Safer Ratios, Riskier Portfolios: Banks' Response to Government Aid[*]

Ran Duchin
Ross School of Business
University of Michigan
duchin@umich.edu

Denis Sosyura
Ross School of Business
University of Michigan
dsosyura@umich.edu

First draft: August 2010

This version: September 2011

Abstract

We study the effect of government assistance on bank risk taking. Using hand-collected data on bank applications for government financial assistance, we control for the selection of fund recipients and investigate the effect of both application approvals and denials. To distinguish banks' risk-taking behavior from changes in economic conditions, we also control for the volume and quality of credit demand based on micro-level data on home mortgages and corporate loans. Our difference-in-difference analysis indicates that after the bailout, bailed banks approve riskier loans and shift investment portfolios toward riskier securities. However, this shift in risk occurs mostly within the same asset class and, therefore, has little effect on the closely-monitored capitalization levels. Consequently, bailed banks appear safer according to the capitalization requirements, but show a significant increase in market-based measures of risk. Overall, our evidence suggests that banks' response to capital requirements may erode their efficacy in risk regulation.

[*] We gratefully acknowledge financial support from the Millstein Center for Corporate Governance at Yale University. We also thank the participants at the 2010 Yale-Oxford Conference on Corporate Governance, the 2011 Financial Intermediation Research Society (FIRS) annual meeting, the 2011 FinLawMetrics Conference at Bocconi University, and seminar participants at the Board of Governors of the Federal Reserve System, the University of Illinois, and the University of Michigan.

The financial crisis of 2008-2009 resulted in an unprecedented liquidity shock to the financial sector. This shock had a substantial impact on the scale of banking activity, both in the U.S. (Gorton, Lewellen, and Metrick, 2010; DeYoung, Gron, Torna, and Winton, 2010) and overseas (Beltratti and Stulz, 2010; Puri, Rocholl, and Steffen, 2011). To stabilize the banking system, governments around the world initiated a wave of capital assistance to financial firms. Many economists and regulators argue that this wave altered the perception of government protection of the financial sector (Kashyap, Rajan, and Stein, 2008) and created a precedent that will have a profound effect on the future behavior of financial institutions.[1] At the forefront of this debate is the effect of the bailout on risk taking by financial institutions (Flannery 2010), as risk taking, coupled with inadequate regulation (Levine 2010), is often blamed for leading to the crisis in the first place. In this paper, we study whether and how the recent bailout affected risk taking in credit origination and investment activities of U.S. financial institutions.

The economic theory offers diverging predictions regarding the effect of government bailouts on bank risk taking. On the one hand, a bailout may be viewed as a signal of implicit government protection of certain financial institutions, which raises the probability that a protected bank will be saved in case of distress in the future.[2] Under this interpretation, the bailout is expected to encourage risk taking by protected banks by reducing investors' monitoring incentives (Flannery 1998) and increasing moral hazard. For example, Merton (1977) and more recently Ruckes (2004) theoretically show that the introduction of government guarantees in other contexts, such as deposit insurance, results in higher risk taking.

A contrasting theoretical view argues that bailouts may reduce risk-taking by protected banks. In particular, a bailout raises the value of a bank charter by reducing the refinancing costs and increasing the bank's long-term probability of survival. In turn, the higher charter value, which a bank would lose in case of failure, acts as a deterrent to risk taking (Keeley 1990). Importantly, the disciplining effect of the charter value is predicted to be amplified under the conditions similar to those observed during the recent wave of bailouts. For example, when the

[1] This view is summarized by the former Fed Chairman, Paul Volker, "What all this amounts to is an unintended and unanticipated extension of the official safety net…The obvious danger is that risk-taking will be encouraged and efforts at prudential restraint will be resisted." (Testimony before the House Financial Services Committee on October 1, 2009).

[2] For example, this view is expressed by the oversight bodies of the Troubled Asset Relief Program (see, for example, Quarterly Report to Congress of the Inspector General of the Troubled Asset Relief Program, January 30, 2010, p. 6)

bailout is discretionary and follows an adverse macroeconomic shock, as was the case during the recent crisis, the risk-reducing effect of the charter value is predicted to outweigh moral hazard, resulting in a lower equilibrium level of risk (Goodhart and Huang 1999; Cordella and Yeyati 2003).

A third hypothesis is that a bailout would have little effect on bank risk-taking behavior. In particular, it is possible that the influence of moral hazard, investors' monitoring, and charter value would cancel each other out, thus muting any net effect on bank behavior. Similarly, it is possible that government oversight of bailed institutions, coupled with institutional restrictions on their corporate policies, would constrain a significant shift in bank behavior.

Our empirical analysis focuses on the financial crisis of 2008-2009, thus exploiting an economy-wide liquidity shock, which simultaneously affected an unusually large cross-section of firms and resulted in the biggest bailout in corporate history – the Troubled Asset Relief Program (TARP). In particular, we study the effect of the first and largest TARP initiative – the Capital Purchase Program (CPP) – which invested $205 billion in financial institutions. Using a hand-collected dataset on the status of bank applications for federal assistance, we are able to observe both banks' decisions to apply for bailout funds and regulators' decisions to grant assistance to specific institutions. This research setting allows us to control for the selection of bailed firms and to study the risk taking implications of both bailout approvals and bailout denials. Our risk analysis spans three channels of bank operations: (1) retail lending (mortgages), (2) corporate lending (large syndicated loans), and (3) investment activities (financial assets).

Our first set of empirical tests focuses on the retail lending market. Our data allow us to observe bank lending decisions on nearly all mortgage applications submitted in the United States in 2006-2009 and to account for key loan characteristics, such as borrower income and demographics, loan amount, and property location. This empirical design enables us to address a critical identification issue – to distinguish supply-side changes in bank credit origination from the demand-side changes in the volume and quality of potential borrowers. In difference-in-difference tests, we do not find a significant change in the volume of credit origination by CPP participants after federal capital injections, as compared to banks that had similar financial characteristics but were not approved for federal investments. We also do not detect a significant change in the distribution of borrowers between government-supported and other financial institutions. Our main finding is that after receiving federal capital, bailed banks shifted their credit origination toward riskier mortgages, as measured by the borrower's loan-to-income ratio and the high-risk loan indicator based on the loan rate. As a result, the fraction of the riskiest mortgages in the originated credit increased for banks approved for CPP, but declined for banks denied by the regulators.

Our findings are qualitatively similar for large corporate loans. Our tests focus on the variation in the share of credit originated by CPP participants at the level of each syndicated loan. As with retail loans, we do not find a significant effect of federal investments on credit origination by program participants relative to their nonparticipating peers with similar financial condition and performance. Instead, in difference-in-difference analysis of banks granted and denied government assistance, we document a robust shift by CPP recipients toward originating higher-yield, riskier loans. After receiving federal assistance, CPP banks increase their share of credit issuance to the riskiest corporate borrowers, as measured by their credit rating and bond yields, and reduce their share of credit issuance to safer firms. Altogether, our findings for both retail and corporate loans suggest that the bailout was associated with a shift in credit rationing rather than the volume of credit, leading to a marked increase in the riskiness of originated credit by government-supported institutions.

We find a similar increase in risk-taking by government-supported banks in their investment activities. After receiving federal capital, CPP participants significantly increased their investments in risky securities, such as equities "acquired to profit from short-term price movements", mortgage-backed securities, and long-term corporate debt. For the average CPP bank, the combined weight of these asset classes in the investment portfolio increased by 10.0%, displacing safer assets, such as Treasury bonds, short-term paper, and cash equivalents. The increase in the allocations to riskier assets is highly significant relative to non-recipient banks, holds after controlling for bank fundamentals, and cannot be explained by the changes in security valuation. Using asset yields as a market measure of risk, our difference-in-differences estimates suggest that the average interest yield on investment portfolios of CPP participants increased by 31.5% after the bailout relative to nonpartcicipating banks.

Overall, our analysis at the micro-level indicates a robust increase in risk taking in both lending and investment activities by bailed financial institutions, as compared to fundamentally similar non-bailed banks. After indentifying the sources of the shift in risk-taking at the micro-level, we present aggregate evidence on the perceived risk of bailed and non-bailed financial institutions. We find that federal capital infusions significantly improved capitalization levels of recipient banks, with the average capital-to-assets ratio for TARP recipients increasing from 9.9% to 10.9% after federal capital infusions. However, the reduction in leverage was more than offset by an increase in the riskiness of the asset mix of recipient banks. The net effect was a marked increase in the riskiness of bailed financial institutions following federal investments as compared to their non-bailed counterparts with similar financial characteristics. This result holds robustly whether bank risk is measured by accounting-based measures (earnings volatility and ROA volatility), market-based proxies of risk (beta and stock volatility), or the aggregate measure of distance to default (z-score). The overall effect on banks risk is also economically significant. For example, the average beta of CPP participants increased from 0.80 in 2008 to 1.01 in 2009, whereas this figure remained largely unchanged for non-bailed institutions.

One important consideration in interpreting our results is the selection of CPP recipients. Since the approval of program applicants is not random, it is possible that the Treasury invested in those financial institutions that were more likely to experience a significant future shock as a result of their crisis exposure or other factors. In this case, it is possible that recipient banks would have experienced an even greater increase in risk without government aid.

We address sample selection in several ways. First, we explicitly control for the declared set of financial criteria used by banking regulators for evaluating financial institutions, such as capital adequacy, asset quality, profitability, and liquidity, as well as for the bank's size and exposure to the crisis (proxied by foreclosures and non-performing loans). In addition to parametric estimation, we repeat our tests in matched samples of recipients and non-recipients based on an array of financial variables and obtain similar results. As another test, we offer evidence from an instrumental variable approach, using banks' political connections as our instrument. Our results remain unchanged under the instrumental variable method.

Another issue important for interpreting our results is to what extent the increase in bank risk taking was the initiative of the recipient banks rather than an outcome of government intervention in credit policies and investment activities of recipient institutions. In this respect, the institutional design of CPP offers a convenient setting, since CPP provided recipient banks with significant flexibility with respect to the deployment of government funds; most important, banks were not required to track or report the use of this capital. Consistent with this view, anecdotal evidence from bank CEOs suggests that many of them viewed CPP capital infusions as cash windfalls (McIntire 2009). Second, to the extent that recipient banks were subject to government regulation as part of CPP, these restrictions were explicitly imposed to reduce rather than increase bank risk taking.[3]

Yet it is still plausible that credit origination toward riskier corporate and retail borrowers may have been part of implicit government mandates or private discussions between recipient banks and their regulators. While this conjecture is inherently difficult to test, we seek to provide evidence in this direction by collecting data on banks that applied for CPP funds, were approved for federal investment, but did not receive TARP funds for various institutional reasons described in the empirical section. We then compare risk taking by this subset of non-recipients relative to the banks that *did* receive the money and were similar in size, financial condition, and performance at the time of CPP approval. If the shift in bank risk taking is associated with the certification of government support in case of distress (i.e. moral hazard), we would expect a similar increase in risk-taking for all banks that were approved for CPP funds, regardless of whether or not they eventually received federal funds. On the other hand, if the risk-taking at CPP banks is associated with implicit government regulation, the increase in risk taking should be observed only at banks that received capital rather than at all approved banks. Our evidence supports the former view. We find a similar increase in risk taking across all banks approved for bailout funds, regardless of whether or not they received the money and were subject to the subsequent government regulation. This analysis suggests that the increase in bank risk taking was attributable, at least partially, to the moral hazard hypothesis postulated in the theoretical literature and predicted as a response to the bailout in the U.S. (Kashyap, Rajan, and Stein, 2008).

Our article has several implications. First, one of the most significant recent events was the credit downgrade of U.S. debt in August 2011 by Standard and Poor's for the first time since the beginning of ratings in 1860. Among the reasons for the downgrade cited by the rating agency was the increased riskiness of U.S.

