Understanding the Accumulation of Bank and Thrift Reserves during the U.S. Financial Crisis

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Abstract

The level of aggregate excess reserves held by U.S. depository institutions increased at the peak of the financial crisis of 2007-09. Although the amount of aggregate reserves is almost entirely determined by the policy initiatives of the central bank that act on the asset side of its balance sheet, the motivations of individual banks in accumulating reserves differ and respond to the impact of changes in the economic environment on individual institutions. We undertake a systematic analysis of this massive accumulation of excess reserves using bank-level data for more than 7,000 commercial banks and almost 1,000 savings institutions during the U.S. financial crisis. We propose a testable stochastic model of reserves determination when interest is paid on reserves, which we estimate using bank-level data and censored regression methods. We find evidence primarily of a precautionary motive for reserves accumulation with some notable heterogeneity in the response of reserves accumulation to external and internal factors of the largest banks compared with smaller banks. We combine propensity score matching and a difference-in-difference approach to determine whether the beneficiaries of the Capital Purchase Program of the Troubled Assets Relief Program accumulated lower reserves than non-beneficiaries. Contrary to anecdotal evidence, we find that banks that participated in the program accumulated fewer reserves than non-participants in the initial quarters after the capital injection.

JEL Classification: E44, E51, G21

Keywords: Commercial Banks, Financial Crisis, Excess Reserves, TARP

1 Introduction

The aggregate level of deposits held by U.S. depository institutions (DIs) at the Federal Reserve Banks (Fed) increased massively at the peak of the financial crisis between the end of August 2008 and the end of December 2008, in parallel with the unprecedented expansion of the Fed balance sheet (Figure 1).[1] This huge change in deposits at the Fed, most of which are excess reserves, prompted some commentators to argue that precautionary hoarding of cash and reserves was impeding loan growth and potentially slowing the recovery from the 2007-09 recession. The fear was that the accumulation of reserves would dampen the effect of Fed operations to revive the economy and at the same time potentially generate inflation. Keister and McAndrews (2009) and Martin et al. (2011) explain clearly that the level of aggregate reserves is determined by the policy initiatives of the Federal Reserve and may only marginally affect aggregate lending. Although this is true at an aggregate level, individual banks can alter the composition of their balance sheets, reducing or increasing lending to firms and consumers while hoarding excess reserves. The biggest question that the massive accumulation of reserves raises is why individual profit-maximizing banks hold excess reserves. Our answer is intuitive: because they are concerned about their balance sheet risk regarding both about the loans they know are bad and those they are not yet sure about. But we are also able to rule out other reasons for reserve accumulation and determine the differential accumulation behavior of small and large banks as well as between banks that received funds under the Capital Purchase Program (CPP) and those that did not.

By studying the determinants of bank-level reserve accumulation, we provide some insight into the heterogeneous effects of the 2007-09 financial crisis and to some extent of the fiscal and monetary policy actions in the commercial banking sector. We undertake a systematic analysis of this massive accumulation of excess reserves using microeconomic data for more than 7,000 commercial banks and almost 1,000 saving institutions. We first discuss a simple stochastic model of reserves choice that incorporates interest on reserves (IOR). We then estimate a log-linearized version of the model using bank-level data and censored regression methods. We empirically identify the determinants of reserve accumulation and find evidence of a precautionary motive. Specifically, we find that institutions in weak financial health appear to hoard

[1] DIs (commercial banks, savings institutions, credit unions, and foreign banking entities) may hold their required reserves as either vault cash or deposits at their regional Federal Reserve Bank. Deposits at the Federal Reserve are the sum of reserve balances with Federal Reserve Banks and required clearing balances; on August 27, 2008, total deposits at Federal Reserve Banks were $20.394 billion; on December 29, 2010, they were $1020.937 billion.

relatively more excess reserves than sounder institutions , similar to the Japanese situation during the Lost Decade. We also show that changes in the spread between yields on safe short-term assets and the IOR are negatively correlated with reserve accumulation. When alternative investment opportunities yield larger returns relative to the IOR, commercial banks tend to decumulate reserves as expected. But we also uncover significant heterogeneity in the responsiveness of reserve accumulation to internal and external factors. We find that large banks' reserves are much more responsive to the interest differential and the penalty rate (for holding insufficient reserves) than small banks, whereas small banks' reserve accumulation is more sensitive to the health of their loan portfolios.

In the second part of our analysis, we study the relationship between the Capital Purchase Program (CPP) of the Troubled Assets Relief Program (TARP) and cash and reserve accumulation by banks.[2] The ideal way to study the effect of capital injections on the banking system would be to have a counterfactual – what would have happened to the balance sheets of the banks that did receive CPP funds had they not received them? Although we cannot observe such counterfactuals for each institution's decision, we can observe banks that were ex ante similar to the CPP beneficiaries but did not receive the capital injections. Operationally, we use propensity score matching to construct a control group of non-CPP institutions that we compare with the CPP beneficiaries. We then estimate the difference-in-difference between pairs of indicators for the two groups of banks to remove unobservable differences between them. Although we are able to match a large number of banks that received CPP funds, an important caveat of our study is that, because almost all large banks (as ranked by assets) received CPP funds, finding an opportune control is unfeasible; therefore we remove the largest 20 banks from our study.

We find that the beneficiaries of the capital injection of CPP funds accumulated lower cash and reserves than non-beneficiaries. Popular opinion at the time of the crisis was that the CPP had failed to improve lending, and ipso facto increased reserves accumulation, by banking institutions who received CPP funding. Earlier studies such as Contessi and Francis (2011) discussed whether banks receiving CPP funds had dissimilar lending patterns from banks that did not receive such funds, but without controlling for selection into the program. They argued that although they found that banks receiving CPP funds actually provided more loans than their counterparts, since

[2]We use CPP and TARP interchangeably, although the CPP was the part of the TARP related to the banking sector.

issues of endogeneity and selection were not dealt with formally, these were tentative statements. The banks that did not receive CPP funds may not have received them for various reasons for example, because they may have been sufficiently capitalized and therefore had no need for the funds, or alternatively, because they may have been in such poor financial health that they were ineligible for the program. In this paper, our analysis addresses the endogeneity and selection concerns. Our result that banks that received CPP funds accumulated fewer excess reserves than those that did not receive CPP funds is consistent with their lending behavior. Our approach, however, provides a first step to construct an appropriate control group and suggestive results about the impact of the CPP program on bank behavior. To the best of our knowledge, this is a rather unique study in adopting propensity score matching in the non-experimental setting of applied banking.

The paper is organized as follows. In Section 2, we present an overview of the existing literature and in Section 3 we discuss the specific case of the United States. In Section 4 we develop the testable model, and Section 5 presents the data and the estimation. Section 6 studies the relationship between the CPP and cash and reserves accumulation. Finally, Section 7 concludes.

2 Related Literature

The literature on banking reserves is large and diverse and includes a number of key contributions. The two most significant branches of the literature for our study consider explanations for reserves accumulation by U.S. banks during the 1930s and the substantial buildup in excess reserves in the Japanese banking system during the 1990s. We also briefly review modern contributions on the role of uncertainty and interest on reserve policies on excess reserve accumulation.

In their influential analysis of the monetary history of the Depression era, and particularly the increase in excess reserve holdings, Friedman and Schwartz (1963) argued that banks desired a higher level of reserves for precautionary purposes after the panic of the early 1930s. On the contrary, Horwich (1963) provided early empirical evidence suggesting banks held excess reserves because of the lack of profitable alternatives to holding cash as a result of low interest rates. Along with these two contributions, many articles in the post-World War II literature tried to rebut the widespread view of reserves accumulation at the time that considered excess reserves to be purely surplus. This view was surprisingly shared by members of the Federal Open Market Committee

(FOMC). According to this view, excess reserves served no useful economic purpose, as commercial banks passively accumulated them due to the lack of good loan opportunities (a view sometimes referred to as the "inertia effect" hypothesis; see Frost, 1971). As a consequence, the Federal Reserve was essentially powerless to expand the money supply because the banking system was caught in a liquidity trap. Bernanke (1983) and Bernanke and Gertler (1990) emphasize the role of high risks and low returns on alternatives during the Depression era, supporting of the view that excess reserve holdings may also reflect an environment with few investment alternatives that have comparable low risks. The theoretical literature on banking reserves dissects the role of uncertainty on bank cash flows and how it differs between periods of crisis and non-crisis (see, e.g. Orr and Mellon, 1961; Poole, 1968; Cooper, 1971; Frost, 1971; Ratti, 1979; Hanes, 2006). As uncertainty plays a role in our analysis, we sketch the main contributions. Technical errors in a paper by Orr and Mellon (1961) spurred a debate on the relationship between stochastic reserve losses and the expansion of bank credit and the conditions under which the introduction of uncertainty into cash flows played a role in reducing lending compared with a deterministic environment (see, e.g., Cooper, 1971; Ratti, 1979).

Frost (1971) models bank demand for excess reserve holdings as an inventory problem, assuming that excess reserves allow banks to reduce the cost of meeting requirements when they face stochastic reserve flows and transaction curves. His model generates kinked demand curves that rationalize excess reserves accumulation during the 1930s. More recently, Hanes (2006) develops a model in which an increase in the reserve supply reduces long-term rates, holding fixed expectations of future overnight rates, and shows that the model is consistent with the relationship between reserve quantities and bond yields over the 1934-39 period.

A series of recent studies discusses the relevance of the constraints exerted by excess liquidity and their role in signaling a bank's own liquidity. Calomiris and Wheelock (2011) use bank-level data to understand whether the doubling of reserve requirements imposed by the Federal Reserve in 1936-37 increased reserve demand and induced a credit contraction, contributing to the deep recession of 1937-38. They find that reserve requirements were not binding on bank reserve demand in 1936 and 1937 and therefore had little impact on credit availability. They thus argue that increases in reserve demand between 1935 and 1937 reflected changes in the fundamental determinants of reserve demand, not changes in reserve requirements. Calomiris and Wilson (2004) argue that increasing reserve demand during periods of financial upheaval may be due to the liquidity signaling effect that high levels of reserves provide to depositors and creditors. Van Horn (2009), examining the years leading up to the Depression era, found that Federal Reserve System non-members, which had no access to the lender of last resort, increased their ratio of excess reserves to assets after the first banking panic much more than member banks, which could access emergency lending through the Fed.

Japan's Lost Decade also offers an important modern episode of steep reserve accumulation. Japanese banks began a sustained increase in excess reserve accumulation in mid-2001, which peaked in 2003:Q3 when the ratio of actual to required reserves reached 5.9. In Figure 2 we offer a comparison between the sharp increase in the ratio of actual to required reserves within the Japanese banking system between 2001 and 2006 and the increase in excess reserves during the Great Depressions and during the recent U.S. Great Financial Crisis (GFC). Although the recent reserves accumulation of Japan and the United States are much more pronounced, it is interesting to note they dwarf the accumulation of reserves during the U.S. Great Recession. Ogawa (2007) studies the determinants of bank-level reserve accumulation in Japan during the 1998-2002 period. His results suggest that a strong precautionary motive induced banks with large numbers of bad loans to accumulate relatively more reserves.[3] He attributed Japanese banks' precautionary behavior to the general instability in the Japanese banking system the health of the individual bank's balance sheets. He found that banks with better capitalization and a sounder portfolio of loans did not have as much incentive to overaccumulate reserves compared with banks that had poorer-quality portfolios and shakier balance sheets. Figures 3, 4, and 5 offer a comparison of the three historical episodes in which the excess-to-required reserve ratio (ERR) is plotted against a short-term rate that represents potential alternative investment opportunities to holding cash. Along with these two series, the graphs plots the 24-month rolling correlations between the two, which is predominantly negative, indicating that times of increases in the EER are times in which this rough measure of the opportunity cost of holding reserves decreases. It is clear the sign of the correlation observed by Ogawa (2007) is the same for the two historical episodes of reserves accumulation in the United states.

To conclude our review, there is a growing literature that discusses excess reserves in the context of contemporary monetary policy when the monetary authority pays

[3]Other work (see, e.g. Uesugi, 2002; Hamilton, 1997; Thornton, 2001) considers the liquidity effect: the proposition that monetary expansion lowers short-term nominal interest rates.

a positive IOR, as practiced, for example, in Canada, the United States (since October, 2008), New Zealand, the euro area, as well as other countries. Goodfriend (2002) discusses the benefits of the additional policy instrument provided by paying IOR. Martin et al. (2011) explain how the payment of IOR can generate a floor that "divorces" money from monetary policy, as the supply of reserves is then not necessarily tied to the target interest rate, thereby allowing central banks to increase the supply of reserves without driving market rates below target. Hornstein (2010) develops a stylized monetary model to explain the mechanics of monetary policy when the central bank pays IOR and finds that, although the responses of inflation and output to innovations in the target interest rate are slightly different from models in which reserves yield zero interest, such differences are small. In the context of the U.S. financial crisis, Bech and Klee (2011) use a market micro-structure approach to study a theoretical model in which bargaining power among traders explains why the federal funds rate remained below the target rate and the rate paid on reserves during the U.S. financial crisis. Ashcraft et al. (2011) use data on intraday account balances held by banks at the Fed combined with Fedwire interbank transactions to identify precautionary hoarding of reserves and reluctance to lend during the first phases of the U.S. financial crisis. They then use these results to develop a model with credit and liquidity frictions in the interbank market consistent with their evidence on precautionary motives. Martin et al. (2011) derive a simple model to show that aggregate bank lending and aggregate reserves are disconnected when interest is paid on reserves. Ennis and Wolman (2012) study a cross-section of banking reserves during the financial crisis, focusing on larger banks, and explain the mechanics of their accumulation in detail.

3 Reserve Accumulation: The U.S. Experience (2007-10)

3.1 Institutional Details

In this subsection, we discuss the institutional structure of the U.S. banking system, which provides a basis for our model in Section 4 and the estimation in Section 5.2.

In the United States, depository institutions must hold an amount of funds in reserve (reserves requirement) against specified deposit liabilities in the form of vault cash or deposits with the regional Federal Reserve Banks. The Federal Reserve Board's Regulation D specifies the dollar amount of a DI's reserve requirement through a reserve ratio applied to reservable liabilities (Table 1). Although reservable liabilities consist of net transaction accounts, non-personal time deposits, and eurocurrency liabilities, since

December 27, 1990, only net transaction accounts carry a nonzero reserve requirement.[4]

The reserve ratio depends on the amount of net transaction accounts at the DI. The Garn-St Germain Act of 1982 imposed a zero percent reserve requirement on the first $2 million of reservable liabilities. The amount of net transaction accounts subject to a reserve requirement ratio of 3 percent was set at $25 million under the Monetary Control Act of 1980.[5] Net transaction accounts over the low-reserve tranche are subject to a 10 percent reserve (see Table 1).

To ensure that DIs can meet their funding needs, eligible DIs can borrow under the primary credit program of the discount window. For example, if a DI experiences operational difficulties with its funds management systems, it is at risk of an overnight overdraft, which it can receive through the discount window or the interbank market. Funding needs at an individual institution can also arise from circumstances in which aggregate reserves in the banking system are significantly lower than what the Open Market Desk was anticipating in its management of the federal funds rate target. During the recent financial crisis, the significant strains in interbank funding markets prompted changes in the terms of discount window borrowing: (i) On August 17, 2007, the Fed extended the maximum term for borrowing to 30 days, renewable at the request of the borrower, and reduced the spread on the federal funds rate target from 100 to 50 basis points. (ii) On March 16, 2008, the Fed further extended the term for borrowing to 90 days and reduced the spread on the federal funds rate target to 25 basis points (see Gilbert et al., 2012).

