

Collateral Uncertainty and the Limits of Shadow-Bank Mortgage Lending

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Shadow banks' share of U.S. mortgage lending has risen substantially, while their expansion has varied widely across local markets. We study whether uncertainty about property values shapes this geographic pattern by making mortgages costlier to sell. Using mortgage and property data, we find that shadow banks have lower local market shares and expand more slowly in higher-uncertainty areas, even among conventional loans below the conforming loan limit. Application data link this pattern to lenders' decisions: denial rates rise more with uncertainty for shadow banks than for banks, with the difference concentrated in refinancing. Consistent with a role for balance-sheet capacity, denial responses are stronger among more sale-dependent shadow banks. We also find evidence consistent with higher distribution costs in higher-uncertainty markets: less use of appraisal alternatives, greater repurchase risk and longer times to sale. Collateral uncertainty constrains shadow-bank expansion and preserves a local role for balance-sheet lending.

Keywords: housing liquidity, shadow bank lending.

JEL codes: G10, G51, R30

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1 Introduction

Since the global financial crisis, shadow banks have expanded substantially in the U.S. mortgage market: their share of mortgage originations rose from approximately 22% in 2007 to 63% in 2024 (Figure 1, Panel a). Shadow banks partly filled the lending gap in markets more exposed to tighter post-crisis bank capital requirements (Buchak et al., 2018), relying on mortgage sales, including to Fannie Mae and Freddie Mac, rather than long-term retention (Buchak et al., 2024). However, this national expansion masks substantial geographic heterogeneity, with local shadow-bank market shares becoming more spatially clustered (Figure 1, Panel b). Even among conventional mortgages below conforming size limits, shadow banks' local market shares still range from below 30% to above 80%.¹ E. X. Jiang and Zhang, 2025 show that collateral valuation uncertainty is persistently higher where housing is less standardized and informative comparable sales are scarce. These local information differences may affect not only how much mortgage credit is available, but also which lenders provide it. We examine how collateral uncertainty shapes shadow banks' geographic expansion through their reliance on mortgage sales.² When uncertainty makes selling less attractive, the ability to retain mortgages can give banks an advantage over lenders that rely on selling their loans.

We find that shadow banks' local market shares are approximately five percentage points lower in the highest than in the lowest collateral-uncertainty decile, equivalent to roughly 12 percent of the average shadow bank market share. We also show that shadow banks expand more slowly in areas with high collateral uncertainty. Focusing on conventional lending below conforming size limits, we estimate that increasing local market share by 10 percentage points takes roughly sixteen months longer in the highest than in the lowest uncertainty decile, a 16% increase in waiting time, controlling for initial market shares and other baseline characteristics.³ The negative relationship between uncertainty and local market shares persists after accounting for local regulatory exposure (Buchak et al., 2018; Gete & Reher, 2021), borrower and market characteristics, and county-by-year fixed effects.

We use application-level data to examine whether lower shadow-bank penetration in high-uncertainty markets reflects a supply-side response. We find that denial rates rise more with collateral uncertainty for shadow banks than for banks, after controlling for applicant and loan

¹Authors' calculations using 2024 HMDA data. We measure shadow banks' share of the dollar volume of conventional purchase and refinance originations below the applicable county one-unit conforming loan limit. The sample includes 13,442 ZIP codes with at least 30 such originations; shares are below 30% in 1,419 markets and above 80% in 943 markets.

²In a May 2023 letter to FHFA, the Community Home Lenders of America, which represents independent mortgage lenders, linked limited comparable sales to appraisal-related repurchase concerns and warned that lenders facing many such requests might reduce lending or require lower loan-to-value ratios (Community Home Lenders of America (CHLA), 2023).

³See Section 3.1.2 for the timing analysis.

characteristics and lender-year and county-year fixed effects. The differential shadow-bank denial response is concentrated in refinancing, where the absence of a contemporaneous transaction price makes collateral values more difficult to verify. Using matched samples, we also show that differences in application denials can explain about 74% of the estimated negative relationship between collateral uncertainty and shadow banks' local refinance market shares. What explains these differences in lending decisions between lender types?

Building on the sale-versus-retention framework of Buchak et al. (2024), we develop a model in which collateral uncertainty can raise the expected cost of selling mortgages. Lenders face the same collateral information and eligibility requirements but differ in their cost of retaining mortgages. Banks with sufficiently low funding and balance-sheet costs can retain mortgages that are unprofitable to sell, whereas shadow banks with higher retention costs may reject the same applications.⁴

Consistent with our mechanism, we find that lenders' responses to collateral uncertainty vary with their reliance on loan sales and ability to retain mortgages. The denial response in refinance applications is stronger among shadow banks with greater historical reliance on loan sales. Furthermore, this effect is even more pronounced for lenders specialized in refinance mortgages. Thus, these findings are particularly relevant for fintech lenders, which represent a prominent subtype of shadow banks, focusing predominantly on refinancing. In contrast, traditional banks' balance-sheet capacity allows them to absorb collateral uncertainty more effectively; consequently, banks' retention rates also rise more with collateral uncertainty than those of shadow banks.

We use Fannie Mae loan performance data to examine the distribution costs associated with collateral uncertainty. Higher uncertainty is associated with fewer appraisal waivers, which provide originators with relief from specified valuation-related warranties. We also find that higher collateral uncertainty is associated with greater put-back risk and longer measured time to sale. For shadow banks, delayed sales and repurchases can tie up capital and increase the cost of short-term warehouse funding (Kim et al., 2018).

Our analysis combines HMDA mortgage application and origination records for 2007–2024 with ZTRAX property and transaction data, supplemented by Fannie Mae loan records for the secondary-market analysis. Following E. X. Jiang and Zhang (2025), we measure collateral uncertainty using transaction-price dispersion after accounting for observed property characteristics and local market conditions. Our baseline market-share comparisons exploit differences across local markets within county-years, while application analyses also compare decisions within lender-years. Our identification strategy addresses two concerns. First, collateral uncertainty

⁴Complementary evidence from a companion paper documents lower subsequent refinancing in higher-uncertainty markets (Amaral & Ruzzier, 2026).

may proxy for other determinants of shadow-bank lending. In addition to the regulatory factors discussed above, we account for borrower composition and digital access (Fuster et al., 2019), local mortgage-market competition (Buchak & Jørring, 2021), and bank funding conditions (Drechsler, Savov, & Schnabl, 2022). Second, the uncertainty measure may reflect contemporaneous housing-market conditions rather than persistent difficulties in valuing collateral. We instrument collateral uncertainty using heterogeneity in predetermined housing-stock characteristics, including property size, construction year and location (E. X. Jiang & Zhang, 2025). This approach targets the component of valuation uncertainty rooted in the pre-existing housing stock. Identification requires that, conditional on the controls and fixed effects, these characteristics affect lending through collateral uncertainty rather than through other credit-demand or supply channels.

Our findings imply that collateral uncertainty can limit shadow banks' geographic expansion because secondary-market access alone is insufficient to eliminate local frictions in mortgage lending, thereby preserving a local role for bank balance sheets, even when mortgages are eligible for sale to the GSEs.

Related literature. Existing research explains the substantial national expansion of shadow-bank mortgage lending through regulatory changes, technological advances and secondary-market conditions (Buchak et al., 2018; Fuster et al., 2019; Gete & Reher, 2021). We document that this expansion has been geographically uneven and accompanied by stronger spatial clustering of local penetration. Our paper is most closely related to Buchak et al. (2024), who show that shadow banks substitute for banks where mortgages can readily be sold, while banks adjust between selling and retaining loans according to their balance-sheet strength. We build on this framework by examining collateral uncertainty as a local friction in mortgage distribution, even within conventional lending below conforming size limits. Related research highlights nonbank originators' reliance on short-term funding and the liquidity and balance-sheet constraints they face (E. Jiang et al., 2020; Kim et al., 2018). E. X. Jiang (2023) shows that shadow banks' dependence on funding from competing banks can limit mortgage-market competition. We identify an additional local constraint: collateral uncertainty can increase the costs and risks of mortgage distribution and limit where sale-dependent lenders expand.

Research on how collateral values affect credit provision emphasizes liquidation values and redeployability (Benmelech & Bergman, 2009; Shleifer & Vishny, 1992) and appraisal distortions associated with borrowers' leverage constraints (Agarwal, Ben-David, & Yao, 2015). E. X. Jiang and Zhang (2025) show that collateral uncertainty restricts credit through lower expected recoveries and noisier appraisals that make loan-to-value constraints more likely to bind. We show how collateral uncertainty can affect lenders differently depending on their balance-sheet capac-

ity. Our contribution therefore concerns not only credit provision but also which intermediaries provide it.

The remainder of the paper is organized as follows. Section 2 describes the data and measurement of collateral uncertainty. Section 3 presents the evidence on shadow banks' local market shares, geographic expansion, and application decisions. Section 4 develops the model and tests the distribution mechanism using evidence on loan-sale dependence, bank retention, and distribution-related frictions. Section 5 concludes.

2 Data

We integrate three datasets. Our analysis combines measures of local collateral uncertainty with mortgage application and origination records to examine shadow banks' market shares, geographic expansion, and lending and financing decisions. Agency loan records provide additional information on property valuation methods and mortgage repurchases. Detailed sample selection criteria and descriptive statistics for each dataset are provided in Appendix B.

Zillow's Transaction and Assessment Database (ZTRAX): Our primary explanatory variable, collateral uncertainty, is constructed using ZTRAX, which provides comprehensive U.S. housing transaction records (deed data) and property-level assessment records (tax data). Following the methodology of E. X. Jiang and Zhang (2025), we use records from 2007 to 2024 to estimate transaction prices conditional on observed property characteristics and local market conditions. We then model the dispersion of the resulting pricing errors and aggregate the predicted property-level uncertainty to the ZIP-code-year level. Higher values indicate greater difficulty predicting property values from observable characteristics. Details of its construction and validation are provided in Appendix A.

HMDA: Mortgage Applications and Originations Our primary dataset is the Home Mortgage Disclosure Act (HMDA) Loan Application Register, covering the near-universe of U.S. mortgage applications from 2007 to 2024. We retain applications on which lenders made an approval or denial decision.⁵ We restrict the sample to first-lien, owner-occupied, site-built properties with one to four units.

Using the Avery files, we classify lenders as shadow banks, banks, or other lenders. Shadow banks comprise independent and depository-affiliated mortgage companies, while banks comprise commercial banks and related subsidiaries. Remaining institution types, including thrifts and credit unions, form the other-lender category.⁶

⁵Approvals include both originated mortgages and applications approved but not accepted by the applicant. We exclude applications withdrawn before a credit decision and files closed for incompleteness. Market-share measures use only originated mortgages.

⁶We match HMDA lender identifiers to Federal Reserve RSSD identifiers by institution and year, using respondent

We map applications to five-digit ZIP codes using the HUD USPS tract-to-ZIP crosswalk and retain observations with valid collateral uncertainty measures.⁷ HMDA provides borrower demographics and loan characteristics, with additional information available from 2018 onward.⁸

Our main geographic outcome is shadow banks' share of mortgage originations in each ZIP-code-year, measured as shadow-bank originated dollar volume divided by total originated dollar volume across all lender groups. We examine geographic expansion through changes in these shares and the time required for shadow banks' local market shares to reach specified thresholds.

At the application level, our main outcome is an indicator equal to one when the lender denies the application and zero when it approves it. We also examine whether collateral is cited among the reasons for denial. This indicator is defined among denied applications and therefore measures the composition of denials rather than the overall denial probability.⁹

We measure historical loan-sale dependence using the fraction of conventional originations sold over the preceding three years outside the application's county. For banks, we identify retention from mortgages reported as not sold.¹⁰

Figure 1 shows national mortgage market shares alongside the geographic pattern of shadow-bank lending. As shadow banks' national share increased, their local shares became more spatially clustered: counties with relatively high shares were increasingly located near other high-share counties, with a similar pattern among low-share counties. The index rises from 0.47 in 2007 to 0.62 in 2024, after peaking in 2020. Appendix B.1 explains its construction and provides county maps.

GSE (Fannie Mae) Public Data: To examine the valuation requirements and continuing obligations involved in mortgage distribution, we use the Fannie Mae Single-Family Loan Performance Data, covering fixed-rate mortgages originated from 2007 to 2024.¹¹ These records contain borrower and loan characteristics, property valuation methods, and monthly loan performance. We use this information to examine the use of appraisal alternatives, including appraisal waivers, and the incidence of subsequent mortgage repurchases.

identifiers before 2018 and Legal Entity Identifiers thereafter. Shadow banks correspond to Avery institution types 40–41 and banks to types 10–14. We identify fintech lenders using the classification of Fuster et al. (2019), updated through 2020.

⁷Using census tract, county, and state identifiers, we assign each application to the ZIP code with the largest residential address share within its tract-year. We exclude unmatched applications, observations outside the 50 states and Washington, D.C., applications with applicant income of \$1,000 or less, and loan amounts below \$50,000.

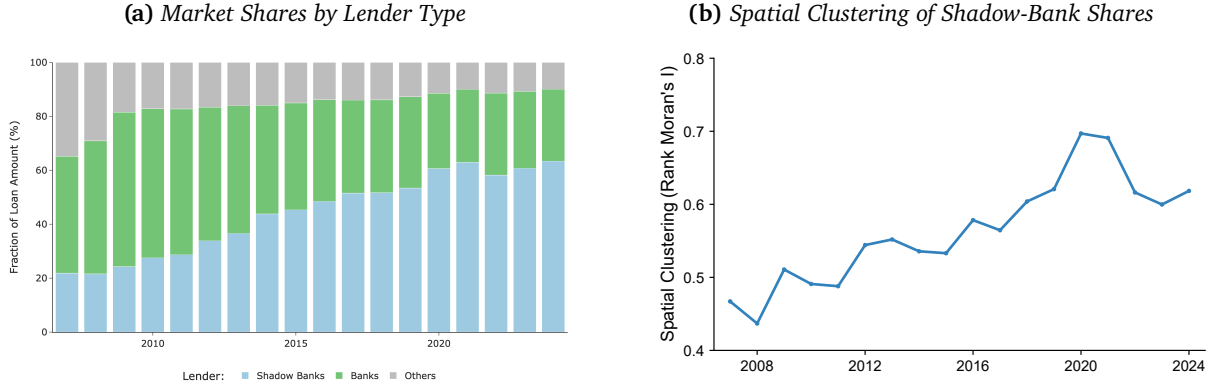
⁸Demographic indicators follow a hierarchical assignment of applicant race and ethnicity: Hispanic, Asian, Black, other, and White.

⁹We identify collateral-related denials when collateral, HMDA denial reason 4, appears among any of the reported denial reasons.

¹⁰HMDA purchaser information records sales within the origination calendar year. Mortgages reported as not sold during that year may subsequently be sold.

¹¹We retain loans with valid credit characteristics and loan amounts of at least \$50,000. The appraisal-alternative analysis covers 2017–2024 originations and includes both waivers and waivers combined with property data collection.

Figure 1: Mortgage Market Shares and Spatial Clustering of Shadow-Bank Lending



Notes: Panel (a) shows each lender type's share of total mortgage origination dollar volume. Panel (b) reports Moran's I for the annual ranks of county shadow-bank market shares, also measured by dollar volume. Higher values mean neighboring counties tend to have similarly high or low local shares. Panel (b) uses a fixed sample of 1,772 counties with positive observed lending in every year from 2007 to 2024 and the Census Bureau's 2010 county adjacency list; counties without neighbors in the sample are excluded.

We also construct a timing measure as the number of months between origination and the sale to Fannie Mae. Because property locations are reported at the three-digit ZIP-code level, we aggregate our collateral uncertainty measure to this level and merge it with the loan records by location and origination year.¹²

3 Empirical Analysis

This section examines how collateral uncertainty relates to shadow banks' local penetration. We first study market shares, accounting for other established drivers of shadow-bank lending. We then measure the pace of local expansion and examine lenders' application decisions.

3.1 Collateral Uncertainty and Shadow Bank Market Share

We first evaluate how shadow banks' local market shares vary with collateral uncertainty. Using HMDA data from 2007 to 2024, we calculate market shares at the ZIP-code-year level. Figure 2, Panel (a), shows the average change in these shares over this period across collateral uncertainty deciles defined using 2007 values. Shadow-bank market shares increased substantially across all deciles, but gains were smaller in areas with higher collateral uncertainty: roughly 45 percentage points in the lowest decile, compared with 35 percentage points in the highest.

We then examine the relationship between annual shadow-bank market shares and ZIP-code-level collateral uncertainty using the following regression:

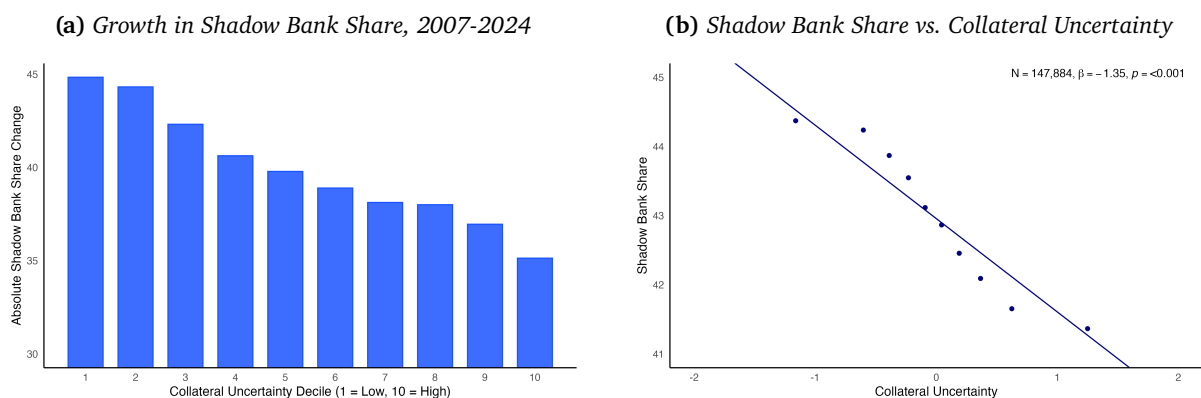
$$\text{Shadow Bank Share}_{z,t} = \beta U_{z,t} + \mathbf{W}'_{z,t} \boldsymbol{\gamma} + \alpha_{c,t} + \varepsilon_{z,t}. \quad (1)$$

¹²We calculate the simple average of the five-digit ZIP-code-year uncertainty measures within each three-digit ZIP prefix.

Here, $U_{z,t}$ is our standardized measure of collateral uncertainty, and $\alpha_{c,t}$ denotes county-by-year fixed effects. The vector $\mathbf{W}_{z,t}$ contains time-varying ZIP-code-level controls: the refinance share, the logarithms of average loan amount and borrower income, the average loan-to-income (LTI) ratio, and average squared LTI. The specification therefore compares ZIP codes within the same county and year, accounting for differences in observed borrower and loan characteristics. Our sample includes ZIP-year observations with at least 50 originated loans, and standard errors are clustered at the county level.

Figure 2, Panel (b), presents a binned scatter plot of this OLS relationship. A one-standard-deviation increase in collateral uncertainty is associated with a 1.35-percentage-point lower shadow-bank market share, with the estimate being statistically highly significant at the 1% level. Applying this estimate to the difference in average uncertainty between the highest and lowest 2007 deciles implies a market-share gap of approximately 5 percentage points.

Figure 2: Collateral Uncertainty, Shadow Bank Penetration (2007 - 2024)



Notes: This figure plots the relationship between collateral uncertainty and shadow bank market penetration. Panel (a) shows the absolute change in the shadow bank market share from 2007 to 2024 across collateral uncertainty deciles. Panel (b) presents a binned scatter plot of the relationship between shadow bank market share (weighted by loan amount) and collateral uncertainty at the ZIP code-year level, controlling for county-by-year fixed effects and average ZIP-code loan characteristics. Data source: HMDA, 2007–2024: ZIP codes with at least 50 originations.

3.1.1 Addressing Confounding Variables Identified in the Literature

Collateral uncertainty may also reflect other local characteristics that influence shadow-bank lending. We therefore augment our baseline specification with controls for the demand- and supply-side factors identified in the literature.

Our baseline specification incorporates county-by-year fixed effects, ensuring that identification stems strictly from within-county variation and inherently absorbing broad macroeconomic or regional trends. However, a residual concern is that hyper-local, neighborhood-level variations might still correlate with collateral uncertainty and confound our estimates.

First, we control for local regulatory exposure to account for geographic differences in the effects of post-crisis regulation. Columns 2 and 3 of Table 1 include measures of local exposure

to the bank-regulation changes studied by Buchak et al., 2018 and the liquidity-regulation shock studied by Gete and Reher, 2021, respectively.

Second, we address demand-side sorting based on borrower demographics and technological access. Fintechs, an important category of shadow banks, attract different borrower profiles and appeal to borrowers who value convenience and rapid processing (Bartlett et al., 2022; Fuster et al., 2019; Howell et al., 2024). To account for demographic sorting, the digital access and housing-market conditions, we augment our models with American Community Survey (ACS) and Zillow data. These specifications control for local racial composition, socioeconomic status, broadband availability and home price appreciation (Columns 4–6 of Table 1).

Third, we account for local banking-market structure and funding conditions. Recent studies emphasize the role of local banking concentration and branch closures in shaping credit availability (Balyuk, Berger, & Hackney, 2026; Buchak & Jørring, 2021; Nguyen, 2019). Shadow banks may also fill credit gaps left by traditional depositories experiencing deposit outflows (Drechsler, Savov, & Schnabl, 2022; Xiao, 2020). Using FDIC Summary of Deposits data, we control for local branch density, the local footprint of large banks and funding shocks (Columns 7 and 8 of Table 1). Column 9 includes all control groups simultaneously.

Table 1: ZIP-Level Shadow Bank Share and Collateral Uncertainty (2007 - 2024)

	Dependent Variable: Shadow Bank Share (% of Loan Amount)								
	Baseline	Robustness and Alternative Specifications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Collateral Uncertainty	-1.350*** (0.135)	-1.253*** (0.127)	-1.358*** (0.140)	-1.121*** (0.130)	-0.949*** (0.149)	-1.286*** (0.144)	-1.436*** (0.136)	-1.391*** (0.135)	-0.907*** (0.144)
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓							✓
Gete & Reher (2021)			✓						✓
Demographics & Risk				✓					✓
Technology					✓				✓
Housing Market						✓			✓
Bank Competition							✓		✓
Drechsler et al. (2022)								✓	✓
Sample Start Year	2007	2007	2007	2011	2017	2008	2007	2007	2017
R2 Adj.	0.904	0.907	0.909	0.891	0.866	0.901	0.906	0.904	0.876
Observations	147 884	134 379	146 590	115 932	66 593	137 454	147 884	147 884	59 658

Note: HMDA data: 2007–2024. The sample includes all zip code-year observations with ≥ 50 loans. All specifications include county-year fixed effects and loan controls, which include: the refinance share, the natural logarithm of the average loan amount, the natural logarithm of average borrower income, the average loan-to-income (LTI) ratio, and the average LTI squared. *p<0.1; **p<0.05; ***p<0.01

The negative relationship between collateral uncertainty and shadow-bank market shares remains highly statistically significant across all specifications. The coefficient’s magnitude is also very stable across specifications. In the combined specification in Column 9, estimated over 2017–2024, the coefficient is 0.91. Detailed variable definitions and additional regression results are provided in Appendix D.3.

Market Segment Heterogeneity Nonbank lenders operate under an originate-to-distribute model that relies heavily on agency securitization markets. Secondary-market conditions therefore play an important role in their funding and lending decisions (Buchak et al., 2024; Gete & Reher, 2021). To examine whether our results reflect differences in the local mix of conforming and jumbo mortgages, we isolate the conforming loan segment, within the size limits of the Fannie Mae and Freddie Mac purchase route. The negative relationship between collateral uncertainty and shadow-bank market share remains statistically significant within this segment. Thus, the relationship is not simply driven by geographic differences in the prevalence of jumbo lending.

