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Liquidity Risk and the Credit Crunch of 2007-2008: Evidence from Micro-Level Data on Mortgage Loan Applications

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Keywords: liquidity risk, bank lending channel, credit lines, core deposits, mortgage credit

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Liquidity Risk and the Credit Crunch of 2007–2008: Evidence from Micro-Level Data on Mortgage Loan Applications

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Abstract

Recent empirical studies have shown that during the financial crisis of 2007–2008 banks that were more heavily exposed to liquidity risk contracted their supply of credit more sharply. I contribute to the identification of this effect by relying on the use of micro-level data on US mortgage loan applications, which allows me to identify liquidity risk as an important determinant of the contraction of credit in the mortgage market, but as separate from the precipitous fall in credit demand, disruptions in the securitization and subprime markets, shifts in asset risk, and changing risk-aversion among loan officers.

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I. Introduction

The financial crisis of 2007–2008 brought about a severe contraction of credit. Two broad categories of mechanisms may account for this contraction. On the demand side, deleveraging by households and firms should have caused the amount of credit demanded to drop. On the supply side, the deterioration in the financial condition of banks may have produced a lower propensity to lend. This paper seeks to empirically identify the effect of a particular supply-side mechanism on the provision of mortgage credit during the crisis, and quantify its impact.

I focus on liquidity risk, the possibility that a bank may suffer an adverse shock to its liquidity position, and ask whether funding illiquidity pressures on banks, or on their non-mortgage loan customers, precipitated a contraction of mortgage lending. In particular, I examine whether high bank reliance on wholesale funding[1] and high accumulated off-balance sheet exposure to unused lines of credit[2] affected the supply of credit in the mortgage market during the financial crisis.

Concerns about liquidity risk became particularly relevant in the US during the financial crisis of 2007–2008, and two recent studies have empirically identified a contractionary effect of exposure to liquidity risk on the supply of credit during this period; Ivashina and Scharfstein (2010) for the syndicated loan market and Cornett,

[1] *Wholesale funding* is the part of funding that does not come from *core deposits*. The two terms will be used frequently in this paper and their effects can be interpreted in relation to each other (i.e., high reliance on core-deposit funding means low reliance on wholesale funding and vice versa).

[2]Unused lines of credit are issued by banks to their customers and they represent commitments to supply credit to the customer, on the customer's request, up to a maximum credit limit. Funding illiquidity strains on a bank's customers can lead to increased requests for credit, thus imposing a strain on the bank's liquidity position.

McNutt, Strahan, and Tehranian (2011) for the aggregate lending portfolio of commercial banks. Identification in these papers is limited by the lack of refined information on credit demand conditions.

I extend the empirical findings of Ivashina and Scharfstein (2010) and Cornett et al. (2011) in three ways. First, I use micro-level data on individual mortgage loan applications, furnished by the Home Mortgage Disclosure Act (HMDA), which provide detailed information on credit demand conditions and allow for the separation of the supply channel from the demand channel. Importantly, the dataset contains the outcome of individual loan applications, and thereby facilitates identification along the loan approval margin, which is a more informative measure of credit supply than shifts in the stock of loans held on balance sheet or shifts in the volume of originations, both of which could be driven by demand conditions.

Second, I utilize information on the quality of credit demanded and the transaction chain of originated loans to identify the effect of liquidity risk as separate from shifts in risk aversion levels by loan officers and disruptions in the securitization and subprime markets. Third, I focus on the mortgage market and produce the first estimates of the economic impact of liquidity risk on this important sector of finance during the financial crisis of 2007–2008.

The data suggest that demand-side drivers of credit activity were indeed important during the crisis. Demand for mortgage credit declined dramatically, and by 2009 the number of applications to commercial banks in my sample dropped to approximately one half of the corresponding pre-crisis levels. In addition, the distribution of borrower characteristics shifted significantly along a number of dimensions moving through the crisis.

To control for the quantity of credit demanded, I condition on the number of applications received and restrict my attention to estimating a model of the approval decision. The model identifies the effect of liquidity risk on credit supply as the structural break in the within-bank relation between lending propensity and exposure to liquidity risk during the funding crunch, as that is evident by the sharp widening of the TED spread in 2007–2008.[3] Estimation is over the period 2006–2009 and the unit of observation is the lender-location-year tuple. The specification controls for the borrower's risk profile, for local economic conditions, and for a number of possibly confounding frictions in the supply channel.

I find that lenders which were more greatly exposed to liquidity risk, through high levels of unused lines of credit and low levels of core-deposit funding, contracted their supply of mortgage credit more during the crisis. This inward shift in the supply curve I find to be important in addition to the effects of shortfalls in bank equity, disruptions in securitization and subprime markets, accumulation of asset risk held on and off balance-sheet, and changing risk aversion among loan officers.

Estimates on subsamples of banks categorised by asset size indicate that liquidity risk did not affect the supply of credit uniformly across size categories. Very small banks ($Assets <$ \$500 million) did not contract their credit supply in response to liquidity risk, possibly due to their low levels of exposure to wholesale funding and credit lines. In addition, liquidity risk arising from off-balance sheet exposures to credit lines only affected the credit supply of large banks ($Assets >$ \$10 billion).

The question remains whether, once controlling for the fall in credit demand and for other confounding explanations, the effect of liquidity risk on credit supply is economically significant. To assess economic significance, I run a counterfactual exercise in which the lenders enter the crisis with their levels of exposure to liquidity risk reduced down to the bottom quartile of the distribution. With the quantity and quality of credit

[3] The TED spread measures funding stresses in the banking sector and is defined as the difference between the 3-month LIBOR rate and the 3-month Treasury rate.

demanded fixed to their crisis levels, I compute the increase in loan originations due to the outward shift in the supply curve that the reduction in exposure to liquidity risk would have effected.

I find that the decrease in exposure would have resulted in an additional $55 billion of mortgage originations for 2007–2008, which represents an increase of 14% over the total volume of mortgages originated by lenders in my sample during this period. As a percentage of the annual volume of originations, the increase would have been greater in 2008 (17%). The estimates also show that the economic effect of credit line exposures is larger than the effect of wholesale funding by approximately a factor of two.

The results are robust to estimating the model using the pre-crisis levels of liquidity risk in order to mitigate the impact of possibly endogenous adjustments to liquidity risk made by banks during the crisis. The results also hold in subsamples which exclude banks that failed after the end date of the sample (2009), or banks which received government assistance through the Capital Purchase Program (CPP), to control respectively for the confounding effects of bank default risk and government interventions during the crisis. Last, the results hold in a subsample which excludes bank-locations in which the bank did not have a continuous presence during the four years of the sample, to account for strategic repositioning across geographical markets by lenders.

The paper builds on three key insights from the literature. First, to identify the supply of credit one must carefully control both for the quantity and quality of credit demand. Second, through balance sheet constraints, shocks specific to a particular line of business of a bank can transfer across the balance sheet and affect the supply of credit in another line of business. Third, the liquidity crisis entered the balance sheets of lenders through exposure to wholesale funding, the markets for which experienced substantial pressures during the crisis, and through off-balance sheet commitments that were drawn upon by clients experiencing funding pressures in their own sectors.

The question of whether frictions in the supply channel may affect credit is not new. Early empirical studies examined the effect of monetary policy on the supply of credit and documented the existence of the "bank channel" of transmission of monetary policy. Due to their coarse treatment of demand conditions these early studies invited alternative interpretations involving the demand channel.[4] This shortcoming was soon addressed in the literature, and subsequent studies improved on identification by utilizing cross-sectional balance sheet data and controlling for demand conditions through the inclusion of variables which capture the lenders' geographical presence and degree of exposure to business cycles in different sectors of the economy (Kashyap and Stein (2000), Cetorelli and Goldberg (2012), and Aiyar, Calomiris, and Wieladek (2012)).

Increased access to micro-level data on individual loan transactions has resulted in a number of recent studies, which examine the impact of financial frictions on the supply of credit while providing an even more granular treatment for demand conditions.[5] My paper contributes to this strand of the literature by utilizing micro-level data on mortgage loan applications to study the effect of liquidity risk on the supply of mortgage credit during the financial crisis of 2007–2008.

[4] Kashyap and Stein (2000) offer a discussion of alternative interpretations involving demand-side explanations of the bank channel effects identified in Bernanke and Blinder (1992), among others.

[5] Dell'Ariccia, Igan, and Laeven (2012) investigate the effect of competition on the supply of mortgage credit before the crisis of 2007–2008, Loutskina and Strahan (2009) the effect of deposit costs and asset liquidity on the supply of non-conforming loans in the US, Puri, Rocholl, and Steffen (2011) the effect of German savings banks exposure to the US subprime crisis on the supply of retail lending in Germany, Jimenez, Ongena, Peydro, and Saurina (2012) the effect of monetary policy and balance sheet strength on the supply of C&I loans in Spain, Paravisini (2008) studies the effect of government interventions in Argentina, and Khwaja and Mian (2008) the effect of a run on dollar deposit accounts due to nuclear testing in Pakistan. The results in these studies uniformly indicate that negative shocks to funding result in a contraction of credit.

Liquidity risk is the possibility that a bank may suffer an adverse shock to its liquidity position. Shocks to a bank's liquidity position can affect credit supply because of the banks' central role in liquidity provision.[6] Through balance sheet constraints, shocks in one line of business can cause a contraction of credit in another line of business, and this channel can operate both across balance-sheets and across borders (Campello (2002), Cetorelli and Goldberg (2012), Peek and Rosengren (1997), and Peek and Rosengren (2000).)

My paper identifies a localised version of this mechanism and tracks the effect of exogenous shocks to liquidity, stemming from stresses in the markets for wholesale funding and drawdowns on lines of credit, on the supply of mortgage credit. Table 1 illustrates the operation of this channel through a series of stylized balance-sheet transactions, where the dependence on a common pool of liquid assets is the resource constraint through which liquidity risk can affect the supply of mortgage credit.