3.2 The IOR after October 2008

DIs prefer to minimize the amount of excess reserves they hold because neither vault cash nor reserves at the Federal Reserve normally yield interest income. However, on October 9, 2008, the Federal Reserve Banks started paying interest on required reserve balances and excess balances. Excess reserves jumped, likely in response to both this policy change and the intensification of the crisis (see Figure 1). In Figure 1, the deep green section shows the increase in bank deposits, representing required and excess reserves, in the Federal Reserve System. The large increase in reserve holdings began in 2008:Q4, reached its peak in 2009 and then remained at a new higher level through 2010:Q4.

[4]The Board of Governors has sole authority over changes in reserve requirements within limits specified by law. See http://www.federalreserve.gov/monetarypolicy/reservereq.htm.

[5]The exemption amount is adjusted each year according to a formula specified by the act. The "low-reserve tranche" is also adjusted each year.

In the first three months of non negative IOR payments, a distinction arose between balances held to fulfill reserve requirements ("required reserve balances") and balances held in excess of required reserve balances and contractual clearing balances ("excess reserve balances"). The rate paid on required reserve balances was 10 basis points below the average federal funds rate target, while the rate paid on excess balances was 75 basis points below the lowest target. The reference window was the maintenance-period federal funds rate. The spreads were subsequently reduced twice before the end of 2008.[6] These intra quarter changes do not affect our discussion as we study quarterly data.

3.3 IOR and Monetary Policy

Ceteris paribus, whether banks have an incentive to lend reserves depends on the relationship between the return on alternative investments and the floor rate. As explained in Keister et al. (2008), the use of the IOR as a floor rate for the relevant policy rate can "divorce" the quantity of reserves from the interest rate target by removing the opportunity cost of holding reserves at the the central bank. The addition of the IOR as another monetary policy tool has been advocated by Woodford (2000), Goodfriend (2002), and others and has been adopted by many central banks (Bowman et al., 2010). The Fed was granted explicit authorization to pay IOR by the Financial Services Regulatory Act of 2006. The implementation date was originally established as October 1, 2011, but was brought forward to October 2008 to provide the Fed with an additional monetary policy tool during the U.S. financial crisis.

The advantages of the IOR are not controversial and have been discussed widely in the literature. In theory, the short-term interest rate target (for example, the federal funds rate) should be larger than the IOR to allow the central bank to alter the supply of reserves without moving the effective short-term interest rate away from its target. In practice, discrepancies may occur both in normal and in crisis times. For example, during most of the U.S. financial crisis and continuing into the next few years, the IOR and the effective federal funds rate differed. Bech and Klee (2011) explain the conditions under which such a discrepancy may emerge for example, when some traders (e.g., Fannie Mae and Freddy Mac) that cannot be paid IOR by law are willing to trade

[6]The first reduction reduced the spread to zero for required balances and 35 basis points for excess balances and both were reduced to zero by the maintenance period ending on November 19, 2008. However, after the December 2008 FOMC meeting, the interest rates on required reserve balances and excess balances were both set at 25 basis points, the upper bound of the newly established target range for the federal funds rate of 0 to 25 basis points. See Bech and Klee (2011) for an excellent discussion.

federal funds below the federal funds target rate.

4 A Simple Model of Excess Reserve Accumulation

In this section we develop a simple model of reserve determination that allows us to focus on the factors impacting reserve accumulation that can also be identified empirically using available bank-level data.

Consider a bank i that faces the problem of allocating a given level of deposits D_i between an interest-bearing asset and cash or reserves at the Federal Reserve.[7]

When r_{IOR} is zero, any positive differential between the returns on the asset (r_A, for example, the yield on 3-month or 1-year Treasury bonds on the secondary market) and the zero-yield reserves induces a profit-maximizing bank to maintain reserves (R_i) at the minimum required level (δD_i, a share δ_i of deposits). When r_{IOR} is positive, banks may have an incentive to hold excess reserves depending on the relationship between the return on the interest-bearing asset and the IOR (among other factors).

Since deposits can be withdrawn at any time, the bank also faces the risk of large unanticipated withdrawals and, in some cases, of a bank run, if the funds for such withdrawals are not available. Although in classical models such as Diamond and Dybvig (1983) bank runs are due to customers' withdrawals, the same logic applies in the shadow banking market system and the interbank market. If this happens, the bank can only obtain funds by paying a penalty rate of $r_p > r_A$.

A bank facing these scenarios is effectively maximizing expected interest income subject to a resource constraint based on required reserves:

$$\max_{R_i} \; r_A(D_i - R_i) + r_{IOR}R_i - r_p E\left[Max\left(0, L_i - R_i\right)\right] \tag{1}$$

$$s.t. \; \delta D_i \leq R_i, \tag{2}$$

where δ_i is the reserve requirement and L_i is the (stochastic) deposit withdrawal rate, or reserve losses. The last term of equation 1 is a convex function of R_i and is differentiable if the random variable and L_i have a continuous density $f(x)$. Since the objective function is concave, using the first-order condition, the optimal amount of reserves is determined by the following equation:

[7] We abstract from the effect of information acquisition on deposit behavior; see Baltensperger and Milde (1976) for an analysis including this feature.

$$r_p \Pr[L_i \geq R_i] = (r_A - r_{IOR}) - \lambda, \tag{3}$$

where $\lambda \geq 0$ is the Lagrange multiplier associated with the required reserves constraint.[8] The key trade-off for a bank is therefore between the expected cost of a liquidity shortage on the left-hand side of equation 3 versus the opportunity cost of holding reserves on the right-hand side.

The larger the stock of reserves, the lower the probability that withdrawals will be larger than reserves and that the bank will have to pay the penalty rate r_p on borrowed funds. On the right-hand side of equation 3, the marginal cost of increasing reserves is determined by the forgone revenues of investing at larger-than-r_{IOR} returns on alternative assets net of the benefit of relaxing the constraint, λ. When the optimal reserve holding R_i^* exceeds the required reserves, then $\lambda = 0$ and the constraint is not binding. The constrained solution, in which $\lambda > 0$ instead, identifies situations in which the bank accumulates only the required reserves δD_i.

Intuitively, the demand for reserves increases when the ratio between the interest rate differential $r_A - r_{IOR}$ and the penalty rate r_p rises. Ogawa (2007) use a version of this model (due to Freixas and Rochet, 1997) to interpret the increase of excess reserve holdings in the Japanese experience during the Lost Decade. The situation in which banks in poorer financial health hold larger reserves for example, to prevent the possibility of a bank run is captured by a decrease of $Pr[L_i \geq R_i]$ in the model. The model can be easily transformed to a log-linearized version that facilitates reduced-form estimation using bank-level data.

We can assume that banks perceive deposit withdrawals L_i as draws from a Pareto distribution with density function

$$f(L_i) = \frac{\theta L_{0,i}^{\theta}}{L_i^{\theta+1}}; \quad L_{0,i} < L_i < \infty, \tag{4}$$

where $L_{0,i} > 0$ denotes the location parameter and $\theta < 0$ the shape parameter for the distribution. The location parameter shifts the distribution right and left, while the shape parameter governs the variance of withdrawals (the larger is θ, the higher the probability of relatively larger withdrawals).

[8] If we consider this cost, $C(R_i)$, the expected cost of a liquidity shortage, to be a convex function $C(R_i) = r_p \int_{R_i}^{+\infty}(x - R_i) f(x)\,\mathrm{d}x$, then $C'(R_i) = -r_p \Pr[L_i \geq R_i]$ and $C''(R_i) = -r_p f(R_i) \geqslant 0$.

Under this specification, the probability that withdrawals exceed reserves becomes

$$\Pr\left[L_i \geq R_i\right] = \left(\frac{R_i}{L_{0,i}}\right)^{-\theta}, \tag{5}$$

which can be inserted in Equation 3, as follows:

$$r_p \left(\frac{R_i}{L_{0,i}}\right)^{-\theta} = r_A - r_{IOR} - \lambda, \tag{6}$$

and so becomes, in logarithmic terms,

$$\log R_i = \log L_{0,i} - \frac{1}{\theta} \log\left(\frac{r_A - r_{IOR} - \lambda}{r_{p,i}}\right). \tag{7}$$

Under this specification, reserves depend negatively on the ratio between the interest rate and penalty rate scaled by a parameter, θ, that governs the variance of deposit withdrawals. A larger location parameter, $L_{0,i}$, translates into a right shift of the withdrawal distribution: For a given level of the ratio of interest to penalty rates, the i-th bank desires to keep larger reserves when $L_{0,i}$ is higher. We assume that this scale parameter depends on the strength of a bank's precautionary motive and is positively correlated with the financial weakness of a bank. Financial weakness can be approximated by a variety of measures. In this paper, we assume that financial weakness shifts the location parameter, $L_{0,i}$, as follows:

$$L_{0,i} = \alpha D_i^{\eta} FW_i; \quad \alpha, \eta, \epsilon > 0, \tag{8}$$

where FW_i is a measure of financial weakness. We assume that financial weakness is a composite measure of bad loans and bank capital. Using the specification for the precautionary motive captured in equation (7) by $L_{0,i}$, we obtain

$$\begin{aligned} \log R_i \quad = \quad & \log \alpha + \eta \log D_i - \frac{1}{\theta} \log\left(\frac{r_A - r_{IOR} - \lambda}{r_p}\right) \\ & + \psi_1 \log BL_i + \psi_2 K_i, \end{aligned} \tag{9}$$

where $B_L i$ represents a measure of bad loans for bank i and K_i represents bank i's capital. Because under $\lambda > 0$ the reserve requirements are constraining ($R_i = \delta D_i$), we have a system of equations as follows:

$$\log R_i - \log \delta D_i = \begin{cases} = 0 \\ = \log \alpha - \log \delta_i + (\eta - 1) \log D_i + \frac{1}{\theta} \log \left(\frac{r_A - r_{IOR}}{r_p} \right) \\ -\psi_1 \log BL_i + \psi_2 K_i \end{cases} \tag{10}$$

that can be estimated using censored regression methods.

5 The Determinants of Reserve Accumulation

5.1 Data and Descriptive Statistics

We create two datasets, one for commercial banks and one for thrifts. Our primary sources of financial information on banks and thrifts that we use are the quarterly Reports of Condition and Income database (commonly called the Call Reports [CRs]) and the Thrift Financial Reports [TFRs].

The CRs contain regulatory information for all banks regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), and the Comptroller of the Currency. In this dataset, banks report their individual-entity activities on a consolidated basis for the entire group of banks owned by the reporting entity at the end of each quarter. Entities typically belong to bank holding companies (BHCs).[9] We use data for the quarters between 2007:Q1 and 2010:Q2. During this period the number of entities in the CRs fell from 8,209 to 7,403 as a result of failures, mergers, and acquisitions.

The TFRs contain similar but less-detailed information. Because there is no one-to-one correspondence between CRs and TFRs for particular variables required for our analysis, we cannot merge the data; instead we carry out two parallel sets of analyses when possible.

We make several adjustments to the data to deal with complications generated by particular entities. We first regroup "new" commercial banks financial entities that were not historically regulated as banks (and hence did not file CRs) but acquired charters in 2008-09 because they either applied for a charter or were acquired by regulated commercial banks.[10] These "banks" are likely to show reserve accumulation patterns

[9] The most frequent proprietary structure is an individual BHC controlling an individual bank. In many instances, however, an individual BHC may control many banks or a combination of banks and thrifts.

[10] Namely, Goldman Sachs, Morgan Stanley, Merrill Lynch, American Express, CIT Group Inc., Hartford Financial Services, Discover Financial Services, GMAC Financial Services, IB Finance Holding Company, and Protective Life Corporation.

that are significantly different from other commercial banks due to the distinct nature of the intermediation function they perform. In addition, we omit foreign-owned banks as they are likely to manage their cash as part of an international network that may be subject to different pressures. There is also some evidence that international banks managed intra-group liquidity within their internal capital market very differently from other banks during the crisis (see Cetorelli and Goldberg, 2011).

In order to estimate the model derived in Section 4, we construct the variables using information from the CRs and the TFRs.[11] Our measure of excess reserves is computed as a difference between total cash and required reserves calculated as a percentage δ of deposits according to the reserve requirements for the period under consideration which are listed in Table 1. This is our key dependent variable and is the empirical counterpart of variable $R_i - \delta D_i$ in the model. Notice that cash and reserves can be maintained in various forms, not necessarily as deposits at the Federal Reserve Bank. Moreover, because we do not have access to actual required reserves data, based on transaction accounts, our construction of required and excess reserves suffers from measurement error. We discuss the steps we take to ensure our results are robust to this problem below.

Figure 6 is a plot of the cross-sectional distribution of our measure of the excess-to-required reserves ratio between 2008:Q2 and 2010:Q2. Each histogram represents one quarter and is left-censored at zero (as no bank holds less than the required reserves) and right-censored at 70 (as our data contain some banks ratios in excess of 70).

We determine excess reserves as the difference between a banks' required reserves and their cash holdings. We calculate required reserves based on information on reserve requirements from the Board of Governors which we collect in table 1. Since we cannot calculate required reserves precisely as the transaction and deposit account holdings they are based on change daily, we consider excess reserves as reserve holdings above either 10 or 50 percent of our calculated required reserves for each bank.[12]

Over the 2008:Q3-2010:Q2 period, we observe that in Figure 6, the distribution of the excess-to-required reserves ratio became more dispersed (less peaked and with a fatter tail) compared to 2008:Q2, indicating that more banks have accumulated larger amounts of excess reserves, in parallel with the expansion of the Federal Reserve budget. This outward movement has also been documented by Ennis and Wolman (2012), but

[11] Table 11 describes the matching between the relevant variables in the CRs and TFRs.

[12] We ran our regressions with each definition of excess reserves and found that our results were robust to either specification. We report results using the specification of excess reserves as 150 percent of required reserves in our tables.

the explanation for why the distributions became more dispersed represents an open research question that we shed some light on in our study.

We use the interest differential between 1-year Treasury bills and IOR as the alternative opportunity for institutions' reserves with a similar risk profile. In addition to a high correlation between these spreads, we found the same sign and significance and similar magnitudes for the coefficient on this variable for these measures. In addition to a high correlation between these spreads, we found the same sign and significance and similar magnitudes for the coefficient on this variable for these measures.

We use total deposits (D_i) as a scale variable and to correct for the heterogeneity in bank sizes. Deposits include (i) total transactions and non-transactions accounts, (ii) non-interest and interest bearing deposits, and (iii) money market deposit accounts.

We then construct the following three measures of financial health or the quality of the bank's loan portfolio, each progressively more inclusive of less-distressed loans. The first measure (*non-accruing loans*, labeled "bad loans 1" in the regression tables) includes the category of loans that are most likely to turn into permanent losses. Non-accruing loans are defined as the outstanding balances of loans and lease financing receivables that the bank has placed in non-accrual status, as well as all restructured loans and lease financing receivables that are in non-accrual status.[13]

The second measure of bad loans (*non-performing loans*, labeled "bad loans 2" in the regression tables) includes both non-accruing loans and loans that are due and unpaid for 90 days or more in addition to all restructured loans and leases.