[3] In particular, the government restricted incentive compensation at recipient banks to prevent excessive risk taking and imposed restrictions on share repurchases and dividend payments to prevent asset substitution.

financial institutions. Our paper identifies the sources of the increased risk in the financial system and links them to the initial bailout policy and predictions of academic theory. Second, our findings suggest an asymmetric response of financial institutions to liquidity constraints. While previous research has shown that a negative shock to bank liquidity forces a cut in lending (Puri, Rocholl, and Steffen, 2011), we find that a significant increase in available capital need not result in increased volume of credit, but, instead may lead to a shift in credit rationing. In particular, CPP capital provisions were associated with an increase in banks' security investments and capital reserves and appear to have had little stimulatory effect on the overall level of lending. Finally, although bank capital requirements are traditionally used as a key instrument in bank regulation (Bernanke and Lown, 1991), we show that the strategic response of financial institutions to this mechanism erodes and, in some cases, reverses its efficacy. Specifically, CPP banks significantly increased their risk within regulated asset classes, while, at the same time, improving their capital ratios.

The rest of the paper is organized as follows. Section 1 reviews related literature. Section 2 describes the data and presents summary statistics. Section 3 reports empirical results. The article concludes with summary and commentary.

1. Related Literature

One of the most prominent features of the past decade has been an increased role of government regulation. During the financial crisis of 2008-2009, this regulation reached unprecedented scale, which was formerly seen as hardly plausible in developed economies – effective nationalization of some of the largest corporations and government assistance to more than 700 financial institutions. Since bailouts of private firms provide perhaps the cleanest, most far-reaching case of government intervention and have major policy implications, this topic has played a key role in the theoretical literature on financial regulation and the optimal design of the financial system.

A central issue in the models of government assistance to the private sector has been the effect of such a policy on firms' risk-taking behavior. On the one hand, a number of studies show analytically that the downside protection from the government encourages risk taking by inducing moral hazard, both by individual banks (Mailath and Mester, 1994) and at the aggregate level (Penati and Protopapadakis, 1988). Yet other studies demonstrate that moral hazard can be more than offset by the disciplining effect of a bank's charter value, ultimately resulting in a lower level of risk (Goodhart and Huang 1999; Cordella and Yeyati 2003). The distinction between these views is critical for the optimal design of the government safety net, a topic recently examined in the theoretical frameworks of Gorton and Huang (2004), Diamond and Rajan (2005, 2011), and Philippon and Schnabl (2010), among others. In addition, the effect of the bailout policy on risk taking is also highly relevant from the perspective of the newly-adopted financial regulation, such as the Dodd-Frank Act of 2010 and Basel III, which aims to promote financial stability and constrain risk taking by financial intuitions.

Despite the important role of this topic in the theoretical frameworks of government intervention and in policy research, the empirical evidence on bailouts has been constrained by the scarcity of such events in the western world. As a result, previous research has mainly examined other forms of government guarantees, such as deposit insurance. The findings in this literature are mixed. Hovakimian and Kane (2000) report evidence of higher risk-taking by banks in the presence of deposit insurance, while Gropp and Vesala (2004) find that explicit deposit insurance is associated with lower risk-taking. In a cross-country study, Laeven and Levine (2009) find mixed evidence on the relation between government guarantees and bank risk-taking and attribute the effect to the heterogeneity in banks' governance structures. Several papers use other proxies for government guarantees, such as bank size or share of government ownership, under the assumption that larger banks or banks with greater government interest are more likely to receive federal assistance in case of distress. These studies also report mixed results. For example, De Nicolo (2001) documents a positive association between the share of government-owned banks and insolvency risk, but Barth, Caprio, and Levine (2004) find no significant relation between government ownership and bank fragility.

In contrast to studies based on indirect proxies for the (likely) government protection, such as bank size or ownership structure, our paper seeks to provide direct evidence on the consequences of explicit approvals and denials of government assistance to financial firms applying for federal aid. Also, our data enables us to directly observe the changes in the volume and quality of credit demand, thus distinguishing the active changes in banks' liquidity creation and risk-taking after the bailout from the changes in economic conditions. To our knowledge, our paper is the first study of government assistance to the financial sector that utilizes data on credit demand. Finally, our empirical setting enables us to study an unusually large cross section of firms subject to a simultaneous, unexpected liquidity shock in the world's largest and most developed financial market. This research design helps overcome the identification issues that confound empirical inference in cross-country studies, where country-level government protection is compared across nations with different legal, regulatory, and governance systems.

Our paper also contributes to the growing literature on government regulation during the recent financial crisis. Levine (2010) argues that the crisis reflected a systemic failure of government regulation, while Harvey (2008) critiques the government's response to the crisis and points out its inefficiencies. Diamond and Rajan (2011) discuss various alternatives to the bailout and assess their costs and benefits. Veronesi and Zingales (2010) calculate the costs and benefits of government capital infusions in the ten largest banks and argue that the first recipients received significant subsidies. In our paper, we refrain from the assessment of bailout alternatives or the evaluation of program performance; rather, our primary goal is to use this research setting to study the effect of government intervention on the risk taking behavior in the financial sector.

Finally, our paper adds to the literature on credit rationing during the recent financial crisis. DeYoung, Gron, Torna, and Winton (2010) study the supply of small business loans before and during the crisis and show that banks' credit origination during the crisis critically depended on the liquidity of existing (overhanging) loans. Puri, Rocholl, and Steffen (2011) study the supply and demand effects of the financial crisis on bank lending in Germany and find that banks more severely affected by the crisis reject more loan applications, particularly if these banks are liquidity constrained. These papers stress the importance of bank liquidity and capitalization for their lending policies. While a sudden drop in bank liquidity constrains lending, the results in our paper show that liquidity infusions need not lead to credit expansion, thus questioning the efficacy of this mechanism in stimulating credit origination.

2. Data and Summary Statistics

2.1 Capital Purchase Program

On October 3, 2008, the Emergency Economic Stabilization Act (EESA) was signed into law. The act authorized TARP – a system of federal initiatives aimed at stabilizing the U.S. financial system. On October 14, 2008, the government announced the Capital Purchase Program (CPP), which authorized the Treasury to invest up to $250 billion in financial institutions. Initiated in October 2008 and terminated in December 2009, CPP invested $204.9 billion in 707 financial institutions, becoming the first and largest of the 13 TARP programs.

To apply for CPP funds, a qualifying financial institution (QFI) – domestic banks, bank holding companies, savings associations, and savings and loan holding companies – submitted a short two-page application (by the deadline of November 14, 2008) to its primary federal banking regulator – the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), the Office of the Comptroller of the Currency (OCC), or the Office of Thrift Supervision (OTS). If the initial review by the banking regulator was successful, the application was forwarded to the Treasury, which made the final decision on the investment.

The review of CPP applicants was based on the standard assessment system employed by bank regulators – the Camels rating system, which evaluates 6 dimensions of a financial institution: *C*apital adequacy, *A*sset quality, *M*anagement, *E*arnings, *L*iquidity, and *S*ensitivity to market risk. The ratings in each category, which range from 1 (best) to 5 (worst), are assigned based on financial ratios and on-site examinations. In Appendix A, we provide a description of our proxies for each of the 6 assessment categories, along with the definitions of other variables used in our study. We use the Camels evaluation criteria as part of our controls for the selection of CPP participants.

In exchange for CPP capital, banks provided the Treasury with cumulative perpetual preferred stock, which pays quarterly dividends at an annual yield of 5 percent for the first five years and 9 percent thereafter. The amount of the investment in preferred shares was determined by the Treasury, subject to the minimum threshold of 1 percent of firms' risk-weighted assets (RWA) and a maximum threshold of 3 percent of RWA or $25 billion, whichever was smaller. In addition to the preferred stock, the Treasury obtained warrants for the common stock of public firms. The warrants, valid for ten years, were issued for such number of common shares that the aggregate market value of the covered common shares was equal to 15 percent of the investment in the preferred stock.

2.2 Sample Firms

To construct our sample of firms, we begin with a list of all public domestically-controlled financial institutions that were eligible for CPP participation and were active as of September 30, 2008, the quarter immediately preceding the administration of CPP. This initial list includes 600 public financial institutions. We focus on public firms because the regulatory filings of public firms allow us to identify whether or not a particular firm applied for CPP funds. The public financial institutions account for the overwhelming majority (92.7 percent) of all capital invested under CPP. In particular, the 295 public recipients of CPP funds obtained $190.1 billion under CPP, according to the data from the Treasury's Office of Financial Stability.

To identify CPP applicants and to determine the status of each application, we read quarterly filings, annual reports, and proxy statements of all CPP-eligible public financial institutions, starting at the beginning of the fourth quarter of 2008 and ending at the end of the fourth quarter of 2009. We also supplement these sources with a search of each firm's press releases for any mentioning of CPP or TARP and, in cases of missing data, we call the firm's investment relations department for verification. Using this procedure, we are able to ascertain the application status of 538 of the 600 public firms eligible for CPP (89.7 percent of all eligible public firms).

From the set of 538 firms with available data, we exclude the first wave of CPP recipients, namely the nine largest program participants announced at program initiation on October 14, 2008, thus arriving at our final sample of 529 firms. The excluded firms comprise Citigroup, JP Morgan, Bank of America, Goldman Sachs, Morgan Stanley, State Street, Bank of New York Mellon, Merrill Lynch, and Wells Fargo (including Wachovia). It has been argued that these firms constitute "too-big-to-fail" institutions. Under this argument, the approval for CPP was likely to have a less significant effect on the perceived government protection of the firms that were already viewed as systemically important. Additionally, there is anecdotal evidence that these firms were asked to participate in CPP by the regulators to provide a signal to the market at the launch of the program.[4] We follow a conservative approach and exclude these firms from our sample. Our results are not sensitive to this sample restriction and remain the same if we retain these nine firms.

Of the 529 firms in our final sample, 424 firms (80.2 percent) submitted CPP applications, and the remaining 105 firms explicitly stated their decision not to apply for CPP funds. Among the 424 submitted applications, 337 applications (79.5 percent) were approved for funding. Finally, among the firms approved for

[4] Solomon, Deborah and David Enrich, "Devil Is in Bailout's Details", *The Wall Street Journal*, October 15, 2008.

funding, 286 (84.9 percent) accepted the investment, while 51 firms (15.1 percent) declined the funds. Figure 1 illustrates the partitioning of eligible firms into each of these subgroups.

Financial data on QFIs come from the quarterly Reports of Condition and Income, commonly known as Call Reports, which are filed by all active FDIC-insured institutions. Our sample period starts in the first quarter of 2006 and ends in the fourth quarter of 2010, the latest quarter with available call reports at the time of the analysis. Panel A of Table 1 provides sample-wide summary statistics for Camels variables and other characteristics for the QFIs included in our sample.

The average (median) QFI has book assets of $2.2 billion ($147.6 million). The Camels variable Capital Adequacy, which reflects a bank's Tier 1 risk-based capital ratio, shows that the vast majority of banks are well capitalized. For example, the 50th percentile of the Tier 1 ratio in our sample is 10.7 percent, nearly double the threshold of 6 percent stipulated by the FDIC's definition of a well-capitalized institution. The variable Asset Quality captures loan defaults and shows the inverse of the ratio of net losses on loans to the average amount of outstanding loans and leases. The variable Earnings, measured as the return on assets (ROA), shows that the average (median) bank in our sample has a quarterly ROA of 0.19 (0.55) percent, consistent with the typical profitability indicators of banking institutions characterized by a large asset base. To proxy for a firm's exposure to the financial crisis, we use the ratio of foreclosed assets to the total value of loans and leases. This ratio for the average (median) bank in our sample was 0.39 (0.15) percent.

2.3 Loan Data

We obtain loan application data from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. This dataset covers approximately 90 percent of mortgage lending in the U.S. (Dell'Ariccia, Igan, and Laeven, 2009), with the exception of mortgage applications submitted to the smallest banks (assets under $37 million) located in rural areas.[5] The unique feature of these data is the coverage of both approved and denied mortgages,

[5] According to the Home Mortgage Disclosure Act of 1975, most depository institutions must disclose data on applications for home mortgage loans, home improvement loans, and loan refinancing. A depository institution is required to report if it has any office or branch located in any metropolitan statistical area (MSAs) and meets the minimum threshold of asset size. For the year 2008, this reporting threshold was established at $37 million.

which enables us to study bank lending decisions at the level of each application. This attribute is important for our empirical tests, since it will allow us to distinguish the changes in credit origination driven by loan demand (the number of applications and their quality) from those driven by credit rationing of financial institutions.