[Table 1 about here]

During the financial crisis of 2007–2008 the primary source of stresses to bank funding conditions arose from the funding illiquidity experienced in the markets for wholesale funding (Adrian and Shin (2009), Gorton and Metrick (2012), and Schwarz (2014)). More specific to the funding structure of commercial banks are core deposits which, as shown in Gatev, Schuermann, and Strahan (2007), can result in increased inflows of funds and can thus help a bank raise its liquid asset buffers during times of low market liquidity. In further support to the stability of core deposits as a source of funding during the recent financial crisis, Ratnovski and Huang (2009) show that Canadian banks that

[6] Berger and Bouwman (2009) construct a measure of liquidity provision based on the composition of assets and liabilities on a bank's balance sheet.

relied more on core-deposit funding fared better in a number of performance metrics than their wholesale-funded counterparts did during the crisis.

Further strains on liquidity can come from takedowns on lines of credit previously issued by the bank. Firms, for example, establish lines of credit with banks as an ex-ante contract to insure against states with negative shocks to liquidity (as in Holmstrom and Tirole (2000)). Ivashina and Scharfstein (2010) provide evidence of increased use of credit lines by firms during the recent financial crisis, and Campello, Giambona, Graham, and Harvey (2011) show how companies substituted between internal liquidity and lines of credit during the crisis. Liquidity pressures faced by a bank's customers can thus be transmitted to the bank's balance sheet through this "drawdown" channel, and displace new lending.

Two recent empirical studies draw the connection between liquidity risk and credit supply during the recent financial crisis. Examining the impact of deposit funding and credit line exposure on the supply of syndicated loans, Ivashina and Scharfstein (2010) show that high exposure to short-term debt and unanticipated drawdowns on lines of credit, due to high levels of co-syndication of revolving lines with Lehman, led to a decrease in new credit origination for large syndicated loans. Using a larger sample and focusing on the aggregate lending portfolio of commercial banks, Cornett et al. (2011) show that exposure to the same two sources of liquidity risk resulted in liquidity-hoarding and a contraction of bank credit during the crisis.[7] Identification in both of these studies is limited by the lack of detailed data on demand conditions during this period, and this paper's main contribution is to use micro-level data on mortgage loan applications to disentangle the demand channel from the supply channel.

The rest of the paper proceeds as follows. Section II discusses the main challenges

[7] Cornett et al. (2011), however, show that it is core deposits rather than total deposits that provided stable funding for banks.

to identification and develops an empirical strategy to address them. Section III describes the data sources used and presents summary statistics which track aggregate demand and supply conditions in the mortgage market moving through the crisis. Section IV presents the main results, Section V tests the results for robustness against a number of alternative specifications, and Section VI concludes.

II. Identification Strategy

Previous studies on the effect of liquidity risk on credit supply rely on the use of imprecise proxies for credit origination, such as the variation in the stock of loans held on the bank's balance sheet, which do not convincingly separate the demand for credit from the supply of credit.[8] Such approaches have certain limitations, which I illustrate in a series of relations shown below for a bank indexed i during a year indexed t, where $\Delta \mathrm{L}_{it}$ is the change in the stock of loans held on the bank's balance sheet.

$$\Delta \mathrm{L}_{it} = \mathrm{ORIGINATIONS\_HELD}_{it} - \mathrm{MATURING\_LOANS}_{it} + \mathrm{DRAWDOWNS}_{it}, \tag{1a}$$

$$\mathrm{ORIGINATIONS}_{it} = \mathrm{ORIGINATIONS\_HELD}_{it} + \mathrm{ORIGINATIONS\_SOLD}_{it}, \tag{1b}$$

$$\mathrm{ORIGINATIONS}_{it} = \mathrm{APPROVE}_{it} \times \mathrm{DEMAND}_{it}, \tag{1c}$$

$$\mathrm{APPROVE}_{it} = \mathrm{SUPPLY}_{it} + \mathrm{BORROWER\_RISK}_{it} + \mathrm{LOCATION}_{it}. \tag{1d}$$

A reduction in the stock of loans held on a bank's balance sheet can be the result of a contraction in loan supply, but can also be driven by the maturity structure of the bank's loan portfolio and by drawdowns on credit lines (1a).[9] In addition, the balance sheet incorporates no information about originated loans that were sold, a limitation which is of

[8] See for example Cornett et al. (2011).

[9] Cornett et al. (2011) work around the effect of drawdowns by normalizing the change in on-balance sheet credit by the sum of assets and unused lines of credit.

particular concern in the domain of mortgage lending (1b).

Assuming that one has access to a "pure" measure of loan originations, for which the aforementioned concerns are no longer relevant, one still needs to account for the fact that loan origination is the product of the quantity of credit demanded and the bank's loan approval propensity (1c). Focusing instead on the approval decision can get around concerns about the quantity of credit demanded, but poses the challenge that the approval decision is determined by a combination of (a) frictions in the supply channel, (b) the risk profile of the borrower and (c) local economic conditions in the area of operation of the lender (1d).

In this paper, I rely on the use of micro-level data on individual mortgage loan applications, which for each application provide the bank's decision to approve or decline the application, as well as a set of characteristics of the borrower, the location of the property for which the application was filed, and the identity of the lender. I estimate the following variant of the main specification used in Cornett et al. (2011):

$$\begin{aligned} \text{APPROVE}_{ijt} = m_{jt} + \alpha_i + \beta \times \text{X}_{it-1} + \gamma \times \text{TED}_t \times \text{X}_{it-1} \\ + \delta \times \text{Y}_{ijt} + \theta \times \text{TED}_t \times \text{Y}_{ijt} + u_{ijt}. \end{aligned} \tag{2}$$

APPROVE_{ijt} is the approval rate of lender i in Metropolitan Statistical Area (MSA) j in year t, m_{jt} are location-year fixed effects capturing the impact of local economic conditions and of other aggregate time-varying factors on lending propensity, α_i are lender fixed effects controlling for unobserved time-invariant heterogeneity across lenders, TED_t is the TED spread for year t, X_{it-1} is a vector of time-lagged bank financial variables measured at end-of-previous-year levels, Y_{ijt} is a vector of borrower characteristics averaged over each lender-location-year unit, and u_{ijt} is an idiosyncratic error term.

All variables are interacted with the TED spread to allow for the response of lenders to financial frictions and borrower risk to evolve flexibly during periods of funding stresses. The TED spread measures funding strains in the banking sector, and as an aggregate measure it is understood to change exogenously to an individual bank's financial condition.

Figure 1 shows daily variation in the TED spread during 2006–2009. The TED spread spiked during August 2007 following uncertainty about the value of some categories of mortgage-backed securities (MBS). It peaked at 457 basis points during October 2008 following a series of failures of banks and other financial institutions, and returned back to July 2007 levels during the spring of 2009 as a result of Federal Reserve and Treasury interventions.

[Figure 1 about here]

During periods of strain on bank funding conditions (i.e., during periods when the TED spread widens) banks with higher levels of exposure to liquidity risk are expected to contract their supply of credit more, and the relation between exposure to liquidity risk and credit supply should therefore undergo structural adjustments. The coefficients of the interaction terms $\text{TED}_t \times \text{X}_{it-1}$ identify the effect of liquidity risk on credit supply by imposing the identification restriction that these structural breaks be aligned with the pattern of structural breaks observed in the TED spread. One limitation of my dataset is that I only know the year in which the loan application was filed, and by necessity I therefore use the average TED spread over each year. As in Cornett et al. (2011), I focus on the four-year window surrounding the main events of the crisis (2006–2009).

I interact location fixed effects with time to account for intertemporal shifts in loan officers' assessment of risk, possibly driven by considerations regarding local economic conditions. For example, areas in which credit standards may have been relaxed in the presence of rapidly rising housing prices prior to the crisis, may have experienced severe credit tightening in response to the collapse of housing prices during the crisis.

I estimate the model using an OLS estimator, with standard errors clustered at the lender level to account for serial correlation in the error term. I weigh the observations by the number of applications using analytic weights to account for the fact that the dependent variable was averaged over lender-MSA-year tuples of different sizes.[10] Continuous variables are winsorized at the 1st and 99th percentiles to limit the impact of outliers.

A. Choice of Control Variables

The explanatory variables are core-deposit funding and unused lines of credit. Core-deposit funding captures the bank's degree of insulation from the negative developments in the markets for wholesale funding during the crisis (repurchase agreements, commercial paper, etc...), and the level of unused lines of credit captures the bank's degree of exposure to the possibility of rapid drawdowns. I expect the coefficient of the interaction of the TED spread with core-deposit funding to enter with a positive sign and the coefficient of the interaction with unused lines of credit to enter with a negative sign.

The financial crisis brought about significant strains on liquidity for banks and their customers. To the extent that (i) the financial crisis and resulting strains were not anticipated by banks and (ii) the shocks to liquidity (drawdowns, withdrawal of wholesale funding) were primarily determined by the actions of actors outside the bank, we can assume these shocks to be exogenous to the bank's endogenous liquidity management

[10] Weighting the observations mitigates the effect of noise coming from lender-MSA-year pairs with a small number of applications. The results presented throughout also hold if in addition I drop all MSA-lender-year pairs that had fewer than 10 loan applications.

operations. The two variables capturing exposures to liquidity risk are the only variables whose coefficients I will interpret causally.

The vector of control variables in the baseline model also includes the natural logarithm of assets to capture size effects, as well as asset liquidity and capital adequacy ratios to control for the overall liquidity and solvency position of the lender. The direction of the effect for each of the control variables is not clear on theoretical grounds and I will thus present their coefficients without further discussion in the results section. With a particular focus on asset liquidity and capital adequacy one could argue that, being measures of financial health, they should enter estimation with positive structural breaks during periods of bank funding strains. The thinking normally employed is that since asset liquidity provides a buffer for negative shocks to liquidity and capital adequacy provides a similar buffer for negative shocks to capital, then the higher the buffer levels the more "immune" the bank is to such shocks, and the more lending it should engage in. Banks, however, may endogenously choose to build these buffers for reasons related to asset risk (as in Calomiris and Wilson (2004)), so high stocks of liquid assets and/or of capital could very well correlate negatively with lending propensity.

