

The Option Value of Public Liquidity: Evidence from Regional Collateral Policies*

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Abstract

Unlike nonbanks, banks have an option to borrow liquidity from public entities – chiefly central banks – by pledging loans. The value of this option is hard to quantify because liquidity usage is endogenous and can undervalue the benefit of unused access. We address this challenge by using variation in the pledgeability of similar loans in the same area and period due to disparities between regional Federal Home Loan Banks’ collateral policies. We show that pledgeable loans are 10–25% more likely to be approved. Pledgeability is more valuable when loans cannot be originated-to-distribute (OTD), and reduces bank’s use of OTD. Pledgeability gives banks a competitive advantage over nonbanks, and increases banks’ risk tolerance. These results reveal a novel originate-to-pledge motive for lending that affects credit supply, risk-taking and market structure even outside crises.

Keywords: Liquidity transformation, liquidity regulation, government-sponsored enterprise, credit supply, mortgages, nonbanks
JEL codes: G21, G28, G23, E50

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1. Introduction

Banks' access to public liquidity distinguishes them from nonbanks and underpins their ability to bear illiquidity risk (Farhi and Tirole, 2019).¹ By pledging loans – including those ineligible in private markets – banks can borrow liquidity from central banks or other public entities while retaining loans on balance sheet. This option can be valuable even when not used, by providing insurance against potential illiquidity and signaling asset quality. Reflecting this value, in 2023 US banks had pledged roughly 5.5 trillion loans to public entities, using only a fraction of it.²

Quantifying the option value of access to public liquidity is difficult, however. Liquidity *take-up* is endogenous and likely to undervalue the *option to borrow*. Banks are unlikely to pledge all the assets they *could* pledge. And central bank collateral policies rarely vary outside crises and within countries. Yet, understanding this value is central to ongoing debates about extending access to nonbanks, liquidity regulation, and the role of public liquidity provision in recent crises.³

We address this challenge by focusing on a different public liquidity provider: the US Federal Home Loan Banks (FHLB). FHLBs provide advances to member banks collateralized primarily by mortgage-related loans. The eleven regional FHLBs set distinct collateral eligibility criteria for their member banks. Therefore, otherwise similar mortgage loans originated in the same region and time can differ in their pledgeability, depending on the originator's FHLB affiliation.

¹ Public liquidity, broadly interpreted, includes liquidity from entities that are part of the government (e.g. central banks) or operate with explicit or implicit government backing (e.g. FHLBs).

² By end-2023, banks' borrowing capacity from the Federal Reserve was around \$1.8 trillion (net of haircuts). Mortgage-related collateral posted with FHLBs was \$3.75 trillion. FHLB collateral could also be posted by insurance companies, but they are likely to pledge securities, not loans.

³ See e.g. Basel Committee on Banking Supervision (2023). Acharya et al. (2023) analyse the role of FHLBs in risk-taking ahead of the 2023 banking turmoil.

Since banks must generally affiliate with the FHLB serving their headquarter state, this variation allows us to isolate the causal effect of pledgeability and therefore access to public liquidity.

We do so by using loan application-level Home Mortgage Disclosure Act (HMDA) data, which covers about 90% of mortgage originations in the U.S. HMDA includes rejected and accepted loan applications, allowing us to estimate approval probabilities conditional on loan demand.

Our main results show that applications for pledgeable loans are between 8 and 15 percentage points more likely to be accepted, holding other loan risk and profitability factors fixed. This effect is economically significant and represents a roughly 10% to 25% increase in acceptance relative to its mean of 65%.

Our set of controls and robustness checks help to rule out a range of alternative interpretations of our results. Estimating approval probabilities rules out that results are driven by borrower self-selection based on banks' FHLB affiliation. Our results are robust to including fixed effects for the roughly 1,200 combinations of the 36 loan characteristics that can determine eligibility as FHLB collateral. By interacting these fixed effects with dummies for FHLB districts, we can rule out the possibility that our results are explained by endogenous links between FHLB criteria and local mortgage market conditions. Our results are also robust to including high-dimensional fixed effects for other key loan heterogeneities, e.g. in terms of LTV, LTI, DTI, loan amount, borrower income, credit score models, underwriting software, and so forth.

As a placebo test, we repeat our main regression for a group of nonbanks that are *not* eligible for FHLB membership (mortgage companies). We find no result. This further suggests that our results are unlikely to reflect confounding local factors. Since nonbanks are, however, eligible to sell loans to the GSEs, this also suggests that our results are unlikely to be explained by

GSEs' own loan purchase criteria. We further confirm this idea by showing that our key finding remains when excluding all loans underwritten with GSE software.

Our main result suggests that pledgeability increases the value of the loan to the originator. This is in line with the idea that pledgeability mitigates illiquidity risk associated with making loans and holding them on balance sheet. Another way for banks to manage liquidity risk is to sell loans (e.g. Irani and Meisenzahl, 2017). Since pledging and loan sales or securitisations should be substitute ways of managing liquidity risk, pledgeability should be particularly valuable for illiquid loans or loans that cannot be sold easily. Consistent with this hypothesis, we find that FHLB pledgeability increases the probability of approval more for jumbo loan applications; for such applications, the effect is between 0.5 and 3 times larger. Next, we explore whether pledgeability affects banks' decision to sell loans vs. hold them on balance sheet. We find that pledgeable loans are more likely to be held on bank balance sheet. In summary, these results suggest that originate-to-pledge is a substitute for originate-to-distribute, and collateral management can drive bank lending decisions.

Finally, we test the link between pledgeability and (credit) risk-taking. Pledgeability could increase banks' risk tolerance, since pledgeable loans are valuable beyond their risk-return characteristics. However, pledgeability could also lower risk appetite, since a defaulting loan would shrink both the bank's equity and collateral pool. In line with the first hypothesis, we find that pledgeability is significantly more valuable for high-LTV mortgages. Since we exclude loans eligible for GSE purchases, this heterogeneity cannot be explained by GSE maximum LTV thresholds. These results suggest that pledgeability could tilt the composition of banks' loan portfolios towards higher-risk eligible loans.

Contribution to the literature Our paper provides novel, causal evidence on the impact of access to public liquidity on mortgage credit supply. Our results shed new light on several literature strands.

Our findings add to long-standing research on the “specialness” of banks, by documenting the importance of access to public liquidity as a comparative advantage in bearing liquidity risk associated with combining illiquid assets (loans) with liquid liabilities (deposits). The existing literature focuses on other sources of banks’ comparative advantages, including deposits that are cheap and “sleepy” (Hanson et al., 2015) and fly into banks at times of stress (Gatev and Strahan, 2006), synergies between asset and liability side liquidity demand (Kashyap et al., 2002), and government guarantees (Farhi and Tirole, 2018).

A growing literature focuses on bank and nonbank specialisation in mortgage markets. Nonbanks’ share of mortgage market originations and servicing has grown significantly since the GFC, due to their technological advances in application processing (Fuster et al., 2018), responsiveness to demand spikes (Fuster et al., 2021), and increased bank regulation (Buchak et al., 2018). Nonbanks tend to specialize in mortgages that are easy to securitise, while banks do more on balance sheet lending. The advantage of banks in on balance sheet lending has been attributed, e.g., to bank capitalization. Our results suggest that differential access to government-sponsored liquidity between banks and nonbanks, specifically to FHLB advances, also partly contributes to the specialisation patterns we observe in the mortgage market.

Our results add to research on bank funding models and the role of collateral. In the OTD model, loans are transferred from banks to a GSE or special-purpose vehicle – along with claims on associated cash flows – and this relaxes banks’ liquidity constraints (e.g. Loutskina and Strahan 2009). Instead, the OTP model we document allows to transform but retain loans, preserving the

traditional banking model. Securities collateral supports banks' access to private funding e.g. through repos (Coen et al. (2024)). We highlight the role of loan collateral, pledged to public entities. A better-documented alternative is to pool loans into bonds. Van Bakkum et al. (2018) find that ABS eligibility as ECB collateral stimulates banks' lending. Our results are consistent but apply to the OTP rather than OTD model.

Our results add to a broader literature on asset pledgeability. Pledgeability relaxes borrowing constraints, but this can distort investment towards less “productive” assets easier to finance (e.g. Holmstrom and Tirole 1997). Pledgeability also leads to a convenience premium on assets like treasuries (e.g. Duffee, 1996). We show that loan pledgeability lowers the weight of fundamental risk-return loan characteristics and increases banks' risk tolerance.