The third measure of all bad loans (*bad loans*, labeled "bad loans 3" in the regression tables) adds to non-performing loans the full outstanding balances (not just delinquent payments) of loans and lease financing receivables that are past due and upon which the bank continues to accrue interest.[14]

Figure 8 provides histograms of these three types of loans (non-accruing, non-performing, and all bad loans) as a percentage of total loans. Each graph plots the frequency of the ratios for the cross-section of banks (top three graphs) and thrifts (bottom three graphs) at the beginning and end of our sample.[15] The figures show

[13]Loans and lease financing receivables are reported as non-accruing status if (i) they are maintained on a cash basis because of deterioration in the financial position of the borrower, or (ii) the principal or interest has been in default for a period of 90 days or more unless the obligation is both well secured and in the process of collection.

[14]In particular, it includes closed-end monthly installment loans, lease financing receivables, and open-end credit in arrears by two or three monthly payments; installment loans with payments scheduled less frequently than monthly when one scheduled payment is due and unpaid for 30 to 89 days; amortizing real estate loans after one installment is due and unpaid for 30 days to 89 days; single-payment and demand notes providing for payment of interest at stated intervals after one interest payment is due and unpaid for 30 days to 89 days; single-payment notes providing for payment of interest at maturity, on which interest or principal remains unpaid for 30 days to 89 days after maturity; unplanned overdrafts, whether or not the bank is accruing interest on them, if outstanding 30 to 89 days after origination.

[15]We collect institutions with ratios larger than 15 (banks) and 10 (thrifts) in a unique bin.

quite strikingly the outward movement of the cross-sectional distribution of bad loans (however measured) between the beginning and the end of the window we consider. The histograms show the number of banks and thrifts with fewer troubled loans (non-accruing, non-performing or all bad loans) declining and the number of banks and thrifts with 10 percent or more of their total loans classified as problematic increased markedly. These shifts are also consistent with the increase in bank and thrift failures during this period as a larger share of bad loans is correlated with the likelihood of an institution failure (Aubuchon and Wheelock, 2010).

We also include a measure of capital adequacy, the equity-asset ratio, adjusted in the numerator and denominator to remove intangibles (primarily good-will). Intangibles shows a strong positive trend due to mergers and acquisitions (see Lee and Stebunovs, 2012) for a discussion). We experimented with other measures of capital adequacy, including a measure of risk-weighted capital based on the ratio of Tier 1 capital to risk adjusted assets. We report the results using the equity-asset ratio as this is a measure that is not as subject to regulatory influence as the Tier 1 capital ratio.

Based on the theoretical model developed in Section 4 for understanding bank demand for excess reserves, we also include a measure of the return to alternative investments and a measure of the penalty rate for holding insufficient reserves. The measure of the return to alternative investments that we use is the difference between the return on 1-year Treasury bills and IOR. We considered a variety of other measures, including the rate on 3-month Treasury bills and the effective federal funds rate, but we felt that the 1-year rate best captured alternative investment opportunities (other than reserves) that were of similar risk but more lucrative.

We estimate a tobit model in which we consider the level of reserves and other variables in logarithmic terms.[16] We include three key variables as regressors: a measure of the return to alternative investments, a measure of the penalty rate for holding insufficient reserves, and alternative measures of bank health (based on our three measures of problematic loans). As discussed above, we also include the log of deposits and a measure of capital adequacy.

As a robustness check, we also run the same set of regressions using a censored least absolute deviations estimator (CLAD) model for data that admits a corner solution, i.e., zero excess reserves is an optimal choice (see Powell, 1984). The advantage of the CLAD estimator over the tobit is that it is robust to heteroscedasticity and is

[16]We also estimated this model using a ratio to total assets for each of relevant variable and obtained similar results. These results are available from the authors on request.

consistent and asymptotically normal for a variety of error distributions.

5.2 Results

We present the results from our tobit model first for all banks and banks differentiated by size, and then we present results from CLAD regressions. The log of excess reserves is the dependent variable. The regressions in Tables 2 and 3 all use the tobit model with a left-censored value at zero; standard errors are in brackets. We include four measures of bank health: the adjusted capital ratio (the ratio of equity to assets adjusted for intangibles), non-accruing loans, non-performing loans, and all problematic loans (bad loans).

5.2.1 All Banks

We find that the coefficient on deposits is positive and significant which is consistent with the fact that this co-variate is a scale variable: The more deposits a bank retains, the larger its reserves. The difference between the 1 year Treasury bill rate and the interest rate paid on reserves has a negative and significant effect on excess reserves, while the penalty rate has a positive and significant effect. These two effects are as predicted by our theoretical model. When the opportunity cost of holding reserves rises, ceterus paribus, banks should reduce excess reserve holdings. The fact that our regressions show that banks were sensitive to the opportunity cost of holding reserves suggests that the lack of alternative investment opportunities was not a frivolous motivation.

When banks face uncertainty about withdrawal rates, their financial health can be interpreted by depositors as making large withdrawals more or less likely and banks react affecting the size of their reserves. We find excess reserves respond strongly and positively to increases in the penalty rate, which measures the penalty banks face for maintaining inadequate reserves. The strength of this response may also be detecting the fact that during the financial crisis banks did not want to provide negative market signals regarding their liquidity by borrowing in the overnight market (see Armantier et al., 2011; Gilbert et al., 2012). Maintaining excess reserves ensures they will not need to use the overnight market.

Next we turn to the impact of measures of bank health and loan performance on reserve accumulation. Our measures of bank health are loan quality, provisions for loan losses and the capital ratio. Bank capital ratio's provide a measure of how adequately a bank is prepared for unexpected losses regardless of their ability to access external capital. There are a variety of capital ratios we could use, including the Tier 1 capital ratio, a simple equity to assets ratio, and the leverage ratio. We wanted a measure that would capture bank provisions for losses and general ability to withstand shocks, but also a measure that would be primarily determined by market rather than regulatory forces. We initially used the Tier 1 capital ratio, which is the ratio of core equity to risk weighted assets, but we felt that the Tier 1 capital ratio was more subject to regulatory influence than a simpler measure. Like Lee and Stebunovs (2012), we decided to use the equity to asset ratio adjusted for intangibles. Intangibles is primarily composed of goodwill. We adjust the equity to asset ratio to exclude intangibles since this type of capital is not as able to absorb loan losses during periods of financial crisis and additionally exhibits a positive time trend.

We find that banks with high capital ratios whether measured by their Tier 1 capital to asset ratio or the equity to assets ratio adjusted for intangibles accumulated more reserves than banks with lower ratios. This result is at odds with our theory: We assume better capitalized banks would be adequately prepared for future losses and not as reliant on cash reserves. Moreover, cash holdings form part of bank assets, thus, increases in cash should reduce capital ratios (however measured). Of course, in our analysis we are considering only current levels of capital ratios and banking reserves not changes in either. In table 2, we find that banks with larger capital ratios have larger excess reserve stocks regardless of which other measures of the quality of the bank's loan portfolio we use and the effect is relatively large[17] We conjecture that banks with high capital ratios have not yet written down their bad-loans and charge-offs and so have accumulated cash for that purpose. Banks with fewer bad-loans and a lower loan-loss provision may have already cleaned their books and hence have lower capital and a lower capital ratio. [18]

Evidence that this conjecture may be correct is provided by the coefficients on loan-loss provisions and the interaction between the capital ratio and loan loss provision. The coefficient on loan loss provisions is uniformly positive and significant across all of our models; banks with larger loan loss provisions accumulated more reserves. We also see that the interaction between the adjusted capital ratio and loan loss provisions has a negative and significant coefficient which suggests that given a particular capital ratio, banks with higher loan loss provisions will accumulate fewer reserves.

The last group of determinants of reserve accumulation we consider is a set of three

[17]The correlation between excess reserves and either the Tier 1 capital ratio or the ratio of adjusted equity to assets is negative and significant as expected since reserve holdings form part of bank assets.

[18]See Calomiris and Wilson (2004) for a discussion of this relationship during the Great Depression.

nested measures of bad loans, where the first measure includes the worst loans (total non-accruing), the second measure includes non-accruing and adds non-performing (90 plus days late) loans, and the third measure includes the first two plus loans that are between 30 and 90 days past due. We find, in general, having more poorly performing loans increases reserve accumulation, however the coefficient on our more broadly defined measure of bad loans was not significant, suggesting that reserve accumulation was only sensitive to the parts of the loan portfolio that were known or expected to be in default and not as sensitive to those loans that were not as suspect.

We also examine whether bank reserve accumulation was a response to increases in macroeconomic uncertainty. We used several measures of uncertainty, including a proxy derived from monthly industrial production and consumer price inflation, changes in the St.Louis Federal Reserve's Financial Stress Index (STLFSI) as well as movements in the VIX.[19]

We did not find evidence that the generalized increase in macroeconomic uncertainty played a role in banks' reserve accumulation patterns in addition to the variables we include in the regressions.[20] We also considered the impact on liquidity hoarding of movements in the spreads between high-yield and risk free bonds and found no effect. We interpret the lack of response to measures of uncertainty or market liquidity as pointing to the fact that banks were primarily concerned about their own balance sheets and managing their own liquidity risks and not as concerned about counterparty risk, a conclusion that Acharya and Merrouche (2013) also reach.

Turning to reserve accumulation by thrifts, we find a similar pattern as for banks, although the coefficients are in general smaller in absolute value for thrifts. We find that the coefficients are about half as large on the response of reserves to the interest differential and to the penalty rate. But the signs are the same as for banks; a larger interest rate differential strongly decreases reserve accumulation by thrifts while a larger penalty rate increases accumulation. For thrifts, we do not have measures of intangibles, therefore we use the Tier 1 capital ratio to measure capital adequacy or likely future solvency. We find that higher Tier 1 capital ratios are positively related to reserves accumulation by thrifts, although when we interact the capital ratio with the loan loss provision we find a decrease in the rate of accumulation (slope). As Tier 1 capital ratio is computed as the ratio of equity and risk-weighted assets, when banks

[19]We use the technique described in (Baum and Ozkan, 2009) of fitting a generalized ARCH model to the monthly industrial production and consumer price inflation series. We then use the quarterly average of the conditional variance derived from this GARCH model as a measure of uncertainty.

[20]These results are not reported here but are available from the authors upon request.

hold more cash risk weighted assets are lower and the ratio increases.

Interestingly, one way in which thrifts' reserve accumulation responds differently to the quality of their loan portfolio than banks' is that higher loan loss provisions result in lower reserve accumulation for thrifts. Although the coefficient on loan loss provisions is negative under our three specifications, it is only significant in the model in which we include the intermediate measure of bad loans. However, when we use a stronger definition of excess reserves (reserves that are 150 percent or more of required reserves, see paragraph under "robustness checks" below), these coefficients are significant and retain their negative sign.

5.2.2 Banks differentiated by size

We now differentiate banks by size and consider whether large banks had different reserve accumulation responses than small banks. We define large banks as the top two percent of banks measured by their asset portfolio and small banks as the remaining 98 percent. Figure 9 displays the cross-sectional distribution of excess reserve accumulation as a ratio to required reserves for small versus large banks.

We find some noteworthy differences. First, we find the reaction of bank reserves to deposits, the differential between the 1 year Treasury Bill rate and the IOR, and the penalty rate to be similar to what we observed for the set of all banks. We find that big banks accumulation of reserves is less responsive to deposits than for small banks; the coefficients are approximately 25 percent of the size though they have the same sign. Conversely reserve accumulation by big banks is much more sensitive to the differential between interest rates and the penalty rate, almost twice as responsive in both cases.

Second, we find that for the largest banks, reserve accumulation is not sensitive at all to their capital ratio (whether measured as the ratio adjusted for intangibles or as the Tier 1 capital ratio), barely sensitive to the loan loss provision and not sensitive at all to the interaction between the capital ratio and the loan loss provision. However, for small banks, the opposite is true. For small banks, reserve accumulation is very sensitive to the adjusted capital ratio, increasing as the ratio increases, as well as quite sensitive to the interaction between the capital ratio and their loan loss provision. Their reserve accumulation is also somewhat responsive to their loan loss provisions, increasing as their loan loss provision rises. When we consider the size of the coefficients on the capital ratio, loan loss provision and the interaction term, we find that the result we had for the sample of all banks was largely accounted for by the accumulation patterns of small banks.[21]

Third, we find that both large and small banks increase their reserve accumulation as their loan portfolio worsens in quality. The impact on reserve accumulation of a poor quality loan portfolio is approximately 10 times as large for large banks than for small banks.

Fourth, we find the reserve accumulation of small banks is influenced by different factors and to different degrees than it is for thrifts. In previous research, Contessi and Francis (2011) found that the lending behavior of thrifts during the financial crisis behaved quite similarly to that of small banks. However, we find that the reserve accumulation of thrifts is not nearly as responsive as that of small banks to the interest rate differential, the penalty rate and the capital ratio. Moreover, while small banks increase their reserves as their loan loss provision increases, thrifts tend to either hold their reserves constant or decrease them. In addition, differences in the regulation framework for thrifts and banks may contribute to explain the differences in behavior we observe.

5.2.3 Robustness checks

We re-ran our three models assuming excess reserves to be reserves accumulated 150 percent beyond what was required.[22] This is a more conservative measure of excess reserves. We find our results robust to this narrower definition of excess reserves as we find similar coefficients, in size, sign and significance. The only difference between the two sets of results we find is that using the narrower definition, we find that the broader definition of bad loans also has a positive significant coefficient. In either case, we find that reserve accumulation is responsive to the differential between the market interest rate and the IOR, the penalty rate, bank capital ratio, loan loss provisions, measures of bad loans and the interaction between the capital ratio and loan loss provisions. We conclude that for banks generally, reserve accumulation was largely driven by prudence in light of the risk composition of their loan portfolios as well as seemingly the lack of alternative investments. Since the coefficient on the differential between the IOR and one measure of the market interest rate (the rate on 1 year Treasury bills) is negative and large, we conjecture that the fact that banks accumulated massive amounts of reserves meant that they believed alternative investment opportunities, of similar risk, were not available.

[21] For a discussion of the aggregate implications of bank-level heterogeneity see Buch et al. (2012).

[22] These results are not reported in the tables but are available from the authors.

We also considered whether using a censored regression method was the correct approach for our data. Typically, in the presence of significant data censoring ordinary least squares estimates will tend to be biased and inconsistent. Tobit methods correct for data sensoring, however, in order for the estimates to be consistent, linearity, homoskedasticity, and normality is required. We computed an LM-statistic and found that we could not reject the null that the tobit specification is appropriate for our model at the 1 percent level.

As an additional pre-caution, we re-ran our regressions for all banks, thrifts, and small and large banks using a CLAD specification. The CLAD model is robust to heteroscedasticity and is consistent and asymptotically normal for a variety of error distributions unlike the tobit. We run the CLAD model for 1,000 replications of the bootstrap standard errors. In table 4, we consider how all banks' and thrifts reserves respond to changes in deposits, the interest rate differential, the penalty rate, two measures of the capital ratio (the adjusted capital ratio from before and the Tier 1 capital ratio), loan loss provisions, an interaction term between the capital ratio and the loan loss provision, and three different measures of bad loans. We find the responses for all banks' and thrifts reserves to these co-variates are roughly the same as we found using a tobit technique.

However, when we disaggregate the data into large and small banks, we find some changes in the results. In table 5, we find that banks with higher adjusted capital ratios have lower reserve holdings in two of the regressions those with the narrower definition of bad loans. This is the result we had expected to find initially. In the regressions with all banks, we had the opposite result and in the tobit regressions with large banks, the coefficients on the adjusted capital ratio, though positive, were not significant. For large banks, better capital adequacy was associated with lower reserve accumulation.

