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**SECURITIZATION AND THE DECLINING IMPACT OF BANK FINANCE ON LOAN SUPPLY:
EVIDENCE FROM MORTGAGE ORIGINATIONS**

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ABSTRACT

Low-cost deposits and increased balance-sheet liquidity raise bank willingness to supply illiquid loans more than loans that are easily sold or securitized. We exploit the inability of Fannie Mae and Freddie Mac to purchase jumbo mortgages to identify an exogenous change in mortgage liquidity. The volume of a bank's jumbo mortgage originations relative to non-jumbo mortgage originations increases with its holdings of liquid assets and decreases with its cost of raising deposits. The result suggests that the increasing depth of the mortgage secondary market fostered by securitization has reduced the effect of lender financial condition on credit supply.

Liquidity transformation – funding illiquid loans with liquid deposits – has been viewed as a fundamental role for banks. Diamond and Dybvig (1983) argue that banks improve welfare by allowing depositors to diversify liquidity risk while investing in high-return but illiquid projects. Securitization has changed the way banks provide liquidity.¹ Today, while real projects remain illiquid, loans have become more liquid because banks often securitize them, thereby replacing deposits with bonds as a source of finance. Today more than 60% of mortgages outstanding are securitized. As loans have become more liquid, credit supply has become less sensitive to changes in bank financial condition. For example, a bank has the option to finance a liquid loan with either deposits or, via securitization, with funds from capital markets. Liquidity provides a substitute source of finance for loan origination because the originator need not hold the loan. In contrast, illiquid loans must be held and thus funded by the originating lender. An increase in the originator's costs of deposits (for example from tight monetary policy) could thus restrict the supply of illiquid loans.

Many financial assets have been securitized in recent years, with the growth of structured products such as collateralized debt obligations (CDOs), collateralized loan obligations (CLOs), credit-card securitizations, asset-backed commercial paper, and so on. Nevertheless, securitization has grown fastest in mortgage markets, in large part due to the secondary-market activities of the government-sponsored enterprises (GSEs, i.e. Fannie Mae and Freddie Mac).² By regulation, the GSEs only buy mortgages below a given size threshold (the jumbo-loan cutoff). Mortgages below this threshold are thus more liquid than those above the threshold. We exploit this difference, showing that while a bank's liquidity and cost of deposits affect its supply of relatively illiquid loans (jumbo mortgages, defined as mortgages larger than the jumbo-loan cutoff), these variables have less effect on its supply of relatively liquid loans (non-jumbos).

We study mortgages because their liquidity falls sharply around the jumbo-loan cutoff. The discrete drop in liquidity is evident in prices – jumbo-loan rates consistently exceed those for non-jumbos. Since pricing data are not available by lender, however, we focus here on lending volumes across the two segments. In our first tests, we regress the difference in lending volumes for non-jumbo and jumbo mortgages on bank-specific financial variables – liquidity and the cost of deposits - and other controls. By modeling *relative lending volumes*, we ‘difference out’ unobservable but potentially confounding demand-side factors. We then study mortgage acceptance rates, and continue to find that banks with liquid balance sheets or low-cost deposits are more willing to approve jumbo mortgages than other banks. In contrast, there is no evidence that these measures of financial condition affect acceptance rates for non-jumbos. Loan liquidity therefore seems to sever the link from a bank’s financial condition to its willingness to supply credit. Mortgage liquidity has increased rapidly over the past 30 years, in part through GSE subsidies. Private-sector financial institutions have also increased loan liquidity in other sectors by securitizing consumer and business loans. Our results therefore extend into these other markets as well.

To understand the main result, consider the difference in average loan originations above and below the jumbo-loan cutoff (scaled by assets), stratified first by banks’ balance-sheet liquidity (liquid securities / assets) and second by cost of deposits (interest expense on deposits / deposits). We find that banks in the top quartile of the liquidity distribution originate 6% more non-jumbo mortgages annually (per dollar of assets) relative to jumbos; this difference increases to more than 14.5% of assets for banks in the bottom quartile of the liquidity distribution. In other words, while all banks seem to originate more non-jumbos than jumbos (because of greater demand), banks flush with liquidity originate relatively more in the illiquid jumbo market

(because they can supply illiquid loans more easily). The same pattern emerges when we stratify banks by cost of deposits: banks with low-cost deposits originate a relatively larger amount of jumbo mortgages compared to banks with high-cost deposits.

To validate these simple comparison of means, we start by describing the institutional features of the mortgage market and argue that these features help identify how liquidity and funding costs affect loan supply. We then estimate how loan volumes in the jumbo and non-jumbo markets vary with bank liquidity, deposit costs and a long list of control variables related to credit quality, neighborhood characteristics, and mortgage demand conditions. Our identification strategy works by differencing out *unobservable* demand conditions. We find the key results, however, are robust to the inclusion or exclusion of *observable* demand conditions, validating that our differencing strategy isolates supply factors. Nevertheless, unobservable demand conditions that alter the relative flow of applications to banks could, in principle, bias our results. So, we also analyze relative mortgage acceptance rates. This approach adds an additional ‘control’ for demand by normalizing our dependent variable by the flow of applications (the numerator equals accepted applications).

This paper contributes to several strands of research at the intersection of finance and macroeconomics. Holmstrom and Tirole (1997) present a theoretical analysis showing how real shocks can be exacerbated by reductions in credit supply. Bernanke (1983) first showed empirically that shocks to finance can have significant effects on the magnitude of business downturns, focusing on the U.S. Great Depression. More recent research has focused on regional downturns, and most studies find that real shocks are amplified by their effects on local banks (e.g. Bernanke and Lown (1991), Ashcraft (2005), Becker (2007)). Our results suggest that securitization mitigates the consequences of shocks to local banks. This result matters

quantitatively because more than 90% of mortgage applications fall below the jumbo-loan cutoff, and because shocks to the local financial system can potentially worsen business downturns.

The results also suggest that expansion of the secondary market in mortgages has dampened the effects of monetary policy on real economic activity. According to the ‘bank lending’ channel of monetary policy, central banks can slow real activity by raising bank funding costs (e.g. the cost of deposits) and thereby constrain the supply of credit. We find no statistically significant link between bank funding costs and mortgage acceptance rates in the non-jumbo mortgage market. Kashyap and Stein (2000) show that banks flush with balance-sheet liquidity respond less to monetary tightening because such banks can continue originating loans by running down their stock of liquid assets. Loutskina (2005) extends their finding by showing that loan liquidity also reduces the effects of monetary-policy shocks. She achieves identification by arguing that liquidity differs across broad categories of loans (e.g. C&I loans v. mortgages).

Both Kashyap and Stein and Loutskina rely on Call Report data and thus test only how growth in loans *held on bank balance sheets* varies with monetary policy. Our approach focuses on mortgage origination volumes, which may differ dramatically from mortgages held on balance sheets, particularly for non-jumbos where securitization is so widespread. We also differ by exploiting the discrete change in liquidity around the jumbo-loan cutoff, and by focusing on a single type of lending. Because we focus on a homogeneous product, and because we can test how our results vary as we move closer to the cutoff, we can more easily sweep out variation in demand. We can therefore be more confident than other studies that the results reflect variation in loan supply. Our results thus extend and support these studies and suggest that the potency of

monetary policy ought to be reduced relative to earlier times when banks were smaller, less well integrated with other banks, and less able to sell their loans into secondary markets (Houston, James and Marcus (1997), Ashcraft (2006), Morgan, Rime and Strahan (2004), Demyanyk, Ostergaard, and Sorensen (2007)).³

Finally, our results shed more light on how non-financial firms' cost of capital depends on their bank's financial condition.⁴ Most of the extant research has tested for effects of monetary policy or bank solvency (capital) shocks on credit supply to bank-dependent firms.⁵ Our results indicate that high costs of deposits or limited balance-sheet liquidity constrain the supply of illiquid loans (jumbo mortgages here, although the result likely generalizes to other illiquid lending such as small business credit). Like the earlier literature, we also find some evidence that bank solvency affects credit supply -- better capitalized banks receive a larger flow of jumbo applications than less capitalized ones. However, we find no direct link from bank capital to mortgage acceptance rates.

I. THE SECONDARY MARKET FOR RESIDENTIAL MORTGAGES

A. Trends in Securitization

Securitization typically involves pooling the cash flows from a number of similar assets (e.g. mortgages or credit card accounts) and selling the pool to a separate legal entity known as a special purpose vehicle (SPV). The pooling process results in a diversified portfolio of cash flows, which are used to support payments on debt securities issued by the SPV. Often, the cash flows come with some additional implicit or explicit guarantees from the originating financial institution (or the originator retains the residual or equity tranche in the SPV). Creating this separate SPV isolates the cash-flow generating assets and/or collateral so that securities issued

by the SPV are not a general claim against the issuer, just against those assets. Cash flows from the original pool of loans can be further stripped and repackaged based on various characteristics (e.g., the prepayment behavior or payment priority) to enhance their liquidity. This process may reduce financial distress costs and thus increase debt capacity (Gorton and Souleles, 2005).

