk, we exclude from the sample the 96 banks that participated in the TARP program. The results, reported in column (5) of Table 1.6, remain unchanged. Therefore, we can conclude that our findings are not driven by the TARP program.

Higher levels of liquidity distress

The TAF banks display higher levels of liquidity risk. It follows that, in extreme cases, TAF banks should have adjusted their exposure more quickly. If this was the case, what the TAF dummy captures is not an effect of the TAF program but, rather, a feature of the TAF banks. We control for this potential issue by implementing propensity score matching with three neighbours and matching TAF and NO TAF banks with respect to liquidity risk measures such as short-term liabilities over short-term assets, short-term liabilities over total liabilities, short-term net liabilities, short-term liabilities over risk-free assets, short-term liabilities and short-term assets. We measure the variables in 2007:Q3. The results reported in column (7) of Table 1.6 confirm the main findings: TAF participation is still significant and has the expected negative sign.

Sample heterogeneity

Since our sample includes all commercial banks that submitted Call Reports, and only a small fraction of those banks received TAF funding, we face a potential problem where the

[28] In October 2008, the US Treasury launched the TARP. One part of it was the Capital Purchase Program (CPP), an equity infusion program created by the US Treasury in favour of credit institutes. Specifically, the US Treasury bought preferred non-voting stocks of U.S. financial institutions for a total value of $250 billion.

uneven distribution of the number of banks between the two groups could drive the main results. More precisely, only 265 out of 7591 banks (3.49%) received the TAF reserves. To alleviate this potential problem, we run a bootstrapping exercise, repeated 1000 times, to generate sub-samples of banks. The sub-samples include all banks that participated in the program and a randomly chosen subset of banks that did not receive TAF funding. Each estimation is based on 1000 observations. In this way, it is possible to construct a distribution based on 1000 estimations for each estimate.[29] As column (6) of Table 1.6 shows, the results are largely unchanged compared to our benchmark case, even if the TAF effect is now greater than in the results for the baseline model. Figure 1.8 shows the distribution of the estimate of the TAF variable obtained from the bootstrapping exercise, as well as the bounds of the 95% confidence interval.

Alternatively, we balance the sample by employing a matching exercise. We use propensity score matching with three neighbours and match TAF and NO TAF banks with respect to *LIQ. RISK*, *CAPBUFFER*, *PF RISK*, *ROA*, *SIZE*, *CASH* and *LIQUIDITY*. We estimate the model by including all TAF banks and 705 matched (with replacement) NO TAF banks. As shown in column (4) of Table 1.6, the direction of the TAF effect is the same, even if the magnitude of the impact has increased.

Sample period and alternative dependent variables

To check whether the results are robust to the sample period chosen before the beginning of the program, in column (3) of Table 1.6 we measure the variables in 2006:Q3 instead of in 2007:Q3, that is, two years before the beginning of the program. The results do not differ with respect to those of the baseline model: The larger value of the estimate is compensated by the longer period considered. Rescaling the estimate appropriately and dividing it by 16 periods we obtain a value of 5.46 percentage points, in line with the baseline results.

Throughout the paper we have used short-term liabilities over short-term assets as the

[29] More details about the bootstrapping exercise are provided in Appendix 1.B.

measure for bank liquidity riskiness. The literature suggests other measures of liquidity risk, which include short-term net liabilities, short-term liabilities over total liabilities, and short-term liabilities over risk-free assets. Table 1.8 compares the estimation results for different measures of liquidity risk. Column (1) reports the baseline results using the ratio of short-term liabilities to short-term assets as a proxy for liquidity risk, while columns (2) to (4) report the results referring to the above-mentioned measures of funding liquidity risk. The estimation results for the TAF dummy in the outcome equation are negative and statistically significant, confirming the baseline findings.

Since the main variable for measuring liquidity risk is a ratio, we are also interested in assessing the impact of the TAF program on short-term liabilities and short-term assets separately. Columns (5) and (6) of Table 1.8 show that TAF affects negatively both short-term liabilities and short-term assets. However, the contraction is larger (more than double) for short-term liabilities.

Too big to fail and solvent banks

During the last financial crisis, systemically important commercial banks were not allowed to fail. Being too big to fail might lead to a moral hazard problem,[30] a potential source of attenuation bias in our findings. To assess the too big to fail effect on the impact of the TAF program on liquidity risk, we focus on the 75th, 90th and 95th percentiles in terms of size. The results of TAF program participation on the change in liquidity risk are confirmed. In particular, the larger the bank, the greater the TAF effect.

Finally, throughout the paper we focused on liquidity issues disregarding solvency aspects related to bank participation in the TAF program. In particular, it could be that banks participated in the TAF program because of solvency problems instead of maturity mismatches. We address this issue by adopting the following strategy. First, we calculate the median of the variables $CAPBUFFER$, $PF\ RISK$, $CASH$, and $ST\ LIAB/RISK\ FREE$ assets of those banks that participated in the TAF program,

[30] If banks internalize that they will always be bailed out with taxpayer money, they might adopt riskier strategies.

but failed nevertheless. Since these banks had access to liquidity, it is highly likely that these banks failed due to solvency problems. Second, we consider only banks that had better fundamentals by considering the aforementioned variables. The new sample includes 67 TAF banks and 3568 NO TAF banks. As reported in column (5) of Table 1.7, the results are consistent with those of the benchmark.

Alternative approaches

The previous results are based on the treatment effects model. Although the treatment effects model is well-suited to deal with the participation issue, we also provide the results based on two alternative estimation methods: ordinary least squares (OLS) and two-stage least squares (2SLS). Column (1) of Table 1.9 reports the results of equation (1.1) estimated using OLS. In column (2) we augment the previous specification by adding the explanatory variables included in the participation equation (1.3). In column (3), we report the estimations using the two-step approach: we first estimate a probit model to compute the predicted participation to the TAF program, based on equation (1.3), then we replace in equation (1.1) the TAF variable by the predicted value. In column (4), we document the results using a treatment effect model estimated using a two-step procedure. In all cases, the TAF coefficient is statically significant and has the expected sign, even if depending on the estimation the magnitude of the impact of the TAF program is different. We can conclude that the main results are not driven by the econometric technique employed.

Shorter time horizons

The main results are based on measuring the impact of the TAF program on the change in liquidity distress before the beginning of the program and after its conclusion. As mentioned earlier this strategy allows us to neutralize any concern coming from an accounting effect. However, the TAF program was set up as an emergency measure with the aim of short-run effect. To measure the short-run effect of TAF on liquidity risk, we estimate the model on shorter time horizons. We compute the change in liquidity risk between the 'after' period and 2007:Q3 and estimate the model. In the columns in Table 1.10 we choose 2008:Q3, 2009:Q1, 2009:Q3 and 2010:Q1 as different after periods. Since not all banks receive TAF at the same time, the number of TAF banks in the estimation changes (as indicated in the last row of Table 1.10). In all cases, TAF has a negative and statistically significant impact. The point estimate of the effect of the TAF program on the change in liquidity risk is larger as the horizon increases. This is consistent with the observations in Figure 1.4.

Additional variables in participation equation

In Table 1.11 we extend the set of variables included in the participation equation. We add ROA as a measure of profitability of the bank, $SIZE$ to identify potential scale effects, and PF_RISK and TOT_LOANS as measures for the asset side of the balance sheets. In columns (1)–(4) of Table 1.11 we add these variables individually, and include them all together in column (5). Also with the extended set of variables in the participation equation, the results show that the coefficient on the TAF dummy remains negative and statistically significant. The estimation results from the participation equation highlight that banks with higher total assets and higher risk-weighted assets are more probable to participate to TAF.

1.6 Conclusion

During the last financial crisis the Federal Reserve promoted several extraordinary actions, including the creation of a number of new facilities for auctioning short-term credit, with the general aim of supporting the financial sector and ensuring that financial institutions had adequate access to liquidity. One of these programs was the Term Auction Facility (TAF). Using a unique dataset and taking an alternative perspective with respect to previous contributions on this topic, which focus on the impact of the TAF program on aggregate spreads, we concentrate on the impact of the TAF program on the specific behaviours of banks. More precisely, the goals of this paper are to assess which type of bank benefited from the program and to quantitatively determine whether banks that received TAF funds reduced their liquidity risk positions.

We show that banks in major funding liquidity distress benefited from the reserves auctioned in the context of the TAF program. Moreover, we find that the TAF program had an impact on the reduction of funding liquidity risk. The higher the amount of reserves received, the stronger the impact. A possible reason is that TAF funds allowed the banks to restructure their liability side of the balance sheet. In particular, the access to TAF funds relieves the immediate pressure to roll-over maturing debt. Although TAF was short-term, it was reasonable to assume for a bank to assume that it will be able to participate at later auctions again. Therefore, not only the immediate lack of funding was resolved, but also the medium-term outlook improved. The fact that a bank has access to TAF was a positive signal to counterparties and the bank was able to find longer-term funding.

Moreover, we find that banks located in US states that experienced an important increase in housing prices during the period 2002:Q1–2006:Q3 are more likely to have participated in the program. This is due to the fact that, in these US states, the number of non-performing loans increased considerably during the crisis, and therefore banks located there were most exposed to the freezing of the interbank market and unable to roll over their short-term liabilities during the crisis. For these banks the TAF reserves were crucial to reduce their exposure and control their funding liquidity risk. Moreover, our findings support the opinion that TAF-like programs are appropriate during situations similar to the last crisis. In particular, our results support the view of those who consider the TAF program an additional countercyclical monetary policy instrument useful in mitigating bank liquidity concerns during economic busts (e.g. Rochet and Vives, 2004).

Our study stresses the importance of banking liability term structure as a source of banking soundness. From this perspective, our contribution provides empirical justification to those arguments in favour of the introduction of liquidity risk measures in international financial regulations. In particular, the new measures, implemented in Basel III, such as the liquidity coverage ratio and the net stable funding ratio, go in the right direction of focusing on liquidity management for the proper functioning of the banking sector and financial markets.

Finally, our results shed light on the behaviour of a particular group of banks. Specifically, we document that only banks in funding liquidity distress obtained loans through TAF. This was the case even if TAF loans were provided at favourable conditions (with the minimum bid rate below the primary credit discount rate and participation in TAF program kept private) and despite the fact that all bids were accepted after the Lehman Brothers collapse. This result raises the question of why the good banks decided not to participate in the TAF auctions. One potential explanation is that, even if the information about the participation was, at least theoretically, private, they were still concerned about the stigma effect.

In this contribution we focused on the effect of the program on the liabilities side of banks' balance sheets. It could also be interesting to assess how banks modified their portfolio risk depending on whether they received reserves associated with the TAF program.

1.A Other facilities launched by the Federal Reserve

Since 2003, depository institutions have had access to primary credit, secondary credit, and seasonal credit, three types of discount window (DW) facilities. As for the TAF program, all regular DW loans had to be fully collateralized with an appropriate haircut applied to the collateral such that the collateral had to exceed the value of the loan. Before the crisis, the primary credit maturity was overnight. With the strengthening of the crisis the maturity was extended up to 90 days. In February 2010, the maturity was again reduced to overnight. Those depository institutions that are not eligible for primary credit can request a secondary credit DW at the cost of being restricted in the uses of the credit received, a higher haircut applied to the value of the collateral, and closer monitoring activity. Usually, the secondary credit's maturity is overnight. Finally, the seasonal credit DW was conceived for small depository institutions with significant seasonal swings in their loans and deposits. To be eligible for this type of DW, depository institutions have to be located in agricultural or tourist areas.[31]

In March 2008 two additional programs were launched by the Federal Reserve. The first was the Term Securities Lending Facility (TSLF), a weekly loan facility, with the aim of promoting the functioning of financial markets, by offering "Treasury general collateral (GC) to the Federal Reserve Bank of New York's primary dealers in exchange for other program-eligible collateral."[32] Its maturity term was 28 days. The main difference between the TSLF and the TAF lies in the fact that the former offered Treasury GC to the New York Federal Reserve's primary dealers in exchange for other program-eligible collateral, while the latter offered short-term funding to depository institutions. Both programs were based on an auction system.

The second program opened in March 2008 was the Primary Dealer Credit Facility (PDCF). As with the previous program its goal was to promote the functioning of financial markets by providing funding to the primary dealer through overnight loan facilities in exchange for any tri-party-eligible collateral. The difference of the PDCF program with respect to the TAF program involves the institutions that benefited from the program (primary dealers versus depository institutions), the maturity terms of the loans (overnight versus 28 days or 84 days), and the type of mechanism employed for allocating the credit (exchange versus auction).

Two other programs were launched by the Federal Reserve between October and November 2008. The Commercial Paper Funding Facility (CPFF) had the goal of "enhancing the liquidity of the commercial paper market by increasing the availability of

[31]See http://www.federalreserve.gov/monetarypolicy/bst_lendingdepository.htm

[32]See http://www.newyorkfed.org/markets/tslf_faq.html

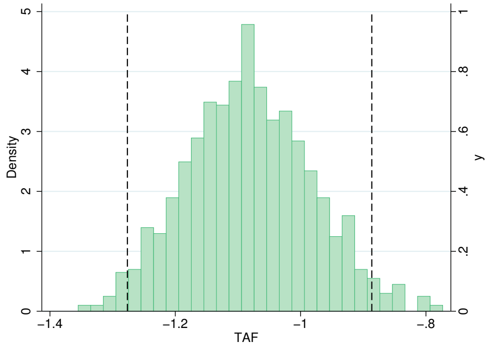
term commercial paper funding to issuers and by providing greater assurance to both issuers and investors that firms will be able to roll over their maturing commercial paper"[33]. Finally, the Term Asset-Backed Securities Loan Facility (TALF) was designed "to increase credit availability and support economic activity by facilitating renewed issuance of consumer and business asset-backed securities at more normal interest rate spreads. Under the TALF, the New York Federal Reserve will provide non-recourse funding to any eligible borrower owning eligible collateral"[34].

Table 1.1 reports the loan maturities, the periods the program operated, the mechanisms to provide funds, the overall amounts provided, and the types of eligible institutions.

1.B Bootstrapping approach

To alleviate the potential problem of the uneven distribution of TAF and NO TAF banks, we run a bootstrapping exercise. In each iteration, the sample includes all TAF banks and a randomly chosen subset of NO TAF banks.

Figure 1.8: TAF estimated coefficient obtained by a bootstrapping approach



[33]See http://www.newyorkfed.org/markets/cpff_faq.html. During this period the Money Market Investor Funding Facility (MMIFF) was also created to complement the CPFF program, but no loans were made under the MMIFF.

[34]http://www.newyorkfed.org/markets/talf_faq.html

Table 1.1: Facilities programs operated by the Federal Reserve during the last financial crisis

Name of the program	Period	Mechanism and Tools	Maturity	Amounts	Beneficiary
Term Auction Facility (TAF)	12.2007-03.2010	A	Between 28 and 84 days	\$3.81 trillion	Depository Institutions (DI)
Term Securities Lending Facility (TSLF)	03.2008-02.2010	B	28 days	\$2 trillion	Primary Dealer
Primary Dealer Credit Facility (PDCF)	03.2008-02.2010	C	Overnight	\$8.95 trillion	Primary Dealer
Commercial Paper Funding Facility (CPFF)	10.2008-02.2010	D	90 days	\$738 billion	Commercial paper issuers
Term Asset-Backed Securities Loan Facility (TALF)	11.2008-06.2010	E	Between 3 and 5 years	\$71 billion	Any U.S. company†
Primary Credit	since 2003		Between 28 and 90 days‡		DI
Secondary Credit	since 2003		Overnight		DI*
Seasonal Credit	since 2003				Small DI**

Notes: To make the programs comparable, one needs to consider both amounts and maturity. $*$ The loans were provided by a limited liability company (LLC), specially created by the Federal Reserve Bank of New York (Fed NY). The LCC was dissolved on August 30, 2010. $\mp$ Five special-purpose vehicles (SVPs) received senior secured funding from the Fed NY to finance the purchase of certain money market instruments from eligible investors. † An entity is a US company if it is (1) a business entity or institution that is organized under the laws of the United States or a political subdivision or territory thereof (US-organized) and conducts significant operations or activities in the United States, including any US-organized subsidiary of such an entity; (2) a US branch or agency of a foreign bank (other than a foreign central bank) that maintains reserves with a Federal Reserve Bank; (3) a US insured depository institution; or (4) an investment fund that is US-organized and managed by an investment manager whose principal place of business is in the United States.‡ Before and after the crisis the loans had an overnight maturity. * Depositary institutions eligible for secondary credit are not eligible for primary credit. ** Depositary institutions with significant seasonal swings. A, auctioned loans; B, auctioned treasury GC; C, loans available in exchange of collateral; D, loans available in exchange of commercial papers; E, loans available in exchange for collateral.

The graph in Figure 1.8 shows the distribution of the estimate of TAF reserves as well as the bounds of the corresponding confidence interval at 95%, obtained by repeating the estimation 1000 times and by using a sample of around 1000 random observations. Before the estimation we check whether the mean of all the variables used of the chosen sub-sample are within a narrow band around the mean of the entire sample (we use 0.2 times the standard deviation as a threshold).