At the level of each application, we are able to observe the characteristics of the borrower (e.g., income, gender, and race), the features of the loan (e.g., loan amount, loan type, and property location), and the decision of the bank on the loan application (e.g., loan originated, application denied, application withdrawn, etc.). While banks are not required to disclose applicants' credit scores or to provide the interest rate for every mortgage, they must report the interest rate spread on loans with an APR of at least 300 (500) basis points above the Treasury of comparable maturity for first-lien (subordinate-lien) loans.[6] Previous research has shown that the rate spread indicator in HDMA data serves as a close proxy for subprime mortgages.[7] The borrower and loan characteristics enable us to study the changes in banks' credit rationing across riskier and safer loans. Finally, the HMDA data provide the location of the property underlying each mortgage application. This location is reported by the U.S. census tract, (median population of 4,066 residents), an area "designed to be homogeneous with respect to population characteristics, economic status, and living conditions".[8] This level of data granularity allows us to focus on the differences in lending decisions by different banks within the same small region, while controlling for the conditions specific to the local housing market.

To construct our sample of mortgage applications, we aggregate financial institutions in HMDA at the level of the bank holding company and match them to our list of QFIs. Among the 529 QFIs in our sample, 508 institutions (which account for 97% of bank assets) reported their mortgage activity under HMDA in 2006-2009. Next, we limit our analysis to applications that were either denied or approved, thus excluding observations with ambiguous statuses, such as incomplete files and withdrawn applications. Since the focus of our analysis is on

[6] For loan applications received on or after October 1, 2009 banks are now required to report the actual rate spread between the APR and the Average Prime Offer Rate if it is at least 150 basis points for first liens or 350 basis points for subordinate liens.

[7] Dell'Ariccia, Igan, and Laeven (2009) show that the classification of subprime loans based on the credit rate spread ensures a correlation of approximately 80% with the classification derived from the list of subprime lenders developed by the U.S. Department of Housing and Urban Development (HUD).

[8] Tract definition from the U.S. Census Bureau, Geographic Areas Reference Manual, p. 10-1. http://www.census.gov/geo/www/GARM/Ch10GARM.pdf

credit origination, we restrict our sample to new loans rather than refinancing and purchases of existing loans. We also exclude loans that were sold in the same calendar year they were originated because these loans have relatively a lesser effect on the risk of the originating QFI. Finally, we also drop observations with missing or imprecise data.

Panel B of Table 1 provides summary statistics for our sample of mortgage applications. Approximately 62.2% of applications are approved, and the average amount of the loan is $166,000. The data show significant variation in the loan-to-income ratio, a measure commonly used in the mortgage industry as an indicator of loan risk. This ratio in our sample ranges from 0.75 in the 25^{th} percentile to 2.7 in the 75^{th} percentile. Approximately 9.7 percent of mortgages have an APR spread over Treasuries of at least 300 basis points, indicating high-risk loans.

To control for temporal dynamics in loan demand within each housing market, we also collect data on macroeconomic variables that influence the demand for home mortgages. For each U.S. census tract, we obtain data on the dynamics of home vacancies and the total number of housing units from the U.S. Postal Service. To control for the changes in the demographic drivers of housing demand, we collect county-level data on per capita income, population, and unemployment from the Bureau of Economic Analysis. We supplement these data with the quarterly index of housing prices by Metropolitan Statistical Area (MSA) from the Federal Housing Finance Agency.

In addition to the analysis of retail lending, we also collect data on corporate credit facilities from DealScan. This dataset covers large corporate loans, the vast majority of which are syndicated, i.e. originated by one or several banks in a syndicate. DealScan reports loans at origination, allowing us to focus on the issuance of new corporate credit and to avoid contamination from the drawdowns of previously-made financial commitments. Each unit of observation is a newly-issued credit facility, which provides such information as the originating bank(s), date of origination, loan amount, interest rate, and the corporate borrower.

According to DealScan, between 2006 and 2009, 179 QFIs in our sample originated $3.5 trillion in corporate credit. The average (median) loan amount during our sample period is $582 ($300) million. Borrowers of these credit facilities are typically large firms. As shown in Panel B of Table 1, over our sample period, the average fraction of CPP recipients in the total number of lenders per loan is 67.3 percent. The breakdown of the newly-issued credit between CPP recipients and nonrecipients at the loan level allows us to control for the changes in investment opportunities of industrial firms. As a result, this data feature enables us isolate the effect of TARP, if any, on firm access to credit, as proxied by the share of loans originated by CPP recipients in the firm's funding mix.

3. Results

3.1 Selection

Our goal is to isolate the effect of government assistance on bank risk-taking, while controlling for the volume and quality of credit demand, as well as for the differences in financial characteristics between the institutions that were granted and denied government aid. It is therefore important that we identify a treatment effect of CPP rather than the potential effect of selection of CPP recipients, since institutions approved for government aid may be selected on attributes correlated with subsequent risk-taking and lending. For example, CPP funds may be intentionally allocated to *ex-ante* safer banks, which were better positioned to increase their risk after receiving government funds. To mitigate selection concerns, we employ two selection models.

Our first model utilizes an Instrumental Variable (IV) approach based on firms' political connectedness. Duchin and Sosyura (2009) show that banks' political connections influenced the distribution of TARP capital (instrument inclusion restriction). In particular, banks headquartered in the election districts of Congress representatives that served on the House Financial Services Committee, banks connected to Treasury, Congress, and banking regulators via boards of directors, banks that lobbied Treasury, Congress and banking regulators on the issues of banking, finance, or bankruptcy in 2008-2009, and banks that made political campaign contributions to the House Financial Services Committee in the 2008 election cycle were more likely to receive TARP funds. Following Duchin and Sosyura, we construct an index of political connectedness by calculating the firm's percentile ranking in our sample on each of the four measures of political influence and then finding the mean of these rankings to derive an aggregate political connections index, normalized to lie between 0 and 1. Appendix A provides further details on the variables used in the construction of the index.

For our purposes, an important observation is that political connectedness has been shown to affect CPP approval, but a priori, it is unlikely to directly affect loan approval rates, investment portfolios, and risk taking of banks (exclusion restriction, which we formally test below). Under this premise, political connectedness is a plausible instrument for CPP approval. Our IV estimations are performed in two stages. In the first stage, CPP approval is regressed on the excluded instrument (political connections index) and a set of independent bank-level control variables included in the second stage regressions. The predicted approval propensity from the first stage is then used in the second-stage regressions. The relevant test statistics of the first-stage regression are reported below. The political connectedness variable is found to have a positive and statistically significant effect on CPP approval. Accordingly, the likelihood ratio Chi-Square test (similar to the F-test in OLS regression) of the significance of the instrument in the first-stage model is highly significant (p-values lower than 0.001). To complement the exclusion likelihood ratio test, we also consider Shea's (1997) partial R-square from the first-stage regressions. The R-square exceeds the suggested (rule of thumb) hurdle of 10%, with an average value of 13.9%. These statistics suggest that our instrument is relevant in explaining the variation of our model's potentially endogenous regressors.

The second selection model relies on a subsample of propensity score-matched firms. Specifically, we construct a subsample of banks that were approved for CPP capital matched on approval propensity to their peers that were not approved for CPP. Since our sample consists of 337 firms that were approved for CPP and only 87 firms that were not approved, we start with the sample of 87 unapproved firms, and match each of them to the approved firm with the closest approval propensity score. The propensity scores are estimated from a probit regression of the approval decision on a host of bank-level variables, which include capital adequacy, asset quality, management quality, earnings, liquidity, sensitivity to market risk, foreclosures, size, age, and the political connections index. This procedure results in a matched sample comprised of 174 firms.

Panel C of Table 1 compares the approved and unapproved matched firms on bank-level observable variables. The evidence indicates that the two groups of matched firms are similar across the measures of financial condition and performance, exposure to the crisis, and demographics. In particular, the capital adequacy, asset quality, earnings, foreclosure rate, size, and age, are all indistinguishable between the two groups at conventional significance levels. We estimate all subsequent tests using both selection models to mitigate selection concerns.

3.2 Retail Lending

In this subsection, we study the effect of CPP on credit rationing across mortgage borrowers with different risk characteristics. We use two proxies for borrower risk in home mortgages. The first proxy is the loan-to-income ratio, which has been shown to be closely associated with credit risk. The second proxy is the interest rate spread on loans with an APR of at least 300 (500) basis points above the Treasury of comparable maturity for first-lien (subordinate-lien) loans.

We begin by presenting nonparametric evidence on the changes in the approval rates for home mortgages between CPP recipients and non-recipients before and after TARP. Since our data on mortgage applications are provided by calendar year, we define the period before TARP as 2006-2008 and the period after TARP as 2009. While each CPP recipient received its federal investment on a different date, nearly all investments in our sample (89.9% by capital amount) were announced in October-December 2008. Therefore, for simplicity and standardization, we define the period beginning in January 2009 as the period "After TARP". Our results are not sensitive to this definition and remain qualitatively unchanged if we use just the year 2008 as the before period and the year 2009 as the after period. As another check for the validity of the data-imposed cutoffs at the end of the calendar year, we repeat the analysis after excluding banks that received CPP capital in the late 2008 or after the first two months of 2009, and obtain similar results.

We divide our sample of mortgage applications into equal quintiles based on the loan-to-income ratio of the borrower. The ranking of quintiles is such that quintile 1 represents safer borrowers (lower loan-to-income ratio), and quintile 5 corresponds to riskier applicants. To illustrate, the average loan-to-income ratio for quintile 1 is 0.40, which would be observed, for example, for a borrower with an annual income of $200,000 taking on a mortgage loan of $80,000. In contrast, the average loan-to-income ratio for quintile 5 is 4.3, corresponding to an applicant with an income of $22,000 wishing to borrow $94,600.

Table 2 presents the results of univariate difference-in-differences comparisons in mortgage loan approval rates across the five loan-to-income quintiles. The results indicate that recipient banks tightened their approval rates for the safer borrowers after TARP and increased the approval rates for the riskier borrowers. To see this, note that the approval rates for recipients dropped from 74.1% to 63.3% in quintile 1, and increased from 48.4% to 53.0% in quintile 5. More importantly, a similar trend emerges after controlling for the change in approval rates of non-recipients. This is evident from the difference-in-differences estimates reported in the last column. Compared to non-recipients (i.e. banks that applied for CPP but were denied government funds), recipient firms cut their approval rates by 15.1% in quintile 1 after TARP, compared to an increase of 2.5% in quintile 5 after TARP. These estimates are all significantly different from zero at the 1 percent level.

We obtain similar results when we use the interest rate spread on loans as an alternative measure of borrower risk. Here, however, the analysis is restricted to approved mortgage applications, since the spread is not reported for unapproved applications. To identify differences in borrower risk, we compare between the fraction of CPP recipients in the total originations of risky loans (defined as loans with an interest rate spread of at least 300 (500) basis points above the Treasury) before and after TARP. These results are reported in the bottom row of Table 2. The estimates show that the fraction of CPP recipients originating risky loans has increased from 91.2% before TARP to 96.7% after TARP. As shown in the last column, the difference-in-difference estimate is statistically significant at the 1 percent level.

After providing suggestive evidence, we proceed with more formal tests of the effect of TARP on bank credit rationing across borrowers and report our results in Table 3. The unit of observation in our analysis is a mortgage application submitted to a QFI during our sample period of 2006-2009. The dependent variable in these tests is an indicator equal to 1 if the mortgage application is approved and 0 otherwise. The main independent variable of interest is the interaction term of the dummy *After TARP* (which takes on the value of 1 in 2009 and 0 otherwise) and the dummy *TARP Recipient*. The coefficient on this variable captures the effect of TARP, if any, on loan approval rates of participating banks. We estimate the regressions separately in each loan-to-income quintile.

To capture the effect of TARP capital infusions, we would like to control for those bank characteristics that are correlated with TARP investments and may also influence a bank's credit origination. Therefore, our set of independent variables includes controls for the following bank characteristics: size (the natural logarithm of book assets), the Camels measures of banks' financial condition and performance used by banking regulators, and a proxy for bank's exposure to the crisis (foreclosures).

Since our focus in on the bank lending decisions, we would also like to control for the variation in the quality of mortgage applications received by CPP participants and other QFIs. We do so in several ways. First, we include housing market fixed effects to compare lending decisions within the same census tract. While the small size of the so-defined housing market should reduce borrower heterogeneity, it is possible that some banks attract stronger or weaker applicants within each market. Therefore, as a second control, we include borrower-level characteristics that affect loan approval, such as loan-to-income ratio as well as the fixed effects for borrower gender, race, and ethnicity. To control for time-variant determinants of loan demand, we also include changes in the demographics of the local housing market: population size, median family income, and fraction of minority population. For brevity, we do not report the egression coefficients on these controls.