We also partition the sample by government backing and loan purpose. The negative relationship is present in conventional and government-backed lending and for both purchase and refinance originations. The full estimates are reported in Table A8, with further discussion in Appendix D.4.

Exogenous Variation in Collateral Uncertainty Lastly, properties that are harder to value may be purchased by less creditworthy borrowers, so our estimates could reflect borrower risk rather than collateral uncertainty. To identify the causal effect of collateral uncertainty, we instrument it using measures of heterogeneity in persistent local housing characteristics, including property size, construction year and location. These measures capture how unusual properties are relative to the local housing stock, after removing linear relationships with their characteristics. E. X. Jiang and Zhang (2025) show that uncertainty instrumented in this way is not significantly associated with borrower income, FICO scores or subsequent mortgage delinquency. Our identifying assumption is that, conditional on controls and fixed effects, this heterogeneity affects shadow-bank market shares only through collateral uncertainty. Appendix C provides details of the instrument construction and identifying assumptions.

Table A6 presents the baseline results for both OLS and IV specifications. Under the identifying assumption above, the 2SLS estimate with loan controls implies that a one-standard-deviation increase in collateral uncertainty reduces shadow banks' local market share by approximately 2.7 percentage points, roughly twice the OLS estimate of 1.35 percentage points. The IV estimate is statistically significant at the 1% level and remains similar in the balanced sample. Additional 2SLS results with alternative controls and across mortgage segments are reported in Appendix Tables A7 and A8.

3.1.2 Collateral Uncertainty as a Limit to Expansion

We next examine whether collateral uncertainty slows shadow banks' local expansion. We study two complementary outcomes: the time needed to increase their local market share by 10 percentage points and the time needed to reach a 50% share. The first measures expansion

relative to the initial market share; the second measures attainment of a majority position.

To measure the pace of local expansion, we follow ZIP-code markets from 2007 to 2024, restricting the sample to markets with more than 50 mortgage originations in 2007.¹³ Market shares are measured by dollar volume within conventional lending below the annual national base conforming loan limit. We record a 10-percentage-point gain when shadow banks' share remains at least 10 percentage points above its 2007 level for two consecutive years.

We follow each local market year by year and estimate the probability that shadow banks record the market-share gain, conditional on not having recorded it earlier. We use a grouped-time hazard model that allows this probability to vary across years (Jenkins, 1995), following related mortgage-market applications (Liebersohn & Rothstein, 2025; Palmer, 2026). We model this annual probability, $p_{z,t}$, as:

$$\log[-\log(1 - p_{z,t})] = \delta_t + \alpha_{s(z)} + \beta U_{z,2007} + \mathbf{W}'_{z,2007} \boldsymbol{\gamma} + f(m_{z,2007}). \quad (2)$$

Here, U measures collateral uncertainty, $\mathbf{W}$ includes borrower, loan and local market characteristics, and $f(m)$ accounts flexibly for the initial shadow-bank share. These characteristics are measured in 2007. Year effects account for common changes over time, while state fixed effects absorb persistent differences across states. The specification therefore uses variation in uncertainty both within and across counties in the same state.

Panel (a) of Figure 3 compares the adjusted cumulative probability of increasing local shadow-bank market share by 10 percentage points between the lowest and highest collateral-uncertainty deciles. Expansion is slower in high-uncertainty markets: over the observation period through 2024, we estimate that gaining 10 percentage points takes roughly sixteen months longer in the highest than in the lowest uncertainty decile, which is about 16% longer, conditional on initial market shares and other baseline characteristics. Appendix Table A10 reports the underlying waiting times and percentage increase.

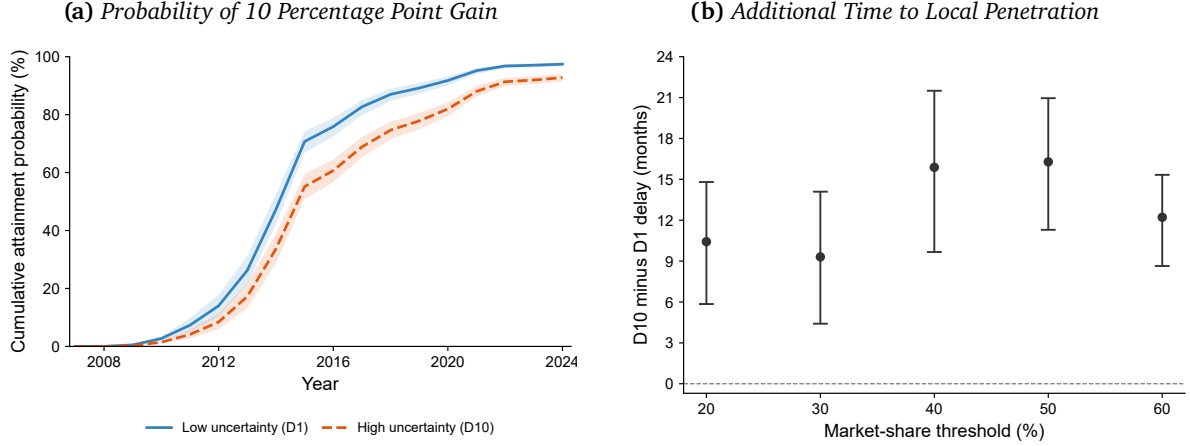
Panel (b) of Figure 3 shows the additional expected waiting time in the highest relative to the lowest uncertainty decile at different market-share targets. Over the observation period through 2024, reaching a 50% share takes approximately sixteen months longer. The estimated delays are also positive and large at the other target shares: ten months at 20%, nine months at 30%, sixteen months at 40%, and twelve months at 60%.

Appendix D.5 reports the robustness checks. Replacing state with county fixed effects yields smaller but statistically significant delays of approximately ten months for the 10-percentage-point gain and eleven months for reaching a 50% share. Adjusting for initial market shares reduces the

¹³The estimation sample comprises 9,908 ZIP codes in 1,332 counties and 36 states.

delay for reaching 50% to about thirteen months, while weighting for observation loss leaves the main estimates largely unchanged. The same pattern of slower expansion holds for gains of 20 and 30 percentage points and for a doubling of market share. Within-county checks restricted to markets with initial shares below 20% or 15% are weaker and not statistically conclusive.

Figure 3: Collateral Uncertainty and the Pace of Local Expansion



Note: The figure displays estimates from grouped-time hazard models tracking local shadow-bank market-share milestones. Milestones require holding the threshold for two consecutive years. Shares measure dollar volume in conventional lending below the conforming limit for ZIP codes with >50 originations in 2007. Panel (a) plots adjusted cumulative probabilities for a 10 percentage point share gain, using 9,908 ZIP codes, 2007 uncertainty, initial-share controls, and state-year fixed effects. Panel (b) plots D10-minus-D1 waiting-time delays across thresholds through 2024, using 10,091 ZIP codes, annually lagged uncertainty, and state-year fixed effects. Predictions compare D1 and D10 uncertainty distributions over a common reference, with the dashed line indicating zero delay. Shading (Panel a) and whiskers (Panel b) show pointwise 95% confidence intervals from 999 whole-county bootstrap resamples.

Shadow banks' lower market shares and slower local expansion may reflect differences in borrower demand as well as lenders' willingness to supply credit. We next examine mortgage applications to assess whether denial rates increase more with collateral uncertainty for shadow banks than for traditional banks.

3.2 Collateral Uncertainty as Supply-driven Friction

Lower shadow-bank market shares in high-collateral-uncertainty areas could reflect weaker borrower demand or a lower willingness of shadow banks to lend. Mortgage applications provide a proxy for borrower demand at each lender.¹⁴ We therefore examine whether shadow-bank denial rates increase more than bank denial rates with collateral uncertainty, conditional on borrower and loan characteristics, county-year conditions and lender-year policies.

We estimate the following linear probability model using purchase and refinance applications from 2007 to 2024:

$$100\text{Denied}_{i,z,t} = \beta U_{z,t} + \theta (\text{SB}_i \times U_{z,t}) + \mathbf{W}_i' \boldsymbol{\gamma} + \alpha_{c(z),t} + \eta_{\ell(i),t} + \varepsilon_{i,z,t}. \quad (3)$$

¹⁴Applications measure observed demand, which may itself reflect pricing, lender availability and anticipated rejection.

Here $U_{z,t}$ is standardized collateral uncertainty and SB_i identifies shadow banks. The interaction coefficient θ measures the additional denial-rate response for shadow banks relative to banks, in percentage points per standard deviation. Controls W_i include income, loan amount, loan-to-income and its square, loan characteristics and demographics, with regulatory controls where indicated. County-year effects account for shared local annual conditions; lender-year effects account for lenders' annual policies. Standard errors are clustered by county. Appendix D.6 provides detailed definitions and the decile specification.

Table 2 reports estimates of equation (3) for all applications and separately for purchases and refinances. A one-standard-deviation increase in collateral uncertainty is associated with a 0.209 percentage point larger increase in the denial rate for shadow banks than for banks in the pooled sample; the estimate is 0.269 with regulatory controls. The positive differential response is concentrated in refinancing, with estimates of 0.291 and 0.375 percentage points, respectively. Purchase interactions are statistically indistinguishable from zero. These findings are robust to including the regulatory-exposure controls based on Buchak et al. (2018) and Gete and Reher (2021): the pooled and refinance interactions remain positive and statistically significant.

Table 2: Collateral Uncertainty and the Probability of Application Rejection (2007 - 2024)

	Dependent Variable: Pr(Rejection) x 100					
	All Loans		Purchase Loans		Refinance Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral Uncertainty	0.798*** (0.084)	0.641*** (0.072)	0.806*** (0.080)	0.615*** (0.076)	0.797*** (0.098)	0.672*** (0.087)
Shadow Bank x Uncertainty	0.209*** (0.065)	0.269*** (0.066)	-0.078 (0.052)	-0.010 (0.053)	0.291*** (0.075)	0.375*** (0.076)
County-Year FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓		✓		✓
Gete & Reher (2021)		✓		✓		✓
Clustered SE	County	County	County	County	County	County
# of Counties	1913	1254	1912	1253	1912	1253
# of ZIPS	13277	7766	13270	7766	13270	7766
# of Lenders	7086	6919	6787	6599	6634	6405
# of Shadow Banks	1968	1954	1924	1910	1888	1871
Observations	88532203	78595401	38985770	34724114	49540612	43864888

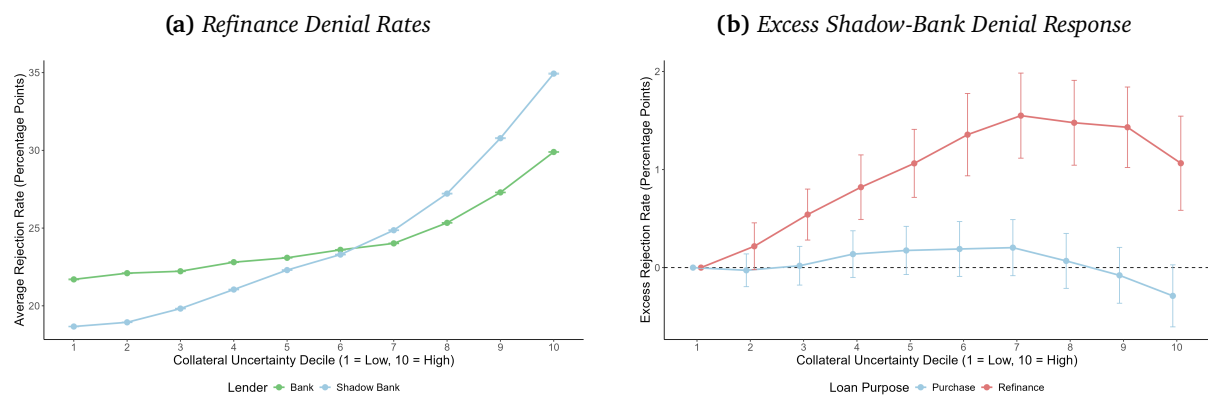
Notes: This table reports linear probability model estimates based on HMDA loan applications from 2007 to 2024, restricted to traditional banks and shadow banks. Columns 1–2 use the full sample (all loans), columns 3–4 restrict to purchase loans, and columns 5–6 restrict to refinance loans. For each sample, the first column presents within-lender estimates (with County-Year and Lender-Year fixed effects), and the second column presents the results controlling for the regulatory shocks by Buchak et al. (2018) and Gete and Reher (2021). All specifications include loan and borrower controls (log income, log loan amount, LTI, LTI squared, conforming loan indicator, loan type, loan purpose, race, and sex). Collateral uncertainty is standardized. Standard errors are clustered at the county level and are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

The regression results show that the differential denial response is concentrated in refinancing. Panel A of Figure 4 examines this segment more closely by plotting banks' and shadow banks' denial rates across the collateral uncertainty distribution. We rank applications by the uncertainty of their ZIP code and divide them into ten approximately equal-sized groups, or deciles, from lowest to highest uncertainty. This allows us to see where in the distribution the difference between lenders emerges. Shadow-bank refinance denial rates start below banks' but overtake them in high-uncertainty markets, reaching approximately 35% compared with 30% in the

highest decile. These raw comparisons may also reflect differences in the applications received by each lender type.

Panel B examines whether the stronger shadow-bank response remains after accounting for borrower and loan characteristics and fixed effects. We estimate separate responses across the ten uncertainty groups rather than impose a constant slope, and compare purchases with refinances. The increase in the shadow-bank-minus-bank denial gap is concentrated in refinancing, reaching approximately 1.5 percentage points in decile 7 relative to the lowest-uncertainty group.¹⁵

Figure 4: Application Denial Rates and Responses by Loan Purpose (2007–2024)



Notes: HMDA applications from 2007 to 2024. Deciles contain approximately equal numbers of applications ranked by their ZIP-code uncertainty, not equal numbers of ZIP codes. Panel A reports unconditional refinance denial rates for banks and shadow banks. Panel B reports shadow-bank interactions with uncertainty deciles, estimated separately for purchases and refinances with borrower and loan controls, county-year effects and lender-year effects. Each interaction is a change in the shadow-bank-minus-bank denial gap relative to decile 1, not its absolute level. Panel B bars are pointwise 95% county-clustered confidence intervals; separate intervals do not directly test the purchase–refinance difference.

The stronger rise in shadow-bank denial rates with collateral uncertainty also remains after accounting for local housing conditions, borrower demographics, digital access and banking-market characteristics. This difference remains statistically significant in the combined purchase and refinance sample (Appendix Table A20).¹⁶

To assess whether these denial patterns are linked to collateral, we also examine lenders' reported reasons for rejecting applications. Among rejected applications, lenders are more likely to cite collateral as a reason in higher-uncertainty areas, for both purchases and refinances (Appendix Figure A5). These reported reasons provide additional support for a collateral-based explanation of the denial patterns.

The concentration of the differential denial response in refinancing also has a natural valuation explanation. A purchase provides a current transaction price that helps establish the property's value. A refinance has no such price benchmark, so valuation relies more heavily on appraisals and information from comparable properties. When a property is difficult to value, it may be

¹⁵Appendix Figure A4 reports the raw purchase loan comparison.

¹⁶Appendix D.6 reports the full decile estimates, sample changes with additional controls, and supplementary two-stage residual-inclusion estimates.

harder to substantiate a value sufficient to support the requested mortgage. The absence of a transaction price can therefore make refinance approvals particularly sensitive to collateral uncertainty. Appendix [E.2](#) develops this intuition further.

Connecting Application Denials to Local Market Shares Can differences in application denials explain the geographic relationship between collateral uncertainty and shadow-bank market shares? We estimate denial and market-share relationships on matched samples of mortgage products and ZIP-years, using a common uncertainty scale. We calculate how the estimated denial responses translate into shadow banks’ dollar shares relative to banks, shadow banks and other lenders, holding application numbers, the fraction of approvals that become originations, and average loan amounts fixed.

In the matched sample, the denial-based calculation can explain about 28% of the estimated negative relationship between collateral uncertainty and shadow banks’ local dollar shares overall. The corresponding fraction is 74% for refinances, compared with 3% for purchases. Differences in application denials can therefore explain a large part of the spatial differences in shadow-bank refinance market shares associated with collateral uncertainty. Appendix [D.7](#) reports the calculation and confidence intervals.

This finding motivates the next section’s focus on lenders’ origination decisions. We examine why uncertainty about collateral values may lead sale-dependent lenders to reject mortgages that lenders with balance-sheet retention capacity can profitably originate.

4 Mechanism: Why Collateral Uncertainty Matters for Loan Sales

Section [3.2](#) shows that denial rates increase more with collateral uncertainty for shadow banks than for banks, with the clearest response in refinancing. In matched samples, differences in application denials can explain a large part of the uncertainty-related spatial pattern in shadow banks’ refinance market shares. We examine a financing explanation: greater uncertainty about a property’s value can raise the lender’s expected cost of selling the mortgage. If originating for sale becomes unprofitable, a lender that can profitably keep the mortgage on its balance sheet may still approve the application. A lender that relies on selling may reject it instead. The framework applies to both purchases and refinances and explains when differences in retention capacity produce different lending responses to collateral uncertainty.

4.1 Economic Framework

We build on Buchak et al. ([2024](#)), who develop a structural model of banks and shadow banks competing for mortgage borrowers. Banks can originate mortgages either to sell them or to keep them on their balance sheets, while shadow banks rely more heavily on loan sales. We take from

their framework this financing choice and the differences in lenders' costs of keeping mortgages. We use a simpler setting, holding the application and mortgage terms fixed to study the lender's decision to approve or reject.

E. X. Jiang and Zhang (2025) model a borrower choosing a mortgage amount before the property appraisal is known. A low appraisal can reduce the amount the borrower is allowed to borrow under the loan-to-value limit, requiring additional funds or preventing the transaction from proceeding. We take from their framework the uncertain appraisal and the requirement that the property's appraised value support the mortgage amount. We hold the requested amount fixed and examine whether the lender can profitably originate the mortgage by selling it or keeping it on its balance sheet.

To connect collateral uncertainty with loan sales, we allow the lender's expected cost of selling a mortgage to increase with collateral uncertainty. If the property's valuation is difficult to verify, meeting the purchaser's requirements may require additional review. Delays in completing the sale can increase financing costs. Valuation or documentation defects may also require the lender to repurchase the mortgage after selling it.¹⁷ We summarize these additional expenses and expected liabilities in the lender's cost of selling the mortgage. Lenders have the same collateral information and selling terms, but different costs of keeping mortgages.

Mortgage applications and collateral requirement. Consider an application for amount $L > 0$ and purpose p , either purchase or refinance, with fixed borrower characteristics and mortgage terms. In the appraisal-required benchmark, let A be the appraised value and U local collateral uncertainty. The appraisal has distribution $F_A(a; U, p)$ and density $f_A(a; U, p)$; $F_A(a; U, p)$ is the probability of an appraisal at or below a . Purpose matters because a purchase provides a current transaction price, whereas a refinance does not.

The lender observes $A = a$ before lending. It can reject the application or approve and either sell or keep the mortgage. Keeping it on the balance sheet is *retention*. We impose the same collateral requirement for both choices: $L \leq \lambda_p a$, where $0 < \lambda_p \leq 1$ is the maximum loan-to-value ratio. Thus, the minimum eligible appraisal is $e_p = L/\lambda_p$. This common requirement isolates financing costs from differences in eligibility rules.

Profits from selling or keeping the mortgage. Meeting the collateral requirement does not necessarily make a mortgage profitable. Let m_p denote the lender's expected earnings from originating the mortgage before the costs listed below. We use the same baseline earnings for

¹⁷Fannie Mae notes that unresolved appraisal defects can require lenders to repurchase a mortgage or provide another remedy. See Fannie Mae, [Appraiser Update](#), September 2023, p. 4. Appendix E.3 describes these obligations in the U.S. setting.

selling and keeping, with all amounts measured at the same valuation date. Expected profits are:

$$\Pi_p^S(a, U) = m_p - c_{0p}(a) - C_p(a, U), \quad \Pi_{\ell p}^R(a) = m_p - \kappa_\ell - h_p(a). \quad (4)$$

For selling, $c_{0p}(a)$ represents ordinary mortgage-distribution costs. The additional cost $C_p(a, U)$ captures expected expenses and liabilities associated with collateral uncertainty, including further valuation reviews, financing costs from delayed sales, and possible repurchase obligations. This is the cost through which collateral uncertainty can make originating a mortgage for sale less profitable.

For keeping, κ_ℓ represents lender ℓ 's funding and balance-sheet costs, while $h_p(a)$ represents the expected loss of mortgage principal. A lower κ_ℓ makes keeping the mortgage less costly. Banks may therefore have an alternative when selling becomes unprofitable, although keeping costs can also differ among banks and among shadow banks.

We assume that, at a given appraisal, greater collateral uncertainty can increase $C_p(a, U)$, after allowing for compensation through the sale price. We hold expected losses on retained mortgages fixed at that appraisal to isolate the selling-cost channel. Expenses already incurred, such as a completed appraisal, are not counted again. Borrower charges received under either financing choice enter the common earnings term m_p .

Approval and retention capacity. After observing the appraisal, the lender compares the profits from selling and keeping the mortgage. It approves the application if the collateral requirement is satisfied and at least one choice is profitable relative to rejection. If both are profitable, it chooses the one with higher expected profit. If neither is profitable, it rejects.

For a fixed loan amount, a higher appraisal means more collateral backing the same debt. To describe approval decisions using simple thresholds, we assume that once selling becomes profitable, it remains profitable at higher appraisals. We make the same assumption for keeping.

Let $t_p(U)$ be the minimum appraisal that satisfies the collateral requirement and makes selling profitable. Similarly, let $r_{\ell p}$ be the minimum appraisal that satisfies the requirement and makes keeping profitable for lender ℓ . Both thresholds are therefore at least $e_p = L/\lambda_p$. Since the lender needs only one profitable choice, its minimum appraisal for approval is the lower of the two:

$$\tau_{\ell p}(U) = \min\{t_p(U), r_{\ell p}\}. \quad (5)$$

The lender rejects applications with appraisals below this threshold. Its denial probability is

therefore the probability that the appraisal falls below $\tau_{\ell p}(U)$:

$$d_{\ell p}(U) = F_A(\tau_{\ell p}(U); U, p).$$

A lender with low keeping costs may have $r_{\ell p} < t_p(U)$. It can approve and keep mortgages whose appraisals are too low for profitable selling. A lender unable to keep those same mortgages profitably must reject them instead.

When do higher selling costs raise shadow-bank denials more? We now ask when an increase in selling costs caused by collateral uncertainty raises shadow-bank denials more than bank denials, and what determines the size of this difference. A mortgage that becomes unprofitable to sell need not be rejected if the lender can profitably keep it.

To isolate this channel, we hold the appraisal distribution, profits from keeping mortgages, and the number and composition of applications fixed. We compare the same type of application across lenders facing the same appraisal distribution.

For lender group $g \in \{\text{SB}, \text{Bank}\}$, let $D_{g,p}$ be the denial rate, weighting lenders by their applications, and let $\Delta_p = D_{\text{SB},p} - D_{\text{Bank},p}$ be the difference in denial rates. Define $\chi_{g,p} = \Pr_g\{r_{\ell p} > t_p(U)\}$. This is the fraction of applications handled by lenders that cannot profitably keep a mortgage whose appraisal is just sufficient for selling. These applications depend on selling for approval. We call this *marginal sale dependence*, distinguishing it from a lender's overall share of loans sold.

A small increase in the selling threshold changes approvals only for these applications. Writing $t_{p,U} = \partial t_p(U) / \partial U$, the resulting denial-rate response is:

$$\left. \frac{\partial D_{g,p}}{\partial U} \right|_{\text{financing}} = f_A(t_p; U, p) t_{p,U} \chi_{g,p}.$$

Subtracting the bank response from the shadow-bank response gives the following proposition, under the regularity conditions stated in Appendix E.2.