1.C Tables

Table 1.2: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Before						After					
	No TAF		TAF		Total		No TAF		TAF		Total	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
ST LIAB / ST ASSET	-4.409	.751	-4.259	.856	-4.404	.755	-4.441	.682	-4.466	.812	-4.442	.687
NET ST LIAB	4.214	18.14	8.059	19.21	4.354	18.19	3.278	16.03	2.485	16.26	3.250	16.04
ST LIAB / PF RISK 0	-1.420	1.309	-1.192	1.634	-1.411	1.322	-2.636	1.398	-3.014	1.450	-2.650	1.401
ST LIAB / TLIAB	.404	.131	.411	.142	.404	.131	.349	.126	.317	.130	.348	.126
ST LIAB / LIQ	-3.862	1.105	-3.547	1.283	-3.850	1.114	-3.870	1.281	-3.849	1.177	-3.869	1.278
ST LIAB	6.164	1.330	8.281	2.140	6.241	1.423	6.180	1.256	8.216	1.961	6.253	1.342
ST ASSET	10.57	1.255	12.54	2.037	10.64	1.343	10.62	1.272	12.68	2.048	10.69	1.362
LIQUIDITY	.209	.139	.156	.118	.207	.139	.199	.143	.162	.120	.197	.143
CASH	.0379	.0398	.0281	.0345	.0375	.0397	.0834	.0790	.0675	.0716	.0829	.0788
CAPBUFFER	.0491	.0592	.0375	.0745	.0486	.0598	.0353	.0429	.0266	.0344	.0350	.0427
SIZE	11.90	1.250	14.06	2.152	11.97	1.355	12.05	1.238	14.23	2.081	12.13	1.341
ROA	.00559	.00716	.00677	.00660	.00564	.00715	.00145	.0120	-.00191	.0188	.00133	.0123
NPTL	.0238	.0245	.0162	.0144	.0236	.0242	.0512	.0594	.0621	.0545	.0516	.0593
PROV	.000972	.00274	.00126	.00200	.000982	.00272	.00368	.00793	.00834	.0115	.00385	.00814
TLOANS	.647	.151	.677	.146	.648	.150	.625	.147	.662	.138	.626	.147
RTESTLOANS	.684	.194	.702	.202	.685	.194	.712	.188	.722	.213	.712	.189
CILOANS	.148	.107	.177	.131	.149	.108	.134	.0951	.158	.124	.134	.0964
INDIVLOANS	.0771	.0907	.0705	.144	.0769	.0932	.0647	.0853	.0735	.175	.0651	.0901
AGRILOANS	.0740	.126	.0177	.0547	.0719	.125	.0715	.124	.0173	.0544	.0696	.123
PF RISK	.692	.125	.761	.115	.695	.126	.666	.119	.716	.111	.668	.119
PF RISK 0	.0259	.0483	.0249	.0620	.0259	.0489	.0732	.0820	.0859	.0926	.0737	.0825
PF RISK 20	.251	.143	.186	.117	.249	.143	.221	.142	.164	.103	.219	.141
PF RISK 50	.162	.120	.131	.0961	.160	.119	.169	.116	.133	.0856	.167	.115
PF RISK 100	.561	.170	.658	.153	.565	.170	.538	.160	.617	.138	.540	.160
Obs	7326		265		7591		7326		265		7591	

Notes: We can distinguish along two dimensions. On the one hand, columns (5) and (11) refer to the average values of the variables measured in 2007:Q3 (before), just before the beginning of the program, and in 2010:Q3, two quarters after the program's conclusion (after). On the other hand, columns (1), (3), (7), and (9) report the average values of the variables by distinguishing between banks that received TAF program reserves and the other banks in each of the two periods.

Table 1.3: Average difference tests, before and after

Variable	Before	After	No TAF	TAF	Diff in Diff
ST LIAB / ST ASSET	0.203***	-0.018	-0.006	-0.227***	-0.221***
	(0.058)	(0.051)	(0.013)	(0.076)	(0.077)
NET ST LIAB	4.641***	-0.629	-0.344	-5.614***	-5.270***
	(1.211)	(1.017)	(0.298)	(1.553)	(1.581)
ST LIAB / PF RISK 0	0.228**	-0.377***	-1.217***	-1.822***	-0.605***
	(0.102)	(0.091)	(0.023)	(0.135)	(0.137)
ST LIAB / TLIAB	0.010	-0.033***	-0.054***	-0.097***	-0.043***
	(0.009)	(0.008)	(0.002)	(0.012)	(0.012)
ST LIAB / LIQ	0.323***	0.025	-0.007	-0.304***	-0.298***
	(0.080)	(0.074)	(0.020)	(0.107)	(0.109)
ST LIAB	2.148***	2.067***	0.063***	-0.018	-0.081
	(0.133)	(0.121)	(0.022)	(0.179)	(0.180)
ST ASSET	1.945***	2.085***	0.069***	0.210	0.140
	(0.129)	(0.127)	(0.021)	(0.179)	(0.180)
LIQUIDITY	-0.051***	-0.034***	-0.007***	0.009	0.017
	(0.007)	(0.008)	(0.002)	(0.010)	(0.011)
CASH	-0.008**	-0.017***	0.046***	0.037***	-0.009
	(0.004)	(0.005)	(0.001)	(0.006)	(0.006)

Notes: Columns (1) and (2) test whether, on average, a difference exists within groups across time (with 2007:Q3 as the before period and 2010:Q3 as the after period). Columns (3) and (4) test whether, on average, a difference exists within time across groups (TAF and NO TAF). Finally, column (5) tests whether there are differences in differences.

Table 1.4: Baseline model

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome equation						
Dependent variable:			Δ ST LIAB ASS			
LIQUIDITY	-.771***	-.476***	-.191**	-1.063***	-.253***	-.771***
	(.154)	(.133)	(.075)	(.176)	(.072)	(.077)
CAPBUFFER	2.702***	3.015***	3.330***	2.475***	3.282***	2.702***
	(.286)	(.285)	(.289)	(.287)	(.306)	(.110)
ROA	-4.273**	-4.374**	-1.715	-4.093*	-2.804	-4.274***
	(2.107)	(2.050)	(2.884)	(2.151)	(3.134)	(.712)
SIZE	-.036***	-.037***	-.044***	-.045***	-.038***	-.036***
	(.008)	(.008)	(.011)	(.008)	(.008)	(.006)
PF RISK 0	1.116***					1.117***
	(.317)					(.176)
PF RISK 20	.995***					.995***
	(.172)					(.096)
PF RISK 50	-.042					-.042
	(.126)					(.089)
PF RISK 100	.297***					.297***
	(.106)					(.078)
HPI 2007:Q3–2010:Q3	-.050***	-.058***	-.046***	-.053***	-.054***	-.050***
	(.012)	(.012)	(.012)	(.011)	(.011)	(.013)
TAF	-.786***	-.834***	-.770***	-.828***	-.807***	-.785***
	(.111)	(.105)	(.106)	(.106)	(.104)	(.064)
PF RISK		-.439***				
		(.155)				
CILOANS			.996**			
			(.447)			
RTESTLOANS			.759*			
			(.417)			
INDIVLOANS			.615			
			(.492)			
AGRILOANS			.559			
			(.441)			
TLOANS				-1.013***		
				(.177)		
PROV					-5.262	
					(5.168)	
NPTL					.641**	
					(.318)	
HPI 2002:Q1–2006:Q3						-.001
						(.014)
Constant		.675***	-.391	1.269***	.309***	
		(.171)	(.486)	(.191)	(.103)	
Participation equation						
CASH	-.017	-.015	-.268	.194	-.268	-.017
	(1.547)	(1.493)	(1.541)	(1.466)	(1.517)	(.660)
ST LIAB / ST ASSET	.384***	.429***	.402***	.404***	.420***	.384***
	(.067)	(.068)	(.067)	(.066)	(.067)	(.037)
MBSO	2.322	2.125	2.372	2.345	2.158	2.323*
	(1.929)	(1.964)	(1.897)	(2.002)	(1.926)	(1.187)
ABS	17.270***	17.398***	17.294***	18.059***	17.556***	17.269***
	(3.280)	(3.156)	(3.192)	(3.354)	(3.182)	(2.884)
HPI 2002:Q1–2006:Q3	.115***	.104***	.111***	.108***	.107***	.115***
	(.034)	(.034)	(.034)	(.034)	(.034)	(.033)
Constant	-.302	-.073	-.205	-.204	-.115	-.302*
	(.315)	(.320)	(.320)	(.311)	(.319)	(.174)
Obs.	7591	7591	7570	7591	7570	7591
ρ	.480	.520	.481	.508	.505	.480
λ	.311	.342	.307	.331	.325	.311
	(.0473)	(.0454)	(.0447)	(.0455)	(.0440)	(.0238)
χ^2	36.53	45.52	40.21	43.32	45.04	61.34

Notes: This table shows the joint estimation of the treatment effects model with the binary dependent variable TAF, using ML. Robust standard errors are in parentheses. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$.

Table 1.5: Different measures for capturing the TAF program effect

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome equation						
Dependent variable:	ΔST LIAB ASS	ΔST LIAB ASS	ΔST LIAB ASS	ΔST LIAB/TLIAB	ΔNET ST LIAB	ΔST LIAB/PF RISK 0
LIQUIDITY	-.798***	-.956***	-.800***	-.044***	-22.713***	.602***
	(.076)	(.078)	(.076)	(.013)	(1.777)	(.176)
CAPBUFFER	2.707***	2.766***	2.714***	.063***	53.304***	1.746***
	(.110)	(.115)	(.110)	(.019)	(2.559)	(.254)
ROA	-4.284***	-.852	-4.264***	.400***	-48.187***	2.499
	(.708)	(.905)	(.708)	(.120)	(16.601)	(2.005)
SIZE	-.033***	-.030***	-.031***	-.008***	-.725***	-.161***
	(.006)	(.006)	(.006)	(.001)	(.145)	(.014)
PF RISK 0	1.105***	.891***	1.082***	.134***	20.574***	8.873***
	(.176)	(.173)	(.176)	(.030)	(4.081)	(.379)
PF RISK 20	.975***	1.109***	.953***	.099***	24.593***	.515**
	(.097)	(.097)	(.097)	(.016)	(2.255)	(.216)
PF RISK 50	-.104	-.138	-.126	-.013	-5.923***	1.144***
	(.091)	(.088)	(.091)	(.016)	(2.106)	(.198)
PF RISK 100	.261***	.181**	.236***	.011	6.159***	.198
	(.080)	(.078)	(.080)	(.014)	(1.848)	(.174)
HPI 2007:Q3–2010:Q3	-.046***	-.050***	-.046***	-.015***	-1.914***	.230***
	(.009)	(.009)	(.009)	(.002)	(.215)	(.020)
TAF AMOUNT 1	-.099***			-.017***	-3.664***	-.072*
	(.012)			(.003)	(.232)	(.041)
TAF AMOUNT 2		-.035***				
		(.003)				
AVG TAF AMOUNT			-.147***			
			(.017)			
Participation equation						
LIQ. RISK MEASURE	3.377***	14.436***	2.332***	15.349***	.220***	1.017***
	(.469)	(1.719)	(.318)	(3.286)	(.021)	(.341)
CASH	-6.121	-6.673	-4.221	-16.091**	1.057	-18.333**
	(7.916)	(27.857)	(5.423)	(8.088)	(6.865)	(8.385)
MBSO	33.929**	107.776**	23.346**	44.136***	21.420*	51.736***
	(13.830)	(49.867)	(9.464)	(14.551)	(12.589)	(14.616)
ABS	179.655***	687.088***	124.212***	144.191***	177.779***	151.735***
	(34.676)	(125.693)	(23.672)	(35.237)	(32.638)	(36.426)
HPI 2002:Q1–2006:Q3	1.500***	5.092***	1.033***	1.548***	1.175***	1.533***
	(.376)	(1.382)	(.258)	(.384)	(.353)	(.383)
Constant	-7.986***	-20.044***	-5.408***	-29.289***	-22.507***	-21.581***
Obs.	7591	7570	7591	7591	7591	7310

Notes: This table shows the joint estimation of the treatment effects model with left-censored dependent variables ($TAF\ AMOUNT$ 1, $TAF\ AMOUNT$ 2, and $AVG\ TAF\ AMOUNT$) using ML. Robust standard errors are in parentheses. *** $= p < 0.01$, ** $= p < 0.05$, * $= p < 0.1$. The variable $TAF\ AMOUNT$ 1 is the log of one plus the overall amount of TAF reserves received; $TAF\ AMOUNT$ 2 is the log of one plus the ratio of the overall amount of TAF reserves received to total loans and $AVG\ TAF\ AMOUNT$ is the log of one plus the ratio of overall amount of TAF funds received by each bank to the number of times a bank received TAF funds.

Table 1.6: Methodologies and sub-samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome equation							
Dependent variable:	MLE	Lehman	Early	Matching I	W/out TARP	Bootstrap	Matching II
LIQUIDITY	-.771***	-.835***	-1.050***	-.867	-.931***	-.135	-.033
	(.154)	(.155)	(.148)	(.626)	(.131)	(.430)	(.302)
CAPBUFFER	2.702***	2.750***	2.408***	1.778	2.956***	2.021**	3.28***
	(.286)	(.285)	(.211)	(1.478)	(.287)	(.876)	(.8037)
ROA	-4.273**	-4.054*	-3.808**	-13.325	-5.495***	-6.975	5.58
	(2.107)	(2.076)	(1.832)	(8.375)	(1.717)	(8.426)	(5.518)
SIZE	-.036***	-.038***	-.033***	-.034	.002	-.029	-.052***
	(.008)	(.009)	(.008)	(.023)	(.009)	(.018)	(.013)
PF RISK 0	1.116***	1.123***	.865***	1.789***	.950***	1.150*	.92**
	(.317)	(.313)	(.247)	(.681)	(.330)	(.633)	(.416)
PF RISK 20	.995***	1.031***	1.247***	1.231	.700***	.707	.867*
	(.172)	(.173)	(.183)	(.755)	(.139)	(.475)	(.319)
PF RISK 50	-.042	-.075	-.025	.594	-.582***	.425	.463
	(.126)	(.129)	(.134)	(.403)	(.126)	(.315)	(.292)
PF RISK 100	.297***	.316***	.313***	.585*	-.172	.353	.645***
	(.106)	(.110)	(.105)	(.305)	(.113)	(.235)	(.192)
HPI 2007:Q3–2010:Q3	-.050***	-.042***	-.056***	-.038	-.050***	-.093***	-.067***
	(.012)	(.012)	(.012)	(.031)	(.012)	(.031)	(.025)
TAF	-.786***	-.562***	-.875***	-1.227***	-.604***	-1.081***	-.993***
	(.111)	(.137)	(.127)	(.138)	(.168)	(.149)	(.087)
Participation equation							
ST LIAB / ST ASSET	.384***	.237***	.365***	.478***	.275***	.575***	.47***
	(.067)	(.071)	(.059)	(.085)	(.098)	(.088)	(.091)
CASH	-.017	-8.271*	-5.825***	-.777	1.155	.777	-1.25
	(1.547)	(4.300)	(2.063)	(1.503)	(1.172)	(1.234)	(1.57)
MBSO	2.322	3.221	1.121	2.114	5.141***	4.864	2.29
	(1.929)	(2.140)	(2.416)	(3.265)	(1.845)	(3.351)	(3.33)
ABS	17.270***	17.172***	13.618***	28.832***	7.629**	31.407***	24.25***
	(3.280)	(3.779)	(3.086)	(10.923)	(3.445)	(11.320)	(6.16)
HPI 2002:Q1 - 2006:Q3	.115***	.122**	.133***	-.010	.143***	.085	-.036
	(.034)	(.054)	(.036)	(.044)	(.044)	(.052)	(.045)
Constant	-.302	-1.338***	-.197	1.523***	-1.139***	1.747***	1.62***
	(.315)	(.324)	(.293)	(.389)	(.439)	(.419)	(.399)
Obs.	7591	7388	7416	970	6646	1000	808
ρ	.480	.303	.514	.866	.295	.790	.800
λ	.311	.191	.347	.783	.181	.641	.596
	(.0473)	(.0411)	(.0564)	(.107)	(.0517)	(.097)	(.0565)
χ^2	36.53	19.70	29.70	90.09	11.49	59.419	115.88

Notes: This table shows the joint estimation of the treatment effects model with binary dependent variable TAF, using ML. Robust standard errors in parentheses. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Column (1) repeats the results of the baseline model using ML estimation. Columns (2) excludes TAF auctions after the collapse of Lehman Brothers; in column (3) the variables before the beginning of the program are measured in 2006:Q3 while in column (4) TAF banks are matched with NO TAF banks, with the variables measured in 2005:Q3. Column (5) excludes banks whose bank holding companies participated in the TARP program. Column (6) reports the result of the bootstrap exercise, while in column (7) we report the results of a matched sample. The matching is based on the different measures of liquidity distress, short-term liabilities and short-term assets, measured in 2007:Q3.

Table 1.7: Too big to fail and solvency

	(1)	(2)	(3)	(4)	(5)
	Full	75% perc.	90% perc.	95% perc.	Solvent
Outcome equation			Δ ST LIAB ASS		
LIQUIDITY	-.773***	-.310	-.965	-1.356	-.804***
	(.156)	(.485)	(.751)	(1.145)	(.170)
CAPBUFFER	2.876***	2.993***	4.971***	5.629***	3.409***
	(.270)	(1.023)	(1.030)	(1.031)	(.436)
ROA	-4.571**	-11.130	-16.173	10.043	-3.137
	(2.098)	(8.952)	(12.970)	(9.812)	(4.964)
PF RISK 0	.646**	-.148	.163	.380	.430
	(.288)	(.326)	(.392)	(.524)	(.325)
PF RISK 20	.598***	.025	.639	1.295	.753***
	(.147)	(.473)	(.711)	(1.046)	(.169)
PF RISK 50	-.468***	-.422**	-.021	.309	-.571***
	(.069)	(.187)	(.363)	(.482)	(.148)
PF RISK 100	-.144***	.045	.102	-.203	-.017
	(.034)	(.108)	(.167)	(.191)	(.146)
HPI 2007:Q3–2010:Q3	-.040***	-.017	.016	.056	-.047**
	(.011)	(.020)	(.032)	(.044)	(.020)
TAF	-.873***	-1.139***	-1.372***	-1.513***	-.754***
	(.108)	(.128)	(.208)	(.216)	(.185)
SIZE					-.010
					(.011)
Participation equation					
ST LIAB / ST ASSET	.394***	.417***	.441***	.380***	.398***
	(.067)	(.087)	(.091)	(.087)	(.126)
CASH	-.054	-3.294	-.138	2.556	2.244*
	(1.577)	(2.653)	(2.409)	(1.965)	(1.220)
MBSO	2.511	-.123	1.744	1.951	5.417**
	(1.981)	(2.099)	(2.026)	(2.063)	(2.423)
ABS	17.697***	18.059***	13.115**	22.941***	14.375***
	(3.349)	(3.641)	(5.332)	(4.875)	(5.116)
HPI 2002:Q1–2006:Q3	.115***	-.040	-.094*	-.155***	.126*
	(.034)	(.042)	(.050)	(.055)	(.072)
Constant	-.252	.681*	1.156***	1.222***	-.630
	(.316)	(.385)	(.412)	(.371)	(.586)
Obs.	7591	1897	759	379	3635
TAF banks	265	183	140	108	67
ρ	.491	.735	.805	.894	.438
λ	.319	.549	.731	.978	.261
	(.0471)	(.0822)	(.148)	(.192)	(.0668)
χ^2	38.44	44.40	32.93	40.33	13.32

Notes: This table shows the joint estimation of the treatment effects model with binary dependent variable TAF, using ML. Robust standard errors are in parentheses. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Column (1) repeats the results of the baseline model using ML estimation, excluding $SIZE$. Columns (2) to (4) consider only banks that are larger (in terms of $SIZE$ of all banks) than the 75th, 90th and 95th quantiles. Column (5) includes only banks with all fundamentals ($CAPBUFFER$, *PF RISK*, $CASH$, and *ST LIAB/RISK FREE ASSETS*) better than the median of the fundamentals of failed TAF banks.