In addition to bank-level characteristics and demand-side effects, we would also like to control for the potential confounding effects of the selection of CPP recipients. To this end, we employ the two selection models discussed in section 3.1. Panel A of Table 3 corresponds to the IV-based approach, whereas Panel B corresponds to the propensity score-matched samples. The definition of the *TARP recipient* variable is therefore different across the two panels. In Panel A, *TARP recipient* is the predicted value from the first stage probit regression. In Panel B, *TARP recipient* is a dummy equal to 1 for the subsample of matched firms approved for CPP and 0 otherwise.

The empirical results, summarized in Table 3, show a significant decline in loan approval rates of participating banks for safer borrowers and a significant increase in approval rates of riskier borrowers among the banks approved for government assistance. These results hold across both selection models and are statistically significant at the 1 percent level. In particular, the coefficient on the interaction term *After TARP x TARP Recipient* is negative and statistically significant at the 1 percent level in the lowest loan-to-income quintile in both Panels A and B. Conversely, it is positive and statistically significant at the 1 percent level for borrowers in the highest loan-to-income quintile across both Panels. This term captures the marginal effect of CPP on the change in loan approval rates between CPP recipients and nonrecipients for each risk category of borrowers. It therefore suggests that compared to nonrecipients, CPP recipients tightened approval rates for the safest borrowers and increased approval rates the riskiest borrowers.

We do not detect a significant effect of CPP on the overall volume of credit origination by participating banks. The first column in both Panels of Table 3 reports the regression estimates for the overall sample of mortgage applications. In Panel A, the coefficient on the interaction term *After TARP x TARP Recipient* is negative and statistically significant at the 1 percent level, suggesting that TARP recipients increased their lending by less than non-recipients. In Panel B, the coefficient on the interaction term *After TARP x TARP Recipient* suggests that the effect of CPP capital infusions on loan approval rates of participating banks is insignificant.

The last column in both Panels of Table 3 corresponds to an alternative measure of borrower risk, the subprime mortgage rate spread. The dependent variable in these regressions is the TARP recipient indicator. In both panels, the coefficient on the *After TARP* dummy is positive and statistically significant at the 1 percent level, suggesting that the fraction of TARP recipients in the total pool of risky loans has increased after TARP.

Taken together, both the nonparametric and regression evidence paint a similar picture. After the administration of CPP, program participants significantly increased their approval rates for riskier borrowers (as compared to other banks), but, at the same time, had a decrease in approval rates for safer borrowers relative to other banks. In other words, following TARP investments, CPP participants increased the tilt in their loan portfolios toward riskier borrowers.

One possible concern in our analysis is that our results are driven by unobservable bank characteristics that may be correlated with CPP approval and subsequent lending and risk taking. While we address this concern in several ways: (1) controlling for *CAMELS* and other bank-level characteristics; (2) controlling for various housing-market and macroeconomic factors; (3) employing two selection models based on instrumental variables and propensity score matching, we also repeat the analysis with bank fixed effects to control for bank-level time invariant unobservable characteristics. These results are reported in Panel A of Table 4. We find qualitatively similar results. In particular, the coefficient on the interaction term *After TARP x TARP Recipient* is negative and statistically significant at the 10 percent level in the lowest loan-to-income quintile. Conversely, it is positive and statistically significant at the 1 percent level for borrowers in the highest loan-to-income quintile across both Panels. These estimates suggest that compared to nonrecipients, CPP recipients cut approval rates for the safest borrowers and increased approval rates the riskiest borrowers.

Another possible concern is that our results are driven by FDIC-facilitated acquisitions. This could be the case, for example, if CPP recipients were asked by the FDIC to acquire distressed institutions, whose lending practices were riskier compared to the average bank. In that case, our findings that CPP recipients increased lending to riskier borrowers may simply reflect the acquisition of riskier lenders. To control for this possibility, we collect data on all FDIC-facilitated acquisitions from the FDIC online directory, and exclude the institutions that took part in such transactions from our sample. Panel B of Table 4 reports the results of re-estimating our tests in this subsample. Once again, we obtain similar results suggesting that CPP recipients decreased their approval rates for safer borrowers and increased their approval rates for riskier borrowers.

We also consider the possibility that our results are driven by an implicit requirement by the government that CPP recipients tilt their lending portfolio toward riskier borrowers to revitalize credit markets. Under this hypothesis, the documented increase in risky mortgage lending of CPP recipients would be driven by a government mandate, possibly implicit, to expand the supply of credit to riskier borrowers.

To evaluate this hypothesis, we collect data on financial institutions that were approved for CPP funds but did not receive federal investments. To identify these banks, we search QFIs' press releases, proxy statements, financial reports (8K and 10Q), and news announcements in Factiva for any mentionings of CPP. We identify 51 banks that were approved for CPP funds but did not receive the actual capital investment. We then read these press releases and news articles to understand the reasons for the bank's decision to decline CPP funds. Among the common reasons, banks mentioned additional restrictions placed on participating institutions, the stigma associated with CPP participation, and the value of losing tax benefits on executive compensation.

Panel C of table 4 compares between the mortgage approval rates of firms that were approved for CPP and firms that were approved for CPP and declined the funds across the different categories of borrower risk. Once again, the coefficient of interest is the interaction term *After TARP x TARP Recipient*, which captures the marginal effect of CPP on the change in loan approval rates between approved firms that received the capital and approved firms that declined the capital. To the extent that our results are capturing an implicit government requirement to increase lending to riskier borrowers, the coefficient on the interaction term should be positive for the riskier borrower quintiles. The results in Panel C, however, suggest that there is no significant difference between approved firms that received capital and approved firms that did not receive the capital. Therefore, our results are unlikely driven by implicit government policies; rather, they are consistent with the moral hazard hypothesis.

An important consideration in our analysis is to separate the effect of CPP on banks' credit supply from its potential confounding effect on borrowers' credit demand across the different risk categories. One plausible hypothesis is that borrowers take into account CPP capital infusions when applying for loans. For instance, riskier borrowers may choose to apply to a CPP recipient rather than a nonrecipient for a mortgage. We test this hypothesis within the same framework we use in our previous tests. The dependent variable is a proxy for loan demand, and the coefficient on the interaction term *After TARP x TARP Recipient* captures the marginal effect of CPP on the change in the demand for loans between CPP recipients and nonrecipients. These results are summarized in Table 5.

Panel A of Table 5 reports the regression results for the number of loans requested by borrowers each year. Specifically, the dependent variable is the natural logarithm of the total number of applications received by a bank each year. The unit of our analysis is therefore the number of annual loan applications to each single bank and not an individual loan application. This reduces our sample size compared to Tables 3 and 4. The regression results indicate that the volume of mortgage applications dropped significantly in 2009 as compared to previous years (2006-2008). This holds across all risk categories, as evident from the coefficient on the *After TARP* dummy across all five loan-to-income quintiles. It is negative and statistically significant at conventional significance levels in all cases. Yet more importantly, there are no significant differences in the demand for loans between CPP recipients and nonrecipients. The coefficient on the interaction term *After TARP x TARP Recipient* is never statistically significant, suggesting that CPP did not have a significant effect on the volume of credit demand across the different risk categories.

Panel B of Table 5 examines whether CPP had an effect on the loan amounts requested by the borrowers. The dependent variable is the natural logarithm of the total amount of loan applications received by a bank each year. The unit of our analysis is therefore once again the total amount of annual loan applications to each single bank and not an individual loan application. The regression results indicate that the total amount of loan applications dropped significantly in 2009 as compared to 2006-2008. This holds across all risk categories, as evident from the coefficient on the *After TARP* dummy across all five loan-to-income quintiles. However, as was the case with the number of loans, here too there are no significant differences between CPP recipients and nonrecipients. The coefficient on the interaction term *After TARP x TARP Recipient* is not statistically significant (except for quintile 2 where it is significant at the 10 percent level), suggesting that CPP did not have a significant effect on the amount of credit demand across the different risk categories.

Overall, the results indicate that there was a significant decline in the demand for loans in 2009, following the financial crisis. CPP capital infusions, however, did not have a material effect on the distribution of the demand for credit across financial institutions. Specifically, there is no evidence of a change in the demand for loans from CPP recipients relative to nonrecipients across the different borrower risk categories. These findings suggest that the decrease in approval rates for safer borrowers and increase in approval rates for riskier borrowers, exhibited by CPP recipients compared to nonrecipients, are likely driven by credit rationing (or the supply of credit) rather than changes in customer demand for loans.

3.3 Corporate Lending

So far, our analysis has concentrated on retail lending. We proceed by studying the effect of CPP on the origination of corporate credit. To isolate the effect of CPP banks on the supply of credit, our tests focus on the variation in the share of credit originated by CPP participants at the level of each loan. Specifically, the dependent variable in the regressions is the number of lenders that are CPP recipients divided by the total number of lenders per syndicated loan. We use the number of CPP recipients rather than their dollar share in the overall loan amount because this information is missing from Dealscan in the vast majority of the cases.

We regress the fraction of CPP recipients per syndicated loan on the *After TARP* dummy, a measure of the borrowing firm's credit risk, and the interaction term *After TARP x Borrower risk*. The main independent variable of interest is the interaction term. It captures the marginal impact of CPP capital infusions on the fraction of loans extended to riskier borrowers by recipient banks relative to other banks. We use two measures of borrower credit risk. The first measure is *bond yield*, calculated as the average spread between the firm's outstanding bond issues and treasury yields with the closest maturity over the month preceding the loan. Data on bond yields are gathered from TRACE. The second measure of risk is the firm's credit rating, calculated as the average credit rating of a company's bond issues in the year preceding the loan. We collect credit ratings data from Mergent's FISD ratings dataset. The regressions include borrower fixed effects to control for time-invariant unobservable borrower characteristics that may affect the demand for loans.

As in previous analyses, we continue to control for the potential confounding effects of the selection of CPP recipients. Therefore, we also report the results for the two selection models discussed in section 3.1. The *Political connections index* model corresponds to the IV-based approach, whereas the *Matched sample* model corresponds to the propensity score-matched samples. The definition of CPP recipients in the calculation of the dependent variable is therefore different across these models. For the *Political connections index* model, we classify banks as CPP recipients if their calculated propensity score (to receive CPP capital) is higher than the median value. For the *Matched sample* model, CPP recipients are the approved firms that are the closest match to the nonrecipients in our sample.

Table 6 summarizes these results. We first consider the evidence on *bond yields*. The interaction term *After TARP x Bond yields* is positive and statistically significant at the 1 percent level across all specifications. These findings indicate that the fraction of CPP recipients in loans to riskier borrowers (with higher bond yields) has increased after TARP compared to nonrecipients. The effects are also economically significant. For instance, based on the *Political connections index* model, an increase of one standard deviation in bond yields corresponds to an increase of 8.7% in the fraction of CPP recipients for the average loan. The results are similar for credit ratings, albeit statistically insignificant without controlling for the selection of CPP recipients. Specifically, the interaction term *After TARP x Credit ratings* is negative across all specifications and statistically significant at the 1 percent level in both selection models. These estimates imply that the fraction of CPP recipients in loans to borrowers with lower credit ratings has increased after TARP compared to nonrecipients.

In summary, the evidence in this section suggests that CPP capital investments had a significant effect on the risk profile of corporate lending. These results echo the impact of CPP investments on mortgage approval rates of riskier borrowers. These findings are consistent across various measures of credit risk and are robust to controlling for loan demand. Taken together, our retail and corporate lending results indicate that within lending categories, CPP recipients tilted their portfolios towards riskier borrowers.

3.4. Investments

The evidence so far suggests that CPP recipients increased the risk of their loan portfolios after receiving TARP funds. If this strategy reflects a general increase in risk taking by CPP banks, we are likely to observe a similar tilt toward higher-risk assets in banks' investments in securities after CPP capital provisions. The advantage of analyzing banks' portfolio investments is that the risk of financial assets is often more transparent and can be estimated based on market information.