Our results also relate to the large literature on central bank liquidity provision. This provision can insure against systemic liquidity shortages,⁴ but may also incentivize moral hazard or risk-shifting, especially if insurance is mispriced (Acharya et al., 2025; Drechsler et al., 2016). While many studies focus on actual *borrowing from* public entities, we identify the role of *access to* public liquidity – also outside crises. A nascent literature explores banks' “pre”-pledging of collateral to the Fed or FHLB system. Gorton et al. (2025) show that liquidity risk, opportunity costs, and stigma affect pre-positioning decisions. Carlson and Styczynski (2025) show that pre-pledging increases the likelihood of Discount Window usage following a liquidity shock. Our paper focuses at an earlier point on the bank's loan production chain to examine whether eligibility for pledging versus actual pledging affects lending decisions.

⁴ This goes back to Bagehot (1873). Unlike central banks, interbank markets only insure idiosyncratic risk (Allen and Gale, 2000). Central bank liquidity provision can stimulate market functioning and bank lending during a crisis (McAndrews et al., 2017; Berger et al. (2017), and others).

Finally, our work is related to the literature on FHLBs. FHLB advances serve as an important alternative to borrowing from the central bank during stress periods like the Global Financial Crisis (Ashcraft et al., 2011) and the regional bank stress of 2023 (Cipriani et al., 2024; Glancy et al., 2024). During the 2010s, advances have grown significantly in response to money market fund reforms and bank liquidity regulation (Gissler and Narajabad, 2017; Sundaresan and Xiao, 2018). We show that pledging to FHLBs has grown even more than advances, and document the effect of access to FHLB liquidity – irrespective of used or not.

Outline The next section provides background on the FHLB system. Section 3 discusses FHLB collateral eligibility rules and how we construct our measure of pledgeability. Section 4 discusses the identification strategy. Section 5 presents the results. Section 6 concludes.

2. Background: FHLB collateral policies

To identify the impact of pledgeability as FHLB collateral on mortgage supply, we exploit differences in collateral policies across regional FHLBs. This section provides background on FHLBs and their collateral policies.

The FHLB system was created in 1932 “to support mortgage lending and related community investment”. The system comprises eleven regional FHLBs covering separate “districts” covering a group of contiguous US states. Each regional FHLB is a separate corporation. Despite their public purpose, FHLBs are capitalised privately, and receive no direct government funds. However, FHLB debt is perceived by investors to be implicitly guaranteed by the U.S. government (Ashcraft et al., 2011).

FHLBs provide loans (“advances”) to their members, with maturities ranging from overnight to 30 years, although most advances have maturities of less than one year (~50%) or

between one and five years (40%) (Gissler and Narajabad, 2017). Advances are structured to facilitate members' asset-liability management and providing short-term funding. FHLB loanable funds are raised by a central agency: the Office of Finance.

Advances must be collateralised. The FHA defines acceptable mortgage categories. FHLBs can accept mortgages, mortgage-related assets (e.g. home equity loans and mortgage backed securities), and U.S. obligations (e.g. Treasury securities). Within acceptable collateral categories however, each FHLB can set their own eligibility criteria.

Five of eleven FHLBs provide detailed public documentation on their collateral policy: Atlanta, Boston, Dallas Des Moines, Topeka. Together, these FHLBs cover 35 US states. Figure 2 presents a map of the FHLB districts. The Des Moines district is particularly large, with eleven states across the US Northwest and Midwest. This district expanded in 2015 when the Des Moines FHLB took over the Seattle FHLB, which had experienced financial difficulties for several years.

For these FHLBs, we focus on three main loan types that are covered in HMDA and for which collateral policies are detailed and comparable: first mortgages (i.e. first-lien fully disbursed mortgage loans), home equity loans (generally second-lien loans), and home equity lines of credit. Together these collateral classes represent around 53% of total collateral posted with FHLBs by year-end 2023.⁵

3. Measuring FHLB pledgeability

To be pledgeable as collateral, a loan must meet all eligibility criteria set by the FHLB that the bank is a member of. To capture pledgeability, our key variable is $Eligible_{i,p}$, where i denotes a

⁵ Other classes not included in our analysis include mainly commercial real estate (CRE) loans (ca. 20% of total pledged collateral), multifamily mortgages (10%) and US agency MBS and CMOs (8.2%). Treasury and agency securities ex-MBS represent a small fraction (1.6%).

bank and p denotes a mortgage product category – defined by a unique combination of loan characteristics. Importantly, eligibility can vary within the same product category, depending on a bank’s FHLB affiliation. We now explain how we measure these dimensions in more detail.

Loan eligibility criteria To measure loan eligibility, we use FHLB policy documents, which we download from their websites. These documents list characteristics that mortgages must meet for eligibility as collateral. For each FHLB and collateral type, we manually identify all eligibility criteria that can be mapped into HMDA variables. For instance, criteria about mortgage loan-to-value (LTV) ratios can be used because loan LTVs are reported in HMDA. Criteria about e.g. the borrower credit history or current arrear status cannot be used since this is not reported in HMDA. (If anything, these omitted criteria would introduce noise in our measure of eligibility, making it less likely that we identify significant impacts).

Across the five FHLBs, we identify a total of 36 individual criteria. Some of these criteria are used only by one FHLB, whereas others are used by several or all FHLBs. We refer to the combined set of 36 criteria as the “FHLB grid”.

Criteria in the grid are listed in the second part of Table 1. Among others, these criteria concern the mortgage type (conventional, FHA-guaranteed, etc.), purpose (house purchase, improvement, refinancing, or cash refinancing), occupancy (primary residence or not), lien (first or second), or special contract features (reverse mortgage, negative mortgage, interest-only mortgage, balloon payment, and other-non-amortizing features). Other criteria include whether critical threshold values are exceeded for the mortgage term, LTV (or combined LTV), interest spread, or prepayment penalty period.

We assign each application to a slot in the FHLB grid based on its loading on the combined set of 36 criteria. In our dataset, we observe approximately 1,200 unique combinations of the

criteria across all applications. For each category, we record whether the product is eligible with a given FHLB. Within the same category, eligibility can differ across FHLBs. For instance, non-owner occupied first mortgages with $LTV < 90$ are eligible as collateral in the FHLB Topeka district, but not in the Boston district.

FHLB membership To assign banks to FHLB districts, our baseline approach uses the bank's observed FHLB membership, as recorded in the so-called HMDA lender file provided by the Federal Reserve Bank of Philadelphia. Banks' FHLB district is largely exogenous to banks, since regulation says that banks must be members of the FHLB whose district includes the bank's headquarters. For robustness, we alternatively assign membership based on the bank's headquarter location rather than reported membership. This makes a difference for the (very) small minority of banks that are either not FHLB members, or members of the FHLB outside their headquarter location.⁶

4. Identification strategy

Our baseline empirical model is:

$$I(Accept)_{l,i,p,d} = \beta \cdot Eligible_{i,p} + Controls + \epsilon_{l,i,p,d} \quad (1)$$

The dependent variable $I(Accept)_{l,i,p,d}$ is a dummy variable that is one if loan application l with product characteristics p is accepted by bank i (a member of FHLB district d), and 0 otherwise.⁷

⁶ This could be for historical reasons, e.g., if the bank relocated across districts.

⁷ Accepted loans include those that are originated and those that are accepted by the bank but not originated.

Our main interest is in parameter β . The baseline hypothesis is that pledgeability increases the value of the loan to the originator (other characteristics being equal). This can be, e.g., because of the option value of monetizing the loan for liquidity management or additional funding, or the signalling value of loan pledging.⁸ If pledgeability increases the loan's value, the originator should be more inclined to accept an application, and β should be positive.

We now discuss the choice of controls and fixed effects and how they address key identification challenges.

a. Fixed effects and controls

Product-grid fixed effects A key challenge is that *Eligible* could correlate with risk or profitability factors (or combinations thereof) that could affect acceptance rates for reasons other than FHLB eligibility. To see this, note that eligibility varies across loan products depending on whether they meet a combination of criteria set by FHLBs. By construction, *Eligible* will thus be correlated with the individual component criteria. This could be addressed by including separate fixed effects for each criterion. However, *Eligible* will also correlate with alternative combinations of criteria that are not relevant for pledgeability but contain subsets of criteria. In turn, these criteria and alternative combinations could capture risk or profitability factors that could affect acceptance rates irrespective of FHLB pledgeability. Therefore, the parameter estimate for beta could reflect the role of these confounding risk or profitability factors rather than FHLB pledgeability.

To address this challenge, a key part of our approach is to include product grid fixed effects. Product grid fixed effects capture each of the roughly 1,200 unique combinations of the 36 individual criteria included in the “FHLB grid” (see Table 1).