Proposition 1 (Selling costs and the difference in denial rates). *Under these assumptions, the change in the difference between shadow-bank and bank denial rates due to higher selling costs is*

$$\left. \frac{\partial \Delta_p}{\partial U} \right|_{\text{financing}} = f_A(t_p; U, p) t_{p,U} (\chi_{\text{SB},p} - \chi_{\text{Bank},p}). \quad (6)$$

The shadow-bank denial rate rises more than the bank denial rate if uncertainty raises the minimum appraisal for profitable selling, applications have positive density near that minimum, and shadow banks are less able than banks to keep the affected mortgages.

Equation (6) has three drivers:

1. *How much selling becomes harder.* A larger $t_{p,U}$ means a greater increase in the appraisal needed for profitable selling.
2. *Whether lenders have an alternative.* A larger $\chi_{SB,p} - \chi_{Bank,p}$ means more shadow-bank applications depend on selling for approval.
3. *How many applications are affected.* A larger $f_A(t_p; U, p)$ means more appraisals lie near the selling threshold, so the same increase changes more approval decisions.

The proposition describes differences in responses, not which lender group has the higher denial rate. It holds the appraisal distribution and the profitability of keeping mortgages fixed; changes in either could reinforce or offset the selling-cost response. Appendix E.2 provides the derivations.

From approvals to lending shares. A stronger denial response can reduce shadow banks' market share when their originations fall proportionately more than banks' originations. Let σ_p denote shadow banks' share of originations by banks and shadow banks, with both groups originating loans. Holding application numbers, average loan amounts and the fraction of approvals that become originations fixed, the selling-cost channel gives:

$$\left. \frac{\partial \sigma_p}{\partial U} \right|_{\text{financing}} = -\sigma_p(1 - \sigma_p) f_A(t_p; U, p) t_{p,U} \times \left[\frac{\chi_{SB,p}}{1 - D_{SB,p}} - \frac{\chi_{Bank,p}}{1 - D_{Bank,p}} \right]. \quad (7)$$

When uncertainty raises the selling threshold and applications have positive density near it, the shadow-bank share falls if $\chi_{SB,p}/(1 - D_{SB,p}) > \chi_{Bank,p}/(1 - D_{Bank,p})$. Marginal sale dependence is divided by each group's approval rate because the same percentage-point increase in denials removes a larger proportion of originations when fewer applications were initially approved. Shadow-bank denial rates need not initially exceed bank denial rates for this condition to hold.

Banks can gain relative market share without increasing their lending or absorbing borrowers rejected by shadow banks. At fixed average loan amounts, the same reasoning applies to dollar shares.

The next section takes the model to the data and tests some hypotheses derived from the economic framework.

4.2 Empirical Test of the Mechanism Framework

The model explains why higher selling costs can lead lenders with limited capacity to keep mortgages to reject applications they would otherwise approve. We now examine this financing explanation. First, we test whether shadow banks that historically sell a larger fraction of their mortgages increase denials more strongly with collateral uncertainty. Second, we examine how

banks and shadow banks adjust the fraction of originated mortgages they keep rather than sell. Finally, we investigate whether collateral uncertainty is associated with additional valuation requirements, longer sale delays and greater repurchase risk. Together, these tests connect lenders' alternatives to selling with the costs and risks of mortgage distribution.

4.2.1 Loan-Sale Dependence and Lending Decisions

One of the hypotheses outlined in our economic framework suggests that shadow banks are heterogeneously affected by collateral uncertainty frictions. The shadow bank sector comprises a diverse set of lenders and business models. In the model, collateral uncertainty is more likely to affect lending by shadow banks with higher retention costs (κ_ℓ), as these lenders have less ability to substitute retention for loan sales. Consistent with the model's mechanism, we restrict attention to shadow banks, whose ability to originate mortgages depends primarily on their ability to sell them and focus exclusively on refinance applications, where this friction should be most binding.

To capture this heterogeneity, we measure a lender's dependence on the originate-to-distribute (OTD) model using the fraction of its loans sold within the same year, averaged over the preceding three years. Because retention costs and balance-sheet capacity are not directly observed, this measure serves as a proxy for a lender's ability to retain mortgages rather than sell them. Crucially, it is constructed excluding the application county, ensuring that it is orthogonal to local geographic conditions. Within the shadow bank group, greater reliance on loan sales should make lending decisions more sensitive to collateral uncertainty.

To address lender sorting concerns and formally test whether OTD-dependent shadow banks are more severely affected, we estimate Equation 8. In this specification, we replace the binary shadow bank indicator with our continuous measure of lender OTD reliance and restrict the sample strictly to shadow bank refinance applications. Because our definition of OTD share requires a multi-year lookback period, two years of historical data are lost, shifting the sample start year to 2009. The model incorporates county-by-year fixed effects ($\alpha_{c,t}$), lender-by-year fixed effects ($\eta_{\ell(i),t}$), and a comprehensive vector of loan- and borrower-level controls ($\mathbf{W}_i$):

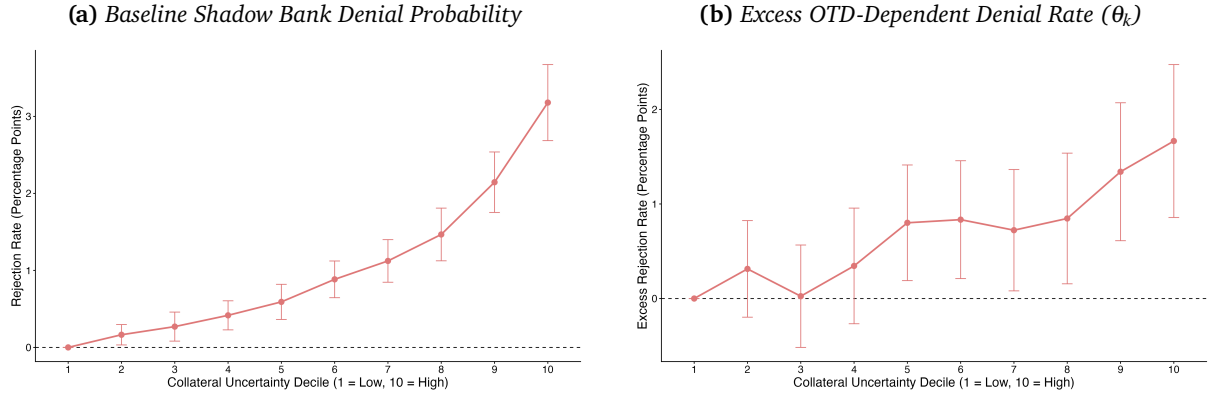
$$100\text{Denied}_{i,z,t} = \sum_{k=2}^{10} \beta_k \mathbb{I}(U_{z,t} = k) + \sum_{k=2}^{10} \theta_k (\text{OTD}_{\ell(i),t} \times \mathbb{I}(U_{z,t} = k)) + \rho \text{OTD}_{\ell(i),t} + \mathbf{W}_i' \boldsymbol{\gamma} + \alpha_{c(z),t} + \eta_{\ell(i),t} + \varepsilon_{i,z,t}. \quad (8)$$

Figure 5 illustrates the empirical results from estimating Equation 8 on shadow bank refinance applications. Panel (a) plots the overall relationship between collateral uncertainty deciles and denial rates (β_k). Importantly, these coefficients are estimated from a specification omitting the OTD share variable and its interaction terms. The figure demonstrates that baseline shadow

bank denial rates increase non-linearly with collateral uncertainty. Overall, this shadow bank subsample analysis reaffirms our earlier findings, demonstrating that shadow banks are substantially more sensitive to collateral uncertainty in the refinance market.

Turning to Panel (b) of Figure 5, we examine the interaction coefficients (θ_k), which isolate the excess denial likelihood of OTD-dependent shadow banks across uncertainty deciles relative to the omitted baseline (Decile 1). The estimates reveal that originate-to-distribute dependence—acting as a proxy for low loan retention capacity (κ_ℓ)—makes shadow banks significantly more sensitive to collateral uncertainty. Excess denial rates exhibit a non-linear upward trajectory, climbing from near zero in Decile 1 to approximately 1.6 percentage points in Decile 10. Ultimately, this heightened sensitivity confirms that limited retention capacity serves as a primary transmission channel restricting shadow bank credit allocation in uncertain environments.

Figure 5: Shadow Bank Denial Probability and Excess OTD-Lender Denial (2009 - 2024)



Notes: This figure plots regression estimates from equation (8) using shadow bank refinance application-level data from 2009 to 2024. Panel (a) displays the overall relationship between uncertainty bins and rejection rates (β_k). Note that in this specification, we estimate equation (8) without the OTD share interaction and variable. Panel (b) plots the interaction coefficients (θ_k), capturing the excess rejection likelihood of OTD-dependent lenders across uncertainty deciles. The lowest uncertainty decile (Decile 1) serves as the omitted baseline. All specifications include county-by-year fixed effects ($\alpha_{c,t}$), lender-by-year fixed effects ($\eta_{l(i),t}$), and rich loan-level and borrower-level controls ($\mathbf{W}_i$). Vertical bars represent 95% confidence intervals with standard errors clustered at the county level.

OTD Model and Lender Refinance Specialization Since collateral uncertainty disproportionately affects refinance applications, we naturally expect this friction to be particularly pronounced for lenders that specialize in refinancing. To investigate whether the OTD business model effect is stronger for refinance-dependent lenders, we construct a parallel measure using the share of originated loans that are refinance mortgages, averaged over the prior three years and excluding the application county.

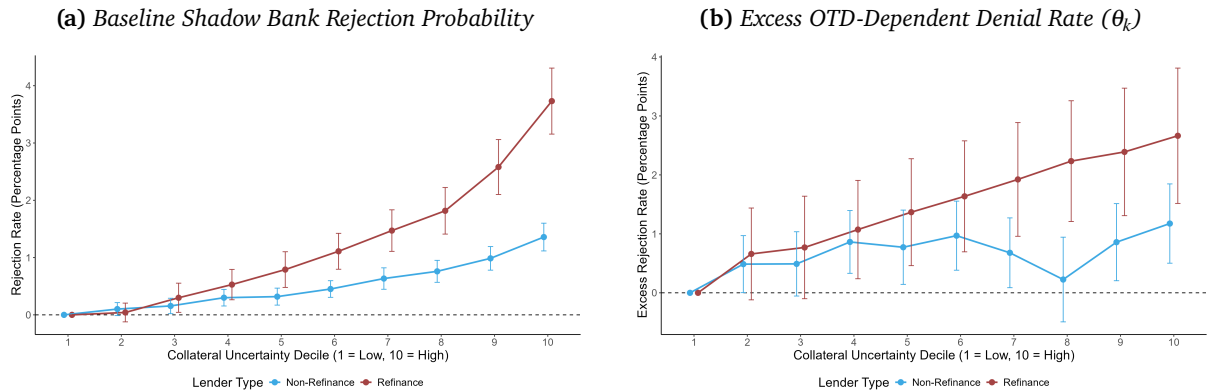
Equipped with this measure, we evaluate application denial behavior by lender refinance specialization. Specifically, we partition the shadow bank sample into two groups based on lender refinance share: refinance-specialized lenders (those with a refinance share exceeding 66%) and non-refinance lenders (those with a share of 33% or lower). We then re-estimate Equation 8

separately for these subsamples to examine how the effect of collateral uncertainty varies by business model specialization.

Figure 6 depicts the resulting patterns across collateral uncertainty deciles for both lender types. Panel (a) displays the overall denial rate trajectory across uncertainty bins for refinance versus non-refinance lenders, showing that collateral uncertainty is significantly more binding for refinance-specialized lenders, whose denial rates increase sharply in high-uncertainty neighborhoods. Notably, this specification is estimated without the OTD share interaction terms, capturing the baseline effect of collateral uncertainty.

Panel (b) plots the excess denial rates of OTD-dependent lenders across uncertainty deciles for both groups (θ_k). Taken together, these patterns provide compelling evidence for the valuation friction mechanism. Panel (a) highlights that refinance-specialized lenders face a much steeper penalty in high-uncertainty markets because refinance loans lack a contemporaneous market transaction price, making these lenders acutely exposed to appraisal noise and collateral risk. Panel (b) demonstrates that this vulnerability is further amplified for lenders with high OTD business model dependence; OTD-dependent lenders within the refinance-specialized sample exhibit a pronounced, upward-sloping excess denial trajectory as collateral uncertainty increases. This confirms that secondary-market distribution constraints and warehousing risks make OTD lenders especially unwilling to absorb hard-to-value collateral, forcing them to curtail credit precisely when valuation frictions are most severe.

Figure 6: Shadow Bank Denial Rates and Excess Denials by Lender Refinance Specialization (2009 - 2024)



Notes: This figure presents regression estimates using shadow bank application-level data (refinance and purchase) from 2009 to 2024, split by lender refinance specialization. Refinance-specialized lenders are defined as those with a refinance share exceeding 66%, while non-refinance lenders have a share of 33% or lower. Panel (a) displays the baseline denial rate across collateral uncertainty deciles for both groups. Note that in this specification, we estimate equation (8) without the OTD share interaction and variable. Panel (b) plots the excess denial rate across uncertainty deciles. The lowest uncertainty decile (Decile 1) serves as the omitted baseline. All models include county-by-year fixed effects, lender-by-year fixed effects, and a comprehensive set of loan-level and borrower-level controls. Vertical bars represent 95% confidence intervals with standard errors clustered at the county level.

To further contextualize these findings, the high-OTD, refinance-specialized shadow banks are, in practice, predominantly fintech lenders. As established by Fuster et al. (2019), technology-

driven lenders are in particular active in the refinance market, where they have a comparative advantage through their faster processing time. Moreover, fintechs are predominantly dependent on the OTD market (Buchak et al. (2024)). Thus, a key implication of our analysis is that fintechs are particularly strongly affected by collateral uncertainty.

Appendix Tables A24 and A25 provide formal statistical tests for the amplification effect of OTD-dependent lenders. In these specifications, we replace the uncertainty bins with continuous measures of collateral uncertainty while maintaining our core empirical design. For each sample—comprising the full dataset, purchase mortgages, and refinance mortgages—we estimate two specifications: first, a baseline specification featuring county-by-year and lender-by-year fixed effects alongside comprehensive application-level controls; second, an extended specification that incorporates the regulatory shock controls of Buchak et al. (2018) and Gete and Reher (2021). Table A24 presents the results for all shadow banks, while Table A25 reports the estimates across the refinance-specialized lender split (high versus low refinance share). Both sets of tables robustly corroborate our findings.

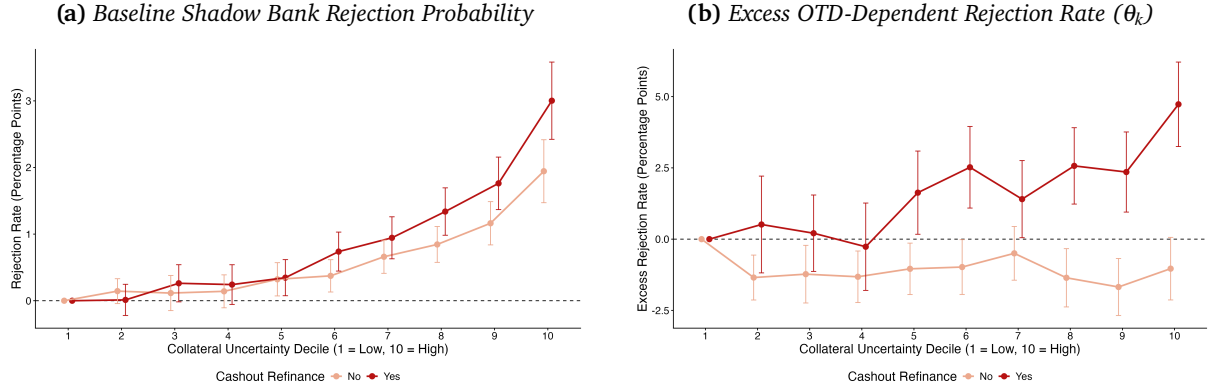
Cash-out vs. Non-Cash-out Refinancing HMDA data since 2018 allows us to distinguish refinance applications into cash-out and non-cash-out categories. Cash-out applications allow the borrower to increase their mortgage amount, thereby raising the loan-to-value (LTV) ratio. Given our mechanism, we would expect collateral uncertainty to be most binding for cash-out refinance applications. To test this, we examine post-2018 refinance applications more closely by re-estimating equation 8 separately for cash-out and non-cash-out loans. Importantly, because HMDA provides additional controls starting in 2018, we include debt-to-income (DTI) and LTV bins as supplementary controls. We thus capture borrower risk using these variables alongside LTI and LTI squared.¹⁸

Figure 7 presents the results. The left plot shows baseline denials without the OTD interaction variable. Denials increase for both types of refinance loans, with a slightly stronger increase for cash-out loans. The right plot displays excess OTD denials. We observe that OTD-dependent lenders excessively reject cash-out applications facing higher collateral uncertainty. Going from the lowest decile to the highest, the effect increases by approximately 4 percentage points. This figure provides additional evidence for our mechanism: OTD-dependent lenders—our proxy for balance sheet capacity—specifically refrain from originating cash-out refinance applications due to their reluctance regarding LTV valuation uncertainty. Crucially, because our identification controls for LTV bins, this excess denial behavior cannot be explained by differences in borrower risk or baseline loan leverage. In line with our model, it is most likely driven by uncertainty

¹⁸The formal regression table is provided in the Appendix Table A26.

around the LTV and the capacity to handle this.

Figure 7: Collateral Uncertainty and Refinancing: Cashout vs Non-Cashout (2018 - 2024)



Notes: This figure presents regression estimates using shadow bank refinance application-level data from 2018 to 2024, split by cash-out status. Panel (a) displays the baseline denial rate across collateral uncertainty deciles for both groups. Note that in this specification, we estimate equation (8) without the OTD share interaction variable. Panel (b) plots the excess denial rate across uncertainty deciles. The lowest uncertainty decile (Decile 1) serves as the omitted baseline. All models include county-by-year fixed effects, lender-by-year fixed effects, and a comprehensive set of loan-level and borrower-level controls, which include LTV and DTI bins. Vertical bars represent 95% confidence intervals with standard errors clustered at the county level.

4.2.2 Retention Capacity of Banks versus Shadow Banks

Following our theoretical framework, higher collateral uncertainty (U) raises appraisal-dependent selling costs, $C_p(a, U)$, thereby increasing the sale cutoff threshold, $t_p(U)$. Because traditional banks face lower balance-sheet retention costs ($\kappa_{\text{Bank}} < \kappa_{\text{SB}}$), they can profitably absorb loans that shadow banks must offload. Consequently, as uncertainty rises, banks' comparative advantage in retention capacity leads to higher relative loan retention rates.

We test this prediction using a linear probability model analogous to Equation 14, replacing the mortgage denial indicator with a measure of loan retention. Specifically, we examine all refinance mortgages originated by traditional banks and shadow banks from 2007 to 2024, where the dependent variable is an indicator equal to one if a loan was retained on the balance sheet and zero otherwise.¹⁹ To isolate the effect of uncertainty on retention margins across lender types, we employ our rigorous baseline identification strategy, incorporating county-by-year fixed effects, lender-by-year fixed effects, and a comprehensive suite of borrower and loan controls.

The interaction coefficients (θ_k) map directly to the model's comparative statics, measuring how the shadow bank retention margin adjusts relative to traditional banks when moving from the omitted baseline uncertainty bin to higher deciles. Consistent with the model, we expect $\theta_k < 0$ in high-uncertainty bins, reflecting the superior balance-sheet absorption capacity of banks when secondary-market selling frictions intensify.

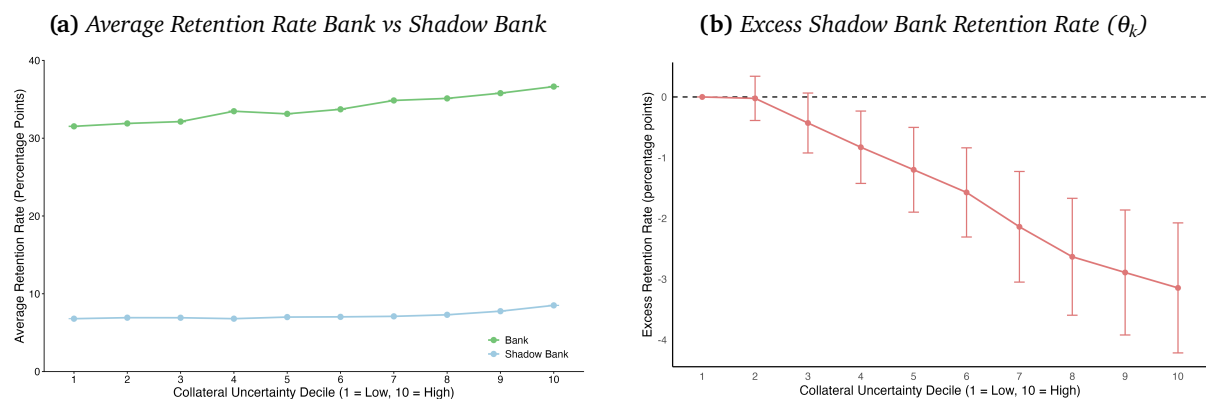
¹⁹Note that HMDA data only identifies sold mortgages if they are sold within the same calendar year; consequently, some loans classified as retained may be sold in subsequent periods.

This test serves as a natural complement to our approval-margin findings: if higher collateral uncertainty increases selling frictions and banks can absorb loans onto their balance sheets at lower cost, differences in retention capacity emerge as a primary mechanism driving lender-type divergences in credit supply.

Figure 8 illustrates the differential retention capacity of banks and shadow banks for refinance applications. Panel (a) plots average retention rates by collateral-uncertainty decile. Banks retain a substantial share of the loans they originate, and this share rises from 31.5% in Decile 1 to 36.6% in Decile 10. Shadow bank retention is an order of magnitude lower and far less responsive: it stays at roughly 7% across most of the distribution and increases only modestly, to 8.5%, in the highest decile. This contrast underscores the shadow banks' structural reliance on secondary-market distribution rather than balance-sheet absorption.

Panel (b) reports the shadow-bank retention differential relative to banks, estimated from the interaction terms (θ_k) by collateral-uncertainty decile. Because Decile 1 is the omitted category, each θ_k measures how much more (or less) shadow-bank retention changes between Decile 1 and Decile k than bank retention does, conditional on the full set of controls and fixed effects. Negative coefficients therefore imply that, as uncertainty rises, shadow banks increase retention by less than banks do, so the retention gap between the two lender types widens. The estimates show a pronounced, nearly monotonic widening across uncertainty tiers, reaching about -3.2 percentage points in Decile 10. This is in line with the raw averages in Panel (a), where banks' retention rises by about 5.1 percentage points between Decile 1 and Decile 10 and shadow banks' by about 1.7. As uncertainty rises and sale-related frictions intensify, the relative value of banks' balance-sheet retention capacity increases.

Figure 8: Mortgage Retention Capacity: Bank vs Shadow Bank (2007–2024)



Notes: This figure uses refinance mortgage originations from 2007 to 2024. Panel (a) plots raw average retention rates (in percentage points) by collateral-uncertainty decile for banks and shadow banks. Panel (b) plots the excess shadow-bank retention rate relative to banks (θ_k), estimated from the interaction between lender type and collateral-uncertainty decile, with Decile 1 (the lowest uncertainty) as the omitted baseline. The regression includes county-by-year fixed effects, lender-by-year fixed effects, and loan- and borrower-level controls (log income, log loan amount, loan-to-income ratio and its square, conforming status, loan type, race, and sex). Vertical bars in Panel (b) represent 95% confidence intervals based on standard errors clustered at the county level.

Appendix Table A27 provides formal OLS estimates of the excess loan retention rate for traditional banks relative to shadow banks using our continuous measure of collateral uncertainty. We further incorporate the regulatory shock controls of Buchak et al. (2018) and Gete and Reher (2021) as robustness checks. The negative and statistically significant interaction coefficients (θ) confirm that as collateral uncertainty increases, shadow banks experience a sharp relative decline in balance-sheet retention compared to traditional banks.

