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Abstract

The level of aggregate excess reserves held by U.S. depository institutions increased significantly at the peak of the 2007-09 financial crisis. Although the amount of aggregate reserves is determined almost entirely 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-differences approach to determine whether the beneficiaries of the Capital Purchase Program of the Troubled Asset Relief Program accumulated less cash, including reserves, than non-beneficiaries. Contrary to anecdotal evidence, we find that banks that participated in the program accumulated less cash, including reserves, than nonparticipants in the initial quarters after the capital injection.

JEL Classification: E44, E51, G21

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

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1. Introduction

The aggregate level of deposits held by U.S. depository institutions (DIs) at the Federal Reserve Banks increased massively at the peak of the financial crisis between the end of August 2008 and the end of December 2008, in conjunction with the unprecedented expansion of the Fed's balance sheet (Fig. 1).[1] This huge change in deposits at the Fed, most of which are excess reserves (ER), 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. (2013) 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, ER holdings are not distributed evenly across banks; individual banks can alter the composition of their balance sheets, changing lending to firms and consumers while hoarding ER and cash.

The biggest question raised by the massive accumulation of reserves is why individual profit-maximizing banks held large ER and cash during the financial crisis. Our answer is intuitive: because they were concerned about balance sheet risk and accessing short-term liquidity.

Our study consists of two parts. In the first part, we undertake a systematic analysis of this massive accumulation of ER using microeconomic data for more than 7,000 commercial banks and almost 1,000 saving institutions to identify motives for accumulation and determine whether these motives differ across DIs by size and type. In the second part, we study the effect of the Capital Purchase Program (CPP) on reserve and cash accumulation.

In the first part of our analysis, 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 estimate a log-linearized version of a simple model of stochastic reserves accumulation using bank-level data and censored regression methods.[2]

[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 $1,020.937 billion.

[2]ER holdings at the micro level are confidential information. To recover a bank-level estimate of ER, we subtract estimated required reserves from reported cash, including total reserve holdings at the Federal Reserve. Therefore, our measure of ER also includes cash in addition to excess balances at the Federal Reserve. We discuss the bias this might

We find evidence of three motives for reserve and cash accumulation: First, there appears to be a strong precautionary motive due to weak balance sheets; second, evidence of concerns about accessing short-term liquidity in the market, particularly for large banks[3]; and third, evidence that banks are sensitive to changes in the opportunity cost of holding low-interest-bearing assets, suggesting that opportunities for low-risk lending were inadequate.

We uncover significant heterogeneity in the responsiveness of reserves accumulation. We find that (i) cash and ER holdings for large banks are much more responsive to the penalty rate than those of small banks, (ii) a different relationship exists between capital ratios and cash and reserves accumulation for large versus small banks, and (iii) large banks are much more sensitive to distressed loans as a percentage of deposits than small banks. We also find that thrifts behave like small banks in terms of the relationship between capital adequacy and reserves accumulation but like large banks in relation to the penalty rate and sensitivity to distressed loans.

These results likely reflect several important changes in the banking environment during this period. First, the federal funds and the repurchase markets experienced significant volume declines during our sample period. These markets are a significant source of short-term funding for banks. Notably, the declines in trading activity were more pronounced for large bank trading than for small banks. Second, increases in the Chicago Board Options Exchange (CBOE) Volatility index (VIX) during this period are suggestive of changes in risk perceptions. Third, there was significant regulatory uncertainty related to new consumer protection laws, changes to capital requirements, and concerns about future litigation.

In the second part of our analysis, we study the relationship between the CPP of the Troubled Asset Relief Program (TARP) and cash and reserves accumulation by banks.[4] The ideal way to study the effect of capital injections on the banking system would be to have a counterfactual. Although we cannot observe what would have happened to the balance sheets of banks that received CPP funds had they not received them, we can observe banks that were ex ante similar to the CPP beneficiaries but did not receive capital injections. Operationally, we use propensity score matching (PSM) to construct a control group of non-CPP institutions that we compare with the CPP beneficiaries. We then estimate the difference-in-differences between pairs of indicators for the two

create in our estimates in Section 5.1

[3] Ashcraft, McAndrews, and Skeie (2011) find similar evidence which we discuss in Section 5.2.

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

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 remaining sample of the beneficiaries of CPP funds accumulated less cash and reserves than non-beneficiaries. Popular opinion at the time of the crisis was that the CPP failed to improve lending because it increased reserves accumulation. On the contrary, Contessi and Francis (2011) found that banks receiving CPP funds provided *more* loans than their counterparts, but since 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 were sufficiently capitalized and therefore had no need for the funds or, alternatively, because they were in such poor financial health they were ineligible for the program. In this paper, we construct an appropriate control group to address problems of endogeneity and selection for our results. To the best of our knowledge, this is the first study to adopt PSM in the non-experimental setting of applied banking. Similarly, Black and Hazelwood (2013) study bank risk-taking after receipt of CPP funds, using an event-study methodology that also carefully controls for differences between CPP and non-CPP recipients.

Our work contributes to the literature on reserves accumulation during crisis episodes. As such it fits into the large and diverse literature addressing the reasons for reserves accumulation by U.S. banks during the 1930s and the substantial buildup in ER in the Japanese banking system during the 1990s. Our work also contributes to the more recent debate on the impact of the financial crisis on the banking system and the conduct of monetary policy in a regime that includes an interest on reserves (IOR) policy; we discuss these issues in section 2.

In their influential analysis of the monetary history of the Depression era, focusing on the increase in ER holdings, Friedman and Schwartz (1963) argued that banks desired a higher level of reserves for precautionary purposes after the panic of the early 1930s. Horwich (1963), on the other hand, provided early empirical evidence suggesting banks held ER because of the lack of profitable alternatives to holding cash as a result of low interest rates. The widespread view in the post-WWII literature was that ER were considered purely surplus during the Great Depression, a view surprisingly shared by members of the Federal Open Market Committee (FOMC). According to this view, ER served no economic purpose, as commercial banks passively accumulated them due to lack of good loan opportunities (a view sometimes referred to as the "inertia effect" hypothesis (see, e.g., Frost, 1971). As a consequence of the large ER holdings, the Federal Reserve was essentially powerless to expand the money supply —the banking system was caught in a liquidity trap, a condition we also find evidence for in the 2007-09 financial crisis. Bernanke (1983) and Bernanke and Gertler (1990) emphasize the role of high risks and low returns on alternatives during the Depression era, supporting the view that ER holdings may reflect an environment with few investment alternatives of comparable risk. These results connect to a large literature examining the role of uncertainty on bank cash flows and the varying impact of uncertainty between periods of crisis and non-crisis (see, e.g., Orr and Mellon, 1961; Poole, 1968; Cooper, 1971; Frost, 1971; Ratti, 1979; Hanes, 2006).

A series of recent studies discusses the importance of the constraints exerted by excess liquidity and their role in signaling a bank's own liquidity. Calomiris et al. (2011) use bank-level data to understand whether the doubling of reserves requirements imposed by the Federal Reserve in 1936-37 increased reserves demand and induced a credit contraction, contributing to the deep recession of 1937-38. They find, on the contrary, that reserves requirements were not binding on bank reserves demand in 1936 and 1937 and therefore had little impact on credit availability. They thus argue that increases in reserves demand between 1935 and 1937 reflected changes in the fundamental determinants of reserve demand. Similarly, Calomiris and Wilson (2004) argue that increasing reserves 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 prior to the Depression era, found that Federal Reserve System non-member banks, which had no access to the lender of last resort, increased their ratio of ER to assets after the first banking panic much more than member banks, which could access emergency lending through the Fed. Ennis and Wolman (2012) find a similar result for uninsured foreign banks during the 2007-09 crisis.

Japan's Lost Decade also provides an important modern example of ER accumulation. Japanese banks began a sustained increase in ER accumulation in mid-2001, which peaked in 2003:Q3 when the ratio of actual to required reserves reached 5.9. Fig. 2 compares the sharp increase in the ratio of actual to required reserves within the Japanese banking system between 2001 and 2006 and the increase in ER during the Great Depression and during the recent U.S. Great Financial Crisis. The recent reserves accumulations of Japan and the United States were much more pronounced, clearly dwarfing the accumulation of reserves (in terms of the ratio of excess to required reserves) during the U.S. Great Depression. Ogawa (2007) studies the determinants of bank-level reserves 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.[5] He attributed Japanese banks' precautionary behavior to the general instability in the Japanese banking system and poor balance sheet health.

We use Fig. 3, 4, and 5 to compare the three historical episodes. In the figures the excess-to-required reserves 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 episodes of increasing ERR are those during which this rough measure of the opportunity cost of holding reserves decreases.

Our paper is organized as follows. Section 2 discusses historical reserves accumulation in the United States. In Section 3 we develop the testable model, and Section 4 presents the data and the estimation. Section 5 studies the relationship between the CPP and cash and reserves accumulation. Section 6 concludes.

2. Reserves accumulation: The U.S. experience (2007-10)

2.1 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 3 and the estimation in Section 4.2.

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 reserves requirement through a reserves 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 reserves requirement.[6]

[5] 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.

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

The reserve ratio depends on the amount of net transaction accounts at the DI. The Garn-St. Germain Depository Institutions 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.[7] Net transaction accounts over the low-reserves tranche are subject to a 10 percent reserve (see Table 1 for current requirements).

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, for which it can receive funds through the federal reserve 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 New York Fed 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).

2.2 The IOR after October 2008

DIs prefer to minimize the amount of ER they hold because neither vault cash nor reserves at the Federal Reserve normally yield interest income. However, on October 9, 2008, Federal Reserve Banks started paying interests on required reserve balances and excess balances. ER jumped, likely in response to this policy change, the intensification of the crisis, and the fact that the Fed stopped sterilizing its open market purchases (see Fig. 1). The darkest green section in Fig. 1 shows the increase in bank deposits, representing required and ER, 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.

In the first three months of nonnegative IOR payments, a distinction arose between

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

balances held to fulfill reserves requirements ("required reserves balances") and balances held in excess of required reserves balances and contractual clearing balances ("excess reserves 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.[8] However, these intraquarter changes do not affect our discussion as we study quarterly data.

2.3 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. Keister et al. (2008) 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, allowing central banks to increase the supply of reserves without driving market rates below target. The use of the IOR as a floor rate for the relevant policy rate removes the opportunity cost of holding reserves at 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) such as the Bank of Canada, the Reserve Bank of New Zealand, and the European Central Bank. The Fed was granted explicit authorization to pay IOR by the Financial Services RegulatoryAct of 2006. The implementation date was originally established as October 1, 2011, but was changed to October 2008 to provide the Fed with an additional monetary policy tool during the U.S. financial crisis.

The advantages of IOR have been detailed in the literature (for example, Goodfriend, 2002; Keister et al., 2008, and the references therein). In theory, the short-term interest rate target 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 in both normal and 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) use a mar-

[8] The first reduction brought the spread to zero for required balances and to 35 basis points for excess balances; 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.

ket micro-structure approach to 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 federal funds below the federal funds target rate.

The literature on the conduct of monetary policy with an IOR policy is diverse and growing. Martin et al. (2013) derive a simple model to show that aggregate bank lending and aggregate reserves are disconnected when interest is paid on reserves. Hornstein (2010) develops a stylized monetary model and finds that, although the responses of inflation and output to innovations in the target interest rate with an IOR policy are slightly different from models in which reserves yield zero interest, such differences are small. 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. Below we develop a more stylized model that focuses on the bank's reserve allocation decision at a lower frequency, consistently with the quarterly data we use.

3. A simple model of excess reserves accumulation

In this section, we develop a simple model of reserve determination that allows us to focus on the factors impacting reserves 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.[9]

When the interest rate paid on reserves holdings, 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 of deposits). When r_{IOR} is positive, banks may have an incentive to hold ER 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

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

withdrawals are not available. Although in classical models such as Diamond and Dybvig (1983) bank runs are the result of customers' withdrawals, the same logic applies in the shadow banking market system and the interbank market. Should this occur, the bank can obtain funds only 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 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:

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

where $\lambda \geq 0$ is the Lagrange multiplier associated with the required reserves constraint.[10] 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 $\lambda > 0$, 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

[10] 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 $C'(R_i) = -r_p \Pr\left[L_i \geq R_i\right]$ and $C''(R_i) = -r_p f(R_i) \geqslant 0$.

rate differential $r_A - r_{IOR}$ and the penalty rate r_p rises. Ogawa (2007) uses a version of this model (following 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 limit the possibility of a bank run—is captured by an increase of $Pr\left[L_i \geq R_i\right]$ 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.
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 the bank. Financial weakness can be approximated by a variety of measures. In this paper, we assume that financial weakness (FW_i) shifts the location parameter, $L_{0,i}$, as follows:

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

We assume that financial weakness is a composite measure of bad loans (BL_i) and bank capital (K_i). 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 BLi represents a measure of bad loans for bank i and K_i represents bank i's capital. Because under $\lambda > 0$ the reserves requirements are constraining ($R_i = \delta D_i$), we have a system of equations as follows:

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

that can be estimated using censored regression methods.