Loan securitization has grown across the board, although most dramatically in the mortgage market. In 1976, the amount of securitized home mortgages was \$28 billion; by the end of 2003 the total amount of securitized home mortgages had grown almost 150 times, reaching \$4.2 trillion. Over the same period, the amount of home mortgages outstanding grew from \$489 billion to \$7.3 trillion. By comparison, there was no securitization of commercial mortgages, business loans (commercial and industrial, or C&I, loans) or consumer loans in 1976. By the end of 2003, \$294 billion of commercial mortgages were securitized, \$104 billion worth of C&I loans were securitized, along with \$658 billion worth of consumer loans (see Loutskina, 2005).

To understand why securitization of mortgages has taken off so dramatically, one needs to appreciate the role of The Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac). Fannie Mae was created by the U.S. Congress with passage of the National Housing Act of 1934. During its first three decades, Fannie Mae was operated as a government agency that purchased mainly mortgages insured by the Federal Housing Authority (FHA). In 1968, Fannie Mae became a public corporation; its role in purchasing FHA mortgages (as well as mortgages insured by the Veteran's Administration) was taken over by a new government agency, the Government National Mortgage Association (GNMA). Freddie Mac was chartered by Congress in 1970 to provide

stability and liquidity to the market for residential mortgages, focusing mainly on mortgages originated by savings institutions. Freddie Mac was privatized in 1986.

By the 1990s, both Fannie Mae and Freddie Mac were heavy buyers of mortgages from all types of lenders, with the aim of holding some of those loans and securitizing the rest. Together they have played the dominant role in fostering the development of the secondary market. As shown by Frame and White (2005), the GSEs combined market share has grown rapidly since the early 1980s. For example, by 1990 about 25% of the \$2.9 trillion in outstanding mortgages were either purchased and held or purchased and securitized by the two major GSEs. By 2003, this market share had increased to 47%. In other words, today approximately half of all mortgages outstanding were sold to the GSEs after origination (neither Fannie nor Freddie is permitted to originate mortgages themselves). GNMA provides a very important source of mortgage finance to low-income borrowers, holding or securitizing about 10% of all mortgages outstanding. However, as we describe below, our tests are designed to ‘difference out’ potentially biasing demand-side factors. We therefore drop the government-insured mortgages typically held or securitized by GNMA because our identification strategy requires homogeneity across the jumbo and non-jumbo segments.

The GSEs enhance mortgage liquidity either by buying and holding mortgages or by securitizing them. When the GSEs buy mortgages, they bear both credit and interest rate risk. When GSEs securitize mortgages, they either buy them and issue mortgage-backed securities (MBS), or they just sell credit protection to the original lender. In the first case, the originating bank retains no stake in the mortgage. In the second case, the bank continues to fund the mortgage and bear the interest rate risk, but obtains the option to sell it off as an MBS (because of the credit protection). In all cases, the GSEs enhance liquidity.⁶

Most important for our identification strategy, the GSEs operate under a special charter limiting the size of mortgages that they may purchase or securitize. These limitations were designed to ensure that the GSEs meet the legislative goal of promoting access to mortgage credit for low and moderate-income households. The GSEs may only purchase ‘non-jumbo’ mortgages, defined in 2006 as those below \$417,000 for loans secured by single-family homes.⁷ The loan limit increases each year by the percentage change in the national average of one-family housing prices, based on a survey of major lenders by the Federal Housing Finance Board. The limit is 50% higher in Alaska and Hawaii. Because the loan limit changes mechanically and only as a function of *national* housing prices, local housing supply or demand conditions have no effect on the jumbo-loan cutoff. Thus, there is a discrete drop in mortgage liquidity around this cutoff that is exogenous to financial intermediary or borrower decisions.

B. Mortgage Market Segmentation

The GSE charter limitation conveniently splits the market into a liquid segment (non-jumbo mortgages) and an illiquid segment (jumbo mortgages). How do we know that liquidity really falls at the cutoff? It is certainly true that jumbo mortgages are sometimes securitized, but our identification strategy only requires an increase in the costs of selling or securitizing loans above the jumbo-loan cutoff. There are several reasons to believe that these costs are higher in the jumbo market. First, in contrast to non-jumbos, most jumbo mortgages are held by the original lender. Second, the GSEs are the only financial institution that will buy *individual* mortgage loans, but they will *only* buy those below the cutoff. Securitization involves pooling a large number of loans, so removing non-jumbos would be especially costly for small banks without the GSEs. Third, mortgage-backed securities issued by GSEs come with required capital

only one-fourth as large as required capital for similar securities (such as jumbo-mortgage securitizations) issued by private financial institutions under the Basel Capital Accord.⁸

The jumbo/non-jumbo spread, which has varied between 10 and 25 basis points over the most of the past 15 years, would seem to offer a direct measure of the value of liquidity and other subsidies from the GSEs. Implicit government guarantees of the bonds issued by Fannie Mae and Freddie Mac reduce their yields, and some of this subsidy is passed on to banks and other lenders (Passmore, Sherlund and Burgess, 2005). We argue that this subsidy is larger at banks with high cost of funds or low balance-sheet liquidity. The jumbo/non-jumbo spread should be wider for such financially constrained banks, but this implication is not directly testable because mortgage rates by lender are not available. Given the lack of pricing data, we focus instead on quantities where we can link loan applications to the originating bank. It is worth noting that the average jumbo/non-jumbo spread widened to 75 basis points in August 2007, when unexpected losses in subprime mortgages reduced liquidity in both the bond market as well as at financial institutions. The lack of liquidity has been evident in the decline in outstandings in the asset-backed commercial paper market, in a general increase in credit spreads, and a slowdown in interbank lending. The dramatic widening in the jumbo/non-jumbo spread is consistent with our identification assumption.

II. DATA & SAMPLE SELECTION

A. HMDA Data on Mortgage Applications

To build our dataset, we start with a comprehensive sample of mortgage applications and originations that have been collected by the Federal Reserve since 1992 under provisions of the Home Mortgage Disclosure Act (HMDA). The sample covers loan applications from 1992 to

2004. HMDA was passed into law by Congress in 1975 and expanded in 1988, with the purpose of informing the public (and the regulators) about whether or not financial institutions adequately serve local credit needs. In addition, regulators use the HMDA data to help identify discriminatory lending. These data are collected by the Federal Reserve under Regulation C, and all regulated financial institutions (e.g. commercial banks, savings institutions, credit unions, and mortgage companies) with assets above \$30 million must report.

To our knowledge, ours is the first study using HMDA data to test how financial variables affect loan supply. The extant research has focused instead on mortgage discrimination. Munnell et al (1996) use a subset of HMDA data from the Boston area, enhanced with financial information not available in the main dataset (e.g. borrower wealth, debt, and the loan-to-value ratio), and report evidence that acceptance rates are lower for minority applicants conditional on a large set of observables. In contrast, Horne (1997) argues that the effects of minority status on acceptance rates vary substantially with small changes in either the sample or specification, thus making it difficult to interpret the results as evidence of discrimination. These studies spawned a large number of articles on mortgages discrimination without resolving the issue. Given these studies, we do control for characteristics possibly related to discrimination, but our conclusions are not sensitive to the inclusion of these variables.

The HMDA data include information on the year of the application (although we know nothing about exactly when during a given year a loan application was made), the dollar amount of the loan, and whether or not the loan was accepted. Lender identity is reported, which we use to collect the funding and liquidity variables (described below). For credit risk, we control for the log of the applicant's income as well as the income-to-loan-size ratio. There is no information on borrower assets, indebtedness or the market value of the property in the HMDA

data. Nevertheless, we can control for economic conditions with an indicator for properties located within Metropolitan Statistical Areas (MSAs) and with the median income in the property's Census Tract. We also include the average size of mortgage applications made by *all* lenders in each bank's markets to absorb variation in property values. Last, we include indicators for minority and female applicants, as well as the share of the population that is minority in the property's Census Tract. As noted, the earlier studies focused on discrimination, so these factors help absorb such effects.

Figure 1 plots a histogram of the frequency distribution of mortgage applications from HMDA data as a function of the ratio of loan size to the jumbo-loan cutoff (Panel A).⁹ The figure shows first that most mortgage applications come in below the cutoff value (i.e. most mortgages can be sold easily into the secondary market). Also, we see a sharp spike in the frequency of loan applications just below the cutoff. This spike suggests that the applicant pool itself is endogenously determined, at least in part, by financial conditions. That is, we know that interest rates are higher for jumbo loans, thus some applicants with loan demand "near" the jumbo-loan cutoff may borrow less than they otherwise would to take advantage of the lower rate.

Panel B of Figure 1 reports the average acceptance rate for mortgages, again as a function of the ratio of the loan amount to the jumbo-loan cutoff. As in Panel A, we see a sharp upward spike in the acceptance rate for loans just below the cutoff. The high acceptance rate just below the cutoff suggests that some of the most creditworthy clients borrow less than the cutoff, either to take advantage of lower rates or because the lender would not approve a jumbo loan for these clients. The figure also shows that acceptance rates appear to fall off sharply for very small loans, and the acceptance rate also falls off gradually as loan size increases beyond the jumbo-

loan cutoff. The very small loans may be riskier due to the low income and wealth of the applicants, while the very large loans may be riskier due to unusually high demand for credit (Stiglitz and Weiss, 1982).