In our analysis of banks' investments we study whether CPP participants increased their allocations to risky securities relative to other assets after obtaining CPP funds. We study both the aggregate measures such as total securities and interest on securities, as well as the breakdown of securities into safer and riskier assets. Specifically, to provide a simple and transparent classification, we define equities, corporate debt, and mortgage-backed securities as "riskier securities". Conversely, we label Treasuries and state-insured securities as "lower-risk securities".

Table 7 shows the results of difference-in-differences tests of investments in all securities, riskier securities, and lower-risk securities between CPP participants and other banks. As in previous analyses, we control for the potential confounding effects of the selection of CPP recipients. In Panel A, *TARP recipient* is the predicted value from the first stage probit regression. In Panel B, *TARP recipient* is a dummy equal to 1 for the subsample of matched firms approved for CPP and 0 otherwise.

We first consider the evidence in Panel A. The results show that CPP participants significantly increased their allocation to investment securities after receiving federal capital. For the average CPP participant, the total weight of investment securities in bank assets increased by 0.9% after TARP relative to non-recipient banks. More importantly, the increase in the allocation to investment securities at CPP participants was primarily driven by higher allocations to riskier securities, which increased at CPP banks by 3.3% after TARP infusions relative to nonrecipients. In contrast, CPP recipients reduced their investment in lower-risk securities by 1.0% relative to nonrecipients other banks. Our results offer additional detail on the interest yields and maturities of financial portfolios of CPP participants relative to other QFIs. The results suggest that CPP banks significantly increased the average yield of their investment securities after TARP, as compared to the banks that did not receive federal capital. Similar conclusions emerge from the analysis of the average maturity of debt assets, suggesting an increase in allocations to bonds with longer maturity and a higher exposure to interest rate risk.

The results in Panel B are qualitatively similar with slightly different point estimates. For example, the total weight of investment securities in bank assets increased after TARP by 2.0% for recipient relative to non-recipient banks. Further, similar to Panel A, the increase in the allocation to investment securities at CPP participants was primarily driven by higher allocations to riskier securities, which increased at CPP banks by 2.4% after TARP infusions relative to nonrecipients.

Overall, the analysis of banks' investment portfolios suggests that TARP participants actively increased their risk exposure after receiving federal capital. In particular, CPP recipients invested capital in riskier asset classes, tilted portfolios to higher-yielding securities, and engaged in more speculative trading, compared to non-recipient banks.

3.5. Bank-level Risk

In this section, we study whether the observed changes in the bank loan origination and investment strategy influenced the overall risk of financial institutions. To measure bank risk, we use both accounting and market-based measures: earnings volatility, leverage, z-score, market beta, and stock return volatility.

In a broad sense, the two primary sources of bank risk include asset composition and leverage. We measure the former risk source by the standard deviation of ROA and the standard deviation of earnings and the latter source by the ratio of equity capital to total assets. Following the literature (e.g., Laeven and Levine, 2009) we also aggregate these two sources of risk into a composite z-score, a measure of bank's distance to insolvency. The z-score is computed as the sum of ROA and the capital asset ratio scaled by the standard deviation of asset returns.

Under the assumption of normally distributed bank profits, this measure approximates the inverse of the default probability, with higher z-scores corresponding to a lower probability of default.[9]

In addition to accounting-based measures, we also use market-based risk proxies – market beta and stock return volatility. Our focus on beta is motivated by the moral hazard hypothesis. According to this hypothesis, banks expect that they will be bailed out in bad states of the world, and this implicit bailout guarantee encourages risk taking. If the government is more likely to intervene in cases that pose a threat to the entire economy rather than just an idiosyncratic bankruptcy of one firm, then the moral hazard argument predicts that managers will increase their exposure to the type of risk for which they are most likely to be bailed out – systemic risk. Therefore, to test the moral hazard hypothesis and to evaluate the declared TARP objective of increasing *systemic* stability, we focus on market betas.

To compute betas, we assume the market model, with the CRSP value-weighted index used as the market proxy. To match the data frequency of other risk measures, which are based on quarterly accounting data, we estimate betas for each calendar quarter, using daily returns. Our results are also similar if we use market betas from a two-factor model, which is often assumed to describe the return generating process for financial institutions.[10] The results are also robust to using longer estimation horizons.

Table 8 provides evidence from panel regressions of bank risk. The dependent variables include ROA volatility, leverage, z-score (measured as the natural logarithm), market beta, and stock return volatility. The independent variables include dummies *After TARP* and *TARP Recipient*, their interaction terms, and a set of controls consisting of size and liquidity.

The results in Table 8 show that CPP recipients significantly increased their asset risk, as proxied by ROA volatility and earnings volatility. This conclusion is consistent with the increase in the riskiness of the loan portfolios and investment assets of CPP participants reported earlier. Regression results for the capital-to-assets

---

9 The intuition for this result was first developed in Roy (1952). For a more recent discussion of the relation between z-score and bank default, see Laeven and Levine (2009).

10 The two-factor model for financial institutions is based on the market risk and the interest rate risk, with the latter factor approximated by daily changes in the Treasury rate (e.g., Flannery and James 1984, Sweeney and Warga 1986, Saunders, Strock and Travlos, 1990; Bhattacharyya and Purnanandam, 2010).

ratio suggest that CPP banks significantly reduced leverage after federal infusions. For the average CPP recipient, the capital-to-assets ratio increased from 9.9% in the third quarter of 2008 (last quarter before TARP) to 10.9% in the first quarter of 2009. This result is consistent with a significant inflow of new capital from TARP, combined with a lack of increase in credit origination relative to non-CPP participants.

One possible explanation for the increase in asset risk and a simultaneous decline in leverage could be a strategic response from financial institutions to federal capital requirements, for example, if the banks followed a strategy designed to increase the profitability of assets (and hence their risk), while, at the same time achieving better capitalization levels monitored by TARP oversight bodies. The net effect of this strategy is an increase in the probability of bank distress, as shown by the significant coefficient on the interaction term *After TARP* x *TARP Recipient* in columns that use the z-score as the dependent variable.

Consistent with the predictions of the moral hazard hypothesis, CPP banks increased their exposure to systemic risk after receiving TARP capital, as indicated by the positive and significant coefficient on the interaction term in the specifications that use the market beta as the dependent variable. This effect is also economically important, indicating an increase in beta from 0.80 to 1.01 for CPP participants after federal capital infusions. In contrast, non-participating banks experienced no changes in systemic risk over the same period.

In summary, we find that CPP investments are associated with a shift in credit origination toward riskier borrowers and with capital reallocations to risky securities by participating banks. This strategy is associated with an increase in systemic risk and the probability of distress of CPP participants, consistent with the moral hazard hypothesis. This evidence suggests that at least some TARP participants responded to the bailout by increasing their risk taking and that this effect appears to outweigh the disciplining role of government monitoring and the regulatory constraints on incentive compensation of TARP participants.

Conclusion

This paper has investigated the effect of government assistance on risk taking of financial institutions. While we do not find a significant effect of the program on the aggregate amount of originated credit, our results suggest a considerable impact of government assistance on the risk of originated loans. After receiving federal funds, CPP participants issue riskier loans and increase capital allocations to riskier, higher-yield financial securities. A fraction of new capital inflows is also used to build cash reserves. Although the cash reserves reduce leverage and improve capitalization ratios, the net effect is a significant increase in systemic risk and the probability of distress due to the higher risk of bank assets.

The evidence in our paper is broadly consistent with the theories of moral hazard, which predict an increase in risk-taking incentives in response to government protection. From a policy perspective, our findings show that any capital provisions should establish clear investment guidelines and provide mechanisms for tracking the deployment of capital by recipient institutions in order to limit the unintended consequences of government aid.

References

Barth, James R., Gerard Caprio, and Ross Levine, "Bank Regulation and Supervision: What Works Best?", *Journal of Financial Intermediation*, 13 (2004), 205–48.

Beltratti, Andrea, and Rene Stulz, "Why did Some Banks Perform Better during the Credit Crisis? A Cross-Country Study of the Impact of Governance and Regulation", working paper, Ohio State University, 2010.

Bernanke, Benjamin, and Christopher Lown, 1991. "The Credit Crunch." *Brookings Papers on Economic Activity*, 2 (1991), 205-247.

Bhattacharyya, Sugato and Amiyatosh K. Purnanandam, "Risk-Taking by Banks: What Did We Know and When Did We Know It?", working paper, University of Michigan, 2010.

Cordella, Tito, and Eduardo L. Yeyati, "Bank Bailouts: Moral Hazard vs. Value Effect", *Journal of Financial Intermediation*, 12 (2003), 300–330.

Diamond, Douglas and Raghuram G. Rajan, "Liquidity Shortages and Banking Crises", *Journal of Finance*, 60 (2005), 615-647.

Diamond, Douglas and Raghuram G. Rajan, "Fear of Fire Sales, Illiquidity Seeking and Credit Freeze", *Quarterly Journal of Economics*, 126 (2011), 557-591.

Dell'Ariccia, Giovanni, Deniz Igan, and Luc Laeven "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market", working paper, the International Monetary Fund, 2009.

De Nicolo, G. "Size, Charter Value, and Risk in Banking: An International Perspective." Federal Reserve of Chicago Proceedings of the 37th Annual Conference on Bank Structure and Competition (2001), 197–215.

DeYoung, Robert, Anne Gron, Gokhan Torna, and Andrew Winton, "Risk Overhang and Loan Portfolio Decisions: The Supply of Small Business Loans before and During the Financial Crisis", working paper, the University of Kansas and the University of Minnesota, 2010.

Duchin, Ran and Denis Sosyura, "The Politics of Government Investment", working paper, University of Michigan, 2009.

Flannery, Mark J., "Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence", *Journal of Money, Credit and Banking* (1998), 273-305.

Flannery, Mark J., "What to Do about TBTF", working paper, University of Florida, 2010.

Flannery, Mark J. and Christopher M. James, "The Effect of Interest Rate Changes on the Common Stock Returns of Financial Institutions", *Journal of Finance*, 39 (1984), 1141-1153.
Goodhart, Charles and Haizhou Huang, "A Model of the Lender of Last Resort", IMF Research Paper 99/29, 1999.

Gorton, Gary and Lixin Huang, "Liquidity, Efficiency, and Bank Bailouts", *American Economic Review*, 94 (2004), 455-483.

Gorton, Gary, Stefan Lewellen and Andrew Metrick, "Bank Capital and Survival during the Financial Crisis", working paper, Yale University, 2010.

Gropp, Reint, and Jukka Vesala, "Deposit Insurance, Moral Hazard, and Market Monitoring", *Review of Finance*, 8 (2004), 571–602.

Harvey, Campbell R., “The Financial Crisis of 2008: What Needs to Happen after TARP,” working paper, Duke University, 2008.

Hovakimian, Armen, and Edward J. Kane, "Effectiveness of Capital Regulation at U.S. Commercial Banks, 1985–1994", *Journal of Finance*, 55 (2000), 451–68.

Kashyap, Anil, Raghu Rajan and Jeremy Stein, “Rethinking Capital Regulation”, working paper, University of Chicago and Harvard University, 2008.

Keeley, Michael C., “Deposit Insurance, Risk, and Market Power in Banking,” *American Economic Review*, 80 (1990), 1183-1200.

Laeven, Luc and Ross Levine, “Bank Governance, Regulation, and Risk Taking,” *Journal of Financial Economics*, 93 (2009), 259-275.

Levine, Ross “The Governance of Financial Regulation: Reform Lessons from the Recent Crisis”, working paper, Brown University, 2010.

Mailath, George and Loretta Mester, 1994, “A Positive Analysis of Bank Closure", *Journal of Financial Intermediation*, 3(1994), 272-299.

Merton, Robert C., “An Analytic Derivation of the Cost of Deposit Insurance and Loan Guarantees”, *Journal of Banking and Finance*, 1 (1977), 3-11.

McIntire, Michael, “Bailout Is a Windfall to Banks, if Not to Borrowers,” *New York Times*, January 17, 2009.

Penati, Alessandro and Aris Protopapadakis, 1988, “The Effect of Implicit Deposit Insurance on Banks’ Portfolio Choices, with an Application to International Overexposure", *Journal of Monetary Economics*, 21(1998), 107-126.

Puri, Manju, Jorg Rocholl, and Sascha Steffen, “Global Retail Lending in the Aftermath of the U.S. Financial Crisis: Distinguishing between Supply and Demand Effects,” *Journal of Financial Economics*, 100 (2011), 556 – 578.