4. The determinants of reserves accumulation

4.1 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 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, 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).[11] For

[11] 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.

our estimation procedures, we use data for the quarters between 2008:Q3 and 2010:Q2 and include 2008:Q2 as a pre-IOR quarter for comparison.[12] The number of entities in the CRs fell from 7,769 in the pre-IOR quarter (2008:Q2) to 7,182 in 2010:Q2 as a result of failures, mergers, and acquisitions. We use the National Information Center's files on bank and thrift mergers, acquisitions, and failures to remove the effects of these discrete events.

For this period, the TFRs contain similar but less-detailed information. Because there is no one-to-one correspondence between CRs and TFRs for the particular variables required for our analysis, we cannot merge the data; instead, we perform two parallel sets of analyses when possible. The number of thrifts reporting in 2008:Q2 was 829; by 2010:Q2, this number was reduced to 753.

We make several adjustments to the data to deal with complications generated by particular entities. We first remove investment banks and financing arms of large corporations that acquired charters in the 2008-09 period from our dataset and exclude them from our analysis of reserves accumulation. These "new" commercial banks are financial entities not historically regulated as banks (and hence did not file CRs), but they acquired charters in 2008-09 because they either applied for a charter or were acquired by regulated commercial banks.[13] These "banks" are likely to have reserves accumulation patterns significantly different from other commercial banks due to the distinct nature of the intermediation function they perform. In addition, we omit foreign-owned banks. There is evidence that international banks managed intragroup 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 3, we construct an empirical counterpart using information from the CRs and the TFRs.[14] Our measure of ER is computed as a difference between total cash, including reserve balances at the Fed, and required reserves calculated as a percentage δ of deposits according to the reserves requirements for the period under consideration (listed in Table 1).[15] This is our key dependent variable and the empirical counterpart of variable $R_i - \delta D_i$ in the model. Cash and reserves can be maintained in various forms, not necessarily as deposits at the Federal Reserve Bank. We calculate required reserves based on information on reserves

[12]Problems in the commercial banking system, including thrifts, did not become apparent in the lending data until 2008:Q3.

[13]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.

[14]Table 13 describes the matching between the relevant variables in the CRs and TFRs.

[15]Total cash and reserve balances at the Federal Reserve is variable rcfd 0010 in the Reports of Income and Condition.

requirements from the Board of Governors (also reported in Table 1). Since we cannot calculate required reserves precisely as the basis for their calculation changes daily, we consider our dependent variable to be cash including ER as any holdings greater than 110 percent of calculated required reserves for each bank.

Accurate measurement of the dependent variable is important for the robustness of our analysis. There are three ways it could be mismeasured. The first two ways involve our calculation of reserves requirements: We may have under or overestimated reserves requirements. If we underestimated reserves requirements, then some ER are actually required reserves. In this case, a change in deposits would automatically produce a change in "ER." To the extent that our covariates are correlated with deposits, increases in deposits could bias the coefficients upward. We check whether the reserves requirements calculated on end-of-quarter deposits are underestimated and find they are to some extent: 174 entity-quarter observations have negative ER; of these 125 are small bank observations, 33 are large banks, and 82 are thrifts. The solution for this is simple: We calculate ER as cash and reserves holdings 110 percent above calculated reserves requirements. Using this restriction, there are zero observations with negative ER. Alternatively, if we overestimated reserves requirements, then our measure of cash and ER holdings would be systematically too small. Since this is a level effect—that is, constant cross-sectionally and over time—it is not clear there would be any systematic bias on our coefficients. Provided this overmeasurement did not affect cross-sectional or time-series variation in a heterogeneous manner (e.g., disproportionately affecting large banks), we would not expect any meaningful impact on our coefficients except the possibility of downward bias. Since we have no evidence of differential impact, we conclude that any overestimation of required reserves has only a level effect, which should be reduced by scaling ER by total deposits (banks with similar amounts of transaction deposits should have the same estimated required reserves).

Finally, as noted earlier, our measure of ER includes cash and other cash-equivalents in addition to reserves holdings at the Federal Reserve. How this type of mismeasurement affects our coefficients is not easy to determine. Since our estimation equation is derived from the first order conditions of the bank's reserves management problem, not a portfolio allocation problem, we are possibly not capturing all the determinants for holding non- or low-interest-bearing assets. If DIs are holding more cash than strictly ER, then for a given change in a covariate that affects ER but not cash in excess of excess reserves, the observed effect would be smaller. In that case, our coefficient estimates provide a minimum bound for the measurement of the relationship between these covariates and ER.

Fig. 6 plots the cross-sectional distribution of our measure of the cash plus ERR ratio between the quarter before our sample begins, 2008:Q2, and 2010:Q2, the last quarter in our sample. Each histogram represents one quarter and is left-censored at zero (as no bank holds less than the required reserves) and right-censored at 75 (as our data contain some ratios in excess of 75).[16]

Over the 2008:Q3–2010:Q2 period, the distribution of the ERR became more dispersed (less peaked and with a fatter tail; see Fig. 6) compared with 2008:Q2, indicating that more banks have accumulated larger amounts of ER, in conjunction with the expansion of the Federal Reserve budget. This outward movement is also documented by Ennis and Wolman (2012), who focus on large banks, but the explanation for the more-disperse distributions represents an open research question that we shed some light on in our study.

Using the theoretical model developed in Section 3 as a guide for choosing appropriate covariates, we choose a set of proxies available in the data. Table 2 displays a set of descriptive statistics for each covariate discussed below.

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-bearing and interest-bearing deposits, and (iii) money market deposit accounts.

We use the interest differential between 1-year Treasury bills and the IOR as the opportunity cost institutions face for holding ER and cash. We considered a variety of other measures, including the rate on 3-month Treasury bills and the effective federal funds rate, but believed that the 1-year rate best captured alternative low-risk investment opportunities. Fig. 7 displays each of the interest rate variables in the empirical model. We discuss other measures of the opportunity cost of holding cash and ER in Section 5.2.3.

For a measure of the penalty rate—the rate banks would theoretically pay for maintaining insufficient cash and reserves—we use an index of daily rates on (30-day) Treasury bill repurchase (repo) agreements aggregated to a quarterly basis using either averaging over the quarter or choosing the last observation in each quarter.[17]

[16] For each of the 9 quarters reported in these histograms, we counted the following number of banks exceeding an ERR of 75: 38, 45, 77, 107, 114, 143, 126, 3, and 4.

[17] This index, called the DTCC GCF Repo Index, is created by the Depository Trust & Clearing Corporation (DTCC). According to the DTCC website, the index tracks the average daily interest rate paid on the most-traded general collateral finance repo contracts for U.S. Treasury bonds, federal agency paper, and mortgage-backed securities (MBS) issued by Fannie Mae and Freddie Mac. The index's rates, according to the website, are par-weighted averages of daily activity in the GCF repo market and reflect actual daily funding costs experienced by banks and investors.

We then construct the following three measures of bank loan health, each progressively more inclusive of less-distressed loans. The first measure (*nonaccruing loans*, labeled "bad loans 1" in the regression tables) contains the category of loans most likely to turn into permanent losses. Nonaccruing loans are defined as the outstanding balances of loans and lease financing receivables the bank has placed in nonaccrual status, as well as all restructured loans and lease financing receivables in nonaccrual status.[18]

The second measure of bad loans (*nonperforming loans*, labeled "bad loans 2" in the regression tables) includes both nonaccruing 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 nonperforming loans the full outstanding balances (not just delinquent payments) of loans and lease financing receivables that are past due and on which the bank continues to accrue interest.[19]

Fig. 8 displays histograms of these three types of loans (nonaccruing, nonperforming, 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.[20] The figures show quite strikingly the outward movement of the cross-sectional distribution of bad loans (in each category) between the beginning and the end of the sample window. During this period, the number of banks and thrifts with fewer distressed loans declined, and the number of banks and thrifts with 10 percent or more of their total loans classified as troubled 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 an institution will fail (see Aubuchon and Wheelock, 2010).

As a measure of capital adequacy, we use the equity-to-assets ratio adjusted in the numerator and denominator to remove intangibles (primarily goodwill). Intangibles show a strong positive trend due to mergers and acquisitions and in general are unable to absorb losses (see Lee and Stebunovs, 2012, for a discussion). We experimented

[18] Loans and lease financing receivables are reported as nonaccruing 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.

[19] 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.

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

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-to-assets ratio as this is a measure primarily determined by market rather than regulatory factors. For thrifts, we lack an adequate measure of equity holdings; therefore, we use the ratio of Tier 1 capital to risk-adjusted assets as a measure of capital adequacy. We note that the effect on ER of changes in Tier 1 capital for thrifts is therefore not directly comparable to the effect of changes in the equity-to-assets ratio for banks due to our inability to control for the expectation of regulatory changes in Tier 1 capital.

Our final measure of loan portfolio health is the ratio of loan loss provision to assets. The loan loss provision is an income statement variable triggered by write-downs of the bank's loan portfolio. When a loan loss provision is taken, the loan loss reserve must be rebuilt depending on the risk assessment of the remaining loan portfolio. The loan loss provision is an indicator of the extent to which a bank has removed nonperforming loans from its books.

We estimate a Tobit model, using the log of the ratio of ER and cash to deposits as the dependent variable and also taking the log of each of our independent quantity variables scaled by deposits.[21] We include four key variables as regressors: a measure of the return to alternative investments, a measure of the penalty rate for holding insufficient reserves, measures of the delinquency status of the loan portfolio (based on our three measures of distressed loans), and a measure of capital adequacy.

We run the same set of regressions using a censored least absolute deviations (CLAD) estimator model for data that admits a corner solution (see Powell, 1984). The advantage of the CLAD estimator is that it is robust to heteroskedasticity and consistent and asymptotically normal for a variety of error distributions. As a quantile regression method, it is also not as sensitive to outliers as the Tobit model. We report results from Tobit and CLAD regressions below.

4.2 Results

In this section, we present the results from our Tobit and CLAD specifications. The log of the ratio of cash including ER (calculated as cash and reserve holdings 110 percent above required reserves) to deposits is the dependent variable. The regressions in Tables 3 and 4 report coefficient estimates from Tobit and CLAD specifications with

[21] We considered whether our problem could be better estimated using a Heckman selection model; see Section 5.2.4 for a discussion.

a left-censored value at zero; clustered (at the entity level) standard errors are listed in parentheses and all regressions include quarterly time dummies (not reported).[22]

4.2.1 All banks

We first look at Tobit and CLAD regressions for all banks (Table 3), second for banks by size (Tables 4 and 5), and third for thrifts (Table 6).[23] We focus on the CLAD results for the reasons outlined above but note they are quite similar for the group of all banks.

Table 3 shows the difference between the 1-year Treasury bill rate and the interest rate paid on reserve balances at the Fed has a negative and significant effect on ER/cash accumulation, 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, *ceteris paribus*, banks should reduce ER holdings. The fact that our regressions show that banks are sensitive to the opportunity cost of holding reserves suggests that the lack of alternative investment opportunities was not a frivolous motivation. Our estimation results imply that a 0.1 percent increase in the opportunity cost of holding reserves is consistent with a decrease in the ER plus cash-to-deposits ratio of 1 percent.

According to our model, when banks face heightened uncertainty about withdrawal rates, they will be more sensitive to movements in the penalty rate for having insufficient reserves. For the regressions reported in Table 3, we use a daily index of Treasury bill repo rates, taking the last observation per quarter as a measure of the penalty rate. During our observation window (2008:Q3–2010:Q2), there was significant disruption in the repo/reverse-repo market, which is a significant source of short-term funding for banks. This disruption, which began with a 30 percent drop in federal funds and reverse-repo trading volumes in November 2008, recovered to some extent by April 2009, after which volumes again declined significantly and continued to decline through the end of our sample. By 2010:Q2, the volume of trading in this market was only 36 percent of its value in 2008:Q3.