B. Bank Financial Variables

To understand how funding costs and liquidity affect the supply of mortgage credit, we collect bank-level data by merging the HMDA loan application data to the *Reports of Income and Condition* for commercial banks (the ‘Call Report’). We merge each application to the Call Report from the fourth quarter of the year prior to the mortgage application using the HMDA bank identification number with call report identification number (RSSD ID) for banks reporting to Federal Reserve Bank, with FDIC certificate ID (item RSSD9050 in Call report) for banks reporting to FDIC, and with OCC ID (item RSSD9055 in Call report) for banks reporting to OCC. The unmatched institutions from HMDA dataset are then matched manually using a bank’s name and the zip code of its location.

C. Samples of Mortgage Applications

In all but one of our set of regressions, we focus on the bank-year as the unit of observation. The dependent variables represent several measures of loan quantity – total volume of originations (scaled by assets), the bank’s overall acceptance rate (approved mortgages / total applications), and the volume of applications. We build these dependent variables from two samples of the HMDA data. The first sample is all inclusive, and thus has the benefit of completeness. In the second approach, we drop refinancing mortgages and focus on applications near the jumbo-loan cutoff to reduce the possibility that our results are driven by unobserved heterogeneity.

The raw HMDA data contain almost 250 million applications. Of these, we first drop mortgages originated by savings institutions, mortgage bankers, credit unions and other non-bank lenders, leaving about 120 million applications to financial institutions reporting to FDIC, FRB, and OCC (mostly commercial banks). We then drop mortgages where borrowers are subsidized by the Federal Housing Authority, the Veterans Administration or other government programs, leaving us with about 106 million loan applications. We then drop applications with missing characteristics such as loan size, property location, or the bank's approval decision on the loan, leaving 72 million applications. After merging this sample to the Bank Call Report, we are left with about 62.5 million applications, which we will call the 'full sample'. In our second sample, we drop applications for refinancing existing mortgages ('refis'), and we keep only those applications between 50% and 250% of the jumbo-mortgage cutoff. Dropping the refis lowers the sample to 10 million, and adding the last filter reduces the sample to about 6 million applications.¹⁰

Table I contains simple summary statistics for the mortgage application data that we use in our two samples. We report the acceptance rate, loan size, applicant income, and the share of loans made in urban areas (i.e. in MSAs). Acceptance rates are lower in the full sample than in the filtered sample (80% v. 91%), reflecting the fall off in acceptance rates for very small loans. Similarly, both average loan size (\$209 thousand vs. \$102) and the mean ratio of loan size to applicant income (2.4 vs. 1.6) are higher in the filtered sample. In the full sample, about 13% of the loan applicants are to minority borrowers, and about 19% are to female borrowers. The median census tract income (averaged across tracts) is \$44 thousand per year. Most of these characteristics are quite stable over time, although the jumbo-loan cutoff increases as housing prices have risen throughout the sample.

Table II reports lender characteristics for data included in our samples (Panel A). We also report these characteristics for banks that are excluded, either because they did not appear in the HMDA dataset or because we were unable to match their identifier to HMDA (Panel B). The median bank in our sample holds about \$85 million in assets, and the median bank received 240 mortgage applications (215 accepted) in a typical year in the full sample; for the filtered sample, the number of applications for the median bank falls to just 16. For the full sample, the flow of applications translates into 7.7% of assets originated annually in non-jumbo mortgages, plus 1.4% of assets originated for jumbos for the median bank. The median deposit cost, defined as interest expenses on deposits divided by total deposits, equals about 3.3%, and the median bank held about 28% of its assets in either cash or other marketable securities. In contrast, the banks excluded tend to be smaller, less focused on lending, and less focused on mortgage lending in particular, although no less profitable. This is reasonable to expect since the HMDA data cover mortgage lenders with total assets in excess of \$30 million.

III. EMPIRICAL STRATEGY

A. Identification

How do funding conditions and liquidity affect an individual bank's willingness to supply credit? Answering the question convincingly creates the challenge of separating the effects of loan *demand* from those of loan *supply*. To understand this identification problem, consider the reduced form regression of loan originations on a bank's cost of raising deposits. If availability of local deposits affects loan supply, then an increase in a bank's cost of deposits ought to be associated with a decline in originations (and an increase in price in the other reduced form). Strong loan demand, however, will tend to increase a bank's appetite for deposits to fund that

demand, thus potentially leading to higher yields on deposits (and a positive correlation between deposit yields and originations). Similarly, a bank's willingness to hold liquid assets – for example, cash or other marketable securities – may be directly affected by loan demand. Where demand is weak, we would expect banks to hold more securities. Thus, demand-side forces will tend to generate a negative correlation between measures of bank liquidity and loan originations.

Our research method specifically addresses these identification problems. We estimate reduced form models linking the quantity of originations to demand and supply shifters, but rather than model overall originations, we instead focus on the *difference* between the volume of non-jumbo mortgage originations and jumbo originations. We assume that unobserved demand-side variables affect the jumbo and non-jumbo mortgages at a given bank-year in the same way, and thus can be eliminated by differencing. The identification strategy allows us to measure the effect of liquidity and deposit costs on the supply of jumbo mortgages relative to the supply of non-jumbos. Since the strategy requires a homogenous pool of loans (to remove demand), we compare the full sample results on overall originations with results from a filtered sample without refis. We then further refine our tests by focusing on acceptance rates for applications around the jumbo cutoff, thereby unpacking the results for total originations. In these refinements, we also compare the full sample with the filtered sample without refis and without mortgages below 50% of the jumbo-loan cutoff or above 250% of the cutoff. By comparing results for loans near the cutoff with results from the full sample we can assess the validity of our identification assumption (i.e. demand homogeneity across the two segments of the market).

B. Estimation

To understand our estimation, consider two reduced form equations relating the volume of mortgage originations to market-level demand-side variables and to bank-level funding characteristics (supply-side variables), as follows:

$$\begin{aligned} VOL^{NJ}_{i,t} &= \gamma^{NJ}_1 Balance\text{-sheet liquidity}_{i,t-1} + \gamma^{NJ}_2 Deposit\ cost_{i,t-1} + \\ &+ \beta_1^{NJ} Borrower\ Risk^{NJ}_{i,t} + \beta_2^{NJ} Bank\ \&\ Market\ Controls_{i,t-1} \\ &+ Unobservable\ Demand\text{-Side}\ Variables_{i,t} + \varepsilon^{NJ}_{i,t} \end{aligned} \quad (1a)$$

$$\begin{aligned} VOL^J_{i,t} &= \gamma^J_1 Balance\text{-sheet liquidity}_{i,t-1} + \gamma^J_2 Deposit\ cost_{i,t-1} + \\ &+ \beta_1^J Borrower\ Risk^J_{i,t} + \beta_2^J Bank\ \&\ Market\ Controls_{i,t-1} \\ &+ Unobservable\ Demand\text{-Side}\ Variables_{i,t} + \varepsilon^J_{i,t} \end{aligned} \quad (1b)$$

where the unit of observation in these regressions is the bank-year. Subscript i indicates bank, and subscript t indicates year. For each bank-year, the dependent variable equals the volume of new originations summed across all non-jumbo (or jumbo) mortgages in year t . We normalize volumes with the bank's assets at the end of prior year so the dependent variable measures the amount of new lending relative to the bank's overall portfolio. (We could alternatively normalize by total loans, although these results are similar to those reported below.)

Each equation may contain demand-side variables that are unobservable, as well as variables reflecting the funding and liquidity position of the potential lender. These unobservable demand factors potentially bias estimation of the direct effects of liquidity and deposit costs on loan origination for the reasons described above. But we expect that banks with more balance-sheet liquidity to be more willing to supply illiquid jumbo mortgages than liquidity-constrained banks. In contrast, liquidity constraints should not affect a bank's

willingness to supply non-jumbo mortgages because these can be converted to mortgage-backed securities (which are liquid), or they can be sold off easily (to one of the GSEs). For funding costs, we expect banks with high deposit costs to reduce loan supply more for illiquid jumbo mortgages than for liquid non-jumbos, again because the bank must hold and thus fund the illiquid ones (Kashyap and Stein, 2000; Campello, 2002). That is, we expect the following relationships to hold:

$$0 \leq \gamma_1^{NJ} < \gamma_1^J \quad \text{and} \quad 0 \geq \gamma_2^{NJ} > \gamma_2^J.$$

If demand-side effects are common across equations (1a) and (1b), then they can be eliminated by subtraction, as follows:

$$\begin{aligned} VOL_{i,t}^{NJ} - VOL_{i,t}^J &= (\gamma_1^{NJ} - \gamma_1^J) Balance\text{-}sheet\ liquidity_{i,t-1} + (\gamma_2^{NJ} - \gamma_2^J) Deposit\ cost_{i,t-1} + \\ &+ \beta^{NJ} Risk_{i,t}^{NJ} - \beta^J Risk_{i,t}^J + (\beta_2^{NJ} - \beta_2^J) Bank \ \& \ Market\ Controls_{i,t-1} + \eta_{i,t} \quad \mathbf{(1c)} \end{aligned}$$

Thus, we can remove the potentially biasing demand-side effects, but we are only able to identify the difference in the coefficients in equations (1a) and (1b). This differencing also removes any other common but unobservable variable affecting acceptance rates in a given bank-year.