Philippon, Thomas and Philipp Schnabl, "Efficient Recapitalization", working paper, New York University, 2010.

Roy, Andrew D., “Safety First and the Holding of Assets”, *Econometrica*, 20 (1952), 431–449.

Ruckes, Martin, "Bank Competition and Credit Standards", *Review of Financial Studies*, 17 (2004), 1073-1102.

Saunders, Anthony, Elizabeth Strock, and Nickolaos Travlos, “Ownership Structure, Deregulation, and Bank Risk Taking”, *Journal of Finance*, 45 (1990), 643–654.

Simon, Ruth and Jessica Silver-Greenberg, “Signs of Risky Lending Emerge”, *Wall Street Journal*, July 14, 2010.

Shea, John (1997), “Instrument Relevance in Multivariate Linear Models: A Simple Measure”, *The Review of Economics and Statistics*, 79 (1997), 348-352.

Sweeney, Richard J. and Arthur D. Warga, “The Pricing of Interest Rate Risk: Evidence from the Stock Market”, *Journal of Finance*, 41 (1986), 393-410.

Veronesi, Pietro, and Luigi Zingales, “Paulson’s Gift,” *Journal of Financial Economics*, 97 (2010), 339-368.

Appendix A

Variable Definitions

1. Bank-level variables

Capital adequacy = tier-1 risk-based capital ratio, defined as tier-1 capital divided by risk-weighted assets. Capital adequacy refers to the amount of a bank's capital relative to the risk profile of its assets. Broadly, this criterion evaluates the extent to which a bank can absorb potential losses. Tier-1 capital comprises the more liquid subset of bank's capital, whose largest components include common stock, paid-in-surplus, retained earnings, and noncumulative perpetual preferred stock. To compute the amount of risk-adjusted assets in the denominator of the ratio, all assets are divided into risk classes (defined by bank regulators), and less risky assets are assigned smaller weights, thus contributing less to the denominator of the ratio. The intuition behind this approach is that banks holding riskier assets require a greater amount of capital to remain well capitalized.

Asset quality = the negative of noncurrent loans and leases, scaled by total loans and leases. Asset quality evaluates the overall condition of a bank's portfolio and is typically evaluated by a fraction of nonperforming assets and assets in default. Noncurrent loans and leases are loans that are past due for at least ninety days or are no longer accruing interest, including nonperforming real-estate mortgages. A higher proportion of nonperforming assets indicates lower asset quality. For ease of interpretation, this ratio is included with a negative sign so that greater values of this proxy reflect higher asset quality.

Management quality = the negative of the number of corrective actions that were taken against bank executives by the corresponding banking regulator (FED, OTS, FDIC, and OCC).

Earnings = return on assets (ROA), measured as the ratio of the annualized net income in the trailing quarter to average total assets

Liquidity = cash divided by deposits.

Sensitivity to market risk = the sensitivity to interest rate risk, defined as the ratio of the absolute difference (gap) between short-term assets and short-term liabilities to earning assets.

Foreclosures = value of foreclosed assets divided by net loans and leases.

Size = the natural logarithm of total assets, defined as all assets owned by the bank holding company, including cash, loans, securities, bank premises, and other assets. This total does not include off-balance-sheet accounts.

Age = age (in years) of the oldest bank owned by the bank holding company.

Political connections index = a firm's average percentile rank in our sample on each of the following four measures of political connections: *House financial services subcommittee* (an indicator equal to 1 if the House member representing the voting district of a firm's headquarters served on the Capital Markets Subcommittee or the Financial Institutions Subcommittee of the House Financial Services Committee in 2008 or 2009), *Connected board member* (an indicator equal to 1 if a firm's board of directors in 2008 or 2009 included a director with simultaneous or former work experience at the banking regulators (Federal Reserve, FDIC, OTS, and OCC), Treasury or Congress), *Lobbying* (an indicator equal to 1 if the firm engaged in lobbying activity targeted at the banking regulators, Treasury, or Congress on the issues of banking, financial institutions, or bankruptcy from the first quarter of 2008 to the first quarter of 2009, inclusive), and *Contributions* (an indicator equal to 1 if the bank made political contributions by its sponsored political action committee(s) to the members of the Capital Markets Subcommittee and the Financial Institutions Subcommittee of the House Financial Services Committee in the 2008 congressional election campaign). The index is scaled to range from 0 (low) to 1 (high). In Panel B, TARP recipient equals 1 if the bank applied and was approved for CPP funds, and 0 if it applied and was not approved.

2. CPP Variables

TARP recipient = The definition of this variable depends on the specification. Without controlling for selection, this variable is an indicator equal to 1 if the financial institution was approved for CPP and 0 otherwise. In IV specifications based on firms' political connectedness, this variable is the predicted value from a probit regression of CPP approval on the political connections index and a set of independent bank-level control variables (Camels, foreclosures, and size). In specifications based on propensity score matching, this variable is an indicator equal to 1 for the subsample of matched firms approved for CPP and 0 for the unapproved firms.

After = an indicator equal to 1 after January 1, 2009.

3. Risk

The Subprime spread indicator is reported by HMDA and equals 1 if the annual percentage rate on the mortgage loan exceeds the rate on the Treasury securities of comparable maturity by at least three percentage points.

Bond yield = the average spread between a company's outstanding bond issues and treasury yields with the closet maturity over the month preceding the loan. Data on bonds' yields is gathered from TRACE.

Credit rating = the average credit rating of a company's bond issues in the year preceding the loan. Data on credit ratings are gathered from Mergent's FISD ratings dataset.

Standard deviation of ROA = For each quarter, the standard deviation of ROA is calculated as the quarterly standard deviation over the previous 4 quarters. ROA is net operating income as a percent of average assets.

Standard deviation of earnings = For each quarter, the standard deviation of earnings is calculated as the quarterly standard deviation over the previous 4 quarters. Earnings are net operating income as a percent of average assets.

Capital asset ratio = Average total equity divided by average assets.

Z-score = ROA plus capital asset ratio divided by the standard deviation of ROA.

Beta = Betas are computed assuming the market model, with the CRSP value-weighted index used as the market proxy. Betas are calculated for each calendar quarter using daily returns.

4. Investments

Lower-risk securities = U.S. Treasury securities and securities issued by states & political subdivisions.

Risky securities = Equity securities, trading account (securities and other assets acquired with the intent to resell in order to profit from short-term price movements), corporate bonds, and Mortgage-backed securities.

Long term debt securities = Debt securities with maturities greater than 5 years.

Figure 1
Sample Firms and their Investment Applications

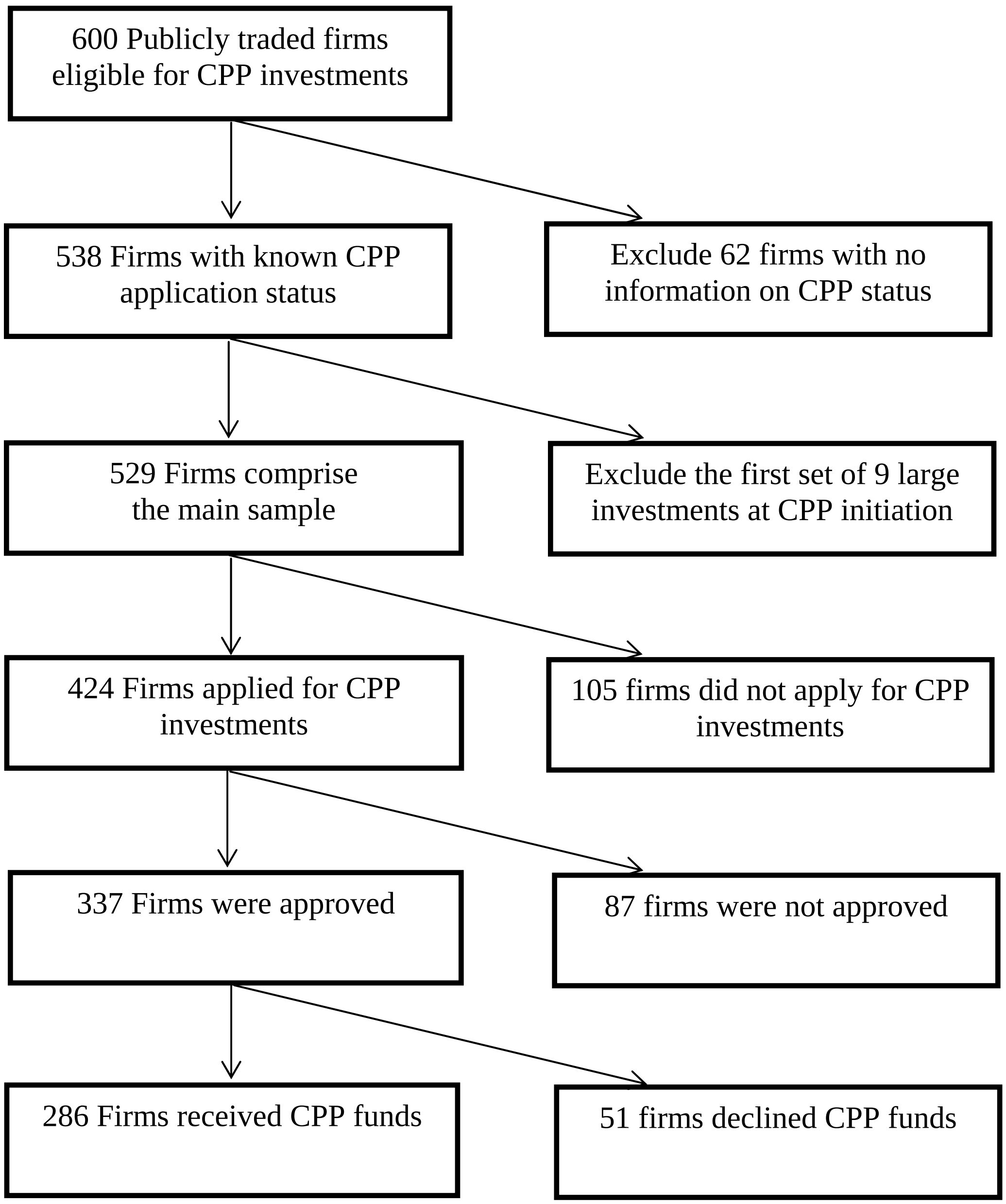

TABLE 1
Summary Statistics

This table reports summary statistics for the data used in the analysis. Panel A reports bank level data. The CPP application indicator is equal to 1 if the firm applied for CPP funds. The CPP approval indicator is equal to 1 if the firm was approved for (conditional on applying) CPP funds. The CPP investment indicator is equal to 1 if the firm received (conditional on approval) CPP funds. The financial condition variables correspond to the Camels measures of banks' financial condition and performance used by banking regulators, augmented with exposure to the crisis (foreclosures). Capital adequacy is the tier-1 risk-based capital ratio, defined as tier-1 capital divided by risk-weighted assets. Asset quality is the negative of noncurrent loans and leases, scaled by total loans and leases. Management quality is the negative of the number of disciplinary orders issued to a firm's management by the firm's banking regulator in 2006-2009. Earnings is return on assets (ROA), measured as the ratio of the annualized net income in the trailing quarter to average total assets. Liquidity is cash divided by deposits. Sensitivity to market risk is the sensitivity to interest rate risk, defined as the ratio of the absolute difference (gap) between short-term assets and short-term liabilities to earning assets. Foreclosures is the value of foreclosed assets divided by net loans and leases. Panel B reports loan level data. The mortgage application data are reported by the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. Application approval is an indicator equal to 1 if the mortgage application was approved. The loan to income ratio is the loan amount divided by the applicant's income. The rate spread indicator is equal to 1 if the annual percentage rate on the mortgage loan exceeds the rate on the Treasury securities of comparable maturity by at least three percentage points. The corporate loan data are gathered from DealScan, which covers large corporate loans, the vast majority of which are syndicated. Number of CPP recipients per loan is the number of loan arrangers that were approved for CPP. Fraction of CPP recipients in the total number of lenders per loan is the number of loan arrangers that were approved for CPP divided by the total number of loan arrangers. Panel C compares between the propensity score-matched sample of CPP recipients and non-recipients. Age is the age of the oldest bank of the bank holding company as of 2009. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation.