Not surprisingly, we find ER and cash holdings respond strongly to increases in the penalty rate. For every 0.1 percent increase in the penalty rate, the ratio of ER and

[22]The interpretation of the coefficients on covariates measured in levels or ratios (the price variables and capital adequacy ratios) requires exponentiation of the coefficients on the level covariates to obtain the effect on the dependent variable, whereas the log-log specification can be read as percentage changes from the tables.

[23]The tables of Tobit results report the effects of the covariates on the latent variable (observing positive ER) rather than the marginal effects because the number of censored observations is sufficiently small that the Tobit coefficients approach their ordinary least squares counterparts so that the marginal effects differ from the reported results only at the fourth decimal place.

cash to deposits increases by approximately 5 percent. The strength of this response may also detect the reluctance of banks to provide negative market signals regarding their liquidity by borrowing in the overnight market during the financial crisis (see Armantier et al., 2011; Gilbert et al., 2012). Maintaining cash and ER reduces banks' reliance on the overnight market.

Next we turn to the impact of measures of bank health and loan performance on cash and reserves accumulation. Our measures of bank health are loan quality, provisions for loan losses, and the capital ratio. Bank capital ratios provide a measure of how adequately a bank is prepared for unexpected losses.

Our results on the effect of capital adequacy are unstable across the Tobit and CLAD methods. Using the Tobit method, we find that a 0.1 percent increase in capital adequacy (equity/assets) results in a 3.5 percent increase in ER and cash as a ratio to deposits, holding the loan loss provision at 0. Under the CLAD specification, we find that a similar increase is consistent with a 0.6 percent decrease in the ratio of ER and cash to deposits, holding the loan loss provision at zero. Although the effects are small in both cases, we believe the CLAD results are more reliable. The total effect of the capital ratio is the sum of its individual effect (for the loan loss provision at zero) plus the coefficient on the interaction times loan loss provision, exponentiating due to the semi-log format. We calculated the total effect of a 1 percent increase in the capital ratio (based on the coefficients in the CLAD regressions) to be -5.2 percent at the median level of loan loss provision, -4.4 at the 75th percentile, 0.03 percent at the 90th percentile, and 8.8 at the 95th percentile of loan loss provision. Banks with well-performing loan portfolios likely have low loan loss provisions and, therefore, higher capital adequacy translates into lower ER and cash accumulation. For banks burdened with large amounts of nonperforming and nonaccruing loans, increases in capital adequacy may be the result of reductions in assets due to write-downs rather than increases in equity, so higher capital adequacy results in more precautionary accumulation of reserves and cash. Another possibility is that banks with high loan loss provisions expect additional write-offs in the near future so that higher capital adequacy is not entirely protective. 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.[24]

These results also make sense of the coefficient instability across specifications. Since the Tobit estimations are more sensitive to outliers, the coefficients on the interaction

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

between capital adequacy and loan loss provision as well as loan loss provisions are likely unduly influenced by banks with large loan provisions (the standard deviation of loan loss provision is larger than the mean).

Evidence that this interpretation may be correct is provided by studying the total effect of loan loss provisions, which equals the coefficient on the ratio of loan loss provisions to assets (holding the capital ratio equal to zero) plus the coefficient on the interaction between loan loss provisions and the capital ratio at various levels of the capital ratio. We find the total effect of a 0.1 percent increase in loan loss provision holding the capital ratio constant at the 50th percentile is a 4.1 percent increase in the ratio of ER and cash to deposits; at the 75th percentile, there is a 5.3 percent increase; at the 95th percentile, an 11 percent increase; and a 158 percent increase at the 99th percentile in the capital ratio. Banks with very high capital ratios (e.g., 99th percentile) possibly have such high ratios due to loan write-downs rather than large increases in equity. An increase in the loan loss provision at such a high ratio is consistent with a strong precautionary accumulation. Alternatively, these may be recently merged banks or banks with recent acquisitions. One last point is that there may also be tax considerations for the timing of loan loss provisions not considered here.

Our last group of the determinants of reserves accumulation is a set of three nested measures of bad loans, where the first measure includes the most troubled loans (total nonaccruing), the second measure includes nonaccruing and adds nonperforming (90+ days late) loans, and the third measure includes the first two bad loans measures plus loans between 30 and 90 days late. We find all our measures have a similar effect on ER and cash accumulation.[25] We find that a 1 percent increase in the ratio of bad loans to deposits results in a 0.3 percent increase in the ratio of ER and cash to deposits, suggesting a precautionary motive for accumulation.

In summary, first, we find evidence of precautionary accumulation by banks from the response of reserves and cash to the deterioration of their loan portfolio and the relationship between capital adequacy and loan loss provisions. Second, we find banks are sensitive to the opportunity cost of holding low-interest-bearing assets, suggesting limited low-risk lending opportunities. Third, we find banks are very sensitive to the penalty for holding insufficient reserves in the event of a payment or withdrawal shock. This result may be related to disruptions in the interbank and repurchase markets that

[25] The fact that the standard errors are significantly different across the two methods suggests some heteroskedasticity in the residuals, though this does not affect the coefficient estimates.

occurred during our sample period.

4.2.2 Banks differentiated by size

We next differentiate banks by size and consider whether large banks had different cash and reserves accumulation responses than small banks. We define large banks as the top 2 percent of banks measured by assets and small banks as those with assets below the 95th percentile (leaving an intermediate group between large and small). In 2008:Q3, there were 148 banks classified in the top 2 percent; by 2010:Q2, there were 128 banks in this category, a 16 percent decline. This attrition reflects mergers, acquisitions, and failures. Since we use a pooled sample rather than a panel, sample attrition is unlikely to have a significant effect. Fig. 9 shows the cross-sectional distribution of excess reserves accumulation as a ratio to required reserves for small versus large banks. Some noteworthy differences are reported in Tables 4 and 5.[26] We focus on the CLAD results, though the Tobit results are similar.[27]

First, we find that large and small banks have a similar response to an increase in the opportunity cost of holding cash and ER: A 0.1 percent increase in the opportunity cost (measured as the difference between the yield on 1-year Treasury bills and the IOR) is consistent with a 1 percent decline in ER and cash holdings. The response is slightly smaller for small banks; tests of the equality of coefficients across groups reject equality at the 1 percent confidence level.

Second, we find a huge response to an increase in the penalty rate (measured by an index of interest rates on Treasury bill repos) for large banks and a much smaller response by small banks (the responses are significantly different at the 1 percent confidence level). For small banks, a 0.1 percent increase in the repo rate is consistent with a 3 percent increase in their ratio of ER and cash to deposits. We find the response of large banks to a 0.1 percent increase in the penalty rate is consistent with an increase in ER and cash of 40 percent. In the previous regressions with "all banks," the strong response to the penalty rate is driven primarily by the response of large banks.

Returning to our discussion of disruptions in the repo and federal funds markets in 2008:Q3–2009:Q2 and 2009:Q4–2010:Q2, we find that small banks experienced a much smaller decline in trading volume in this market than large banks. While there was a decline in volumes of small bank activity, the decline, particularly between the end

[26] Approximately 2 percent of the observations for the large bank sample and 0.15 percent of the small bank sample are censored.

[27] The large coefficients on the 1-year Treasury bill yield minus the IOR measure of the opportunity cost for large banks are similar to the coefficients in the CLAD regression when exponentiated.

of 2009 and mid-2010, was much smaller than the decline in large bank activity. For large banks, trading volume dropped by more than half (in 2010:Q2, trading volume was 27 percent of what it was in 2008:Q3 for large bank trading). For small banks, trading volume was 51 percent of what it was in 2008:Q3.

To determine the effect of a larger capital ratio on ER and cash accumulation, we consider the total effect, which is the sum of the coefficient on the adjusted capital ratio and the coefficient on the interaction term for various levels of loan loss provision (exponentiated). In considering the effect of the capital ratio on large banks, holding the loan loss provision at 0, we find a 1 percent increase in the capital ratio results in about a 25 percent increase in the ratio of ER plus cash to deposits (focusing on the two specifications where there is significance). Holding the loan loss provision at zero, for small banks we find a 1 percent increase in capital adequacy results in a 4 percent decline in ER and cash holdings. These differences are statistically significant at the 1 percent level. What causes this discrepancy? To answer this question, we consider the total effect first for large banks and then for small banks, focusing on the coefficients for the regression that includes "bad loans 2," since the coefficients on the relevant covariates are significant for both large and small banks for this specification.

When loan loss provisions are held constant at the 50th percentile, for large banks the total effect of a 1 percent rise in capital adequacy is a 27 percent increase in the ratio of ER and cash holdings to deposits. With loan loss provisions at the 75th percentile, the effect is a 19 percent increase. With loan loss provisions at the 95th and 99th percentiles, the effect is an 11.5 percent *decrease* and a 42.4 percent *decrease*, respectively, in cash and ER holdings. For small banks, the pattern is the opposite. When loan loss provisions are held constant at the 50th percentile, the total effect of a 1 percent rise in capital adequacy is a 3 percent decrease in the ratio of ER and cash holdings to deposits. With loan loss provision at the 75th percentile, the effect is a 2 percent decease. However, at the 90th, 95th, and 99th percentiles of loan loss provision, there is a 2.7 percent increase, a 3 percent increase, and a 13 percent increase, respectively, in ER and cash holdings.

The behavior of small banks makes sense: As loan provisions increase, the probability of near-future write-downs rises, so we observe a small positive relationship between the capital ratios (which may be increasing due to the increase in loan loss reserves) and ER and cash accumulation—the high loan loss provisions reflect a risky position for small banks.

The behavior of the large banks is more difficult to understand. Loan assets are reported on bank balance sheets net of the loan loss reserve. When the bank increases its loan loss provision (an expense item against profits on the income statement), its loan loss reserves increase by the same amount. Therefore, higher loan loss provisions mean lower net assets (net of loan loss reserves), increasing the capital ratio. When a loan is written off, loan receivables are decreased by the size of the loan and the loan loss reserve is also reduced by the amount of the loan. These actions should not change net asset positions in the quarter in which the charge-off occurred. However, in the next quarter, the loan loss provision needs to be rebuilt; therefore, the loan loss provision increases. Banks may increase their loan loss reserves when the probability of imminent losses is higher. These accounting facts make disentangling the relationships among capital ratios, loan loss provisions, and ER and cash accumulation more difficult.

Then, why do large banks with high loan loss provisions decrease their ER holdings? When we examine large bank behavior for the broader category of problem loans (bad loans 3), we find a 4 percent and 22 percent decline in ER at the 95th and 99th percentiles, respectively, of loan loss provisions for a 1 percent rise in the capital ratio—a smaller effect compared with the previous specification, but we still find the unusual decrease in cash and reserve holdings. Another consideration is that large banks may use a different strategy to increase their loan loss provisions than small banks. Large banks may have high loan loss provisions as an attempt to smooth income (i.e., for the tax savings they generate in times of reduced income). Thus, their loan portfolio is not as risky at the 99th percentile as the loan portfolio of small banks and therefore they are not concerned about holding more ER and cash. Alternatively, these results may reflect TARP-CPP funds. Most large banks received TARP funding during this period and the differential behavior of ER holdings may be due to higher equity holdings (in addition to lower asset holdings) from TARP investments.

We can examine the effect of loan loss provisions at a given capital ratio to attempt to answer these questions. When the capital ratio is held constant at the 50th percentile, the total effect effect of the loan loss provision on excess reserve and cash accumulation is a 41 percent decrease for large banks and a 30 percent decrease for small banks. For a capital ratio at the 90th percentile, the reduction in ER and cash is 60 percent for large banks and 46 percent for small banks. For a capital ratio at the 95th, the reduction is 70 percent for large banks and 57 percent for small banks. Thus, the differential effect of increasing capital ratios for a given loan loss provision must be related to some difference in how large and small banks account for loan loss provisions.

Finally, considering the effect of distressed loans on reserve and cash accumulation, we find larger effects for large banks, in the range of 0.6 to 1 percent, while the effect for small banks is between 0.1 and 0.2 percent. Large banks have significantly higher ratios of bad loans to deposits than small banks, and the variation across large banks is significantly higher than across small banks (the standard deviation of the ratio of bad loans 1 to deposits for large banks is 132, whereas it is 0.03 for small banks). These effects are significantly different at the 1 percent confidence level.