Equation (1c) represents our benchmark regression.

To control for characteristics of the pool of loans used to build the dependent variable, we include the following: the ratio of the loan size to applicant income; the log of applicant income; the share of properties located in MSAs; the percent minority in the population around the property; the median income in the area around the property; and shares of female and minority loan applicants. We construct these characteristics by averaging across all of the non-jumbo loans ($Risk_{i,t}^{NJ}$) and across all of the jumbo loans ($Risk_{i,t}^J$). We allow the coefficients on these risk characteristics to differ by loan type.¹¹

To control for property values, we include the log of average application size for *all* loans in the bank's market (MSA or non-MSA county).¹² For banks receiving applications from multiple markets, we use an equally-weighted average of the mean application sizes across these markets. We also include three additional measures of MSA-level market demand conditions and demographics: the unemployment rate; the growth in income; and the percent of the population over 65 for the state-year. These variables are substituted by the state-level characteristics for properties outside of the MSA areas. We also include bank size (log of assets), an indicator equal to one for banks owned by multi-bank holding companies, a measure of leverage (the capital-asset ratio), and accounting profits (net income to assets). Because there may be additional unobserved bank effects or some autocorrelation in the residual, we cluster the error in the model by bank in constructing standard errors.¹³

Changes in the stance of monetary policy could in principle be included in our model to test how aggregate funding shocks (e.g. an increase in the Fed Funds rate) affect the supply of liquid v. illiquid loans. Unfortunately, the HMDA loan application data are not 'time stamped'. All we can observe is the year in which a given application is made. Since Federal Reserve policy can change sharply over the course of a single year, we simply absorb year effects with a set of indicator variables. We also incorporate state indicator variables in all of our models. According to Passmore, et al (2005), removing state effects is important, both because of differences in foreclosure laws across states, and because the jumbo-mortgage market is much better developed in states with relatively high housing costs, compared to states with lower-priced houses.

IV. RESULTS

A. Volume regressions

Table III reports the benchmark results. We report three specifications across the full sample, and the same specifications for the sample without refis. The first two specifications (columns 1-2 and 4-5) focus on balance-sheet liquidity and deposit cost individually. Then, we report one specification with both together (columns 3 & 6). In all of our models we include the full set of loan-pool and market control variables.¹⁴

All six specifications suggest that banks with more balance-sheet liquidity and banks with lower cost of deposits supply more credit to the illiquid sector (jumbos) relative to the liquid sector (non jumbos). The effects are robust across the specifications and samples, although we find larger coefficients in the full sample than in the sample without refis. To understand the magnitudes, consider an increase in balance-sheet liquidity variable from the 25th to the 75th percentile of its distribution (an increase of 17.5% of assets). This change would increase the volume of jumbo originations by 2.8% (1.7% in the sample without refis) of assets relative to non-jumbos. This increase is large relative to the overall distribution of loan originations, where the median bank originates 5.6 percentage points more non-jumbos than jumbos (see Table II). For deposits, a move from the 25th to 75th percentile in the distribution of yields (and increase of 1.1 percentage points) is associated with a relative increase in originations of a little more than 0.8% of assets (0.5% in the smaller sample).

The effects of bank size and capital also confirm our overall findings. Large banks and well capitalized banks originate more jumbo mortgages than smaller, less well-capitalized banks. Because there are many differences in the operating and financial policies of large and small banks, we include these mainly as control variables. But the size result may reflect, in part, large

banks' better access to alternative sources of funds, as well as their greater ability to manage liquidity risk. For example, large banks have a greater ability to borrow in the Fed Funds market than smaller banks. Similarly, with better ability to borrow in capital markets, large banks are also less reliant on deposits as a marginal source of funds for their lending.

Before continuing, it is worth recalling that our identification strategy attempts to isolate supply-side effects of both balance-sheet liquidity and deposits by differencing out unobservable demand factors. But we do include three observable variables to absorb demand: the log of average application size (a proxy for the property value), the growth in local personal income (MSA, or state for properties outside MSAs), and the local unemployment rate. We also include the share of population over 65 in the state-year as a crude measure of population mobility. The log of average application size – a proxy for property values – enters negatively ($T > 10$), because markets with high housing prices will have much greater demand for jumbo loans than other markets. The other effects, which are less statistically powerful, are harder to interpret because they represent the differential effect of the variable on loan volumes (non-jumbo minus jumbo). But, the key results *are not sensitive to the inclusion or exclusion* of any of these demand proxies. Since results are insensitive to the inclusion or exclusion of observable demand-side proxies, it seems unlikely that omitted unobservable demand variables could bias our results.

Last, in an unreported robustness test we introduce bank fixed effects. This test is very stringent because our differencing strategy removes time-varying, bank-specific factors that are common to the jumbo and non-jumbo segments. Adding a bank fixed effect removes all cross-bank variation, and will take out any residual differences in relative demand across the two sectors. In these regressions, the coefficient on balance sheet liquidity falls to -0.035 ($t=3.5$), while the coefficient on the cost of deposits falls to 0.16 ($t=1.3$). These results are much less

statistically powerful because liquidity and financing costs tend to vary much more in cross-section than over time.

B. Mortgage Acceptance Rates

We next regress the average acceptance rates for jumbo mortgages relative to non-jumbos by bank-year, against the same set of variables as in Table III. This approach offers two advantages over the volume regressions. First, acceptance rates reflect specific decisions of the lender, and thus are more naturally linked to the supply side of the market. Second, the dependent variable is, by construction, normalized by the overall flow of applications (total approved mortgages / total application), which can be seen as another means to sweep out effects from loan demand (which drives the denominator).

To further validate our identification strategy, we compare the results using all loans with results for a sample filtered both to remove refis and to remove loans that are very large (greater than 250% of the cutoff) or very small (less than 50% of the cutoff). The full sample provides us with less noisy estimates of the acceptance probabilities because the number of loan applications is 20 to 50 times higher for each bank than in the filtered sample. Inspection of Figure 1 shows, however, that the acceptance rates fall off for small loans, suggesting that these borrowers may be very different from borrowers near the cutoff. The filtered sample thus ensures compatibility of loans and hence may account better for demand-side effects.

The acceptance-rate results, reported in Table IV, are qualitatively consistent with those reported on total loan volumes. Banks flush with balance-sheet liquidity are more likely to approve jumbo mortgages, as are banks with low costs of deposits. These effects are consistent across specifications and samples. The robustness across samples is especially notable given the large difference in the number of bank-years (14,821 vs. 21,354) as well as the large difference

in the number of loan applications used to build the dependent variable (the full sample contains 10 times as many applications as the filtered sample). Magnitudes are somewhat larger in the full sample, although the difference is less than two standard errors for both the coefficient on balance-sheet liquidity and deposit costs.¹⁵

C. Sorting and Loan-Application Size

While qualitatively similar, the economic magnitudes in Table IV are considerably smaller than those reported in Table III. For example, moving balance-sheet liquidity from the 25th to the 75th percentile increases the jumbo-loan acceptance rate by about 0.6 percentage points. If applications were randomly distributed across lenders, then this shift in bank-loan acceptance rates should explain all of the shifts in loan volumes. However, only about 20% of the 2.8% relative increase in total jumbo-loan originations can be explained by differences in acceptance rates ($0.6/2.8 = 0.21$).

Loan applications are evidently not randomly assigned to lenders. As we noted above, application size may be endogenously determined by banks' ability to securitize or sell off mortgages below the jumbo-loan cutoff. This notion seems consistent both with the flow of applications, which spikes upward for loans just below the cutoff (Figure 1A), and with acceptance rates, which also spike upward just below the cutoff (Figure 1B). We do not observe exactly how a bank might influence its applicants, although it seems likely that influence could be accomplished with carrots ('lower interest rates below the cutoff...') or sticks ('the loan will only be accepted if it comes in below the cutoff...').

Even when loan-size is not endogenous, advertising to customers, mortgage brokers, and internet search services likely lead to non-random sorting of applications across banks. We thus argue that banks with liquid balance sheets and low-cost deposits will experience a greater flow

of jumbo loan applications than other banks. To test this notion, we focus separately on marginal and non-marginal loan applications. Marginal applications are those where individuals may *choose* to borrow less than they otherwise would, for example to take advantage of pricing differentials around the cutoff. Non-marginal applications are those further away from the cutoff, where loan-size choice is not plausibly linked to pricing incentives, but sorting across banks may be important. We construct the share of marginal non-jumbo loans as the number of applications between 95% and 100% of the cutoff, divided by the number all applications near the cutoff (95% to 105% of the cutoff). To test for sorting effects, we construct the number of non-marginal non-jumbo loans (less than 95% of the cutoff) divided by the number of all non-marginal applications (i.e. loans less than 95% or greater than 105% of the cutoff). We then relate these two variables to the same set of bank financial conditions as before.