⁸ If the loan is pledged, the bank effectively receives from the FHLB a certificate of its collateral value, and the bank can use it as an external signal of the asset's quality or of the bank's liquidity.

By including FHLB grid fixed effects, we discard variation across different combinations, and instead focus on variation within groups of products that are exactly similar in every possible combination of criteria – not only those relevant to FHLB criteria. Crucially, these fixed effects still preserve variation in pledgeability within each unique combination, since pledgeability criteria can differ across the different regional FHLBs.

Borrower fixed effects and controls Within each unique combination of criteria, loans can still differ in residual dimensions that are not part of the FHLB grid.

The FHLB grid includes the vast majority of loan and borrower characteristics reported in HMDA. However several characteristics not part of the grid could still be plausibly relevant factors. For instance, FHLBs criteria cannot include the borrower race or gender. In addition, for continuous loan characteristics (e.g. LTVs, DTIs, borrower income, loan amount and terms), the FHLB grid only includes a limited number of critical threshold values. For instance, the grid includes whether the loan LTV exceeds 90%, 100%, but not whether it's e.g. above 80%.

In itself, that residual variation does not need threaten identification. Identification rests not only on variation in terms of loan characteristics, but on the *combination of loan and bank* characteristics (in terms of FHLB affiliation). To bias our results, any residual variation would thus need to be relevant to lending decisions *and* to vary across banks in a way that correlates to their FHLB affiliation. The fact that affiliation is largely pinned down by banks' headquarter location helps narrow down the potential for bias.

To further mitigate that risk, we include additional loan controls and fixed effects to capture key dimensions of heterogeneity considered by existing literature.

First, we include fixed effects for bins of LTV, DTI, borrower income, and loan amount, values. For each variable, loans are split into around ten bins, with threshold values following

existing literature. Bins for LTV (and DTI) are designed to capture GSE mortgage pricing matrices – which we discuss in more details in section 4. Controlling for bins rather than continuous values discards information about within-bin variation. However, controlling for continuous variables (or squared variables) would amount to imposing a specific (linear) relationship that might be unrealistic. For instance, differences between 10 and 20% LTVs should not be important, whereas differences between 80 and 100% might be crucial. That said we check that our results are robust to controlling for these variables using continuous levels rather than bins.

Second, we include controls for the following characteristics not part of the FHLB grid: applicant race and ethnicity dummies (non-Hispanic white, black, Asian, Hispanic white, other, missing, or joint), male applicant dummy, co-applicant dummy, credit scoring model fixed effect, underwriting system fixed effects, and manufactured home dummy.

Geography and bank fixed effects Following the bulk of the literature, we also include county fixed effects as a further line of defense against demand-side confounding factors. Our results are robust to using census tract fixed effects instead. When using confidential HMDA data for robustness, we can include county-by-month fixed effects, to absorb differences in loan demand within a county and month. Finally, we add bank fixed effects. This absorbs heterogeneities across banks, including but not limited to their FHLB affiliation.

b. Discussion: identification challenges

Loan demand One concern is that *Eligible* could correlate with confounding drivers of loan demand. For instance, depending on the characteristics of the loan or borrower, loan applicants could choose to direct applications to banks for which the loan would be eligible as FHLB collateral. Our key line of defence against this concern is our dependent variable. In effect, $I(\text{Accept})_{l,i,p,d}$ represents the bank’s choice to originate a loan *conditional on the demand*

(application) for this loan. Additional lines of defence come from fixed effects and controls for various borrower product and characteristics, that could capture confounding heterogeneities in loan demand.

Endogenous bank-FHLB matching Another concern is that banks choose to affiliate with a FHLB based on its collateral policies. For instance, banks with expertise in a given product type could prefer membership with a FHLB that accepts this product as collateral. This could bias our results if this greater expertise affects mortgage acceptance rates.

There are strong regulatory limits to this concern. Since 2016, the FHLB Act states that banks must be members of the FHLB where their "home office" is located (*December 2016 FHA Final Rule*).⁹ In line with this rule, 99.9% of FHLB member banks in our (2024) sample are affiliated with the FHLB whose district includes the bank's headquarter state. Therefore, regional FHLB affiliation appears to be pinned down by headquarter location, rather than a strategic choice of the bank. In robustness checks below, we find similar results when assigning each bank to their local FHLB rather than using their observed membership. This rules out that endogenous affiliation plays any role for our result.

A related concern is that the choice to be a member of the FHLB *system* is endogenous. In principle, it is up to banks to decide whether to be FHLB members. In practice however, there is not much variation across banks. In our (2024) sample, 97% of banks are FHLB members. In robustness checks below, we find similar results when excluding all non-members from the sample. Therefore, endogenous FHLB membership cannot explain our result.

⁹ Beforehand, the rule only referred to the bank's "principal place of business".

Endogenous collateral policies A third challenge is that FHLB collateral policies partly reflect conditions in their district. For instance, one FHLB could choose to accept subprime mortgages as collateral if it is concerned about the supply of such mortgages in its district. FHLB's concern could be due to characteristics of subprime applications that we cannot control for, e.g. borrowers' liquid wealth or credit histories. In turn, these characteristics could bias our result if they affect acceptance rates.

To address this concern, in our most stringent specification we interact product-grid fixed effects with district dummies, based on the location of the loan. These fixed effects discard variation within products but originated in different districts. This still leaves variation in eligibility within a given district as long as there are banks that operate in multiple districts. In that case, even for the same district and product category, there can be differences in FHLB eligibility. For instance, consider a subprime mortgage originated within the Boston FHLB district. These mortgages are eligible as FHLB Boston collateral, but not as FHLB Topeka collateral. If some FHLB Topeka member banks operate in the Boston district, we can compare their originating behaviour to that of FHLB Boston members.

A related concern is that FHLB collateral policies are driven by the preferences or expertise of their member banks. For instance, FHLB Boston might accept subprime mortgages as collateral because their member banks have expertise in these loans, whether for borrowers in the Boston district or elsewhere.

To address this concern, our most stringent specification also interacts product-grid fixed effects with district dummies based on the location of banks (not loans). These fixed effects preserve variation in pledgeability because within some locations, a small minority of banks are either not FHLB members, or affiliated to a FHLB whose district does not include the bank's

headquarter. For instance, consider a subprime mortgage originated by banks headquartered within the Boston FHLB district. Within these banks, these mortgages are eligible for FHLB Boston members, but not for members of other FHLBs, or non-members.

GSE eligibility A final concern is that criteria for FHLB eligibility can partly overlap with criteria for sales to GSEs. If these criteria affect banks' acceptance rates, our results could reflect the role of GSE eligibility, rather than FHLB eligibility.¹⁰

Unlike FHLB pledgeability, GSE eligibility depends on loan characteristics but not on the banks' FHLB membership. Since our regressions include product fixed effects, in itself the variation in *Eligible* coming from product characteristics is not sufficient our results. Instead our results must be driven by the combination of product-level and bank-level variation in FHLB membership status and district.

Another key difference is that GSEs buy loans from any originator type (banks or nonbank), whereas types of nonbanks (e.g. mortgage companies) cannot be FHLB members. Below, we replicate our main analysis for a group of nonbanks that could sell loans to GSEs but are ineligible as FHLB members. We find no effect. This is further indication that GSE eligibility cannot drive our results.

In section 5.3, we provide further evidence that GSE eligibility cannot explain our main results by expanding the set of fixed effects to include more detailed GSE criteria.

5. Empirical Analysis

¹⁰ Eligibility for sale to the FHA is less of a concern because almost all FHA-eligible loans (i.e. loans guaranteed by the FHA) are sold to Ginnie Mac. In our baseline regressions, sold loans are excluded from the sample. We return to FHA eligibility when analysing the link between FHLB pledgeability and loan sales in section x.

5.1 Data

Our empirical analysis combines hand-collected data on FHLBs' collateral eligibility rules with HMDA data on mortgage applications. FHLB collateral eligibility rules are gathered from the websites of individual FHLBs. Five out of eleven FHLBs publicly disclose their collateral eligibility rules: Atlanta, Boston, Dallas, Des Moines, and Topeka. Figure 2 presents a map of the FHLB districts. As shown in the figure, the combined geographic area covered by five FHLBs in our sample includes 35 states. FHLB websites only contain current versions of FHLB collateral policy documents. By using internet archive websites, we retrieve historical versions. Collateral eligibility criteria do not appear to have changed since at least 2020.