In summary, we find that large banks have a much stronger response to increases in the penalty rate than small banks, a stronger precautionary accumulation motive, and the relationship among loan loss provisions, capital ratios, and ER is significantly different between large and small banks — a fact that is possibly explained by accounting issues or different sources of liquidity.

Our results can be compared to those of Ashcraft et al. (2011), who examine high-frequency (intradaily) movements in ER balances rather than the lower-frequency quarterly data we use. They find that small banks appear to have credit constraints that prevent them from actively borrowing in the interbank market as large banks do; they also have limited borrowing or lending at the end of the day and hold larger intradaily and overnight reserve balances. Controlling for balance sheet characteristics, small banks are reluctant to lend at the end of the day, potentially due to the unpredictability of their payment shocks and the large fixed cost to enter the interbank market. Ashcraft et al. (2011) find that in response to higher uncertainty about payments, banks—especially small banks—were reluctant to lend ER when balances were high and borrowing banks were more aggressive in bidding for borrowed funds when balances were low. Even though large banks may be relatively unconstrained and able to access funds easily on the market, aggregate reserve balances can become stuck in the accounts of small banks at the end of the day, leading unconstrained large banks to also keep precautionary balances. Our results are consistent in the sense that the stronger response of large banks to increases in the penalty rate and distressed loans could be caused by lack of available liquidity in the interbank market.

4.2.3 Thrifts

Thrifts are savings and loans institutions with separate charters from domestic commercial banks. Thrifts were originally created with a special function: to channel loans to the housing market. Their loan portfolios and the types of securities they can hold are also more closely regulated than commercial banks (Kwan, 1998). For example, thrifts have restrictions on the percentage of consumer and commercial and industrial loans in their asset portfolio and the percentage of nonconforming loans secured by residential or farm property that banks do not have (Office of the Comptroller of the Currency, 2013). There are also a number of other restrictions on lending that would reduce the risk of thrifts' loan portfolios. In addition, in order to maintain its status as a qualified thrift lender, a thrift is required, among other things, to maintain qualified thrift investments equal to at least 65 percent of its asset portfolio. These investments include loans to purchase, refinance, and so on, domestic residential or manufactured housing, home equity loans, educational loans, small business loans, and loans made through credit cards, as well as securities based on mortgages on domestic residential or manufactured housing. Our results likely reflect these restrictions.

Thrifts respond similarly to all banks to the opportunity cost of holding ER: A 0.1 percent increase in the opportunity cost is consistent with a 1 percent decrease in ER and cash. Thrifts have a large positive response to increases in the penalty rate (the repo rate evaluated at the mean)—larger even than the response of large banks.[28] We do not have a comparable measure of equity holdings for thrifts, so we use the Tier 1 capital ratio as a measure of capital adequacy. We find that thrifts behave similarly to small banks in terms of the relationship among Tier 1 capital requirements, loan loss provisions, and ER and cash accumulation: A 1 percent increase in the capital ratio when loan loss provisions are zero is consistent with a 17 percent decrease in ER and cash accumulation. Holding loan loss provisions at the 50th percentile, a 1 percent increase in the capital ratio generates a 16.5 percent decrease in ER and cash holdings. As the loan loss provision rises, a 1 percent increase in capital adequacy has a sequentially smaller negative effect on ER and cash accumulation. When loan loss provisions are at the 99th percentile, a 1 percent increase in capital adequacy generates only a 1 percent decrease in ER and cash holdings.

Thrifts' reserve and cash accumulation response to an increase in distressed loans is similar to the response of large banks: A 1 percent increase in bad loans generates a 6 percent increase in ER and cash as a ratio to deposits.

In previous research, Contessi and Francis (2011) found the lending behavior of thrifts during the financial crisis behaved quite similarly to that of small banks. We find that thrift cash and ER accumulation patterns are similar to those of small banks except in two dimensions: The response to the penalty rate is much more similar to that of large banks, and the responsiveness to bad loans is much greater than that of

[28]We could not separately identify the effect of the opportunity cost and penalty rate using the last observation in the quarter for the index of Treasury repo rates, which was our penalty rate for banks.

small banks. Differences in the regulatory framework for thrifts and banks may explain these observed differences. For instance, on average, thrifts have a larger portion of their loan portfolios invested in residential loans and small bank lending. Thrifts also have greater restrictions on other assets and securities they can hold. Their loan portfolios are also subject to much stricter controls, in terms of capital adequacy and the percentage of assets they can leverage, than are banks' portfolios. This may make thrifts especially sensitive to the penalty rate, but their loan portfolios may be better managed.

We also performed a number of robustness checks. We considered whether a censored regression technique was appropriate, whether there were selection concerns, and we tested different specifications for the dependent variable, the penalty rate, the opportunity cost of holding cash and ER, and the measure of capital adequacy. We found that our results were qualitatively and quantitatively robust under these alternative specifications. As a last robustness check, we considered whether we ought to consider reserves held at the bank holding company level rather than the individual bank level. We found our results to be quantitatively similar using this higher level of aggregation. A more detailed discussion of these robustness checks is available in an online appendix.[29]

4.3 Responsiveness of cash and reserves accumulation

Table 7 analyzes the responsiveness of ER and cash accumulation to changes in the penalty rate, opportunity cost, and distressed loans. We first look at the response of ER and cash to unit variations in these covariates for all banks, large banks (top 2 percent by assets), small banks (bottom 95 percent), and thrifts.

We find that ER and cash do not respond very strongly (less than unit elasticity) to the opportunity cost (yield on 1-year Treasury bills minus IOR) or the average interest rate on Treasury bill repurchase agreements, but there are some differences between banks by size. The elasticity of the opportunity cost and repo rate for large banks is significantly higher than for small banks (though still below unit elasticity). The elasticity of distressed loans is significantly higher for large banks than for small banks—in fact, the elasticity on the broadest category of distressed loans is above unity and positive, meaning that a 1-unit increase in distressed loans generates more than a 1 percent increase in ER and cash holdings. This suggests that cash and ER

[29] Detailed discussion of our robustness tests is available here in an online appendix available here http://research.stlouisfed.org/wp/more/2013-029.

accumulation by large banks was strongly influenced by precautionary motives, much more so than small bank accumulation. The elasticity of penalty rates and opportunity costs for thrifts is similar to that for large banks, but the elasticity of distressed loans is more similar to that of small banks: very small and not significant.

4.4 Response of reserve and cash accumulation to uncertainty

We consider two measures of macroeconomic uncertainty. One is based on the CBOE VIX, which is an estimate of market expectations of short-term volatility based on movements in the S&P 500 stock index option prices (see Goldberg and Grisse, 2013), for a discussion of the relationship between the VIX and asset prices). The other is based on a measure of macroeconomic uncertainty derived from movements in industrial production.

Our second measure of uncertainty is calculated based on a technique outlined in Baum, Caglayan, and Ozkan (2009) of fitting a generalized autoregressive conditionally heteroskedastic (GARCH) model to the monthly industrial production series and using the conditional variance derived from the model as a measure of uncertainty (they also fit a GARCH model to the consumer inflation series, but we focus only on industrial production). They find that macroeconomic uncertainty generates a misallocation of banks' loanable funds. Assuming that a similar mechanism might affect ER and cash holdings (which is part of the portfolio allocation problem), we believed this would be a good measure of uncertainty relevant for bank behavior.

We find no effects of these measures when we combine all banks, but separating them into large and small banks, we realize the reason for this. Table 8 includes the results for the effect of the VIX level, changes in the VIX, and the conditional variance of industrial production for large and small banks. We report the coefficients on only our three measures of uncertainty, but the Tobit regressions include the covariates from our previous regressions, focusing on the bad loans 1 case (the signs and significance of the other coefficients remain the same as previously reported). The dependent variable is the log of the ratio of ER (and cash) ratio to deposits. For large banks, a 1-unit increase in the VIX results in a 0.1 percent decrease in ER and cash holdings; a similar effect occurs for the growth in the VIX. For small banks, there is no effect. This is not necessarily the result we expected: We assumed increased macroeconomic uncertainty would cause all banks to *increase* their cash and reserve holdings.

Turning to the conditional variance of industrial production, we find that for large banks, a 1-unit increase in this measure results in a 0.8 percent increase in the ER and cash-to-deposit ratio. For small banks, a 1-unit increase is consistent with a 0.03 percent decrease in the ratio of ER and cash-to-deposits ratio. These results are closer to our prior assumptions. We also considered the St. Louis Fed Financial Stress Index and the impact on reserve and cash accumulation of movements in the spreads between high-yield and risk-free bonds and found no effect.

Although these results are suggestive of the mechanism through which heightened macroeconomic uncertainty could impact banks' precautionary behavior, they are to some extent inconsistent with the model we developed. Thus we are cautious about their interpretation. The only role for uncertainty in our theoretical model is through an increase in payment volatility, captured by the θ parameter. We expect that an increase in the VIX or its growth rate (or other measures of uncertainty) would affect reserves and cash accumulation only through its effect (if any) on the volatility of payments (or withdrawals), not as an independent additive effect. The primary effect of macroeconomic uncertainty for banks is likely to be associated with new lending or the allocation of liquidity across different assets. If a bank has a good portfolio of loans and is adequately capitalized, it is unclear how an increase in macroeconomic uncertainty would independently affect reserves and cash accumulation, setting aside the risks associated with securities holdings. Our results also point 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.

One aspect of uncertainty we have not explored is the effect of regulatory uncertainty. The financial crisis generated many proposals for new regulations on both banking activity and sources of bank funding, such as overdraft fees. In addition, DIs may also have been concerned about future litigation. This type of heightened regulatory and litigation uncertainty could generate excessive cash and reserves accumulation. This is an avenue we intend to explore in future work.

5. Did TARP beneficiaries accumulate more ER?

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

5.1 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 after the program's inception in October 2008.[30] Fig. 10 plots the patterns of monthly disbursements and repayments derived from these data using the TARP Transaction Reports releases.[31] The figure shows the total number of beneficiaries by month (vertical bars), the total disbursement (open circles), and the monthly disbursement net of repayments (solid circles). Over its first 15 months of life, the CPP allowed the injection of almost $205 billion of capital into approximately 730 financial entities (Department of the U.S. Treasury, 2009).[32] 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 holdings (as detailed in footnote 30) 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,

[30] The allocation of CPP funds to BHCs, instead of individual banks and thrifts, has raised some criticism (Coates and Scharfstein, 2009) 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 four categories. (i) 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. (ii) 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. (iii) Additionally, we differentiated between the funds distributed to large lenders and other beneficiaries that are either non-financial institutions (namely, General Motors and Chrysler) or (iv) new commercial banks and thrifts.

[31] 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.

[32] 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.

it is impossible to determine the ultimate beneficiary of the CPP, so we retain the BHC identifier. We sum the relevant CR variables for all subsidiaries that belong to the BHC group that received the CPP funds 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.[33] 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 9 (all DIs) and 10 (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 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 and have slightly larger leverage and lower deposits-to-assets ratios. These differences characterize both the thrifts and the banks that received CPP funds.

5.2 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 with its performance 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

[33] The largest imbalance found was a three-unit BHC in which a thrift held about 5 percent 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.

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, invalidating the use of simple correlation estimation.

We use PSM techniques to control for endogeneity.[34] The basic idea is to construct control and treatment groups, where receiving CPP funds 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 that 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, and (ii) we use the BHC identifier to match each bank with our proxy for management quality.[35]

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:

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

which is the difference between the dynamic path of the cash-to-assets ratio for BHCs that received CPP funds (first term) and the analogous outcome for the same BHCs had they not been granted CPP funds (second term).

The PSM technique is used to approximate the unavailable counterfactual by drawing comparisons conditional on the observables, X (see Dehejia and Wahba 2002 for a discussion). We thus assume that, conditional on the observable characteristics relevant to 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

[34] 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 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.

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

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.

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

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

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 that 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. Blundell and Costa Dias (2000) emphasize the benefits of combining matching and a difference-in-differences approach to control for observable as well as unobservable constant differences between treatment and control units.