Using the CLAD technique, however, we did not find that large banks' loan loss provision had any impact on their reserve accumulation when we used the adjusted capital ratio as our measure of capital adequacy. The coefficient on the interaction term between the loan loss provision and the adjusted capital ratio is also significant only in the case where we use the narrowest measure of bad loans. For large banks, the quality of their loan portfolio did impact their reserve accumulation, as we also found using the tobit technique.

Turning to small banks, using the CLAD technique, we find a similar result to what we found for all banks, namely that a higher capital ratio (whether measured as the adjusted ratio or as the Tier 1 capital ratio) was associated with more reserve accumulation, a result which was significant at the 1 percent level. For small banks, larger capital ratios are not negatively related with reserve accumulation, moreover, small banks' reserve accumulation is sensitive to their loan loss provisions. This result, which we also saw earlier using the tobit technique, may reflect banks that have been slow in writing down bad loans (as we speculated above).

The last robustness check we perform is to consider bank holding companies as our unit of observation. Our results may be influenced by the fact we are using individual bank call reports rather than considering balance sheets consolidated across all banks within a bank holding company (BHC). There is evidence that liquidity problems, for example, may be weaker for banks operating under the umbrella of a multi-bank holding company. Internal capital markets within BHCs may reduce constraints faced by individual banks who had trouble accessing funds, either through raising deposits or issuing equity, during the crisis, see Campiello (2002). Reserve accumulation by banks belonging to financial conglomerates may thus be less sensitive to external market factors such as interest rate differentials and the penalty rate as well as to their own balance sheets. Therefore, as a third robustness check, we re-ran our regressions for BHCs. We find the results consistent with those obtained for banks on their own: The signs and significance of the coefficients did not change. The only notable difference between the two groups was that the coefficients on the interest rate differential and penalty rate were somewhat smaller in absolute value for the BHCs than for the banks.

5.3 Responsiveness of Reserve Accumulation

We analyze how responsive reserve accumulation is to changes in deposits, bad loan portfolios and the interest rate differential in table 6. We first look at how all banks respond to unit variations in these covariates and then arbitrarily divide banks into the top 2 percent by assets ("large" banks) and the remaining 98 percent ("small" banks). We find that reserves respond almost one for one with increases in deposits for all banks, but that reserve accumulation is not very responsive to changes in the quality of banks' loan portfolio or the interest rate differential. We find a slightly greater response to the interest rate differential than to deterioration in the loan portfolio. When we divide banks into large and small banks we find an interesting pattern. For large banks, reserves are not very responsive to changes in deposits, but they are more responsive to changes in the interest rate differential. For small banks, however, reserve accumulation responds quite strongly to changes in deposits and not very strongly to changes in the interest rate differential. This finding suggests that the strategy and reasons for reserve accumulation differs between the largest banks and the remaining set.

6 Did TARP Beneficiaries Accumulate More Excess Reserves?

In this section, we discuss whether the CPP program under the TARP umbrella induced banks that were beneficiaries of the program to over-accumulate cash and reserves. We first describe our data and empirical methodology and then the results of our analysis.

6.1 Data

To allow for this comparison, we attempt to identify systematic differences between these two groups. We first describe the notable features of CPP beneficiaries using non-CPP DIs for comparison. We group institutions using information on the TARP funds distribution from the TARP Transaction Reports that were updated weekly by the U.S. Treasury since the program's inception in October 2008.[23] Figure 11 plots the patterns of monthly disbursements and repayments derived from these data using the TARP Transaction Reports releases.[24] The figure shows the total number of beneficiaries by month (vertical bars), the total disbursement (squares), and the monthly disbursement net of repayments (circles). Over the first 15 months of its life, the CPP allowed the injection of almost \$205 billion of capital into approximately 730 financial entities (U.S.Treasury, 2009).[25] As of December 31, 2009, 71 institutions had redeemed their preferred stocks and about \$83 billion remained invested in the remaining beneficiaries. It should be noted that the observational units in the Transaction Reports are financial

[23] The allocation of CPP funds to BHCs, instead of individual banks and thrifts, has raised some criticism (Coates and Scharfstein, 2009) of this strategy in terms of whether it promotes more lending at the bank level. It also creates various issues in our dataset because, unlike the TFRs and the CRs, which provide us with financial information, the TARP Transaction Reports list the BHCs. Therefore, we organized the data as follows. First, we determined the entity identification numbers for all DIs listed to make the TARP information compatible with our CR and TFR information. By using the Competitive Analysis and Structure Source Instrument for Depository Institutions (CASSIDI) database managed by the Federal Reserve Bank of St. Louis and the Federal Financial Institutions Examination Council's institutional history database we determined the set of institutions each BHC controls, BHC by BHC. We organized our data into five categories. If the BHC controls only a single bank or thrift, we match the TARP Transactions Report information with the single bank or thrift's Federal Reserve entity identification number. When the BHC controls several different banks or a mix of banks and thrifts, all of the loans (and other financial information) at the individual bank and thrift level are totaled and the group is given the BHC's entity identification number. Additionally, we separated out the funds distributed to large lenders and other beneficiaries that are either non-financial institutions (namely, General Motors and Chrysler) or "new" commercial banks and thrifts.

[24] See the relevant files on the Financial Stability website. The Congressional Oversight Panel (2009) reported some difficulties in confirming the exact value of the Treasury disbursements using these figures.

[25] The latest available TARP Transaction Report was accessed on January 31, 2010, and contains information for the period ending January 13, 2010. See http://www.financialstability.gov/latest/reportsanddocs.html for details.

holdings (as detailed in footnote 23) and not individual banks or thrifts per se. The institutions that received funding under the program could allocate the funds to any of the institutions (e.g., banks and thrifts) they control. Therefore, in the remainder of the analysis we reaggregate individual DIs that have a charter (and an entity number in the CRs and TFRs) into a consolidated entity. In our dataset, 28 CPP "multi-unit" beneficiaries control 110 banks and thrifts.

We match the Treasury data on the CPP disbursements with the unbalanced panel created from the CRs. With few exceptions, most capital injections were granted to BHCs, not to banks. In the case of a single-bank BHC, we attribute the capital injection to the bank that maintains its CR identifier. In the case of a multi-unit BHC, it is impossible to determine the ultimate beneficiary of the CPP so we keep the BHC identifier, instead of each subsidiary bank, in our dataset. We sum the relevant CR variables for all subsidiaries that belong to the BHC group that received the CPP and use the BHC identifier. We analyze case by case and include the banks in the panel only if the substantial majority of the banking group activity (measured by deposits) is carried out by commercial banks in the group.[26] After creating appropriate banking groups for multi-unit banks, we matched the CPP information collected from the TARP Transaction Reports using either the CR identifiers or the BHC identifiers. Our TARP/CPP information includes the amount of the CPP, the date of the CPP announcement, dummy variables and dates for double payments, repayments, and the number of banks and thrifts in the multi-unit BHCs.

Tables 7 (all DIs) and 8 (banks and thrifts separately) compare relevant variables and ratios across institutions that received CPP funding (first column) and those that did not (second column), as well as the entire population of DIs (third column). Summary statistics are calculated before the regrouping of multi-unit DIs, which leaves 614 banks and 54 thrifts for a total of 668 CPP beneficiaries. The number of observations is reported in the tables. All variables for banks and thrifts are comparable except for cash.

The comparison between CPP and non-CPP DIs shows that CPP beneficiaries are larger than non-beneficiaries in terms of total loans and in terms of total assets (on average about 20 times larger, but this is skewed by the fact that the largest DIs, e.g., Citibank, JP Morgan Chase, and Bank of America, received CPP support). CPP DIs extend a slightly larger share of real estate and commercial and industrial loans

[26] The largest imbalance we found was a three-unit BHC in which a thrift held about 5% of the total group deposit. In all other cases, the share held by thrifts was substantially smaller. While there is a chance that all of the CPP injection was channeled into the thrift, we think this is an unlikely event.

and have slightly larger leverage and lower deposit-to-assets ratios. These differences characterize both the thrifts and the banks that received CPP funds.

6.2 Estimation Strategy

To evaluate the impact of the CPP, ideally we would like to compare the performance of a BHC that receives a capital injection to what its performance would have been had it not received support. Although this counterfactual is not available, performance comparisons between the beneficiaries and the non-beneficiaries can be made provided we can minimize the econometric problems that arise from such a comparison. The main econometric concern is the sample selection problem, namely, the BHCs receiving CPP funds are not a random sample from the population (as would be the case in an experimental setting). If better-performing banks were awarded funds from the CPP, CPP status becomes endogenous, and this endogeneity invalidates simple correlation estimation, e.g., ordinary least square estimation.

To control for endogeneity, we use propensity score matching (PSM) techniques. The basic idea is to construct control and treatment groups, where receiving funds through the CPP is the treatment. Our goal is to find a set of control banks that are a priori equally likely to receive a capital injection as those banks which ultimately did receive one. PSM is then combined with a difference-in-differences approach to measure the average divergence in the performance paths between the BHCs in the CPP group and those in the non-CPP group.

We match individual bank identifiers to BHC identifiers. Information available at the BHC level is assumed to carry over to individual banks within the BHC group. For example, (i) we collect information on whether BHCs are publicly traded from a publicly available dataset at the Federal Reserve Bank of New York and construct a dummy variable equal to 1 for each bank in the publicly traded BHC; (ii) we use the BHC identifier to match each bank with our proxy for management quality.[27]

The first part of our strategy to control for the endogeneity of TARP status is to use PSM. To formalize the PSM procedure, we define the cash-to-assets ratio that we would like to evaluate as Y. Let Y^1 and Y^0 denote cash-to-assets ratios for the BHCs in the CPP group and the non-CPP group, respectively. Let CPP be a binary variable indicating whether a BHC received CPP support. The aim of the analysis is to estimate the following causal effect of CPP funds on the outcome Y:

[27] The "CRSP-FRB Link" dataset is available at this url: http://www.newyorkfed.org/research/banking_research/datasets.html.

$$E\left[Y^1 - Y^0|CPP = 1\right] = E\left[Y^1|CPP = 1\right] - E\left[Y^0|CPP = 0\right], \tag{11}$$

which is the difference between the dynamic path of the cash-to-assets ratio for BHCs that received CPP (first term) and the analogous outcome for the same BHCs had they not been granted CPP (second term). The complication here is that the outcome of any one BHC is observed under either the CPP or non-CPP status, but never both, thus making the latter an unobserved counterfactual.

The PSM technique is used to approximate the unavailable counterfactual by drawing comparisons conditional on the observables, X. As stated in Dehejia and Wahba (2002), "When the relevant differences between any two units are captured in the observable (pretreatment) covariates, which occurs when outcomes are independent of assignment to treatment conditional on pretreatment covariates, matching methods can yield an unbiased estimator of the treatment impact."Hereafter, we impose an assumption for the validity of the procedure conditional on the observable characteristics that are relevant for the CPP decision the mean of the outcome for the BHCs in the CPP group, had they not been granted CPP funds, should be the same as the mean for those in the non-CPP group:

$$E\left[Y^0|X, CPP = 1\right] = E\left[Y^0|X, CPP = 0\right], \tag{12}$$

that is, the selection bias is removed, conditional on X.

However, the high dimensionality of the observable characteristics increases the difficulty of finding exact matches for each BHC in the CPP group. Conditioning on a vector of variables, therefore, requires a choice regarding which dimensions should be used to match across units or which weighting scheme to apply. Rosenbaum and Rubin (1983) and Dehejia and Wahba (2002) demonstrate that the propensity score provides a natural weighting scheme that yields unbiased estimators of the treatment impact. Thus, conditioning on the propensity score is equivalent to conditioning on all variables in the treatment model, hence reducing the dimensionality issue.

The propensity score is the probability that a BHC receives CPP funds conditional on a set of covariates, denoted as $p(X)$. We define

$$p(X) = Prob(CPP = 1|X) = E\left[CPP|X\right]. \tag{13}$$

Using this result, we compare the performance of BHCs that received CPP funds and those that did not, matched on the basis of the propensity score.

The second part of our strategy is to adopt a difference-in-differences approach. This approach enables us to determine differences in the evolution of the cash-to-assets ratio between the BHCs who received CPP funds and the matched control BHCs that had characteristics similar to those BHCs that received CPP funds in the quarter before they were awarded funds. The analysis begins in the quarter preceding the receipt of CPP funds and focuses on the change in cash-to-assets ratios over the subsequent quarters. Blundell and Costa Dias (2000) emphasize the benefits of combining matching and a difference-in-differences approach, thus controlling for observable as well as unobservable constant differences between treatment and control units. While matching accounts for differences in observable characteristics, the addition of difference-in-differences analysis allows us to account for constant unobservable determinants of BHCs performance.

We further conduct a difference-in-differences analysis. Define the average treatment effect on the treated group (ATT) as follows. Assume that t denotes the quarter that the BHCs received CPP funds (TARP quarter), $t-1$ is the pre-CPP (pre-TARP) quarter, and $t+1, t+2, \cdots, t+6$, are the first, second, $\cdots$, sixth quarters after the TARP quarter, respectively. Let $ATT1_{t+j}$, where $j = 0, 1, \cdots, 6$, be the ATT in the TARP quarter and the following quarters compared with the ATT in the previous quarter. The expression for the ATT1 is thus

$$ATT1_{t+j} \quad = \quad \frac{1}{n_j}\sum_{i=1}^{n_j}\left(Y^1_{i,t+j} - Y^0_{i,t+j}\right) - \frac{1}{n_{j-1}}\sum_{i=1}^{n_{j-1}}\left(Y^1_{i,t+j-1} - Y^0_{i,t+j-1}\right),$$

where $n_{-1}, n_0, n_1, \cdots, n_6$ is the count of the matched BHCs in the pre-TARP quarter, the TARP quarter, and the first, $\cdots$, sixth quarters after the TARP quarter. We also construct $ATT2_{t+j}, j = 0, 1, \cdots, 6$, the ATT in the TARP quarter and the following quarters compared with the ATT in the pre-TARP quarter:

$$ATT2_{t+j} \quad = \quad \frac{1}{n_j}\sum_{i=1}^{n_j}\left(Y^1_{i,t+j} - Y^0_{i,t+j}\right) - \frac{1}{n_{-1}}\sum_{i=1}^{n_{-1}}\left(Y^1_{i,t-1} - Y^0_{i,t-1}\right).$$

6.3 Timing

In order to get the timing correct for the pre-TARP and post-TARP quarters outlined above, we need to use information about the CPP from the U.S. Treasury as well as media sources. When the CPP was announced in October 2008, a number of applications were submitted to the U.S. Treasury. However, at this point, and despite various lawsuits under the Freedom of Information Act of 1966, the U.S. Treasury has not disclosed the list and the timing of applications. Thus, we must rely on informal evidence on the application timing and the pool of applicants. We have two pieces of information that can assist us with the timing. First, Treasury officials revealed that "thousands of applications" for funds were received, but only a few hundred BHCs qualified for funds through the CPP based on their CAMEL scores. Second, the United States Department of Financial Stability (2010) stated that the rate at which applications were submitted declined rapidly in early 2009. The report cites three key reasons for this decline. (i) In February 2009, Congress adopted more restrictive executive compensation requirements for all TARP recipients. (ii) Many banks felt there was a stigma associated with participation in the program. (iii) The impact of the crisis on DIs started to appear less dramatic.