Panel A: Bank-level data

Variable	Mean	25th percentile	Median	75th percentile	Standard deviation
CPP					
CPP application indicator	0.802	1.000	1.000	1.000	0.399
CPP approval indicator (if applied)	0.795	1.000	1.000	1.000	0.404
CPP investment indicator	0.849	0.000	1.000	1.000	0.359
Bank size					
Total assets ($000)	2,167,517	67,963	147,636	344,765	41,900,000
Assets in financial securities ($000)	349,912	8,952	23,610	60,849	6,080,917
Financial condition					
Capital adequacy (%)	12.750	9.690	10.657	12.644	9.008
Asset quality (%)	-0.071	-0.061	-0.007	0.000	0.245
Management quality	-0.314	-1.000	0.000	0.000	0.464
Earnings (%)	0.194	0.040	0.547	0.867	1.900
Liquidity (%)	3.914	2.272	3.030	4.202	3.877
Sensitivity to market risk (%)	14.588	5.382	10.900	19.670	12.485
Foreclosures (%)	0.390	0.034	0.148	0.410	1.078

Panel B: Loan-level data

Variable	Mean	25th percentile	Median	75th percentile	Standard deviation
Mortgage application data					
Application approval indicator	0.622	0.000	1.000	1.000	0.485
Loan to income ratio	1.915	0.750	1.703	2.708	1.473
Rate spread indicator	0.097	0.000	0.000	0.000	0.296
Loan amount ($000)	165.8	51.0	110.0	220.0	156.2
Applicant income ($000 per year)	99.6	43.0	71.0	123.0	81.8
Corporate loan data					
Loan amount ($000)	582,000	135,000	300,000	675,000	918,000
Number of CPP recipients per loan	2.766	1.000	2.000	4.000	1.631
Fraction of CPP recipients in the total number of lenders per loan	0.673	0.376	0.601	0.854	0.184

Panel C: Matched Samples

Variable	Unapproved	Approved	Difference	t-statistic
Capital adequacy (%)	11.548	12.893	1.344	1.092
Asset quality (%)	-0.052	-0.046	0.006	0.304
Management quality (%)	-0.310	-0.276	0.034	0.497
Earnings (%)	-0.921	-0.786	0.135	0.336
Liquidity (%)	4.061	3.856	-0.206	0.326
Sensitivity to market risk (%)	11.508	9.878	-1.630	1.194
Foreclosures (%)	0.315	0.298	-0.017	0.312
Size (log assets)	13.922	13.610	-0.312	1.631
Age	36.285	34.908	-1.377	0.455

TABLE 2

Nonparametric Evidence on Application Approval Rates and Loan Risk

This table reports difference-in-difference mean estimates of the likelihood of loan application approval by quintiles sorted on the loan-to-income ratio, as well as the frequency of approved applications whose rate spread indicator is equal to 1, for TARP recipients and non-recipients. Loan application approval is an indicator equal to 0 if the application was denied and 1 if was is approved. We consider 2006-2008 as the period before TARP and 2009 as the period after TARP. TARP recipients (non-recipients) are banks that applied and were (not) approved for CPP funds. The loan-to-income ratio is the loan amount divided by the applicant's income. The rate spread indicator is equal to 1 if the annual percentage rate on the mortgage loan exceeds the rate on the Treasury securities of comparable maturity by at least three percentage points. The individual loan application data come from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry and cover the period 2006-2009. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation. T-statistics are reported in parentheses. The difference-in-difference (DD) estimate is printed in bold.

Loan-to-income ratio rank	Before TARP			After TARP			Diff-in-diff (t-statistic)
	Non-recipients	Recipients	Difference (t-statistic)	Non-recipients	Recipients	Difference (t-statistic)	
Lowest	0.788	0.741	-0.047	0.832	0.633	-0.199	**-0.151**
			(9.330)			(12.164)	**(9.520)**
2	0.679	0.570	-0.109	0.707	0.462	-0.245	**-0.136**
			(22.033)			(15.175)	**(8.100)**
3	0.651	0.530	-0.121	0.716	0.528	-0.188	**-0.067**
			(35.724)			(12.902)	**(4.230)**
4	0.649	0.533	-0.117	0.705	0.567	-0.138	**-0.022**
			(24.951)			(9.498)	**(3.410)**
Highest	0.526	0.484	-0.042	0.547	0.530	-0.017	**0.025**
			(9.275)			(1.199)	**(3.660)**
Rate spread indicator	8.780	91.220	82.440	3.260	96.740	93.480	**11.040**
							(24.590)

TABLE 3
Regression Evidence on Application Approval Rates and Loan Risk

This table reports regression estimates of the relation between the likelihood that a bank accepts a loan application and TARP across different borrower risk categories. The dependent variable is an indicator variable equal to 1 if a loan was approved, except the last column, in which the dependent variable is the TARP recipient indicator. In Panel A, TARP recipient is the predicted likelihood that a bank is approved for CPP funds, conditional on applying, from a probit regression of CPP approval on a bank's political connections index. *Political connections index* is a firm's average percentile rank in our sample on each of the following four measures of political connections: *House financial services subcommittee* (an indicator equal to 1 if the House member representing the voting district of a firm's headquarters served on the Capital Markets Subcommittee or the Financial Institutions Subcommittee of the House Financial Services Committee in 2008 or 2009), *Connected board member* (an indicator equal to 1 if a firm's board of directors in 2008 or 2009 included a director with simultaneous or former work experience at the banking regulators (Federal Reserve, FDIC, OTS, and OCC), Treasury or Congress), *Lobbying* (an indicator equal to 1 if the firm engaged in lobbying activity targeted at the banking regulators, Treasury, or Congress on the issues of banking, financial institutions, or bankruptcy from the first quarter of 2008 to the first quarter of 2009, inclusive), and *Contributions* (an indicator equal to 1 if the bank made political contributions by its sponsored political action committee(s) to the members of the Capital Markets Subcommittee and the Financial Institutions Subcommittee of the House Financial Services Committee in the 2008 congressional election campaign). The index is scaled to range from 0 (low) to 1 (high). In Panel B, TARP recipient is equal to 1 if the bank applied and was approved for CPP funds. For each bank that was not approved, we match the closest approved bank on propensity scores estimated from an probit regression estimating the likelihood of CPP approval using the political connections index, Camels variables, and foreclosures. The individual loan application data come from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry and cover the period 2006-2009. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation. We consider 2006-2008 as the period before TARP and 2009 as the period after TARP. All regressions include bank level controls, demographic controls, housing market controls, in addition to borrower gender, borrower race, and borrower ethnicity, and tract fixed effects, which are not shown to conserve space. Bank level controls include the Camels variables, exposure to market risk, and size. Demographic controls include the median family income, population size, and the percentage of minority population. Housing market controls include regional housing prices and vacancy rates. All variables are defined in Appendix A. The t-statistics (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the census tract level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: TARP approval predicted by the political connections index

Risk Measure	Overall sample	Loan-to-income ratio rank					Rate spread indicator=1
		Low	2	3	4	High	
Dependent variable	Application approval indicator						TARP recipient
After TARP	0.354*** [7.107]	0.479*** [6.338]	0.404*** [5.784]	0.109** [2.155]	0.196*** [3.443]	0.284*** [3.613]	0.040*** [10.597]
TARP recipient	0.177** [2.500]	-0.076 [1.123]	0.040 [0.583]	0.162** [1.975]	0.200** [2.058]	0.251** [2.523]	
After TARP x TARP recipient	-0.262*** [4.734]	-0.477*** [5.487]	-0.363*** [4.765]	0.004 [0.075]	0.060 [0.931]	0.136*** [3.573]	
Observations	698,955	124,488	110,676	125,807	135,133	147,963	55,977
R-Squared	0.118	0.086	0.110	0.151	0.156	0.143	0.538

Panel B: TARP approval propensity score matched sample

Risk Measure	Overall sample	Loan-to-income ratio rank					Rate spread indicator=1
		Low	2	3	4	High	
Dependent variable	Application approval indicator						TARP recipient
After TARP	0.030 [1.059]	0.045* [1.790]	0.011 [0.353]	-0.024 [0.826]	0.006 [0.207]	-0.051 [1.149]	0.196*** [2.841]
TARP recipient	-0.072*** [2.803]	0.013 [0.449]	-0.046 [1.401]	-0.110*** [3.979]	-0.112*** [4.324]	-0.065** [2.164]	
After TARP x TARP recipient	0.058 [1.623]	-0.123*** [3.808]	0.019 [0.436]	0.076 [1.148]	0.109*** [2.938]	0.175*** [3.835]	
Observations	120,417	22,534	17,705	19,085	21,229	28,297	9,202
R-Squared	0.226	0.142	0.209	0.256	0.270	0.249	0.461

TABLE 4
Robustness

This table reports regression estimates of the relation between the likelihood that a bank accepts a loan application and TARP across different borrower risk categories. The dependent variable is an indicator variable equal to 1 if a loan was approved, except the last column, in which the dependent variable is the TARP recipient indicator. In Panels A and B, TARP recipient is the predicted likelihood that a bank is approved for CPP funds, conditional on applying, from a probit regression of CPP approval on a bank's political connections index. *Political connections index* is a firm's average percentile rank in our sample on each of the following four measures of political connections: *House financial services subcommittee* (an indicator equal to 1 if the House member representing the voting district of a firm's headquarters served on the Capital Markets Subcommittee or the Financial Institutions Subcommittee of the House Financial Services Committee in 2008 or 2009), *Connected board member* (an indicator equal to 1 if a firm's board of directors in 2008 or 2009 included a director with simultaneous or former work experience at the banking regulators (Federal Reserve, FDIC, OTS, and OCC), Treasury or Congress), *Lobbying* (an indicator equal to 1 if the firm engaged in lobbying activity targeted at the banking regulators, Treasury, or Congress on the issues of banking, financial institutions, or bankruptcy from the first quarter of 2008 to the first quarter of 2009, inclusive), and *Contributions* (an indicator equal to 1 if the bank made political contributions by its sponsored political action committee(s) to the members of the Capital Markets Subcommittee and the Financial Institutions Subcommittee of the House Financial Services Committee in the 2008 congressional election campaign). The index is scaled to range from 0 (low) to 1 (high). The regressions in Panel A include Bank fixed effects. In Panel B, we exclude banks that were involved in FDIC-facilitated acquisitions. In Panel C, TARP recipient is a dummy that equals 1 if a bank was approved for CPP and received capital, and 0 if a bank was approved for CPP but subsequently did not receive capital. Each approved bank that did not receive capital is matched to its closest approved counterpart that received capital. Matching is based on the propensity to not receive capital conditional on approval from a probit model in which the independent variables include the Camels variables, foreclosures, and size. The individual loan application data come from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry and cover the period 2006-2009. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation. We consider 2006-2008 as the period before TARP and 2009 as the period after TARP. All regressions include bank level controls, demographic controls, housing market controls, in addition to borrower gender, borrower race, and borrower ethnicity, and tract fixed effects, which are not shown to conserve space. Bank level controls include the Camels variables, exposure to market risk, and size. Demographic controls include the median family income, population size, and the percentage of minority population. Housing market controls include regional housing prices and vacancy rates. All variables are defined in Appendix A. The t-statistics (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the census tract level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: Bank Fixed Effects

Risk Measure	Overall sample	Loan-to-income ratio rank				
		Low	2	3	4	High
Dependent variable		Application approval indicator				
After TARP	0.023	0.226*	0.006	0.108	0.087	0.177
	[0.198]	[1.655]	[0.059]	[1.118]	[0.707]	[1.065]
After TARP x TARP recipient	-0.037	-0.265*	-0.016	-0.012	0.092	0.199***
	[0.269]	[1.734]	[0.132]	[1.007]	[0.633]	[2.993]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	896,081	156,710	162,778	171,327	168,182	172,062
R-Squared	0.259	0.203	0.255	0.297	0.289	0.273

Panel B: Excluding FDIC-facilitated Acquisitions

Risk Measure	Overall sample	Loan-to-income ratio rank					Rate spread indicator=1
		Low	2	3	4	High	
Dependent variable		Application approval indicator					TARP recipient
After TARP	0.054 [0.967]	0.298*** [2.862]	0.157*** [3.062]	0.134** [2.156]	0.010 [0.136]	0.078 [0.856]	0.026*** [7.337]
TARP recipient	-0.218*** [4.120]	-0.206*** [2.851]	-0.314*** [5.289]	-0.258*** [4.418]	-0.234*** [3.212]	-0.136* [1.780]	
After TARP x TARP recipient	-0.196*** [2.939]	-0.447*** [3.559]	-0.280*** [4.749]	-0.263*** [3.626]	0.071 [0.657]	0.152*** [3.827]	
Observations	423,513	76,964	63,223	79,742	82,122	85,267	31,013
R-Squared	0.191	0.120	0.172	0.207	0.246	0.225	0.463