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

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

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:

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

5.3 Timing

To ensure the timing is correct for the pre-TARP and post-TARP quarters outlined above, we use information about the CPP from the U.S. Treasury and 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 for 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 CAMELS scores.[36] 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, with the exception of foreign banks, which were excluded from receiving funds under the program, as the pool of applicants. We also exclude new commercial banks (credit card companies and investment banks) for reasons explained in Section 4. We conjecture that the majority of applications were submitted in the fall of 2008. Based on this assumption, we estimate the probability of receiving CPP funds based on observable characteristics measured at the end of 2008:Q3.

5.4 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 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

[36] A bank's CAMELS score is a confidential regulatory bank rating metric based on six factors: C, capital adequacy; A, asset quality; M, management quality; E, earnings; L, liquidity; S, sensitivity to Market Risk.

conditions, along with key bank-level characteristics, affect the probability of applying for and being granted CPP funds. The explanatory variables are measured at the end 2008:Q3, as the application process opened in 2008:Q4, and according to U.S. Treasury documents, most applications were received by the beginning of 2009.[37]

The results for the probit estimates are listed in Table 11. 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, 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; 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, loan losses provisions as a share of earning assets, loan losses as a share of equity, and net loan charge-offs as a share of total loans.[38]
- Composition of liabilities: We use deposits as a share of total assets and borrowed funds with maturities 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 on a regional Federal Reserve Bank 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 (2012), 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 or

[37] 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 the first few months of the program.

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

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 be eliminated by the difference-in-differences approach.[39]

- Management quality: We construct a proxy of management quality using the number of corrective actions taken against bank management by its regulator in the 2006-09 period.[40]

- 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. All coefficients reported in Table 11 are significant at the 5 percent level or better. 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 5.2.

5.5 Results

First, we consider the BHC characteristics that increased the probability of receiving TARP-CPP funds. We find that larger banks (higher log of total assets) and banks with more commercial lending were more likely to receive TARP funds. Banks with a higher loan loss provision—indicating significant default risk in their loan portfolio—a larger percentage of loans in non-current status, higher loan loss ratios, and loan charge-offs as a percent of total loans were less likely to receive TARP funds. However, banks with larger loan loss reserves were more likely to receive TARP funds. A loan loss provision is taken when the risk of loan default is higher. Loan loss reserves are based on a risk assessment of the loan portfolio but could be a measure of prudence.

We find evidence that publicly traded and larger (e.g., BHCs in the top 40 BHCs by asset size) banks were more likely to receive funds. BHCs with higher real estate

[39] 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.

[40] As in Duchin and Sosyura (2012), 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.

exposure or in states with more unemployment insurance claims were also more likely to receive TARP funds.

The most significant variables for understanding the allocation of TARP funds relate to capital adequacy. 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 nonlinear, 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 threshold Tier 1 capitalization, separating healthy from unhealthy (or likely to fail) institutions, were more likely to apply for and be granted a capital injection.

Assuming that our propensity scoring exercise created a well-matched set of treated and control BHCs by removing observable differences, we can now use difference-in-differences estimation to consider how cash-to-assets ratios of the treated and control groups differed, removing unobservable fixed differences between the two groups.

First, we find our matching procedure performs well as our matched pairs of BHCs are only 0.07 percentage points apart in terms of the propensity score. Moreover, the cash-to-assets ratio for the TARP group in the pre-TARP and TARP quarters is larger than for the non-TARP groups (first two rows and columns of Table 12).

Second, we report the average treatment effects (average treatment on the treated) in two different ways as described in Section 5.2. While $ATT1$, which compares cash-to-assets ratios in the target quarter with those in the previous quarter, does not produce a general pattern, $ATT2$, which compares cash-to-assets ratios in the target quarter with those in the pre-TARP quarter, does exhibit a notable pattern. The fact that cash-to-assets ratios experienced a rising trend during this period is a possible explanation for the different patterns between the two measures.

We find that the cash-to-assets ratio for both groups increased over time (examining $ATT2$ rows or, alternatively, comparing actual cash-to-assets ratios in the top two rows). Comparing the treatment group (that received TARP funding) with the control group between the pre-TARP period and one period following the treatment, we find that treated banks had approximately 1 percent lower cash-to-assets ratios than the control group (see $ATT2$ in Table 12). We find this effect persists for at least four quarters beyond treatment. In the period of treatment, the average treatment effect (on the treated) is small and not significant. 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 reduced their cash holdings (possibly by increasing their lending, though they may have alternatively purchased other assets, such as securities), effectively maintaining lower cash-to-assets ratios on average. This interpretation is consistent with the view that the capital injection provided precautionary liquidity for the beneficiaries. Alternatively, considering reasons for the larger increase in the control group's cash-to-assets, these banks, on average, may have moved more loans into nonaccrual status, thereby reducing their asset position and raising their cash-to-assets ratio.

Although treated banks subsequently had lower ratios than untreated banks, there is a rising trend for cash-to-asset ratios during this period. Deposits were increasing by an average of 1 percent: 3.5 percent for CPP banks and 0.52 percent for non-CPP banks. Increasing deposits likely affected banks' cash holdings, both as a matter of accounting (deposits are initially most likely held as cash and cash equivalents) and banks' heightened sensitivity to penalty rates. In addition, the results noted in the previous section may reflect an environment with insufficient low-risk lending opportunities. The fact that banks receiving CPP funds in this environment accumulated less cash suggests that the CPP injection possibly resulted in more risk-taking in the form of new lending and less precautionary accumulation; see Black and Hazelwood (2013) for a formal analysis of this conjecture. Our results are suggestive regarding lending, but we cannot draw formal inference based on them. For example, lower cash ratios, *ceteris paribus*, are also consistent with larger securities holdings.

In conclusion, based on our matching procedure, we find evidence that banks (or BHCs) receiving TARP funds maintained approximately 1 percent lower cash-to-assets ratios (and thus excess reserves ratios) post-treatment than similarly matched banks for at least one period following their receipt of TARP funds.

6. Conclusion

This paper undertakes a systematic analysis of the massive accumulation of ER using bank-level data for more than 7,000 commercial banks and almost 1,000 savings institutions during the U.S. financial crisis.

To answer the question "Why would profit-maximizing banks hoard liquidity?", we focus on institutions' balance-sheet risk, concerns about payment shocks, and the opportunity cost of hoarding liquidity. As do the findings of Acharya and Merrouche (2013), our evidence points strongly to precautionary motives for reserves accumulation due to banks' concerns about their balance-sheet risks and doubts about the availability of short-term liquidity. We do not find evidence that the generalized rise in macroeconomic uncertainty, as measured by standard markers, played a role in banks' reserves accumulation strategies, suggesting that concerns about counterparty risk as the crisis developed were not a prime factor. Another potential explanation is that the frequency of our data may not capture high-frequency changes in counterparty risk or, alternatively, that such risks were heightened during our period of observation and therefore not separately identifiable.

We also examined whether CPP funding contributed to the massive reserves accumulation by combining PSM technique with a difference-in-differences approach. We found that bank holding companies that received CPP funds accumulated fewer cash and reserves. This evidence is consistent with the view that the capital injection provided precautionary liquidity for the beneficiaries.

Although our analysis provides information on the determinants of ER and cash accumulation, we do not provide any link between reserves accumulation (at the individual depository institution level) and lending behavior. The question we are most interested in is "How did reserve and cash accumulation during and shortly after the crisis affect lending?" With the guidance of recent theoretical contributions (Martin et al., 2013), empirically examining the effects of reserves and cash accumulation on lending in the aggregate, as well as across the distribution of banks by size, capitalization, institution type, and by receipt of TARP funds, is an important exercise that we leave for future research.

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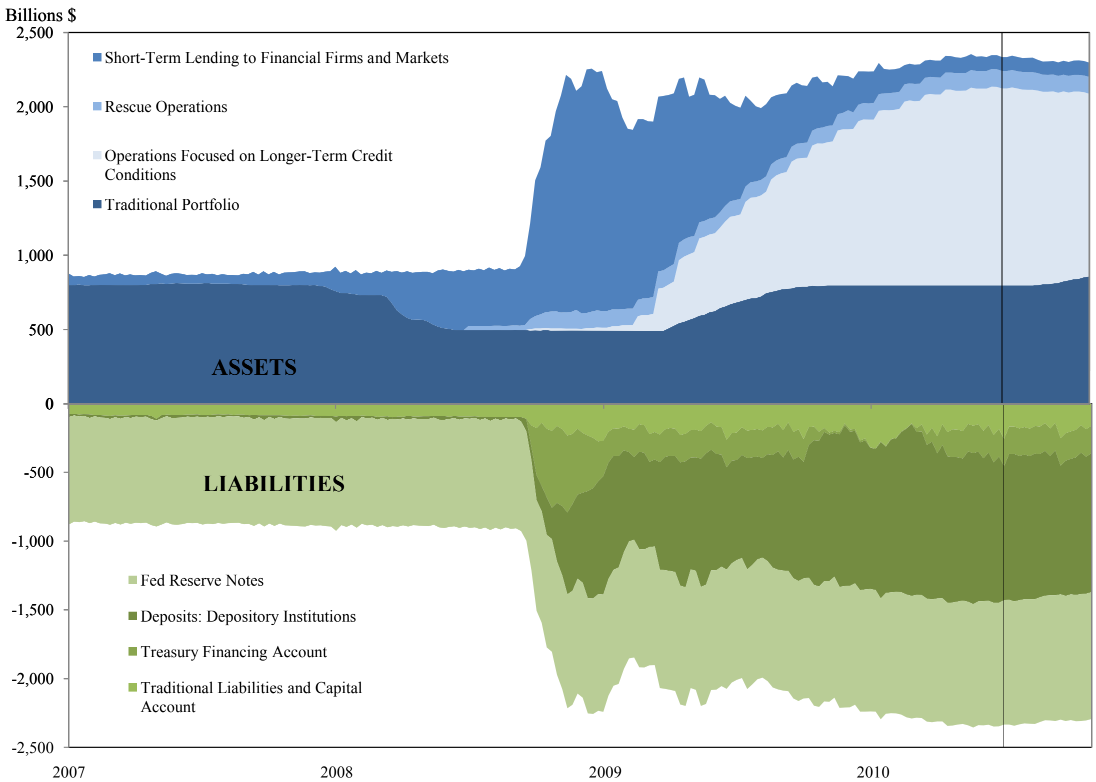
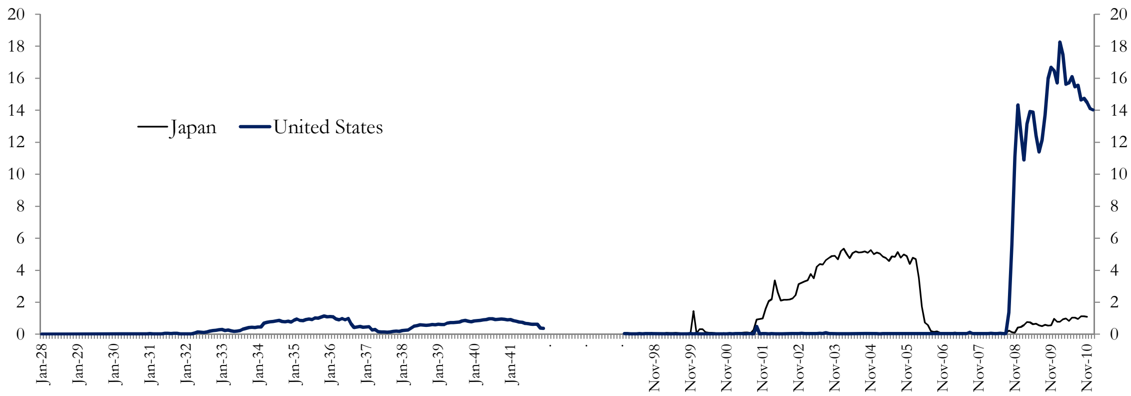
Figure 1: Federal Reserve Bank Balance Sheet (2007-2010)



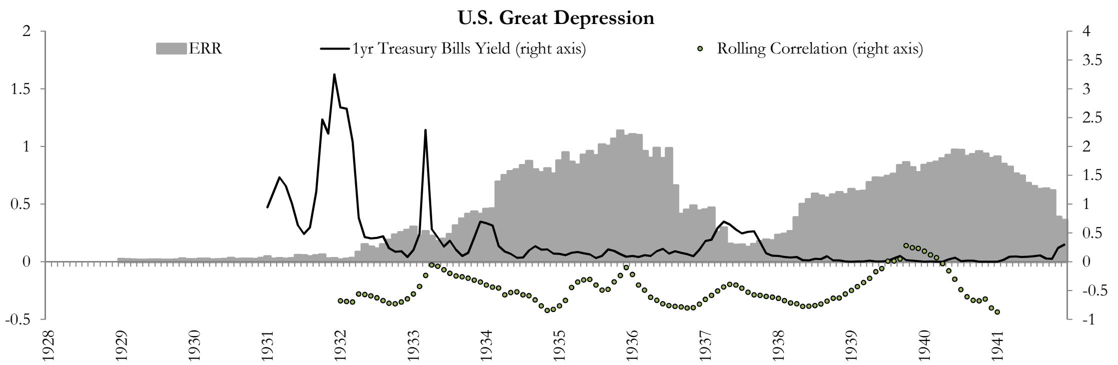
Source: Federal Reserve Board.