Our initial sample consists of mortgage applications recorded in the 2023 HMDA data. HMDA data covers about 90% of the U.S. mortgage market (Gerardi et al., 2025). Using the Avery file, we limit the sample to applications received by banks (depositories regulated by FDIC, OCC, Fed, or CFPB) headquartered in the 35 states that belong to FHLBs that publicly disclose their collateral policies.¹¹ We drop mortgage types with insufficient information to determine pledgeability (sold mortgages, cash-out refinancings, multi-unit loans, and mortgages for business purposes).¹² Put differently, we focus on coding FHLB eligibility (a dummy) for three types of loans: first mortgages, home equity loans, and home equity lines of credit. This process was described in full detail in Section 3.

For each mortgage application, we observe whether the application was accepted or denied by the bank and whether a loan was ultimately originated. In addition, HMDA records whether an originated loan was sold to a third party by the end of the calendar year. The HMDA data also

¹¹ A placebo test uses applications received by nonbanks.

¹² A later test examines sold loans.

include information about the applicant, property, and loan, for example, loan amount, property location, loan purpose, and borrower income and demographics, and more. The confidential version of the data differs from the public version in two important ways. The first is that it records the exact date of the application, while the public version only provides the year. The second is that, since 2018, it includes additional fields not provided in the public data like borrower credit score, DTI ratio, and combined LTV.

Table 1 presents summary statistics for our final sample of mortgage applications, using the public version of the HMDA data. The mean application acceptance rate is roughly 65% and about 85% of applications would be eligible collateral at the lender's FHLB if the loan were originated. The table also reports summary statistics on other borrower, property, and loan characteristics that we use as controls.

5.2 Pledgeability and mortgage credit supply

Table 2 presents the results from estimating equation (1) on public HMDA data for the year 2023. The baseline specification, in column (1), includes only bank fixed effects, and standard errors are clustered by bank and county. The coefficient on *Eligible* is statistically significant at the 1% level and indicates that applications for mortgages that would be eligible for pledging at the lender's FHLB are 18.5 percentage points more likely to be accepted. This effect is economically significant compared to a mean acceptance rate of 65% implying that pledgeability increases mortgage acceptance by nearly 30%.

In subsequent columns of the table, we gradually include additional controls and fixed effects to address the threats to identification discussed in the prior section. Column (2) adds borrower controls linearly, while Column (3) replaces linear controls with bins, as described in the prior section. Column (4) adds fixed effects for the county where the property is located. Column

(5) adds underwriting fixed effects for the type of automated underwriting system and credit score that were used. Column (6) adds product fixed effects for individual criteria in the FHLB grid. Column (7) replaces these product fixed effects with grid fixed effects for each possible combination of the individual criteria, interacted with FHLB district. As Table 1 shows, the effect of FHLB pledgeability on mortgage acceptance is robust across specifications, suggesting that pledgeability boosts acceptance by 0.09 to 0.193 percentage points, or approximately 14% to 30%.

5.3 Robustness

Additional variables from confidential HMDA data In Table 3, we repeat the analysis in Table 2 using confidential HMDA data. The confidential version of the data includes additional fields not available in the public version. First, we observe not only the year of the application but the precise date. We therefore replace county fixed effects with county-by-month fixed effects to better control for loan demand and any other factors that vary by time and property location that might affect acceptance rates. Second, the confidential version includes additional borrower and loan characteristics (since 2018). These are: credit score, debt-to-income ratio, and combined loan-to-value ratio.¹³ As shown in Table 1, several of these characteristics are used to determine whether mortgages are FHLB-eligible collateral (e.g. subprime status, which is based on credit score, etc.).

The results reported in Table 3 show that our key coefficient remains positive and statistically significant, suggesting that FHLB eligibility increases mortgage acceptance even after this refinement to the controls and fixed effects. In our most saturated specification, in Column (7), the magnitude of the effect is very similar to that obtained with the public data, around 0.14.

¹³ The public version of the HMDA data reports binned DTI only.

In less saturated specifications, the inclusion of controls from the confidential data produces a somewhat smaller coefficient, up to about half as large as those obtained in Table 2.

Effect across banks We return to using public HMDA data and estimate our main coefficient *Eligible* separately for three groups of banks split up by size: large (total assets above \$250bn) medium (between \$50bn and \$250bn) and small (below \$50bn). Among other factors, the threshold values capture differences in liquidity regulation. In particular, the Liquidity Coverage Ratio (LCR) applies fully only to large banks. A milder form applies to medium-sized banks, and small banks are fully exempt (Acharya et al., 2023).

The LCR is relevant to our study because banks are known to use FHLB advances to boost their LCR (Sundaresan and Xiao, 2019). The LCR is the ratio of bank's High Quality Liquid Assets (HQLA) (e.g. reserves and government securities) to expected outflows during a 30-days stress period. Banks must keep this ratio above one – i.e. HQLA must fully cover expected outflows. Borrowing from FHLBs increase banks' reserves, boosting their HQLA one-for-one. In contrast, expected outflows increase by less, since FHLB advances have a relatively low assumed outflow rate. Therefore, the LCR increases.

The results reported in column 1 of Table 4 suggest that pledgeability boosts acceptance rates for all three bank categories. The coefficient for small banks not subject to the LCR is larger than that of large banks. While the difference is not statistically significant, this result suggest that LCR-driven collateral transformation is not the only reason why FHLB pledgeability is valuable to banks. This points to other potential reasons, such as the option value of monetizing loans for liquidity management or additional loanable funds, or the signaling value of pledging.

Endogenous FHLB membership Only a small minority (3%) of banks in our sample choose not to be members of the FHLB system. In principle however, our results could still be biased by self-selection by banks into FHLB membership depending on unobserved factors that might also affect mortgage acceptance rates. To address this concern, in column 2 of Table 4, we exclude all non-FHLB member banks from the sample. Results are unchanged.

Placebo test In column 3 of Table 4, we run a placebo experiment. Instead of the baseline sample of banks, we run the main regression using a sample of nonbanks that are not eligible for FHLB membership. Specifically, we use non-insurance, non-depository institutions, which mainly include mortgage companies. Since these firms don't have an FHLB membership, we measure *Eligible* by using the lender location. Effectively, this assigns collateral eligibility using the criteria for the FHLB in which the nonbank's headquarters are located. The estimate for *Eligible* is indistinguishable from zero. This suggests that *Eligible* does not capture confounding loan risk or profitability factors that might drive mortgage acceptance irrespective of FHLB eligibility.

GSE sales eligibility Even if they partly overlap with FHLB criteria, GSE sales criteria are unlikely to explain our results. Unlike FHLB criteria, GSE criteria do not vary with the bank's headquarter location. We also found no result for nonbanks, which can sell loans to GSEs just as banks but cannot be FHLB members. Furthermore, a majority of headline GSE criteria are included in the FHLB criteria grid. In particular, to be GSE eligible, mortgages must be conventional (not guaranteed by the FHA or other agencies, fully disbursed (not revolving), and not a reverse mortgage. Since we include product grid fixed effects, these criteria cannot explain our results – individually or in combination.

One GSE criterion not part of the FHLB grid is the loan's jumbo status. The jumbo limit is the (property location specific) loan amount value above which loans are ineligible for GSE sales. In column 1 of Table 5, we add fixed effect for the loan's jumbo status. In column 2, we interact jumbo status with FHLB grid fixed effects. This controls for the possibility that the jumbo status affects acceptance rates in conjunction with other GSE criteria part of the FHLB grid. Results are unchanged in both cases.

In addition to headline criteria, GSEs set maximum LTV limits. LTV thresholds for GSE eligibility are fully spanned by our LTV bin fixed effects. In themselves, these thresholds therefore cannot explain our results. However, GSE thresholds vary with the loan's occupancy (owner-occupied or other), purpose (cash-out refinancing or not), and interest rate type (adjustable or fixed rate). Therefore, LTV limits could affect acceptance rates in conjunction with these characteristics. In column 3 we therefore interact LTV bin fixed effects with the FHLB grid (which includes dummies for the loan occupancy and purpose) and the jumbo dummy. Results are unchanged.¹⁴

In column 4 we estimate our main coefficient separately for loans underwritten by GSE proprietary automated underwriting system or not. Using GSE systems is required for loans to be eligible for sale to GSEs. The results suggest that pledgeability boosts acceptance rates for both GSE-underwritten loans and other loans. This provides further indication that our main result cannot be explained by GSE sales criteria.

5.4 Originate-to-pledge vs. Originate-to-distribute

Our main result suggests that pledgeability increases the value of the loan to the originator. This is in line with the idea that pledgeability mitigates illiquidity risk associated with making

¹⁴ HMDA does not report the interest rate type (adjustable or fixed).

loans and holding them on balance sheet. Another way for banks to manage liquidity risk is to sell loans (e.g. Irani and Meisenzahl, 2017). Since pledging and selling or securitising should be substitute ways of managing liquidity risk, pledgeability should be particularly valuable for illiquid loans or loans that cannot be sold easily.