Last, I include a set of control variable that capture shifts in borrower risk. The loan-to-income ratio proxies for the repayment capacity of the borrower, with a higher ratio expected to result in a lower probability of approval. I include a binary indicator variable for minority applicants to capture the impact of important unobservable loan characteristics that may correlate with race. For example, for a sample of applicants in the Boston MSA, Munnell, Tootell, Browne, and McEneaney (1996) show that minority applicants have on average lower wealth, weaker credit histories, and higher loan-to-value ratios than non-minority applicants. I also include a dummy variable for loan amounts which exceed the conforming loan size threshold (jumbo loans),[11] as Loutskina and Strahan (2009) provide evidence of higher denial rates for non-conforming loans, due to their relative illiquidity. I include the natural logarithms of applicant income and loan size to control for additional unobserved wealth effects. For completeness, I also include a set of variables for the effect of which I do not have a strong prior, but which could nonetheless be relevant determinants of the loan decision. These are binary indicator variables for female applicants, manufactured housing, and properties under a junior lien. Detailed definitions for each variable can be found in Table 2.

[Table 2 about here]

III. Data Sources and Summary Statistics

I compile data from two different sources: home mortgage application data from the *Home Mortgage Disclosure Act (HMDA)* and bank financial data from the quarterly *Reports of Condition and Income (Call Reports)*. To achieve a more uniform sample, I prune the data along a number of dimensions, and data selection is discussed in detail in the Appendix. There is strong support in the data for the presence of shifts in loan demand and borrower risk, both of which the identification strategy described in the previous section is designed to address.

A. Mortgage Loan Data (HMDA)

HMDA was enacted by Congress in 1975 and implemented by the Federal Reserve Board's Regulation C. It requires lending institutions to report data on mortgage loan applications and its purpose is to enhance the enforcement of anti-discriminatory laws and publish

[11] The threshold is taken from Fannie Mae guidelines.

information that would guide public investment in housing. The database covers a significant portion of all lending activity in the home mortgage market, with reporting requirements effectively resulting in the exclusion of small lenders in rural areas (Dell'Ariccia, Igan and Laeven (2012)).

The dataset reports the year of application but not exactly when during the year the application was filed, loan attributes (amount, purpose, etc...), borrower characteristics (income, sex, race, etc...), as well as demographic variables for the location in which the property is located (median salary, percentage of population that are minorities). Importantly, the dataset provides information about the outcome of the application. This decision is solely controlled by the lender and, as discussed in Section II, is a much more informative measure of credit supply than aggregate measures of lending, such as variation in the stock of loans held on a bank's balance sheet or variation in the volume of loan originations.

B. Bank Financial Data (Call Reports)

I obtain financial data for lending institutions from the Reports of Condition and Income (Call Reports) made available online in summary form by the Federal Reserve Bank of Chicago. The reports are filed by commercial banks, and contain detailed financial data in a number of different schedules (balance sheet, income statement, securities holdings, etc). As a number of studies have documented the operation of internal capital markets for banks belonging to bank holding companies (Campello (2002), and Cetorelli and Goldberg (2012)) financial data are aggregated up at the bank holding company level.

The literature has traditionally studied differences in bank behavior by dividing lenders across the size dimension, as this is the dimension most likely to sort out major differences in important unobservables across lenders.[12] To account for the possibility of a large-small bank dichotomy in the results, I divide the sample into four categories of lenders based on size: (1) Assets≤\$500 million, (2) \$500 million<Assets≤\$1 billion, (3) \$1 billion<Assets≤\$10 billion, and (4) Assets>\$10 billion, and refer to these categories respectively as "very small", "small", "medium", and "large" lenders. The division is based on the average asset size of each bank over 2006–2009, and I use the average to ensure that the estimates are not affected by exits and re-entries into the different size categories due to lenders crossing the threshold for each category across time. The summary statistics, as well as the regression estimates, will be presented separately for these four categories.

C. Aggregate Trends in the Mortgage Market

Figure 2 plots the path of mortgage loan originations for 2006–2009 for the four groups of lenders. Graph A shows the number of originations, and Graph B shows an index with the number of originations normalized to the 2006 levels for each lender group.[13] As shown in Graph A, the vast majority of mortgage loans were originated by the group of large lenders (Assets>\$10 billion).

[Figure 2 about here]

The three smaller groups of lenders exhibit the first signs of a decline in originations as early as 2007, but for the group of large lenders originations slightly

[12]See Allen and Saunders (1986) for differences in the costs faced in the federal funds market, and Kashyap and Stein (2000) for differences in the strength of the bank lending channel of transmission of monetary policy.

[13]All of the patterns remain virtually identical if one considers the \$ volume of originations instead.

increase in 2007.[14] Originations drop sharply in 2008 for all groups of lenders, a trend which continues, albeit at a slower pace, into 2009; the only exception is medium-sized lenders that experience a small increase in originations. Observing the normalized patterns shown in Graph B, we see that large lenders generated the sharpest drop in originations from 2006, with originations in 2009 being at around 40% of the 2006 levels.

Providing support for the identification concerns discussed in Section II, Figure 3 traces one of the major drivers of the precipitous fall in loan originations back to the rapidly declining numbers of loan applications; the patterns are strikingly similar. Focusing on large lenders to get a sense of the magnitude of this decline, it can be seen that even if every single application filed in 2008 was approved, the number of originations would still fall short of 2006 levels. To the extent that the rate of decline in loan applications was not uniform in the cross-section of lenders, this graph also suggests that balance-sheet measures of credit supply may well be capturing variation in loan demand rather than variation in supply.

[Figure 3 about here]

Conditioning on the quantity of mortgage credit demanded (number of applications) frictions in the supply channel should have caused a decline in loan approval rates. Figure 4 plots loan approval rates against time and does indeed trace part of the contraction of mortgage lending back to lower approval rates. Approval rates by lenders in my sample followed a declining path from 2006 to 2008, with the sharpest tightening generated by the group of large lenders, which were however the only lender category with a partial recovery in approval rates in 2009.

[14]This is only true for the subsample of lenders considered in this paper, which are the lenders present in HMDA for the complete period 2006–2009. In the complete sample of large lenders, which includes lenders which exited during this period, originations decline in 2007 too.

[Figure 4 about here]

The time-series variation in approval rates is likely to have been driven both by shifts in the risk profile of borrowers and by frictions in the supply channel. Table 3 shows summary statistics for bank financial variables and loan characteristics for the period 2006–2009, which indicate significant time-series variation across both dimensions.

[Table 3 about here]

D. Shifts in Borrower Characteristics

Larger lenders receive a greater portion of applications from minority and female applicants. Moving through the crisis, there was a decrease in the proportion of applications from minority applicants across all banks, but the proportion of female applicants remained relatively stable over time. Larger banks also attract higher income applicants purchasing more expensive properties, with a higher loan to income ratio; across all bank categories the values of these variables increased during the crisis. In an environment of rapidly declining property values, these trends would suggest a shift in the composition of the applicant pool towards wealthier borrowers with higher, however, loan to income ratios. As expected due to the higher loan sizes, larger banks receive a higher portion of applications for non-conforming (jumbo) loans; the percentage of jumbo loans, however, remains relative stable over time. Larger banks receive a lower portion of applications for manufactured properties but a higher portion for properties on which they would only hold a junior lien; the latter portion has been declining steadily across all bank categories.

The summary statistics suggest that the distribution of borrower characteristics shifted along several dimensions during the crisis. These shifts could have been driven by the banks' choices regarding the locations in which they operate, and the identification strategy employed in this paper controls both for borrower characteristics and for the banks' locational mix.

E. Shifts in Lender Characteristics

Table 3 also provides summary statistics for lender characteristics. Financial variables are reported at end-of-previous-year (fourth quarter) levels, securitization and subprime activity variables are averages taken over lender-MSA-year tuples and measured during the lending year. Lender size has been increasing steadily during 2006–2009 across all lender categories. Smaller banks have higher Tier 1 capital ratios (measured on a risk-weighted basis) and higher asset liquidity. As expected, liquidity decreased across all bank categories moving through the crisis. Capital buffers on the other hand remain relatively flat during this period, possibly because loan losses started becoming apparent with a time lag in 2009 and because the sample includes only banks which did not fail during 2006–2009.

Larger banks hold more agency-issued and private-label MBS, though the average holdings of private-label MBS are close to zero due to the fact that only a small number of commercial banks held these assets on their balance sheets. Holdings of residential real estate loans are approximately equal across lender categories. Large banks hold the lowest portion of assets invested in non-residential real estate loans.

Balance-sheet measures of credit supply are particularly uninformative in the mortgage market, where a significant portion of originated loans are sold and thus never enter the originating institution's balance sheet. Larger banks sell a higher portion of their originated loans to GSEs and a lower portion to non-GSEs than smaller banks. The percentage of loans sold to GSEs has increased sharply through the crisis, whereas the percentage sold to non-GSEs has decreased over the same period. Significant differences exist in subprime activity across lender categories, as smaller lenders tend to originate a higher portion of potentially subprime loans.[15] For medium and large banks this percentage has decreased after 2008, but the presence of a similar trend is not evident for smaller banks.

Figure 5 plots the time-series variation in the lenders' average levels of core-deposit funding (Graph A) and unused lines of credit (Graph B) moving through the crisis. The graphs clearly illustrate a positive relation between lender size and the level of exposure to liquidity risk. Moving through the crisis, we observe a decline in core-deposit funding a trend which for the largest lenders started reversing entering 2009.