4.2.3 Collateral Uncertainty and Loan-Sale Frictions

We next provide direct evidence on the channels through which collateral uncertainty raises the expected cost of loan sale, $C_p(a, U)$. First, we show that greater uncertainty reduces the likelihood of appraisal waivers, increasing upfront appraisal costs and delays. Second, we find that uncertainty increases post-sale repurchase (putback) risk from GSEs, exposing originators to greater tail liabilities. Third, we provide evidence that uncertainty lengthens time to sale, tying up capital on warehouse lines of credit and increasing interim financing costs. Together, these findings support $C_{p,U} \geq 0$, increasing the minimal appraisal threshold for profitable selling, $t(U)$, and widening the shadow-bank denial gap in uncertain markets.

To investigate these costs, we rely on the Fannie Mae dataset. For our main results we focus on refinance loans. This dataset allows us to examine appraisal waivers, putbacks, and the time to sale.²⁰ Crucially, this dataset only provides 3-digit ZIP code-level regional information; therefore, our measure of collateral uncertainty will also be aggregated to the 3-digit level. Moreover, instead of relying on county-by-year identification, we use commuting-zone fixed effects since 3-digit ZIP codes span multiple counties.²¹

Valuation requirements First, we investigate how idiosyncratic housing markets affect automated valuation models. Using Fannie Mae loan-level data from 2017 to 2024, we examine the relationship between the probability of an appraisal waiver²² and our 3-digit ZIP code measure of collateral uncertainty. We restrict our sample to begin in 2017 because the Fannie Mae dataset systematically reports appraisal waivers starting from this year onward.

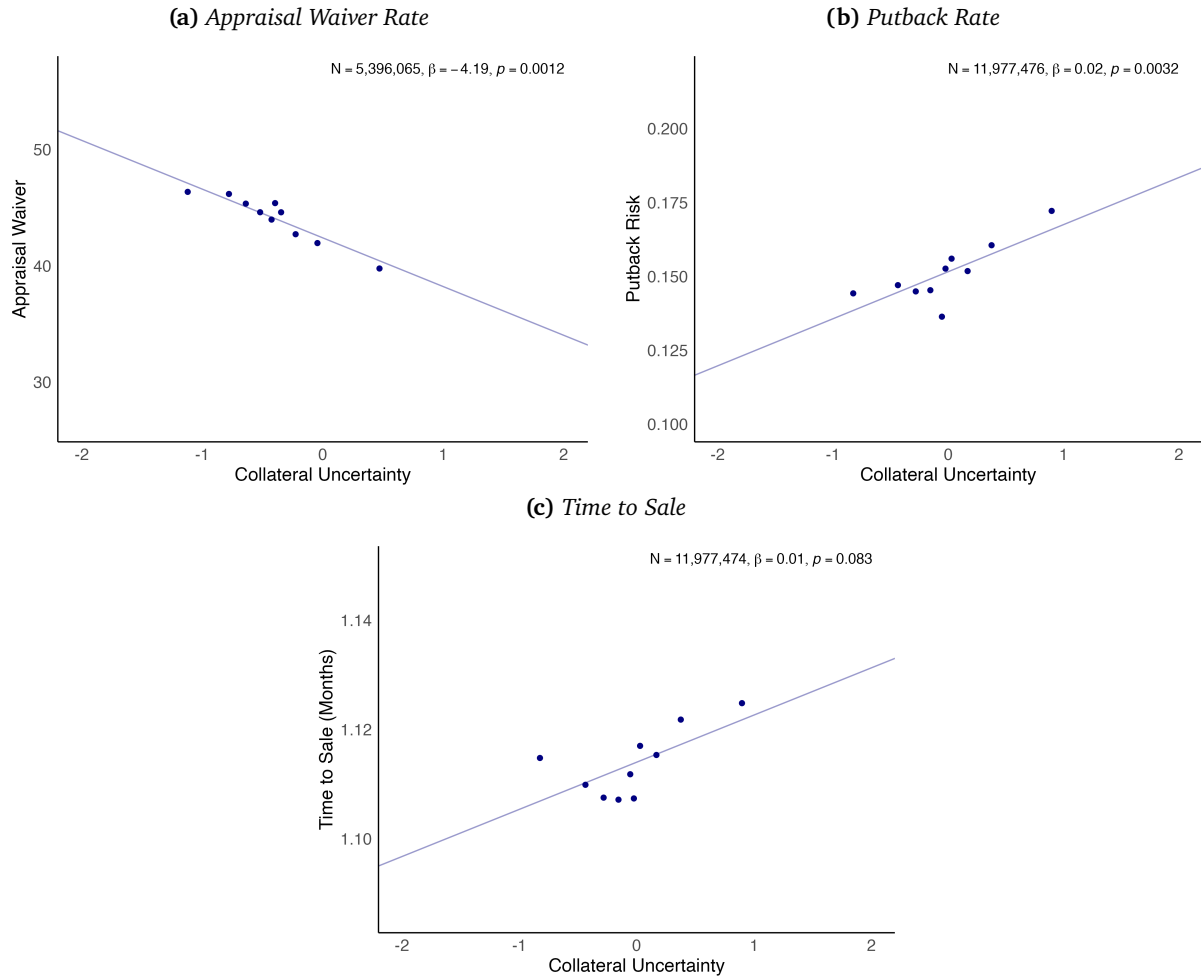
Figure 9, Panel (a), presents a binned scatter plot of this relationship using refinance loans from 2017 to 2024. To isolate the effect of collateral uncertainty, the plot absorbs commuting-zone-by-quarter-by-year fixed effects to account for unobserved regional demand shocks, while controlling for average loan characteristics within the 3-digit ZIP code—specifically log loan

²⁰In contrast to the Freddie Mac dataset, we observe the origination and selling date; thus, we are able to estimate the time to sale.

²¹For more information on the Fannie Mae dataset, see Section 2 and Appendix B.

²²We define appraisal waiver, if the reported "Property Valuation Method" is either C: 'Appraisal Waiver plus Property Data Collection', 'P': 'Appraisal Waiver plus Property Data Collection', or 'W': 'Appraisal Waiver'.

Figure 9: Collateral Uncertainty and Loan-Sale Frictions



Notes: This figure plots residualized collateral uncertainty against appraisal-waiver probability in Panel (a), putback risk in Panel (b), and time to sale, measured in months, in Panel (c). The appraisal-waiver Panel uses Fannie Mae refinance loans originated from 2017 to 2024, while the putback-risk and time-to-sale panels use refinance loans originated from 2007 to 2024. All variables are residualized with respect to commuting-zone-by-quarter-year fixed effects and the loan- and borrower-level controls included in the corresponding regressions. Collateral uncertainty is standardized to have a mean of zero and a standard deviation of one.

amount, log loan maturity, FICO score and its square, loan-to-value (LTV) and debt-to-income (DTI) bins, a refinance indicator, and a first-time homebuyer indicator.²³ The figure reveals a clear negative relationship: greater collateral uncertainty is associated with a lower probability of appraisal waivers.

Appendix Table A28 provides formal statistical estimates for the appraisal waiver rate. Because the outcome is binary, we estimate the model using both OLS and Poisson Pseudo-Maximum Likelihood (PPML) across the full sample, as well as separate subsamples for purchase (non-refinance) and refinance mortgages. The coefficient on collateral uncertainty remains negative and statistically significant across all specifications. Under the linear specification for the full sample, a one-standard-deviation increase in collateral uncertainty is associated with a 3.09 percentage point decrease in the appraisal waiver probability. Given a sample mean appraisal waiver rate of 29.21%, this constitutes a roughly 10.5% relative decrease. The negative association is even stronger in absolute terms for refinance loans, where a one-standard-deviation increase in collateral uncertainty reduces the waiver probability by 4.18 percentage points; however, the baseline mean for refinances is higher at 44.08%.

A natural question is why lower appraisal waiver rates constitute a friction for lenders, given that borrowers typically pay out-of-pocket for traditional appraisals. We argue that appraisal requirements impose significant indirect frictions on lenders through three main channels. First, traditional appraisals introduce operational and administrative delays, increasing warehouse line costs and slowing pipeline velocity. Second, appraisal shortfalls increase deal fallout, destroying upfront origination investments when transactions collapse or require renegotiation. Third, traditional appraisals expose lenders to post-closing repurchase and putback risk from the GSEs if valuation defects are later uncovered—a liability that appraisal waivers completely eliminate.²⁴

Liability after sale. The OTD model depends on rapidly re-investing capital by selling newly originated loans to GSEs. Within this pipeline, collateral uncertainty transforms from a standard underwriting friction into a severe secondary market risk. While the OTD framework historically insulated originators from direct credit losses (Purnanandam, 2011), the modern institutional landscape leaves them acutely exposed to post-sale repurchase (or putback) risk if valuation errors are later uncovered (Fuster et al., 2013; McCoy & Wachter, 2017; Piskorski, Seru, & Witkin,

²³Note that we omit lender-year fixed effects. Lender identifiers in the Fannie Mae dataset are suppressed and reported as "Other" for any institution representing less than 1% of quarterly origination volume, restricting explicit lender-level tracking to a select subset of top nationwide issuers. For the same reason, we cannot distinguish between traditional bank and shadow bank lenders.

²⁴Fannie Mae: A2-2-06, Representations and Warranties on Property Value: According to Fannie Mae's framework, when a lender exercises a appraisal waiver, Fannie Mae formally relieves the lender of standard representations and warranties regarding value, marketability, and physical property characteristics.

2015).²⁵

Figure 9, Panel (b), presents a binned scatter plot of the putback rate (e.g., share of post-sale repurchase) using refinance loans from 2007 to 2024. We again account for commuting-zone-by-quarter-by-year fixed effects and for the same loan-level characteristics as above. The figure reveals a clear positive relationship: greater collateral uncertainty is associated with a higher rate of loan repurchases (putbacks).

Appendix Table A29 provides the formal statistical tests for putback risk. Because loan repurchases are rare events with low unconditional prevalence (sample average of 0.16%), Poisson Pseudo-Maximum Likelihood (PPML) estimation is particularly important alongside OLS to properly account for the skewed dependent variable. We estimate the model across the full sample, as well as separate subsamples for purchase and refinance mortgages.

The empirical results confirm that higher collateral uncertainty significantly increases the incidence of post-sale putback risks, adding a major cost component to $C_p(a, U)$. Specifically, the linear specification for the refinance sample suggests that a one-standard-deviation increase in collateral uncertainty is associated with a 0.016 percentage point increase in the probability of a putback, which is roughly 11% of the sample mean (given a baseline mean of 0.15%). Moving from the 10th to the 90th percentile of collateral uncertainty—a 2.56-standard-deviation increase—raises the probability of a putback by approximately 0.041 percentage points, representing an increase of about 27% relative to the baseline incidence. Given the low frequency of putbacks, PPML is arguably the more appropriate specification, with these estimates confirming a robust exponential increase. A one-unit increase in collateral uncertainty is associated with a statistically significant 10.9% increase in the expected incidence of loan putbacks ($\exp(0.103) - 1$). Furthermore, comparing across loan purposes reveals that this uncertainty-driven repurchase risk is weakly more pronounced for refinance mortgages than for non-refinance purchase loans, especially the PPML coefficient.

Timing and interim financing. Third, we examine the duration a loan remains on the originator's balance sheet before being successfully acquired by the secondary market. This test is our proxy for the warehouse funding channel. For shadow banks operating an OTD model, warehouse lines of credit are the primary source of origination capital (Kim et al., 2018).²⁶ When collateral valuations are uncertain, GSE automated underwriting systems (such as Fannie Mae's

²⁵In Senate [testimony](#) on HARP refinancing, Quicken Loans CEO Bill Emerson reported that appraisal disputes had led to repurchase demands and additional appraisal and loan-to-value restrictions. See Senate Banking Committee, May 24, 2012, S. Hrg. 112-709, pp. 23–24. The testimony concerns HARP refinancing, including underwater mortgages.

²⁶Warehouse financing can depend on the loan's eligibility for subsequent sale. For example, Rocket Mortgage's August 2022 agreement with JPMorgan requires eligible loans to be saleable to an approved investor and supported by an agency-acceptable appraisal or permitted alternative. See the [First Amended and Restated Master Repurchase Agreement](#), August 11, 2022, Section 2(a), definition of Eligible Mortgage Loan, and Exhibit B(z).

Collateral Underwriter) are significantly more likely to flag the appraisal for manual review or dispute. Clearing these secondary market conditions requires additional documentation, human intervention, and negotiation.²⁷ These frictions delay the loan's acquisition, trapping capital on the shadow bank's balance sheet and accumulating costly warehouse interest expenses. Moreover, extended time-to-sale exposes shadow banks to severe "aging risk." Tardy sales trigger additional interest, margin calls, penalties, and higher future equity haircuts, and warehouse contracts may eventually force the outright removal of aging loans (Kim et al., 2018).

Figure 9, Panel (c), presents a binned scatter plot illustrating this time-to-sale relationship for refinance loans from 2007 to 2024. To isolate the effect of collateral uncertainty, the plot again absorbs commuting-zone-by-quarter-by-year fixed effects while controlling for rich loan-level characteristics. The figure reveals a positive relationship, showing that greater collateral uncertainty extends the time required to sell refinance mortgages.

Appendix Table A30 provides the formal statistical tests for time-to-sale outcomes. Consistent with the lack of a contemporaneous price anchor for refinances, the positive relationship between collateral uncertainty and time-to-sale is weakly statistically significant exclusively for the refinance subsample, whereas the estimates for non-refinance purchase loans are statistically indistinguishable from zero.

Because origination and sale dates are observed only at a monthly frequency rather than at the daily level, our time-to-sale measure contains inherent measurement noise, limiting the precision with which small delays can be detected. For example, a one-day increase in the average time to sale would generally not change the recorded number of months for most loans. Nevertheless, we estimate a robust and weakly statistically significant effect: a one-standard-deviation increase in collateral uncertainty is associated with an approximately 0.009-month increase in time to sale for refinance loans. Relative to the sample mean of 1.11 months, this corresponds to an increase of approximately 0.8%, indicating a modest but measurable slowdown in pipeline velocity.

To mitigate concerns regarding bunching and data coarseness at the monthly level, we further examine whether collateral uncertainty increases the likelihood of extended pipeline delays. Specifically, we examine whether collateral uncertainty increases the probability that a refinance loan takes longer than two months to sell. Appendix Table A30, Columns 4 and 5, report the OLS and PPML estimates, respectively. Both estimates are positive and statistically significant.

The OLS estimate implies that a one-standard-deviation increase in collateral uncertainty raises this probability by 0.178 percentage points. Relative to the baseline incidence of approximately 3.97 percent, this represents an increase of about 4.5 percent. A move in collateral

²⁷ See Fannie Mae Collateral Underwriter Fact Sheet [Lender Letter LL-2015-02](#): "Fannie Mae expects the lender to use human due diligence in combination with the CU feedback" (p. 2).

uncertainty from its 10th to 90th percentile—a 2.56-standard-deviation increase—is associated with a 0.46-percentage-point increase in the probability of an extended delay. Relative to the baseline incidence, this is an increase of about 11.5 percent. The PPML estimate implies a 4.3 percent increase in expected incidence, closely corroborating the OLS result. Thus, collateral uncertainty is associated with a higher likelihood of extended pipeline delays.

4.2.4 Can the Loan-Sale Frictions Account for the Excess Denial Rates?

To evaluate the economic magnitude of our estimated loan-sale frictions, we assess whether these costs can quantitatively explain the excess denial rates observed for shadow banks in the data.

Time to Sell As established above, higher collateral uncertainty increases the probability that a lender must hold a newly originated mortgage on its balance sheet for an extended period. Specifically, the likelihood that a loan takes longer than three months to sell rises with collateral uncertainty. While the unconditional increase in this probability may appear small, the potential economic impact on thinly capitalized originators is sizable. Thus, it increases the potential tail risk.

For a shadow bank facing a conservative 2.7% annualized warehouse funding rate,²⁸ holding a typical \$284,000 mortgage²⁹ for three months instead of the 1.1-month average increases direct interest expenses from roughly \$703 to \$1,917. The resulting \$1,214 incremental cost absorbs 81–43% of the typical \$1,500–\$2,800 net gain-on-sale profit of an independent mortgage³⁰. This calculation is conservative: delayed sales may also trigger penalty interest rates (Kim et al., 2018). Because shadow banks rely heavily on commercial banks for warehouse funding (E. X. Jiang, 2023), these penalties further increase the cost of prolonged loan retention.

Furthermore, this delay acts as a punitive liquidity tax. As detailed by Kim et al., 2018, warehouse lines typically provide advance rates of around 95%, requiring the originator to post a 5% equity haircut. Delayed sales can trigger immediate margin calls and higher future haircuts, making the origination even more equity-intensive. Therefore, loans stuck in the pipeline trap scarce capital, preventing the shadow bank from recycling that equity to fund new originations. In contrast, traditional banks, shielded by stable, low-cost deposit funding, can easily absorb these delays without tying up their origination capacity. To protect their razor-thin margins and preserve warehouse liquidity, shadow banks must preemptively reject marginal applicants in

²⁸Average warehouse credit costs are based on Kim et al., 2018 and are roughly in line with the approximations reported by Gete and Reher, 2021 for the 2013 to 2015 period.

²⁹This reflects the average mortgage amount in our originated sample; see Table A3.

³⁰Net gain-on-sale estimates are drawn from historical averages in the Mortgage Bankers Association's *Quarterly Mortgage Bankers Performance Reports*.

high-uncertainty segments, driving the stark institutional divergence in credit supply.

Putback Risk Higher collateral uncertainty also increases exposure to putback risk. A putback imposes two distinct costs on shadow banks. First, the lender must repurchase the loan and finance it until it can be resold. Even assuming that resale takes only one month, financing a typical \$284,000 mortgage at a 2.7% annualized warehouse rate entails approximately \$639 in additional interest expense. Second, a loan repurchased following an appraisal dispute may need to be liquidated in the scratch-and-dent market, where estimated haircuts range from 5% to 7% (Goodman, Zhu, & Neal, 2023). At the lower end of this range, a 5% haircut on a \$284,000 mortgage implies a \$14,200 capital loss. Including the additional financing cost, a single putback can therefore erase the gain-on-sale profits from approximately five to ten successful originations ($(\$14,200 + \$639)/\$2,800 \approx 5.3$). This large downside relative to origination margins makes even small increases in putback risk economically meaningful for shadow banks.

5 Conclusion

Nonbank mortgage lending has expanded strongly in the United States, but that expansion has been uneven across local markets. We show that collateral valuation uncertainty helps explain this pattern: shadow banks have lower market shares and expand more slowly in markets where collateral is harder to value. Their rejection rates also rise disproportionately with collateral uncertainty. We trace these patterns to lenders' reliance on loan sales. When uncertainty raises the cost of selling a mortgage, lenders with limited retention capacity become less willing to originate, while banks can instead retain the loan. Consistent with this mechanism, collateral uncertainty matters most for shadow banks that rely heavily on originate-to-distribute financing, while banks increasingly retain loans as uncertainty rises

Our findings highlight a limit to the scalability of originate-to-distribute lending. Loan sales allow lenders to expand without substantial balance-sheet capacity, but this model becomes less effective where collateral is difficult to value and loans are harder to sell. This friction can generate persistent differences in the geographic and product-market presence of lenders with different intermediation models, even when they face similar borrowers' risk.

The implications are particularly important for shadow banks that specialize in refinancing, including fintech mortgage lenders. Refinances lack a current transaction price, making collateral valuation more dependent on appraisals and comparable sales. In high-uncertainty markets, some mortgages may therefore remain unprofitable to originate for sale, even when technology lowers origination costs. Borrowers in these areas may consequently have less access to the faster processing and other efficiencies offered by fintech lenders. Local collateral conditions can thus limit the geographic reach of fintech lending and lead to an uneven distribution of its benefits.

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Supplemental Appendix for “Collateral Uncertainty and the Limits of Shadow-Bank Mortgage Lending”

A Construction and Validation of the Collateral Uncertainty Measure

This section provides additional information about the collateral uncertainty measure introduced in Section 2.

A.1 Construction of the Collateral Uncertainty Measure

To capture local variations in collateral value and market liquidity, we follow the methodology established by E. X. Jiang and Zhang (2025) to construct a ZIP-code-year measure of housing collateral uncertainty, estimating the property-level models separately within counties. Uncertainty in the housing market is closely tied to the degree of asymmetric information and valuation dispersion inherent in property transactions. In thin markets, properties often exhibit substantial pricing dispersion, which lenders perceive as heightened collateral risk when evaluating mortgage applications. For an in-depth discussion of the construction, we refer to the paper Amaral and Ruzzier (2026); we use exactly the same data as in this paper. Subsequently, we outline a condensed methodology.

Property-Level Pricing Errors We begin by estimating expected house price dispersion at the individual property transaction level. For each county separately, we run a hedonic regression of the natural logarithm of transaction prices on a comprehensive set of fixed effects and property characteristics:

$$\ln(p_{i,t_q}) = \delta_m + \alpha_{z,t_q} + f_c(x_i, t_y) + u_{i,t_q}$$

where p_{i,t_q} is the transaction price for property i in year-quarter t_q . δ_m represents year-month fixed effects to capture broad, high-frequency housing price movements. α_{z,t_q} denotes year-quarter zip-code fixed effects, absorbing localized trends such as gentrification or neighborhood-specific shocks. $f_c(x_i, t_y)$ is a second-order polynomial function of apartment characteristics x_i (including age, square footage, number of rooms, and number of bathrooms) interacted with year fixed effects t_y , allowing different property types to appreciate at distinct rates.

The residual u_{i,t_q} represents the discrepancy between the actual transaction price and the expected market valuation based on observable characteristics. Consequently, the squared residual u_{i,t_q}^2 serves as an ex-post measure of idiosyncratic price dispersion at the transaction level.

Expected Idiosyncratic Price Dispersion Because realized residuals u_{i,t_q} are observed ex post, they do not fully reflect the ex-ante information set available to lenders or investors prior to a purchase. Following E. X. Jiang and Zhang (2025), we estimate a second-stage auxiliary regression:

$$\begin{aligned} u_{i,t_q}^2 &= g_c(x_i, t_q) + \varepsilon_{i,t_q}, \\ \hat{\sigma}_{i,t_q}^2 &= \hat{g}_c(x_i, t_q). \end{aligned}$$

Here, $g_c(x_i, t_q)$ is a smooth, second-order polynomial function interacting quarter fixed effects with property size, age, and geographic coordinates (latitude and longitude). The fitted value estimates the property-level variance; $\hat{\sigma}_{i,t_q}$ denotes the corresponding nonnegative standard deviation.

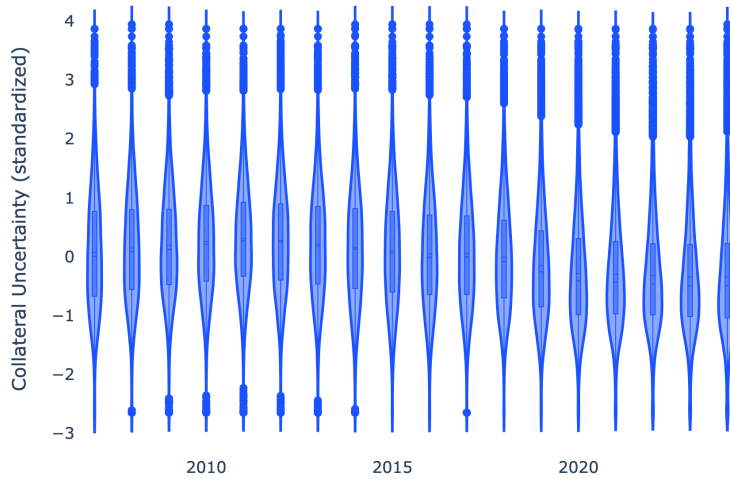
ZIP-Year Aggregation We average these property-level standard deviations within each ZIP-code-year. Let $\mathcal{J}_{z,t}$ be the set of property transactions in ZIP code z during year t , with $N_{z,t} = |\mathcal{J}_{z,t}|$. Then

$$\hat{\sigma}_{z,t} = \frac{1}{N_{z,t}} \sum_{(i,t_q) \in \mathcal{J}_{z,t}} \hat{\sigma}_{i,t_q}.$$

This metric captures average predicted price dispersion within a ZIP-code-year.