Based on this information, we treat the entire population of banks (more than 7,000 institutions), with the exception of foreign banks, which were excluded from receiving funds under the program, as the pool of applicants. We also conjecture that the majority of applications were submitted in the fall of 2008. Based on this assumption, we proceed to estimate the probability of receiving CPP funds based on observable characteristics measured at the end of the third quarter of 2008.

6.4 An Empirical Model of the Capital Purchase Program

The first part of our approaches relies on a reduced-form empirical model of CPP participation. CPP beneficiaries differ from non-CPP banks along many dimensions (Contessi and Francis, 2011) and, in fact, our data reveal substantial dissimilarities in terms of capital ratios, size, and loan composition. We observe banks becoming CPP beneficiaries (a 1-0 outcome) along with a matrix of observable indicators. A natural approach to model this event is to use a probit model for the probability a bank received CPP funds based on a set of observable characteristics. We assume that local economic conditions affect the probability of applying for and being granted CPP funds, along with key bank-level characteristics. The explanatory variables are measured at the end of the third quarter of 2008, as the application process opened in the fourth quarter of 2008, and according to U.S. Treasury documents, most applications were received by the beginning of 2009.[28]

[28] An alternative route is to estimate a probit model based on observables measured at the end of the quarter in which CPP funding was granted; however, anecdotal evidence suggests that a large number of applications were submitted in

We remove foreign banks from our sample, as they were excluded from participating in the CPP. We also exclude "new" commercial banks (credit card companies and investment banks) for reasons explained in Section 5.

We report our results for the probit estimates in Table 9. We estimate the probit model using three groups of regressors: a set of standard financial indicators for banks, geographic variables meant to capture changes in demand, and other variables likely to affect selection into the program. We use the following specific variables in our specification of the probit model:

- Capital adequacy: We use three measures of capital adequacy-the ratio of total equity to total assets, and the Tier 1 capital ratio in levels and squared.
- Asset size and composition: We use the logarithm of total assets, commercial and industrial loans as a share of total assets, and cash and reserves as a share of total assets, and all "other securities" (quarterly average) as a share of total assets.
- Bad loans: We use loan-loss reserves, the provision of possible loan losses as a share of earning assets, loan losses as a share of equity, and net loan charge-offs as a share of total loans.[29]
- Composition of liabilities: We use deposits as a share of total assets and borrowed funds with maturity longer than one year as a share of total assets.
- Other variables: We include a measure of leverage (the ratio between total loans and deposits), a dummy variables for whether a BHC is publicly traded or a top 40 BHC ranked by assets, as well as a dummy variable equal to 1 if any of the managers of a BHC is also sitting on a regional Federal Reserve Board in the fall of 2008. Hypothetically, a BHC may be more likely to receive CPP funds if its political connection is stronger. Duchin and Sosyura (2010), for example, argue that political connections as measured by contributions to House members on finance committees and representation at the Federal Reserve as board members have significant positive marginal effects on the probability of a bank being granted CPP (TARP) funds. Alternatively, a BHC could have been excluded from CPP funding because a bank manager did not apply for them due to his/her strong anti-government intervention beliefs (CNNMoney.com, 2010). These types of unobservable determinants of CPP funding are likely to be time-invariant and can

the first few months of the program.

[29]The sum of net loans charge-offs and the loan-loss provision is defined as gross charge-offs.

be eliminated by the difference-in-differences approach. [30]

- Management quality: We construct a proxy of management quality using the number of corrective actions taken against bank management by their regulator in the 2006-09 period.[31]
- Earnings: We use the the ratio of pretax net income and total earning assets (the sum of total loans and total securities) and the ratio of net income to operating income to capture earnings.

For the probit estimation, we perform both forward and backward stepwise procedures and select the model specification with the highest pseudo-R-squared. We compute the predicted probability, i.e., propensity score, based on the parameter estimates in the selected model, and match the BHCs in the TARP group with those in the non-TARP group using one-to-one nearest neighbor matching on the propensity score. The average TARP effect on the TARP group is then calculated using a difference-in-differences approach described in Section 6.2.

6.5 Results

In estimating the probit model, we have no clear prior about the sign of the coefficient on the capital adequacy variables. A positive coefficient suggests that the decision to grant CPP funds was geared toward reinforcing the capital position of healthy banks. A negative coefficient, on the other hand, suggests that funds predominantly supported relatively weaker banks. As the relationship may be non-linear, we introduced a quadratic term.

We find that the coefficient on Tier 1 capital is negative and the coefficient on the quadratic term is positive, indicative of a convex relationship between receipt of CPP funds and capital adequacy. This result could be interpreted as supportive of the spirit of the CPP legislation. Banks with weaker capitalization, but still above a certain Tier 1 capital level separating healthy from non-healthy (likely to fail) institutions, were more likely to apply and be granted a capital injection.

Turning to our difference-in-differences analysis of the ratio of cash-to-assets for TARP and control groups, our matching procedure performs well as our matched pairs

[30] We include this variable because a banker who is a member of a regional Board may be more likely to know about TARP perhaps because of better information on the program.

[31] As in Duchin and Sosyura (2010), who generously provided the raw data, we have a total of 1,681 orders issued to 961 commercial banks. Enforcement actions include prohibitions from further participation in banking activities, orders to cease and desist, and orders to pay civil monetary penalties.

of BHCs are only 0.07 percentage point apart in terms of the propensity score. Moreover, the ratios of cash-to-assets for the TARP group in the pre-TARP and TARP quarters are larger than for the non-TARP groups (first two rows and columns of Table 10). However, this trend is reversed in the subsequent quarters after receiving TARP. We report the average treatment effects in two different ways as described in Section 6.2. While ATT1, which compares cash-to-assets ratio in the target quarter with that in the previous quarter, does not provide a general pattern, ATT2, which compares cash-to-assets ratio in the target quarter with that in the pre-TARP quarter, does exhibit a notable pattern.

We find that the cash-to-assets ratio for both groups increased over time. After one quarter, the cash-to-assets ratio is 12 percent lower for the TARP group compared to the control group and this difference persists in sign and magnitude (6-12 percent lower in cash-to-assets ratio for the TARP group) for at least 4 quarters. Although not reported in the table, our data suggest this reduction in cash-to-assets holdings of treated banks persists for 6 quarters beyond the date of treatment. Our interpretation of this result is that the capital injections were initially left idle on the asset side of the balance sheet (when the payment was made), but in subsequent quarters, TARP treated banks maintained lower cash-to-asset ratios on average. This interpretation is consistent with the view that the capital injection provided precautionary liquidity for the beneficiaries.

Thus, based on our matching procedure, we find evidence that banks (or BHCs) that received TARP funds had approximately 9 percent lower cash-to-assets ratios (and thus reserve ratios) for at least one year beyond their receipt of TARP funds than similar banks. Moreover, compared with the pre-TARP quarter, the gap of the cash-to-assets ratio between the TARP and non-TARP banks remained for at least 4 to 6 quarters after banks in the TARP group received funds.

7 Conclusion

This paper undertakes a systematic analysis of the massive accumulation of excess reserves using bank-level data for more than 7,000 commercial banks and almost 1,000 savings institutions during the U.S. financial crisis. We propose a simple stochastic model of reserve determination when interest is paid on reserve holdings. We derive a log-linearized version of our model that we estimate using bank-level data and censored regression methods. We find evidence of a precautionary motive for reserve accumulation as well as evidence that banks respond strongly to the differential between interest on reserves and an alternative investment option. We also find substantial heterogeneity between the reserve accumulation behavior of large and small banks, with small banks being more sensitive to the health of their loan portfolio, and large banks more concerned about the differential between the interest paid on reserves and alternative investment options as well as the penalty rate for insufficient accumulation. We cautiously interpret the responsiveness of large banks' reserve accumulation to the penalty rate to be the reaction to the problems in the interbank market that surfaced during the crisis. Lack of liquidity in the interbank lending market, which large banks access to meet short-term liquidity needs, was likely an important factor in reserve accumulation although our analysis does not allow us to draw sharp conclusions about this avenue.

To answer the question – why would profit-maximizing banks hoard liquidity – we focus on institutions' balance sheet risk, both about the loans they knew were bad and about those for which they were not yet sure, as well as their concerns about withdrawals. Like Acharya and Merrouche (2013), our evidence points strongly to precautionary motives for reserve accumulation, due to banks' concerns about their balance sheet risks and consequently their probability of being shut out of external financing opportunities. We did not find evidence that the generalized rise in macroeconomic uncertainty or steep changes in market liquidity, as measured by standard markers, played a role in banks' reserve accumulation strategy, suggesting that concerns about counter-party risk as the crisis developed were not a prime factor. Another potential explanation is that the frequency of our data may not be enough to capture high-frequency changes in counter-party risk.

We then examine whether Capital Purchase Program funding contributed to the massive reserve accumulation by combining a propensity score matching technique with a difference-in-difference approach. We find that banks who received CPP funds accumulated fewer reserves. Bank holding companies who received CPP funds had cash to asset ratios that were 1 percent lower for at least one year beyond their receipt of funds. Our interpretation of this result is that the capital injections were initially left idle on the asset side of balance sheet when the payment was made while in later quarters, banks maintained, on average, lower cash-to-asset ratios. This interpretation is consistent with the view that the capital injection provided precautionary liquidity for the beneficiaries.

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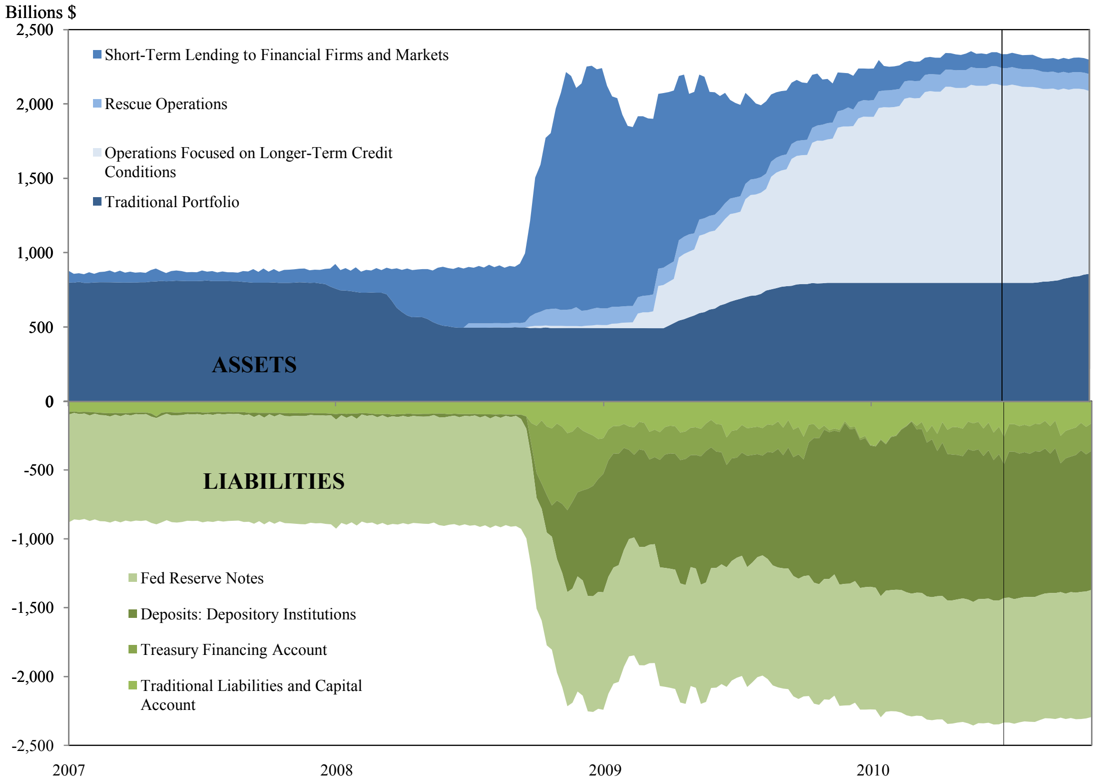
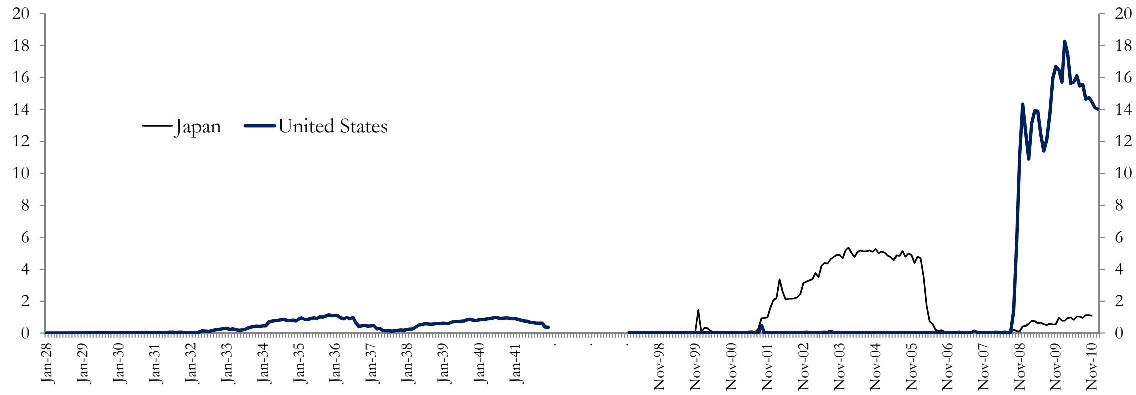
Figure 1: Federal Reserve Bank Balance Sheet, 2007-2010



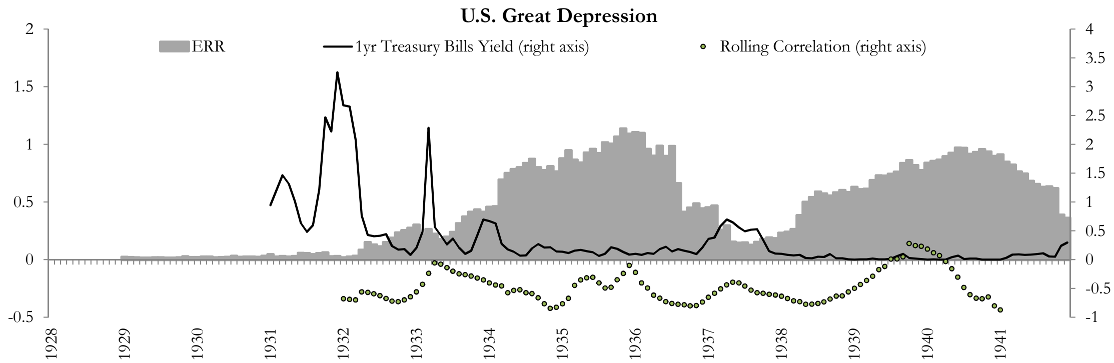
Source: Federal Reserve Board.