[Figure 5 about here]

The level of exposure to unused lines of credit remains relatively flat entering 2008, but there is a uniform decline across all lender categories entering 2009. In principle, this decline could have been driven by two mechanisms. First, banks were cancelling or not renewing credit lines. This mechanism would suggest that banks which entered the year with high exposure to credit lines, faced little liquidity risk during the year because they could limit the exposure before drawdowns materialized. The second mechanism that could justify the drop in the levels of unused credit lines involves drawdowns on credit lines, and the realization (or possibility of realization) of drawdowns is a source of liquidity risk; it is the presence of this latter mechanism and its effect on credit supply that I seek to identify in this paper.

[15] The HMDA dataset does not explicitly identify subprime applications. For *originated* loans, however, it does contain a rate-spread measure reported only when the borrowing rate exceeds a certain threshold when compared against the rate on a treasury security of comparable maturity. This is a broad proxy rather than a precise measure of subprime activity, as it does not take into account up-front fees, adjustable-rate schedules, etc..., but should serve well as a first order approximation for variation in subprime activity.

IV. Estimation Results

In this section I discuss the results obtained from the estimation of the model.

A. Baseline Model

Columns (1)-(4) of Table 4 show the estimated coefficients for the baseline model for the four categories of lenders classified by asset size. As the coefficients on the interaction terms (TEDx) indicate, during the crisis lenders that relied more on core-deposit funding contracted their supply of credit less. This effect is present across all lender categories except for very small lenders. For very small lenders the absence of an effect could be a non-linearity due to their high levels of reliance on core-deposit funding (conversely, due to their low levels of exposure to wholesale funding). Liquidity risk from exposure to credit lines on the other hand, resulted in a contraction of mortgage credit only for large lenders. These initial findings have the causal interpretation that high levels of liquidity risk resulted in a contraction of credit, though drawdown risk appears to have impacted the supply of credit only for large lenders.

[Table 4 about here]

B. Accounting for Securitization and Subprime Lending

The results presented above show that banks which operated through the crisis on a business model which relied less on core-deposit funding and accumulated significant off-balance sheet exposures to credit lines, contracted their supply of credit more. The identification strategy utilizes the rich information in the HMDA dataset to separate the effect of credit supply from that of credit demand. The focus on the mortgage market, however, potentially poses additional challenges for identification. Of particular concern are securitization and subprime activity during this period, as one may assume that banks which were more heavily exposed to liquidity risk were also more actively involved in securitisation and subprime markets.

Mian and Sufi (2009) show that securitization rates were an important driver of credit before the crisis and Keys, Mukherjee, Seru, and Vig (2010) show that the ease of securitization led to the origination of loans with higher default rates for applicants with almost identical risk profiles. A significant portion of originated loans are securitized and, as securitization markets were severely disrupted during the crisis, banks which relied more heavily on securitization are expected to have contracted lending more during the crisis. A related component of the crisis is the market for subprime loans. Lenders which were more active in this market are believed to have adopted looser credit standards before the crisis, standards which would have been subsequently tightened during the crisis.

The baseline model includes lender fixed effects which would capture time-invariant features of the lender's business model, such as an emphasis on the originate-to-distribute model or a focus on subprime lending. To account for variation in securitization opportunities across lenders and time, I include the rates at which originated loans were sold to GSEs and to non-GSES. I also include a measure of the proportion of originated loans which could be potentially classified as subprime, to control for the extent to which the lender was active in the subprime market. All variables are measured at the lender-MSA-year level.

I augment the baseline model to include these additional control variables and the estimated coefficients are shown in columns (5)-(8) of Table 4. The effect of core-deposit funding on lending remains relatively unchanged by the addition of these controls. The effect of credit line exposure for large banks increases appreciably in magnitude, but the size of the standard error suggests that the coefficient is statistically undifferentiated from the one obtained from the baseline model.[16]

C. Accounting for Asset Risk

An important determinant of credit supply is asset risk. Banks which are exposed to high levels of asset risk are more likely to substitute low risk assets for high risk ones (as in Calomiris and Wilson (2004)). This is a concern for identification, as banks which were more exposed to liquidity risk may have also held a higher portion of high-risk assets on their balance sheets. During the crisis, and in response to materialized or anticipated losses on these assets, the banks may have actively begun rebalancing their portfolios towards lower-risk assets. The higher propensity to curtail mortgage credit during the crisis could thus reflect the banks' response to asset risk, and not to liquidity risk.

To control for asset risk I introduce the ratio of non-performing loans to total loans,[17] as well as four additional ratios which capture the lender's exposure to the real estate sector through the composition of its marketable securities and loan portfolios. These are the holdings of agency-issued MBS, private-label MBS, residential real estate loans, and non-residential real estate loans, all normalized by total assets.[18] The results are shown in columns (9)-(12) of Table 4.

The estimated coefficients indicate that liquidity risk is an important determinant

[16]In unreported regressions, I reestimate the model while dropping from the sample originated loans that were sold to GSEs. This robustness test is performed to account for the possibility that the loan approval margin operates differently along the GSE securitization channel, which is understood to not have been as severely impaired during the crisis. The results remain qualitatively unchanged, though the coefficients for large banks increase somewhat in magnitude.

[17]The results remain unchanged if I use the ratio of non-performing residential real estate loans instead.

[18]Other proxies for asset risk that rely on regulatory weights may not reflect the true underlying risk of asset categories such as commercial real estate (Cole and White (2012)).

of credit supply even after accounting for asset risk. The model estimated in columns (9)-(12) is the full model that will be used throughout the remaining sections of the paper. For brevity, in subsequent tables only the estimated coefficients for liquidity risk will be presented.

D. Economic Significance

In this subsection I estimate the economic impact of liquidity risk on credit origination in the mortgage market. The counterfactual exercise I perform fixes the quantity and quality of credit demand to their crisis levels, and asks how much higher the number (or $ volume) of mortgage originations would have been, had banks moved through the crisis with their levels of exposure to liquidity risk reduced down to the lowest quartile of the distribution.

To assess the impact of core-deposit funding on lending, I only consider banks in size categories for which the effect of liquidity risk was statistically significant, that is all but very small banks. For each year, I take banks with levels of core-deposit funding below the 75th percentile for the year and raise their reliance on core-deposit funding up to the 75th percentile.[19] This involves an adjustment in core-deposit funding of $\Delta\mathrm{CD}_{it}$, which is equal to the value of the 75th percentile for the year minus each affected bank's actual level of core-deposit funding. I then compute the corresponding adjustment in approval rates for each lender-MSA-year tuple as $\Delta\mathrm{A}_{ijt} = \gamma_{\mathrm{CD}} \times \mathrm{TED}_t \times \Delta\mathrm{CD}_{it}$, where γ_{CD} is the estimated coefficient of the interaction term for core-deposit funding for the full model, and is taken from columns (10)-(12) of Table 4. I right-censor the estimated changes in approval rates where needed, to ensure that the new adjusted approval rates do not exceed

[19] The percentiles are taken over the distribution of all lenders, and not separately for each size category.

1. I then multiply the adjustment in approval rates by the ratio of originated to approved loans, to get a measure of the adjustment in origination rates. In a final step, I multiply the adjustment in origination rates by the number ($ volume) of applications in each lender-MSA-year observation and sum over all observations for each year to obtain the estimated increase in the number ($ volume) of originations per year for the counterfactual.

The corresponding exercise for credit line exposures is very similar, the two differences being that (a) I reduce the exposure down to the 25th percentile and (b) I only consider adjustments for the largest lenders, which were the only category with a statistically significant effect for credit line exposures. I also consider the impact of jointly reducing the exposure to unused credit lines and increasing the reliance on core-deposit funding.[20] The results are shown in Table 5, where Panel A reports the adjustments in the number of originations and Panel B reports the corresponding percentage increases compared to the actual number of originations for each year. Panels C and D repeat for the $ volume of originations.

[Table 5 about here]

The results indicate that though the two sources of liquidity risk generated contractions of the same order of magnitude, the impact of credit line exposures was larger by approximately a factor of 2. For the period of the crisis combined (2007–2008) a joint reduction in exposure to the two sources of liquidity risk would have resulted in a 253,000 increase in the number of originations ($55 billion), corresponding to a 14% increase over total originations during this period.

[20] Although I use a linear model, the adjustment in approval rates from the joint reduction in the two sources of liquidity risk is typically lower than the sum of the two individual adjustments, because I right-censor the combined adjustment to ensure that the adjusted approval rates do not exceed 1.

Considering the two years of the crisis in isolation, the largest percentage increase in the number (and $ volume) of originations would have taken place at the epicenter of the crisis in 2008, and would have been approximately equal to 17%. The level increase in the number (and $ volume) of originations on the other hand, would have been marginally higher in 2007 due to the considerably higher demand for mortgage loans during this period.

V. Robustness Tests

This section discusses a number of robustness exercises, which test the main results against the possibility of endogenously-adjusted levels of liquidity risk, the impact of bank exits and government intervention, the strategic determination of the banks' locational mix, and a number of alternative explanations for the identified effects.

A. Endogenous Determination of Exposure to Liquidity Risk

In the face of deteriorating liquidity conditions during the crisis, banks are likely to have attempted to reduce their exposure to liquidity risk. Also, banks with better lending opportunities during the crisis may have chosen to raise funds in the deposit markets, which were the lower-cost source of funding during the crisis. I argue that the margin of such endogenous adjustments cannot have been significant enough to severely bias the main results of the paper. To test this hypothesis, I re-estimate all the models shown in Table 4 using the 2006 levels of exposure to liquidity risk for both the base terms and the interactions with the TED spread. The results are shown in Table 6 and, except for small changes in magnitude, are consistent with the ones obtained using the crisis levels of exposure to liquidity risk, thus rejecting the hypothesis that the original estimates are biased by the endogenous determination of exposure to liquidity risk during the crisis.

[Table 6 about here]

B. Post-Crisis Bank Failures

Though the main estimates only include lenders that did not exit the sample during the period 2006–2009, a significant number of commercial banks failed after 2009. To test whether the results are driven by the banks that exited the sample after 2009, and thus perhaps driven by default risk rather than liquidity risk, I re-estimate the full model on a subsample which excludes both BHCs that failed after 2009 and BHCs which held a bank that failed after 2009. I collect data on bank failures from FDIC's list of failed banks. The results are shown in columns (1)-(4) of Table 7 and are similar to the results over the full sample, the only exception being the slight decrease in the magnitude of the coefficient of core-deposit funding for medium banks (column 3).