Figure A1 provides the standardized distribution of the collateral uncertainty measure over time. The distribution is relatively stable over time with a slightly decreasing trend.

Figure A1: *Distribution of Collateral Uncertainty Measure*



Note:

A.2 Validation of the Collateral Uncertainty Measure

Amaral and Ruzzier ([2026](#)) provide additional validation evidence for the collateral uncertainty measure. Given that we use exactly the same measure, we refrain from reporting the results again. For an in-depth discussion see the paper; here is a short outline of their main evidence:

Appraisal-Based Uncertainty: Our measure is strongly correlated with appraisal-based uncertainty, including the appraisal-sale price gap and both the number and distance of comparable properties used in the appraisal process.

Market Liquidity Outcomes: Areas with higher collateral uncertainty also exhibit longer time on the market and lower sale-to-list price ratios.

We interpret these patterns as evidence that our measure captures valuation difficulty in thinner and less liquid housing markets, where comparable transactions are less informative, rather than merely systematic differences in average house prices or housing quality.

B Sample Construction and Descriptive Statistics

Additional information for Section 2.

Activity requirements differ across analyses. The annual ZIP-year market-share regressions use the volume requirement described below. The local-expansion analysis fixes activity eligibility in 2007 (Appendix D.5), while Figure 1 uses the broader retained mortgage sample (Appendix B.1).

ZIP Code-level Dataset using HMDA data 2007–2024 We construct a ZIP code-year panel covering the period 2007–2024 by aggregating loan-level Home Mortgage Disclosure Act (HMDA) data. To ensure data quality and focus on economically meaningful transactions, we apply several loan-level filters prior to aggregation. Specifically, we restrict the sample to mortgages with loan amounts of at least \$50,000 and reported borrower incomes of at least \$1,000. We also drop observations lacking valid information on loan purpose or loan type. Geographically, we limit the sample to the 50 U.S. states and the District of Columbia, systematically excluding U.S. territories and outlying areas. Following these loan-level restrictions, we aggregate the data to the ZIP-year level.

Finally, we refine our aggregated panel based on two criteria. First, we merge the panel with ZTRAX data and strictly restrict our analysis to ZIP codes that possess a valid collateral uncertainty measure after spatial and temporal interpolation. Second, to mitigate noise from low-density areas, we require each ZIP-year observation to contain more than 50 total loan originations. Crucially, we do not restrict the dataset to a balanced panel; ZIP codes are retained for any year in which they satisfy the 50-loan threshold, allowing them to independently enter or exit the panel across sample years.

Table A1 presents the summary statistics for our final ZIP code-year panel covering the period 2007–2024. As shown in Panel A, the sample consists of 156,768 ZIP-year observations, representing 8,950 unique ZIP codes across 1,425 U.S. counties.

Table A1:
Descriptive Statistics of ZIP Code-Level Mortgage Market: 2007–2024

	Mean	Std	p10	p25	p50	p75	p90
Panel A: Geographic and Lender Scope							
Observations	156,768						
Number of ZIP Codes	8,950						
Number of Counties	1,425						
Panel B: Mortgage Market Composition (% indicate: measured in % of Loan Amount)							
Total Lending (\$M)	151.00	201.00	19.00	37.00	85.00	185.00	353.00
Conventional Share (%)	75.10	16.70	52.10	64.60	77.20	88.30	95.40
Conforming Share (%)	64.40	19.70	40.70	56.30	68.40	77.70	84.40
Non-Conforming Share (%)	10.70	21.10	0.00	0.00	2.20	9.10	32.70
Government-backed Share (%)	24.90	16.70	4.60	11.70	22.80	35.40	47.90
FHA Share (%)	15.60	12.20	2.50	6.60	13.00	21.50	31.90
VA Share (%)	7.60	8.60	0.70	2.20	5.20	9.90	16.10
Refinance Share (%)	43.90	18.50	19.10	29.20	43.30	58.90	69.10
Purchase Share (%)	53.70	18.20	28.90	38.90	54.20	68.10	78.10
Rejection Rate (%)	19.70	8.10	10.70	13.90	18.20	24.00	30.60
Panel C: Shadow Bank Market Share (in % of Loan Amount)							
Total Share (%)	43.00	20.20	17.30	26.30	41.50	58.30	71.20
Conventional Share (%)	36.20	19.80	12.20	20.00	33.30	50.60	64.70
Conforming Share (%)	37.80	21.50	10.60	20.40	36.30	54.40	67.70
Non-Conforming Share (%)	10.90	19.80	0.00	0.00	0.00	16.00	33.30
Government-backed Share (%)	64.00	22.10	32.70	48.30	67.70	81.80	90.00
FHA Share (%)	67.90	23.70	34.50	50.90	72.50	87.40	95.40
VA Share (%)	56.20	28.00	9.90	38.50	61.00	77.30	89.30
Refinance Share (%)	41.50	20.60	16.50	24.50	38.70	57.30	71.20
Purchase Share (%)	45.80	21.50	16.70	28.70	45.80	62.30	74.80
Rejection Rate (%)	20.40	10.70	9.30	12.70	17.80	25.50	35.40
Panel D: Shadow Bank Lender Composition (ZIP-Average)							
OTD-Dependence	80.60	14.80	57.60	75.10	87.00	90.70	92.50
Refinance-Dependence	56.80	12.40	40.70	47.20	57.10	65.70	73.30
Panel E: Independent Variable							
Collateral Uncertainty	0.00	1.00	-1.20	-0.70	-0.10	0.60	1.30
Panel F: ZIP-Code Baseline Controls							
Average Refinance Rate (%)	46.10	17.90	22.30	32.10	45.40	60.70	70.40
Average Loan Amount (log)	12.30	0.50	11.80	12.00	12.30	12.60	13.00
Average Income (log)	11.50	0.40	11.10	11.20	11.50	11.70	12.10
Average Loan-to-Income Ratio	2.70	0.50	2.10	2.30	2.60	3.00	3.30
Average LTI Ratio Squared	7.40	2.70	4.40	5.40	6.80	8.90	11.20
Panel G: Additional ZIP-Code Controls							
Fraction Female	50.80	2.40	48.20	49.60	50.90	52.10	53.30
Fraction Hispanic	12.80	16.10	1.50	3.00	6.60	15.30	33.10
Fraction African American	9.90	15.00	0.40	1.30	4.00	11.60	27.20
Fraction with Bachelors or Higher	23.20	12.60	9.60	13.40	20.10	30.90	41.90
Fraction with Less than 12th Grade	7.10	4.70	2.20	3.60	6.10	9.50	13.40
Fraction of Risky LTI Amount	15.40	11.40	3.80	6.90	12.30	21.30	31.80
Fraction of Risky LTI Count	14.00	10.70	3.20	6.00	10.90	19.60	29.60
Population Density	911.80	1533.50	32.50	79.50	342.80	1209.30	2335.60
House Price Appreciation (12m)	3.90	8.20	-5.70	-0.10	4.40	8.30	12.70
Log House Value Index	12.40	0.60	11.60	11.90	12.30	12.80	13.20
Mortgage Market HHI	5.40	3.17	2.78	3.47	4.62	6.35	8.72
Top 5 Share	40.10	10.50	27.80	32.30	38.70	46.30	54.30
Total Deposits (\$M)	749.51	6,914.13	1.35	77.74	258.69	633.69	1,262.46
Deposit HHI	3.77	2.89	0.84	1.87	2.90	5.05	10.00
Number of Bank Branches	6.20	5.70	1.00	2.00	5.00	9.00	14.00
Number of Large Bank Branches	3.70	3.80	0.00	1.00	3.00	6.00	9.00
Is Banking Desert	0.10	0.30					
Deposit Growth	0.20	47.50	-0.10	-0.00	0.00	0.10	0.20

Note: This table presents summary statistics for our main ZIP-level HMDA dataset. The panel consists of 8,950 ZIP Codes from 2007 to 2024, totaling 156'768 ZIP Codes-year observations. All year-ZIP Codes must have a collateral uncertainty measure and at least 50 originated mortgages.

Application-level Dataset using HMDA data 2007 – 2024 For the loan-level analysis, we construct an application-level dataset covering the period 2007–2024. We apply the same baseline loan-level restrictions as in the ZIP-level analysis, requiring loan amounts of at least \$50,000, reported borrower incomes of at least \$1,000, valid loan purpose and loan type identifiers, and geographic location within the 50 U.S. states or the District of Columbia.

To incorporate demographic controls, we construct mutually exclusive classifications for borrower gender and race. Gender is categorized into *Male*, *Female*, or *Joint* applications, where joint applications are defined as those involving dual-gender co-applicants or an applicant selecting both genders. Race and ethnicity are mapped into mutually exclusive categories: *Hispanic*, *Asian*, *Black*, *White*, and *Other*. Finally, we drop any observations with missing values in the key analysis variables, specifically loan amount, borrower income, loan type, loan purpose, race, or sex.

Table A2 presents the summary statistics for our final application-level dataset covering the period 2007–2024.

Table A2:
Descriptive Statistics of Application-Level Variables: 2007–2024

Panel A: Sample Dimensions (Loan-Level Panel)								
Number of ZIP-codes	13,272							
Number of Counties	1,916							
Number of Lenders	7,297							
Total Loan Observations (<i>N</i>)	88,535,647							
	Observations	Mean	Std	p10	p25	p50	p75	p90
Panel B: Continuous Loan Controls								
Loan Amount (\$, ths)	88,535,647	276.74	276.72	99.00	145.00	225.00	344.00	487.00
Loan-to-Income (LTI) Ratio	88,535,647	2.89	1.30	1.35	1.93	2.72	3.68	4.66
Applicant Income (\$, ths)	88,535,647	107.80	85.53	39.00	55.00	84.00	129.00	198.00
Panel C: Independent Variable								
Collateral Uncertainty	88,535,647	0.00	1.00	-1.13	-0.71	-0.13	0.57	1.34
Panel D: Shadow Bank Lenders								
OTD-Dependence	42,154,785	84.48	24.42	50.92	87.52	92.97	97.31	99.61
Refinance-Dependence	42,154,785	56.79	25.41	22.44	37.31	58.50	77.02	89.92
	Percentage of Applications							
	Overall	Shadow Bank						
Panel E: Lender and Loan Characteristics (%)								
Bank Lender	45.66	0.00						
Shadow Bank	54.34	100.00						
Conventional Loan Indicator	75.43	67.22						
Conforming Loan	67.64	63.03						
Non-Conforming Loan	7.78	4.19						
Gov-backed Loan Indicator	24.57	32.78						
FHA Loan	17.03	22.53						
VA Loan	6.23	8.85						
Refinance Share	55.96	51.98						
Purchase Share	44.04	48.02						
Panel F: Loan Outcomes								
Loan Rejection	18.00	16.58						
P(Collateral Reason Rejection)	17.83	15.23						
Panel G: Applicant Demographics (%)								
Race Characteristics								
White	62.89	58.39						
Hispanic	10.43	12.28						
Asian	6.81	6.88						
Black	6.86	7.61						
Other Race	0.88	0.90						
Race Not Available	12.12	13.94						
Sex Characteristics								
Male	31.06	33.40						
Female	21.51	22.38						
Joint (M+F)	40.57	36.76						
Sex Not Available	6.86	7.46						

Note: This table presents summary statistics for all mortgage applications between 2007 and 2024 in HMDA. The sample is restricted to applications with complete information on loan characteristics. Rejections due to collateral represent the share of total rejections attributed to collateral.

Origination-Level Analysis: HMDA 2007–2024 Table A3 presents the summary statistics for our final origination-level dataset covering the period 2007–2024. We use the same data filter as in the application dataset, but then additionally restrict it to only originated mortgages.

Table A3:
Descriptive Statistics of Originated Loan-Level Variables: 2007–2024

Panel A: Sample Dimensions (Loan-Level Panel)								
Number of ZIP-codes	13,272							
Number of Counties	1,916							
Number of Lenders (RSSDs)	7,297							
Total Loan Observations (<i>N</i>)	68,650,648							
	Percentage of Applications							
	Overall	Shadow Bank						
Panel B: Dependent Variables (Loan Outcome)								
Loan Retained	18.95	7.64						
Loan Sold	74.58	83.30						
Sold to GSE	51.89	53.52						
Sold to Private	0.84	1.02						
Sold to Other Financial	21.85	28.76						
Panel C: Lender and Loan Characteristics (%)								
Bank Lender	44.43	0.00						
Shadow Bank	55.57	100.00						
Conventional Loan	76.10	68.72						
Conforming Loan	69.27	65.50						
Non-Conforming Loan	6.83	3.22						
Government-backed Loan	23.90	31.28						
FHA Loan	16.19	21.14						
VA Loan	6.31	8.64						
Refinance	51.25	47.03						
Purchase	48.75	52.97						
Panel D: Applicant Demographics (%)								
Race Characteristics								
White	64.98	60.40						
Hispanic	10.01	12.22						
Asian	7.10	7.23						
Black	5.82	6.62						
Other Race	0.81	0.85						
Race Not Available	11.27	12.67						
Sex Characteristics								
Male	30.34	32.68						
Female	21.14	22.21						
Joint	42.25	38.47						
Sex Not Available	6.26	6.65						
	Observations	Mean	Std	p10	p25	p50	p75	p90
Panel E: Independent Variable								
Collateral Uncertainty	68,650,648	0.00	1.00	-1.13	-0.71	-0.13	0.57	1.33
Panel F: Continuous Loan Controls								
Loan Amount (\$, ths)	68,650,648	283.79	238.08	105.00	151.00	231.00	351.00	498.00
Loan-to-Income Ratio	68,650,648	2.84	1.24	1.35	1.92	2.69	3.61	4.54
Applicant Income (\$, ths)	68,650,648	111.77	86.83	41.00	58.00	88.00	134.00	204.00
Panel G: Shadow Bank Lenders								
Lender OTD-Dependence	34,291,583	84.30	24.61	50.87	87.49	92.96	97.18	99.61
Lender Refinance-Dependence	34,291,583	54.25	24.91	21.23	34.79	54.79	73.88	86.31

Note: This table presents summary statistics for originated loans in HMDA from 2007 to 2024.

Fannie Mae loan-level dataset (2007–2024): The mechanism estimates use Fannie Mae loan-level data, with 2007–2024 originations for timing and repurchase/defect outcomes and 2017–2024 originations for the broad waiver indicator. We merge uncertainty at the three-digit ZIP level. Controls are log principal, log maturity, FICO and its square, LTV and DTI bins, refinance status, and first-time-buyer status.

Table A4:
Descriptive Statistics of Fannie Mae Loan-Level Variables: 2007–2024

	Observations	Mean	Std	p10	p25	p50	p75	p90
Panel A: Sample Dimensions								
Number of ZIP codes	621							
Number of Commuting Zones	302							
Panel B: Dependent Variables (Loan Outcomes)								
Appraisal Waiver (%)	9,231,295	28.90	45.33					
Putback (%)	18,742,629	0.16	4.02					
Putback Delinquency (%)	18,742,629	0.07	2.60					
Time to Sale (Months)	18,742,626	1.11	0.93	0.00	1.00	1.00	1.00	2.00
Panel C: Independent Variable								
Collateral Uncertainty	18,742,629	0.00	1.00	-1.20	-0.72	-0.10	0.68	1.36
Panel D: Loan Characteristics								
Loan Amount (\$, logs)	18,742,629	12.22	0.60	11.43	11.81	12.25	12.68	12.95
Loan Maturity (logs)	18,742,629	5.71	0.31	5.19	5.48	5.89	5.89	5.89
FICO Score	18,742,629	756.80	45.84	689.00	727.00	768.00	794.00	807.00
Loan-to-Value (LTV) Ratio	18,742,629	70.24	18.20	44.00	59.00	75.00	80.00	95.00
Debt-to-Income (DTI) Ratio	18,742,629	33.62	10.17	20.00	26.00	34.00	42.00	46.00
Panel E: Loan Indicators (%)								
FHA Loan	18,742,629	15.49	36.18					
Refinance	18,742,629	63.91	48.03					
Purchase	18,742,629	36.09	48.03					

Note: This table presents summary statistics for the Fannie Mae loan-level data from 2007 to 2024.

B.1 Spatial Pattern of Local Market Shares

Figure 1, Panel (b), uses the same underlying loan and eligible ZIP-year universe as Panel (a), aggregated to actual reported loan counties. We do not assign a ZIP code’s full lending volume to its modal county. The descriptive sample retains all mortgage products and purposes, without a minimum ZIP-origination-count screen. It therefore differs from the narrower estimation samples described above. The retained source already requires valid tract-to-ZIP mapping, mapped ZTRAX ZIP codes, borrower income above \$1,000, balances of at least \$50,000, and ZIP-years with an observed or interpolated collateral uncertainty measure.

We use a constant county geography in the contiguous states and Washington, D.C., excluding Connecticut throughout because its reported counties change to planning regions in 2024. Alaska and Hawaii are outside this comparison. Former Bedford city is combined with Bedford County in every year, and the Shannon/Oglala Lakota rename is harmonized. Requiring positive retained mortgage dollars in all 18 years gives 1,778 counties. Removing six counties with no included neighbor leaves 1,772 counties and 4,407 undirected links in 15 connected components. This fixed set retains between 96.68% and 97.79% of Panel (a)’s mortgage dollars across years. A constant observed county set does not imply constant within-county ZIP coverage.

The neighbor graph uses the Census Bureau’s published 2010 county adjacency list, including reported relationships whose common boundary lies in water. It is held fixed across years. Let $R_{c,t}$ be county c ’s rank in the distribution of local shadow-bank dollar shares in year t , with average ranks for ties, and let $\tilde{R}_{c,t} = R_{c,t} - \bar{R}_t$. With binary symmetric weights w_{cj} equal to one for included

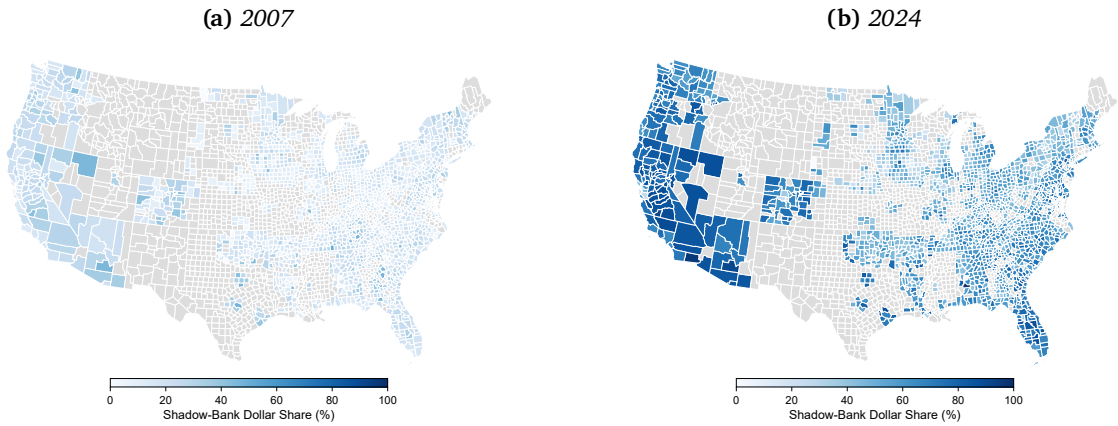
neighbors and zero otherwise, we calculate

$$I_t = \frac{n}{S_0} \frac{\sum_c \sum_j w_{cj} \tilde{R}_{c,t} \tilde{R}_{j,t}}{\sum_c \tilde{R}_{c,t}^2}, \quad S_0 = \sum_c \sum_j w_{cj}. \quad (9)$$

Higher values indicate stronger positive spatial association of counties' relative penetration. The index is not a market share, a fraction of counties, or a proportion of variance explained. A common strictly increasing transformation of all local shares preserves their ranks and this statistic. Geographic clustering of penetration is distinct from concentration of shadow-bank lending dollars or loan counts across counties.

A directly interpretable companion groups counties into the highest and lowest fifths of local shares in each year. Fractional membership at the boundary, shared equally across any tied counties, keeps each group at exactly one fifth of the sample. For each focal county, we calculate the fraction of its included neighbors belonging to the same group, weighting those neighbors equally and retaining any fractional boundary membership. We then average across focal counties using their group-membership weights. For the highest fifth, this average rises from 47.7% in 2007 to 55.6% in 2024. The corresponding lowest-fifth average rises from 45.4% to 53.7%. These are separate neighbor-membership percentages, not interpretations of the numerical value of Moran's I. Both the rank index and these comparisons describe the retained sample and do not identify an effect of collateral uncertainty on geographic clustering.

Figure A2: County Shadow-Bank Market Shares in 2007 and 2024



Note: Both maps use the same 1,772 counties and underlying broad mortgage sample as Figure 1, Panel (b), with a common 0–100% color scale. Gray counties are outside the fixed comparison set. County area does not represent mortgage-dollar weight. Boundaries are drawn from the Census 2020 cartographic files and harmonized to the analysis units.

C Instrumental Variables Strategy for Collateral Uncertainty

Following Amaral and Ruzzier (2026), we construct our instrumental variable for collateral uncertainty in three steps using the same data. First, we compute the squared distance of key housing attributes—building age, square footage, bedrooms, and geographic location—from the county-year mean for each transacted property. Second, we residualize these distances on the levels of the same housing characteristics and transaction-date fixed effects to capture relative nonstandardization rather than housing quality levels. Third, we aggregate these residualized distances to the ZIP-year level, capturing the extent to which the local housing stock is atypical along durable dimensions of the built environment.

In the subsequent sections, we investigate the IV assumptions: relevance and exogeneity.

C.1 First Stage Regression

To test the relevance of the instruments, we estimate the first-stage regression across three distinct HMDA datasets: (1) all applications from 2018 to 2024, (2) all originated loans from 2018 to 2024, and (3) a ZIP-code level aggregated dataset from 2007 to 2024.

The empirical specification is given by:

$$U_{z,t} = \pi_1 \text{Geo}_z + \pi_2 \text{Ln}(\text{Area})_z + \pi_3 \text{YearBuilt}_z + \pi_4 \text{Baths}_z + \alpha_{c,t} + \varepsilon_{z,t}^{\text{IV}} \quad (10)$$

where $U_{z,t}$ is measured in ZIP code z , county c , and year t , and is standardized across the sample. The model includes spatial and structural housing residuals as instruments alongside county-by-year fixed effects ($\alpha_{c,t}$) to absorb local macroeconomic shocks and time-varying regional trends.

Table A5 reports the corresponding estimation results, including the coefficient estimates, standard errors, and first-stage F-statistics across all three data samples. The estimation results confirm the strong relevance of our chosen instruments across all three HMDA specifications. Specifically, the structural attributes—namely the Log Area Residual and Bath Residual—exert a statistically significant positive effect on collateral uncertainty at the 1 percent level. Larger properties and those with more bathrooms consistently exhibit higher uncertainty, aligning with theoretical expectations regarding valuation complexity for non-standard homes.

The first-stage F-statistics provide definitive evidence against weak instrument concerns. Across the loan-level samples (Applications and Originated Loans), the F-statistics exceed 18, while the ZIP-code-level aggregated dataset yields an F-statistic of 16, well above the standard threshold of 10.

Table A5: First Stage Regression Results

	Dependent Variable: Collateral Uncertainty * 100		
	Loan-Level		ZIP-Level
	(1) Applications	(2) Originated	(3) Originated
Geo Residual	0.032 (0.089)	0.040 (0.089)	-0.013 (0.082)
Log Area Residual	8.333*** (1.905)	8.275*** (1.878)	7.021*** (2.071)
Year Built Residual	0.101*** (0.035)	0.099*** (0.035)	0.178*** (0.040)
Bath Residual	2.500*** (0.404)	2.467*** (0.408)	2.761*** (0.407)
County-Year FE	✓	✓	✓
Clustered SE	County	County	County
F-stat	19.40	18.37	23.98
Observations	34,149,712	27,245,776	156,768
# of Zips	12,786	12,779	8,950
# of FIPS	1,783	1,782	1,425
Sample Period	2018 – 2024	2018 – 2024	2007 – 2024

Notes: This table reports first-stage regression results for collateral uncertainty, which is measured at the ZIP-code-year level and is standardized. For illustration, the dependent variable (collateral uncertainty) is scaled by 100, and "year built residual" is scaled by 1/100. All specifications include county-by-year fixed effects. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C.2 Instrument Exogeneity and Balance

The identifying assumption is that, conditional on borrower controls, county fixed effects, and local-time fixed effects, this housing-stock-driven component affects outcomes solely through valuation difficulty rather than borrower credit risk. E. X. Jiang and Zhang (2025) provide supporting evidence for this instrument in mortgage lending, showing it is unrelated to ex-ante borrower characteristics and does not predict ex-post mortgage delinquency.