Following the existing literature (Loutskina and Strahan, 2009), we consider jumbo loans relatively less liquid than non-jumbo loans. This follows from the fact that GSEs like Fannie and Freddie by regulation only buy mortgages below the jumbo cutoff. We then repeat our main specification, adding an interaction between FHLB eligibility and jumbo loan status. Specifically, we run the following regression:

$$I(Accept)_{l,p,i,d} = \beta \cdot Eligible_{p,i} + \gamma \cdot Eligible_{p,i} \times Jumbo_l + \lambda \cdot Jumbo_l + Controls + \epsilon_{l,p,i,d} \quad (2)$$

If FHLB eligibility has a stronger effect on approval for jumbo loans, the coefficient on $Eligible_{p,i} \times Jumbo_l$ should be positive and statistically significant.

Table 6 presents the results, which confirm our hypothesis. The coefficient on the key interaction term is positive and statistically significant nearly all specifications, notably in Column (7) which has the most stringent controls and fixed effects. The magnitude of the coefficient suggests that the effect of pledgeability is between 0.5 and 3 times larger for jumbo loans than non-jumbo loans.

Next, we explore whether pledgeability affects banks' decision to sell loans versus retain them on balance sheet. To do so, we shift our focus from loan applications to originated loans.¹⁵

¹⁵ This sample differs from the one used in our baseline analysis of approval rates in two ways. First, approved loans include those that were approved but not originated. Second, in the earlier analysis, we dropped originated loans that were sold.

Each originated loan is classified as retained or sold, based on information available in HMDA.¹⁶

We run the following specification:

$$I(Sold)_{l,p,i,d} = \beta \cdot Eligible_{p,i} + Controls + \epsilon_{l,p,i,d} \quad (3)$$

Table 7 presents the results. The coefficient on *Eligible* is negative and statistically significant in all specifications. The point estimate in Column (7), the specification with the most saturated controls and fixed effects, suggests that originated loans are 86% less likely to be sold when they are pledgeable. This compares to a mean sold rate of around 36%.

In summary, pledgeability boosts approval more for illiquid loan applications and originated loans are less likely to be sold when they are pledgeable. Taken together, these results suggest that originate-to-pledge is a substitute for originate-to-distribute, and collateral management can drive bank lending decisions.

5.5 Implications for market structure

The option to pledge could allow banks to originate loans at a lower interest rate (for a given risk). Banks could thus have a comparative advantage vis-a-vis other potential originators without the option to pledge, including most nonbanks. While insurance companies can be FHLB members, this is not the case for other nonbanks that are important for mortgage lending – chiefly mortgage companies. However nonbanks might have other competitive advantages vis-à-vis banks, including lighter capital requirements (Buchak et al., 2018) and advanced origination

¹⁶ HMDA tracks whether a loan was sold by the end of the year in which it was originated. Since the process of securitisation takes several months on average, this likely leads to under-detection of loan sales for loans originated later in the year. In robustness checks underway, we address this issue using the approach of Favara and Giannetti (2017) which is to drop loans originated in the last quarter of the year. This can only be done on the confidential data which has the precise application date.

technology (Fuster et al., 2019). Therefore, the effect of OTP on competitive dynamics between banks and nonbanks is an empirical question.

To confront these ideas, we pool HMDA data from 2019 (the first year when more detailed HMDA data became available) to 2024 for both banks and nonbanks (mortgage companies). We collapse the data by bank vs. nonbanks, originator FHLB district location, and product type (i.e. unique combinations of FHLB grid characteristics). We then estimate:

$$\%(Banks)_{p,d,t} = \beta \cdot Eligible_{p,d} + Controls + \epsilon_{p,d,t} \quad (4)$$

The dependent variable is the share of all loans in a product category p , district d , and year t that are originated by banks rather than nonbanks. If the option to pledge gives banks a comparative advantage vs. nonbanks, the bank market share should be higher for loans in district-product pairs that are pledgeable to FHLBs.

Results are reported in Table 8. In column 1, controls include fixed effects for the district, product category, and year. In line with our prior, pledgeability is associated with larger bank market shares. Inevitably, given the large number of product characteristics, the number of loans per product-district-year pairs is highly heterogenous. To focus on economically meaningful market segments, from column 2 we only include pairs with at least 100 loans. In column 3, we additionally control for the mean value of all loan controls not included in the FHLB grid (race, income, LTV, etc.) in each pair. In column 4 we use district-year and product-year fixed effects to control more finely for heterogeneities in loan demand. Finally in column 5 we only use pairs with at least 1,000 loans. Across columns, the sample shrinks but the estimate remains highly significant and increases in economic magnitude. Specifically, the estimate suggests that pledgeability increases banks' market shares by 3 (column 1) to 14 percentage points (column 5), compared to an 89% average bank market share.

5.6 Pledgeability and risk-taking

Our main result suggests that bank lending decisions can partly reflect collateral production considerations. A corollary is that collateral considerations could affect the weight that banks put on other, more fundamental (risk-return) considerations. The direction of this effect is ambiguous. On the one hand, if a loan can serve as collateral, the bank might accept a higher risk loan for a given return. On the other hand, if a loan can serve as collateral, then if the loan defaults the bank loses not only equity but also collateral capacity.¹⁷ Therefore, pledgeability could weaken or amplify the importance of credit risk.

To confront these ideas, we estimate how pledgeability affects the link between loan credit risk and application acceptance. To do so, we interact the main coefficient *Eligible* with an indicator for each loan LTV bin.

Results are displayed in Figure 3. Each dot represents the estimate for a given bin, along with 95% confidence intervals. The results suggest that pledgeability increases acceptance rates for all 19 LTV bins except one. However there is clear variation in economic magnitudes. The effect of pledgeability is relatively flat until LTV approaches 80%; it then increases strongly and stays high for higher LTVs.

To see this variation more clearly, Figure 4 estimates the same regression without the dummy for the 10% LTV bin. Therefore, remaining parameter estimates capture the differential effect of pledgeability relative to the 10% LTV bin. The results suggest until LTV is around 90, pledgeability is relatively stable. Most LTV bins above 90 are significantly higher than the reference category. Magnitudes are substantial. For a 95-LTV mortgage, pledgeability increase acceptance rates by around 25 percentage points, versus around 15 points for an 80-LTV loan. Our

¹⁷ FHLBs generally require loans not to be in arrears or non-performing to be eligible as collateral.

results imply that pledgeability can affect the composition of bank lending in two ways: towards eligible mortgages, and towards higher credit risk mortgages. Given GSEs only buy mortgages below specific LTV thresholds (section 5.3), could these results be due to eligibility for sale to GSEs rather than pledgeability to FHLBs? To find out, we re-run the same regression excluding all loans underwritten with GSE software, which would therefore not be eligible for GSE sale (subject to some exceptions). As Figure 5 shows, estimates are generally larger but variation across LTV bands is almost indistinguishable from those in Figure 3. Therefore, eligibility for sales to GSEs is unlikely to explain our results.

6. Conclusion

U.S. banks pledge large amounts of collateral to secure access to contingent liquidity from the Federal Reserve and Federal Home Loan Bank (FHLB) System. Yet little is known about how access to government liquidity affects lending behaviour, lending standards, and market structure in the mortgage market. Using hand-collected data on collateral eligibility rules for FHLBs, we show that pledgeability increases loan acceptance rates by 10% to 25%. The option to pledge appears to be more valuable when a loan cannot be sold to the GSEs, and pledgeability makes it more likely that a bank retains the loan on balance sheet. These findings suggest that bank lending can be motivated by collateral production.

While the effect of pledgeability on bank risk-taking is a priori ambiguous, our results suggest that pledgeability tilts the composition of banks' loan portfolios towards higher-risk eligible loans. In addition, our paper highlights some broader implications of the FHLB System for the structure of the mortgage market and may inform current debates around granting nonbanks access government liquidity.

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Figure 1. Banks' FHLB pledging and advances

This figure plots data on FHLB pledging and advances as reported in annual bank filings between 2007 and 2023. The gray line plots total borrowing capacity scaled by loans, averaged across reporting banks. This is based on the lendable value of collateral pledged to FHLBs. The blue line plots average FHLB advances (scaled by loans). The orange line plots dry powder, or available borrowing capacity (scaled by loans), which is defined as total capacity minus advances. Data for borrowing capacity are hand-collected from bank holding companies' annual 10-k reports available from the SEC or bank websites. Data for advances are from end-year bank-level Call Reports, aggregated by bank holding company.