Table 1.8: Different dependent variables

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome equation						
Dependent variable:	Δ ST LIAB ASS	Δ ST LIAB TOT LIAB	Δ ST NET LIAB	Δ ST LIAB PF RISK O	Δ LN LIAB	Δ LN ASSET
LIQUIDITY	-.771***	-.042**	-22.063***	.658***	-.549***	.265**
	(.154)	(.018)	(2.573)	(.241)	(.123)	(.111)
CAPBUFFER	2.702***	.064*	52.480***	1.823***	4.126***	1.402***
	(.286)	(.035)	(3.983)	(.440)	(.267)	(.171)
ROA	-4.273**	.403*	-48.971	2.910	-8.079***	-3.854**
	(2.107)	(.216)	(37.746)	(3.100)	(1.850)	(1.962)
SIZE	-.036***	-.009***	-.878***	-.157***	.006	.040***
	(.008)	(.001)	(.159)	(.015)	(.006)	(.007)
PF RISK 0	1.116***	.138***	21.378***	8.628***	.123	-.960***
	(.317)	(.030)	(4.912)	(.698)	(.173)	(.260)
PF RISK 20	.995***	.107***	25.857***	.440	.213*	-.766***
	(.172)	(.020)	(2.875)	(.275)	(.127)	(.134)
PF RISK 50	-.042	-.001	-3.267	1.117***	-.382***	-.274***
	(.126)	(.016)	(2.302)	(.214)	(.086)	(.104)
PF RISK 100	.297***	.024	8.244***	.199	-.106	-.377***
	(.106)	(.015)	(2.077)	(.194)	(.083)	(.084)
HPI 2007:Q3–2010:Q3	-.050***	-.016***	-2.031***	.219***	-.004	.040***
	(.012)	(.002)	(.264)	(.023)	(.010)	(.009)
TAF	-.786***	-.146***	-27.306***	-1.575***	-.457***	-.244***
	(.111)	(.017)	(1.307)	(.216)	(.051)	(.086)
Participation equation						
LIQ. RISK MEASURE	.384***	1.970***	.026***	.169***	.379***	.367***
	(.067)	(.309)	(.002)	(.035)	(.021)	(.022)
CASH	-.017	-.817	.770	-1.580	1.779	.010
	(1.547)	(1.813)	(1.240)	(1.491)	(1.308)	(1.145)
MBSO	2.322	3.240**	1.140	4.069***	.711	2.225
	(1.929)	(1.453)	(1.487)	(1.484)	(1.389)	(1.435)
ABS	17.270***	12.570***	17.227***	14.378***	7.811**	1.197
	(3.280)	(3.759)	(3.065)	(3.600)	(3.130)	(3.877)
HPI 2002:Q1–2006:Q3	.115***	.103***	.060*	.098***	.020	.050
	(.034)	(.034)	(.034)	(.033)	(.035)	(.033)
Constant	-.302	-2.743***	-1.990***	-1.684***	-4.485***	-6.003***
	(.315)	(.150)	(.073)	(.095)	(.166)	(.254)
Obs.	7591	7591	7591	7305	7591	7591
ρ	.480	.499	.734	.480	.454	.308
λ	.311	.0551	11.38	.659	.227	.170
	(.0473)	(.00595)	(.478)	(.0842)	(.0201)	(.0282)
χ^2	36.53	67.78	277.0	47.74	140.1	30.29

Notes: This table shows the joint estimation of the treatment effects model with binary dependent variable TAF, using ML. Robust standard errors are in parentheses. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$.

Table 1.9: Alternative econometric techniques

	(1)	(2)	(3)	(4)
Outcome equation				
Dependent variable:		Δ ST LIAB ASS		
Estimation technique:	OLS	OLS	2SLS	Treatreg
LIQUIDITY	-.813***	-.788***	-1.063***	-.749***
	(.156)	(.163)	(.319)	(.101)
CAPBUFFER	2.720***	2.744***	4.659***	2.647***
	(.286)	(.285)	(.750)	(.143)
ROA	-4.280**	-4.240**	-5.053*	-4.274***
	(2.092)	(2.110)	(2.676)	(.945)
SIZE	-.040***	-.036***	.455***	-.029***
	(.008)	(.009)	(.151)	(.008)
PF RISK 0	1.144***	1.134***	-4.445**	1.001***
	(.310)	(.311)	(1.872)	(.227)
PF RISK 20	1.037***	.995***	-4.559***	.894***
	(.175)	(.178)	(1.705)	(.124)
PF RISK 50	-.053	-.099	-6.103***	-.020
	(.126)	(.132)	(1.842)	(.114)
PF RISK 100	.338***	.298***	-4.926***	.325***
	(.107)	(.111)	(1.599)	(.099)
HPI 2007:Q3 - 2010:Q3	-.035***	-.042***	.021	-.059***
	(.009)	(.011)	(.032)	(.010)
TAF	-.107**	-.095*	-11.946***	-3.524***
	(.054)	(.053)	(3.685)	(.351)
MBSP		-.082		
		(.159)		
MBSO		.420		
		(.770)		
ABS		-9.059***		
		(2.476)		
HPI 2002:Q1 - 2006:Q3		-.011		
		(.014)		
Obs.	7591	7591	7591	7591

Notes: This table shows the estimation of the baseline model using different econometric techniques. More precisely, we use OLS in columns (1) and (2), in column (3) we employ a 2SLS (the instruments employed are the explanatory variable of equations (1.1) and (1.3)), while in column (4) we estimate the treatment effects model with binary dependent variable TAF, using a two-step approach (we report only the outcome equation results). Robust standard errors are in parentheses. *** $= p < 0.01$, ** $= p < 0.05$, * $= p < 0.1$.

Table 1.10: Shorter time horizons

	(1)	(2)	(3)	(4)	(5)
Outcome equation					
Dependent variable:			Δ ST LIAB ASS		
After period:	2008q3	2009q1	2009q3	2010q1	2010q3
LIQUIDITY	-0.561***	-0.910***	-0.828***	-0.825***	-0.771***
	(0.120)	(0.112)	(0.127)	(0.138)	(0.154)
CAPBUFFER	2.610***	2.915***	2.833***	2.828***	2.702***
	(0.267)	(0.265)	(0.286)	(0.289)	(0.286)
ROA	-6.251***	-5.397***	-5.068**	-4.391**	-4.273**
	(1.782)	(1.937)	(2.013)	(2.068)	(2.107)
SIZE	0.020***	0.011	-0.006	-0.027***	-0.036***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
PF RISK 0	0.466	0.326*	0.473**	1.014***	1.116***
	(0.334)	(0.195)	(0.211)	(0.324)	(0.317)
PF RISK 20	0.216*	0.533***	0.768***	0.928***	0.995***
	(0.124)	(0.118)	(0.136)	(0.150)	(0.172)
PF RISK 50	-0.346***	-0.432***	-0.188*	-0.071	-0.042
	(0.091)	(0.095)	(0.104)	(0.113)	(0.126)
PF RISK 100	-0.258***	-0.104	0.069	0.257**	0.297***
	(0.086)	(0.087)	(0.094)	(0.101)	(0.106)
HPI 2007:Q3 - **After**	-0.012***	-0.022***	-0.028***	-0.033***	-0.040***
	(0.004)	(0.005)	(0.007)	(0.008)	(0.009)
TAF	-0.343***	-0.440***	-0.643***	-0.682***	-0.786***
	(0.116)	(0.109)	(0.102)	(0.110)	(0.111)
Participation equation					
CASH	-7.422**	-0.961	-0.211	0.051	-0.017
	(3.101)	(2.298)	(1.778)	(1.612)	(1.547)
ST LIAB / ST ASSET	0.166**	0.288***	0.339***	0.374***	0.384***
	(0.068)	(0.070)	(0.063)	(0.069)	(0.067)
MBSO	5.513***	3.552*	4.461***	4.144***	2.322
	(1.386)	(1.962)	(1.466)	(1.436)	(1.929)
ABS	15.617***	14.163***	14.914***	14.867***	17.270***
	(4.711)	(5.009)	(4.435)	(4.056)	(3.280)
HPI 2002:Q1 - 2006:Q3	0.123**	0.102***	0.122***	0.111***	0.109***
	(0.049)	(0.037)	(0.033)	(0.032)	(0.032)
Constant	-1.669***	-0.873***	-0.575**	-0.361	-0.302
	(0.318)	(0.326)	(0.288)	(0.321)	(0.315)
Obs.	7591	7591	7591	7591	7591
No. of TAF banks	73	183	245	265	265
ρ	0.156	0.311	0.402	0.445	0.480
λ	0.0769	0.168	0.235	0.277	0.311
	(0.0220)	(0.0366)	(0.0416)	(0.0451)	(0.0473)
χ^2	11.45	19.77	27.39	30.96	36.53

Notes: This table shows the estimation of the baseline model using different shorter time horizons. In particular, we focus on the following "after periods": 2008:Q3, 2009:Q1, 2009:Q3 and 2010:Q1. The results are based on joint estimation of the treatment effects model with binary dependent variable TAF, using ML. Robust standard errors are in parentheses. *** $= p < 0.01$, ** $= p < 0.05$, * $= p < 0.1$.

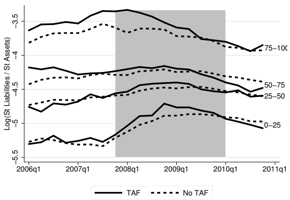
Table 1.11: Adding variables to the participation equation

	(1)	(2)	(3)	(4)	(5)
Outcome equation					
Dependent variable:			Δ ST LIAB ASS		
LIQUIDITY	-.826***	-.771***	-.777***	-.799***	-.819***
	(.156)	(.155)	(.155)	(.155)	(.157)
CAPBUFFER	2.736***	2.705***	2.737***	2.700***	2.765***
	(.287)	(.287)	(.289)	(.286)	(.289)
ROA	-4.285**	-4.083*	-4.090*	-4.229**	-4.394**
	(2.105)	(2.095)	(2.113)	(2.109)	(2.073)
SIZE	-.019**	-.036***	-.036***	-.037***	-.015*
	(.009)	(.008)	(.008)	(.008)	(.009)
PF RISK 0	.977***	1.113***	1.014***	1.114***	.858***
	(.311)	(.317)	(.318)	(.317)	(.314)
PF RISK 20	.832***	.992***	.928***	.992***	.750***
	(.174)	(.173)	(.174)	(.172)	(.176)
PF RISK 50	-.275**	-.046	-.071	-.008	-.339***
	(.131)	(.126)	(.125)	(.127)	(.132)
PF RISK 100	.096	.296***	.332***	.318***	.072
	(.118)	(.106)	(.105)	(.106)	(.113)
HPI 2007:Q3 - 2010:Q3	-.034***	-.040***	-.039***	-.040***	-.033***
	(.009)	(.009)	(.009)	(.009)	(.009)
TAF	-.606***	-.783***	-.909***	-.852***	-.732***
	(.109)	(.114)	(.088)	(.103)	(.096)
Participation equation					
CASH	1.679	.031	2.415*	1.021	3.415***
	(1.231)	(1.540)	(1.430)	(1.480)	(1.147)
ST LIAB / ST ASSET	.248***	.379***	.501***	.396***	.398***
	(.076)	(.068)	(.068)	(.066)	(.076)
MBSO	-.105	2.367	3.676	3.433	1.246
	(1.440)	(1.938)	(2.332)	(2.147)	(1.493)
ABS	10.151***	16.794***	17.978***	18.876***	11.796***
	(3.093)	(3.326)	(3.297)	(3.397)	(3.150)
HPI 2002:Q1 - 2006:Q3	.022	.113***	.031	.086**	-.031
	(.035)	(.033)	(.034)	(.034)	(.036)
SIZE	.347***				.327***
	(.023)				(.024)
ROA		5.129			-10.318
		(3.714)			(7.891)
PF RISK			2.825***		2.847***
			(.371)		(.408)
TLOANS				1.099***	-.478
				(.250)	(.336)
Constant	-5.190***	-.361	-1.767***	-.973***	-5.929***
	(.504)	(.314)	(.307)	(.301)	(.509)
Obs.	7591	7591	7591	7591	7591
ρ	.386	.478	.584	.530	.495
λ	.248	.310	.381	.345	.320
	(.0469)	(.0484)	(.0403)	(.0458)	(.0453)
χ^2	25.62	34.55	70.21	46.24	42.15

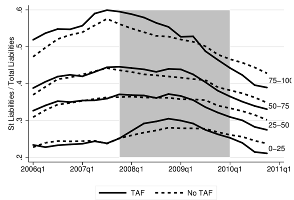
Notes: The different columns expand the set of variables added to the participation equation. Joint estimation of the treatment effects model with binary dependent variable TAF using ML. Robust standard errors are in parentheses. *** $= p < 0.01$, ** $= p < 0.05$, * $= p < 0.1$.

1.D Figures and map

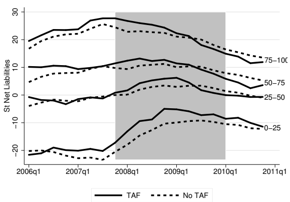
Figure 1.9: Liquidity risk measures, by percentile



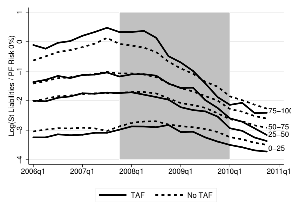
(a) ST Liabilities / ST Assets



(b) ST Liabilities / Total Liabilities



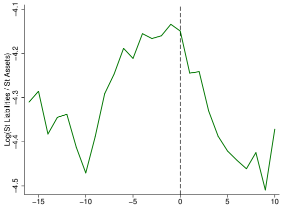
(c) ST Net Liabilities / Total Assets



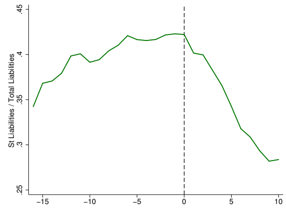
(d) ST Liabilities / PF Risk 0%

Notes: For the four measures of liquidity risk employed in this paper ($ST\ LIAB/ST\ ASS$, $ST\ LIAB/TLIAB$, $STNETLIAB$, and $ST\ LIAB/PF\ RISK\ ZERO$), Figure 1.9 documents the by-group behaviour of the 25th, 50th and 75th percentiles by group. The period when the TAF program was operating is denoted in gray.

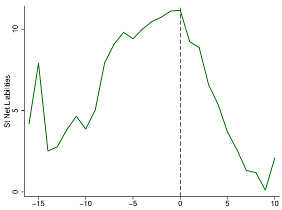
Figure 1.10: Average bank liquidity risk behaviour per quarter, excluding 2008:Q4 and 2009:Q1



(a) ST Liabilities / ST Assets



(b) ST Liabilities / Total Liabilities

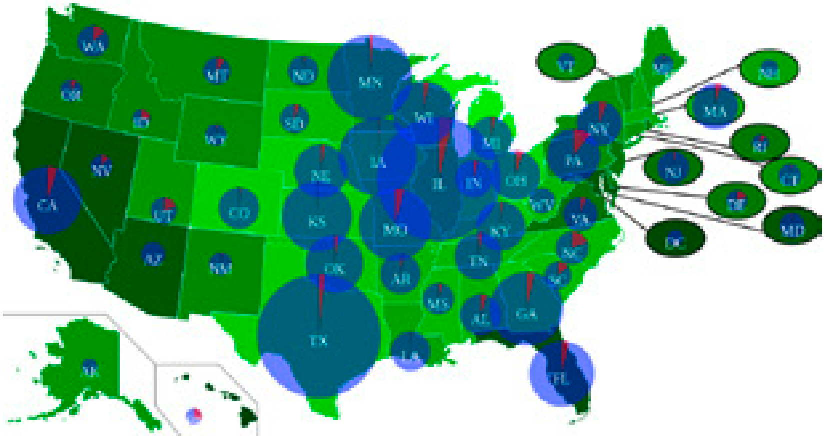


(c) ST Net Liabilities / Total Assets

(d) ST Liabilities / PF Risk 0%

Notes: For TAF banks only, excluding those banks that received TAF support for the first time in 2008:Q4 and 2009:Q1, we document the average behaviour of the following measures of liquidity risk from 15 quarters before to 10 quarters after the first time the banks obtained the reserves: $ST\ LIAB/ST\ ASS$, $ST\ LIAB/TLIAB$, $ST\ NET\ LIAB$ and $ST\ LIAB/PF\ RISK\ ZERO$.