Table V reports the results, with the same set of specifications reported in Table IV. As before, balance-sheet liquidity and funding costs are significantly related to the flow of loan applications. The applicant flow is skewed toward the relatively liquid mortgages (those below the cutoff) for banks with lower levels of balance-sheet liquidity or higher cost of deposits. These results support the idea that more liquid banks and banks with cheaper deposits are better financially positioned to supply illiquid loans. Presumably banks encourage customers to borrow in the non-jumbo market using pricing incentives, although we can not directly test this notion due to lack of bank-level data on mortgage rates.

The coefficients in Table V suggest that the shifts in the loan-application distribution are most pronounced for loans near the jumbo cutoff, which makes sense because both sorting across banks as well as shifts in the amount borrowed will tend to occur together. In contrast, for loans away from the cutoff we are only observing the impact of non-random sorting of borrowers to

banks. Borrowers demanding large loans tend to apply at banks with high levels of liquid assets and with low-cost deposits. In terms of the coefficient magnitudes, the effect of balance-sheet liquidity is again notable. A move from the 25th to the 75th percentile in the distribution is associated with an increase of 1.8 percentage points in the share of jumbo loans around the cutoff. Thus, the total effect of balance-sheet liquidity and deposit costs is explained in part by a shift in acceptance rates and in part by the shift in the distribution of applications.

D. Financial Effects away from the Jumbo-Loan Cutoff

We have tried to rule out demand by differencing across the jumbo loan cutoff, by focusing on a homogeneous sample, and by varying the set of potential demand-side variables included in the models. Next, we offer a test of the basic premise of the paper, namely that loan liquidity falls discretely around the jumbo loan cutoff. If true, then the effects that we observe should *not* show up at other size-related cutoffs. For example, we should see no correlation between bank balance-sheet liquidity and relative acceptance rates of loans bigger or smaller than 75% of the jumbo-loan cutoff. Similarly, we should see no correlation between bank balance-sheet liquidity and relative acceptance rates of loans bigger or smaller than 150% of the jumbo-loan cutoff. All of the action should happen around the cutoff, *but nowhere else across the distribution*.

We now provide a formal test, as follows. For each bank-year, we construct the volumes and acceptance rates (defined as before) in the following four loan-size bins: 50% to 75% of the jumbo-loan cutoff; 75% to 100% of the cutoff; 100% to 150% of the cutoff; and 150% to 250% of the cutoff. We thus have four observations of the dependent variable for each bank-year.¹⁶ We regress volume and acceptance rates on the same set of variables as before, including interactions between bin-size indicators and the continuous variables. The first set of

interactions multiplies the jumbo indicator by balance-sheet liquidity and the cost of deposits. We add another set of interactions between an indicator for loans 75% to 100% of the cutoff and the financial variables, and a third set for loans 150% to 250% of the cutoff. Thus, the coefficients on the linear terms reflect the correlation between the volumes and acceptance rates for small loans (50%-75% of the cutoff) and the financial variables. The coefficients on the interactive terms with the 75%-100% indicator test whether loans that are larger but not yet above the cutoff respond differently to financial variables than other small loans; the 150%-250% interactions test whether jumbo loans that are very large respond differently to financial variables than other jumbo loans.

Table VI offers very strong support for our identification strategy. There is no effect of balance-sheet liquidity or deposits on either origination volumes or acceptance rates for any category of mortgages below the cutoff. For jumbo loans, balance-sheet liquidity is positively related to acceptance rates, but there is no incremental effect for very large mortgages (i.e. the interaction is positive but not significant). We see a similar pattern for the costs of deposits. The financing effects shift dramatically at the jumbo-loan cutoff (because liquidity falls there), but not at other arbitrarily chosen size cutoffs (because liquidity does not fall at 75% or 150% of the cutoff).

E. Acceptance Rates for a Homogenous Sample

In our last test, we design an experiment that considers only loans with a change in classification in adjacent years due to the exogenous increase in the jumbo cutoff. During our sample period, the jumbo-loan cutoff rose each year, starting from \$202 thousand in 1992 and ending at \$334 thousand by 2004. For a given year, we include only jumbo loans that will be classified as non-jumbo in the next year, when the cutoff is increased to reflect higher housing

prices. Similarly, we include only non-jumbo loans that would have been classified as jumbo one year earlier. Thus we intentionally create a sample of very similar loans. Since the sample is much smaller, we analyze the acceptance probability by loan rather than by bank-year in a probit model. We randomly select at most 1,000 applications for a given bank-year to mitigate the influence of very large banks.

We include the same set of regressors as before, and we interact each with the jumbo-loan indicator. Table VII reports these last results, and again shows the same impact of both balance-sheet liquidity and deposits as before. Banks with more liquidity are more likely to approve jumbo loans, but no more likely to approve non-jumbos. The same holds for deposits – no effect of deposit costs on approval probability for non-jumbos, but a negative effect for jumbos.

V. CONCLUSIONS

Traditional banks originated illiquid loans and funded them with liquid deposits. As a result, a decline in deposit supply reduced loan supply. Banks also needed to hold enough cash and marketable securities to satisfy random demands for liquidity from depositors and borrowers with credit lines. Securitization is changing the model of banking from one of ‘originate and hold’ to one of ‘originate and sell’, thereby mitigating the effects of both deposit supply and balance-sheet liquidity of individual lenders on their willingness to supply credit. As evidence, we show that jumbo mortgage volumes and approval rates depend on both the lender’s cost of deposits and holdings of liquid assets. In contrast, financial condition has no effect on acceptance rates for non-jumbo loans. More broadly, loan securitization (as well as the growth of loan sales and syndication) fosters financial integration. With integration, capital can flow rapidly between markets, thereby dampening the consequences of shocks to local banks and

other lenders. The downside to integration is that aggregate shocks like the drop in real estate values in the U.S. and U.K. spread rapidly across the whole financial system, as we have seen during the 2007 subprime mortgage crisis.

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Figure 1A: Histogram of Loan Applications to All Financial Institutions, 1992-2004

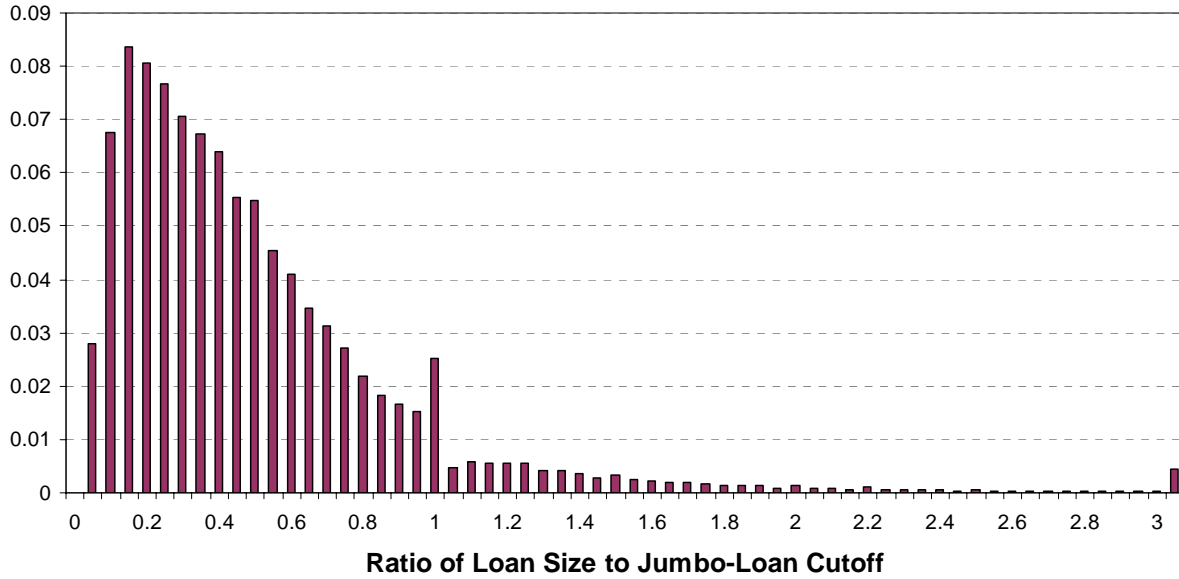
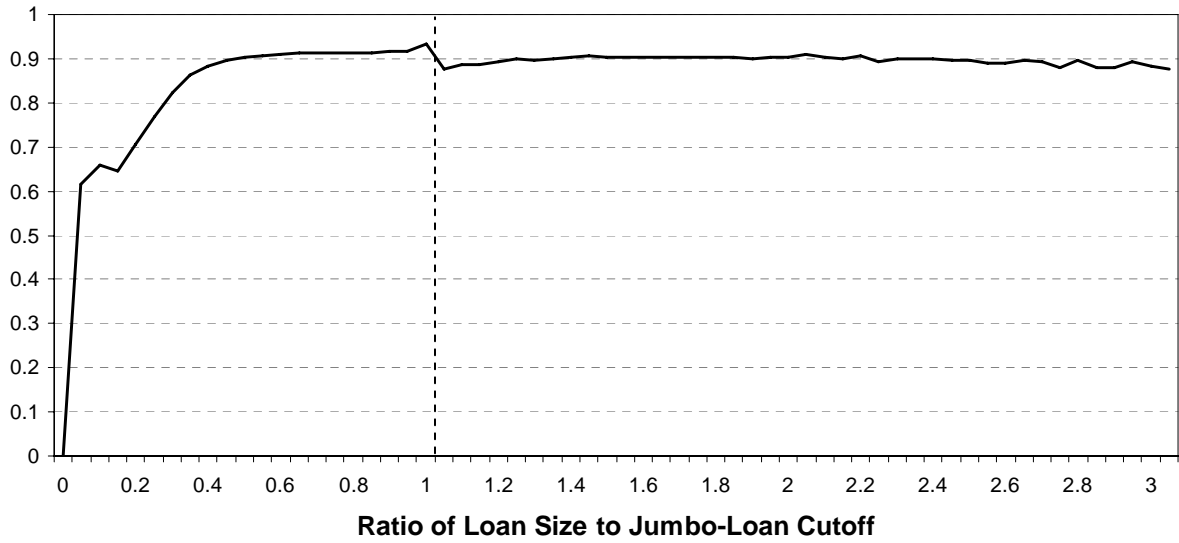