Figure 2: Excess-to-Required Reserves Ratio: Japan and the United States (1928:M1–2010:M12)



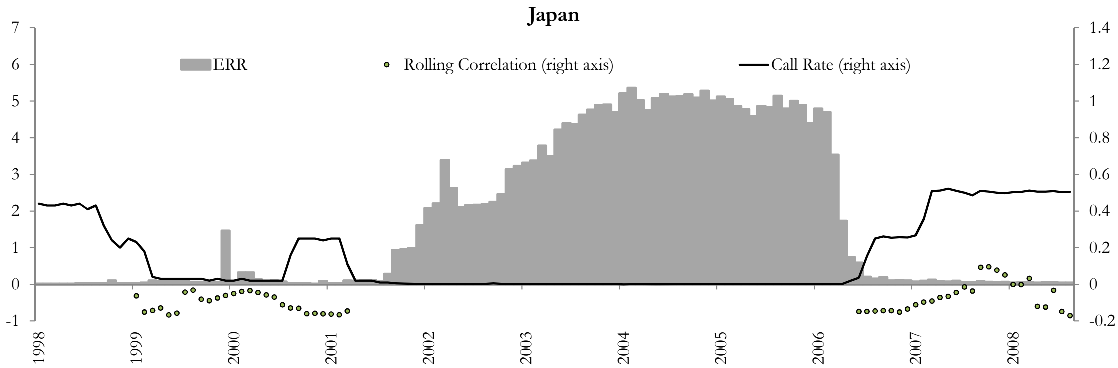
Source: Bank of Japan, Federal Reserve Board.

Figure 3: Yield on 1-year Treasury Bonds and ERR in the United States During the Great Depression



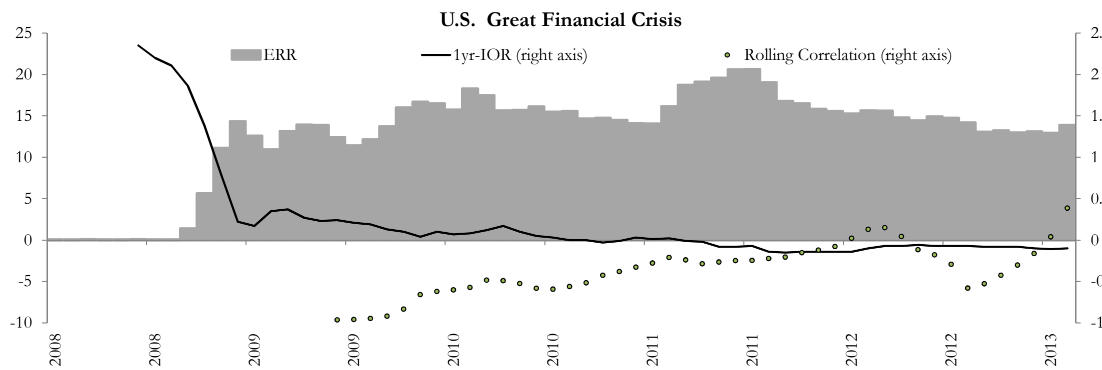
Note: ERR is the excess-to-required reserves ratio. Source: FRASER and FRED II, Federal Reserve Bank of St. Louis.

Figure 4: Call Rate and ERR in Japan during Quantitative Easing Years



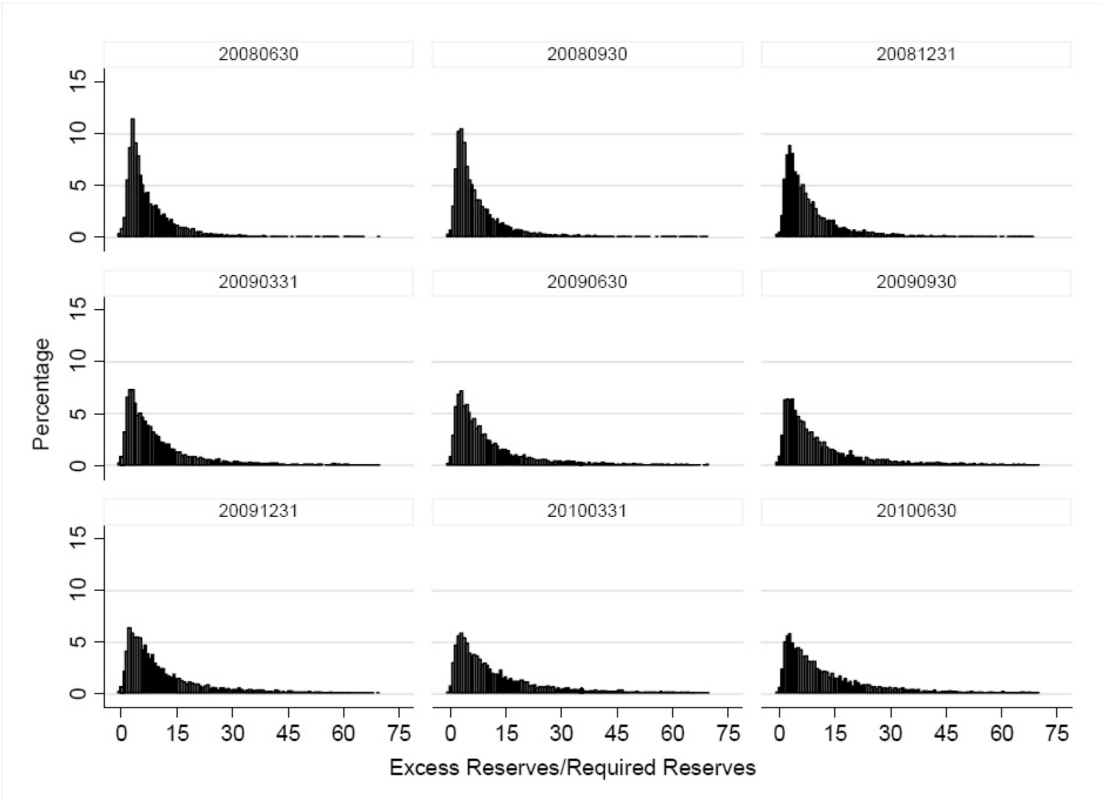
Note: ERR is the excess-to-required reserves ratio. Source: Bank of Japan.

Figure 5: Differential between Yield on 1-year Treasury Bonds and IOR and ERR in the United States Since the Great Financial Crisis Began



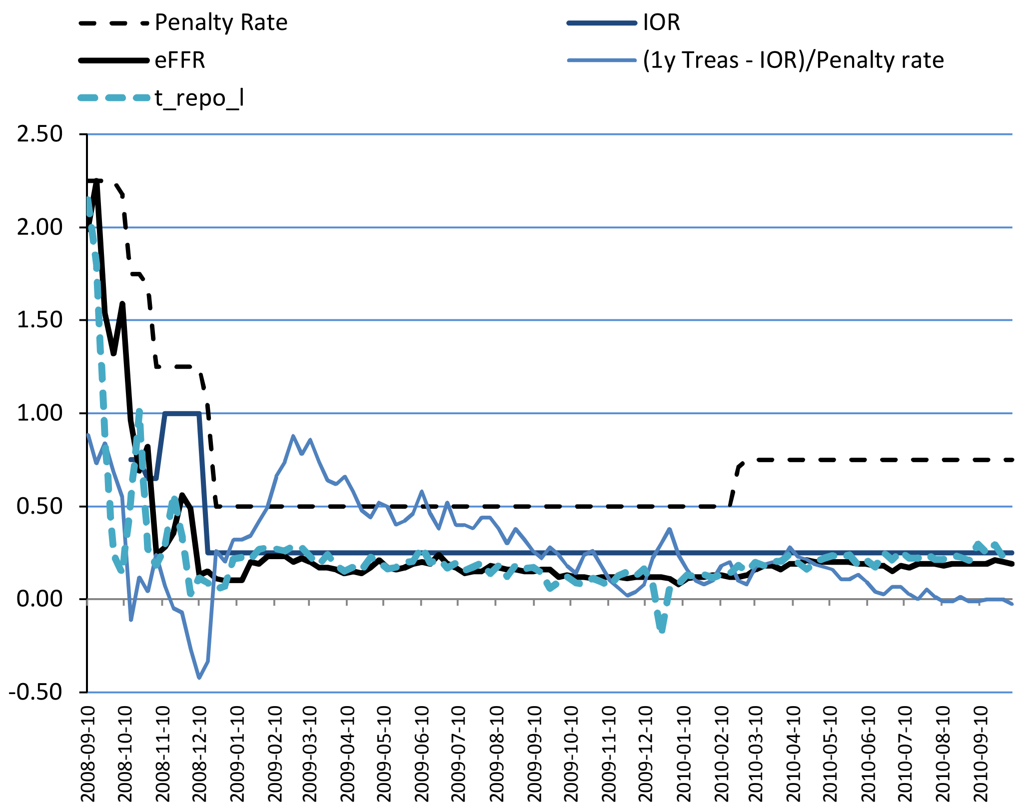
Note: ERR is the excess-to-required reserves ratio. Source: FRED II, Federal Reserve Bank of St. Louis.

Figure 6: Cross-Sectional Distribution of ERR for Commercial Banks (2008:Q2–2010:Q2)



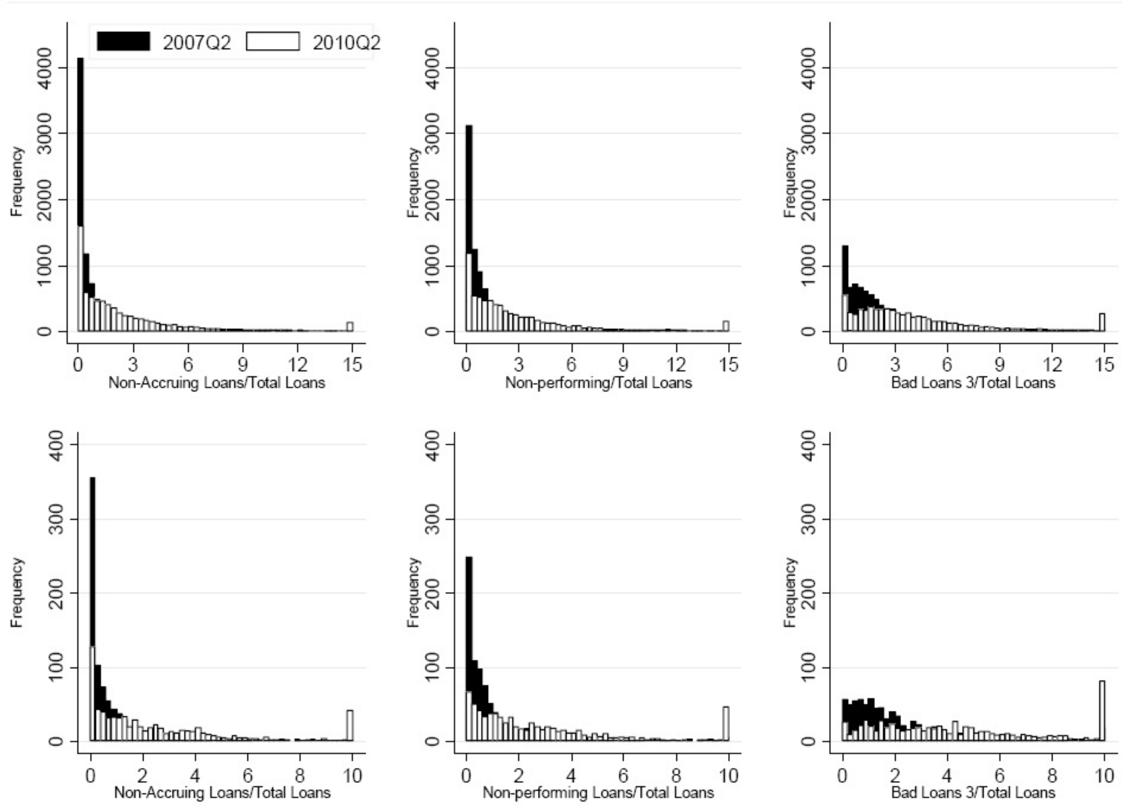
Note: We truncate our histograms at a ratio of 70. Source: Authors' calculations based on the Reports of Income and Condition.