Figure 1.11: HPI change, banking sector size, and TAF participation



Notes: The colors of the US states indicate changes in housing prices between 20002:Q1 and 2006:Q4. The darker green an area, the more house prices increased. For example, Florida (FL) and California (CA) experienced high increases. The size of the pie shows the aggregate asset sizes of banks (with the main ZIP codes in the respective state). For the sake of clarity, some pies are shown larger than they actually are. The red part of the pie highlights the fraction of banks (in terms of size) that benefited from the TAF program.

Table 1.12: Sources and definitions of the variables

Variable Label	Variable definition	Chicago Fed Label	Source
TAF	Dummy variable. It takes value 1 if a bank received TAF reserves at least once, and 0 otherwise.		Federal Reserve Board
AMOUNT	Overall amount of TAF funds received by each bank.		Federal Reserve Board
NUM	Number of times a bank received TAF funds.		Federal Reserve Board
TAF AMOUNT 1	log of one plus the overall amount of TAF reserves received	log(1+AMOUNT)	Federal Reserve Board
TAF AMOUNT 2	log of one plus the ratio of the overall amount of TAF reserves received and the total loans	log[1+(AMOUNT/TLOANS)]	Federal Reserve Board
AVG TAF AMOUNT	log of one plus the ratio of the average amount received	log[1+(AMOUNT/NUM)]	Federal Reserve Board
ST ASS	log of Short term assets	log(UBPRE583)	U.S. Call Reports
TOTAL ASSETS	On- and Off-Balance Sheet assets	RCFDB644 + RCFDB696 + RCFDB697 + RCFDB698 + RCFDB699	U.S. Call Reports
TOT ASSETS S.T. RISK W	On- and Off-Balance Sheet assets, subject to risk-weighting	TOTAL ASSETS - RCFDB644	
ST ASS / ST LIAB	Short term assets over short term liabilities	UBPR598	U.S. Call Reports
TLIAB	Total liabilities	RCFD2950	U.S. Call Reports
ST LIAB	log of Short term liabilities	log(UBPRE583/UBPR898)	U.S. Call Reports
ST LIAB / ST ASS	log of Short term liabilities over short term assets	log(1/UBPR598)	U.S. Call Reports
ST LIAB / TLIAB	100 times Short term liabilities over total liabilities	100 × (ST LIAB/RCFD2950)	U.S. Call Reports
ST NET LIAB	Short term liabilities - Short tern assets over Total assets	UBPRE599	U.S. Call Reports
ST LIAB / PF RISK 0	log of Short term liabilities over Risk Free assets	log(ST LIAB /PF RISK 0)	U.S. Call Reports
LIQUIDITY	Liquid assets over total assets	(RCFD3545 + RCFD1773 + RCFD1754) /TOTAL ASSETS	U.S. Call Reports
CASH	Cash and balances due from depository institutions over total assets	RCFD0010/TOTAL ASSETS	U.S. Call Reports
PF RISK	Ratio of the risk-weighted assets to total assets subject to risk-weighting	RCFDA223/ TOTAL ASSETS S.T. RISK-W	U.S. Call Reports
PF RISK 0	Assets with a risk weight 0% over total assets subject to risk-weighting	RCFDB696 / TOTAL ASSETS S.T. RISK-W	U.S. Call Reports
PF RISK 20	Assets with a risk weight 20% over total assets subject to risk-weighting	RCFDB697 / TOTAL ASSETS S.T. RISK-W	U.S. Call Reports
PF RISK 50	Assets with a risk weight 50% over total assets subject to risk-weighting	RCFDB698 / TOTAL ASSETS S.T. RISK-W	U.S. Call Reports
PF RISK 100	Assets with a risk weight 100% over total assets subject to risk-weighting	RCFDB699 / TOT ASSETS S.T. RISK-W	U.S. Call Reports
TLOANS	Total loans and Leases, Gross over total assets	RCFD1400/TOTAL ASSETS	U.S. Call Reports
CI LOANS	Commercial and Industrial Loans over total loans	RCFD1766/RCFD1400	U.S. Call Reports
REST LOANS	Real Estate Loans over total loans	RCFD1410/RCFD1400	U.S. Call Reports
INDIV LOANS	Loans to Individuals over total loans	RCFD1975/RCFD1400	U.S. Call Reports
AGRI LOANS	Agricultural Loans over total loans	RCFD1590/RCFD1400	U.S. Call Reports
ABS	Ratio of Asset-Backed Securities* over Total Assets	(RCONC988+RCON027)/TOTAL ASSETS	U.S. Call Reports
MBS	Ratio of Mortgage* Backed (pass-through) over Total Assets	(RCON1699+RCON1702+RCON1705+RCON1707+ RCON1710+RCON1713)/TOTAL ASSETS	U.S. Call Reports
MBS OTHER	Ratio of other type of Mortgage* over Total assets	(RCON1734+RCON1736)/TOTAL ASSETS	U.S. Call Reports
CAPBUFFER	Tier 1 capital ratio minus 6%**	RCFD8274-.06	U.S. Call Reports
ROA	Ratio of the income before income taxes and extraordinary items and other adjustments over total assets	RIAD4301/TOTAL ASSETS	U.S. Call Reports
SIZE	Log of banks total asset	log(TOTAL ASSETS)	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
PROV	Ratio of loan loss provision over total loans	RIAD4230/RCFD1400	U.S. Call Reports
HPI	Quarterly percentage change in housing prices at state level		Federal Housing Finance Agency

Notes: * Securities held to maturity or available-for-sale at their fair value. ** The minimum requirement established by the banking authorities.

Chapter 2

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

with **Stefano Puddu**, University of Neuchatel

Using a unique data set based on US commercial banks and county level loan origination for the period 2005–2010, we measure whether banks that benefited from the Troubled Asset Relief Program (TARP) increase small business loan originations. We propose an identification strategy which exploits the ownership structure of bank holding companies. We find that TARP banks provide on average 19% higher small business loan originations than NO TARP banks. The disaggregated data allows us to control for the potential demand side effects. When considering poverty and unemployment rates at a county level we show that TARP is effective only in counties suffering from unemployment. Several robustness checks confirm the main result.

2.1 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...*" **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**, March 4, 2011.

The two opposing views on TARP summarise the ambiguity and disagreement in judging the results of the largest rescue plan ever promoted by the US Treasury. This asymmetry in assessing the success of TARP is partially due to the conflicting goals of the program. Through TARP, 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 TARP were asked to keep providing credit to firms, small businesses and households. Potentially, the two goals are in conflict: if banks keep on providing loans to distressed and insolvent businesses, this might further weaken the banking system. The current debate on the TARP program discusses the potential cost for the US taxpayer, but 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 went to bank bondholders while the cost was incurred by the US taxpayers. By contrast, the Treasury Secretary, Timothy Geithner, stresses 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].

The main driver of TARP was to soften the credit crunch, in particular to small businesses. Yet, the literature so far has not discussed the effect of the TARP program on bank lending to small businesses. We focus our attention to small businesses because of its relative importance to the US economy. 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

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

[...] vulnerable because of their dependence on financial institutions for external funding. These firms simply do not have access to public capital markets." This is confirmed from data collected by the 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 analysing TARP bank features and assessing the impact of the TARP program on small business loan originations. We meet our goal by creating a unique data set based on bank balance sheets, TARP program participation, small business loan originations and county socio-economic features. More precisely, the bank balance sheet data were obtained from the Call reports. The information about TARP program participation was downloaded from the US Treasury, while the data covering small business loan originations comes from the Community Reinvestment Act (CRA) data set and was retrieved through the Federal Financial Institutions Examination Council (FFIEC) website. Finally, the county socio-economic features were downloaded from the US Census Bureau and the Bureau of Labor Statistics. The period under examination goes from 2005 to 2010, and data are per annum. We distinguish banks depending on their participation in the TARP program.

Comparing the groups of banks in 2005, TARP banks provide on average larger amounts of loan origination to small businesses, exhibit lower levels of capital buffer and they are less exposed to non performing loans than the rest of the banks. Finally, TARP banks are more likely to provide loans in counties that suffer from higher poverty and unemployment levels. In 2010, once the program is over, TARP banks still provide more new loans, and they are more likely to be located in counties with poverty and unemployment problems, but they also show a higher level of capital buffer and higher exposure to non performing loans than the rest of the banks. These differences may shed light on how banks employed TARP financial support apart from continuing to finance small businesses: increasing their buffer, lending to lower quality borrowers, or revealing the true quality of existing assets.

TARP participation was not random: banks decide whether to apply for TARP. This feature, if not properly treated, might lead to biased results. In order to address this issue, we exploit the ownership structure of bank holding companies (BHC). In particular, we focus on BHCs that received TARP and that control more than one bank. We assume that TARP participation for a BHC is not driven by the average financial strength (which we measure by the capital ratio) of all subsidiary banks, but by the banks in distress (banks with low capital ratios). Within a BHC, to banks with high capital ratios, TARP participation can thus be considered exogenous. In other words, if these banks were alone in the market, they were not likely to go for TARP. Using the above identification strategy, we show that the results are not driven by the selection issue. Moreover, TARP banks increase small business loan originations compared to the rest of the banks. This effect is statistically as well as economically significant: a TARP bank increases small business loan origination by about 19% in the years after receiving TARP equity.

Once we have established that TARP banks provide more loans compared to the rest of banks, we must make sure that this effect is a credit crunch, and not just the result of lower demand for credit. Here lies our second main contribution: the data set we use provides information on loan originations for each bank within each county. This within-county variation of TARP and NO TARP banks allows us to control for the fact that TARP banks might be located in sounder counties, with a high demand for loans. This is achieved by including bank-county fixed effects in the specifications.

We are also able to characterise which variables determine the effectiveness of TARP on a local level. To the baseline model we add measures of poverty and unemployment in each county. Poverty captures persistent economic problems, while unemployment reflects more temporary economic issues, because it is strongly related with the business cycle. The results highlight that higher levels of unemployment and poverty decrease loan provision. We find that TARP has a positive and statistically significant effect on small business loan originations only in counties suffering from high unemployment.

Our study contributes to a small but increasing literature on the effects of the TARP program. Taliaferro (2009) finds that TARP banks exhibit higher commitments (i.e., opportunities for new lending), are more exposed to troubled loan classes and show higher leverage and expected costs of regulatory downgrades. Moreover, he finds that for 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. 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 financial support 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 for each dollar provided to the banks through the TARP program one-third was 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. They find that TARP financial support increases risk taking behaviour for big banks while the relation goes in the opposite direction in the case of small banks. These findings are confirmed when spreads instead of risk ratings are employed.

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

The paper serves as an empirical test of the macro models which feature a "financial accelerator". Models like Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) and others focus on credit constraints faced by non-financial borrowers. The recent financial crisis though showed that there were substantial disruptions in the financial intermediation process. Gertler and Kiyotaki (2010) therefore propose a model with an agency problem that potentially constrains the ability of intermediaries to raise funds from depositors.

When the constraint is binding, the intermediary's balance sheet limits its ability to obtain deposits. In times of crisis, the model predicts a significant increase of the cost of credit that non-financial borrowers face. The model by Gertler and Kiyotaki (2010) predicts that government equity injection relieves the intermediary's borrowing constraint and thus increases credit to, and production by the non-financial sector.

The most important innovations of this paper are the data set and the way of addressing program participation. This is the first study to exploit the CRA data set, allowing us to focus on small business loan originations, which represents, as previously mentioned, a relevant fraction of the US economy. We provide a new approach to address the selection bias issue related to the voluntary participation in the TARP program. In particular, we exploit the relationship between BHCs and controlled commercial banks (we focus on BHCs with more than one controlled commercial bank, having received TARP financial support) to construct an exogenous TARP bank group.

2.2 TARP and Community Reinvestment Act

2.2.1 Troubled Asset Relief Program

The Troubled Asset Relief Program (TARP) was launched by the US Treasury in 2008 after the collapse of Lehman Brothers. TARP is the largest program ever promoted by the US Government with $700 billion available funds, and $420 billion effectively used. TARP consists of Bank Support Programs ($250.46 billion), Credit Market Programs ($26.52 billion), Housing Programs ($45.60 billion) and other programs for AIG and the automobile sector ($147.53 billion). The programs of interest are the Bank Support Programs, which can be divided into the Target Investment Program, which exclusively addressed Citigroup and the Bank of America, the Capital Purchase Program (CPP), and the Community Development Capital Initiative (CDCI). Our analysis focuses on the CPP.

The CPP is 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 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 support financial institutions to keep financing firms, small businesses and households. Only solvent institutions were eligible for CPP.

2.2.2 Community Reinvestment Act

Data about small business loan originations is from the Community Reinvestment Act (CRA) data set. The Federal Financial Institutions Examination Council (FFIEC) collects information about bank loan activity as well as features and characteristics of borrowers. According to the CRA, all insured institutions that exceed specific total asset thresholds, defined by the federal bank regulatory agencies, must be periodically evaluated in their activity of helping meet the credit needs of the areas where they are located. This evaluation is used in case an institution applies for deposit facilities, or in case of mergers and acquisitions.[2]

The Community Reinvesting Act was 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"[3]. The law was introduced to counteract discriminatory

[2]The Office of the Comptroller of the Currency, the Federal Reserve System, the Federal Deposit Insurance Corporation, and the Office of Thrift Supervision are the federal bank regulatory agencies which define the total asset threshold. Further information about the CRA examinations is available at http://www.ffiec.gov/cra/history.htm

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

loan practices, commonly referred to as "redlining", where loan providers used to mark the borders of specific areas they did not intend to serve with any type of loans in red (see for instance Figure 2.3 in the Appendix).

2.3 Data and Descriptive Analysis

2.3.1 Data set

The data set we employ is the result of a merging process. Data concerning financial institution balance sheets[4] is obtained from the Report of Condition and Income (generally referred to as Call Reports). We access 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 on TARP is publicly available on the website of the US Treasury. We consider the period from the end of October 2008, when the 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.

We obtain information on bank loan originations at county level from the FFIEC website and the poverty and unemployment rates are from the US Census Bureau and the Bureau of Labor Statistics. Data are recorded yearly and the period considered goes from 2005 to 2010. We list the sources also in Table 2.11 of the Appendix.

2.3.2 Combining Call Reports, TARP and CRA data sets

We focus on annual data, because the variable of interest (loan originations) are only available at a yearly frequency. For quarterly data we measure the series in the fourth quarter of each year. The sample period goes from 2005 to 2010. We drop the nine banks that were forced to participate in TARP; these institutions are Citigroup, Wells Fargo,

[4]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.

JPMorgan, Bank of America, Goldman Sachs, Morgan Stanley, State Street, Bank of New York Mellon, and Merrill Lynch. There are two types of institutions that benefited from the TARP program: individual banks and Bank Holding Companies (BHC). As our analysis is led at the bank level, we map each commercial bank with its BHC. Therefore, for each depository institution included in our final data set, we can assess whether it benefited (directly or indirectly) from TARP. From the original Call Report data set, we drop all foreign banking organizations (FBOs) and banks that report capital ratios smaller than 0%, since these banks were not eligible for TARP.

After the above-mentioned merging and filtering procedures, in 2005, the final data set contains 794 banks, and of those 213 received financial support through the TARP program. Overall, banks provide loans in 2634 counties, while the TARP banks provide loans in 2026 counties. In 2010, the data set contains 635 banks that provide loans in 2650 counties. Of these banks 255 received the TARP financial support and they provide loans in 2113 counties. Our data set includes around 10 percent of institutions that hand in Call Reports, and around 50 percent of all TARP banks. The data set is a panel of banks tracked for five years.

2.3.3 Description of variables

The baseline measure of small business loan originations is $LOANS\,0$. It is defined as the log of one plus the sum of total loan origination. Small business loan originations 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 small business loan originations of the respective size. These variables are on a bank-county level.

The majority of the variables included in our data set 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 Gozzi and Goetz (2010), 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.

We also consider a set of variables that refer to the socio-economic features of the counties included in the CRA data set. In particular, we obtained the series on poverty, county median income and unemployment from the US Census Bureau and the Bureau of Labour Statistics. 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[5]. A detailed list of the original names of the series employed in this paper, definitions and labels is provided in Table 2.11 in the Appendix.

2.3.4 Main facts

Descriptive statistics

In Table 2.2, for each of the variables, we report the number of observations, banks and counties when this is feasible, the mean, the standard deviation, and the 10th, 50th and the 90th percentiles. All variables are measured in 2005. The analysis of the different loan variables is on a bank-county basis, whereas the rest of the variables are on a bank basis. Focusing on the loan variables, from Table 2.2, it follows that on average $LOANS$ 2 are lower than the other two loan types. Moreover, $LOANS$ 0 show the lowest level of

[5]See http://www.census.gov/did/www/saipe/ and http://www.bls.gov/cps/tables.htm for more information.

dispersion around the average, and finally, the 10th percentile of bank-pairs of $LOANS$ 2 and $LOANS$ 3 are zero, indicating that banks focus more on small size loans.

Unconditional average differences

We divide the banks in two groups (TARP and NO TARP) depending on whether they participated in TARP 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:

$$Y_{s,t} = \alpha + \beta_1 time_t + \beta_2 TARP_s + \beta_3 TARP_s \times time_t + \epsilon_{s,t} \tag{2.1}$$

In Equation (2.1) 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 participate in TARP, zero otherwise) and an interactive dummy variable, $TARP \times time$, capturing the difference-in- difference. Table 2.A in the Appendix provides a quick view of the possible combinations.

We are interested in testing average differences within groups across time and within time across groups. When fixing the bank group (TARP or NO TARP), we assess whether there are on average differences within the group and across periods. Instead, when fixing the time dimension (AFTER or BEFORE) we test whether there are on average differences across groups and within periods. Finally, taking the difference-in-difference, we assess whether there are statistical significant differences across groups and across periods. As can be seen in Table 2.A, this effect is captured by β_3. The results are reported 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 less than NO TARP banks (columns 3 and 4). As a consequence, the difference-in-difference is positive and statistically significant for all loan types (column 5). The 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 more than NO TARP banks (columns 3 and 4). The difference-in-difference is positive and statistically significant (column 5). Finally, looking at 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: the TARP program alleviates the drop in loans; TARP banks use the financial support, at least partially, to increase their capital buffer; the quality of TARP bank borrowers decreases over time faster than that of the rest of the banks.