Figure 1B: Probability of Acceptance for Loan Applications to All Financial Institutions, 1992-2004



Legends for Figures 1A and 1B

Figure 1A: This figure plots the frequency distribution of all mortgage applications in the HMDA data from 1992 to 2004 by the size of the application divided by the jumbo-loan cutoff. For example, the vertical axis plots the share of mortgage applications greater than or equal to 95% of the jumbo-loan cutoff but strictly less than the cutoff above the value 1 on the horizontal axis in the figure.

Figure 1B: This figure plots the share of all mortgage applications that are accepted using all HMDA data from 1992 to 2004. We plot these acceptance rates by the size of the application divided by the jumbo-loan cutoff. For example, the vertical axis plots the acceptance rate for mortgage applications that are greater than or equal to 95% of the jumbo-loan cutoff but strictly less than the cutoff above the value 1 on the horizontal axis in the figure.

Table I: Summary Statistics for Mortgage Applications Characteristics

This table contains summary statistics for our two samples of mortgages. The first sample is based on all home mortgage applications to commercial banks from the HMDA data, collected by the Federal Reserve Board. The second sample includes only mortgage applications between 50% and 250% of the jumbo-loan cutoff and omits refinancings.

	Full Sample	Mortgages between 50%-250% of Jumbo Cutoff, without Refis
Number of Loan Applications	62,587,880	6,435,270
Probability of Acceptance (%)	79.93	90.85
Average Loan Amount (thousands)	\$102	\$209
Average Applicant Income (thousands / year)	\$79	\$120
Average Area Income (thousands / year)	\$44	\$51
Average Loan-to-Income Ratio	1.60	2.4
Percent Minority	12.75	14.14
Percent of Minority Population in the Area	16.81	14.83
Percent Female	19.01	15.02
Percent of Loans in MSA	84.17	91.84

Table II: Summary Statistics for Bank Characteristics

This table reports information on the distribution of characteristics for banks that we matched to the mortgage application data, and for banks that we exclude from our analysis. Liquid assets equals cash plus marketable securities. The cost of deposits equals interest expense on deposits to total deposits.

	<i>Panel A: Banks Included in Our Sample</i>			<i>Panel B: Excluded Banks</i>		
	25th Percentile	Median	75th Percentile	25th Percentile	Median	75th Percentile
<i>Total Assets (millions of \$s)</i>	42.6	84.4	194.1	17.4	32.5	62.9
<i>Financial Structure & Liquidity (%)</i>						
Liquid Assets / Assets	19.9	27.8	37.4	22.9	32.7	43.9
Cost of Deposits	2.7	3.3	3.9	2.7	3.5	4.1
Capital / Assets	7.4	8.5	10.1	8.0	9.4	11.6
<i>Loan Shares (% of assets)</i>						
Total Loans	53.9	63.3	71.1	47.0	58.1	67.4
Commercial & Industrial Loans	9.7	17.6	27.4	14.4	25.7	41.4
Home Mortgages	20.2	31.2	46.3	14.3	25.2	37.8
Commercial Mortgages	10.7	18.1	26.9	4.9	10.7	19.4
Consumer Loans	4.9	9.9	17.5	7.6	12.8	20.4
<i>Loan Originations (% of assets)</i>						
Non-Jumbo Mortgages	3.09	7.74	16.26	n/a	n/a	n/a
Jumbo Mortgages	0.65	1.38	3.05	n/a	n/a	n/a
Non-Jumbo Mortgages less Jumbo Mortgages	1.33	5.57	13.41	n/a	n/a	n/a
<i>Loan Originations without Refinancing (% of assets)</i>						
Non-Jumbo Mortgages	1.56	3.83	7.55	n/a	n/a	n/a
Jumbo Mortgages	0.44	0.91	1.97	n/a	n/a	n/a
Non-Jumbo Mortgages less Jumbo Mortgages	0.44	2.46	5.87	n/a	n/a	n/a
<i>Profit (%)</i>						
Net Income / Assets	0.7	1.0	1.3	0.7	1.1	1.4
<i>Mortgage applications</i>						
Number of loan applications	90	240	627	n/a	n/a	n/a
Number of loans Issued	79	215	564	n/a	n/a	n/a
Probability of Acceptance (%)	85.5	91.5	95.6	n/a	n/a	n/a
<i>Mortgage applications between 50-250% of jumbo cutoff w/o refis</i>						
Number of loan applications	6	16	54	n/a	n/a	n/a
Number of loans Issued	5	15	50	n/a	n/a	n/a
Probability of Acceptance (%)	88.9	96.5	99.0	n/a	n/a	n/a

Table III: Regression of Loan Volumes for Non-Jumbo Mortgages Relative to Jumbos on Bank Characteristics

This table reports regressions of the volume of approved non-jumbo minus jumbos mortgages, divided by beginning of period assets. The unit of observation is the bank-year, from 1992 to 2004. The regressions include the following controls for the loan-pool characteristics in each bank-year: the share of loans made to borrowers in MSAs; percent minority applicants in the bank's lending markets; mean loan-to-income ratio; log of mean applicant income; average median income in bank's lending markets; the share of minority applicants; and the share of female applicants. We allow the coefficient on each of these variables to be different for the two segments of the market (jumbo and non-jumbo). Regressions also include three measures of local market demand conditions and demographics: the MSA-level unemployment rate (state for properties not in MSAs); the MSA-level growth in income (state for properties outside MSAs); and the percent of population over 65 for the state-year. All regressions also include year and state fixed effects.

<i>Dependent Variable:</i>	(Volume of Approved Non-Jumbos - Volume of Jumbos)/Assets _{t-1}					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bank Financial Condition</i>						
Liquid Assets / Assets	-0.166 (11.59)***		-0.161 (11.31)***	-0.099 (10.90)***		-0.096 (10.71)***
Cost of Deposits		1.001 (4.51)***	0.704 (3.23)***		0.657 (4.79)***	0.489 (3.67)***
<i>Bank Controls</i>						
Log of Bank Assets	-0.015 (10.49)***	-0.015 (10.41)***	-0.015 (10.49)***	-0.009 (10.49)***	-0.009 (10.41)***	-0.009 (10.55)***
Bank owned by Holding Company	-0.021 (4.22)***	-0.018 (3.56)***	-0.019 (3.75)***	-0.009 (3.09)***	-0.007 (2.45)**	-0.008 (2.54)**
Capital / Assets	-0.224 (3.01)***	-0.305 (4.09)***	-0.207 (2.76)***	-0.101 (2.46)**	-0.147 (3.60)***	-0.088 (2.15)**
Net Income / Assets	0.02 (0.08)	-0.138 (0.54)	0.005 (0.02)	-0.148 (0.98)	-0.222 (1.42)	-0.144 (0.95)
<i>Market Controls</i>						
Log of Average Application Size ¹	-0.058 (5.63)***	-0.057 (5.44)***	-0.058 (5.62)***	-0.038 (5.85)***	-0.038 (5.70)***	-0.038 (5.83)***
Percent over 65	0.046 (4.07)***	0.045 (3.97)***	0.048 (4.23)***	0.013 (1.89)*	0.013 (1.82)*	0.014 (2.08)**
Local Personal Income Growth	0.349 (3.70)***	0.327 (3.48)***	0.351 (3.72)***	0.164 (2.93)***	0.157 (2.79)***	0.168 (2.99)***
Local Unemployment Rate	0.017 (6.05)***	0.018 (6.30)***	0.017 (5.89)***	0.003 (1.67)*	0.003 (1.86)*	0.002 (1.45)
<i>Loan-Pool Characteristics Included?</i>						
<i>Sample</i>		<i>Yes</i>			<i>Without Refinancings</i>	
<i>Observations</i>	32,982	All mortgages			27,372	27,372
<i>R-squared</i>	0.17	0.16	0.18	0.11	0.10	0.11

T-statistics in parentheses, based on errors clustered at the bank level.