Figure 7: Interest Rate Variables (2008:M7–2010:M12)



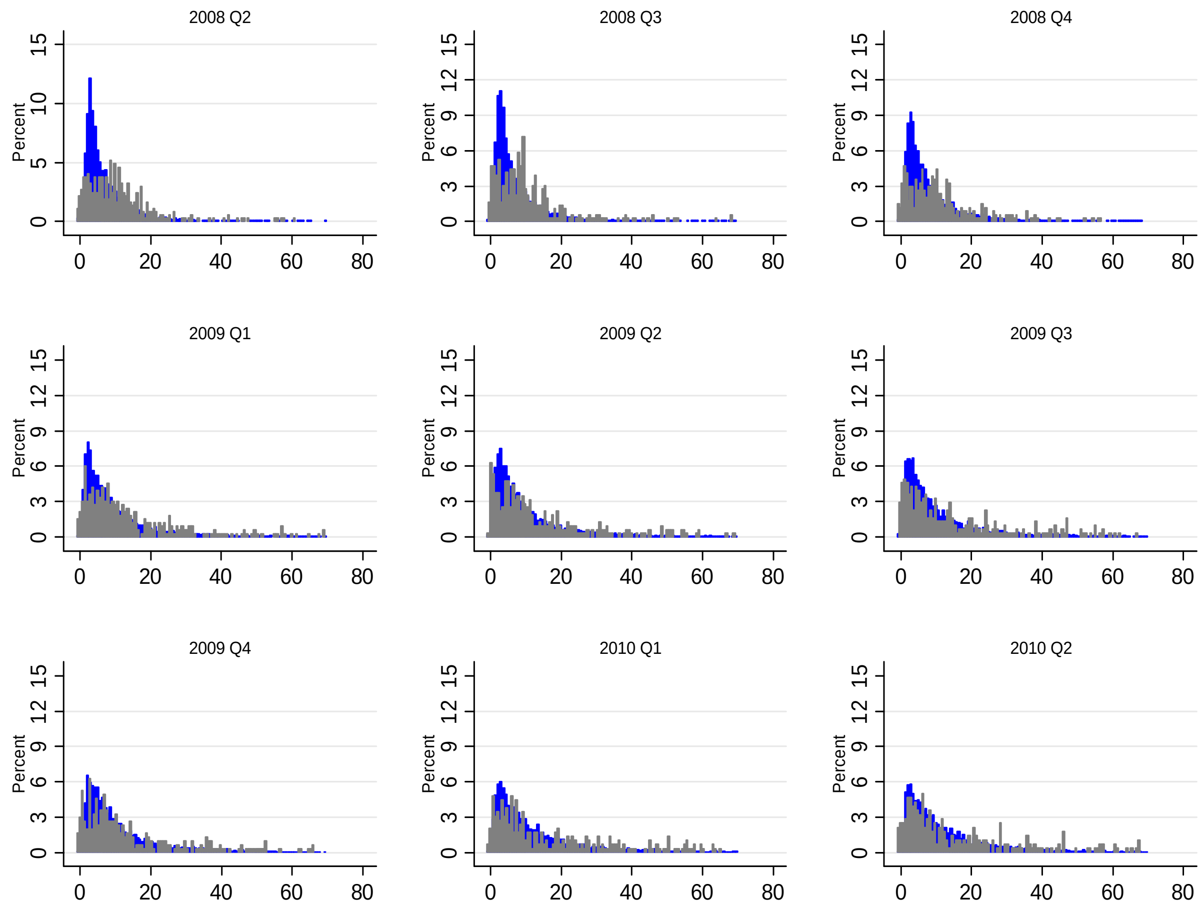
Note: eFFR is the effective federal funds rate; IOR is interest on reserves; t-repo-l is the last observation per quarter of an index of Treasury bill repurchase interest rates; penalty rate is the effective federal funds rate plus 25 basis points, and 1-yr Treas is the yield on 1-year Treasury bills. Source: FRED II data repository, Federal Reserve Bank of St. Louis, and the Depository Trust Clearing Corporation (DTCC).

Figure 8: Cross-sectional Distribution of Bad, Nonperforming, and Nonaccruing Loans of Banks and Thrifts (2007:Q2–2010:Q2)



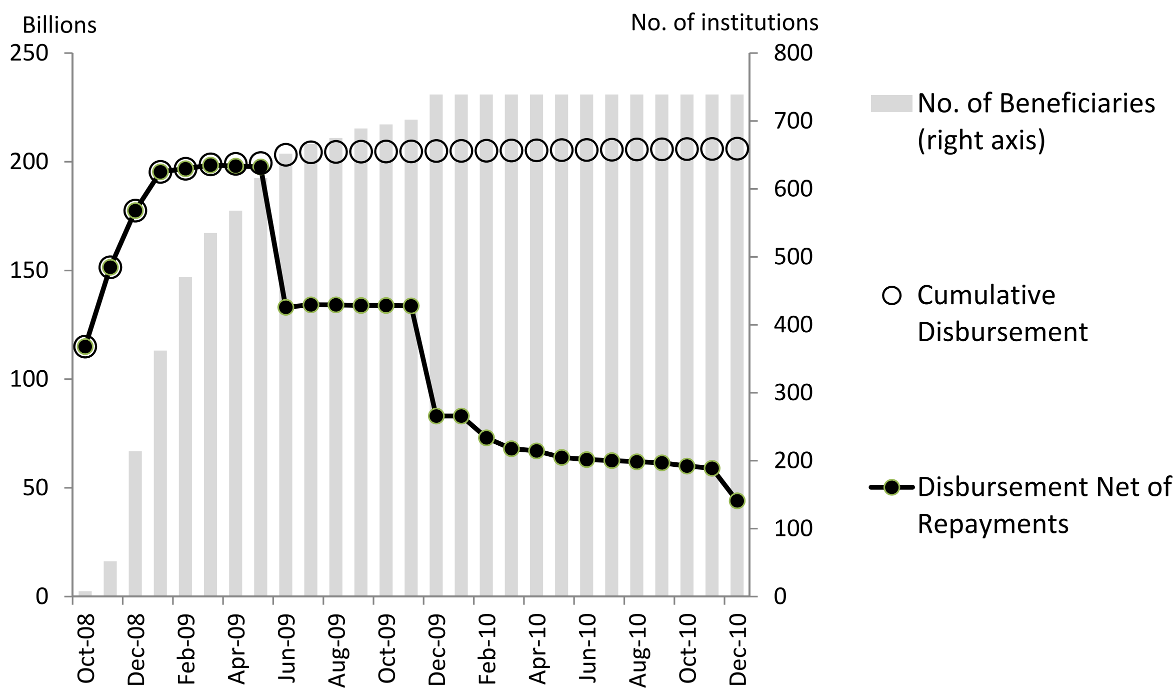
Note: These figures represent the frequency of three ratios of bad loans to assets in the population of banks (top) and thrifts (bottom). Black bars identity the first quarter used in our analysis (2007:Q1) and white bars identify the last quarter (2010:Q2). From left to right in each panel: (i) nonaccruing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

Figure 9: Cross-sectional Distribution of Excess-to-Required Reserves Ratio for Large and Small Commercial Banks (2008:Q2–2010: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 CRs.

Figure 10: CPP Disbursements and Repayments (2008:M10–2010:M12)



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

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 System.

Table 2: Descriptive Statistics for Banks and Thrifts

All Banks	No. of Obs.	Mean	Std. Dev.	Min	Max
Log ER/Deposits	58124	-2.998403	1.041908	-12.81178	9.16059
r1yr-IOR	59747	0.0032707	0.0038605	0.0008	0.0131
Treasury repo (last)	59747	0.001097	0.0018296	-0.00193	0.00474
Adjusted capital ratio	58846	0.1144739	0.0979229	-2.679617	1
Adj cap ratio X Loan loss	58846	0.0004159	0.0012071	-0.0175545	0.0938285
Log of loan loss provision (to dep)	50627	-5.993882	1.45527	-15.00516	8.49254
Log bad loans 1 (to dep)	50753	-4.618918	1.529698	-13.57177	8.868217
Log bad loans 2 (to dep)	53790	-4.486885	1.483462	-13.57177	7.736125
Log bad loans 3 (to dep)	56182	-3.83434	1.231332	-12.07498	8.151846

Thrifts	No. of Obs.	Mean	Std. Dev.	Min	Max
Log ER/Deposits	6140	-4.274379	1.216473	-11.82187	2.813491
r1yr-IOR	6280	0.0032914	0.0038753	0.0008	0.0131
Treasury repo (mean)	6280	0.0040954	0.0056216	0.0010527	0.0185442
Tier 1 capital ratio	6280	0.1340678	0.1280314	-0.2382593	0.9819683
Tier 1 capital X Loan loss	6275	0.0003924	0.0028135	-0.0407261	0.0847798
Log of loan loss provision (to dep)	5037	-6.738302	1.595352	-12.6494	-1.401558
Log bad loans 1 (to dep)	5241	-4.440089	1.46893	-12.6937	2.477554
Log bad loans 2 (to dep)	5716	-4.334777	1.397109	-12.34652	2.477554
Log bad loans 3 (to dep)	5919	-3.563909	1.124428	-11.09375	2.624031

Notes: These data are based on the quarterly Reports of Condition and Income database (commonly called the Call Reports and the Thrift Financial Reports). Interest rate data are from the FRED II repository of the Federal Reserve Bank of St. Louis, and the Treasury repo rate is from the DTCC-GCF Repo Index of Treasury bill repurchase agreements. The negative values for the adjusted capital ratio and interaction term are due to the fact that equity is calculated net of unrealized losses on marketable equity securities. The capital ratio is adjusted for intangibles, which may make the numerator (equity net of intangibles) negative when intangibles are large.

Table 3: Tobit and CLAD Regressions of (log) Excess Reserves to Deposits Ratio: All Banks

	Tobit			CLAD		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
r1yr-IOR	-2.727***	-2.729***	-2.735***	-4.434***	-4.455***	-4.383***
	(0.08)	(0.079)	(0.079)	(0.234)	(0.205)	(0.221)
Treasury repo (last)	1.900***	1.911***	1.923***	1.790***	1.183***	1.602***
	(0.152)	(0.152)	(0.151)	(0.493)	(0.432)	(0.462)
Adjusted capital ratio	0.301***	0.301***	0.301***	-0.0567***	-0.0822***	-0.0629***
	(0.003)	(0.003)	(0.003)	(0.0161)	(0.0143)	(0.0153)
Adj cap Ratio X Loan loss	2.878***	2.822***	2.859***	3.822***	3.636***	3.898***
	(0.149)	(0.148)	(0.144)	(0.563)	(0.577)	(0.569)
Log of loan loss provision	0.00564***	0.00564***	0.00564***	-0.000357	-0.000745*	-9.44e-05
	(0.0001)	(0.0001)	(0.0001)	(0.000480)	(0.000431)	(0.000457)
Log bad loans 1	0.00266***			0.00276***		
	(0.0001)			(0.000390)		
Log bad loans 2		0.00266***			0.00281***	
		(0.0001)			(0.000344)	
Log bad loans 3			0.00266***			0.00293***
			(0.0001)			(0.000367)
Constant	0.731***	0.731***	0.731***	0.767***	0.769***	0.771***
	(0.0006)	(0.0006)	(0.0006)	(0.00287)	(0.00261)	(0.00274)
sigma	0.101***	0.101***	0.101***			
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,831	45,831	45,831	45,929	45,807	45,855