Figure 2: Ratio of Excess-to-Required Reserves in Japan and the U.S., 1928:M1-2010:M12



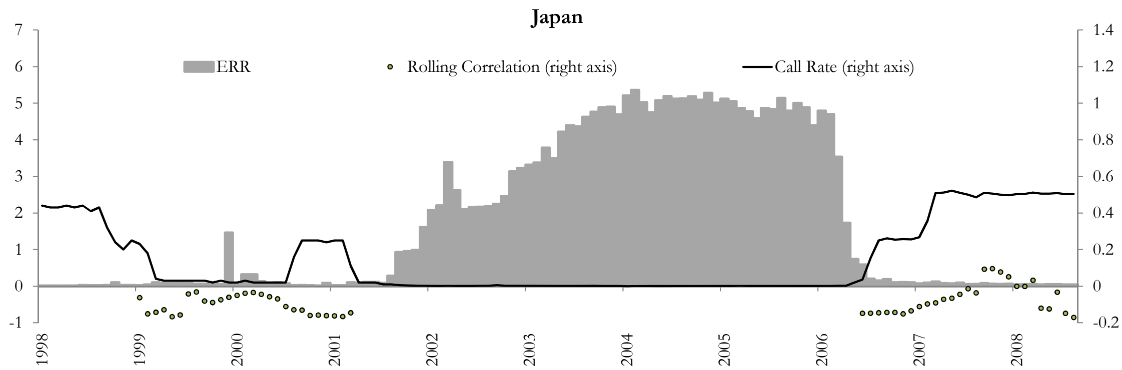
Source: Bank of Japan, Federal Reserve Board.

Figure 3: Yield on 1-year Treasury Bonds and Excess Reserves Ratio in the United States during the Great Depression



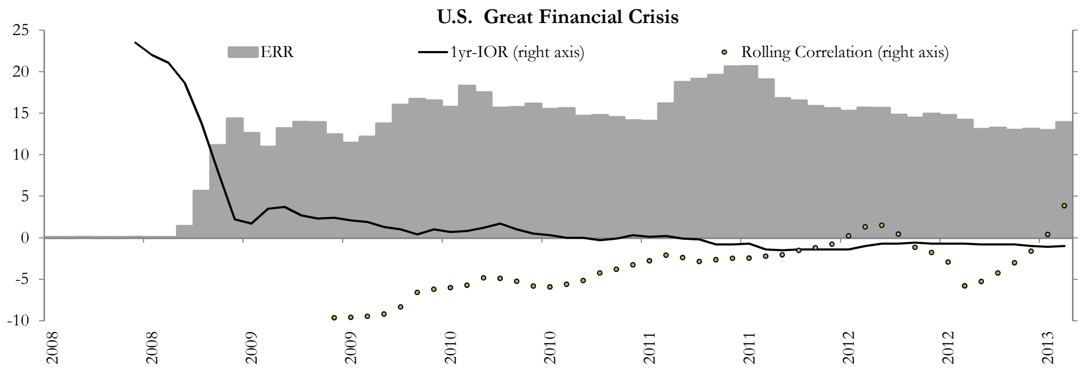
Source: Fraser and Fred II of the Federal Reserve Bank of St. Louis.

Figure 4: Call Rate and Excess Reserves Ratio in Japan during the Quantitative Easing Years



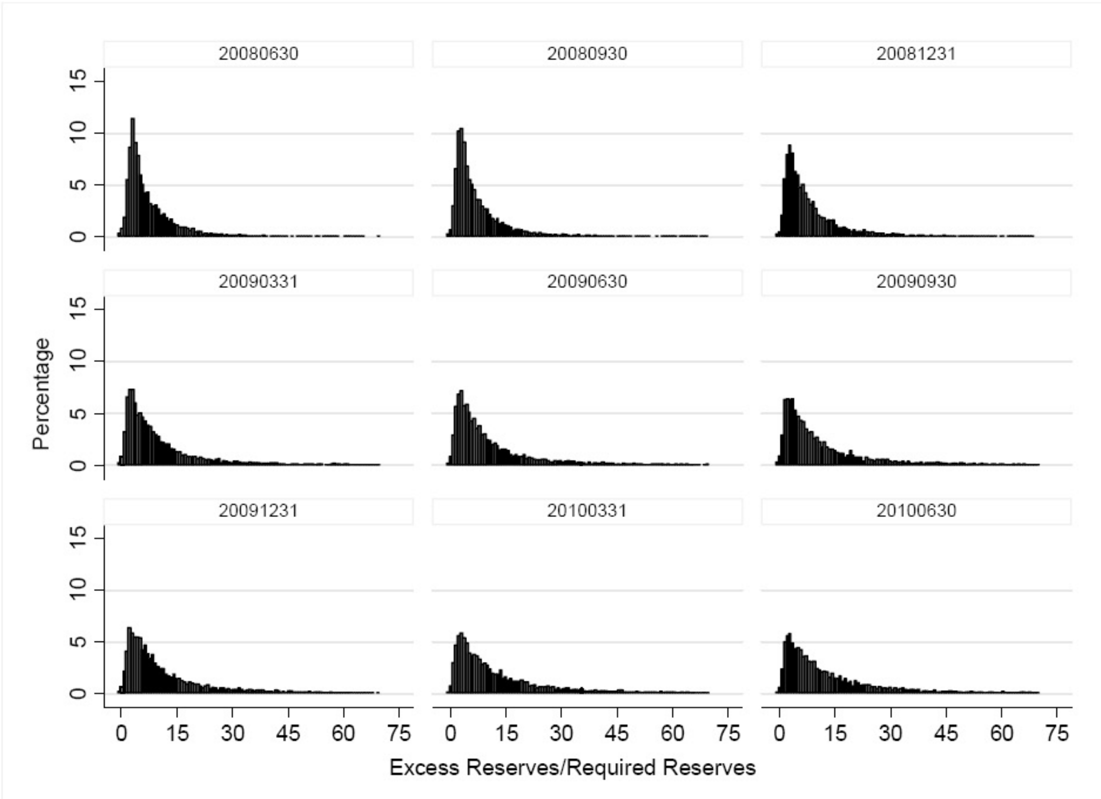
Source: Bank of Japan.

Figure 5: Differential between Yield on 1-year Treasury Bonds and IOR and Excess Reserves Ratio in the United States since the beginning of the Great Financial Crisis



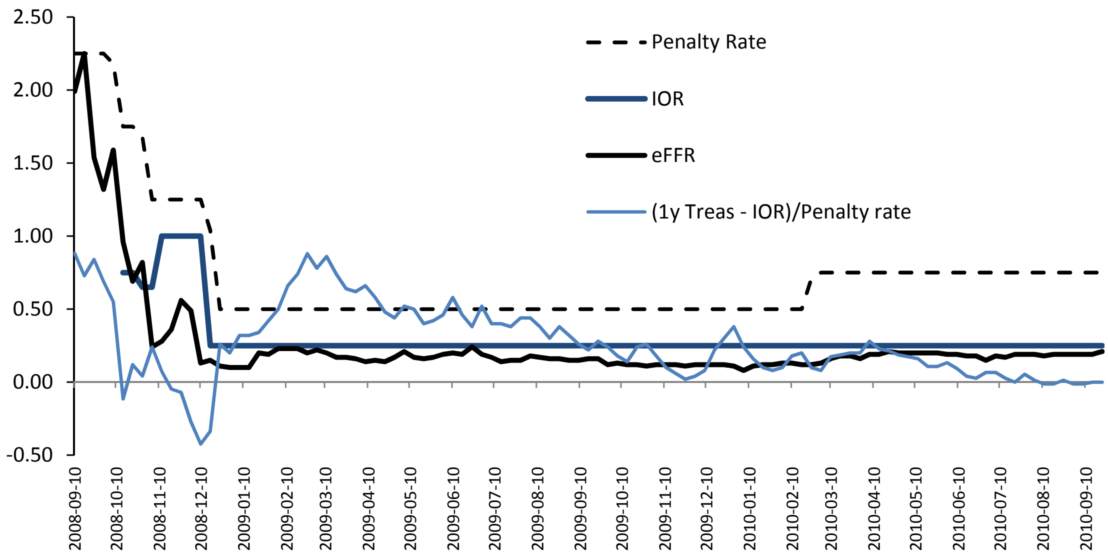
Source: Fred II of the Federal Reserve Bank of St. Louis

Figure 6: Cross-Sectional Distribution of Excess Reserves Ratio for Commercial Banks, 2008:Q2-2010:Q2



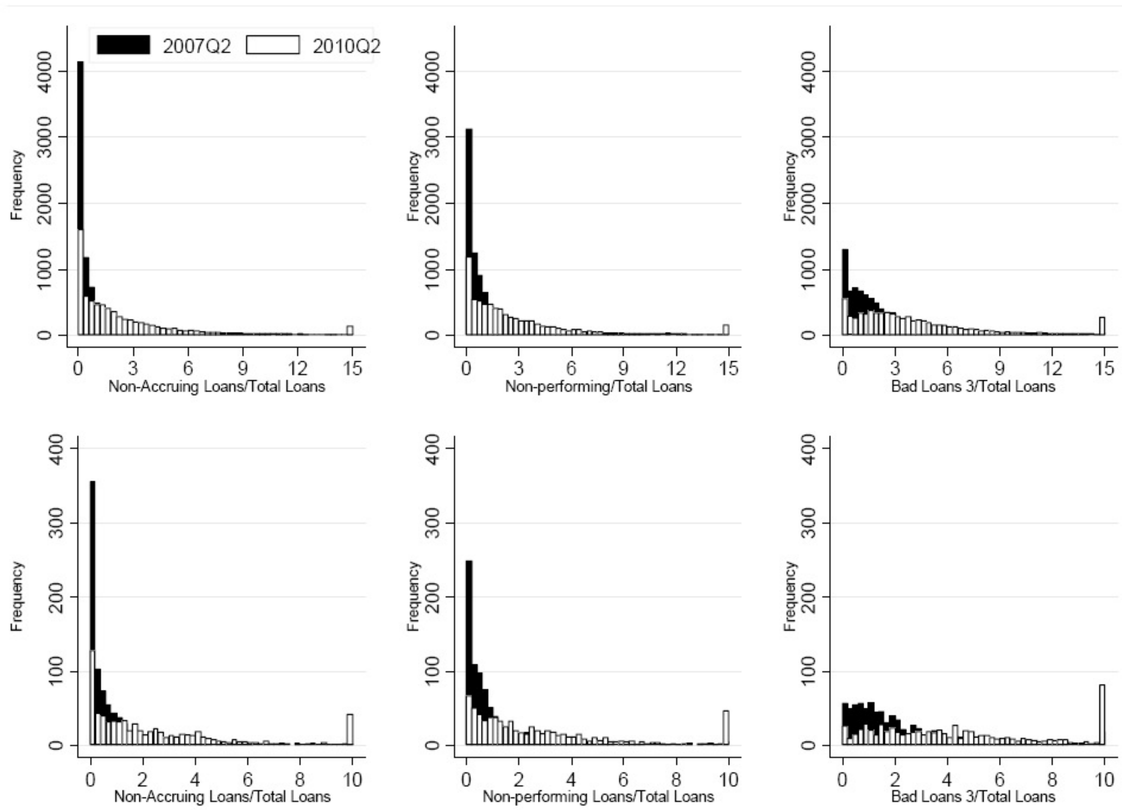
Note: We truncate our histograms at a ratio of 70. Source: Authors' calculations based on the Call Reports.

Figure 7: Federal Funds Rates, Interest on reserves, Primary Credit Rate, and adjusted Differential between 1 Year Treasury Bonds and Interest on Reserves, 2008:M7-2010:M12



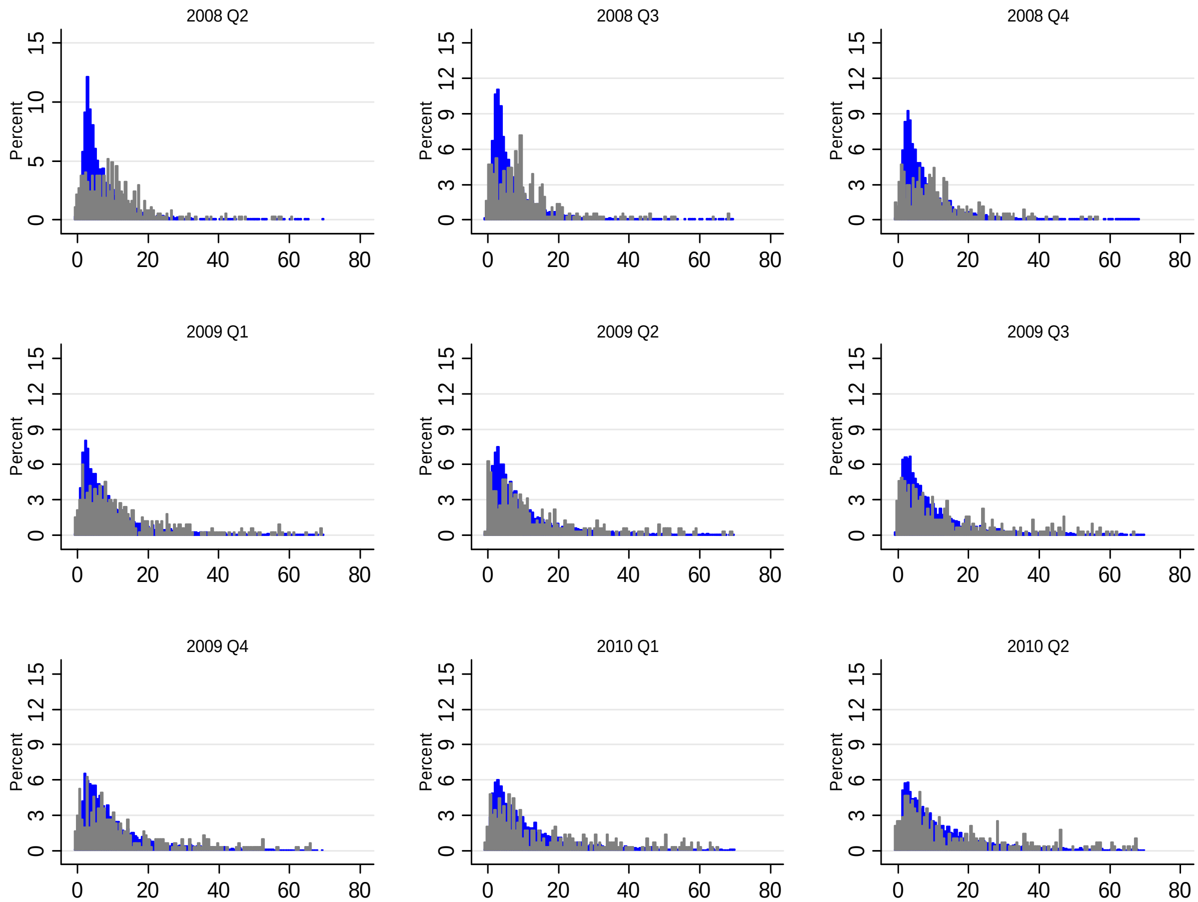
Source: Fred data repository, Federal Reserve Bank of St. Louis.