[Table 7 about here]

C. Capital Injections through TARP

The definition of bank failure employed in the previous robustness test only includes banks which were placed under FDIC receivership. One could hypothesize that the number of government interventions which took place during the crisis distorted the true picture of bank failures, by rescuing banks which would have failed absent government support. Prominent among these interventions was the Troubled Asset Relief Program (TARP), and in particular the Capital Purchase Program (CPP), which was announced as part of TARP and was "launched to stabilize the financial system by providing capital to viable financial institutions of all sizes throughout the nation".[21]

[21]In February 2009, the Treasury announced another program, the Capital Assistance Program (CAP), which on the results of a stress test would provide capital assistance to the bank, if the needed capital

I test whether liquidity risk remains a relevant driver of credit contraction when I also drop from the sample CPP-participating institutions as potentially failing banks. I obtain CPP participation data from the U.S. Treasury's CPP transaction report. The results are shown in columns (5)-(8) of Table 7 and are even stronger in magnitude than the main results estimated over the complete sample.

D. Endogenous Adjustments to the Banks' Locational Mix

Banks with high levels of liquidity risk may have shifted their operations away from markets of high borrower risk. To test whether the results are driven by the endogenous determination of the banks' locational mix, i.e., by time-series variation in the composition of the cross-section of lender-MSA pairs, I balance the panel keeping only the lender-MSA pairs that were present in all four years during 2006–2009, and re-estimate the model. The results are shown in columns (9)-(12) of Table 7 and are similar to the ones obtained over the unbalanced panel. The only noticeable change is the reduction in the magnitude of the effect for core-deposit funding for small banks (column 10), but this could be due to the significant reduction in observations for this group of lenders.

E. Unobserved Applicant Exits

A concern is that liquidity risk may have had an effect on loan demand by inducing unobserved applicant exits. For example, applicants who understood that they were less likely to be approved for a loan, under more stringent standards possibly driven by liquidity risk, may have exited the market for mortgage loans. These "would be" applicants will not be documented in HMDA data, and conditioning the estimates on the number of loan applications would ignore this contractionary effect on demand. For most

could not be raised privately. CAP closed in November 2009, without making any investments.

applicants, however, such tightening of lending policies only becomes evident after an application for a mortgage loan is filed, and they thus do not exit the market before their application is registered in HMDA. Assuming, however, that it is the case that liquidity risk does lead to unobserved applicant exits, then the main estimates of the paper would be lower bounds in magnitude to the true effect. Therefore, the results would have been even stronger had this assumed effect on demand not been present.[22]

A related concern is that banks with lower levels of liquidity risk may have experienced a rise in the volume of applications during the crisis, and due to capacity constraints had to ration credit by tightening their lending standards. In unreported regressions I test for the possibility that sudden shifts in credit demand may affect the estimates, by including as an additional control variable the aggregate volume of applications received by the lender normalized by total lender assets; the results remain virtually unchanged.

F. Other Robustness Tests

The results are robust to a number of other alternative hypotheses. First, the omitted category of non core-deposit funding contains long-term sources of funding which could conceivably be considered stable sources of funding. I test this hypothesis by including as an additional explanatory variable the ratio of long-term non core-deposit funding divided

[22]In general, the results do not carry through if one replaces the dependent variable with a measure of originations, such as the natural logarithm of the number of originations. This raises the possibility that lenders with higher levels of liquidity risk actually experienced a surge in demand during the crisis. However, the identification strategy employed in the paper is not designed to identify the *causal* impact of liquidity risk on credit *demand*, and one needs to be cautious in making causal inferences from estimates where shifts in the dependent variable are influenced by demand dynamics.

by total assets.[23] I find the coefficient for core-deposit funding to be economically and statistically larger in magnitude than the coefficient for long-term non core-deposit funding, confirming the superiority of core deposits as a stable source of funding during the crisis.

Second, for large lenders, exposure to the two sources of liquidity risk may be correlated with off-balance sheet exposures to Structured Investment Vehicles (SIVs), and the identified effects could thus be capturing strains from SIV exposures rather than the effect of liquidity risk. I test this hypothesis by adding as control variables (a) the ratio of credit enhancements provided to SIVs over total assets and (b) the ratio of liquidity enhancements provided to SIVs over total assets; the results remained unchanged.

Third, for some lenders the relevant market may not be the MSA but rather a more refined subdivision.[24] Levels of unemployment, for example, may vary within an MSA. To the extent that some lenders, due to size or other strategic reasons, operate in distinct smaller areas, one might need to look to an additional level of geographic refinement, such as census-tract units, to adequately control for local economic conditions. To test this hypothesis I would ideally want to take the average approval rate over a smaller unit of aggregation than the MSA, but doing so would increase the number of fixed effects by at least an order of magnitude and make the computational cost prohibitive. Instead, I include as additional control variables local income as a percentage of MSA income and the percentage of minority population, both measured at the census-tract level for each property. Should the unit of aggregation be a significant driver of the results, the inclusion of these two variables should have an impact on the estimated coefficients for liquidity risk; I find that it does not.

[23] I define long-term non-core funding as other borrowed money and uninsured time deposits with a maturity greater than 12 months.

[24] A similar concern is expressed in Mian and Sufi (2009).

Last, to ameliorate the effects of end-of-year window-dressing operations on the bank's balance sheet, I re-estimate the models using financial data obtained from the September call reports; the results remain unchanged.

VI. Conclusion

In this paper I use micro-level data on mortgage loan applications to estimate the extent to which liquidity risk contributed to a contraction in the supply of mortgage credit during the financial crisis of 2007–2008. The data allow me to separate shifts in loan supply from shifts in loan demand, and identify the effect of liquidity risk on the supply of mortgage credit as separate from the effect of other possible supply shifters, such as disruptions in securitization and subprime markets, and asset risk.

I find that liquidity risk was an important driver behind the credit crunch. In particular, banks with higher levels of unused lines of credit and lower levels of core-deposit funding, tightened lending more than banks that were less exposed to these two sources of liquidity risk. In counterfactual analysis, I estimate that had the banks entered the crisis with their levels of exposure to liquidity risk reduced down to the lowest quartile of the risk distribution, the total number of mortgage loans originated during 2007–2008 would have been higher by 14%.

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Appendix: Sample Selection

To focus on a relatively homogeneous sample, I perform data pruning along a number of dimensions. First, I restrict my attention to commercial banks and exclude other institution types, such as thrifts, credit unions, etc... that operate under different legal frameworks and corporate governance structures. To limit the impact of bank exits or entries in the sample, I drop lenders that were not present in all four years of the period I consider (2006–2009).

I also perform pruning on the mortgage loan application dataset. First, I drop loan applications for properties not located in Metropolitan Statistical Areas (MSAs) and for loan purposes other than home purchase. I drop applications with loan amounts smaller than $1,000 (because the loan amount is reported in thousands and rounded to the nearest integer) or those with applicant income equal to $1,000 (because income is left-censored at that value). I then drop loans for the purchase of multi-family dwellings, federally insured loans, and refinancing loans. Multi-family dwellings are sizeable structures that share risk characteristics that are significantly different from those of 1-4 family dwellings, and are treated as a separate category of mortgage loans by banks (bank financial reports make that distinction too). Federally insured mortgage loans and refinances have a different risk profile and information structure than non-insured mortgage loans and are thus expected to be subject to different decision rules.

From the remaining sample I only keep loans that resulted in one of the following actions: (1) lender approved and borrower execution, (2) lender approved but no borrower execution, and (3) lender denial, thus dropping purchases of already originated loans by a financial institution, and loan applications that were either withdrawn by the applicant or not pursued further due to incomplete information. I treat (1) and (2) as loan approvals, effectively defining loan approval as the bank's willingness to price a loan application. The results presented throughout hold if I drop all applications corresponding to outcome (2) and thus use loan origination as the sole instance of a successful loan application.

Figure 1

The TED Spread for the Period 2006–2009

This figure shows monthly and annual averages of the TED spread for the period 2006–2009. The TED spread measures funding stresses in the banking sector and is defined as the difference between the 3-month LIBOR rate and the 3-month Treasury rate. Data on rates obtained from the Federal Reserve Economic Data (FRED), available online by the Federal Reserve Bank of St. Louis.

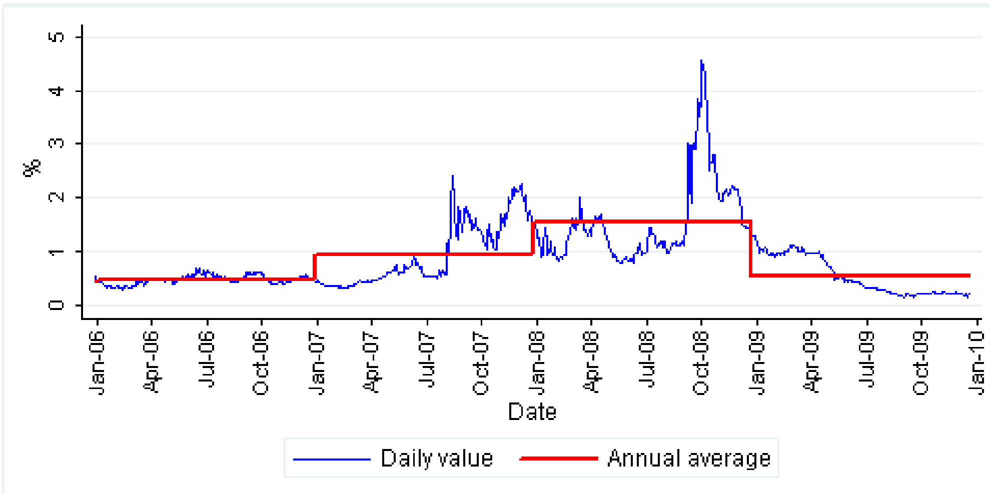

Figure 2

Mortgage Loan originations for Commercial Banks for 2006–2009

This diagram shows aggregate levels of mortgage loan originations for four groups of lenders in my sample, categorized by asset size, for 2006–2009. Graph A displays the number of originations and Graph B normalizes to 2006 levels. Data are obtained from the Home Mortgage Disclosure Act (HMDA). Sample selection is discussed in the Appendix.