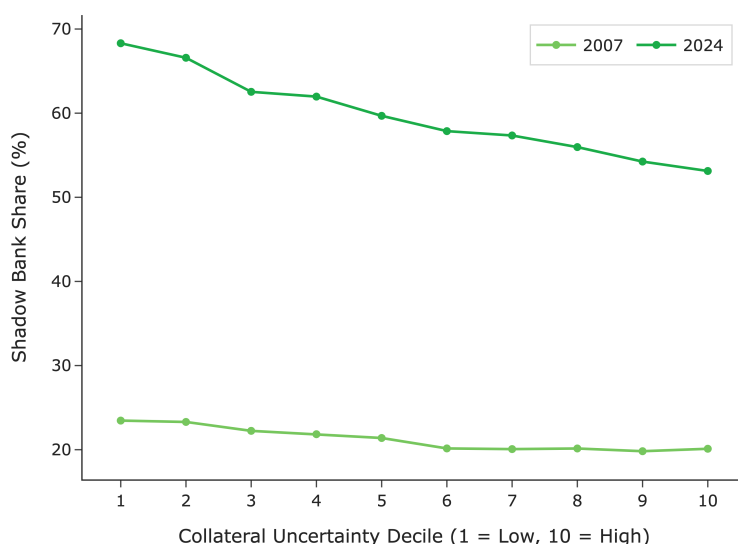
D Additional Results: Section Empirical Analysis

This appendix supplements the results in Section 3. Sections D.1 and D.3 provide additional market-share evidence and checks for other drivers of shadow-bank lending. Section D.4 compares mortgage segments. Section D.5 gives the methods and additional results for local expansion, and Section D.6 examines application denials. Section D.7 connects denial patterns to market shares on matched samples.

D.1 Collateral Uncertainty and Shadow Bank Market Share

Additional Evidence on Shadow Bank Penetration This section provides supplementary empirical evidence demonstrating that the negative relationship between collateral uncertainty and shadow bank market penetration is robust across alternative measurement specifications.

Figure A3: *Collateral Uncertainty and Shadow Bank Penetration Dynamics*



Notes: Figure plots the actual shadow bank market shares in 2007 and 2024 across collateral uncertainty deciles. Data source: HMDA, 2007–2024.

Figure A3 complements our baseline findings by examining the long-term levels of shadow bank market shares across local collateral uncertainty deciles.

The figure presents the cross-sectional distribution of actual shadow bank market shares in 2007 versus 2024. In 2007 (before the post-crisis structural shift), shadow bank market shares were relatively flat and low across all uncertainty deciles, averaging around 20% to 23%. By 2024, shadow bank participation expanded dramatically across the entire board. However, a pronounced negative gradient emerged: highly uncertain mortgage markets exhibit systematically lower shadow bank penetration (falling to roughly 53% in decile 10) compared to transparent markets where shadow banks capture nearly 69% of the market (decile 1). This divergence

reinforces the conclusion that collateral valuation frictions impose a binding constraint on shadow bank intermediation capacity.

D.2 2SLS Results

In this section, we provide additional statistical evidence for the results discussed in Section 3.1.

Table A6 reports the corresponding regression estimates with and without loan-level controls. Column 1 presents the baseline OLS within-county estimates, Column 2 introduces average zip-level loan characteristics, and Column 3 estimates the specification with full controls using a balanced sample, where we only include zip codes that have at least 50 originated loans in each year between 2007 and 2024. In our preferred specification with the full suite of controls (Column 2), the estimated coefficient on collateral uncertainty is 1.35 and statistically significant at the 1% level. The effect is also robust when restricting the sample to only ZIP codes that originated at least 50 mortgages in each year from 2007 to 2024 (Column 3).

While our baseline specification absorbs county-by-year macroeconomic shocks and controls for average loan characteristics, we must consider whether our measure of collateral uncertainty is endogenous to unobserved neighborhood dynamics. Importantly, our reliance on strictly within-county variation effectively holds constant the broader regional market structure, rural/urban geography, and overarching demographic trends. Therefore, omitted variable bias poses a threat only if unobserved factors, such as localized economic distress or hyper-local demand shocks, vary dramatically across zip codes within the same county and simultaneously correlate with our valuation metric.

Identification To systematically address these remaining endogeneity concerns and isolate the causal effect of collateral uncertainty, we implement an instrumental variables (IV) approach. Following E. X. Jiang and Zhang (2025), we instrument for local collateral uncertainty using measures of physical housing heterogeneity. Specifically, we construct instruments based on the squared deviations of individual house characteristics—such as age, size, bedrooms, bathrooms, and geolocation—from their local averages. To ensure these metrics capture local market "thinness" rather than the linear effects of the underlying housing features themselves, we purge them of linear variations in house characteristics. At the regional level, this aggregated instrument serves as an index of the physical heterogeneity of the local housing stock. Appendix C provides a more detailed discussion of the construction.

For this instrument to be valid, it must satisfy both relevance and exclusion criteria. The relevance condition dictates that physical housing heterogeneity strongly and positively predicts collateral valuation uncertainty. Economically, regions with highly heterogeneous housing stocks

have thinner local markets for comparable properties, which mechanically increases pricing dispersion and valuation noise. Empirically, we test this condition via our first-stage regressions, confirming that the instruments are jointly significant predictors of uncertainty and yield a first-stage F -statistic exceeding standard thresholds for weak instruments. All preceding regression tables indicate the first-stage F -statistics. For a detailed first-stage regression table, we refer to Appendix C.

Second, the exclusion restriction requires that the physical heterogeneity of a neighborhood's housing stock does not directly influence contemporary market shares through channels other than collateral valuation uncertainty. Because the physical composition of local housing is historically predetermined and highly persistent, it is plausibly orthogonal to modern, unobserved shocks such as localized shifts in banking competition, short-term demographic sorting, or changes in borrower preferences. Furthermore, as demonstrated by E. X. Jiang and Zhang (2025), while raw price dispersion might be confounded with borrower characteristics (e.g., creditworthiness or income), the instrumented variation derived from non-linear physical heterogeneity is decoupled from these buyer fundamentals. Thus, the instrument isolates the friction of collateral valuation without capturing underlying differences in borrower profiles that might independently drive shadow bank adoption. Appendix C provides a more detailed discussion of the exogeneity assumption.

IV Results Table A6 above presents the IV results. When restricting our analysis to this exogenous variation, the negative impact on shadow bank penetration becomes substantially more pronounced. First, the instrument proves highly relevant; the first-stage F -statistic exceeds at least 20 for all specifications. In the second stage, the coefficient on collateral uncertainty increases substantially in magnitude. While the OLS specifications yield coefficients of -2.1 (without average loan controls) and -1.4 (with controls), the corresponding IV estimates increase to -5.3 and -2.7 , respectively. Thus, the IV estimates suggest an effect that is over two times larger than the baseline OLS results.

Table A6: Relationship between ZIP-Level shadow bank Share and Collateral Uncertainty

	Dependent Variable: Shadow Bank Share (% of Loan Amount)					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral Uncertainty	-2.125*** (0.334)	-1.350*** (0.135)	-1.463*** (0.147)	-5.261*** (1.075)	-2.691*** (0.475)	-2.725*** (0.447)
County-Year FE	✓	✓	✓	✓	✓	✓
ZIP Controls		✓	✓		✓	✓
Balanced Sample	—	—	✓	—	—	✓
Clustered SE	County	County	County	County	County	County
First Stage F-stat	—	—	—	23.97	22.91	20.66
# of Counties	935	935	874	935	935	874
# of ZIPs	8457	8457	7716	8457	8457	7716
Observations	147884	147884	138892	147884	147884	138892

Note: HMDA data: 2007–2024. ZIP controls include: the refinance share, the natural logarithm of the average loan amount, the natural logarithm of average borrower income, the average loan-to-income (LTI) ratio, and the average LTI squared. The full sample includes all zip code-year observations with ≥ 50 loans. Balanced sample restricts to zip codes with ≥ 50 loans in all years. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

D.3 Addressing Confounding Variables

This section provides the exact variable definitions, the regression specifications, and results for 3.1.1.

Borrower Demographics and Discrimination: A primary concern is that collateral uncertainty might proxy for underlying neighborhood demographic and socioeconomic sorting. Shadow bank lenders—particularly tech-enabled nonbanks and fintechs—frequently cater to distinct borrower profiles that place a premium on convenience and rapid processing (Buchak et al., 2018; Fuster et al., 2019). Furthermore, because automated digital platforms mitigate face-to-face subjective discretion, minority borrowers may systematically sort into nonbank lending channels to avoid traditional banking discrimination (Bartlett et al., 2022; Erel & Liebersohn, 2022; Fuster et al., 2022; Howell et al., 2024). If neighborhoods characterized by high collateral uncertainty systematically overlap with specific demographic or socioeconomically disadvantaged groups due to historical housing disparities, our baseline estimates could capture demographic sorting rather than an information friction. While our baseline specification absorbs local macroeconomic trends via county-by-year fixed effects alongside loan-level applicant controls, we further saturate the model with local characteristics to test the resilience of the collateral uncertainty penalty.

Columns 2 through 4 of Table A7 report the results of these saturated specifications against the baseline estimate in Column 1. In Column 2, we directly control for demographic sorting by introducing the ZIP-code level shares of female, Hispanic, and Black borrowers. In Column 3, we account for broader socioeconomic stratification by controlling for educational attainment (the share of the population with a bachelor’s degree or higher, and the share with less than a 12th-grade education) alongside the proportion of low-income households (income under \$35,000). This isolates the collateral uncertainty effect from the possibility that shadow bank penetration

simply mirrors the financial constraints or digital literacy of lower-income communities. In Column 4, we introduce the local share of high-risk mortgages (loan-to-income ratio exceeding 4) by both aggregate loan volume and loan count to ensure our estimates do not reflect localized credit risk concentrations where regulated depository institutions face stricter capital requirements.

The empirical results confirm that the negative impact of collateral uncertainty on shadow bank market share remains remarkably stable across these demographic and socioeconomic dimensions. In Panel A (OLS), the estimated coefficient remains strictly negative and statistically significant at the 1% level across all specifications: -1.458 with race and gender controls (Column 2), -1.235 with socioeconomic controls (Column 3), and -1.283 with credit risk controls (Column 4), all closely tracking the baseline estimate of -1.350 .

The instrumental variable estimates in Panel B corroborate this robustness. Accounting for racial and gender composition yields an IV coefficient of -2.729 , virtually unchanged from the baseline estimate of -2.691 . Controlling for local high-risk borrowing (Column 4) similarly preserves the magnitude and precision (-2.614). Even under the demanding socioeconomic controls in Column 3, the IV estimate remains negative and statistically significant at the 5% level (-1.632 , with a first-stage F -statistic of 14.06). Overall, these results demonstrate that the dampening effect of collateral uncertainty on shadow bank market share represents a structural informational barrier rather than an artifact of demographic sorting or local borrower risk profiles.

Broadband Access and Technological Literacy: A second potential confounder is the physical and technological infrastructure required to access digital financial services. Digital access can matter particularly for applications to fintech lenders, a prominent tech-driven subset of shadow banks, though it is not a defining requirement for all nonbank originators. Consistent with this, Fuster et al. (2019) document a positive relationship between nonbank market share and local digital infrastructure. This presents an identification challenge: if neighborhoods with high collateral uncertainty also suffer from poor internet connectivity, our baseline results might simply capture a digital divide rather than a collateral valuation friction.

At the same time, treating broadband access as an exogenous control introduces a classic proxy or bad control concern. In real estate markets, broadband and fiber infrastructure are deeply intertwined with the physical geography of housing: areas lacking high-speed connectivity are typically rural, low-density, and illiquid markets with sparse, highly idiosyncratic housing stock. Consequently, local broadband coverage does not merely measure consumer internet access; it acts as a direct proxy for the structural market thinness that creates collateral uncertainty in the first place. Controlling for broadband can therefore over-control for the very informational friction we seek to isolate, mechanistically draining identifying variation from the model.

To empirically evaluate this margin, we draw on data from the ACS to construct granular controls for population density, the share of households with any active broadband subscription, and fixed high-speed internet availability (cable, fiber, or DSL). Controlling for population density isolates pure spatial rurality from digital infrastructure, ensuring that any residual penalty is driven by the opacity of the collateral rather than geographic isolation. Importantly, the broadband and high-speed internet information at the ZIP code level are only available since 2017. Thus, when including these controls, we will restrict our sample to only 2017-2024.

Columns 5 through 7 of Table A7 report the results of these specifications against the baseline model. Column 5 establishes a geographic baseline by controlling solely for population density. Column 6 introduces a broad measure of digital connectivity (the fraction of households with any type of broadband subscription), while Column 7 employs a narrower threshold for fixed high-speed connectivity (cable, fiber, or DSL).

The results in Panel A (OLS) highlight the degree to which information frictions interact with local technological infrastructure. When controlling for population density alone (Column 5), the negative relationship between collateral uncertainty and shadow bank share remains virtually identical to the baseline and highly significant (-1.436). Introducing controls for broadband connectivity in Column 6 and high-speed fiber in Column 7 attenuates the point estimates to -1.012 and -0.984 , respectively, though both remain statistically significant at the 1% level. Turning to our instrumental variable strategy in Panel B, we examine the sensitivity of our estimates to additional regional controls. While the estimated penalty remains large and statistically significant when conditioning on population density (Column 5, -2.696), introducing explicit digital connectivity controls in Columns 6 and 7 yields smaller coefficients (0.037 and -0.029) that lose statistical significance, accompanied by wider standard errors and lower first-stage F -statistics (9.54 and 8.93 , compared to 19.66 in Column 5 and 20.66 in the baseline).

Importantly, this loss of precision does not indicate a failure or weakness of our instrumental variable strategy. Rather, because our IV strategy exploits narrow local variation in collateral uncertainty that is inherently intertwined with technological infrastructure, including explicit digital connectivity controls amounts to an over-controlling or misspecified model. These controls absorb the very housing characteristics we seek to identify, introducing severe multicollinearity.

The persistent and robust negative point estimates across our OLS specifications confirm that collateral uncertainty continues to impose a genuine structural drag on shadow bank market penetration.

Housing Market Heat and the Value of Speed: A third identification concern relates to processing speed and local housing market dynamics. Fuster et al. (2019) establish that a primary

competitive advantage of tech-enabled nonbank lenders is their ability to process applications significantly faster than traditional institutions. This speed premium is especially valuable to prospective buyers in hot, competitive housing markets where fast financing contingencies are essential to securing a home. Consequently, if neighborhoods with high collateral uncertainty systematically coincide with sluggish, less liquid, or lower-priced housing markets, the reduced shadow bank presence might merely reflect muted borrower demand for speed rather than a collateral valuation friction. To ensure our uncertainty metric does not simply proxy for cold housing markets, we utilize data from Zillow to control for local home price appreciation (HPA) and the baseline local home value index (HVI). By holding these market dynamics constant, we isolate the supply-side friction of collateral opacity from demand-side preferences for expedited origination.

Columns 8 and 9 of Table A7 report the results when controlling for these housing market characteristics. In Column 8, we control for home price appreciation to capture short-term market momentum and bidding pressures. In Column 9, we introduce the local Home Value Index to account for baseline property valuations and wealth levels.

The results across both Panel A (OLS) and Panel B (IV) firmly reject the hypothesis that our findings are an artifact of weak borrower demand for speed in stagnant markets. In the OLS specifications, the negative relationship between collateral uncertainty and shadow bank market share remains remarkably stable, yielding point estimates of -1.433 in Column 8 and -1.218 in Column 9, both statistically significant at the 1% level and closely aligning with the baseline estimate of -1.350 .

The instrumental variable estimates in Panel B further solidify this conclusion. Isolating exogenous variation in collateral uncertainty yields coefficients of -2.635 when conditioning on home price appreciation in Column 8 and -2.379 when conditioning on home value levels in Column 9, virtually identical to the baseline IV estimate of -2.691 . The first-stage instruments remain highly relevant, with F -statistics well above conventional thresholds (22.38 in Column 8 and 21.16 in Column 9). These findings demonstrate that even when holding housing market temperature and local property price levels constant, collateral uncertainty continues to restrict shadow bank lending, confirming a supply-side informational friction rather than a demand-side artifact.

Local Banking Competition and Branch Density: A natural concern regarding our collateral uncertainty measure is that it may simply proxy for a lack of local lender competition. However, including lender concentration in our baseline specification introduces a classic bad control problem: if structural collateral uncertainty causes traditional or automated lenders to adjust

their market participation, localized market concentration is an equilibrium outcome of that uncertainty rather than an exogenous confounder. Furthermore, standard measures of mortgage market competition are typically defined at the county or state level, which our within-county identification (via county-by-year fixed effects) absorbs by design.

Nevertheless, recent literature highlights the critical importance of hyper-local spatial competition. As Buchak and Jørring (2021) demonstrate, mortgage markets are fundamentally local, with localized concentration leading to higher upfront markups and tighter lending standards. Relatedly, a growing literature examining the rise of digital and nonbank lenders argues that shadow bank penetration is heavily shaped by local banking structure. For instance, Balyuk, Berger, and Hackney (2026) and Erel and Liebersohn (2022) show that non-depository lenders often step in to fill credit voids in areas with limited physical branch presence or highly concentrated localized banking markets. As Nguyen (2019) demonstrates, local branch closures permanently reduce credit supply because soft information cannot be seamlessly transferred to distant lenders. If high collateral uncertainty systematically correlates with banking deserts or markets where incumbent institutions exert local monopoly power, baseline estimates might reflect local market power rather than a collateral valuation friction.

To alleviate this concern and isolate our proposed information channel, we conduct a battery of stress tests conditioning on both mortgage origination concentration and physical branch networks. First, using HMDA data, we construct three ZIP-level origination competition metrics: a localized Herfindahl-Hirschman Index (HHI), the top-5 lender market share, and the local market share of traditional commercial banks. We deliberately include the traditional bank market share as an extreme stress test. Because mortgage originations are essentially a zero-sum market split between traditional depository banks and shadow banks, conditioning on bank share on the right-hand side introduces a severe mechanical bad-control dynamic that directly soaks up the outcome's variation.

Second, we merge our panel with the FDIC Summary of Deposits (SOD) to control for the physical footprint and liquidity of depository institutions. We include ZIP-level total deposits, deposit HHI, the total number of bank branches, and the number of large bank branches (defined as institutions with over \$10 billion in national deposits). A long-standing literature establishes that large banks rely primarily on standardized, hard information, whereas small community institutions rely on relationship lending and soft information (Balyuk, Berger, & Hackney, 2026; Berger et al., 2005; Liberti & Petersen, 2019; Petersen & Rajan, 1994; Stein, 2002). Because collateral uncertainty introduces severe noise into hard data, large depository lenders face similar valuation obstacles as tech-enabled nonbanks. By controlling for the local footprint of these

institutions, we ensure that our coefficient reflects collateral valuation opacity rather than general institutional presence.

Columns 10 through 16 of Table A7 report the results of these specifications. In Columns 10 and 11, controlling for origination concentration yields OLS coefficients of -1.293 and -1.248 , and IV coefficients of -2.528 and -2.419 , virtually identical to our baseline estimates (-1.350 in OLS; -2.691 in IV). These results indicate that the dampening effect of property valuation opacity is independent of local mortgage concentration.

Column 12 presents the extreme stress test controlling for traditional bank market share. As expected from the mechanical zero-sum tradeoff, the point estimate attenuates considerably: the OLS coefficient drops to -0.181 , while the IV estimate falls to -0.496 . Although the statistical power naturally weakens when the dependent variable's direct counterweight is held constant, the penalty remains negative and statistically discernible.

Columns 13 through 16 incorporate the FDIC Summary of Deposits metrics. Controlling for total deposits (Column 13), deposit concentration (Column 14), total bank branches (Column 15), and large bank branches (Column 16) leaves the OLS coefficients remarkably stable between -1.391 and -1.488 . In Panel B, the IV point estimates expand slightly to between -2.844 and -3.314 , maintaining statistical significance at the 1% level alongside strong first-stage F -statistics exceeding 21. This stability confirms that the lower market penetration of shadow banks in opaque areas is not an artifact of banking deserts or depository branch density, but rather stems directly from collateral valuation frictions.

Monetary Policy Tightening and Bank Funding Shocks: The macroeconomic environment of our sample period introduces an important alternative mechanism. Shifts in the interest rate environment can trigger the "deposit channel" of monetary policy: traditional depository institutions experience deposit outflows, prompting them to contract mortgage lending (Drechsler, Savov, & Schnabl, 2022). This localized contraction can create a credit vacuum that shadow banks readily fill (Xiao, 2020).

This dynamic poses an identification challenge: if collateral uncertainty happens to correlate with markets where local bank branches are especially sensitive to funding shifts, the relative footprint of shadow banks might reflect the retreat of deposit-constrained commercial banks rather than an informational friction. To isolate our mechanism from this funding transmission channel, we control for localized bank funding shocks using FDIC Summary of Deposits data. Specifically, we incorporate both simple total deposit growth and the branch-weighted deposit growth of traditional banks operating within the ZIP code. By holding the local funding supply of depository institutions constant, we verify that the shadow bank penalty is driven by the opacity

of the collateral rather than traditional bank distress.

Columns 17 and 18 of Table A7 report the results when conditioning on these funding dynamics. Across both specifications, the estimated effect remains remarkably stable. In Panel A (OLS), the coefficient on collateral uncertainty is identical at -1.391 whether controlling for unweighted total deposit growth (Column 17) or branch-weighted deposit growth (Column 18), closely matching the baseline estimate of -1.350 .

The instrumental variable results in Panel B confirm this resilience. The IV point estimates remain unchanged across both specifications at -2.851 , compared to the baseline IV coefficient of -2.691 . The first-stage instruments retain strong identification power, yielding an F -statistic of 22.70 in both columns. The fact that the coefficients remain virtually untouched after absorbing local deposit shocks demonstrates that our collateral valuation friction operates independently of deposit-driven credit cycles.

Regulatory Arbitrage: A final identification concern relates to the role of regulatory arbitrage in driving shadow bank expansion. As documented by Buchak et al. (2018) and Gete and Reher (2021), a significant catalyst of shadow bank growth has been the retrenchment of traditional depository institutions facing heightened post-crisis regulatory burdens, with nonbank lenders expanding to fill these regulatory voids (E. Jiang et al., 2020). This dynamic poses a potential confounder: if areas with high collateral uncertainty were historically served by depository institutions less exposed to post-crisis regulatory tightening, lower shadow bank penetration might simply reflect fewer regulatory arbitrage opportunities rather than a collateral valuation friction.

While standard regulatory exposure measures are often constructed at the county level—variation that our county-by-year fixed effects naturally absorb—meaningful heterogeneity in bank regulatory exposure can persist across neighborhoods within the same county. To account for this within-county variation, we adapt the methodology of Buchak et al. (2018) to construct localized, ZIP-level measures of depository regulatory exposure. By conditioning on these hyper-local regulatory shocks, we hold the local regulatory environment constant, ensuring that our collateral uncertainty metric isolates property valuation opacity rather than localized regulatory pressure.

Columns 19 through 21 of Table A7 report the results when conditioning on these regulatory shocks. Following the literature, we deploy three distinct measures: the commercial bank Capital Ratio shock (Column 19), the Mortgage Servicing Rights (MSR) shock (Column 20), and the dissolution of the Office of Thrift Supervision (OTS) shock (Column 21).