Panel C: Moral Hazard

Risk Measure	Overall sample	Loan-to-income ratio rank					Rate spread indicator=1
		Low	2	3	4	High	
Dependent variable		Application approval indicator					TARP recipient
After TARP	0.149*** [7.714]	0.056*** [2.602]	0.095*** [5.308]	0.152*** [6.988]	0.158*** [5.986]	0.204*** [7.602]	-0.039 [0.857]
TARP recipient	-0.062*** [2.658]	-0.090*** [2.665]	-0.098*** [3.530]	-0.069*** [3.017]	-0.053* [1.829]	-0.040 [0.852]	
After TARP x TARP recipient	0.035 [1.249]	-0.001 [0.035]	-0.063 [1.495]	0.024 [0.529]	0.029 [0.624]	0.014 [0.375]	
Observations	32,269	4,490	5,708	6,940	5,943	5,474	1,996
R-Squared	0.257	0.305	0.296	0.285	0.311	0.299	0.748

TABLE 5

Regression Evidence on Loan Demand across Risk Categories

This table reports regression estimates of the relation between the demand for loans and TARP across different borrower risk categories. In Panel A, the dependent variable is the natural logarithm of the total number of applications received by a bank each year. In Panel B, the dependent variable is natural logarithm of the total amount of loan applications received by a bank each year. The individual loan application data come from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry and cover the period 2006-2009. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation. We consider 2006-2008 as the period before TARP and 2009 as the period after TARP. All regressions include bank level controls, which include the Camels variables, foreclosures, and size. All variables are defined in Appendix A. The t-statistics (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the bank level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: Number of Loan Applications

Risk Measure	Overall sample	Loan-to-income ratio rank				
		Low	2	3	4	High
Dependent variable		Annual number of loan applications				
After TARP	-0.469*** [4.085]	-0.472*** [2.819]	-0.568*** [3.631]	-0.475*** [2.993]	-0.320* [1.913]	-0.469*** [2.913]
TARP recipient	0.143 [1.195]	0.316** [2.072]	0.173 [1.111]	0.078 [0.474]	-0.003 [0.018]	0.052 [0.371]
After TARP x TARP recipient	0.138 [1.325]	0.157 [0.992]	0.204 [1.436]	0.187 [1.333]	0.066 [0.440]	0.084 [0.571]
Observations	6,429	1,021	1,076	1,106	1,065	1,074
R-Squared	0.429	0.368	0.423	0.476	0.454	0.516

Panel B: Amount of Loan Applications

Risk Measure	Overall sample	Loan-to-income ratio rank				
		Low	2	3	4	High
Dependent variable		Annual total amount of loan applications				
After TARP	-0.509*** [4.776]	-0.610*** [3.534]	-0.601*** [4.039]	-0.442*** [2.738]	-0.258 [1.640]	-0.554*** [3.530]
TARP recipient	0.057 [0.521]	0.251* [1.821]	0.036 [0.260]	0.047 [0.280]	-0.034 [0.214]	-0.029 [0.203]
After TARP x TARP recipient	0.132 [1.352]	0.254 [1.516]	0.236* [1.719]	0.083 [0.584]	-0.031 [0.214]	0.150 [1.042]
Observations	6,429	1,021	1,076	1,106	1,065	1,074
R-Squared	0.434	0.429	0.5	0.543	0.498	0.52

TABLE 6
Regression Evidence on Corporate Lending and Risk

This table reports regression estimates of the relation between the risk of corporate borrowers and TARP funds. The dependent variable is the ratio of the number of lenders classified as TARP recipients to the total number of participants per syndicated loan. We consider two selection models. In the Political connections index model, TARP recipient is the predicted likelihood that a bank is approved for CPP funds, conditional on applying, from a probit regression of CPP approval on a bank's political connections index. In the matched sample model, TARP recipient equals 1 if the bank applied and was approved for CPP funds, and 0 if it applied and was not approved. For each bank that was not approved, we match the closest approved bank on propensity scores estimated from an probit regression estimating the likelihood of CPP approval. After TARP is an indicator that equals 1 in 2009-2010 and 0 otherwise. Data on corporate loans is gathered from Dealscan and cover the period 2006-2010. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. We employ to measures of borrowers' risk. Bond yield is the average spread between a company's outstanding bond issues and treasury yields with the closet maturity over the month preceding the loan. Credit rating is the average credit rating of a company's bond issues in the year preceding the loan. Data on bonds' yields are gathered from TRACE, whereas credit ratings are gathered from Mergent's FISD ratings dataset. All variables are defined in Appendix A. The t-statistics (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the borrower level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Risk measure	Bond yields			Credit ratings		
Selection model	None	Political connections index	Matched sample	None	Political connections index	Matched sample
After TARP	0.023*** [3.284]	0.007 [0.300]	0.084 [0.247]	-0.107 [0.774]	-0.216*** [3.561]	0.119 [0.885]
Risk	0.008*** [5.751]	0.006 [1.521]	0.062** [2.770]	-0.007 [1.479]	-0.015*** [8.196]	0.000 [0.742]
After TARP x Risk	0.005*** [2.801]	0.004*** [2.751]	0.006*** [2.622]	-0.009 [1.087]	-0.014*** [4.133]	-0.011*** [3.638]
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,021	2,007	1,072	937	937	926
R-Squared	0.847	0.846	0.971	0.015	0.933	0.866

TABLE 7
Regression Evidence on Banks' Investment Securities

This table reports regressions explaining banks' securities holdings. Safe securities include U.S. Treasury securities and securities issued by states & political subdivisions. Risky securities include equity securities, trading account (securities and other assets acquired with the intent to resell in order to profit from short-term price movements), corporate bonds, and Mortgage-backed securities. Long term debt securities include all maturities greater than 5 years. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation. Quarterly data on banks is gathered from Call Reports and cover the period 2006-2010. In Panel A, TARP recipient is the predicted likelihood that a bank is approved for CPP funds, conditional on applying, from a probit regression of CPP approval on a bank's political connections index. In Panel B, TARP recipient equals 1 if the bank applied and was approved for CPP funds, and 0 if it applied and was not approved. For each bank that was not approved, we match the closest approved bank on propensity scores estimated from a probit regression estimating the likelihood of CPP approval. After TARP is an indicator equal to 1 in 2009-2010 and 0 otherwise. All other variables are defined in Appendix A. The t-statistics (in brackets) are based on standard errors that are heteroskedasticity consistent. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: TARP approval predicted by the political connections index

Dependent variable	Total securities/assets	Total interest income on securities/assets	Lower-risk securities/total securities	Riskier securities/total securities	Long-term debt securities/total debt securities
After TARP	0.005 [1.173]	-0.001 [1.169]	-0.013** [2.188]	0.127*** [5.579]	0.037*** [3.836]
TARP recipient	-0.002 [1.076]	-0.000*** [5.003]	-0.001 [0.412]	-0.012*** [3.445]	0.033*** [5.925]
After TARP x TARP recipient	0.009** [2.782]	0.000*** [4.860]	-0.010* [1.838]	0.033*** [3.105]	0.002 [0.296]
Observations	5,745	5,745	5,713	5,713	5,704
R-Squared	0.003	0.017	0.001	0.034	0.010

Panel B: TARP approval propensity score matched sample

Dependent variable	Total securities/assets	Total interest income on securities/assets	Lower-risk securities/total securities	Riskier securities/total securities	Long-term debt securities/total debt securities
After TARP	0.005 [1.172]	-0.001 [1.169]	-0.013** [2.187]	0.127*** [5.576]	0.037*** [3.835]
TARP recipient	-0.018*** [7.829]	-0.000*** [5.564]	-0.034*** [22.301]	-0.005 [1.051]	0.013 [1.513]
After TARP x TARP recipient	0.020*** [4.398]	0.000*** [4.526]	-0.006 [1.229]	0.024** [2.254]	0.008 [0.769]
Observations	2,280	2,280	2,248	2,248	2,239
R-Squared	0.005	0.015	0.010	0.039	0.01

TABLE 8
Regression Evidence on Overall Bank Risk

This table reports results from regressions where the dependent variable is a measure of bank risk-taking. Quarterly data on banks is gathered from Call Reports and cover the period 2006-2010. The sample consists of 529 publicly-traded financial firms eligible for participation in the Capital Purchase Program (CPP) with available data on program application status. The sample excludes the nine CPP investments in the largest banks announced at program initiation. In Panel A, TARP recipient is the predicted likelihood that a bank is approved for CPP funds, conditional on applying, from a probit regression of CPP approval on a bank's political connections index. In Panel B, TARP recipient is equal to 1 if the bank applied and was approved for CPP funds. For each bank that was not approved, we match the closest approved bank on propensity scores estimated from an probit regression estimating the likelihood of CPP approval. After TARP is an indicator equal to 1 in 2009-2010 and 0 otherwise. ROA is net operating income as a percent of average assets. Earnings are net operating income as a percent of average assets. For each quarter, the standard deviation of ROA and earnings is calculated as the quarterly standard deviation over the previous 4 quarters. The capital asset ratio is average total equity divided by average assets. Z-score is the natural logarithm of the sum of ROA and capital asset ratio divided by the standard deviation of ROA. To compute betas, we assume the market model, with the CRSP value-weighted index used as the market proxy. Betas are calculated for each calendar quarter using daily returns. All variables are defined in Appendix A. The t-statistics (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the bank level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: TARP approval predicted by the political connections index

Risk Measure	Z-Score	Standard deviation of ROA	Standard deviation of earnings	Capital asset ratio	Beta	Stock return volatility
Model	(1)	(2)	(3)	(4)	(5)	(6)
After TARP	-0.161 [0.656]	0.056*** [4.213]	0.057*** [4.322]	-0.041*** [4.502]	-0.181 [0.953]	0.070*** [4.103]
TARP recipient	5.407*** [8.103]	-0.043*** [6.409]	-0.041*** [6.114]	-0.069*** [7.073]	-0.952*** [6.574]	-0.039** [2.951]
After TARP x TARP recipient	-0.261*** [2.933]	0.061*** [4.164]	0.062*** [4.264]	0.044*** [4.124]	0.408** [2.592]	0.061*** [5.350]
Liquidity	-0.000*** [7.703]	0.000*** [3.290]	0.000*** [3.888]	0.000*** [7.247]	0.000 [0.728]	0.000*** [6.421]
Size	-0.217*** [11.615]	-0.001 [0.658]	-0.001 [0.644]	-0.001*** [3.931]	0.373*** [11.689]	0.002* [1.989]
Observations	7,122	7,178	7,178	7,185	5,632	5,632
R-squared	0.194	0.255	0.255	0.054	0.371	0.151

Panel B: TARP approval propensity score matched sample

Risk Measure	Z-Score	Standard deviation of ROA	Standard deviation of earnings	Capital asset ratio	Beta	Stock return volatility
Model	(1)	(2)	(3)	(4)	(5)	(6)
After TARP	-0.326*** [4.485]	-0.005*** [4.207]	-0.005*** [4.044]	-0.024*** [10.531]	0.011 [0.087]	0.036** [2.633]
TARP recipient	0.155*** [7.995]	-0.003*** [6.552]	-0.004*** [7.009]	0.003*** [3.760]	0.039* [2.082]	-0.004* [2.131]
After TARP x TARP recipient	-0.239*** [6.854]	0.010*** [13.527]	0.010*** [14.524]	0.020*** [8.615]	0.048** [2.547]	0.010** [2.725]
Liquidity	-0.069*** [8.163]	0.001*** [8.184]	0.001*** [8.596]	0.000 [1.586]	0.021** [2.545]	0.001*** [3.445]
Size	-0.243*** [11.815]	-0.001 [0.785]	-0.001 [0.708]	-0.009*** [11.837]	0.403*** [13.308]	0.001 [0.941]
Observations	2,229	2,274	2,274	2,279	1,751	1,751
R-squared	0.120	0.068	0.070	0.127	0.305	0.174