Graph A. Level of Originations *Graph B. Index of Originations*

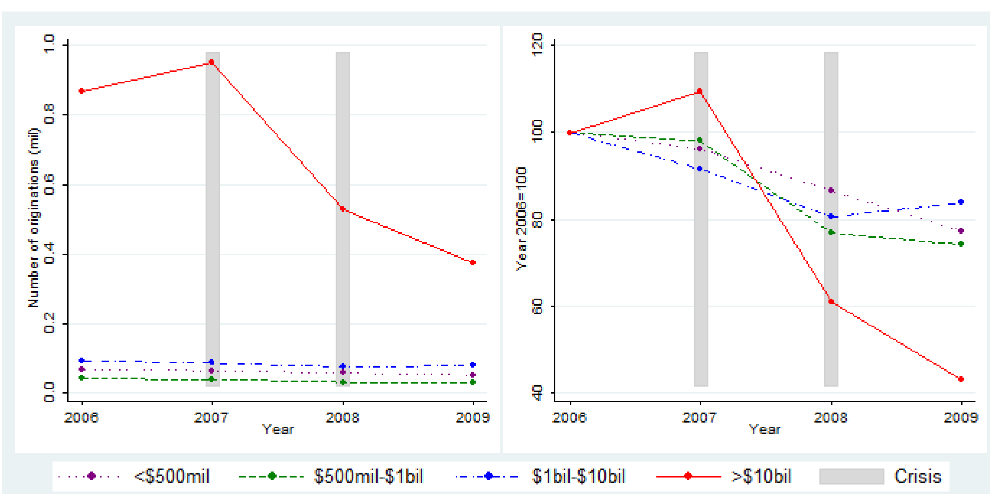

Figure 3

Mortgage Loan Applications to Commercial Banks for 2006–2009

This diagram shows aggregate levels of mortgage loan applications for four groups of lenders in my sample, categorized by asset size, for 2006–2009. Graph A displays the number of applications and Graph B normalizes the data to 2006 levels. Data are obtained from the Home Mortgage Disclosure Act (HMDA). Sample selection is discussed in the Appendix.

Graph A. Level of Applications *Graph B. Index of Applications*

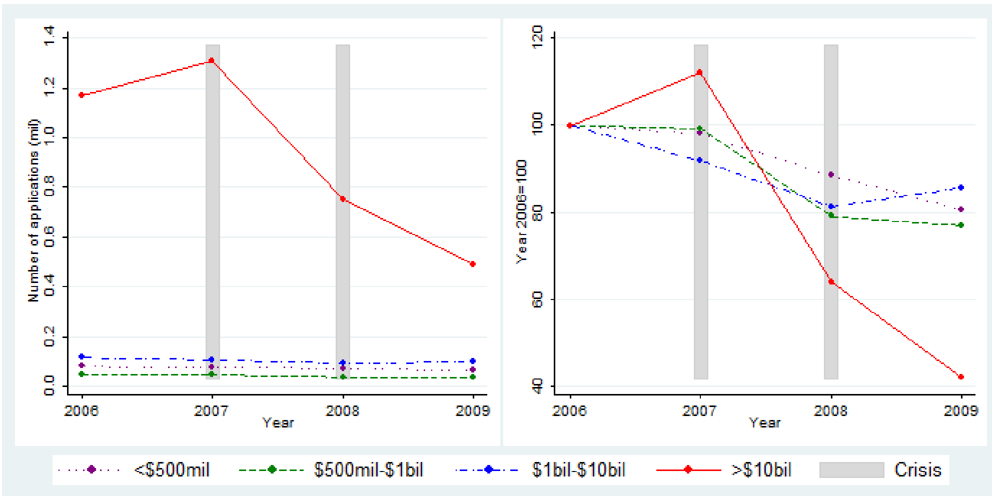

Figure 4

Mortgage Loan Approval Rates of Commercial Banks for 2006–2009

This diagram shows average approval rates for four groups of lenders in my sample, categorized by asset size, for 2006–2009.Graph A displays average approval rates and Graph B normalizes to 2006 levels. Data are obtained from the Home Mortgage Disclosure Act (HMDA). Sample selection is discussed in the Appendix.

Graph A. Level of Approval Rates *Graph B. Index of Approval Rates*

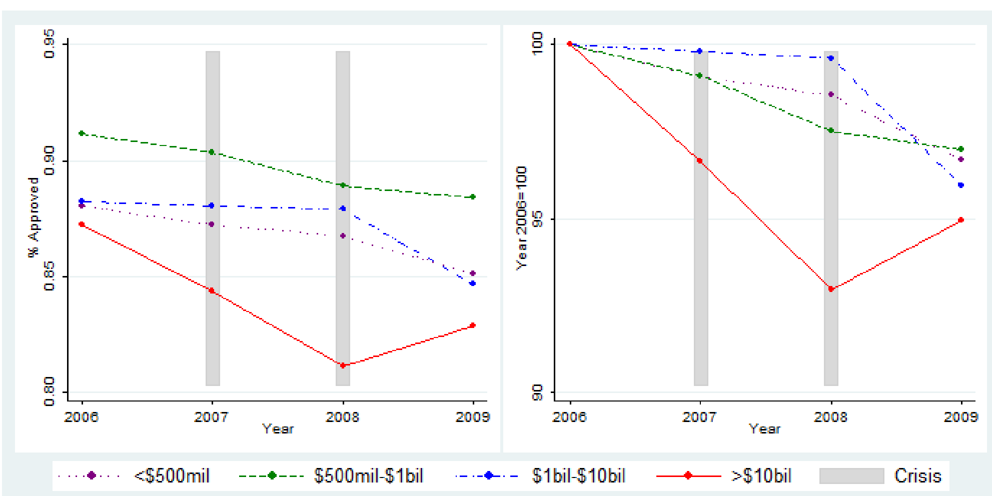

Figure 5
Liquidity Risk Across Time

These figures display the time-series variation in the two sources of liquidity risk examined in this paper for four groups of lenders in my sample, categorized by asset size, for 2006–2009. Graph A displays variation in *core-deposit funding* and Graph B in *unused lines of credit.* Bank financial data are obtained from the Reports of Condition and Income (Call Reports), measured at beginning of year levels, aggregated up to the Bank Holding Company (BHC) level, and averaged over all banks within each year and bank size category. Sample selection is discussed in the Appendix and descriptions of the explanatory variables are provided in Table 2.

Graph A. Core Deposits Across Time *Graph B. Credit Line Commitments Across Time*

Table 1

Balance Sheet Dynamics

Panel A shows a stylized balance sheet for a bank. Panels B, C and D show on- and off- balance-sheet adjustments for a $1 withdrawal of wholesale funding, a $1 drawdown on an unused line of credit, and a $1 mortgage loan origination,respectively.

Panel A. Stylized Bank Balance Sheet and Off-Balance Sheet Commitments

BALANCE SHEET				
ASSETS		LIABILITIES		
Liquid assets		Core deposits		
Mortgage loans		Wholesale funding		
Other loans		Capital		

OFF- BALANCE SHEET	
Unused lines of credit	

Panel B. Balance Sheet Adjustments for a $1 Withdrawal of Wholesale Funding

BALANCE SHEET			
ASSETS		LIABILITIES	
Liquid assets	**-$1**	Core deposits	
Mortgage loans		Wholesale funding	**-$1**
Other loans		Capital	

OFF- BALANCE SHEET	
Unused lines of credit	

Panel C. On- and Off-Balance Sheet Adjustments for a $1 Drawdown on a Line of Credit

BALANCE SHEET			
ASSETS		LIABILITIES	
Liquid assets	**-$1**	Core deposits	
Mortgage loans		Wholesale funding	
Other loans	**+$1**	Capital	

OFF- BALANCE SHEET	
Unused lines of credit	**-$1**

Panel D. Balance Sheet Adjustments for a $1 Mortgage Loan Origination

BALANCE SHEET			
ASSETS		LIABILITIES	
Liquid assets	**-$1**	Core deposits	
Mortgage loans	**+$1**	Wholesale funding	
Other loans		Capital	

OFF- BALANCE SHEET	
Unused lines of credit	

Table 2
Definitions

Panel A. Measured at the lender-MSA-year level

Variable	Source	Definition
Minority	HMDA	Applicant is a minority
Female	HMDA	Applicant is female
Loan to Income Ratio	HMDA	Loan amount divided by applicant income
log Applicant income	HMDA	Natural logarithm of the applicant's income
log Loan amount	HMDA	Natural logarithm of the loan amount
Jumbo loan	HMDA	Loan size exceeds the jumbo threshold
Manufactured property	HMDA	Loan is for manufactured housing
Junior lien	HMDA	Loan is secured by junior lien
Pct sold to GSEs	HMDA	Percentage of originated loans sold to Government Sponsored Enterprises
Pct sold to non-GSEs	HMDA	Percentage of originated loans sold to all other entities
Pct subprime	HMDA	Percentage of originated loans that are potentially subprime

Panel B. Measured at the lender-year level

Variable	Source	Definition
Core-deposit funding	Call Reports	The sum of demand deposits, MMDA and other savings deposits, NOW, ATS and other interest-bearing transaction accounts, and insured time deposits scaled by total assets
Unused commitments	Call Reports	Total unused commitments to fund loans divided by the sum of total unused commitments plus total assets
log Assets	Call Reports	Natural logarithm of assets
Tier 1 capital ratio	Call Reports	Tier 1 capital divided by risk-weighted assets
Asset liquidity	Call Reports	The sum of cash, federal funds sold, securities purchased under agreement to resell, available-for-sale and held-to-maturity securities, excluding all asset backed securities (MBS and others)
Non-performing loans	Call Reports	Loans over 90 days late plus loans not accruing divided by total loans
Agency-issued MBS	Call Reports	All MBS issued or guaranteed by Government Sponsored Enterprises divided by total assets
Private-label MBS	Call Reports	All other MBS divided by total assets
Residential RE loans	Call Reports	The sum of closed-end and revolving open-end loans secured by 1-4 family residential properties divided by total assets
Non-residential RE loans	Call Reports	All other real estate loans divided by total assets

Table 3
Summary Statistics

The table displays annual means of variables for 2006–2009 for commercial banks grouped in four categories by asset size. Values are percentages unless indicated otherwise. Bank financial data are obtained from the Reports of Condition and Income (Call Reports), measured at beginning of year levels, and averaged over all banks within each year and bank size category. Data on securitization, subprime lending activity, and borrower characteristics are obtained from the Home Mortgage Disclosure Act (HMDA), measured during the current year, and averaged over all applications received by banks within each year and bank size category. All data are aggregated up to the Bank Holding Company (BHC) level. Sample selection is discussed in the Appendix and descriptions of the variables are provided in Table 2.