Across all three specifications, the results confirm that our baseline findings are not driven by localized regulatory arbitrage. In Panel A (OLS), the estimated coefficient on collateral uncertainty remains virtually identical to the baseline (-1.350) and statistically significant at the 1% level

across all specifications: -1.374 when controlling for capital ratios (Column 19), -1.393 for MSR exposure (Column 20), and -1.432 for the OTS shock (Column 21).

The instrumental variable estimates in Panel B further solidify this finding. Isolating the exogenous variation in collateral uncertainty yields point estimates of -2.734 (Column 19), -2.767 (Column 20), and -2.864 (Column 21), all statistically significant at the 1% level and tightly aligned with the baseline IV coefficient of -2.691 . The first-stage instruments remain highly relevant, generating F -statistics well above conventional thresholds (19.34 to 19.93).

Next, we address the regulatory shock identified by Gete and Reher (2021). The implementation of the Liquidity Coverage Ratio (LCR) between 2013 and 2015 increased GNMA mortgage-backed security (MBS) prices while lowering funding costs for shadow banks specializing in Federal Housing Administration (FHA) loans. Consequently, zip codes with a higher baseline FHA share experienced differential, policy-driven shadow bank expansion.

To ensure our collateral uncertainty measure is not capturing this regulatory credit shift, we construct a pre-determined exposure measure by interacting the standardized 2013 zip-code-level FHA share with a post-2013 indicator ($\text{FHA Share}_{2013} \times \mathbb{1}[\text{Year} > 2013]$) (Column 22), as well as a flexible year-by-FHA interaction series using 2013 as the reference year (Column 23). This absorbs any unobserved trends favoring shadow bank growth in FHA-heavy local markets. Restricting our sample to zip codes observed in 2013, our results remain virtually unchanged, confirming that the negative relationship between collateral uncertainty and shadow bank market penetration operates independently of LCR-induced regulatory arbitrage.

Overall, these results demonstrate that even after conditioning on hyper-local regulatory exposure, collateral valuation frictions continue to impose a strong, independent constraint on shadow bank market penetration.

Table A7: Relationship between ZIP-Level Shadow Bank Share and Collateral Uncertainty: Controlling for Confounding Variables (2007 - 2024)

	Dependent Variable: Shadow Bank Share (% of Loan Amount)																						
	Baseline	Demographics			Rurality & Technology			Housing Market		Competition & Bank Presence						Drechsler et al. (2022)		Buchak et al. (2018)			Gete & Reher (2021)		
	(1)	R & G (2)	SocEco (3)	Risk (4)	Density (5)	BB (6)	Fiber (7)	HPA (8)	HVI (9)	HHI (10)	Top 5 (11)	Bank % (12)	Deposit (13)	Dep HHI (14)	Branches (15)	Large Br (16)	Total (17)	Weighted (18)	Cap Ratio (19)	MSR (20)	OTS (21)	Post-2013 (22)	Year Int. (23)
Panel A: OLS																							
Collateral Uncertainty	−1.350*** (0.135)	−1.458*** (0.145)	−1.235*** (0.147)	−1.283*** (0.136)	−1.436*** (0.142)	−1.012*** (0.148)	−0.984*** (0.150)	−1.433*** (0.143)	−1.218*** (0.138)	−1.293*** (0.134)	−1.248*** (0.130)	−0.181** (0.077)	−1.392*** (0.135)	−1.443*** (0.137)	−1.488*** (0.137)	−1.483*** (0.137)	−1.391*** (0.135)	−1.391*** (0.135)	−1.374*** (0.134)	−1.393*** (0.149)	−1.432*** (0.140)	−1.356*** (0.147)	−1.358*** (0.140)
Panel B: Instrumental Variables																							
Collateral Uncertainty	−2.691*** (0.475)	−2.729*** (0.582)	−1.632** (0.688)	−2.614*** (0.472)	−2.696*** (0.551)	0.037 (1.048)	−0.029 (1.171)	−2.635*** (0.499)	−2.379*** (0.505)	−2.528*** (0.473)	−2.419*** (0.466)	−0.496* (0.275)	−2.844*** (0.485)	−3.164*** (0.527)	−3.262*** (0.522)	−3.314*** (0.518)	−2.851*** (0.485)	−2.851*** (0.485)	−2.734*** (0.505)	−2.767*** (0.505)	−2.864*** (0.508)	−2.812*** (0.468)	−2.788*** (0.464)
First-stage F	22.910	17.220	14.060	22.820	19.660	9.540	8.930	22.380	21.160	22.780	22.550	21.570	22.700	22.300	21.920	21.880	22.700	22.700	19.340	19.930	19.410	22.120	22.040
Sample Start Year	2007	2011	2011	2007	2011	2017	2017	2008	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County	County
Observations	147884	115932	115932	147884	115947	66593	66593	137454	145315	147884	147884	147884	147884	147884	147884	147884	147884	147884	134379	134379	134379	146590	146590

Notes: Sample covers HMDA mortgage applications merged with FDIC Summary of Deposits, ACS, and Zillow data from 2007 to 2024, restricted to zip codes with at least 50 mortgages. The dependent variable is the ZIP-code shadow bank loan volume share (%). Panel A presents OLS specifications; Panel B presents 2SLS IV estimates. Column (1) presents the baseline estimate. Columns (2)–(21) sequentially saturate the baseline model with local demographic, technology, housing market, banking competition, deposit growth, and post-crisis regulatory exposure controls. Each specification includes county-year fixed effects and baseline controls: average refinance share, log average zip loan amount, log average zip income, average zip LTI and its square. Standard errors clustered at the county level are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

D.4 Heterogeneous Mortgage Market Segments

To assess the structural stability of our baseline results and rule out alternative institutional explanations, we explore how the relationship between collateral uncertainty and shadow bank market share varies across distinct institutional segments of the mortgage market. We partition the sample along three key dimensions: the presence of federal credit guarantees, secondary market securitization boundaries, and loan purpose. To make the results comparable across market segments, we standardize the shadow bank share. Thus, these estimates can be interpreted as standardized effects: a one standard deviation increase in collateral uncertainty leads to a one standard deviation change in shadow bank market share within a given market segment. Table A8 presents the results across these subsegments, utilizing both our baseline OLS (Panel A) and IV (Panel B) specifications.

Conforming versus Non-Conforming Loans. First, we examine whether our results are mechanically driven by secondary market liquidity boundaries. Shadow banks rely heavily on an originate-to-distribute model funded by warehouse credit lines rather than sticky deposits (Buchak et al., 2024). Because nonbanks depend crucially on the programmatic liquidity provided by Fannie Mae and Freddie Mac (Gete & Reher, 2021), they structurally concentrate in conforming mortgages and are largely absent from the non-conforming (jumbo) market, which is predominantly held on depository bank balance sheets.

If geographic areas with high collateral uncertainty systematically correlate with higher jumbo loan volumes, lower shadow bank penetration might simply reflect these securitization boundaries rather than an informational friction. To evaluate this channel, we isolate conforming mortgages (Column 3) from non-conforming mortgages (Column 4).

The results reject the hypothesis that our findings are merely a byproduct of GSE securitization access. Within the conforming segment (Column 3)—where shadow banks face a level playing field with depository lenders—the negative effect of collateral uncertainty remains robust and highly statistically significant (OLS: -0.049 ; IV: -0.075). Interestingly, the penalty is slightly larger in the non-conforming segment (Column 4), yielding an OLS coefficient of -0.069 and an IV coefficient of -0.130 . Rather than being an artifact of securitization limits, collateral uncertainty compounds the balance-sheet disadvantage shadow banks face in the jumbo segment, while exerting a clear, independent friction even within their core conforming market.

Loan Purpose: Refinance versus Purchase. Finally, we test for heterogeneity across loan purposes by splitting originations into refinancing transactions (Column 8) and purchase mortgages (Column 9). Across both specifications, collateral uncertainty exerts a strong, statistically signif-

ificant negative drag on shadow bank market share. For refinances, the estimated coefficient is -0.048 in OLS and -0.104 in IV. For purchase transactions, the negative effect is larger, yielding an OLS estimate of -0.075 and an IV estimate of -0.138 . While application-level rejection margins demonstrate that automated screening struggles acutely with refinances in uncertain areas (as discussed in Section 4.2), the aggregate loan-volume market share reveals that shadow bank penetration is curtailed across both segments, with purchase markets experiencing an even larger aggregate volume reduction. This indicates that while the underwriting friction surfaces prominently via elevated rejection rates on refinances, collateral uncertainty exerts an overarching contraction on total shadow bank market presence across all transaction types.

Table A8: Relationship between ZIP-Level shadow bank Share and Collateral Uncertainty: Mortgage Market Segments (2007 -2024)

	Dependent Variable: Shadow Bank Share (% of Loan Amount)								
	Baseline	Loan Types				Government Backed		Loan Purpose	
	All (1)	Conventional (2)	Conforming (3)	Non-Conforming (4)	Gov. Backed (5)	FHA (6)	VA (7)	Refinance (8)	Purchase (9)
Panel A: OLS Specifications									
Collateral Uncertainty	−0.067*** (0.007)	−0.083*** (0.009)	−0.049*** (0.006)	−0.069*** (0.008)	−0.019*** (0.004)	−0.017*** (0.005)	−0.033*** (0.006)	−0.048*** (0.006)	−0.075*** (0.008)
Panel B: Instrumental Variables									
Collateral Uncertainty	−0.133*** (0.024)	−0.146*** (0.026)	−0.075*** (0.018)	−0.130*** (0.030)	−0.030 (0.021)	−0.066* (0.036)	−0.052** (0.024)	−0.104*** (0.019)	−0.138*** (0.026)
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	County	County	County	County	County	County	County	County	County
Observations	147 884	147 884	147 884	147 884	147 884	147 884	147 884	147 884	147 884

Note: HMDA ZIP-level data: 2007–2024, restricted to zip codes with at least 50 mortgages. Each specification includes county-year fixed effects and baseline controls: average refinance share, log average zip loan amount, log average zip income, average zip LTI and its square. The outcome variable is the shadow bank share within the specified market relative to banks and other lenders. Both the share and collateral uncertainty are standardized. Standard errors clustered at the county level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

D.5 Additional Evidence on Local Expansion

This section documents the sample, timing models and robustness checks supporting Section 3.1.2.

Sample, market shares and attainment. We select ZIP codes with more than 50 mortgage originations in 2007 from the cleaned sample described in Section 2. Eligibility counts all mortgage products, and markets need not remain above this activity threshold in later years. Local shadow-bank shares are measured in originated dollars within conventional lending below the annual national base conforming-size limit; the all-mortgage check includes all products and sizes in the cleaned sample.³¹

Of the 11,611 eligible ZIPs, 10,091 have usable starting information for the absolute-threshold analysis, spanning 1,373 counties and 47 state or District of Columbia jurisdictions. The gain analysis uses 9,908 ZIPs in the 36 states with at least 50 eligible ZIPs and observed 2007 uncertainty. This state-size restriction avoids very small state samples and is not imposed on the threshold analysis.

Attainment requires two consecutive qualifying years and is dated to the second: a gain is measured relative to the 2007 share, while an absolute target is a specified share level. The earliest gain event is therefore 2009; absolute targets can qualify in 2007–2008. The main threshold cohort includes markets already above the target in 2007. Follow-up ends at attainment, 2024 or the first missing required observation, without re-entry or treating missing shares as zero. Gains require annual shares but only baseline uncertainty; thresholds also require observed uncertainty lagged one year.³²

Annual timing model and controls. We estimate a complementary-log-log model for the annual probability $p_{z,t}^{(q)}$ of attaining target q , conditional on no earlier attainment (Jenkins, 1995):

$$\log \left[-\log(1 - p_{z,t}^{(q)}) \right] = \alpha_{s(z)}^{(q)} + \delta_t^{(q)} + \beta_q U_{z,\tau(t)} + \mathbf{W}_{z,2007}' \boldsymbol{\gamma}_q + f^{(q)}(m_{z,2007}). \quad (11)$$

State effects $\alpha_{s(z)}^{(q)}$ absorb persistent state differences and year effects $\delta_t^{(q)}$ allow a flexible common timing path. Uncertainty is measured in 2007 for gains and lagged annually for absolute targets, with a common slope across years. The main gain model includes the initial-share function $f^{(q)}$;

³¹The activity sample contains first-lien, owner-occupied, site-built mortgages with balances of at least \$50,000 and borrower income above \$1,000, using the existing ZIP mapping. The base conforming limit is \$417,000 in 2007–2016 and reaches \$766,550 in 2024. To exclude reporting intervals overlapping the limit, we add \$500 to reported balances before 2018 and \$5,000 thereafter before comparing them with the limit. Geography is fixed from each ZIP's most common county in 2007, breaking ties by the smallest county code.

³²The gain sample records 9,274 events, 230 early outcome gaps and 404 nonattainers through 2024. The 50% target records 5,907 events and 1,892 early required-data gaps; the 60% target records 4,150 events and 2,189 gaps. Attainment recorded before a later gap is retained.

the main threshold model omits it. County specifications replace state effects with county effects.

Table A9 lists the twelve baseline controls, measured in 2007 using the broader cleaned loan sample. The same transformations and initial-share spline are maintained across specifications and bootstrap draws.³³

Table A9: Baseline Controls in the Local Expansion Models

2007 control	Mean	Standard deviation
Mean loan-to-income ratio	2.702	0.458
Square of the mean loan-to-income ratio	7.510	2.532
Refinance share	0.514	0.116
Log mean borrower income	11.379	0.404
Log mean loan amount	12.207	0.492
Share of loan dollars with loan-to-income ratio above 4 (%)	14.579	9.698
Share of loans with loan-to-income ratio above 4 (%)	13.195	9.304
Mortgage origination concentration (HHI)	502.168	243.962
Total retained originations	480.836	444.572
Indicator for no recorded bank branch	0.128	0.334
Deposit concentration (HHI)	4015.275	3138.866
Number of bank branches	5.688	5.796

Notes: All values refer to 2007 in the 9,908-ZIP gain sample. The same twelve controls and frozen transformations enter the absolute-threshold models. HHI denotes the Herfindahl–Hirschman concentration index. The branch-data merge assigns zero branches and zero deposit HHI to ZIPs without a matched branch record; the no-branch indicator follows this coding. Deposit growth is unavailable in 2007 and is not included. These models do not include the full set of technology, demographic, housing-market, or regulatory interactions used elsewhere in the paper.

Adjusted waiting times and inference. Uncertainty deciles are formed over the 9,908 ZIPs in 2007, not over applications; ties are ordered by ZIP code. Each extreme decile contains 991 ZIPs, with mean uncertainty of 0.150 and 0.563. Adjusted predictions average over each decile’s full uncertainty distribution and a common distribution of other characteristics and geographic effects. Threshold predictions use the same benchmarks held constant through follow-up, although estimation uses annually updated uncertainty.

Let $S_{zq}(k)$ be the predicted probability of no attainment by elapsed year k . Restricted expected waiting time is

$$W_q = \frac{1}{N} \sum_{z=1}^N \sum_{k=0}^{16} S_{zq}(k). \quad (12)$$

Nonattainers remain in the calculation. We convert the D10-minus-D1 difference in W_q to months by multiplying by twelve; waiting time is restricted through 2024.

Confidence intervals use 999 whole-county resamples, refitting all coefficients and weighting the prediction reference by the same county frequencies. Eligibility, exposure benchmarks, transformations and spline knots remain fixed. Matched specifications use paired draws. Intervals are

³³Controls are centered and scaled using the original gain sample. Origination counts enter in levels; no transformations or winsorization are added beyond the stated logarithms and squared loan-to-income term. The initial-share adjustment is a three-term natural cubic spline with internal knots at 17.658% and 24.220% and boundary knots at 0% and 61.805%.

pointwise, not simultaneous.³⁴

Waiting time for a 10 percentage point gain. Table A10 reports adjusted expected waiting times under the main state-effects specification with initial-share adjustment. The expected waiting time is 8.16 years in the lowest uncertainty decile and 9.44 years in the highest. The difference of 15.45 months corresponds to a 15.8% increase relative to the lowest decile.

Table A10: *Adjusted Waiting Time for a 10 Percentage Point Gain in Shadow-Bank Market Share*

Statistic	Estimate	95% confidence interval
Expected waiting time: lowest uncertainty decile (D1)	8.16 years	[7.87, 8.47]
Expected waiting time: highest uncertainty decile (D10)	9.44 years	[9.10, 9.79]
Additional waiting time (D10 minus D1)	15.45 months	[11.39, 19.19]
Percentage increase relative to D1	15.8%	[11.4%, 19.9%]

Notes: The annual timing model includes state and year effects, the twelve baseline controls measured in 2007, and a flexible adjustment for initial market shares. Predictions average over the fixed D1 and D10 uncertainty distributions using a common reference population. Waiting times are measured from 2007 and restricted through 2024; nonattainers remain in the calculation. Confidence intervals use 999 paired whole-county bootstrap draws. The percentage increase is $100(W_{D10}/W_{D1} - 1)$, where W denotes restricted expected waiting time. Differences and percentages use unrounded estimates.

Geographic comparisons and other milestones. Table A11 reports the absolute-target delays. At 50%, the state-effects estimate is 16.3 months [11.3, 21.0], compared with 10.6 [6.1, 15.4] under county effects. County effects remove persistent differences across counties. Table A12 gives the underlying state-based waiting times: 12.46 years for D1 and 13.81 for D10 at the 50% target.

Table A11: *Additional Waiting Time for Absolute Market-Share Targets*

Target share	ZIPs	Events	State effects	County effects
20%	10,091	9,254	10.4 [5.8, 14.8]	9.2 [5.0, 13.2]
30%	10,091	8,462	9.3 [4.4, 14.1]	6.5 [1.7, 11.0]
40%	10,091	7,402	15.9 [9.7, 21.5]	8.3 [4.3, 12.1]
50%	10,091	5,907	16.3 [11.3, 21.0]	10.6 [6.1, 15.4]
60%	10,091	4,150	12.2 [8.6, 15.3] [†]	9.0 [5.0, 13.2] [†]

Notes: Entries are the highest- minus lowest-uncertainty-decile delay in months, followed by a 95% county-bootstrap interval. Both models use the same 10,091 ZIPs, annually updated uncertainty lagged one year, twelve 2007 controls, annual effects, outcome histories, and prediction reference. No initial-share adjustment is included. All 999 county draws are retained. [†]The displayed 60% values are midpoints of the identification ranges described in the text; the intervals retain all prediction bounds.

³⁴Zero-event groups or years remain at the zero-rate limit. Where a reference component has no informative timing observation, predictions retain bounds rather than dropping the component or draw. Confidence envelopes use the 2.5th percentile of lower bounds and the 97.5th percentile of upper bounds. At the 60% target, full-sample delay ranges are 12.206–12.224 months with state effects and 8.373–9.711 with county effects. Reported centers are midpoints; intervals retain the full bounds. The state range reflects one Mississippi ZIP with only its first uninformative follow-up interval.

Table A12: Adjusted Waiting Times by Target Share

Target share	Lowest uncertainty decile	Highest uncertainty decile
20%	5.00 [4.69, 5.36]	5.87 [5.52, 6.26]
30%	8.15 [7.77, 8.54]	8.93 [8.51, 9.40]
40%	10.30 [9.94, 10.73]	11.63 [11.10, 12.16]
50%	12.46 [12.06, 12.90]	13.81 [13.35, 14.29]
60%	14.43 [14.07, 14.79] [†]	15.45 [15.04, 15.79] [†]

Notes: Entries are expected years after 2007, restricted through 2024, followed by 95% county-bootstrap intervals. State-effects annual models use the same cohort, controls, and persistent uncertainty benchmarks as Table A11. Nonattainers remain in the reference population. [†]The displayed 60% centers are identification-range midpoints. Each range is less than 0.002 years wide; the full confidence envelope is retained.

Table A13 shows positive delays for gains of 20 and 30 percentage points and for doubling the initial share under both state and county specifications. The absolute-gain models retain 9,908 ZIPs; doubling uses 9,890 ZIPs in 1,330 counties after excluding three zero initial shares and fifteen above 50%. Doubling requires different percentage-point gains across starting shares.

Table A13: Additional Waiting Time for Alternative Market-Share Gains

Outcome	ZIPs	State	State + initial share	County	County + initial share
10 percentage points	9,908	13.3 [9.6, 16.8]	15.4 [11.4, 19.2]	7.3 [3.4, 11.6]	9.8 [5.2, 14.9]
20 percentage points	9,908	16.0 [11.6, 20.5]	17.9 [12.9, 22.9]	8.7 [3.7, 14.0]	10.3 [4.3, 16.5]
30 percentage points	9,908	14.0 [10.2, 18.0]	16.3 [11.8, 20.6]	7.2 [3.0, 11.1]	8.4 [4.4, 13.0]
Double the initial share	9,890	11.5 [6.7, 16.0]	16.9 [12.0, 21.2]	7.4 [2.1, 12.7]	9.9 [4.6, 15.2]

Notes: Entries are highest- minus lowest-uncertainty-decile delays in months with 95% county-bootstrap intervals. Every outcome requires two consecutive qualifying years and uses 2007 uncertainty, the twelve baseline controls, shared annual effects, and the stated geography. Initial-share adjustment uses the same frozen natural spline. The 10-, 20-, and 30-point models use the same cohort and 999 paired county draws. Doubling uses its own 999 draws on the feasible 9,890-ZIP cohort. Waiting time is restricted through 2024.

Starting shares, observation loss and geographic support. Adding the initial-share spline to the state-based 50% model reduces the delay to 13.1 months [8.9, 17.1] (Table A14). This conditions on starting positions that may already reflect earlier collateral uncertainty.

We assess observation loss by weighting observed market-years by the inverse probability of remaining observed, estimated from prior information. The weights affect estimation, not the prediction population, and are re-estimated in every county draw.³⁵ Weighting leaves the state-based 50% delay at 16.0 months [11.3, 20.5] and the county estimate at 10.7 [6.2, 15.3], compared with 10.6 unweighted. The gain estimate remains close to 15.4 months (Table A15).³⁶

³⁵Pooled logistic observation models use a unit ridge penalty on non-intercept coefficients. Threshold models include prior observed uncertainty, log one plus prior total loan counts, baseline-uncertainty and prior-share splines, baseline controls, and state and year effects. The county check uses prior log total originations. Gain models use baseline uncertainty and controls, initial and prior shares, prior loan counts and dollars and their available changes, past uncertainty availability, and state and year effects. The first missing transition is included and later returns excluded. Weights are inverse cumulative continuation probabilities, optionally capped at the risk-row 99th percentile; the cap and both models are re-estimated in each draw. Only county frequencies weight the prediction reference.

³⁶For the state-based 50% check, the uncapped estimate is 16.47 months. The weight cap is 2.282, compared with an

Table A14: Starting Shares and Observation Loss

State-based 50% model	Delay (months)	95% interval
Main specification	16.3	[11.3, 21.0]
Add initial-share adjustment	13.1	[8.9, 17.1]
Weight for observation loss	16.0	[11.3, 20.5]

Notes: All rows use the same 10,091 ZIPs, 1,373 counties, 47 state or District of Columbia jurisdictions, 5,907 events, annual lagged uncertainty, twelve 2007 controls, state effects, and annual effects. Delays compare the full frozen D10 and D1 uncertainty distributions and are restricted through 2024. The initial-share check adds the frozen natural spline. The observation-loss check changes the outcome weights and recalculates them and their cap in every draw. All intervals use the same 999 whole-county resamples; draws with an unidentified prediction component retain conservative bounds.