* significant at 10%; ** significant at 5%; *** significant at 1%

¹The average applicant size reflects the typical size of mortgages in a lender's market. For banks lending in more than a single market (MSA), we construct and equally-weighted average the applicant sizes across markets.

Table IV: Regressions of Acceptance Rates for Non-Jumbo Mortgages Relative to Jumbos on Bank Characteristics

This table reports regressions of the acceptance rate for non-jumbo mortgages minus the acceptance rate for jumbos by bank-year, from 1992 to 2004. The regressions include the following controls for the loan-pool characteristics in each bank-year: the share of loans made to borrowers in MSAs; percent minority applicants in the bank's lending markets; loan-to-income ratio; log of mean applicant income; average median income in bank's lending markets; share of minority applicants; share of female applicants. We allow the coefficient on each of these variables to be different for the two segments of the market - jumbo and non-jumbo. Regressions also include the log of application size, the MSA-level unemployment rate (state for properties not in MSAs); the MSA-level growth in income (state for properties outside MSAs); and the percent of population over 65 for the state-year. All regressions also include year and state fixed effects.

<i>Dependent Variable:</i>	Acceptance Rate for Non-Jumbos - Acceptance Rate for Jumbos					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bank Financial Condition</i>						
Liquid Assets / Assets	-4.012 (4.28)***		-3.607 (3.93)***	-2.366 (2.61)***		-2.142 (2.39)**
Cost of Deposits		72.482 (4.65)***	66.839 (4.35)***		43.377 (2.75)***	40.299 (2.57)**
<i>Other Bank Controls</i>						
Log of Bank Assets	-0.785 (7.60)***	-0.79 (7.71)***	-0.787 (7.67)***	-0.32 (3.93)***	-0.328 (4.04)***	-0.324 (4.00)***
Bank owned by Holding Company	-1.134 (3.76)***	-0.865 (2.84)***	-0.866 (2.84)***	-0.38 (1.25)	-0.214 (0.68)	-0.206 (0.66)
Capital / Assets	4.77 (1.37)	4.769 (1.38)	6.581 (1.86)*	0.432 (0.12)	0.154 (0.04)	1.248 (0.36)
Net Income / Assets	6.686 (0.44)	3.544 (0.23)	6.878 (0.45)	-14.589 (0.91)	-16.293 (1.01)	-14.664 (0.91)
<hr/>						
<i>Loan-Pool Characteristics Included?</i>				Yes		
<i>Market Controls Included?</i>				Yes		
<hr/>						
<i>Sample</i>			<i>Mortgages between 50-250% of jumbo cutoff</i>			
<i>Observations</i>	21,354	<i>All mortgages</i>		<i>without refis</i>		
<i>R-squared</i>	0.10	0.10	0.10	0.03	0.03	0.03

T-statistics in parentheses, based on errors clustered at the bank level.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table V: Regressions of the Share of Non-Jumbo Applications on Bank Characteristics

This table reports regressions of the share of applications that are non-jumbo by bank-year, from 1992 to 2004. The regressions include the following controls for the loan-pool characteristics in each bank-year: share of loans made to borrowers in MSAs; percent minority applicants in the bank's lending markets; loan-to-income ratio; log of applicant income; average median income in bank's lending markets; share of minority applicants; share of female applicants. We allow the coefficient on each of these variables to be different for the two segments of the market - jumbo and non-jumbo. Regressions also include the log of application size in the MSA, the MSA-level unemployment rate (state for properties not in MSAs); the MSA-level growth in income (state for properties outside MSAs); and the percent of population over 65 for the state-year. All regressions also include year and state fixed effects.

<i>Dependent Variable:</i>	Non-Marginal Applications - Away from the Cutoff			Marginal Applications - Near Cutoff		
	Number of applications between 50% & 95% of cutoff / Number of applications between 50-95% plus 105-250% of cutoff			Number of applications between 95% & 100% of cutoff / Number of applications between 95% and 105% of cutoff		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bank Financial Condition</i>						
Liquid Assets / Assets	-0.060 (4.26)***		-0.061 (3.94)***	-0.113 (6.25)***		-0.112 (6.25)***
Cost of Deposits		0.786 (5.89)***	0.671 (5.26)***		0.322 (2.17)***	0.361 (2.01)**
<i>Other Bank Controls</i>						
Log of Bank Assets	0.007 (5.83)***	0.007 (5.84)***	0.007 (5.83)***	0.017 (9.46)***	0.016 (9.45)***	0.017 (9.47)***
Bank owned by Holding Company	-0.007 (2.26)**	-0.007 (2.49)**	-0.007 (2.48)**	0.015 (2.54)**	0.015 (2.57)**	0.016 (2.68)***
Capital / Assets	-0.199 (4.53)***	-0.198 (4.49)***	-0.203 (4.58)***	-0.294 (4.27)***	-0.342 (4.97)***	-0.289 (4.15)***
Net Income / Assets	0.487 (3.13)***	0.498 (3.21)***	0.492 (3.19)***	-0.325 (1.23)	-0.405 (1.51)	-0.32 (1.21)
<i>Loan-Pool Characteristics Included?</i>						
<i>Market Controls Included?</i>						
Observations	34,306	34,306	34,306	11,056	11,056	11,056
R-squared	0.43	0.43	0.43	0.19	0.19	0.19

T-statistics in parentheses, based on errors clustered at the bank level.

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table VI: Regressions Analysis of Volumes & Acceptance Rates for Mortgages
By Size Relative to the Jumbo Cutoff**

This table reports regressions of the acceptance rate for mortgages of different sizes. For each bank-year, there are 4 observations representing the acceptance rate for loans 50-75% of the jumbo cutoff, 75-100% of the cutoff, 100-150% of the cutoff, and from 150 to 250% of the cutoff. The regressions include the following controls for the loan-pool characteristics in each bank-year: share of loans made to borrowers in MSAs; percent minority applicants in the bank's lending markets; loan-to-income ratio; log of applicant income; average median income in bank's lending markets; share of minority applicants; share of female applicants. The coefficients on each variable differ for the four loan-size bins. These regression also include indicators for each loan size bin, as well as the other bank controls from the earlier tables (log of applicant size, log of bank size, BHC indicator, capital/assets and net income/assets). Regressions also include the following controls for demand and demographics: the MSA-level unemployment rate and income growth rate (state-level for properties outside MSAs) and the share of population over 65 in the state-year. Regressions also include year and state fixed effects.

<i>Dependent Variable:</i>	Volume / Assets _{t-1}			Loan Acceptance Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bank Financial Condition</i>						
Liquid Assets / Assets	-0.222 (9.27)***	-0.219 (9.11)***	-0.521 (0.56)		-0.262 (0.29)	
Liquid Assets / Assets * Indicator for loans 75-100% of jumbo cutoff	0.044 (1.51)	0.042 (1.27)	1.298 (1.64)		1.115 (1.42)	
Liquid Assets / Assets * Jumbo indicator	0.148 (7.71)***	0.144 (7.52)***	2.812 (2.71)***		2.383 (2.32)**	
Liquid Assets / Assets * Indicator for loans 150-250% of jumbo cutoff	0.01 (1.34)	0.007 (1.36)	0.61 (0.49)		0.571 (0.46)	
Cost of Deposits		0.802 (1.29)	0.476 (1.36)		45.633 (1.53)	46.049 (1.57)
Cost of Deposits * Indicator for loans 75-100% of jumbo cutoff		-0.191 (1.36)	-0.142 (1.02)		-14.781 (1.54)	-13.803 (1.47)
Cost of Deposits * Jumbo indicator		-0.86 (6.31)***	-0.727 (5.44)***		-74.208 (5.59)***	-71.859 (5.46)***
Cost of Deposits * Indicator for loans 150-250% of jumbo cutoff		0.001 (0.01)	0.002 (0.03)		-9.279 (0.57)	-8.761 (0.54)
<i>Other Bank Characteristics Included?</i>				Yes		
<i>Loan-Pool Characteristics Included?</i>				Yes		
<i>Market Controls Included?</i>				Yes		
<i>Sample</i>	<i>All Mortgages between 50-250% of jumbo cutoff (refis included)</i>					
<i>Observations</i>	131,854	131,854	131,854	106,192	106,192	106,192
<i>R-squared</i>	0.06	0.05	0.06	0.09	0.09	0.09

T-statistics in parentheses, based on errors clustered at the bank level.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table VII: Probit Regressions for Loan Acceptance Rates for Jumbo and Non-Jumbo Mortgages Including only Mortgages Near the Jumbo Cutoff