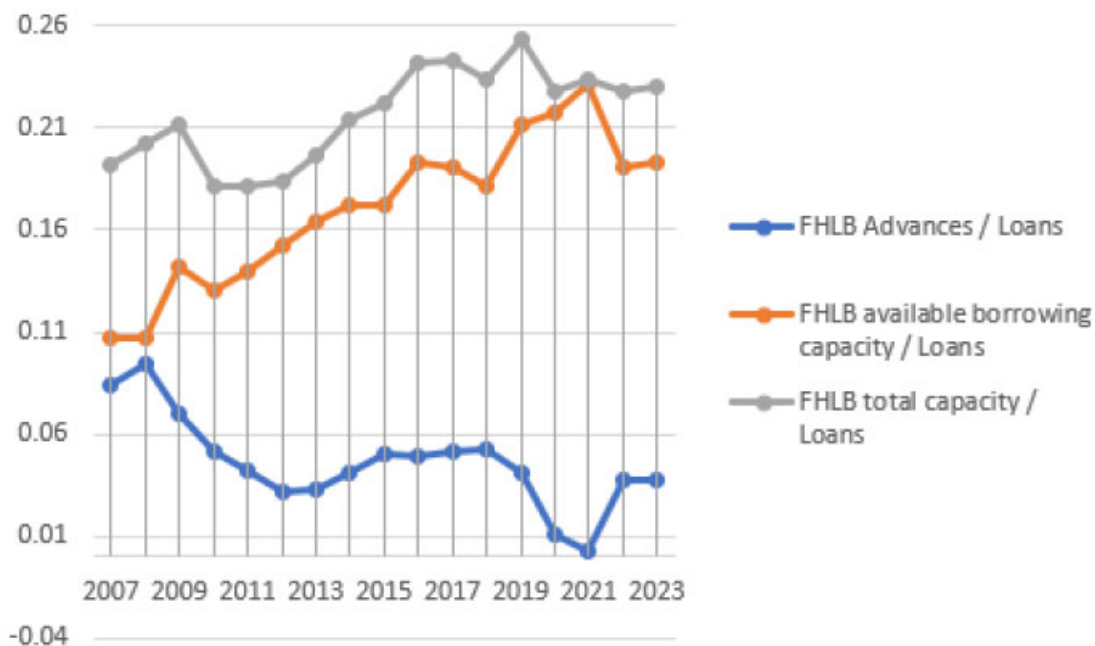


Figure 2. The FHLB System's districts

This map shows the eleven districts of the Federal Home Loan Bank System. Our analysis uses data from five FHLBs that provide detailed public documentation on their collateral policy: Atlanta, Boston, Dallas, Des Moines, and Topeka. This region covers 35 U.S. states. In 2015, the Federal Home Loan Bank of Seattle was merged into Des Moines.

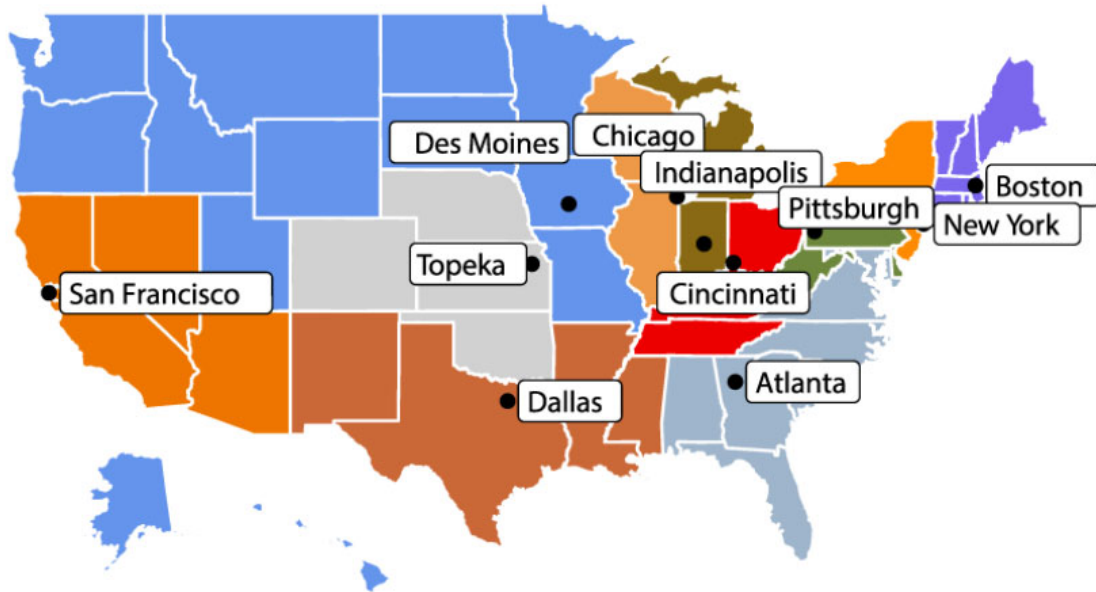


Figure 3. Effect of pledgeability on mortgage acceptance rates at different LTV bins.

The y-axis shows the magnitude of the estimate for Eligible x LTV bin. The x-axis shows the maximum LTV in a given bin.

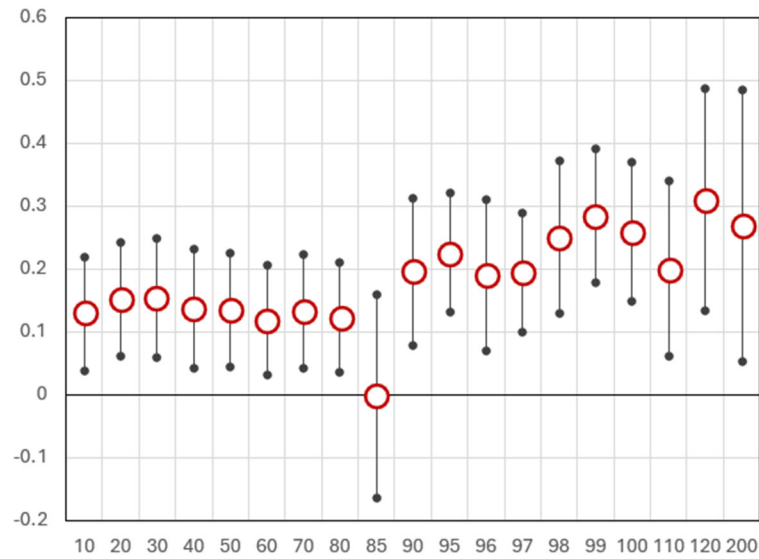


Figure 4. Differential effect of pledgeability on mortgage acceptance rates at different LTV bins, relative to 10% LTV bin.

The y-axis shows the magnitude of the estimate for Eligible x LTV bin. The x-axis shows the maximum LTV in a given bin. The regression omits the coefficient for Eligible x 10-LTV bin.

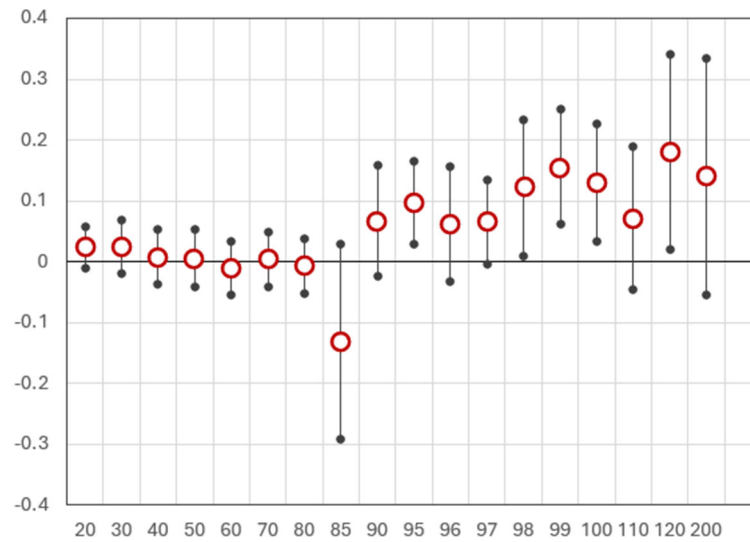


Figure 5. Effect of pledgeability on mortgage acceptance rates at different LTV bins for non-GSE underwritten mortgages.