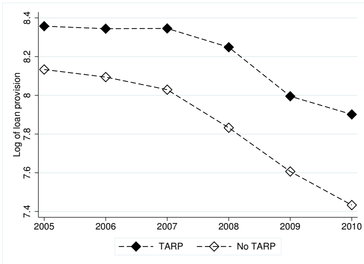
The results from the unconditional averages tests are confirmed by a visual counterpart (see Figure 2.1). For the different measures of small business loan originations, we document the per-quarter averages distinguishing between bank groups (TARP vs NO TARP)[6].

County socio-economic features

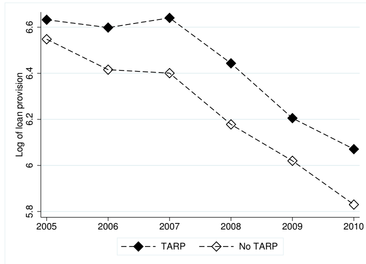
The importance of leading the analysis per county can also be motivated by the uneven density of banks across counties, which might reflect an unequal distribution of business opportunities. These differences could drive our results. Therefore, it is of relevance to conduct an accurate analysis of the relationship between bank investment strategies and county features. For each bank and year, we compute the average of the unemployment rate, the poverty rate and the median income of the counties where the bank has loan activities. We are interested in assessing the relationship between these indicators and bank size. As documented in Figure 2.2, there are no substantial differences across the two groups of banks. This is true independently of the period considered. In particular,

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

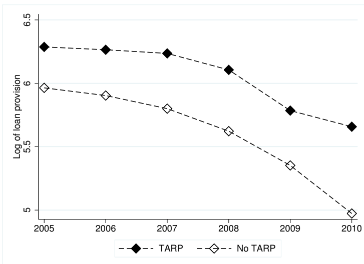
Figure 2.1: Per-quarter-group, averages



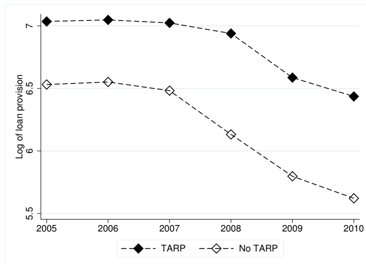
(a) LOANS 0



(b) LOANS 1



(c) LOANS 2

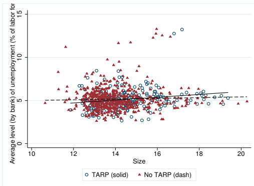


(d) LOANS 3

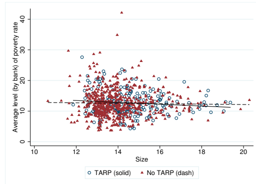
Notes: Per-quarter average small business loan originations for TARP and NO TARP banks. Aggregation by giving each bank-county observation the same weight.

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.

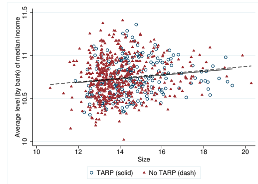
Figure 2.2: Scatter plot of average level of different socio-economic indicators of counties where banks provide loans and bank size



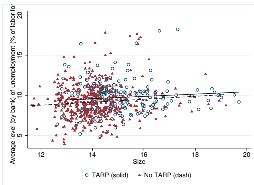
(a) Unemployment, 2005



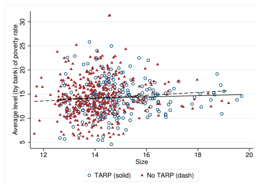
(b) Poverty, 2005



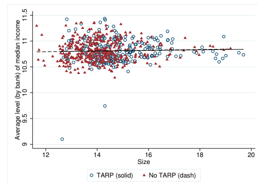
(c) Median income, 2005



(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 dashed lines refer to the fitted values for the TARP and NO TARP groups.

2.4 Econometric Strategy

2.4.1 Specification

We estimate a panel regression based on the following specification:

$$\begin{aligned}
LOANS_{i,j,t} = {} & \beta_1 TARP_{i,t} + \beta_2 TARP \times SIZE_{i,t} + \beta_3 TARP \times CAPRATIO_{i,t} \\
& + \beta_4 SIZE_{i,t} + \beta_5 NPL_{i,t} + \beta_6 TOTLOANS_{i,t} + \beta_7 RELOANS_{i,t} \\
& + \beta_8 CAPRATIO_{i,t} + \beta_9 NOCORE_PA_{i,t} + \beta_{10} TOT_UNCOMM_{i,t} \\
& + \alpha_{i,j} + \delta_t + \xi_{i,j,t} \qquad (2.2)
\end{aligned}$$

The dependent variable is total small business loan origination by bank i in county j

during year t. We include bank-county[7] and year fixed effects ($\alpha_{i,j}$ 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. $RELOANS$ controls for bank exposure in the real estate market. $CAPRATIO$ is added to measure the potential impact of bank soundness on bank loan provision. Finally, $TOT\ UNCOMM$ and $NOCORE\ PA$ capture, the potential liquidity risk, and the effect of the bank's financing sources (in particular for wholesale funding) on the dependent variable. The inclusion of this set of variables is in line with previous contributions in the same field (see Gozzi and Goetz, 2010). The effect of the TARP program on small business loan originations is captured by $TARP$, which takes value one from the moment the bank benefits from the TARP program and zero otherwise. In the main specification, we also include two interaction variables. Firstly, the interaction of TARP with $SIZE$ captures a size effect as documented by Li (2011): mostly small banks participated in TARP (with the exception of the nine banks that were forced to participate, which we exclude, as described earlier). Secondly, the TARP interaction with $CAPRATIO$ controls for the capitalisation effect: less well capitalised banks might use TARP funds to increase their capital buffer instead of providing loans. In all estimations we cluster standard errors per bank.

2.4.2 Selection

TARP participation is not random: banks first decide to apply for TARP and are then evaluated by the US Treasury for eligibility. As Taliaferro (2009) points out, the Treasury rejected less than 16% of the institutions that applied for TARP. The main issue about selection thus concerns the bank's decision to participate in TARP.

To identify a causal relation between TARP participation and loan origination we use the ownership structure of a bank and in particular whether a bank is part of a bank

[7] We also estimate the model by employing bank and county fixed effects separately. The main results do not change and are available upon request.

holding company (BHC). In our sample, there are three different cases: BHCs controlling more than one bank; BHCs with a unique bank; and banks not controlled by a BHC. The aim is to create a group of TARP banks which is not prone to the selection issue.

As described above, TARP was a direct equity infusion for the bank by the US treasury. A major driver for participation in TARP was financial distress, which can be measured by low capital ratios. When considering participation in TARP of BHCs, the main assumption behind our top-down perspective is that a BHC's decision to participate in TARP relies not on the overall financial strength of all controlled banks, but on the banks in financial distress (that is, on banks with low capital ratios). Therefore, to banks within a BHC with high capital ratios, TARP participation can be considered as exogenous. In other words, banks with high capital ratios, if not belonging to a BHC controlling banks with low capital ratios, would not need extra financial support through rescue programs such as TARP. In sum, to create the exogenous TARP banks group, we proceed as follows. Using 2007 data, we compute the average Tier 1 capital ratio for each BHC. A bank is included in the exogenous TARP banks group if it belongs to a BHC that received TARP funds, and if it has a Tier 1 capital ratio higher than the BHC average.

We then proceed to choose a comparable control group. Since our TARP group consists only of banks owned by a BHC, we restrict the control group to NO TARP banks with a BHC.[8] In a first step, we choose all NO TARP banks that are part of a BHC. Since our TARP group only features banks with relatively high capital ratios, we further restrict the control group to NO TARP banks that have comparable levels of $CAPRATIO$. Technically, we use propensity score matching on $CAPRATIO$ to select the nearest neighbour for each included TARP bank.

[8] We run the baseline regressions also for the entire sample and find that our results hold.

2.5 Hypotheses and Results

2.5.1 TARP effect on bank loans

Equation (2.2) allows us to test the hypothesis as to 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 2.4 confirm *H1.* In particular, as shown in column (1), the TARP program increases bank small business loan originations by 19%. In column (2) we add the interaction terms $TARP \times SIZE$ and $TARP \times CAPRATIO$. 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 between 2007 and 2010. Although the marginal effect of TARP for the average bank is statistically not significant, column (2) highlights that the TARP effect depends on a bank's Size and on the Capital Ratio. In particular, banks with already high capital ratios increase loan origination more when benefiting from TARP. From this first analysis we can conclude that the TARP program met its goal to help banks in financing small businesses and households. The results can be justified by using a simple banking model[9], 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 (1995) 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.

[9]See for instance Shrieves and Dahl (1992), Jacques and Nigro (1997), Aggarwal and Jacques (2001), Jokipii and Milne (2011).

2.5.2 Disentangling the demand side effect

Until now we control for the demand side effect only through county dummy variables. Since we have socio-economic information on a county level, we are able to focus on the effect of specific characteristics at the county level. We add variables to Equation (2.2): $POVERTY$, $UNEMPLOYMENT$ and the interactions with the TARP program dummy variable: $TARP \times POV$ and $TARP \times UNEMP$. The two socio-economic variables might be correlated, as for example an extensive period of high unemployment in a county leads to higher poverty rates. However, we claim that the two variables capture different issues: $POVERTY$ captures chronic economic problems, while $UNEMPLOYMENT$ is more related to temporary economic frictions. To support our claim, we calculate for each county the standard deviation over time of the two variables and then calculate the average values over all counties. We find that unemployment shows higher variability than poverty (.98 versus .74), confirming our intuition that unemployment captures higher frequency issues.

Table 2.1: Autocorrelation of POVERTY and UNEMPLOYMENT

		UNEMPLOYMENT		
		t	$t-1$	$t-2$
	t	1.0000		
UNEMPLOYMENT	$t-1$	0.8552	1.0000	
	$t-2$	0.6393	0.8180	1.0000

		POVERTY		
		t	$t-1$	$t-2$
	t	1.0000		
POVERTY	$t-1$	0.9647	1.0000	
	$t-2$	0.9453	0.9641	1.0000

Our second hypothesis takes the following form:

H2: 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 *H2* 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 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 support. 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 2.6 confirm our intuitions: unemployment and poverty negatively impact the provision of new loans. Moreover, the positive coefficients of $TARP \times UNEMPLOYMENT$ highlight the TARP increase loan origination in counties with temporary economic problems (high unemployment). Instead, the negative coefficients on $TARP \times POVERTY$ show that the program is useless in counties that suffer from more persistent economic issues (high poverty). When computing the total effect of the TARP program for the average TARP bank and the average county, we find that TARP still has a positive and statistically significant effect on loan origination for LOANS 0 and LOANS 1.

2.6 Robustness

2.6.1 Loan size

As described in Section 2.3, the CRA data set provides data about loans distinguishing by small, medium and large loans. We test our hypotheses by using LOANS 1, LOANS 2 and LOANS 3 as dependent variables separately. As reported in Table 2.4 (columns (3)–(8)), the result for TARP effectiveness is different for different loan sizes, but does qualitatively not change much.

2.6.2 Loan provision

As documented in subsection 2.3.3 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 ascribed to this feature of the TARP banks. To control for this potential issue, we adopt two alternative strategies.

Placebo experiment

The first strategy consists in running a "placebo" experiment. More precisely, we consider the sample period from 2001 to 2007, prior to the crisis and the policy action. We still distinguish between TARP and NO TARP banks, but we fictionally assume that TARP participation took place four years earlier. Accordingly, a bank that participated in the true TARP program in 2009, participated in 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. The results of the placebo experiment, reported in Table 2.8 confirm our intuition. In all the cases the TARP effect is always not significant. The only exception is column (1) when we do not include the interaction terms $TARP \times SIZE$ and $TARP \times CAPRATIO$. In this case the marginal effect is negative, but statistically significant only at 10%. According to the results, we can safely claim that our results are not driven by the fact that TARP banks always provide more loans than the rest of the banks.

Matching

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 measured in 2005. In this way, we consider only banks that ex-ante show similar features but the participation in the TARP program. In the matched sample there are 594 banks (TARP and NO TARP) and 2744 counties[10]. The results of the baseline regression estimated using the matched sample are reported in Table 2.8. The results show that the TARP effect is still positive and statistically significant for all loan types. These results, together

[10] The results of the average differences between TARP and NO TARP groups after the matching exercises are reported in Table 2.10 of the Appendix.

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.

2.6.3 TARP amount

In the baseline analysis we do not control for the size of the financial support 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[11]. 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 2.9, show that a 1 percentage point increase in TARP leads to a 4 percent increase in total small business loan originations. It follows that the participation as well as the amount received play a crucial role in the loan provision process.

2.6.4 Discussion

In this contribution we focus on the effect of the TARP program, and in particular of the CPP program, on small business loan originations. 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 small business loan originations. TARP banks provide on average 19 percent more loans than the rest of the banks. From this perspective the US Treasury through the CPP program avoided a stronger contraction in bank loan activity.

Our results highlight that TARP was effective when banks were investing in counties that were not in an economically distressed situation, or in those counties that suffer from

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

cyclical economic problems. TARP is not effective in cases where banks invest in counties with persistent economic problems. The policy implication that follows is that TARP-like programs are more effective to alleviate temporary distressed situations. In contrast, to solve or reduce chronic episodes of economic distress the policy maker should implement alternative measures, and not necessarily through the banking system.

2.7 Conclusion

According to a report by 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 is confirmed from data collected by the 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 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) to help banks in their lending activity to support small businesses and households. Contrasting opinions characterise the debate about TARP. We assessed whether TARP through CPP achieved the goal of helping banks in sustaining loan activity to small businesses. We used a unique data set obtained by merging information from bank balance sheets (Call Reports, Fed of Chicago), TARP participation (US Treasury) and small business loan originations (Federal Financial Institutions Examination Council, FFIEC). We consider an annual data set from 2005 to 2010 with observations for each bank-county pair. Using a panel data approach (bank-county fixed effects, standard errors clustered by banks), our results highlight that TARP banks provide on average 19% higher small business loan originations than other banks. 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 participated in TARP 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, TARP-like programs may suffer from selection bias, because the participation in the program is not random. Our identification strategy is based on the BHC structure to construct an exogenous TARP banks group. The results show that the main findings are robust to the selection issue. 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 TARP was effective, but at the same time we provide evidence that local conditions play a role. In particular, we show that TARP is longer effective in counties suffering from high poverty.

2.A Tables

Table 2.2: 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 2.3: Averages diff in diff (Unconditional)

	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

Variable	Before β_2	After $\beta_2+\beta_3$	No TARP β_1	TARP $\beta_1+\beta_3$	Diff in Diff β_3
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: ***, **, * represent significance at the 1, 5, 10% level, respectively. 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 support through the TARP program, while NO TARP includes the rest of the banks.

Table 2.4: TARP increases loan origination

Dependent variable:	LOANS 0		LOANS 1		LOANS 2		LOANS 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP	0.193**	-1.541**	0.195**	-0.867	0.081	-0.875**	0.128*	-1.246***
	(0.091)	(0.674)	(0.089)	(0.628)	(0.062)	(0.393)	(0.074)	(0.474)
TARP × Size		0.065**		0.027		0.043**		0.064***
		(0.031)		(0.032)		(0.019)		(0.022)
TARP × Tier 1 ratio		0.075**		0.071*		0.028		0.036
		(0.034)		(0.043)		(0.021)		(0.024)
Size	0.477***	0.420***	0.412***	0.378**	0.347***	0.309***	0.274**	0.219*
	(0.151)	(0.160)	(0.156)	(0.172)	(0.100)	(0.107)	(0.113)	(0.116)
Total Uncomm.	0.948	0.940	0.425	0.425	0.368	0.350	1.295***	1.266**
	(0.705)	(0.721)	(0.691)	(0.696)	(0.406)	(0.418)	(0.494)	(0.507)
Non-Core Fin.	1.130**	1.117***	0.546	0.524	0.708***	0.711***	0.875**	0.883***
	(0.439)	(0.428)	(0.360)	(0.351)	(0.260)	(0.253)	(0.349)	(0.338)
Tier 1 Ratio	0.010	0.000	0.001	-0.008	0.009	0.005	0.010	0.003
	(0.014)	(0.016)	(0.011)	(0.010)	(0.007)	(0.009)	(0.008)	(0.010)
Total Loans	0.531	0.372	0.381	0.266	1.123***	1.018***	1.114***	0.969***
	(0.448)	(0.448)	(0.358)	(0.386)	(0.302)	(0.301)	(0.320)	(0.301)
Real Est. Loans	-0.682	-0.690	-0.648	-0.658	-0.328	-0.328	-0.329	-0.328
	(0.712)	(0.705)	(0.513)	(0.509)	(0.468)	(0.465)	(0.431)	(0.424)
Non-Perf. Loans	-2.637***	-2.887***	-1.108*	-1.336*	-1.526***	-1.697***	-1.966***	-2.209***
	(0.853)	(0.961)	(0.617)	(0.684)	(0.504)	(0.593)	(0.486)	(0.582)
Marginal effect TARP	0.193	0.0835	0.195	0.154	0.0814	0.00935	0.128	0.0206
p-value	0.0344	0.261	0.0293	0.0888	0.192	0.851	0.0824	0.732
Obs.	19276	19276	18392	18392	15904	15904	15279	15279
Banks	354	354	350	350	353	353	350	350
Counties	2031	2031	2017	2017	1897	1897	1833	1833

Notes: ***, **, * represent significance at the 1, 5, 10% level. Estimates of a panel regression including bank-county and time fixed effects for the sample period 2005–2010. Standard errors are clustered by bank and shown in parentheses. The "Marginal effect TARP" is the sum of the estimated coefficients of TARP, TARP × Size and TARP × Capratio, where Size and Capratio are evaluated at their average values for TARP banks between 2007 and 2010. Columns (1), (3), (5), and (7) do 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 small business loan originations, while columns (3)–(8) refer to the different type of loans: ≤ 100k, ≤ 250k and ≤ 1m.