Figure 8: Cross-Section Distribution of bad, non-performing, and non accrual loans of banks and thrifts, 2007:Q2-2010:Q2



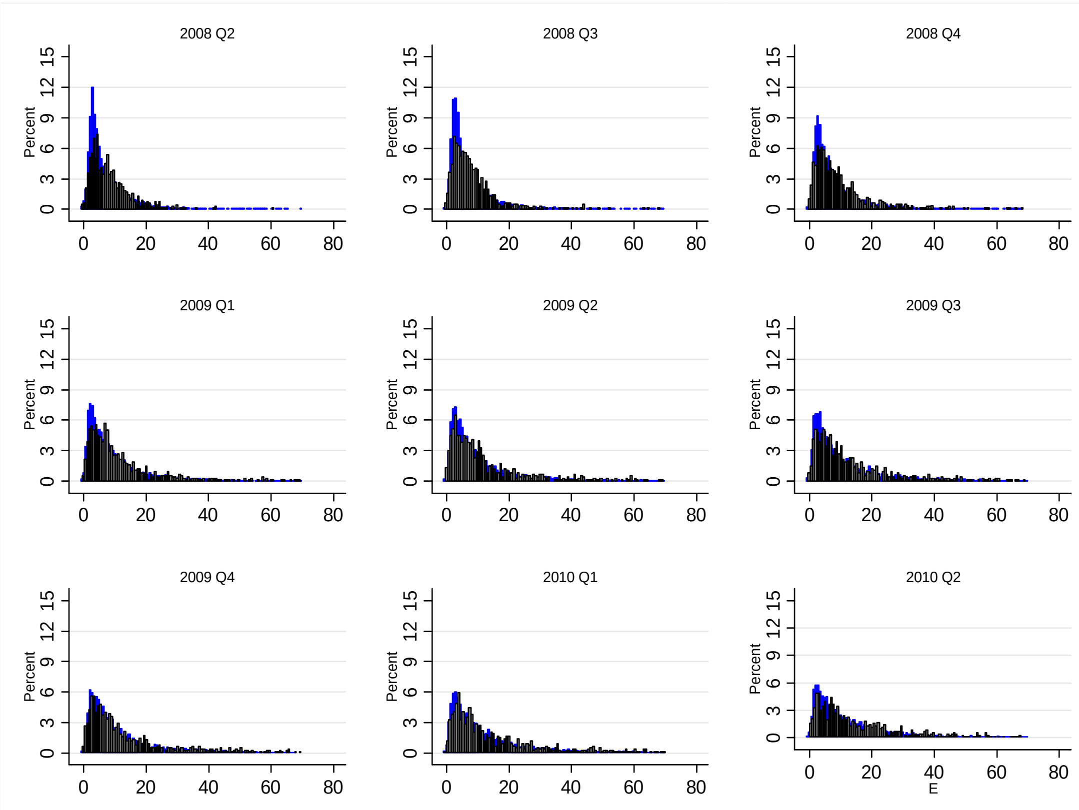
Note: These figures represent the frequency of three ratios of bad loans to assets in the population of banks (top three histograms) and thrifts (bottom three histograms). Black bars identity the first quarter used in our analysis (2007Q1) and white bars identify the last quarter (2010Q2). From left to right: (i) Non-accruing loans as a share of total assets, (ii) Non-accruing loans and non-performing loans with payments due for 90 days or more as a share of total assets, and (iii) Non-accruing loans and non-performing loans with payments due for 30 days or more as a share of total assets. We right-censored the histogram at 15 for banks and at 10 for thrifts. Source: Authors' calculations based on CRs and TFRs.

Figure 9: Cross-Section Distribution of Excess Reserves Ratio for large and small commercial Banks, 2008:Q2 through 2010:Q2



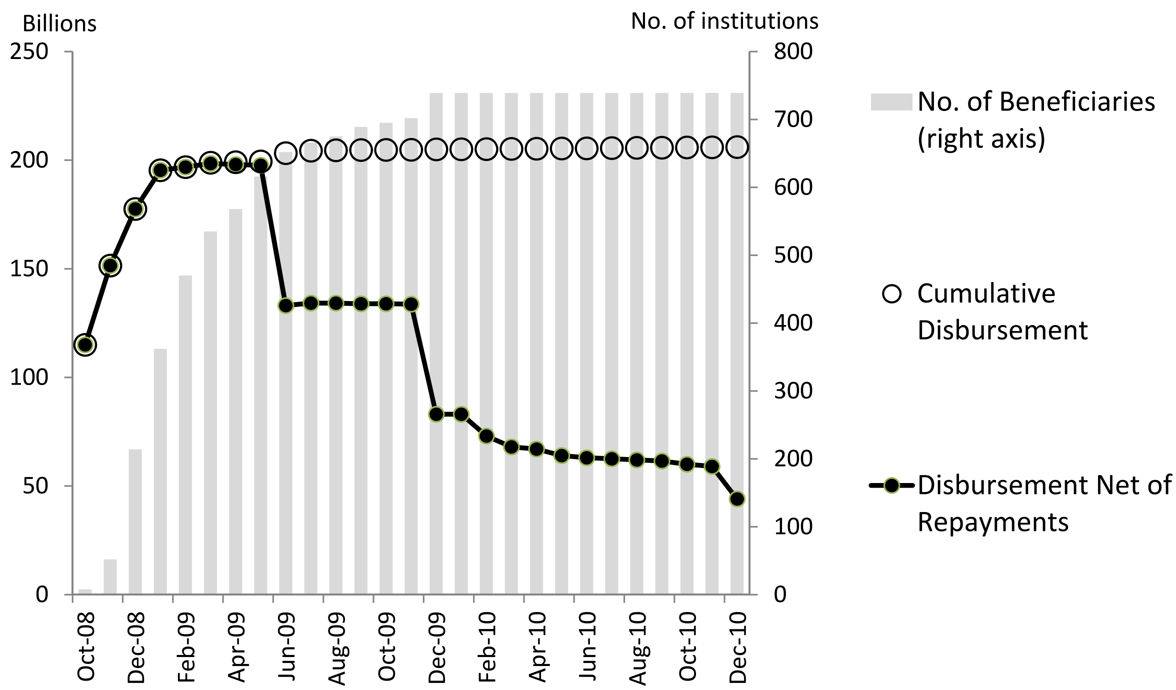
Note: These Figures represent the distribution (by percent) of the excess-to-required reserves ratio (ER-RR) for large (grey bars) and small (blue bars) commercial banks for the period analyzed in the paper. Source: Authors' calculations based on CR.

Figure 10: Cross-Section Distribution of Excess Reserves Ratio for CPP beneficiaries and non-beneficiaries for Commercial Banks, 2008:Q2 through 2010:Q2)



Note: Blue bars are non-CPP, dark grey are CPP. Source: Authors' calculations based on CR. Note: These Figures represent the distribution (by percent) of the excess-to-required reserves ratio (ER-RR) for CPP beneficiary (grey bars) and non beneficiary (blue bars) commercial banks for the period analyzed in the paper. Source: Authors' calculations based on CR.

Figure 11: CPP disbursements and repayments, 2008:M10-2010:M12



Source: Authors calculations based on U.S. Treasury Transaction Reports data. Note: This figure represents the U.S. Treasury disbursement of CPP funds in billions of U.S. dollars, the disbursement net of repayment and the number of beatifically institutions.

Table 1: U.S. Reserves Requirements

Liability Type	Percent of Liabilities	Effective Date
Net Transaction Accounts		
$0 to $9.3 million	0	12/20/2007
$0 to $10.3 million	0	1/1/2009
$0 to $10.7 million		12/31/2009
$9.3 million to $43.9 million	3	12/20/2007
$10.3 million to $44.4 million	3	1/1/2009
$10.7 million to $55.2 million	3	12/31/2009
More than $43.9 million	10	12/20/2007
More than $44.4 million		1/1/2009
More than $55.2 million		12/31/2009
Non-personal time deposits	0	12/27/1990
Eurocurrency liabilities	0	12/27/1990

Source: Board of Governors of the Federal Reserve.

Table 2: Tobit Regressions of (log) Excess Reserves, All Banks and Thrifts

All Banks	(1)	(2)	(3)
log_Dep	0.862***	0.848***	0.849***
	(0.006)	(0.006)	(0.006)
r1yr_IOR	-117.3***	-115.7***	-116.8***
	(3.692)	(3.655)	(3.617)
penalty	61.97***	60.26***	60.72***
	(2.690)	(2.665)	(2.640)
adj cap ratio	6.713***	5.121***	5.386***
	(0.421)	(0.371)	(0.355)
log loan loss prov.	0.093***	0.057***	0.063***
	(0.007)	(0.007)	(0.007)
adj-cap ratio*loanloss	-1.057***	-0.631***	-0.675***
	(0.067)	(0.058)	(0.057)
log bad-loans 1	0.014***		
	(0.003)		
log bad-loans 2		0.012***	
		(0.004)	
log bad-loans 3			0.044
			(0.004)
Constant	-2.317***	-2.005***	0.957***
	(0.077)	(0.073)	(0.071)
Sigma	0.949***	0.957***	0.960***
	(0.002)	(0.002)	(0.002)
Observations	44,075	45,932	47,283

All Thrifts			
log_Dep	0.808***	0.814***	0.838***
	(0.019)	(0.020)	(0.021)
r1yr_IOR	-78.66***	-88.76***	-90.67***
	(13.42)	(13.78)	(13.59)
penalty	38.13***	44.88***	45.73***
	(9.862)	(10.08)	(9.954)
Tier 1 KR	3.125***	2.081***	1.986***
	(0.352)	(0.315)	(0.296)
log loan loss prov.	-0.018	-0.045***	-0.023
	(0.017)	(0.017)	(0.016)
Tier 1 ratio*loanloss	-0.280***	-0.129**	-0.119**
	(0.063)	(0.059)	(0.056)
log bad-loans 1	0.0785***		
	(0.0137)		
log bad-loans 2		0.0643***	
		(0.015)	
log bad-loans 3			0.010
			(0.0175)
Constant	-1.495***	-1.305***	-1.278***
	(0.195)	(0.198)	(0.195)
Sigma	1.133***	1.167***	1.165***
	(0.008)	(0.012)	(0.012)
Observations	4,507	4,807	4,922

Notes: Standard errors are reported in parentheses. The data is left censored at zero. *** p<0.01, ** p<0.05, * p<0.1. We define excess reserves as funds over 110 percent of what banks and thrifts are required to hold as reserves. $r1yr-IOR$ is the difference between the one year return on US treasury bills and the interest paid on reserves. Bad-loans 1, 2, and 3 are nested, with bad-loans 1 being the narrowest definition and bad-loans 3 the broadest. adj-cap ratio*loanloss is the interaction effect between the adjusted capital ratio and the loan loss provision; for thrifts we use Tier 1 capital*loan loss to measure a similar interaction effect. The remaining variables are defined in the text.

Table 3: Tobit Regressions of Excess Reserves (log), Banks by Size

Large Banks	(1)	(2)	(3)
log_Dep	0.275***	0.285***	0.270***
	(0.044)	(0.040)	(0.040)
r1yr_IOR	-196.9***	-178.0***	-182.7***
	(59.16)	(59.19)	(58.99)
penalty	122.7***	115.2**	115.0***
	(42.86)	(42.88)	(42.85)
adj cap ratio	4.377	2.106	2.260
	(12.05)	(11.93)	(11.91)
log loan loss prov.	0.213*	0.110	0.007
	(0.118)	(0.118)	(0.118)
adj-cap ratio*loanloss	-0.236	-0.082	-0.053
	(1.050)	(1.028)	(1.026)
log bad-loans 1	0.118*		
	(0.066)		
log bad-loans 2		0.314***	
		(0.0795)	
log bad-loans 3			0.510***
			(0.0850)
Constant	3.827***	2.417*	1.138
	(1.225)	(1.241)	(1.274)
Sigma	2.212***	2.252***	2.260***
	(0.050)	(0.050)	(0.050)
Observations	1,013	1,046	1,047

Small Banks			
log_Dep	0.862***	0.848***	0.849***
	(0.006)	(0.006)	(0.006)
r1yr_IOR	-117.7***	-115.7***	-116.8***
	(3.692)	(3.655)	(3.617)
penalty	61.97***	60.26***	60.72***
	(2.690)	(2.665)	(2.640)
adj cap ratio	6.713***	5.121***	5.386***
	(0.421)	(0.371)	(0.355)
log loan loss prov.	0.093***	0.057***	0.063***
	(0.007)	(0.007)	(0.007)
adj-cap ratio*loanloss	-1.057***	-0.631***	-0.675***
	(0.067)	(0.058)	(0.057)
log bad-loans 1	0.014***		
	(0.003)		
log bad-loans 2		0.0121***	
		(0.004)	
log bad-loans 3			0.004
			(0.004)
Constant	-2.317***	-2.005***	-1.987***
	(0.077)	(0.073)	(0.071)
Sigma	0.949***	0.957***	0.960***
	(0.002)	(0.002)	(0.002)
Observations	44,075	45,923	47,283

Notes: Standard errors are reported in parentheses. The data is left censored at zero. We define excess reserves as funds over 110 percent of what banks are required to hold as reserves. $r1yr - IOR$ is the difference between the one year return on US treasury bills and the interest paid on reserves. Bad-loans 1, 2, and 3 are nested, with bad-loans 1 being the narrowest definition and bad-loans 3 the broadest. adj-cap ratio*loanloss is the interaction effect between the adjusted capital ratio and the loan loss provision. The remaining variables are defined in the text.*** p<0.01, ** p<0.05, * p<0.1 .

Table 4: CLAD Regressions for Excess Reserves (log), All Banks and Thrifts

All Banks	(1)	(2)	(3)	(4)	(5)	(6)
log_Dep	0.862***	0.847***	0.862***	0.855***	0.842***	0.850***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
r1yr_IOR	-145.8***	-141.7***	-144.1***	-137.9***	-152.8***	-145.3***
	(4.875)	(4.223)	(4.870)	(4.684)	(4.472)	(4.159)
penalty	80.68***	78.31***	78.02***	75.22***	84.85***	79.07***
	(3.573)	(3.095)	(3.572)	(3.430)	(3.278)	(3.049)
adj cap ratio	8.497***	8.235***	8.507***			
	(0.540)	(0.429)	(0.467)			
log loan loss prov.	0.125***	0.128***	0.126***	0.086***	0.059***	0.090***
	(0.010)	(0.008)	(0.009)	(0.008)	(0.005)	(0.006)
adj-cap ratio*loanloss	-1.346***	-1.325***	-1.257***			
	(0.086)	(0.067)	(0.075)			
Tier 1 KR				4.674***	3.477***	5.044***
				(0.271)	(0.112)	(0.152)
Tier 1 KR *loanloss				-0.559***	-0.350***	-0.599***
				(0.047)	(0.024)	(0.028)
log bad-loans 1	0.0241***			0.0223***		
	(0.005)			(0.004)		
log bad-loans 2		0.0209***		0.0325***		
		(0.004)			(0.004)	
log bad-loans 3			0.0125**			0.0218***
			(0.006)			(0.005)
Constant	-2.642***	-2.420***	-2.601***	-2.438***	-2.218***	-2.427***
	(0.092)	(0.076)	(0.087)	(0.079)	(0.067)	(0.064)
Observations	45,963	47,902	49,310	45,866	47,513	49,415
All Thrifts						
log_Dep	0.781***	0.739***	0.807***			
	(0.020)	(0.022)	(0.018)			
r1yr_IOR	-104.2***	-85.94***	-117.9***			
	(13.57)	(14.65)	(11.30)			
penalty	53.29***	38.80***	67.23***			
	(9.935)	(10.680)	(8.269)			
Tier 1 KR	2.893***	2.039***	2.479***			
	(0.362)	(0.319)	(0.254)			
loan-loss prov.	-0.017	-0.005***	0.009***			
	(0.017)	(0.018)	(0.014)			
Tier 1 KR *loanloss	-0.218***	-0.094	0.172***			
	(0.065)	(0.062)	(0.049)			
log bad-loans 1	0.073***					
	(0.014)					
log bad-loans 2		0.067***				
		(0.016)				
log bad-loans 3			0.013			
			(0.015)			
Constant	-1.083***	-0.540**	-1.147***			
	(0.204)	(0.214)	(0.164)			
Observations	4,483	4,814	4,940			

Notes: We define excess reserves as funds over 110 percent of what banks are required to hold as reserves. $r1yr - IOR$ is the difference between the one year return on US treasury bills and the interest paid on reserves. Bad-loans 1, 2, and 3 are nested, with bad-loans 1 being the narrowest definition and bad-loans 3 the broadest. adj-cap ratio*loanloss is the interaction effect between the adjusted capital ratio and the loan loss provision. The remaining variables are defined in the text. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 .