The y-axis shows the magnitude of the estimate for Eligible x LTV bin. The x-axis shows the maximum LTV in a given bin. The regression excludes all applications underwritten via GSE automated software and FHA-guaranteed mortgages

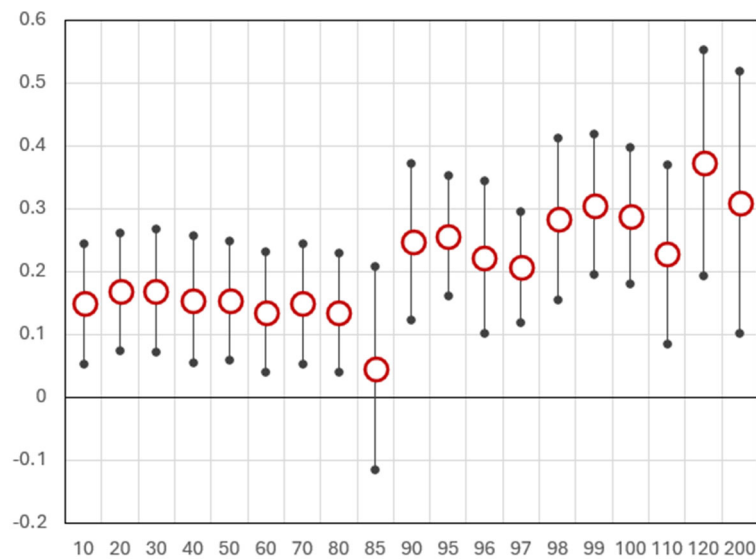


Table 1: Summary statistics

This table presents summary statistics on the sample of mortgage applications. Data are from the public version of 2023 HMDA, subject to the restrictions described in Section 4 of the paper. Data include only applications not sold, except where indicated with an asterisk. In that case, data include only accepted applications. Accept indicates whether the application was accepted or denied by the bank. Eligible indicates whether the loan would be eligible for pledging with the bank's FHLB. Jumbo is a dummy that takes the value of 1 if the loan amount is above the conforming loan limit for the property location, zero otherwise.

	(1) Count	(2) Mean	(3) StDev	(4) Median
Dependent variables				
Accept	900447	0.649	0.477	1.000
Sold*	846039	0.355	0.478	0.000
Main explanatory variables				
Eligible	900447	0.892	0.310	1.000
Loan-level characteristics not part of FHLB grid				
Race: Non-hispanic White	900447	0.585	0.493	1.000
Race: Black	900447	0.100	0.299	0.000
Race: Asian	900447	0.063	0.243	0.000
Race: Hispanic White	900447	0.074	0.262	0.000
Race: Other	900447	0.014	0.117	0.000
Race: Missing	900447	0.143	0.350	0.000
Race: Joint	900447	0.022	0.146	0.000
Male	900447	0.591	0.492	1.000
Automated Underwriting Software: Fannie/Freddie	900447	0.112	0.315	0.000
Automated Underwriting Software: FHA	900447	0.015	0.120	0.000
Manufactured property	900447	0.030	0.171	0.000
Log(income)	854525	4.777	0.855	4.736
Log(loan amount)	900447	11.903	1.110	11.884
Loan term	794372	316.003	86.686	360.000
Total loan costs	900447	1476.567	4726.050	0.000
Co-applicant dummy	900447	0.444	0.497	0.000
Jumbo	900447	0.057	0.233	0.000
Loan characteristics part of FHLB grid				
Loan type: conventional	900447	0.957	0.203	1.000
Loan type: FHA-guaranteed	900447	0.019	0.137	0.000
Loan type: VA-guaranteed	900447	0.022	0.148	0.000
Purpose: Purchase	900447	0.382	0.486	0.000
Purpose: Improve	900447	0.394	0.489	0.000
Purpose: Refi	900447	0.170	0.376	0.000
Purpose: Cash-out	900447	0.054	0.226	0.000

Occupancy: Primary residence	900447	0.916	0.277	1.000
Occupancy: Not owner-occupied	900447	0.041	0.197	0.000
Income reported	900447	0.957	0.203	1.000
Debt-to-income reported	900447	0.974	0.160	1.000
First lien	900447	0.581	0.493	1.000
Payment features: Reverse mortgage	900447	0.000	0.001	0.000
Payment features: Revolving	900447	0.467	0.499	0.000
Payment features: Negative mortgage	900447	0.000	0.003	0.000
Payment features: Interest-only mortgage	900447	0.249	0.432	0.000
Payment features: Balloon payment	900447	0.075	0.264	0.000
Payment features: Other non-amortizing features	900447	0.001	0.034	0.000
Loan term: >40 years	900447	0.000	0.002	0.000
Loan term: >30 years	900447	0.038	0.190	0.000
Combined LTV: >100	900447	0.027	0.162	0.000
Combined LTV: >80	900447	0.239	0.427	0.000
Combined LTV: >104	900447	0.011	0.103	0.000
LTV: >104	900447	0.005	0.067	0.000
LTV: >100	900447	0.010	0.098	0.000
LTV: >80	900447	0.183	0.387	0.000
Violates HOEPA	900447	0.000	0.014	0.000
Prepayment penalties>3 years	900447	0.000	0.003	0.000
Prepayment penalties>5 years	900447	0.000	0.002	0.000
Interest rate spread>6.5	900447	0.004	0.063	0.000
Total points>5	900447	0.000	0.008	0.000
Total points>8	900447	0.000	0.005	0.000
Total points>\$1,020	900447	0.001	0.031	0.000
Loan amount>\$20,391	900447	0.973	0.161	1.000
Secured by manufactured home and not land	900447	0.000	0.014	0.000
Texas property	900447	0.094	0.291	0.000

Table 2: The effect of pledgeability on mortgage credit supply

This table presents the results from regressing mortgage application acceptance on FHLB eligibility. The dependent variable, *Accept*, takes the value of 1 if a mortgage application is accepted by the bank, 0 otherwise. Accepted applications include those that are originated as well as those that are approved but not accepted, and exclude applications that are denied. The key independent variable is *Eligible*, which takes the value of 1 if the loan is eligible for pledging to the lender's FHLB. The sample period is 2023. Controls and fixed effects are summarized in the table below, where "Y" indicates their inclusion in a specification. Borrower controls include log(income), log(loan amount), LTV, loan term, total loan costs, borrower race and ethnicity dummies, borrower gender, a manufactured housing dummy, and a co-applicant dummy. Borrower fixed effects include borrower controls from Column 2, except uses binned versions of income, loan amount, and LTV. County fixed effects are self-explanatory. Underwriting fixed effects include dummies for credit score type and automated underwriting system type. Product fixed effects include fixed effects for all of the loan characteristics listed as part of the FHLB grid in Table 1. Product grid by district fixed effects are dummies for unique combinations of the product fixed effects by district. Standard errors are clustered by bank and county. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Dependent variable: Accept						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eligible	0.185*** (4.85)	0.201*** (5.30)	0.185*** (8.29)	0.180*** (8.37)	0.193*** (7.56)	0.0960*** (2.95)	0.138*** (3.18)
Bank FE	Y	Y	Y	Y	Y	Y	Y
Borr. controls		Y	Y	Y	Y	Y	Y
Borr. FE			Y	Y	Y	Y	Y
County FE				Y	Y	Y	Y
UW FE					Y	Y	Y
Prod. FE						Y	
Prod. Grid × Dist. FE							Y
N	895795	746398	688344	688346	688246	688245	684801
Adj. R ²	0.148	0.263	0.434	0.443	0.449	0.467	0.498

Table 3: The effect of pledgeability on mortgage credit supply, confidential version

This table repeats the specifications from Table 2 on confidential HMDA data, which provides access to additional data fields. First, we replace county fixed effects with county-by-month fixed effects. Second, we augment the set of controls to include fields only available in the confidential version: FICO score, DTI, and combined loan-to-value ratio. The dependent variable, *Accept*, takes the value of 1 if a mortgage application is accepted by the bank, 0 otherwise. Accepted applications include those that are originated as well as those that are approved but not accepted, and exclude applications that are denied. The key independent variable is *Eligible*, which takes the value of 1 if the loan is eligible for pledging to the lender's FHLB. The sample period is 2023. Controls and fixed effects are summarized in the table below, where "Y" indicates their inclusion in a specification. Controls and fixed effects are the same as in Table 2 except they are augmented with confidential fields where applicable. Specifically, FICO score and DTI are added to borrower controls, and calculated LTV is replaced with combined LTV. FICO, DTI, and combined LTV bins are added to borrower fixed effects. County fixed effects are replaced with county-by-month fixed effects. Product fixed effects are augmented with FICO and DTI thresholds. Standard errors are clustered by bank and county. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent variable: Accept						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eligible	0.198*** (8.73)	0.118*** (4.08)	0.072*** (3.53)	0.072*** (3.57)	0.080*** (3.19)	0.064*** (3.01)	0.145*** (5.66)
Bank FE	Y	Y	Y	Y	Y	Y	Y
Borr. controls		Y	Y	Y	Y	Y	Y
Borr. FE			Y	Y	Y	Y	Y
County FE				Y	Y	Y	Y
UW FE					Y	Y	Y
Prod. FE						Y	
Prod. Grid $\times$ Dist. FE							Y
N	907624	706100	693792	688371	688371	688370	677574
Adj. R ²	0.156	0.406	0.519	0.525	0.529	0.539	0.606