Table 2.5: TARP increases loan origination, with matched control group

Dependent variable:	LOANS 0		LOANS 1		LOANS 2		LOANS 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP	0.255***	-1.093*	0.248***	-1.200*	0.212**	-0.841*	0.174	-1.053**
	(0.096)	(0.603)	(0.093)	(0.617)	(0.095)	(0.452)	(0.110)	(0.450)
TARP × Size		0.046		0.043*		0.048***		0.050**
		(0.029)		(0.022)		(0.018)		(0.022)
TARP × Tier 1 ratio		0.071**		0.089*		0.033		0.049**
		(0.030)		(0.050)		(0.024)		(0.022)
Size	0.840***	0.731***	0.593***	0.488***	0.582***	0.474***	0.679***	0.566***
	(0.135)	(0.167)	(0.124)	(0.130)	(0.110)	(0.114)	(0.120)	(0.134)
Total Uncomm.	-0.802	-0.841	-0.993	-1.018	-0.370	-0.425	-0.012	-0.069
	(0.577)	(0.581)	(0.735)	(0.695)	(0.515)	(0.485)	(0.497)	(0.496)
Non-Core Fin.	1.584***	1.529***	1.011	0.881	0.806*	0.844*	1.140**	1.165**
	(0.550)	(0.515)	(0.629)	(0.561)	(0.447)	(0.454)	(0.543)	(0.541)
Tier 1 Ratio	0.022	-0.000	0.026	-0.003	0.028**	0.015	0.017	-0.001
	(0.019)	(0.016)	(0.026)	(0.018)	(0.012)	(0.013)	(0.014)	(0.014)
Total Loans	1.581***	1.257**	1.115**	0.719	0.983**	0.762	1.284***	1.023*
	(0.491)	(0.544)	(0.530)	(0.628)	(0.474)	(0.468)	(0.484)	(0.524)
Real Est. Loans	-0.856	-0.940	-1.073	-1.193	-0.539	-0.525	-1.995**	-2.039**
	(0.878)	(0.877)	(0.760)	(0.768)	(1.084)	(1.084)	(0.970)	(0.969)
Non-Perf. Loans	-6.389***	-7.338***	-5.423***	-6.513***	-4.734***	-5.414***	-3.471**	-4.335**
	(2.035)	(2.147)	(1.735)	(1.815)	(1.719)	(1.754)	(1.690)	(1.758)
Marginal effect TARP	0.255	0.215	0.248	0.219	0.212	0.158	0.174	0.122
p-value	0.00991	0.0430	0.00977	0.0491	0.0290	0.114	0.118	0.265
Observations	4377	4377	4222	4222	3754	3754	3640	3640
Banks	70	70	70	70	70	70	68	68
Counties	865	865	857	857	804	804	768	768

Notes: ***, **, * represent significance at the 1, 5, 10% level. Estimates of a panel regression including bank-county and time fixed effects for the sample period 2005–2010. Standard errors are clustered by bank and shown in parentheses. The control group is constructed by using propensity score matching to select only NO TARP banks that are part of a BHC and have comparable levels of capital ratios as the TARP group. The "Marginal effect TARP" is the sum of the estimated coefficients of TARP, TARP × Size and TARP × Capratio, where Size and Capratio are evaluated at their average values for TARP banks between 2007 and 2010. Columns (1), (3), (5), and (7) do 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 small business loan originations, while columns (3)–(8) refer to the different type of loans: $\leq$ 100k, $\leq$ 250k and $\leq$ 1m.

Table 2.6: Demand side effect: poverty and unemployment

Dependent variable:	LOANS 0	LOANS 1	LOANS 2	LOANS 3
	(1)	(2)	(3)	(4)
TARP	.383	.505	.405	.228
	(.454)	(.518)	(.343)	(.354)
TARP × Size	-.015	-.027	-.015	-.007
	(.020)	(.025)	(.017)	(.017)
TARP × Tier 1 ratio	-.011	.001	-.017	-.012
	(.022)	(.024)	(.016)	(.017)
TARP × Δ UNEMPL	.019*	.005	.012	.025***
	(.010)	(.009)	(.008)	(.006)
TARP × Δ POVERTY	-.007**	-.008**	-.006**	-.004*
	(.003)	(.003)	(.002)	(.002)
Δ POVERTY	-.005	-.001	-.004	-.005
	(.003)	(.004)	(.003)	(.004)
Δ UNEMPLOYMENT	-.020*	-.013	-.012	-.029***
	(.012)	(.010)	(.008)	(.009)
Size	.328***	.340**	.246***	.219**
	(.112)	(.139)	(.094)	(.097)
Total Uncomm.	.211**	.117	.122	.473*
	(.086)	(.117)	(.178)	(.274)
Non-Core Fin.	.739**	.728*	.511**	.595**
	(.370)	(.385)	(.258)	(.262)
Tier 1 Ratio	-.006	-.019	.002	-.001
	(.014)	(.023)	(.012)	(.010)
Total Loans	.395	.109	.600**	.593*
	(.346)	(.369)	(.264)	(.302)
Real Est. Loans	-.011	.134	-.057	-.205
	(.419)	(.493)	(.327)	(.309)
Non-Perf. Loans	-2.164***	-1.426**	-1.297***	-1.754***
	(.668)	(.662)	(.438)	(.518)
Marginal effect TARP	.0852	.126	.0507	.0494
p-value	.0732	.00702	.193	.257
Obs.	57497	55580	48054	46872
Banks	1038	1022	1021	1024
Counties	2725	2718	2599	2514

Notes: ***, **, * represent significance at the 1, 5, 10% level. Estimates of a panel regression including bank-county and time fixed effects for the sample period 2005–2010. Standard errors are clustered by bank and shown in parentheses. The "Marginal effect TARP" is the sum of the estimated coefficients of TARP, TARP × Size, TARP × Capratio, TARP × Δ Poverty and TARP × Δ Unemployment where Size and Capratio are evaluated at their average values for TARP banks between 2007 and 2010, and Δ Poverty and Δ Unemployment are evaluated at their average values for TARP banks between 2000 and 2010. Columns (1) to (4) report the results for the entire sample.

Table 2.7: Matching NO TARP banks on observables

Dependent variable:	LOANS 0		LOANS 1		LOANS 2		LOANS 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TARP	0.138**	0.298	0.097	0.544	0.080	0.428	0.118*	0.168
	(0.065)	(0.458)	(0.066)	(0.564)	(0.051)	(0.349)	(0.063)	(0.368)
TARP × Size		-0.007		-0.024		-0.012		0.001
		(0.020)		(0.026)		(0.017)		(0.017)
TARP × Tier 1 ratio		-0.005		-0.004		-0.019		-0.008
		(0.024)		(0.028)		(0.018)		(0.018)
Size	0.369***	0.371***	0.378***	0.383***	0.258**	0.264**	0.227**	0.228**
	(0.124)	(0.124)	(0.144)	(0.146)	(0.104)	(0.104)	(0.108)	(0.108)
Total Uncomm.	0.030	0.035	-0.255	-0.228	0.128	0.128	0.376	0.370
	(0.400)	(0.401)	(0.487)	(0.489)	(0.284)	(0.281)	(0.308)	(0.308)
Non-Core Fin.	0.942**	0.937**	0.828*	0.778*	0.564*	0.578*	0.873***	0.894***
	(0.413)	(0.410)	(0.466)	(0.433)	(0.319)	(0.324)	(0.316)	(0.318)
Tier 1 Ratio	-0.017	-0.015	-0.025	-0.022	-0.004	0.004	-0.008	-0.004
	(0.019)	(0.021)	(0.024)	(0.032)	(0.014)	(0.016)	(0.012)	(0.013)
Total Loans	0.140	0.149	-0.007	0.046	0.309	0.315	0.402	0.391
	(0.422)	(0.432)	(0.433)	(0.439)	(0.329)	(0.337)	(0.374)	(0.385)
Real Est. Loans	-0.071	-0.092	0.319	0.250	0.077	0.037	-0.251	-0.248
	(0.463)	(0.453)	(0.554)	(0.519)	(0.393)	(0.389)	(0.381)	(0.361)
Non-Perf. Loans	-2.347***	-2.316***	-1.482*	-1.377*	-1.592**	-1.514**	-2.117***	-2.111***
	(0.842)	(0.846)	(0.766)	(0.793)	(0.642)	(0.649)	(0.737)	(0.743)
Marginal effect TARP	0.138	0.152	0.0972	0.150	0.0796	0.0980	0.118	0.114
p-value	0.0339	0.0116	0.144	0.00512	0.118	0.0403	0.0608	0.0534
Obs.	44923	44923	43751	43751	37502	37502	36446	36446
Banks	405	405	403	403	402	402	402	402
Counties	2589	2589	2577	2577	2466	2466	2398	2398

Notes: ***, **, * represent significance at the 1, 5, 10% level. Estimates of a panel regression including bank-county and time fixed effects for the sample period 2005–2010. Standard errors are clustered by bank and shown in parentheses. The "Marginal effect TARP" is the sum of the estimated coefficients of TARP, TARP × Size and TARP × Capratio, where Size and Capratio are evaluated at their average values for TARP banks between 2007 and 2010. We estimate our model using a matched sample, where the matching is performed using propensity score matching with nearest neighbour on the variables $SIZE$, $CAPRATIO$, TOT_UNCOMM, $NOCORE\_PA$, TOT_LOANS $REALOANS$, NPL, $POVERTY$ and $UNEMPLOYMENT$ in 2005. Columns (1), (3), (5), and (7) do 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 small business loan originations, while columns (3)–(8) refer to the different type of loans: ≤ 100k, ≤ 250k and ≤ 1m.

Table 2.8: 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	-.083	1.524***	2.075***	1.783***	2.367***	.117**	.306	.561	.362	.172
	(.053)	(.495)	(.639)	(.666)	(.664)	(.056)	(.464)	(.536)	(.357)	(.375)
TARP × Size		-.066**	-.096***	-.077**	-.094***		-.009	-.027	-.012	-.002
		(.026)	(.037)	(.031)	(.033)		(.020)	(.026)	(.017)	(.017)
TARP × Tier 1 ratio		-.065**	-.074**	-.073*	-.109***		-.005	-.003	-.014	-.007
		(.029)	(.037)	(.041)	(.037)		(.023)	(.025)	(.017)	(.018)
Size	.376***	.418***	.393***	.554***	.564***	.357***	.360***	.352***	.271***	.241**
	(.102)	(.085)	(.119)	(.128)	(.119)	(.114)	(.115)	(.133)	(.096)	(.100)
Total Uncomm.	.234	.292*	.098	.643*	.409	.034	.039	-.212	.075	.442
	(.161)	(.167)	(.215)	(.378)	(.265)	(.375)	(.376)	(.449)	(.244)	(.290)
Non-Core Fin.	-.175	-.245	-.002	-.452	-.484	.788**	.780**	.696*	.559**	.728***
	(.343)	(.302)	(.381)	(.493)	(.539)	(.344)	(.340)	(.359)	(.260)	(.261)
Tier 1 Ratio	-.020	-.005	-.017	-.011	.008	-.017	-.015	-.020	-.002	-.006
	(.019)	(.011)	(.020)	(.023)	(.019)	(.016)	(.016)	(.024)	(.013)	(.011)
Total Loans	.736***	.713***	.969**	.244	1.265***	.092	.101	.143	.478*	.507*
	(.275)	(.256)	(.376)	(.431)	(.447)	(.363)	(.369)	(.363)	(.273)	(.306)
Real Est. Loans	-.375	-.374	-.312	-.644	-.215	-.099	-.120	.248	.102	-.138
	(.322)	(.283)	(.407)	(.399)	(.517)	(.440)	(.435)	(.455)	(.341)	(.315)
Non-Perf. Loans	-1.266	-1.089	3.131	-2.399	-3.826	-2.768***	-2.740***	-1.294**	-1.645***	-2.094***
	(1.158)	(1.059)	(2.119)	(1.772)	(2.432)	(.603)	(.604)	(.594)	(.455)	(.517)
Marginal Effect TARP	-.0827	.0408	.0865	.0771	.126	.117	.135	.136	.0721	.0820
p-value	.121	.346	.143	.264	.115	.0376	.0112	.00444	.0773	.0910
Obs.	54994	54994	54994	54994	54994	56333	56333	54441	46778	45579
Banks	985	985	985	985	985	702	702	698	701	701
Counties	2752	2752	2752	2752	2752	2752	2752	2746	2629	2551

Notes: ***, **, * represent significance at the 1, 5, 10% level, respectively. Estimates of a panel regression including bank-county and time fixed effects for the sample period 2001–2007 (columns (1)–(5)) or 2005–2010 (columns (6)–(10)). Standard errors are clustered by bank and shown in parentheses. The "Marginal effect TARP" is the sum of the estimated coefficients of TARP, TARP × Size and TARP × Capratio, where Size and Capratio are evaluated at their average values for TARP banks between 2003 and 2005 (columns (1)–(5)) or between 2007 and 2010 (columns (6)–(10)). Columns (1)–(5) perform a Placebo experiment, where we anticipate the TARP treatment by 4 years. Columns (6)–(10) use a matched sample, where the matching is performed using propensity score matching with nearest neighbour on the variables small business loan originations $LOANS\,1$, $LOANS\,2$ and $LOANS\,3$ in 2005. Columns (1) to (5) report the results based on the placebo experiment. Columns (1) and (6) do not include the interaction terms between TARP and SIZE and TARP and CAPRATIO.

Table 2.9: The effect of TARP increases with TARP amount

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
Counties	2812	2805	2684	2599

Notes: ***, **, * represent significance at the 1, 5, 10% level, respectively. Estimates of a panel regression including bank-county and time fixed effects for the sample period 2005–2010. Standard errors are clustered by bank and shown in parentheses. Columns (1) refers to total small business loan originations, while columns (2), (3), and (4) refer to the different type of loans: $\leq$ 100k, $\leq$ 250k and $\leq$ 1m.

Table 2.10: Descriptive statistics matched groups

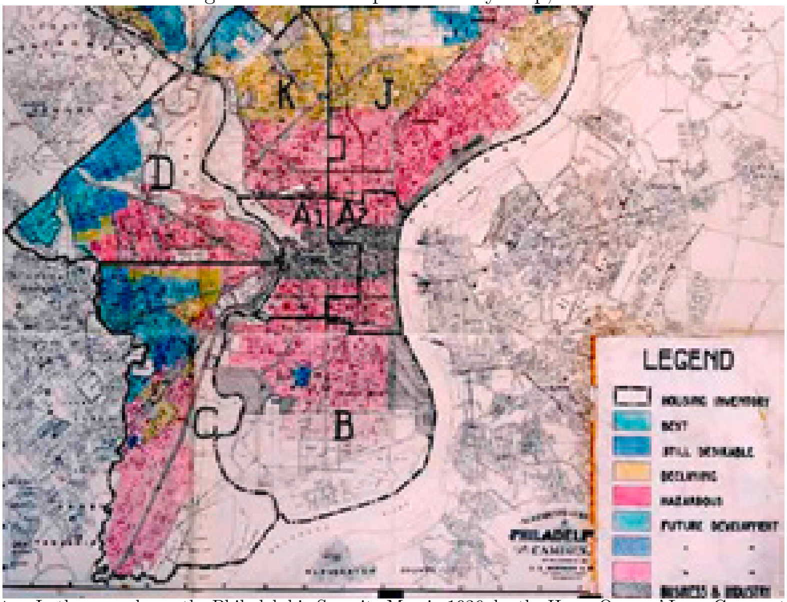
Matching 1: year 2005, bank level	TARP	No TARP	Diff in Diff
Size	14.641	14.415	0.226
			(0.146)
Tier 1 Ratio	8.221	8.430	-0.209
			(0.182)
Total Uncomm.	0.223	0.234	-0.011
			(0.032)
Non-Core Fin.	0.267	0.270	-0.003
			(0.012)
Total Loans	0.671	0.679	-0.007
			(0.011)
Real Est. Loans	0.712	0.707	0.005
			(0.016)
Non-Perf. Loans	0.012	0.014	-0.003***
			(0.001)
Obs.	213	192	405

Matching 2: year 2005, bank-county level	TARP	No TARP	Diff in Diff
SBL 0	8.893	8.701	0.192
			(0.173)
SBL 1	7.115	6.720	0.395*
			(0.205)
SBL 2	6.998	6.795	0.204
			(0.242)
SBL 3	7.699	7.579	0.120
			(0.284)
Obs.	213	292	505

Matching 3: year 2007, BHC level	TARP	No TARP	Diff in Diff
Tier 1 Ratio	9.262	9.506	-0.244
			(0.739)
Obs.	39	31	70

Notes: ***, **, * represent significance at the 1, 5, 10% level, respectively. Standard errors in parenthesis. Propensity score matching refers to 2005 data. Matching 1 is based on the following variables: $SIZE$, $CAPRATIO$, TOT_UNCOMM, $NOCORE\_PA$, TOT_LOANS $REALOANS$, NPL, $POVERTY$ and $UNEMPLOYMENT$. Matching 2 is based on the following variables: $LOANS1$, $LOANS2$ and $LOANS3$. Matching 3 is based on $CAPRATIO$.