Table 5: CLAD Regressions for Excess Reserves (log), Banks by size

Large Banks (top 2 %)	(1)	(2)	(3)	(4)	(5)	(6)
log_Dep	0.356***	0.364***	0.279***	0.475***	0.369***	0.352***
	(0.022)	(0.022)	(0.026)	(0.019)	(0.023)	(0.021)
r1yr_IOR	-184.0***	-138.4***	-136.8***	-144.0***	-35.37	-66.41***
	(28.50)	(29.11)	(37.79)	(24.69)	(33.03)	(29.62)
penalty	118.1***	80.87***	90.57***	83.60***	6.50	28.35
	(20.61)	(21.01)	(27.73)	(17.80)	(23.79)	(21.45)
adj cap ratio	-21.59***	-10.55*	-8.600			
	(7.390)	(5.815)	(7.305)			
log loan loss prov.	0.063	0.021	0.086	0.336***	0.270***	0.023
	(0.065)	(0.060)	(0.073)	(0.051)	(0.074)	(0.074)
adj-cap ratio*loanloss	1.822***	0.665	0.563			
	(0.635)	(0.501)	(0.623)			
Tier 1 KR				17.54***	13.06**	-2.020
				(3.833)	(5.826)	(5.810)
Tier 1 KR *loanloss				-0.791***	-0.546	-0.603
				(0.350)	(0.527)	(0.522)
log bad-loans 1	0.234***			0.099***		
	(0.033)			(0.026)		
log bad-loans 2		0.331***			0.240***	
		(0.041)			(0.043)	
log bad-loans 3			0.369***			0.407***
			(0.055)			(0.044)
Constant	3.280***	2.64***	2.542***	-0.942*	0.220	1.127
	(0.687)	(0.615)	(0.822)	(0.540)	(0.796)	(0.785)
Observations	1,022	1,054	1,033	1,005	1,046	1,051
Small banks (bottom 98%						
log_Dep	0.831***	0.825***	0.856***	0.837***	0.842***	0.826***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
r1yr_IOR	-142.2***	-143.4***	-156.3***	-143.4***	-148.4***	-141.3***
	(4.729)	(3.956)	(4.514)	(4.148)	(4.254)	(4.720)
penalty	78.59***	79.19***	86.11***	79.59***	81.45***	76.48***
	(3.464)	(2.897)	(3.307)	(3.038)	(3.116)	(3.457)
adj cap ratio	7.726***	6.745***	8.422***			
	(0.563)	(0.393)	(0.465)			
log loan loss prov.	0.117***	0.086***	0.129***	0.087***	0.071***	0.068***
	(0.010)	(0.007)	(0.009)	(0.007)	(0.006)	(0.006)
adj-cap ratio*loanloss	-1.311***	-1.011***	-1.408***			
	(0.091)	(0.062)	(0.075)			
Tier 1 KR				4.951***	4.221***	3.896***
				(0.229)	(0.164)	(0.160)
Tier 1 KR *loanloss				-0.638***	-0.515***	-0.489***
				(0.041)	(0.031)	(0.031)
log bad-loans 1	0.021***			0.028***		
	(0.005)			(0.004)		
log bad-loans 2		0.020***			0.018	
		(0.004)			(0.004)	
log bad-loans 3			-0.008			0.0187***
			(0.005)			(0.006)
Constant	-2.216***	-1.972***	-2.315***	-2.275***	-2.152***	-1.914***
	(0.101)	(0.079)	(0.092)	(0.078)	(0.075)	(0.081)
Observations	5,220	5,704	5,796	5,252	5,802	5,989

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 .

Table 6: Responsiveness of Excess Reserves, All Banks and Banks by Size

All Banks	(1)	(2)	(3)
log Dep	0.821***	0.806***	0.800***
r1yr_IOR	-0.341***	-0.338**	-0.346***
log bad-loans 1	0.032***		
log bad-loans 2		.032***	
log bad-loans 3			.036***

Large Banks	(1)	(2)	(3)
log Dep	0.276***	0.285***	0.270***
r1yr_IOR	-0.610***	-0.549***	-.565***
log bad-loans 1	0.122**		
log bad-loans 2		.315***	
log bad-loans 3			.510***

Small Banks	(1)	(2)	(3)
log Dep	0.858***	0.849***	0.850***
r1yr_IOR	-0.342***	-0.339***	-.345***
log bad-loans 1	0.018***		
log bad-loans 2		.013***	
log bad-loans 3			.005

Note: when the covariates are in logs, since the dependent var is a log, the log covariate elasticities are evaluated as dLog(y)/dLog(x). When the covariates are rates or ratios, the elasticities are evaluated as (dLog(y)/dx)*x.

Table 7: Descriptive statistics for selected variables (2009:Q3)

All Depository Institutions

Observations		CPP N= 924 Mean	CPP Median	CPP Max.	Non-CPP N= 7,186 Mean	Non-CPP Median	Non-CPP Max.	All DI N= 8,110 Mean	All DI Median	All DI Max.
Total loans	***	($) 9.64 b	305 m	740 b	481,840	88 m	361 b	1.53 b	101 m	740 b
Total assets	***	($) 19.50 b	434 m	1670 b	891,658	134 m	548 b	3.01 b	151 m	1670 b
Real estate loans	***	($) 5.56 b	231 m	448 b	313,717	64 m	201 b	0.91 b	74 m	448 b
C&I loans	***	($) 1.93 b	40 m	154 b	72,693	9 m	70.8 b	0.28 b	10 m	154 b
Individual loans	***	($) 1.25 b	6 m	114 b	67,806	3 m	92.8 b	0.20 b	3 m	114 b
Real estate/Total loans	***	0.78	0.81	1	0.77	0.80	1	0.77	0.80	1
C&I/Total loans	***	0.17	0.15	1	0.15	0.12	1	0.15	0.13	1
Individual/Total loans	***	0.05	0.02	1	0.08	0.05	1	0.08	0.05	1
Loans/Assets	***	0.69	0.71	1	0.60	0.63	1	0.61	0.64	1
Deposits/Assets	***	0.79	0.81	0.98	0.82	0.84	0.98	0.82	0.83	0.98
Leverage	***	10.4	10.4	64.1	10.1	9.9	99.1	10.2	10.0	99.1
Cash/Assets	***	0.06	0.03	0.67	0.07	0.04	0.81	0.07	0.04	0.81

Notes: Includes all banks and thrifts in our sample (subject to the exclusion of investment banks and "new banks" discussed in the data section above). C&I refers to commercial and industrial loans; individual loans are loans to consumers typically with no collateral provided e.g., credit card lines. b=billions; m=millions. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level in a t-test for difference in the mean of each variable between CCP and non-CPP DIs.

Table 8: Descriptive Statistics for Selected Variables (2009:Q3)

Banks

Observations		CPP N= 860 Mean	CPP N= 860 Median	CPP N= 860 Max.	Non-CPP N= 6,493 Mean	Non-CPP N= 6,493 Median	Non-CPP N= 6,493 Max.	All Banks N= 7,353 Mean	All Banks N= 7,353 Median	All Banks N= 7,353 Max.
Total loans	***	($) 10.2 b	301 m	740 b	448 m	86 m	361 b	1.6 b	98 m	740 b
Total assets	***	($) 20.8 b	425 m	1670 b	850 m	130 m	548 b	3.2 b	148 m	1670 b
Real estate loans	***	($) 5.9 b	227 m	448 b	278 m	61 m	201 b	0.9 b	70 m	448 b
C&I loans	***	($) 2.0 b	40 m	154 b	75 m	9 m	70.8 b	0.3 b	11 m	154 b
Individual loans	***	($) 1.3 b	6 m	114 b	65 m	3 m	92.8 b	0.2 b	4 m	114 b
Real estate/Total loans	***	0.78	0.81	1	0.76	0.79	1	0.76	0.79	1
C&I/Total loans	***	0.18	0.15	0.96	0.16	0.13	1	0.16	0.14	1
Individual/Total loans	***	0.05	0.02	1	0.08	0.05	1	0.08	0.05	1
Loans/Assets	***	0.68	0.71	0.95	0.59	0.62	1	0.60	0.63	1
Deposits/Assets	***	0.80	0.81	0.98	0.82	0.84	0.98	0.82	0.84	0.98
Leverage	***	10.4	10.3	64.1	10.2	9.9	99.1	10.2	10.0	99.1
Cash/Assets	***	0.06	0.04	0.67	0.07	0.05	0.81	0.07	0.05	0.81

Thrifts

Observations		CPP N= 64 Mean	CPP N= 64 Median	CPP N= 64 Max.	Non-CPP N= 693 Mean	Non-CPP N= 693 Median	Non-CPP N= 693 Max.	All Thrifts N= 757 Mean	All Thrifts N= 757 Median	All Thrifts N= 757 Max.
Total loans		($) 1667 m	463 m	19.8 b	794 m	125 m	50.1 b	867 m	135 m	50.1 b
Total assets		($) 2410 m	531 m	31.6 b	1280 m	177 m	89.7 b	1375 m	186 m	89.7 b
Real estate loans		($) 936 m	374 m	9.1 b	651 m	110 m	36.5 b	674 m	115 m	36.5 b
C&I loans		($) 503 m	25 m	12.8 b	49 m	2 m	11.5 b	87 m	3 m	11.5 b
Individual loans		($) 228 m	8 m	6.0 b	94 m	2 m	16.7 b	105 m	2 m	16.7 b
Real estate/Total loans	***	0.83	0.89	1	0.89	0.94	1	0.89	0.94	1
C&I/Total loans	***	0.11	0.08	0.70	0.06	0.02	1	0.06	0.03	1
Individual/Total loans	***	0.06	0.03	0.34	0.05	0.02	1	0.05	0.02	1
Loans/Assets	*	0.73	0.74	0.93	0.69	0.74	1	0.69	0.74	1
Deposits/Assets		0.74	0.75	0.91	0.76	0.78	0.98	0.76	0.78	0.98
Leverage	*	10.5	10.7	23.0	9.9	9.5	97.9	9.9	9.7	97.9
Cash/Assets		0.02	0.01	0.08	0.02	0.01	0.34	0.02	0.01	0.34

Notes: Includes all banks and thrifts in our sample (subject to the exclusion of investment banks and "new banks" discussed in the data section above). C&I refers to commercial and industrial loans; individual loans are loans to consumers typically with no collateral provided e.g., credit card lines. b=billions; m=millions. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level in a t-test for difference in the mean of each variable between CCP and non-CPP DIs.

Table 9: Probit Estimates for TARP Beneficiaries and Non-TARP Banks

Specification	Estimates	Standard errors
Total equity/TA	4.2972	1.5750
Total noncurrent loans/TL	-9.2568	1.7117
Loan-loss provision/TA	-42.184	21.4046
Commercial Loans/TA	2.3500	0.3865
Loan Loss Reserves/TL	33.2920	8.800
Pre-tax net income/TA	-14.8823	2.7643
Brokered deposits/TA	0.5483	0.2760
Other borrowed funds maturing 1Yr/TA	1.0752	0.6340
Pledged securities/TA	0.2387	0.0884
Pre-tax net Income/TA	-9.0192	2.7835
Log of TA	0.0928	0.0268
Tier 1 Capital ratio	-12.144	1.3878
Tier 1 Capital ratio squared	2.4288	0.3814
Loans/Deposits	0.6880	0.1578
Loan-losses/Equity	-3.8049	1.1162
Net loan charge-offs/TL	-48.2618	22.3336
Gross charge-offs/TL	33.3657	17.6223
Net income/Operating income	-0.0929	0.0377
Net interest income/Earning assets	-12.5649	4.9608
All other securities (Q average)/TA	-1.4425	0.6729
Cash and reserves/TA	-0.0681	0.8837
Publicly traded	0.8230	0.0872
Management penalties	0.0248	0.0102
Business bankruptcy filings	-0.0004	0.0002
Business bankruptcy filings (y-y)	0.0027	0.0009
Conventional mortgage home price index (y-y)	-0.0464	0.0165
Unemployment insurance claims	0.000004	1.45e-06
Unemployment insurance claims (y-y)	0.0027	0.001
Top 40	1.379	0.5504
Fed Board	0.5051	0.2036
ints55y5	0.0688	0.0267
Constant	-2.0308	0.4437
Psedo-R^2	0.2816	
Log-Likelihood	-1414.077	

Notes: This is the final probit result from running a forward and backward stepwise procedure to determine the vector of significant covariates we use in calculating the propensity score. We estimate this probit at the level of BHC. ints55y5 is the interaction of real estate loan shares with real estate prices, top 40 indicates the bank holding company is among the largest 40 BHCs by assets. Fed Board is a dummy variable for whether any of the managers of the BHC have a current position on a regional Federal Reserve Board in the fall of 2008.

Table 10: Difference-in-Differences Analysis: Cash-to-Assets

	Pre-TARP	TARP	TARP+1	TARP+2	TARP+3	TARP+4
TARP group	0.0387	0.0475	0.0492	0.0538	0.0574	0.0634
Non-TARP group	0.0318	0.0425	0.0556	0.0583	0.0649	0.0678
ATT1		-0.0019	-0.0102^*	0.0013	-0.0019	0.0031
		(0.0038)	(0.0031)	(0.0034)	(0.0031)	(0.0034)
ATT2		-0.0019	-0.0121^*	-0.0109^*	-0.0127^*	-0.0097^*
		(0.0038)	(0.0042)	(0.0044)	(0.0048)	(0.0054)
Number of matched pairs	539	523	519	513	517	497

ATT1 is the difference between the ratio of cash-to-assets in the target quarter and that in the previous quarter; ATT2 is the difference between the ratio of cash-to-assets in a quarter and that in the last TARP quarter before the bank was granted TARP funds. $*$ indicates statistical significance at the 5% level.

Table 11: Variables List and Correspondence from the CRs and TFRs

Call Reports	**Thrift Financial Reports**
rcfd2170 Total assets	svgl2170 Total assets (SC60)
riad4635 Charge-Offs on Allowance for Loan and Lease Losses	Sum of svgl3885, svgl 3909, svgla650, and svgla674 - Total
	Loans Charge-offs (Sum of VA46, VA56, VA48, and VA58)]
riad4230 Loan Loss Provision	svgl0484 Provision for loan and lease losses (SO321)
rcfd1406 Total Loans and Lease financing receivables: Past Due 30-89 Days and Still Accruing	svgl3936 Past Due 30-89 Days and still accruing, total ( )
rcfd1407 Total Loans and Lease financing receivables: Past Due 90 Days and Still Accruing	svgl3942 Past Due 90 Days or more and still accruing, total ( )
scfd1403 Total Loans and Leases Finance Receivables: Nonaccrual	svgl3948 Non-accrual, Total ()
rcfd2200 Total deposits	Sum of svgl2339, svgl 2728, and svgl2071 - Deposits (Sum of SC710, SC715, and SC712)
rcfd8274 Tier 1 capital	svcc5279 Tier 1 Capital (CCR20)
rcfd a223 Risk-adjusted assets (Net Risk-weighted Assets)	svcc2375 Net Risk-Weighted Assets (CCR78)
rcfd 7205 Risk-based Capital Ratio	svcc7205 Risk-based Capital Ratio