Notes: Clustered (bank-level) standard errors are reported in parentheses. CLAD regressions have bootstrapped standard errors with 1000 repetitions. Approximately 0.2 percent of the observations are left-censored at zero. The standard deviation of the ratio of the log of excess reserves to deposits is 0.116. We define excess reserves and cash as funds over 110 percent of reserves requirements. *r1yr-IOR* is the difference between the 1-year return on U.S. 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 X loan loss is the interaction effect between the adjusted capital ratio and the loan loss provision as a ratio to assets. The remaining variables are defined in the text. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Tobit Regressions of (log) Excess Reserves-to-Deposits Ratio: Banks by Size

	Large banks > 97th percentile by assets			Small banks < 95th percentile by assets		
	(1)	(2)	(3)	(4)	(5)	(6)
r1yr-IOR	-843.7***	-843.7***	-843.7***	-1.869***	-1.869***	-1.869***
	(207.2)	(207.2)	(207.2)	(0.071)	(0.071)	(0.071)
Treasury repo	83.42***	83.42***	83.42***	2.266***	2.266***	2.266***
	(20.43)	(20.43)	(20.43)	(0.123)	(-0.123)	(0.123)
Adjusted capital ratio	0.675*	0.675*	0.675*	-0.0234***	-0.0234***	-0.0234***
	(0.316)	(0.316)	(0.316)	(0.005)	(0.005)	(0.005)
Adj cap ratio X Loan loss	-23.36**	-23.36**	-23.36**	1.965***	1.965***	1.965***
	(8.469)	(8.469)	(8.469)	(0.147)	(0.147)	(0.147)
Log of loan loss provision	0.053***	0.053***	0.053***	0.0001	0.0001	0.0001
	(0.015)	(0.015)	(0.015)	(0.00001)	(0.0001)	(0.0001)
Log bad loans 1	0.0257			0.001***		
	(0.013)			(0.0001)		
Log bad loans 2		0.0257			0.001***	
		(0.013)			(0.0001)	
Log bad loans 3			0.0257			0.001***
			(0.013)			(0.0001)
Constant	1.915***	1.915***	1.915***	0.763***	0.763***	0.763***
	(0.25)	(-0.25)	(-0.25)	(-0.0005)	(-0.0005)	(-0.0005)
sigma	0.167***	0.167***	0.167***	0.0805***	0.0805***	0.0805***
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,013	1,013	1,013	42,673	42,673	42,673

Notes: Clustered (bank-level) standard errors are reported in parenthesis. Approximately 2 percent of large bank data and 0.15 percent of small bank data are left-censored at zero. We define excess reserves as funds 110 percent of reserves requirements. *r1yr-IOR* is the difference between the 1-year return on U.S. 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 X Loan loss is the interaction effect between the adjusted capital ratio and the loan loss provision. The remaining variables are defined in the text. The coefficient estimates are significantly different across bank size at the 1 percent level. *** $p<0.01$, ** $p<0.05$, * $p< 0.10$.

Table 5: CLAD Regressions of Excess Reserves (log): Banks by Size

	Large banks > 97th percentile by assets			Small banks < 95th percentile by assets		
	(1)	(2)	(3)	(4)	(5)	(6)
r1yr-IOR	-6.956***	-6.827***	-5.069***	-4.372***	-4.334***	-4.162***
	(0.814)	(0.947)	(0.844)	(0.247)	(0.230)	(0.267)
Treasury repo (last)	10.13***	10.97***	3.766**	1.327**	1.130**	0.714
	(1.762)	(1.991)	(1.803)	(0.519)	(0.482)	(0.561)
Adjusted capital ratio	0.112	0.285***	0.165**	-0.0479***	-0.0343**	-0.0252
	(0.0758)	(0.0798)	(0.0722)	(0.0169)	(0.0161)	(0.0184)
Adj cap ratio X Loan loss	-5.947***	-11.01***	-5.599***	5.117***	4.716***	3.129***
	(1.042)	(1.511)	(1.146)	(0.739)	(0.618)	(0.815)
Log of loan loss provision	0.0219***	0.0246***	0.0220***	-0.00201***	-0.000782	-0.00130**
	(0.00169)	(0.00189)	(0.00162)	(0.000527)	(0.000481)	(0.000574)
Log bad loans 1	0.00788***			0.00251***		
	(0.00154)			(0.000408)		
Log bad loans 2		0.0130***			0.00132***	
		(0.00171)			(0.000384)	
Log bad loans 3			0.00571***			0.00236***
			(0.00145)			(0.000446)
Constant	0.943***	0.962***	0.933***	0.753***	0.753***	0.755***
	(0.00760)	(0.00828)	(0.00736)	(0.00323)	(0.00298)	(0.00356)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,015	1,008	1,009	42,730	42,766	42,727

Notes: Bootstrapped standard errors are reported in parentheses. Approximately 2 percent of large bank data and 0.15 percent of the small bank data are left-censored at zero. We define excess reserves as funds over 110 percent of reserves requirements. *r1yr-IOR* is the difference between the 1-year return on U.S. 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 X Loan loss is the interaction effect between the adjusted capital ratio and the loan loss provision ratio to assets. The remaining variables are defined in the text. The coefficient estimates are significantly different across bank size at the 1 percent level. *** p<0.01, ** p<0.05, * p< 0.10.

Table 6: Tobit and CLAD Regressions for (log) Excess Reserves-to-Deposits Ratio: Thrifts

	TOBIT			CLAD		
	(1)	(2)	(3)	(4)	(5)	(6)
r1yr-IOR	-367.2**	-272.6**	-267.8**	125.5	-568.4***	-134.3
	(148.0)	(137.4)	(133.9)	(204.3)	(192.4)	(196.6)
Treasury repo (mean)	97.15**	71.14*	70.38*	-33.45	162.1***	32.84
	(43.69)	(40.96)	(39.96)	(60.90)	(57.22)	(58.42)
Tier 1 capital ratio	-0.319***	-0.330***	-0.322***	-0.169***	-0.224***	-0.184***
	(0.0724)	(0.0720)	(0.0726)	(0.00970)	(0.00979)	(0.00906)
Log of loan loss provision	-0.00333	-0.00107	0.000490	-0.450***	0.0446	-0.322**
	(0.00252)	(0.00262)	(0.00249)	(0.143)	(0.122)	(0.148)
Tier 1 capital ratio X Loan loss	5.268***	5.012***	4.949***	4.399***	3.874***	4.210***
	(1.067)	(1.270)	(1.278)	(0.519)	(0.510)	(0.495)
Log bad loans 1	0.00146			0.0670***		
	(0.00312)			(0.002)		
Log bad loans 2		-0.00285			0.0633***	
		(0.00371)			(0.00203)	
Log bad loans 3			-0.00675			0.0574***
			(0.00446)			(0.00234)
Constant	0.845***	0.791***	0.785***	0.589***	0.951***	0.732***
	(0.0765)	(0.0706)	(0.0691)	(0.102)	(0.0961)	(0.0982)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
sigma	0.115***	0.119***	0.119***	-	-	-
	(0.00688)	(0.00697)	(0.00682)	-	-	-
Observations	4,506	4,806	4,921	6,275	6,275	6,275

Notes: Clustered (at the thrift level) standard errors and bootstrapped (for CLAD estimation) standard errors are reported in parenthesis. We define excess reserves and cash as funds over 110 percent of reserves requirements. Approximately 1.9 percent of the sample is left-censored at 0. *r1yr-IOR* is the difference between the 1-year return on U.S. 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. Tier 1 cap ratio X Loan loss is the interaction effect between the ratio of Tier 1 capital to risk-adjusted assets and the loan loss provision as a ratio to assets. The remaining variables are defined in the text. *** p<0.01, ** p<0.05, * p< 0.10.

Table 7: Elasticities of Excess Reserve: All Banks and Thrifts

All Banks	(1)	(2)	(3)
r1yr-IOR	-0.159***	-0.163***	-0.166***
Treasury repo rate (last)	0.027***	0.0281***	0.0281***
Log (bad loans 1/dep)	0.0445**		
Log (bad loans 2/dep)		0.0453***	
Log (bad loans 3/dep)			0.0503***

Large Banks	(1)	(2)	(3)
r1yr-IOR	-0.4524***	-0.312***	-0.2808**
Treasury repo rate (last)	0.367***	0.250***	0.187**
Log (bad loans 1/dep)	0.640***		
Log (bad loans 2/dep)		0.920***	
Log (bad loans 3/dep)			1.154***

Small Banks	(1)	(2)	(3)
r1yr-IOR	-0.139***	-0.1427***	-0.147***
Treasury repo rate (last)	0.008**	0.008**	0.009***
Log (bad loans 1/dep)	0.023***		
Log (bad loans 2/dep)		0.0151*	
Log (bad loans 3/dep)			0.0007

Thrifts	(1)	(2)	(3)
r1yr-IOR	-0.294***	-0.237***	-0.261***
Treasury repo rate (mean)	0.409***	0.325***	0.349***
Log (bad loans 1/dep)	-0.000238		
Log (bad loans 2/dep)		-0.04522	
Log (bad loans 3/dep)			-0.0833

Note: These coefficients measure the elasticity of ER to changes in each of the covariates. Since the first two covariates are logs and the dependent variable is a log, the log covariate elasticities are evaluated as dLog(y)/dLog(x). The second group of covariates are levels or ratios so they are evaluated as (dLog(y)/dx)X x-covariates. All variables are defined in the text. *** p<0.01, ** p<0.05, * p< 0.10.

Table 8: Role of Uncertainty: Tobit Regressions of Excess Reserves (log)—Banks by Size

	Large banks (> 97th percentile by assets)			Small banks (< 95th percentile by assets)		
	(1)	(2)	(3)	(5)	(6)	(7)
VIX	-0.0100***			0.0002		
	(0.0026)			(0.0002)		
Δ VIX		-0.008***			0.0001	
		(0.0020)			(0.0002)	
IP con-var			0.579***			-0.0345***
			(0.147)			(0.0003)
Observations	1,013	1,013	1,013	42,673	42,673	42,673

Notes: We define excess reserves as funds over 110 percent of reserves requirements. Regressions include time dummies, *r1yr-IOR*, Treasury repo rate, bad loans 1, loan loss provision, adjusted capital ratio, and the interaction between loan loss provision and the adjusted capital ratio. IP con-var is a measure of the conditional variance of industrial production estimated from a GARCH model. Clustered (at the bank level) standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Descriptive Statistics for Selected Variables (2009:Q3)

All Depository Institutions

Observations		CPP N= 924			Non-CPP N= 7,186			All DI N= 8,110		
		Mean	Median	Max.	Mean	Median	Max.	Mean	Median	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). 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. t-tests for differences in the mean of each variable between CCP and non-CPP DIs are significant at the 1 percent confidence level (*** $p<0.01$).

Table 10: Descriptive Statistics for Selected Variables (2009:Q3)

Banks

Observations		CPP N= 860 Mean	CPP Median	CPP Max.	Non-CPP N= 6,493 Mean	Non-CPP Median	Non-CPP Max.	All Banks N= 7,353 Mean	All Banks Median	All Banks 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 Median	CPP Max.	Non-CPP N= 693 Mean	Non-CPP Median	Non-CPP Max.	All Thrifts N= 757 Mean	All Thrifts Median	All Thrifts 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). 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. t-tests for differences in the mean of each variable between CCP and non-CPP DIs are significant at the 1 percent confidence level (*** p<0.01) or 10 percent confidence level (* p<0.10)

Table 11: Probit Estimates for TARP Beneficiaries and Non-TARP Banks

Variables	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
Pretax net income/TA	-14.8823	2.7643
Brokered deposits/TA	0.5483	0.2760
Other borrowed funds maturing within 1-yr/TA	1.0752	0.6340
Pledged securities/TA	0.2387	0.0884
Pretax 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
Federal Reserve Board	0.5051	0.2036
ints55y5	0.0688	0.0267
Constant	-2.0308	0.4437
Pseudo-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 used in calculating the propensity score. We estimate this probit at the level of BHC. TA refers to total assets; TL refers to total loans; ints55y5 is the interaction of real estate loan shares with real estate prices; top 40 indicates the BHC is among the largest 40 BHCs by assets. Federal Reserve 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. y-y designates year over year. All covariates are significant at the 5 percent confidence level or better.

Table 12: Difference-in-Differences Analysis: Cash-to-Asset Ratios

	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 cash-to-assets ratio in the target quarter and that in the previous quarter; $ATT2$ is the difference between the cash-to-assets ratio in a given quarter and the previous quarter. ** $p<0.05$.

Table 13: 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

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