Table 4. Variation across lenders

This table examines variation in the effect of FHLB eligibility on loan acceptance across different types of lenders. The dependent variable, *Accept*, takes the value of 1 if a mortgage application is accepted by the bank, 0 otherwise. The key independent variable is *Eligible*, which takes the value of 1 if the loan is eligible for pledging to the lender's FHLB. Column (1) subsets banks into three size categories, based on whether they are subject to full, partial, or no liquidity regulation. Column (2) limits the sample to banks that are FHLB members. In column (3), *Eligible (headq. loc.)* takes the value of 1 if a loan meets the eligibility requirements of the FHLB district in which the bank is headquartered. *Member* takes the value of 1 if the bank is a member of the FHLB system. Column (4) drops banks and focuses on nonbanks, which are never FHLB members so the eligibility dummy in this regression is based on the property location. Controls and fixed effects correspond to specification (7) in Table 2. Standard errors are clustered by bank and county. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent variable: Accept		
	All	FHLB members	Nonbanks
	(1)	(2)	(3)
Eligible $\times$ (Assets $\geq$ 250B)	0.0918* (1.69)		
Eligible $\times$ (250B < Assets $\leq$ 50B)	0.167*** (3.67)		
Eligible $\times$ (Assets < 50B)	0.129*** (2.83)		
Eligible		0.139*** (3.18)	
Eligible (headq. loc.)			0.0195 (1.10)
N	684801	684753	211768
Adj. R ²	0.498	0.498	0.491

Table 5. FHLB pledgeability vs. GSE eligibility

This table runs several specifications to distinguish the effects of FHLB eligibility and eligibility for sales to GSEs. All specifications repeat the specification in Table 2, Column (7) with additional fixed effects. Column (1) adds a fixed effect for the loan's jumbo status. Column (2) adds fixed effects for the interaction of jumbo status with the FHLB grid. Column (3) adds fixed effects for the interaction of LTV bins, the FHLB grid, and the jumbo dummy. Column (4) estimates the effect of eligibility separately for loans likely to be eligible for sale to GSEs and not. We interact *Eligible* with a dummy indicating whether the loan was underwritten with any of the GSEs' proprietary automated underwriting systems (AUS). GSEs require an approval decision from their own AUS as a condition for loan purchase. Other controls and fixed effects correspond to specification (7) in Table 2. Standard errors are clustered by bank and county. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Dependent variable: Accept			
	Conventional- Jumbo FE	Prod- Jumbo FE	Prod- Jumbo- LTV Bin FE	AUS- specific
	(1)	(2)	(3)	(4)
Eligible	0.139*** (3.18)	0.139*** (3.18)	0.130*** (2.96)	
Eligible × GSE AUS				0.166*** (3.32)
Eligible × non-GSE AUS				0.122*** (2.97)
N	684801	684801	678392	684801
Adj. R2	0.491	0.491	0.499	0.498

Table 6. The effect of pledgeability is stronger for illiquid loans

This table examines whether the effect of FHLB pledgeability is stronger for more illiquid loans. A loan's jumbo status is a proxy for illiquidity. We repeat the specifications from Table 2 adding a control for a loan's jumbo status and its interaction with eligibility. The dependent variable, *Accept*, takes the value of 1 if a mortgage application is accepted by the bank, 0 otherwise. Accepted applications include those that are originated as well as those that are approved but not accepted, and exclude applications that are denied. The key independent variable is *Eligible*, which takes the value of 1 if the loan is eligible for pledging to the lender's FHLB. Controls and fixed effects are summarized in the table below, where "Y" indicates their inclusion in a specification. Controls and fixed effects are the same as in Table 2. In Column (2) the jumbo dummy is dropped from the regression because of the inclusion of log(loan amount) as a control. Standard errors are clustered by bank and county. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Dependent variable: Accept						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eligible	0.213*** (6.88)	0.196*** (10.51)	0.177*** (7.14)	0.173*** (7.44)	0.191*** (6.03)	0.128*** (4.15)	0.0496* (1.88)
Eli. × Jumbo	0.118** (2.02)	--	0.0865* (1.91)	0.0854** (2.02)	0.0592 (1.44)	0.0917*** (2.59)	0.117*** (3.62)
Jumbo	-0.178*** (-3.33)	--	-0.0879** (-2.06)	-0.0930** (-2.22)	-0.0886** (-2.12)	-0.132*** (-3.98)	-0.149*** (-5.17)
Bank FE	Y	Y	Y	Y	Y	Y	Y
Borr. controls		Y	Y	Y	Y	Y	Y
Borr. FE			Y	Y	Y	Y	Y
County FE				Y	Y	Y	Y
UW FE					Y	Y	Y
Prod. FE						Y	
Prod. Grid × Dist. FE							Y
N	793280	749662	799627	799571	799571	799569	795592

Table 7. Effect of pledgeability on loan sales

This table examines whether loans eligible for pledging to FHLBs are less likely to be sold (i.e. more likely to be held on balance sheet). The sample consists of originated loans from 2023 HMDA. The dependent variable *Sold*, takes the value of 1 if the loan was marked in HMDA as having been sold, 0 otherwise. HMDA tracks loan sales through the end of the calendar year of origination. Controls and fixed effects are summarized in the table below, where “Y” indicates their inclusion in a specification. Controls and fixed effects are the same as in Table 2. Standard errors are clustered by bank and county. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Dependent variable: Sold						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eligible	-0.682*** (-13.49)	-0.604*** (-10.18)	-0.628*** (-10.55)	-0.627*** (-10.53)	-0.515*** (-8.01)	-0.527*** (-9.67)	-0.850*** (-22.98)
Bank FE	Y	Y	Y	Y	Y	Y	Y
Borr. controls		Y	Y	Y	Y	Y	Y
Borr. FE			Y	Y	Y	Y	Y
County FE				Y	Y	Y	Y
UW FE					Y	Y	Y
Prod. FE						Y	
Prod. Grid × Dist. FE							Y
N	844252	737856	682350	682270	682269	682268	680251
Adj. R2	0.670	0.729	0.765	0.769	0.822	0.829	0.907

Table 8. Pledgeability's effect on bank-nonbank market shares

This table examines the effect of FHLB eligibility on bank market shares. Nonbanks cannot be FHLB members. The sample consists of mortgage originations from HMDA for the years 2019 through 2024. Data is collapsed by lender type (bank or nonbank), FHLB district, and product type. *%Banks* is the share of all loans in a product category, district, and year, that are originated by banks. *Eligible* takes the value of 1 if the loan is eligible for pledging to the lender's FHLB or, for nonbanks, their pseudo-FHLB. For nonbanks, pseudo-FHLB is assigned based on their headquarters location. Column (1) includes the full sample of originations. Column (2) limits the sample to product categories, districts, and years with at least 100 loans. Column (3) adds controls for the mean value of all loan controls not included in the FHLB grid in each product category, district, and year. Column (4) adds district x year and product x year fixed effects. Column (5) limits the sample to product categories, districts, and years with at least 1000 loans. Controls included from column 3 product-district averages of: applicant race and ethnicity dummies (non-Hispanic white, black, Asian, Hispanic white, other, missing, or joint), male applicant dummy, co-applicant dummy, manufactured house dummy, log borrower income, log loan amount, and LTV ratio Fixed effects in all columns are year, product, and FHLB district fixed effects. From column 4, fixed effects are product-year and product-year fixed effects Standard errors are clustered by product. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Dependent variable: %Banks				
	All loans	>100 loans	Add controls	Add interacted FEs	>1000 loans
	(1)	(2)	(3)	(4)	(5)
Eligible	0.0279*** (5.22)	0.0605*** (3.55)	0.0815*** (4.65)	0.0852*** (4.91)	0.147*** (5.74)
N	26128	2411	2306	1883	391
Adj. R2	0.631	0.751	0.772	0.796	0.847