	Panel A. Very Small Banks				*Panel B. Small Banks*				*Panel C. Medium Banks*				*Panel D. Large Banks*			
	Assets≤$500mil				*$500mil<Assets≤$1bil*				*$1bil<Assets≤$10bil*				*Assets>$10bil*			
VARIABLE	2006	2007	2008	2009	2006	2007	2008	2009	2006	2007	2008	2009	2006	2007	2008	2009
Liquidity risk																
Core-deposit funding	67.87	65.98	65.32	64.55	62.86	61.29	61.44	61.09	60.45	59.26	59.33	59.54	50.88	50.15	49.57	52.31
Unused commitments	10.39	10.18	9.54	8.55	13.72	13.61	13.31	11.46	15.67	15.75	15.48	13.41	22.61	23.04	22.63	20.16
Baseline controls																
Assets ($mil)	173	189	202	216	596	665	722	783	2,199	2,448	2,693	2,955	116,600	136,400	159,000	187,500
Tier 1 capital ratio	14.76	14.34	14.02	13.58	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.10	0.10	0.10	0.10
Asset liquidity	23.41	22.65	20.87	18.76	0.19	0.18	0.16	0.14	0.17	0.16	0.14	0.12	0.16	0.15	0.13	0.13
Additional controls																
Non-performing loans	0.61	0.70	1.05	1.93	0.46	0.54	0.98	2.08	0.47	0.50	1.01	2.29	0.59	0.64	1.20	2.56
Agency-issued MBS	4.67	4.38	4.85	6.17	6.08	5.71	6.10	7.46	7.94	6.97	7.37	9.09	9.12	8.12	7.91	9.66
Private-label MBS	0.10	0.11	0.19	0.27	0.27	0.27	0.44	0.50	0.52	0.53	0.66	0.68	1.20	1.14	1.50	1.26
Residential RE loans	18.71	18.43	18.71	19.73	16.99	16.49	16.47	17.13	16.15	16.02	15.85	16.41	17.27	17.35	16.85	16.57
Non-residential RE loans	29.89	31.39	32.37	32.44	35.97	37.85	39.34	39.56	34.61	36.25	37.47	37.57	20.02	21.83	22.42	22.80
Pct sold to GSEs	6.24	6.07	5.77	9.99	8.11	7.37	8.99	19.37	9.33	10.85	18.76	38.48	32.37	38.36	57.91	60.69
Pct sold to non-GSEs	29.84	31.78	22.63	21.06	35.69	40.00	30.58	30.29	37.77	37.12	25.92	21.24	24.19	22.01	16.76	8.43
Pct subprime	21.26	21.27	25.60	25.51	15.41	12.84	17.22	15.71	13.35	10.68	13.25	9.50	10.40	10.19	8.42	4.80
Loan characteristics																
Minority applicant	9.51	10.16	8.65	8.15	10.21	9.95	8.36	6.96	18.62	15.88	13.94	9.72	19.29	21.35	16.20	11.02
Female applicant	22.38	22.60	21.88	23.24	21.98	22.99	22.59	24.79	25.80	25.45	24.54	25.54	28.54	29.39	27.55	26.39
Loan to income (ratio)	1.80	1.87	1.82	1.81	1.84	1.95	1.94	2.05	1.95	2.05	2.07	2.15	2.06	2.21	2.35	2.34
Applicant income ($000s)	89	95	104	99	98	99	110	106	98	103	113	114	120	123	132	128
Loan amount ($000s)	127	136	140	133	142	147	159	164	153	164	176	188	210	222	245	241
Jumbo loan	2.83	3.05	3.16	2.27	3.28	3.30	4.04	3.67	4.66	5.21	5.12	5.58	10.44	10.26	8.60	9.76
Manufactured property	12.31	11.17	11.19	10.89	8.44	7.97	8.46	6.89	6.23	6.09	6.05	4.07	1.82	1.29	1.53	2.43
Junior lien	7.90	6.56	4.25	3.75	10.12	8.43	5.35	4.32	13.65	10.20	6.26	5.01	19.63	17.55	7.01	3.54
Number of banks	1,842	1,846	1,846	1,847	347	347	347	347	289	289	289	289	54	54	54	54
Number of observations	5,231	5,507	5,444	5,065	2,166	2,282	2,164	2,083	3,723	3,747	3,709	3,356	5,072	5,802	5,325	4,553
Number of applications (000s)	79	77	70	64	46	46	37	36	115	106	93	98	1,168	1,310	748	491
Number of originations (000s)	66	64	58	51	40	39	31	30	93	85	75	78	869	951	529	374
Volume of applications ($bil)	10.02	10.50	9.82	8.45	6.57	6.76	5.81	5.83	17.55	17.28	16.42	18.49	245.14	291.13	183.03	118.36
Volume of originations ($bil)	8.64	8.73	8.15	7.01	5.80	5.86	4.93	4.93	14.43	14.04	13.30	14.88	186.21	212.49	128.00	91.50
Approval rate	88.04	87.24	86.76	85.12	91.17	90.35	88.90	88.41	88.23	88.06	87.89	84.65	87.26	84.34	81.10	82.86

Table 4

The Effect of Liquidity Risk on the Approval Decision

The table reports estimates for the model shown in Equation 2 and estimated over the period 2006–2009. The dependent variable is the average approval rate of bank i in MSA area j in year t. Analytic weights are employed to account for differences in the number of loan applications over which the averages are taken. Structural breaks due to the impact of the crisis are captured by the TEDx terms, which correspond to an interaction term of each variable with the TED spread. The main explanatory variables, which capture the causal impact of liquidity risk on lending propensity during the crisis, are the interaction terms of the TED spread with *Core-deposit funding* and *Unused commitments*. Columns (1)-(4) correspond to estimates over four subsamples of banks categorized by average asset size, for a baseline model which includes exposure to liquidity risk as the explanatory variables, a baseline set of additional bank controls, and a host of borrower characteristics (coefficients suppressed for brevity). Columns (5)-(8) expand the list of controls to include securitization and subprime activity. Columns (9)-(12) include controls for securitization, subprime activity, on-balance sheet exposures to the real estate sector, and overall asset risk. All regressions include lender and MSA-year fixed effects. Bank financial data are obtained from the Reports of Condition and Income (Call Reports) and measured at beginning of year levels. Data on securitization, subprime lending activity, and borrower characteristics, are obtained from the Home Mortgage Disclosure Act (HMDA) and are averaged over the unit of observation (lender-MSA-year tuple). All data are aggregated up to the Bank Holding Company (BHC) level. Sample selection is discussed in the Appendix and descriptions of the variables are provided in Table 2. *Observations* indicate the number of lender-MSA-year tuples used in estimation, *Applications* and *Banks* indicate the number of loan applications and lenders, respectively in each bank category. Standard errors in parentheses are clustered at the bank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A. Baseline Model				*Panel B. Securitization and Subprime*				*Panel C. Asset Risk*			
	<$500mil	$500mil $1bil	$1bil $10bil	>$10bil	<$500mil	$500mil $1bil	$1bil $10bil	>$10bil	<$500mil	$500mil $1bil	$1bil $10bil	>$10bil
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Core-deposit funding	0.014	-0.100*	-0.108	-0.521***	0.017	-0.106*	-0.101	-0.471***	0.014	-0.098**	-0.056	-0.491***
	(0.04)	(0.06)	(0.08)	(0.13)	(0.04)	(0.05)	(0.08)	(0.14)	(0.04)	(0.05)	(0.08)	(0.14)
TEDx(Core-deposit funding)	0.025	0.089*	0.139***	0.200***	0.032	0.083	0.154***	0.184***	0.033	0.091*	0.122***	0.114***
	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)
Unused commitments	-0.014	0.022	-0.124	0.589*	-0.029	0.019	-0.253**	0.696*	-0.077	-0.028	-0.425***	0.538
	(0.10)	(0.14)	(0.09)	(0.35)	(0.11)	(0.14)	(0.13)	(0.37)	(0.11)	(0.13)	(0.11)	(0.41)
TEDx(Unused commitments)	0.042	0.027	0.040	-0.270**	0.046	0.015	0.075	-0.382***	0.050	-0.022	0.022	-0.345***
	(0.06)	(0.09)	(0.08)	(0.10)	(0.07)	(0.09)	(0.08)	(0.12)	(0.07)	(0.08)	(0.08)	(0.11)
log Assets	-0.000	-0.001	-0.001	0.000	0.000	-0.001	-0.001	0.000	-0.000	-0.001	-0.001*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TEDx(log Assets)	-0.000	-0.001	0.000	0.001**	-0.000	-0.001	0.000	0.001**	-0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tier 1 capital ratio	-0.038	0.265	0.331	0.431	-0.029	0.269	0.320	0.814	-0.064	0.186	0.142	0.157
	(0.08)	(0.24)	(0.30)	(0.66)	(0.09)	(0.22)	(0.30)	(0.64)	(0.10)	(0.19)	(0.27)	(0.60)
TEDx(Tier 1 capital ratio)	0.015	-0.104	-0.511**	-0.156	0.004	-0.126	-0.525**	-0.485	0.038	-0.087	-0.329	-0.484
	(0.06)	(0.15)	(0.25)	(0.70)	(0.06)	(0.15)	(0.25)	(0.71)	(0.07)	(0.15)	(0.23)	(0.70)
Asset liquidity	0.029	-0.010	-0.069	-0.023	0.054	0.014	-0.081	-0.110	-0.020	0.017	-0.098	-0.408
	(0.05)	(0.09)	(0.11)	(0.12)	(0.05)	(0.09)	(0.11)	(0.13)	(0.08)	(0.13)	(0.16)	(0.37)
TEDx(Asset liquidity)	-0.030	0.002	-0.039	0.185**	-0.031	-0.003	-0.043	0.212**	-0.057	0.001	-0.022	0.353**
	(0.03)	(0.05)	(0.06)	(0.08)	(0.03)	(0.05)	(0.06)	(0.08)	(0.04)	(0.07)	(0.06)	(0.15)
Observations	21,275	8,697	14,546	20,752	21,275	8,697	14,546	20,752	21,275	8,697	14,546	20,752
Applications	290,201	164,279	412,068	3,717,000	290,201	164,279	412,068	3,717,000	290,201	164,279	412,068	3,717,000
Banks	1,848	347	289	54	1,848	347	289	54	1,848	347	289	54
Adjusted-R2	0.56	0.60	0.70	0.72	0.58	0.60	0.71	0.73	0.58	0.61	0.71	0.73