Figure 2.3: 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 2.11: Sources and definitions of the variables

Variable Label	Variable definition	Source
TARP	Takes value 1 if a bank received TARP sustain at least once, and 0 otherwise.	Federal Reserve Board
TARPDUMMY	Takes value 1 from the year (quarter) a bank received TARP sustain and zero before.	Federal Reserve Board
ALO_1	Amount of Small Business Loan Originations $\leq$ 100k	CRA
ALO_2	Amount of Small Business Loan Originations $\leq$ 250k	CRA
ALO_3	Amount of Small Business Loan Originations $\leq$ 1m	CRA
ALO_0	$ALO_1 + ALO_2 + ALO_3$	CRA
$LOANS_1$	log of $(1 + ALO_1)$	CRA
$LOANS_2$	log of $(1 + ALO_2)$	CRA
$LOANS_3$	log of $(1 + ALO_3)$	CRA
$LOANS_0$	log of $(1 + ALO_0)$	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

Chapter 3

Liquid Assets in a Cash-in-Advance Model

I construct a model where both money and a fraction of real assets can be used to purchase consumption goods, and are therefore considered as liquid. I investigate how this set up of competing media of exchange affects the static allocation of real assets and I document the dynamic response of the endogenous variables to shocks. I find that asset holdings increase when a larger fraction of the asset can be used for transactions, and that the effect increases with inflation. Also, with higher inflation, the liquidity premium of the asset increases. The dynamic response of the real variables remains close to the standard model for most variables, but the nominal interest rate reacts much stronger.

3.1 Introduction

The analysis of monetary policy and the interaction between real and nominal variables have long been a subject of study in macroeconomics. To discuss monetary policy, nominal features and liquidity issues, money has to be introduced into general equilibrium macro models. One way to do so is to impose that money is required to purchase consumption goods, a framework known as cash-in-advance models.

The cash-in-advance is a useful framework to model monetary policy at the aggregate level. The model has initially been introduced by Lucas (1982) in order to study the determination of prices, interest rates, and exchange rates. In the present paper, the cash-in-advance constraint serves to model the existence of money in a stripped-down version of the real business cycle model.

The reason to use a cash-in-advance model instead of the now widely adopted New Keynesian framework lies in the fundamental role that money plays in the two frameworks. In the New Keynesian context, money is a unit of account, and arises because of the nominal rigidities in the models, most often because of price and/or wage stickiness. Such a model is of limited use when trying to model the liquidity of assets.

Although there exist numerous extensions of the original model proposed by Lucas (1982), there is no model which allows that at least a fraction of real assets can be used in transactions. This paper aims to answer the question how the static allocation and dynamic response to shocks of the model change once a real asset with some degree of liquidity is being introduced. Throughout the paper I use the term liquidity to describe the ability to purchase consumption goods. In other words, a liquid asset provides liquidity services to its holder. In equilibrium then, an asset will not only be valued according to its fundamental value (the discounted future payoffs). Instead, also the fact that the asset can be used in transactions will be valued, potentially leading to a liquidity premium.

The original version of the CIA model assumes that agents can only use real money balances taken over from the last period to purchase goods in the current period. In the model proposed by Lucas (1982), the bond market opens first and then the goods market opens. So, agents allocate their portfolio between cash and bonds at the beginning of each period, after observing any current shocks but prior to purchasing goods. In this model, households would never bring excessive cash to the next period, and thus the cash-in-advance constraint always binds. Svensson (1985) changed the timing of the model slightly, and he assumes that the goods market opens before the bond market. Therefore, for precautionary reasons, the household brings too much money to the next period, sometimes leading to a slack cash-in-advance constraint. In this paper I adopt the version proposed by Lucas (1982).

Lucas and Stokey (1987) analyse a model where the use of money is motivated by the introduction of a cash-in-advance constraint only for a subset of consumption goods. The distinction of cash and credit goods leads to a time-varying velocity of money. Since the household have to use cash for the cash good, they lose the interest rate. If the interest rate is high, the household tends to consume more of the credit good.

An analysis similar to this paper is led by Lagos and Rocheteau (2008), who consider an environment where money and capital act as competing media of exchanges. Different than in this paper, the authors employ a search-theoretic approach to introduce the potentially beneficial role of money. They establish the conditions under which fiat money can be valued, that is when a monetary equilibrium exists. If the condition is satisfied, then liquid capital is being traded at a liquidity premium in the nonmonetary equilibrium.

However, the discussion about productive assets that are used as means of transactions dates back to earlier research. For example, Sargent and Wallace (1983) study the efficiency of commodity money systems, investigate which assets may naturally emerge as commodity money and how the commodity money competes with (interest-bearing) inside money.

There are also real world examples where productive assets have been used as currency. Einzig (as cited in Lagos and Rocheteau, 2008) finds that “Goats and cattle were until comparatively recently the principal currency of a large part of Kenya.” Also metal coins could be considered as assets which were either used in the production process or served as medium of exchange in transactions.

The paper is organised as follows. In section 2 I present the model and discuss the differences compared to the simple cash-in-advance model. In section 3 I let the liquidity parameter to fluctuate over time and discuss the implications of the model.

3.2 Model

There is one representative household that lives forever. Time is discrete. The household maximizes its lifetime utility

$$U = \max \sum_{t=0}^{\infty} u(c_t) \tag{3.1}$$

with $u(c) = \log(c)$ where c_t is real consumption. The household owns a technology which produces output y. The production function is $y = f(a)$ and requires as input real asset, a. I will use the production function $f(a) = za^{\kappa}$, with $0 < \kappa < 1$, where z is a measure of productivity and follows the AR(1) process

$$\log z_t = \rho_z \log z_{t-1} + \varepsilon_t^z \tag{3.2}$$

The stock of real assets depreciates at rate δ and depreciation occurs after production takes place. Furthermore, the household can acquire risk-free nominal bonds B_{t+1} in period t, which yield $(1 + i_{t+1})B_{t+1}$ in the next period. Finally, in period t the household also chooses to bring the amount of money, M_{t+1}, to the next period.

The household's period t budget constraint is then

$$c_t + \frac{M_{t+1}}{P_t} + \frac{B_{t+1}}{P_t} + a_{t+1} = f[(1-\phi)a_t] + (1-\delta)a_t + \frac{M_t}{P_t} + (1+i_t)\frac{B_t}{P_t} + \tau_t \tag{3.3}$$

where P_t is the price level in period t and τ_t are transfers. The parameter $(1 - \phi)$ will be explained further down.

The cash-in-advance (CIA) constraint differs from the standard CIA model described by Lucas (1982) and Svensson (1985). Here, I implement a further element, not present in the existing forms of CIA models. To model the assumption that the asset also provides liquidity services, I allow a fraction ϕ of the asset being used for purchases of the current period consumption. Then, the cash-in-advance constraint is

$$c_t \leq M_t/P_t + \phi a_t \tag{3.4}$$

where $0 < \phi < 1$ measures the fraction of the asset that is immediately available for purchases. However, as the budget constraint in Equation (3.3) highlights, the amount of the asset which is used for purchases is no longer available for productive purposes, hence $f[(1-\phi)a_t]$. Therefore, there is a trade-off between the productive and the liquidity providing usage of the asset. The reason for this is the timing convention. I assume that in order to purchase goods, the agent has to put down the amount the purchase requires, and only then production takes place. At this point, the asset which is used for the purchase can not be used in the production process.

The Bellman equation for this problem is

$$
\begin{aligned}
V(a_t, M_t, B_t) = u(c_t) &+ \beta E_t V(a_{t+1}, M_{t+1}, B_{t+1}) \\
&+ \lambda_t \left\{ f[(1-\phi)a_t] + (1-\delta)a_t + \frac{M_t}{P_t} + \tau_t + (1+i_t)\frac{B_t}{P_t} \right. \\
&\left. -c_t - \frac{M_{t+1}}{P_t} + \frac{B_{t+1}}{P_t} - a_{t+1} \right\} \\
&+ \mu_t \left[c_t - M_t/P_t - \phi a_t \right]
\end{aligned}
\tag{3.5}
$$

The first-order conditions

- c_t

$$\frac{1}{c_t} = \lambda_t + \mu_t \tag{3.6}$$

- a_{t+1}

$$\lambda_t = \beta V_a(a_{t+1}, m_{t+1}, b_{t+1})$$

- B_{t+1}

$$\frac{\lambda_t}{P_t} = \beta V_b(a_{t+1}, m_{t+1}, b_{t+1})$$

- M_{t+1}

$$\frac{\lambda_t}{P_t} = \beta V_m(a_{t+1}, m_{t+1}, b_{t+1})$$

and the following envelope conditions

$$V_a(a_t, M_t, B_t) = \lambda_t \left[(1-\phi)f'[(1-\phi)a_t] + (1-\delta)\right] + \mu_t\phi$$

$$V_b(a_t, M_t, B_t) = \frac{\lambda_t}{P_t}(1+i_t)$$

$$V_m(a_t, M_t, B_t) = \frac{\lambda_t + \mu_t}{P_t}$$

Combining the FOCs of a, B, and M together with the respective envelope conditions yields

$$\lambda_t = \beta\lambda_{t+1}\left[(1-\phi)f'[(1-\phi)a_t] + (1-\delta)\right] + \beta\mu_{t+1}\phi \tag{A}$$

$$\lambda_t\Pi_{t+1} = \beta\lambda_{t+1}(1+i_{t+1}) \tag{B}$$

$$\lambda_t\Pi_{t+1} = \beta\left[\lambda_{t+1} + \mu_{t+1}\right] \tag{M}$$

where $\Pi_{t+1} = \frac{P_{t+1}}{P_t}$ is the gross inflation rate between periods t and $t+1$.

Equation (A) describes the inter-temporal trade-off between renouncing on one unit of wealth today and investing it into the real asset. Tomorrow, the real asset has a return from the production usage, plus the non-depreciated amount. In addition, the real asset also relieves tomorrow's cash-in-advance constraint, measured by μ_{t+1}.

Similarly, Equation (B) describes the inter-temporal trade-off for the nominal bond. Investing one unit in the nominal bond today yields $(1+i_{t+1})$ units tomorrow. Since the bond is nominal, it is being discounted by the gross inflation rate $1/\Pi_{t+1}$.

Finally, Equation (M) describes the trade-off for money. Although money does not yield any return, it also relieves the cash-in-advance constraint. Again, since it is a nominal asset, it is being discounted by the gross inflation rate.

3.2.1 Equilibrium

Equilibrium is defined as the set of functions $\langle c(\cdot), a(\cdot), M(\cdot), P(\cdot), i(\cdot), \lambda(\cdot), \mu(\cdot)\rangle$ which satisfy the FOC with respect to c_t (Equation (3.6)), the intertemporal Equations (A), (B), and (M), the CIA constraint described in Equation (3.4), the market clearing constraint for the asset:

$$c_t + a_{t+1} = f[(1-\phi)a_t] + (1-\delta)a_t \tag{3.7}$$

and the description of monetary policy, which is assumed to be passive:

$$\log M_{t+1} - \log M_t = (1-\rho_m)\theta + \rho_m\left(\log M_t - \log M_{t-1}\right) + \varepsilon_t^m \tag{3.8}$$

with $0 < \rho_m < 1$. The nominal variables are not stationary because money supply M grows at a constant rate. However, dividing all nominal variables through the price level yields stationary values. By adding and subtracting $\log P_{t+1} - \log P_t$ on the left hand side of Equation (3.8) and $\rho_m\left(\log P_t - \log P_{t-1}\right)$ the nominal variables can be transformed into real variables.

$$\begin{aligned}
&(\log M_{t+1} - \log P_{t+1}) - (\log M_t - \log P_t) + (\log P_{t+1} - \log P_t) = \\
&\qquad (1-\rho_m)\theta + \rho_m\left[(\log M_t - \log P_t) - (\log M_{t-1} - \log P_{t-1})\right. \\
&\qquad \left.+\ (\log P_t - \log P_{t-1})\right] + \varepsilon_t^m \\
&\log m_{t+1} - \log m_t + \pi_{t+1} = (1-\rho_m)\theta + \rho\left(\log m_t - \log m_{t-1} + \pi_t\right) + \varepsilon_t^m
\end{aligned} \tag{3.9}$$

where $\pi_{t+1} = \Pi_{t+1} - 1$ is the net inflation rate between periods t and $t+1$.

3.2.2 Steady State

Since the model can not be solved analytically, it is necessary to linearise the model around the steady state. This section describes how the steady state is derived and some of its properties. Since the model describes a closed economy, outstanding bonds have to be zero in steady state, so $B = 0$. From the law of motion of productivity z, described in

Equation (3.2), the steady state value of z is derived

$$\begin{aligned} \log z_t &= \rho_z \log z_{t-1} + \varepsilon_t^z \\ z &= 1 \end{aligned} \tag{3.10}$$

The money supply described in Equation (3.9) determines the (net) inflation rate π. From the law of motion of the money supply

$$\log m_{t+1} - \log m_t + \pi_{t+1} = (1-\rho_m)\theta + \rho\left(\log m_t - \log m_{t-1} + \pi_t\right) + \varepsilon_t^m$$

So for $m_t = m_{t-1}$, it has to be that $\pi = \theta$, that is inflation is equal to the growth rate of money supply. Since the (nominal) money supply M_t grows at a constant rate, the newly printed money has to be distributed amongst the household. In particular, the transfers to the household in steady state are

$$\tau = m\theta \tag{3.11}$$

The price level P, and therefore the amount of real money balances m will be determined by the cash-in-advance constraint.

In steady state, Equation (A) is

$$\lambda = \beta\lambda\left[(1-\phi)f'[(1-\phi)a] + (1-\delta)\right] + \beta\mu\phi \tag{3.12}$$

and can be combined with Equation (M) to eliminate the Lagrange multipliers

$$1 = \beta\left[(1-\phi)f'[(1-\phi)a] + (1-\delta)\right] + \phi(\Pi-\beta) \tag{3.13}$$

As $f'[(1-\phi)a] = \kappa z\left[(1-\phi)a\right]^{\kappa-1}$, the expression for real assets in steady state is

$$a = (1-\phi)^{\frac{\kappa}{1-\kappa}}\left[\frac{\beta\kappa z}{1-\phi(\Pi-\beta)-\beta(1-\delta)}\right]^{\frac{1}{1-\kappa}} \tag{3.14}$$

Compared to the standard cash-in-advance constraint model without labour decision, the level of assets now depends on the inflation rate Π. Also, a in steady state depends on the newly introduced parameter ϕ. I will discuss the comparative statics in the following subsection.

From the resource constraint, and knowing a from Equation (3.14), one can then derive the level of consumption in steady state.

$$c = f[(1-\phi)a] - \delta a \tag{3.15}$$

Combining the first-order condition with respect to consumption (Equation (3.6)) together with Equation (M) and using Equation (3.15) yields the Lagrange multiplier λ.

$$\lambda = \frac{\beta}{\Pi}\frac{1}{c} \tag{3.16}$$

Then, using again Equation (3.6),

$$\mu = \lambda - \frac{1}{c} \tag{3.17}$$

Comparing this to the above expression of λ highlights that the cash-in-advance constraint is binding whenever $\Pi > \beta$, that is, whenever inflation exceeds the discount rate.

3.2.3 Comparative statics

Equation (A) describes the level of assets in steady state. First, I show that the level of the asset is strictly increasing in inflation, Π.

$$\frac{\mathrm{d}a}{\mathrm{d}\Pi} = (1-\phi)^{-\kappa}\frac{\phi a}{1-\kappa} > 0 \tag{3.18}$$

Since $a > 0$, $0 < \phi < 1$, and $0 < \kappa < 1$, the expression in Equation 3.18 is unambiguously positive. The reason is that higher inflation induces a higher opportunity cost of money, as the cash-in-advance constraint requires to cover the consumption expenditures with money holdings from the last period. Since the real asset also provides liquidity services to some extent, the relative utility of the asset compared to money increases.

Equation (3.14) also allows to investigate how the steady state level of real assets depends on the parameter ϕ. In any equilibrium where the agent's cash-in-advance constraint binds, the computation of the partial derivative $\frac{\mathrm{d}a}{\mathrm{d}\phi}$ indicates that for a wide range of sensible parameter values, the steady state level of real assets positively depends on ϕ.[1] That is, the more liquid the asset is, the higher the amount of assets in steady state.

The fact that assets increase with ϕ alone is not surprising, because the set up of the model imposes that with a higher ϕ, the available amount of assets for productive uses decrease. Therefore, the interesting feature of the model is whether the amount of assets available for production, $(1-\phi)a$, move with a change in ϕ. The derivative is equal to

$$\frac{\mathrm{d}(1-\phi)a}{\mathrm{d}\phi} = \frac{a}{1-\kappa}\left\{-\frac{1}{1-\phi}+\frac{\Pi-\beta}{1-\phi(\Pi-\beta)-\beta(1-\delta)}\right\} \lesseqgtr 0 \tag{3.19}$$

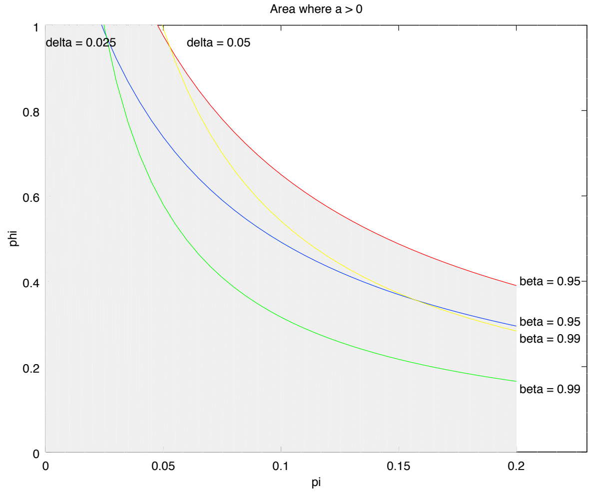
Whether (3.19) is positive or negative, depends crucially on the steady state money growth rate θ, and therefore the inflation rate, Π. Keeping all other parameters as given in Table 3.1, I find that $\frac{\mathrm{d}a}{\mathrm{d}\phi} > 0$ if the money growth rate exceeds the $\underline{\theta} = 0.0238$. For sufficient high steady state inflation then, production increases with ϕ.

This can be justified by the fact that the asset bears a liquidity premium, in addition to the real return from production. However, whether the benefit from this liquidity services are big enough, depends on the cost that holding money involves. In particular, if inflation is sufficiently low, the inflation tax is low enough and the cost of increasing assets is too high. If instead inflation is sufficiently high, then the asset provides useful liquidity, and the household is willing to accept a lower marginal return on the asset.