This table reports probit regressions of acceptance rates for mortgages of different sizes, where the unit of observation is the individual mortgage application. We include only mortgages that are non-jumbo but would be deemed jumbo during the preceding year, and mortgages that are jumbo but will be deemed non-jumbo in the subsequent year. From this pool of loans, we draw up to 1,000 applications for each bank-year. In cases where there are fewer than 1,000 applications, we use all mortgage applications that meet the selection criterion defined above. We report marginal effects rather than probit coefficients. The probit regressions include the following additional controls: the jumbo-loan indicator; the loan-to-income ratio; log of applicant income; average median income in the property market; share of minority applicants; share of female applicants. Regressions also include the following controls for demand and demographics: the MSA-level unemployment rate and income growth rate (state-level for properties outside MSAs) and the share of population over 65 in the state-year. Regressions also include year and state fixed effects

<i>Dependent Variable:</i>	1 if Loan is Approved and 0 Otherwise					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bank Financial Condition</i>						
Liquid Assets / Assets	0.026 (0.96)		0.025 (0.96)	0.004 (0.18)		0.003 (0.14)
Liquid Assets / Assets * Jumbo Indicator	0.056 (3.39)***		0.061 (4.12)***	0.021 (2.48)***		0.018 (2.93)***
Cost of Deposits		-0.039 (0.11)	0.012 (0.04)		-0.264 (0.72)	-0.261 (0.72)
Cost of Deposits * Jumbo Indicator		-1.206 (5.05)***	-1.248 (5.66)***		-1.141 (4.94)***	-1.133 (4.70)***
<i>Other Bank Controls</i>						
Log of Bank Assets	-0.011 (4.86)***	-0.011 (5.21)***	-0.011 (5.13)***	-0.003 (1.78)*	-0.003 (2.17)**	-0.003 (2.15)**
Bank owned by Holding Company	-0.31 (2.10)**	-0.311 (2.13)**	-0.319 (2.20)**	-0.05 (0.63)	-0.058 (0.73)	-0.062 (0.78)
Capital / Assets	-0.015 (0.37)	-0.004 (0.11)	-0.007 (0.19)	-0.031 (0.92)	-0.025 (0.81)	-0.025 (0.80)
Net Income / Assets	0.156 (0.43)	0.103 (0.27)	0.162 (0.46)	0.377 (1.41)	0.386 (1.49)	0.392 (1.52)
<i>Applicant Characteristics Included?</i>			<i>Yes</i>			
<i>Market Controls Included?</i>			<i>Yes</i>			
<i>Sample</i>	<i>Sampling from All Mortgages</i>			<i>Sampling without Refis</i>		
<i>Observations</i>	353,181	353,181	353,181	166,875	166,875	166,875
<i>Pseudo R-squared</i>	0.14	0.14	0.14	0.11	0.11	0.11

T-statistics in parentheses, based on errors clustered at the bank level.

* significant at 10%; ** significant at 5%; *** significant at 1%

Endnotes

¹ Kashyap, Rajan and Stein (2002), Gatev and Strahan (2006), Gatev, Schuermann and Strahan (2005), and Gatev, Schuermann and Strahan (2007) show that bank liquidity production also now stems from the asset side via loan commitments and lines of credit, but that this liquidity risk tends to be offset or diversified by funding through transactions deposits.

² In recent years, the GSEs have opted to hold rather than securitize many of the mortgages that they buy to take advantage of subsidized borrowing rates. Policymakers have become concerned about the resulting expansion of interest rate risk at the GSEs (Greenspan, 2004). As of 2003, for example, Fannie Mae and Freddie Mac held over \$1.5 trillion in mortgages (Frame and White, 2005). Passmore, Sherlund and Burgess (2005) argue that most (but not all) of the benefits of GSE subsidized borrowing benefits their shareholders rather than mortgage borrowers. Vickery (2005) shows that GSE subsidies are concentrated in the fixed-rate mortgage (FRM) segment rather than the adjustable-rate mortgage segment, explaining why FRMs dominate in the U.S. relative to the U.K. While the effects of this government subsidy are important for public policy, they are not the focus here.

³ For evidence that bank size and scope reduces the potency of monetary policy, see Ashcraft (2003), Campello (2002), Jayaratne and Morgan (2000), Kashyap and Stein (2000), and Loutskina (2005).

⁴ Petersen and Rajan (1994) show that small firms benefit by concentrating their business with a single lender, and their results suggest that such borrowers face high costs of switching banks. Thus, many small firms are 'bank dependent'. The geographical scope of loan markets,

particularly for bank dependent firms, tends to be limited geographically because local lenders have better information than competing lenders. Technology has increased the average distance between small-business borrowers and lenders, but physical proximity continues to affect bank lending supply and pricing (Petersen and Rajan, 2002; Degryse and Ongena, 2005). Our results suggest that bank dependent firms' cost of capital depends on the financial condition (cost of deposits and liquidity) of local lenders.

⁵ Bernanke (1983) focused on credit effects of bank failures during the Depression. More recently, Bernanke and Lown (1991) show that credit in regions with many poorly capitalized banks suffered most during the 1991-92 recession. Peek and Rosengren (2000) show that distressed Japanese banks reduced credit supply to borrowers in California (relative to California banks). Ashcraft (2005) shows that local output falls when the FDIC closes even *healthy* banks. Slovin, Sushka and Polonchek (1993) provide evidence that borrowers from Continental Illinois were potentially harmed by that bank's failure. Hubbard, Kuttner and Palia (2002) show that low capital banks price business loans at higher yields than better-capitalized banks. Like our paper, Mian and Khwaja (2005) and Paravisini (2007) focus on how liquidity shifts loan supply. Mian and Khwaja exploit bank runs following Pakistan's unexpected nuclear test in 1998; they show that firms borrowed less from banks experiencing greater runs and more from banks experiencing smaller runs. Paravisini finds that profitable lending expands following an infusion of liquidity by the Argentine government into banks.

⁶ We have also added the ratio of mortgage-backed securities to total assets to our regressions. In these robustness tests, there is no additional effect of mortgage-backed securities, suggesting

that our coefficient represent shifts in bank behavior in response to variation in liquidity. We thank Scott Frame for suggesting this test to us.

⁷ The GSEs will buy most but not all non-jumbo mortgages, but they may not buy any of the jumbo mortgages. We are able to identify all jumbo mortgages in our dataset. For loans below the jumbo-loan cutoff, some do not meet the other criteria used to determine whether a mortgage is ‘conforming’ and thus can be sold to the GSEs. For example, a mortgage must have a loan-to-value ratio below 0.8 or be credit enhanced with personal mortgage insurance, and there are additional income verification and property criteria that we can not observe in our dataset. Thus, some of the non-jumbo loans can not be sold to the GSEs, which will tend to bias our coefficients against finding a difference between the jumbo and non-jumbo segments.

⁸ The extent to which the yield differentials reflects liquidity, rather than differences in credit risk, between non-jumbo mortgages and jumbos remains somewhat controversial. A recent study by Ambrose, LaCour-Little and Sanders (2004) controls carefully for credit risk and concludes that the yield differential is only about 5 basis points between non-jumbo and jumbo mortgages. Nevertheless, there seems to be little doubt that there is an increase in yields for jumbos, and that some of that increase reflects differences in liquidity.

⁹ Here we consider only single-family home purchase mortgage applications across the lending financial institutions in the United States.

¹⁰ The frequency distribution and acceptance rates for mortgages in our full sample (with refis) and our filtered sample look very similar. For example, in both we see a spike in the number of

applications and a jump in the acceptance rate just below the jumbo-loan cutoff. We also see the same fall off in the acceptance rate as the size of the mortgages falls, and as mortgage size increases beyond the cutoff.

¹¹ We have also estimated a more parsimonious approach, in which we control for average bank-specific loan pool characteristics, and obtain results that are very similar to those reported here.

¹² In computing average application size, we include all mortgage applications, including those to other lenders such as savings institutions, mortgage bankers and so on.

¹³ We have also estimated standard errors clustered by state and clustered by year. We find similar levels of statistical significance in each of these alternative approaches to those reported here.

¹⁴ In an earlier draft we report specifications without borrower control variables and find that our main results are not sensitive to the inclusion of these variables.

¹⁵ In Table III, we build origination volumes including all accepted applications, but we only include bank-years with at least one loan application in both the jumbo and non-jumbo segments. There are about 12,000 bank-year observations where all loan applications fell below 75% of the jumbo cut-off. Our identification strategy does not work for these banks, so we drop them from the analysis. In Table IV, we require banks to have at least 3 applications in each market segment in order to be able to estimate an acceptance rate, hence the sample size falls relative to

Table III. If we estimate the volume regression from Table III using the same smaller sample in Table IV, however, we get similar results.

¹⁶ Since we are slicing the data into four bins instead of just two, we report the results with refis to allow us to get precise estimates in each bin. The four bins contain the following number of observations in the loan volume regressions: 50-75% of the cutoff: 53,483 bank-years; 75-100% of the cutoff: 40,012 bank-years; 100-150% of the cutoff: 22,876 bank-years; and 150-250% of the cutoff: 15,483 bank-years. There are fewer in the acceptance rate models because we require a bank to have at least 3 applications in a bin to be included.