Table 5

Economic Impact of Liquidity Risk

The table reports the estimated effect of liquidity risk on mortgage originations during 2007–2008 in a counterfactual exercise where banks move through the crisis with their exposure to liquidity risk reduced down to the 25th percentile of the distribution. I only consider large banks (Assets>$10 bil) for the effect of credit line exposures, and reduce the exposure of all banks above the 25th percentile of the distribution for each year down to the 25th percentile. For the impact of core-deposit funding, I raise core-deposit funding up to the 75th percentile of the distribution for each year for all but very small banks. The affected banks are subjected to the average TED spread for each of the years of the crisis (2007–2008) and I use the coefficients estimated in columns (9)-(12) of Table 4. The adjusted approval rates for each lender-MSA-year tuple are right-censored to ensure that they do not exceed 1, and scaled down by the proportion of originated to approved loans. Panel A reports the total increase in the number of originations for each of the years 2007–2008 obtained from adjusting the exposure to core-deposit funding (CD) and to unused commitments (UC) individually and jointly (Both). Panel B reports percentage increases compared to the actual number of originations in each year. Panels C and D repeat for the total $ volume of originations.

	Panel A. Number of Originations				*Panel B. Percentage Change*		
Year	Actual	(CD)	(UC)	(Both)	(CD)	(UC)	(Both)
2007	1,139,000	47,700	104,600	137,300	4.19	9.18	12.05
2008	692,400	46,900	91,200	116,000	6.77	13.17	16.75
TOTAL	1,831,400	94,600	195,800	253,300	5.17	10.69	13.83

	Panel C. Volume of Originations ($ billion)				*Panel D. Percentage Change*		
Year	Actual	(CD)	(UC)	(Both)	(CD)	(UC)	(Both)
2007	241	9	21	28	3.84	8.91	11.81
2008	154	10	21	27	6.63	13.29	17.28
TOTAL	395	19	42	55	4.93	10.62	13.95

Table 6
Accounting for Endogenous Management of Exposure to Liquidity Risk

The table reports estimates for the model shown in Equation 2 and estimated over the period 2006–2009. The dependent variable is the average approval rate of bank i in MSA area j in year t. Analytic weights are employed to account for differences in the number of loan applications over which the averages are taken. Structural breaks due to the impact of the crisis are captured by the TEDx terms, which correspond to an interaction term of each variable with the TED spread. The main explanatory variables, which capture the causal impact of liquidity risk on lending propensity during the crisis, are the interaction terms of the TED spread with *Core-deposit funding* and *Unused commitments*. The set of control variables mirrors those shown in columns (1)-(12) of Table 4, but the coefficients are suppressed for brevity. All regressions include lender and MSA-year fixed effects. Bank financial data are obtained from the Reports of Condition and Income (Call Reports) and measured at beginning of year levels, except for the two variables capturing exposure to liquidity risk which are measured at their pre-crisis (beginning of 2006) levels. Data on securitization, subprime lending activity, and borrower characteristics, are obtained from the Home Mortgage Disclosure Act (HMDA) and are averaged over the unit of observation (lender-MSA-year tuple). All data are aggregated up to the Bank Holding Company (BHC) level. Sample selection is discussed in the Appendix and descriptions of the variables are provided in Table 2. *Observations* indicate the number of lender-MSA-year tuples used in estimation, *Applications* and *Banks* indicate the number of loan applications and lenders, respectively in each bank category. Standard errors in parentheses are clustered at the bank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A. Baseline Model				*Panel B. Securitization and Subprime*				*Panel C. Asset Risk*			
	<\$500mil	\$500mil \$1bil	\$1bil \$10bil	>\$10bil	<\$500mil	\$500mil \$1bil	\$1bil \$10bil	>\$10bil	<\$500mil	\$500mil \$1bil	\$1bil \$10bil	>\$10bil
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TEDx(Core-deposit funding)	0.018	0.078*	0.106***	0.185***	0.026	0.077*	0.120***	0.163***	0.028	0.086**	0.126***	0.123***
	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)
TEDx(Unused commitments)	0.011	0.120	0.008	-0.282***	0.001	0.124	-0.012	-0.372***	0.005	0.078	-0.091	-0.301***
	(0.06)	(0.09)	(0.05)	(0.07)	(0.06)	(0.09)	(0.06)	(0.08)	(0.06)	(0.08)	(0.07)	(0.11)
Observations	21,275	8,697	14,546	20,752	21,275	8,697	14,546	20,752	21,275	8,697	14,546	20,752
Applications	290,201	164,279	412,068	3,717,000	290,201	164,279	412,068	3,717,000	290,201	164,279	412,068	3,717,000
Banks	1,848	347	289	54	1,848	347	289	54	1,848	347	289	54
Adjusted-R2	0.56	0.60	0.70	0.72	0.58	0.60	0.71	0.72	0.58	0.61	0.71	0.73

Table 7

Additional Robustness Tests

The table reports estimates for the model shown in Equation 2 estimated over the period 2006–2009. The dependent variable is the average approval rate of bank i in MSA area j in year t. Analytic weights are employed to account for differences in the number of loan applications over which the averages are taken. Structural breaks due to the impact of the crisis are captured by the TEDx terms, which correspond to an interaction term of each variable with the TED spread. The main explanatory variables, which capture the causal impact of liquidity risk on lending propensity during the crisis, are the interaction terms of the TED spread with *Core-deposit funding* and *Unused commitments*. Columns (1)-(4) correspond to estimates over a subsample that excludes all BHCs which held a bank that was placed under FDIC receivership after 2009. Columns (5)-(8) correspond to estimates over a subsample that in addition excludes all BHCs and banks which received a capital injection through TARP's Capital Purchase Program (CPP). Columns (9)-(12) correspond to a balanced panel that is constructed by excluding from the original sample lender-MSA pairs that were not present in all four years of estimation (2006–2009). The set of control variables mirrors those of the full model shown in columns (9)-(12) of Table 4, but the coefficients are suppressed for brevity. All regressions include lender and MSA-year fixed effects. Bank financial data are obtained from the Reports of Condition and Income (Call Reports) and measured at beginning of year levels. Data on securitization, subprime lending activity, and borrower characteristics, are obtained from the Home Mortgage Disclosure Act (HMDA) and are averaged over the unit of observation (lender-MSA-year tuple). Data on bank failures are obtained from FDIC's list of failed banks and TARP(CPP) participation data from the U.S. Treasury's CPP transaction report. All data are aggregated up to the Bank Holding Company (BHC) level. Sample selection is discussed in the Appendix and descriptions of the variables are provided in Table 2. *Observations* indicate the number of lender-MSA-year tuples used in estimation, *Applications* and *Banks* indicate the number of loan applications and lenders respectively in each bank category. Standard errors in parentheses are clustered at the bank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A. FDIC Failures				*Panel B. FDIC Failures and TARP*				*Panel C. Balanced Panel*			
	<$500mil	$500mil $1bil	$1bil $10bil	>$10bil	<$500mil	$500mil $1bil	$1bil $10bil	>$10bil	<$500mil	$500mil $1bil	$1bil $10bil	>$10bil
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TEDx(Core-deposit funding)	0.037	0.098*	0.097***	0.121***	0.031	0.115*	0.130**	0.492***	0.042	0.050	0.125***	0.119***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.06)	(0.05)	(0.14)	(0.03)	(0.06)	(0.04)	(0.04)
TEDx(Unused commitments)	0.059	-0.024	0.047	-0.365***	0.117	-0.068	0.114	-0.705**	0.008	-0.027	-0.043	-0.371***
	(0.07)	(0.08)	(0.09)	(0.11)	(0.08)	(0.11)	(0.11)	(0.27)	(0.07)	(0.10)	(0.08)	(0.11)
Observations	19,877	8,233	13,468	20,653	17,926	6,211	7,738	7,684	10,316	3,420	6,140	12,624
Applications	273,670	159,038	379,313	3,714,000	248,196	121,131	247,224	2,059,000	262,549	148,659	367,632	3,553,000
Banks	1,742	323	264	52	1,610	242	151	19	1,796	343	286	53
Adjusted-R2	0.59	0.61	0.72	0.73	0.59	0.64	0.77	0.84	0.63	0.72	0.77	0.76