To conclude the discussion of Equation (3.14), note that not all value of the parameters ensure a solution. The relevant part is the numerator in the expression, which has to be positive in order to yield a real solution. Figure 3.1 documents the area where particular values of the deep parameters β, δ, Π, and ϕ lead to a solution where $a > 0$.

[1] Details on the parameter range where $\frac{\mathrm{d}a}{\mathrm{d}\phi} > 0$ are reported in the Appendix.

Figure 3.1: Area where $a > 0$



3.2.4 Calibration

The parameters are calibrated so that one period reflects a quarter. Where feasible, the values of the deep parameters are taken from Cooley and Hansen (1989) and are standard in the literature[2]. The particular choice of the log utility function already restricts the coefficient of risk aversion to be $\sigma = 1$. The discount factor β, the exponent in the production function κ, and the depreciation rate δ are the same as used by Cooley and Hansen (1989).

The autoregressive coefficients on the technology and the money supply shock as well as the standard deviations of these shocks are taken over from Cooley and Hansen (1989).

The new parameter introduced in this model is ϕ, and the calibration of this parameter is somewhat arbitrary. Ideally, one would estimate the parameter. However, in the absence of data on what fraction of assets are used to provide liquidity services, I will use alternative values $\phi = 0.05$ and $\phi = 0.1$ below.

[2]For example, King and Rebelo (1999) use a very similar specification.

Table 3.1: Calibration baseline model

Variable	Description	Value
β	Discount factor	0.99
δ	Depreciation rate	0.025
κ	Production function	0.33
θ	Growth rate of money supply	0.03
ϕ	Liquidity parameter of asset	$\{0.05, 0.1\}$
ρ_z	AR(1) of Total Factor Productivity	0.95
ρ_m	AR(1) of money supply	0.48
σ_z	Std. deviation of technology shock	0.00721
σ_m	Std. deviation of money supply shock	0.008

3.2.5 Dynamics

I log-linearize the model around the steady state described above and solve the model using Dynare. In the following I will compare the impulse response functions to a positive technology and a positive monetary shock of the models for the specifications where $\phi = 0$ (blue, solid line), $\phi = .05$ (red, dashed line), and $\phi = 0.1$ (green, dash-dotted line).

In each case, the linearised system starts at the steady state and is then subject to a one standard deviation technology (ε_t^z) or a monetary (ε_t^m) shock. The figures then show the evolution of the endogenous variables over time as deviations from the steady state.

Productivity shock

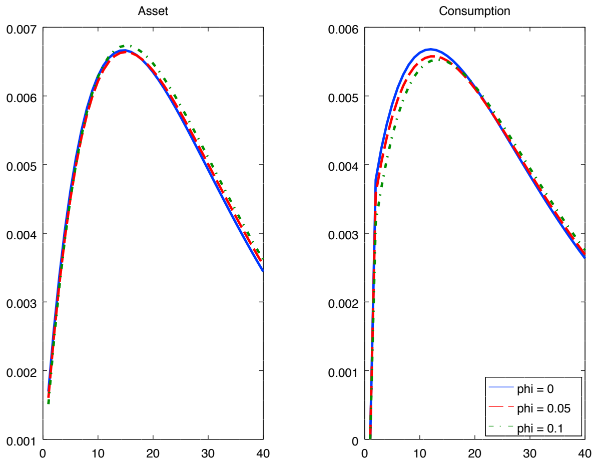
The productivity shock affects the production function through total factor productivity.

$$y = f[(1-\phi)a] = z\,[(1-\phi)a]^{\kappa}$$

A positive productivity shock increases the amount of output for a given input.

Figure 3.2 shows the impulse response functions of the real variables (asset holdings and consumption) after a technology shock. Since the positive technology shock increases the marginal return of the asset, there is an immediate positive effect on asset holdings. With increasing production, also consumption can be increased by roughly the same percentage amount as the asset. The differences between the specifications of the model

Figure 3.2: IRFs of real variables to technology shock

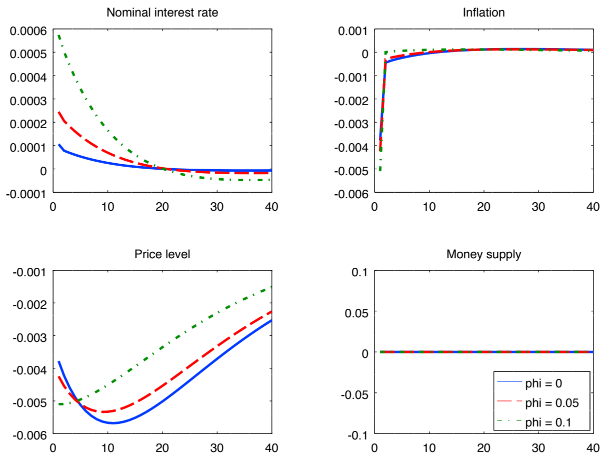


Notes: Impulse response functions to a positive one standard deviation technology shock. Both assets and consumption are shown as percentage deviations from their steady state values (0.01 = 1%).

($\phi = \{0, 0.05, 0.1\}$ are rather small. With a higher ϕ, the expansion of asset holdings increases. This is driven by the fact that the asset also carries the liquidity premium.

The response of the nominal variables to a technology shock are shown in Figure 3.3. In all three specifications, inflation drops immediately after the shock, but recovers quickly to the steady state level. Instead, the price level is more persistent. In all three specifications, the price level initially falls by about 0.5 percent. The initial drop is higher for the specification with $\phi = 0.1$. However, while the impulse response function of the price level for the models with $\phi = 0$ and $\phi = 0.05$, this cannot be seen in the case of $\phi = 0.1$. The differences between the model specifications are mostly visible from the nominal interest. While in the case of $\phi = 0$, the nominal interest rate hardly moves (initially less than 0.01 percentage points, the increase is nearly sixfold for the specification with $\phi = 0.1$.

Figure 3.3: IRFs of nominal variables to technology shock



Notes: Impulse response functions to a positive one standard deviation technology shock. The nominal interest rate and inflation are shown as absolute deviations from their steady state values (0.01 = 0.01 percentage points). The price level and the money supply are the percentage deviations from their steady state values (0.01 = 1%.

Monetary shock

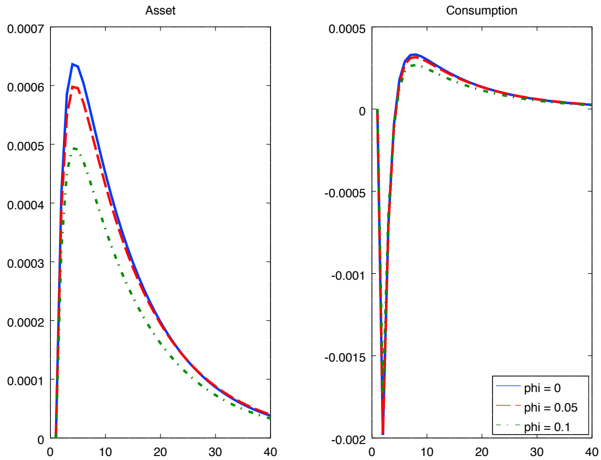
Monetary policy in this model is described by Equation (3.8),

$$\log M_{t+1} - \log M_t = (1-\rho_m)\theta + \rho_m(\log M_t - \log M_{t-1}) + \varepsilon_t^m$$

A positive monetary shock ε_t^m temporarily increases the growth rate of (nominal) money supply.

The initial aim of introducing a cash-in-advance constraint was to analyse the linkages between nominal and real variables and to study the effects of monetary policy. Here, monetary policy is simply described as the money supply growth rule and the shock to money supply growth. Figure 3.4 depicts the impulse response function of the real variables after a positive monetary shock. The left panel shows how the asset increases in response to the monetary shock, while the right panel indicates that consumption

Figure 3.4: IRFs of real variables to money supply shock

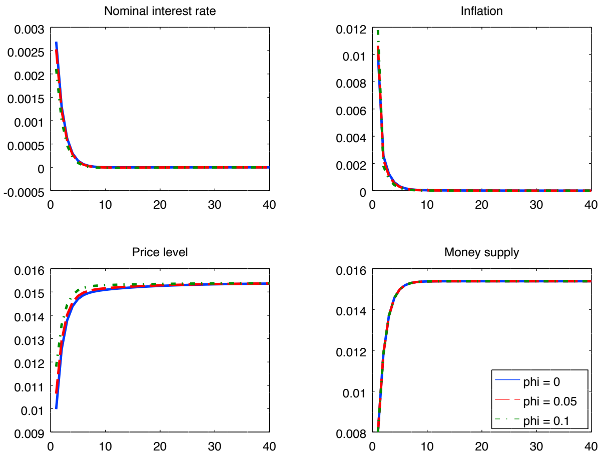


Notes: Impulse response functions to a positive one standard deviation money supply shock. Both assets and consumption are shown as percentage deviations from their steady state values ($0.01 = 1\%$).

initially drops. The reason is that inflation is a tax on holders of money. In the absence of the cash-in-advance constraint, household's would not want to hold money. If the cost of holding money increases because of higher inflation, the household will try to substitute away from money. Due to the constraint they can not substitute money for consumption, so the household will basically substitute money for investment. Therefore, consumption drops in the short-term, while assets increase. The differences between the three specifications are negligible for consumption, but more evident for the asset. For higher ϕ, the asset increases less.

Finally, Figure 3.5 shows the impulse response functions of the nominal variables to a monetary shock. Money supply M increases briefly as a result of the shock, which in turn increases inflation. Since the AR(1) coefficient in the law of motion of money supply, takes on a value of $\rho_m = 0.5$, the effect of the shock dies out rather quickly. In particular, money supply and inflation are back to their steady state values after just 10 periods. The relative abundance of money drives down the price of the consumption good in monetary

Figure 3.5: IRFs of nominal variables to money supply shock



Notes: Impulse response functions to a positive one standard deviation money supply shock. The nominal interest rate and inflation are shown as absolute deviations from their steady state values (0.01 = 0.01 percentage points). The price level and the money supply are the percentage deviations from their steady state values (0.01 = 1%.

terms, therefore leading to a brief drop in the price level. By the Fisher equation, the nominal interest rate increases, as inflation increases and the real interest rate drops slightly (since the asset holdings increase, as documented above). This is consistent with the fact that nominal assets, such as the risk-free bonds, in times of high inflation must be remunerated with a higher nominal interest rate in order to establish an equilibrium.

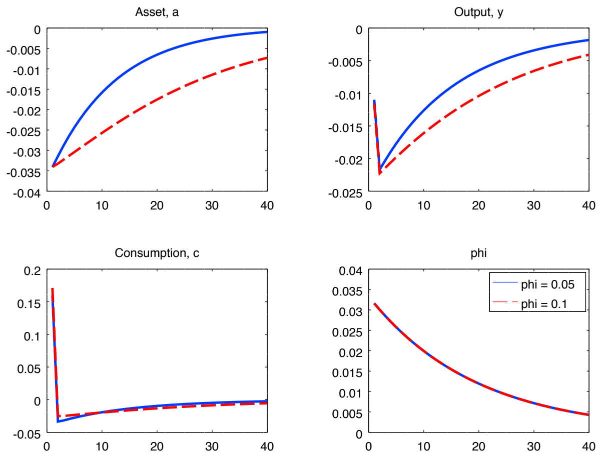
Overall, the introduction of the liquid asset in the cash-in-advance model brings some interesting results. The differences are most notable for the nominal variables in response to a technology shock and for the real variables in response to a monetary shock. Other authors such as King and Watson (1996) have already pointed out that monetary shifts on output are small in cash-in-advance models. This also applies to the present model, especially for the specifications with positive ϕ. The reason for the quasi-neutrality of money in the $\phi > 0$ case is that the liquidity providing feature of the real asset makes the real asset respond even less to monetary shocks.

3.3 A shock to the liquidity of the real asset

Up to now it was assumed that the parameter ϕ is constant and exogenous. In this section I extend the above model and allow ϕ to vary over time. In particular, I assume that ϕ follows the process

$$\phi_t = (1 - \rho_\phi)\overline{\phi} + \rho_\phi \phi_{t-1} + \varepsilon_t^\phi$$

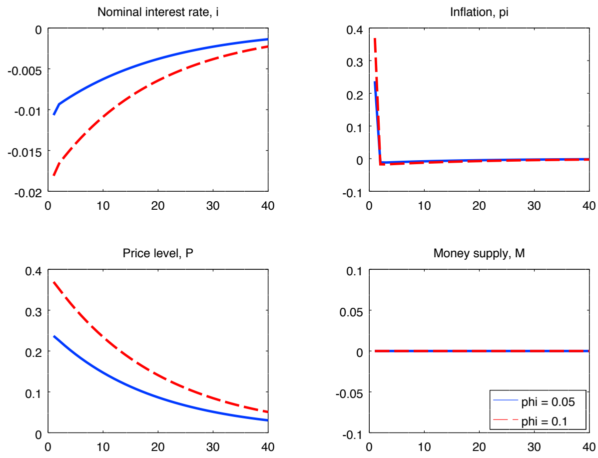
Figure 3.6: IRFs of real variables to ϕ-shock



Notes: Impulse response functions to a positive 0.01 unit shock to ϕ. Assets, output and consumption are shown as percentage deviations from their steady state values ($0.01 = 1\%$). ϕ is shown as absolute deviation from its steady state value.

The positive shock to ϕ leads to a significant drop in asset holdings. At first, this seems counterintuitive, since the static analysis of the steady state value of assets in Equation (3.14) indicated that a depended positively on ϕ. However, Figure 3.6 indicates the dynamic response to a *temporary* and *unanticipated* shock to ϕ. In particular, although the higher ϕ relieves the cash-in-advance constraint, the immediate effect is that less assets are available for productive uses, which depresses output and therefore the available resources. The household reduces investment into the asset starkly, allowing it to expand consumption for a short period of time. However, the drop in investment must lead to a drop in the asset.

Figure 3.7: IRFs of nominal variables to ϕ-shock



Notes: Impulse response functions to a positive 0.01 unit shock to ϕ. The nominal interest rate and inflation are shown as absolute deviations from their steady state values ($0.01 = 0.01$ percentage points). The price level and the money supply are the percentage deviations from their steady state values ($0.01 = 1\%$).

Figure 3.7 shows the impulse responses of the nominal variables to a shock to ϕ. Notably, the price level and therefore inflation spike on impact.

3.4 Conclusion

I presented a model which extends the standard cash-in-advance model originally proposed by Lucas (1982). In the standard model, the cash-in-advance constraint requires the representative household to hold money in order to purchase consumption goods. In the model presented here, money is not the only asset which can be used to purchase consumption goods. In particular, I allow that a certain fraction of the real asset can also be employed in such transactions. However, the fraction of the assets used in transactions is not available for consumption in the same period.

The proposed model offers additional features compared to the standard cash-in-advance model. In particular, the real asset is not only valued for its productive usage in the production sector, but there is a second component linked to the liquidity providing feature of the asset. The fact that the real asset can also be used to purchase consumption goods leads even in a risk-less steady state to a positive liquidity premium of the asset, if the inflation rate is high enough.

I also find that the mere fact of having a partially liquid asset does not affect the dynamic response of real and nominal variables to a productivity or a monetary shock. In particular, it remains true that money remains nearly neutral, even with the introduction of the partial liquidity of the real asset. The only exception is the fact that the nominal interest rate reacts much stronger to the shocks. One important finding is that a shock to the fraction of the asset that can be used to purchase consumption goods does have relatively large effects on the real variables. For future research, it would be interesting to measure empirically how much variability in real variables can be explained by a varying ϕ.

The model used in this paper excluded for simplicity many features now usually built into dynamic stochastic general equilibrium models. It would be interesting to investigate the effects of the liquidity providing feature in a more complete model, including for example a labour-leisure decision. Also, one can think about a model where there are multiple real assets, each with a different degree of liquidity. Furthermore, the monetary policy side of the model could be more active. The question arises then, whether the monetary authority are able to (temporary or permanently) mitigate the effects of changes to the liquidity of the asset by monetary policy (conventional or not).

3.A Appendix

The expression for assets in steady state, as described in Equation (3.14).

$$a = (1-\phi)^{\frac{\kappa}{1-\kappa}} \left[\frac{1-\phi(\Pi-\beta)-\beta(1-\delta)}{\beta\kappa z} \right]^{\frac{1}{\kappa-1}} \tag{3.20}$$

The derivative with respect to ϕ

$$\begin{aligned} \frac{\mathrm{d}a}{\mathrm{d}\phi} = &\frac{\kappa}{1-\kappa}(1-\phi)^{\frac{\kappa}{1-\kappa}-1} \cdot (-1) \Big[\dots \Big]^{\frac{1}{\kappa-1}} + \\ &+ (1-\phi)^{\frac{\kappa}{1-\kappa}} \left(\frac{1}{\kappa-1} \right) \Big[\dots \Big]^{\frac{1}{\kappa-1}-1} \left(\frac{-(\Pi-\beta)}{\beta\kappa} \right) \end{aligned}$$

Extracting the common terms

$$\frac{\mathrm{d}a}{\mathrm{d}\phi} = \frac{a}{1-\kappa} \left\{ -\frac{\kappa}{1-\phi} + \frac{\Pi-\beta}{1-\phi(\Pi-\beta)-\beta(1-\delta)} \right\} \tag{3.21}$$

Table 3.2 indicates the range of values a parameter can take, for the derivative of a with respect to ϕ to be positive, while all other parameters take the value indicated in the calibration section (see Table 3.1).

Table 3.2: Sensitivity

Variable	$\phi = 0.05$		$\phi = 0.1$	
	low	high	low	high
β		1.0322		1.0323
δ		0.2068		0.2110
κ		1.0896		1.0951
θ	-0.0248		-0.0239	
ϕ		1.0385		1.0385

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