Table A15: Observation-Loss Weighting for the 10-Point Gain

Gain-model check	Without initial-share adjustment	With initial-share adjustment
Original follow-up	13.3 [9.6, 16.8]	15.4 [11.4, 19.2]
Observation-loss weighting	13.3 [9.6, 16.9]	15.4 [11.4, 19.3]
Weights capped at the 99th percentile	13.3 [9.6, 16.9]	15.5 [11.4, 19.3]

Notes: State-effects gain models retain the same 9,908 ZIPs, 2007 uncertainty, controls, prediction benchmarks, and reference. Entries are highest- minus lowest-decile delays in months with 95% intervals from 999 whole-county resamples. Inverse observation probabilities weight outcome risk rows, not the prediction population. Capped estimates truncate only the censoring-weight component at the county-frequency-weighted risk-row 99th percentile, recomputed in each draw. The table concerns actual outcome loss, rather than an artificial cutoff at later missing uncertainty.

Missing starting uncertainty excludes 1,520 eligible ZIPs, which later weighting cannot recover. At the 50% target, early required-data loss affects 9.5% of D1 and 38.8% of D10 markets, mostly through missing uncertainty. Gain-model outcome loss is lower, at 1.0% and 5.2%. These rates alone do not establish the direction of bias, since slower attainment also lengthens exposure to data loss.

The common prediction population need not contain both extreme deciles within each county. Thirty-two of the 36 gain-sample states and 48 counties, containing 1,170 reference ZIPs, contain both. Restricting predictions to those counties and their observed uncertainty values gives initial-share-adjusted gain delays of 13.0 months [9.3, 17.1] with state effects and 8.5 [4.5, 13.0] with county effects. This local check changes the population and contrast; county resampling does not create exposure overlap.

The estimates describe conditional associations in market-share attainment, not causal differences in lending volumes or spatial clustering. Shares can rise when other lenders contract, without growth in shadow banks' own originations.

uncapped maximum of 198.5; the same cap and maximum apply to the county check. Weighting addresses selection related to the recorded history, not unobserved selection.

Alternative timing specifications. We also estimate county-stratified Cox models with Efron treatment of annual ties:

$$\lambda_z^q(t) = \lambda_{0,c(z)}^q(t) \exp(\beta_q U_{z,t-1} + \mathbf{W}_{z,2007}' \boldsymbol{\gamma}_q). \quad (13)$$

Each county has its own baseline timing path. These models use the threshold cohort, lagged uncertainty and baseline controls. Their conditional hazard ratios compare the D10 and D1 mean uncertainty values rather than averaging predictions over their distributions.

Table A16 reports a full-cohort 50% hazard ratio of approximately 0.48, remaining below one after initial-share adjustment. Restricting initial shares below 20% or 15% weakens the evidence: both bootstrap intervals include one.

Table A16: County-Stratified Hazard Estimates

County-stratified model	ZIPs	Events	Conditional hazard ratio [95% CI]
20% target	10,091	9,254	0.629 [0.503, 0.786]
30% target	10,091	8,462	0.660 [0.528, 0.819]
40% target	10,091	7,402	0.653 [0.530, 0.805]
50% target	10,091	5,907	0.482 [0.365, 0.633]
60% target	10,091	4,150	0.359 [0.257, 0.512]
50%, initial-share adjustment	10,091	5,907	0.499 [0.383, 0.652]
50%, initial share below 20%	4,543	1,784	0.542 [0.299, 1.148]
50%, initial share below 15%	2,155	529	0.690 [0.257, 1.913]

Notes: Conditional hazard ratios compare uncertainty of 0.563 with 0.150, the frozen D10 and D1 means. They are calculated from the common Cox uncertainty slope and do not equal adjusted marginal probability ratios. Models stratify by county, use Efron ties, and include the twelve baseline controls. Each interval uses all 999 whole-county bootstrap refits. The initial-share adjustment uses the frozen natural spline. Restricted initial-share cohorts use the same full-cohort county draws mapped to their members.

Table A17 reports checks using initially-below-target markets, county-by-initial-size strata, annually lagged controls and all mortgage products. The size strata use quartiles of 2007 total originations; the updated controls use the same twelve variables and do not substitute zero for unavailable 2007 deposit growth. Intervals here use county-clustered sandwich standard errors, rather than bootstrap refits.

Table A17: Additional Conditional Checks for the 50% Target

50% threshold check	ZIPs	Events	Conditional hazard ratio [95% CI]
Initially below the 50% target	10,076	5,895	0.485 [0.362, 0.648]
County-by-initial-size strata	10,091	5,907	0.487 [0.345, 0.688]
Annually updated, lagged controls	10,091	5,907	0.496 [0.377, 0.653]
All retained mortgage types	10,091	6,712	0.331 [0.262, 0.418]

Notes: Ratios use the same fixed decile-mean uncertainty contrast as Table A16. Intervals are based on county-clustered sandwich standard errors for the log hazard coefficient; they are not 999-draw bootstrap intervals. The all-mortgage outcome uses all retained loan products and sizes. The other rows retain the conventional below-limit outcome. Each row changes only the stated feature of the county-stratified threshold specification.

Finally, Table A18 compares the annual model with lognormal and Weibull accelerated-failure-time models on the same sample. The annual model reduces the maximum pooled attainment-path discrepancy from 8.8–10.4 percentage points to less than one point and has lower AIC, supporting its use for the displayed waiting times.

Table A18: Matched Fit Comparison for the 10-Point Gain

Model	Initial-share adjustment	AIC	Maximum pooled fit gap (pp)
Lognormal AFT	No	43949.7	8.92
Weibull AFT	No	43291.2	10.44
Lognormal AFT	Yes	42895.2	8.77
Weibull AFT	Yes	41906.3	10.24
Annual timing	No	40588.8	0.59
Annual timing	Yes	39245.8	0.79

Notes: All models use the same 9,908 ZIPs, 2007 uncertainty and controls, state effects, event clock, and censoring rules. The fit gap is the maximum absolute difference between the fitted pooled cumulative attainment path and its Kaplan–Meier counterpart, in percentage points. AIC compares the full matched likelihoods and penalizes additional parameters. These are fit diagnostics, not new confidence intervals or identification tests.

D.6 Application Denials

This section reports the estimates supporting Section 3.2.

Sample and controls We use HMDA purchase and refinance applications submitted to banks and shadow banks from 2007 to 2024. The dependent variable equals 100 for denied applications and zero otherwise, so regression coefficients are measured in percentage points. We standardize collateral uncertainty using the pooled application sample before exclusions for missing regression variables. For the decile specifications, we rank applications by collateral uncertainty and divide them into ten groups. These groups therefore contain approximately equal numbers of applications, not ZIP codes.

We control for log borrower income, log loan amount, the loan-to-income ratio and its square, conforming status, loan type, borrower race and sex, and loan purpose in the pooled regressions. Debt-to-income and loan-to-value ratios are not consistently available over 2007–2024 and are therefore excluded. County-year fixed effects absorb local conditions shared by applications in the same county and year. Lender-year fixed effects absorb characteristics and lending policies common to each lender’s applications in that year. Standard errors are clustered by county.

Denial gaps across uncertainty deciles We estimate:

$$\begin{aligned}
 100\text{Denied}_{i,z,t} = & \sum_{k=2}^{10} \beta_k U_{k,z,t} + \sum_{k=2}^{10} \theta_k (\text{SB}_i U_{k,z,t}) \\
 & + \mathbf{W}'_i \boldsymbol{\gamma} + \alpha_{c(z),t} + \eta_{\ell(i),t} + \varepsilon_{i,z,t}.
 \end{aligned} \tag{14}$$

Here, $U_{k,z,t}$ indicates uncertainty decile k , and SB_i identifies a shadow-bank lender. The lowest uncertainty decile is omitted. The vector $\mathbf{W}_i$ contains the controls listed above; $c(z)$ denotes the county and $\ell(i)$ the lender. The county-year and lender-year fixed effects are $\alpha_{c(z),t}$ and $\eta_{\ell(i),t}$. The shadow-bank dummy is absorbed by lender-year effects.

The coefficient β_k measures banks' adjusted denial-rate change relative to decile 1. The interaction θ_k measures the additional change for shadow banks. For example, $\theta_k = 0.8$ means that the shadow-bank-minus-bank denial gap is 0.8 percentage points larger than in decile 1. It does not necessarily mean that shadow banks have higher denial rates than banks in decile k .

Table A19 shows that, for all applications, the adjusted shadow-bank-minus-bank denial gap is 0.78 percentage points larger in the highest uncertainty decile than in the lowest (standard error 0.22). This pattern is concentrated in refinancing: the additional shadow-bank response reaches 1.55 percentage points in decile 7 and remains 1.07 percentage points in decile 10 (standard error 0.25). Purchase applications show no comparable positive pattern, with interactions generally small and statistically indistinguishable from zero. Adding the regulatory controls preserves these findings.

As a supplementary check, we estimate a residual-inclusion specification (2SRI). We first regress continuous collateral uncertainty and its shadow-bank interaction on the housing-stock instruments and their lender-type interactions, using the same controls and fixed effects. We then add both first-stage residuals to the decile denial regression. For refinances, the highest-decile interaction remains positive at 1.11 percentage points (standard error 0.48), or 0.91 with regulatory controls (standard error 0.53). The highest-decile pooled estimates and the purchase interactions are not statistically distinguishable from zero. These results broadly support the refinance pattern but are less precise than OLS. Reported standard errors do not incorporate first-stage estimation uncertainty.

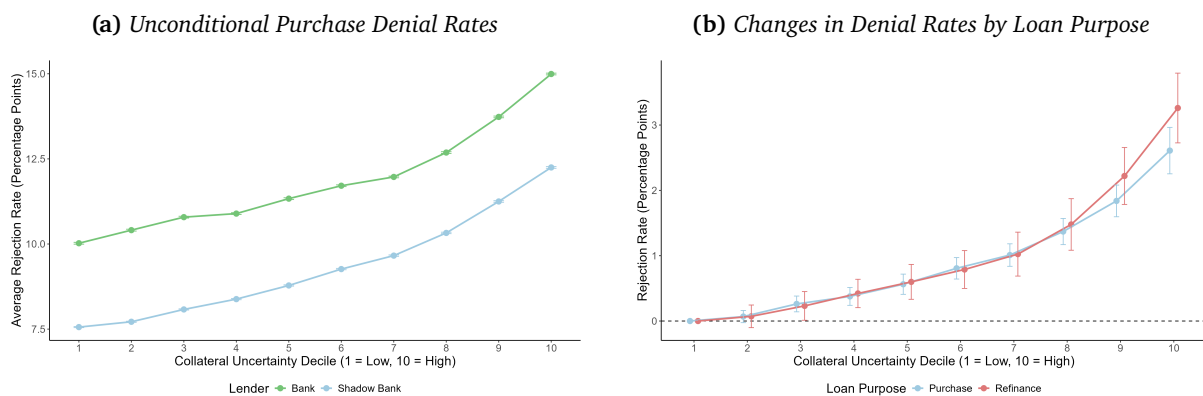
Table A19: Decile Split Regressions: Shadow Bank Rejections across Uncertainty Deciles

	Dependent Variable: Pr(Rejection) x 100											
	All Loans				Purchase Loans				Refinance Loans			
	OLS		2SRI		OLS		2SRI		OLS		2SRI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
UC Decile 2	-0.054 (0.090)	-0.105 (0.088)	0.129 (0.113)	0.116 (0.105)	0.087 (0.069)	0.076 (0.068)	0.251** (0.098)	0.287*** (0.088)	-0.077 (0.124)	-0.148 (0.121)	0.065 (0.142)	0.024 (0.133)
UC Decile 3	-0.033 (0.107)	-0.069 (0.112)	0.244 (0.166)	0.265* (0.138)	0.247*** (0.089)	0.225** (0.092)	0.494*** (0.146)	0.544*** (0.135)	-0.127 (0.140)	-0.174 (0.142)	0.089 (0.197)	0.086 (0.176)
UC Decile 4	0.011 (0.124)	-0.032 (0.133)	0.368* (0.200)	0.400** (0.178)	0.285** (0.111)	0.266** (0.118)	0.604*** (0.185)	0.678*** (0.173)	-0.100 (0.160)	-0.141 (0.164)	0.179 (0.233)	0.196 (0.197)
UC Decile 5	0.113 (0.140)	0.085 (0.151)	0.551** (0.239)	0.616*** (0.213)	0.451*** (0.127)	0.406*** (0.137)	0.843*** (0.231)	0.913*** (0.219)	-0.051 (0.185)	-0.043 (0.188)	0.291 (0.274)	0.371 (0.230)
UC Decile 6	0.227 (0.153)	0.188 (0.157)	0.750*** (0.274)	0.823*** (0.240)	0.688*** (0.135)	0.630*** (0.142)	1.156*** (0.258)	1.237*** (0.240)	-0.002 (0.203)	-0.003 (0.202)	0.406 (0.319)	0.493* (0.260)
UC Decile 7	0.376** (0.173)	0.320* (0.175)	0.991*** (0.321)	1.068*** (0.267)	0.887*** (0.145)	0.800*** (0.156)	1.438*** (0.305)	1.515*** (0.284)	0.148 (0.231)	0.148 (0.223)	0.628* (0.369)	0.731** (0.291)
UC Decile 8	0.863*** (0.189)	0.781*** (0.191)	1.590*** (0.373)	1.667*** (0.315)	1.324*** (0.148)	1.193*** (0.163)	1.975*** (0.342)	2.039*** (0.321)	0.646** (0.256)	0.631*** (0.241)	1.215*** (0.429)	1.321*** (0.342)
UC Decile 9	1.556*** (0.197)	1.326*** (0.221)	2.445*** (0.479)	2.410*** (0.423)	1.869*** (0.167)	1.627*** (0.190)	2.664*** (0.443)	2.661*** (0.423)	1.416*** (0.261)	1.222*** (0.282)	2.111*** (0.536)	2.068*** (0.440)
UC Decile 10	2.645*** (0.274)	2.126*** (0.229)	3.855*** (0.544)	3.593*** (0.459)	2.738*** (0.235)	2.053*** (0.217)	3.825*** (0.515)	3.461*** (0.491)	2.606*** (0.331)	2.217*** (0.282)	3.548*** (0.607)	3.357*** (0.475)
UC Decile 2 x SB	0.165* (0.099)	0.211** (0.092)	0.106 (0.104)	0.116 (0.111)	-0.027 (0.085)	-0.019 (0.082)	-0.083 (0.098)	-0.105 (0.096)	0.218* (0.122)	0.297*** (0.113)	0.211* (0.125)	0.244* (0.137)
UC Decile 3 x SB	0.423*** (0.117)	0.467*** (0.113)	0.341** (0.139)	0.330** (0.151)	0.019 (0.101)	0.001 (0.099)	-0.060 (0.130)	-0.124 (0.133)	0.541*** (0.133)	0.644*** (0.130)	0.537*** (0.156)	0.570*** (0.181)
UC Decile 4 x SB	0.631*** (0.143)	0.675*** (0.142)	0.532*** (0.165)	0.504*** (0.174)	0.138 (0.121)	0.112 (0.121)	0.040 (0.164)	-0.044 (0.168)	0.820*** (0.168)	0.928*** (0.167)	0.822*** (0.181)	0.838*** (0.202)
UC Decile 5 x SB	0.776*** (0.151)	0.805*** (0.149)	0.657*** (0.188)	0.598*** (0.204)	0.175 (0.125)	0.167 (0.127)	0.058 (0.192)	-0.021 (0.198)	1.063*** (0.177)	1.133*** (0.178)	1.069*** (0.206)	1.026*** (0.234)
UC Decile 6 x SB	0.977*** (0.177)	1.004*** (0.172)	0.837*** (0.215)	0.760*** (0.226)	0.190 (0.143)	0.163 (0.145)	0.052 (0.213)	-0.060 (0.222)	1.356*** (0.214)	1.434*** (0.209)	1.366*** (0.238)	1.309*** (0.261)
UC Decile 7 x SB	1.123*** (0.186)	1.167*** (0.181)	0.960*** (0.249)	0.880*** (0.261)	0.204 (0.146)	0.187 (0.147)	0.042 (0.254)	-0.074 (0.263)	1.550*** (0.221)	1.646*** (0.218)	1.563*** (0.265)	1.499*** (0.289)
UC Decile 8 x SB	1.048*** (0.193)	1.144*** (0.189)	0.859*** (0.288)	0.808*** (0.304)	0.068 (0.143)	0.100 (0.146)	-0.120 (0.287)	-0.206 (0.300)	1.477*** (0.221)	1.633*** (0.215)	1.497*** (0.309)	1.463*** (0.341)
UC Decile 9 x SB	1.014*** (0.187)	1.093*** (0.181)	0.782** (0.372)	0.681* (0.395)	-0.079 (0.145)	-0.030 (0.153)	-0.309 (0.371)	-0.405 (0.388)	1.431*** (0.209)	1.558*** (0.202)	1.455*** (0.382)	1.350*** (0.425)
UC Decile 10 x SB	0.781*** (0.220)	0.844*** (0.208)	0.470 (0.464)	0.289 (0.492)	-0.288* (0.161)	-0.106 (0.166)	-0.601 (0.452)	-0.614 (0.471)	1.065*** (0.245)	1.183*** (0.228)	1.109** (0.483)	0.907* (0.532)
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Gete & Reher (2021)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
# of Counties	1913	1254	1913	1254	1912	1253	1912	1253	1912	1253	1912	1253
# of ZIPS	13277	7766	13277	7766	13270	7766	13270	7766	13270	7766	13270	7766
# of Lenders	7086	6919	7086	6919	6787	6599	6787	6599	6634	6405	6634	6405
# of Shadow Banks	1968	1954	1968	1954	1924	1910	1924	1910	1888	1871	1888	1871
Observations	88532203	78595401	88532203	78595401	38985770	34724114	38985770	34724114	49540612	43864888	49540612	43864888

Notes: The outcome is application denial multiplied by 100. Deciles are formed over pooled eligible purchase and refinance applications from 2007 to 2024; decile 1 is omitted. Each sample reports ordinary estimates and residual-inclusion (2SRI) estimates, each with and without the regulatory controls. All models include the borrower and loan controls listed in the text, county-year effects and lender-year effects. Interaction coefficients describe changes in the shadow-bank-minus-bank denial gap relative to decile 1, not the level of that gap. Reported standard errors are clustered by county and, in the residual-inclusion columns, treat the estimated first-stage residuals as regressors rather than refitting both stages in a county bootstrap. *p<0.1; **p<0.05; ***p<0.01.

Purchase and refinance applications. Figure A4 provides additional evidence by loan purpose. Panel A plots unadjusted purchase denial rates across collateral-uncertainty deciles: shadow-bank rates remain below bank rates throughout the distribution. Panel B shows adjusted changes in denial rates relative to the lowest uncertainty decile, estimated separately for purchases and refinances while pooling banks and shadow banks. Denial rates increase in the higher uncertainty deciles for both purposes. Panel B therefore describes the overall denial pattern, rather than differences in responses between lender types.

Figure A4: Additional Application-Denial Evidence by Loan Purpose



Notes: HMDA applications from 2007 to 2024. Panel A reports unconditional purchase denial rates for banks and shadow banks. Panel B reports changes in denial rates relative to decile 1 from separate purchase and refinance regressions pooling banks and shadow banks and omitting the lender-type interaction. Panel B includes borrower and loan controls, county-year effects and lender-year effects; it does not show a bank–shadow-bank denial-gap response. Panel B bars are pointwise 95% county-clustered confidence intervals. The raw refinance rates and adjusted lender-type interactions appear in Figure 4 in the main text.

Other drivers of shadow-bank growth Table A20 adds ZIP-level controls for regulatory exposure following Buchak et al. (2018) and Gete and Reher (2021), together with borrower composition, digital access, housing conditions, banking competition and funding conditions (Drechsler, Savov, & Schnabl, 2022). The controls are described in Appendix D.3. In the combined purchase and refinance sample, the stronger shadow-bank denial response remains positive and statistically significant across all specifications. The estimated additional response per standard deviation of uncertainty is 0.21 percentage points in the baseline and 0.27 with all controls (standard error 0.08). These results support the robustness of the baseline finding. Because the additional controls are not available for every ZIP-year, the columns use different samples.

Table A20: Robustness of Shadow Bank Rejection Sensitivity to Alternative Growth Drivers

	Dependent Variable: Pr(Rejection) x 100								
	Baseline	Robustness and Alternative Specifications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Collateral Uncertainty	0.798*** (0.084)	0.546*** (0.094)	0.685*** (0.066)	0.194*** (0.051)	0.166** (0.074)	0.629*** (0.053)	0.556*** (0.086)	0.597*** (0.086)	0.112 (0.073)
Shadow Bank x Uncertainty	0.209*** (0.065)	0.267*** (0.075)	0.271*** (0.063)	0.381*** (0.072)	0.291*** (0.077)	0.228*** (0.065)	0.272*** (0.071)	0.264*** (0.071)	0.274*** (0.084)
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓							✓
Gete & Reher (2021)			✓						✓
Demographics & Risk				✓					✓
Technology					✓				✓
Housing Market						✓			✓
Bank Competition							✓		✓
Drechsler et al. (2022)								✓	✓
Sample Start Year	2007	2007	2007	2011	2017	2008	2007	2007	2017
Observations	88532203	78744511	83667664	64588197	36719835	77959598	83969016	83969016	34341414
# of Counties	1913	1256	1579	1577	1509	1565	1589	1589	1209
# of ZIPS	13277	7831	8699	8854	8740	8830	8873	8873	7684
# of Lenders	7086	6920	7031	5292	3697	6518	7036	7036	3621
# of Shadow Banks	1968	1954	1963	1345	1077	1715	1963	1963	1073

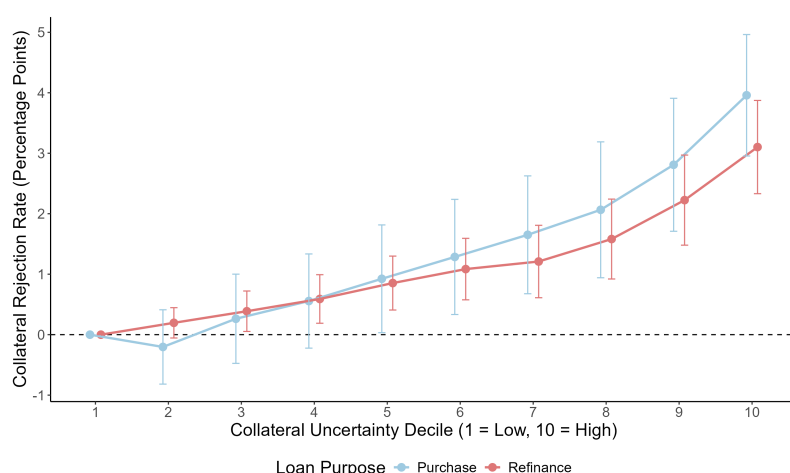
Notes: The outcome is application denial multiplied by 100. Each column includes county-year effects, lender-year effects, and the baseline borrower and loan controls. Additional ZIP-level control blocks are added separately in columns 2–8 and jointly in column 9. Uncertainty is standardized over the pooled application input. Missing controls change the sample and, for some columns, the observation period; these are not comparisons on a common sample. County-clustered standard errors appear in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Reasons for denial We also examine whether lenders cite collateral when rejecting an application. We restrict the sample to denied applications and define $C_{i,z,t} = 1$ if collateral appears among any reported denial reasons, and zero otherwise. We estimate the following regression separately for purchases and refinances, pooling banks and shadow banks:

$$100C_{i,z,t} = \sum_{k=2}^{10} \beta_k B_{k,z,t} + \mathbf{W}_i' \boldsymbol{\gamma} + \alpha_{c(z),t} + \eta_{\ell(i),t} + \varepsilon_{i,z,t}. \quad (15)$$

The controls and fixed effects follow the denial analysis, and the lowest uncertainty decile is omitted. Figure A5 shows that lenders are more likely to cite collateral in higher-uncertainty areas for both purchases and refinances. The estimates describe reported reasons among denied applications, pooling lender types.

Figure A5: Collateral Cited among Application Denials



Notes: The sample contains denied applications by banks and shadow banks from 2007 to 2024. Separate purchase and refinance regressions model whether collateral is cited among any reported denial reasons. The lowest uncertainty decile is omitted. Coefficients are measured in percentage points and account for borrower and loan characteristics, county-year effects and lender-year effects. The specification pools lender types and does not estimate a difference in the collateral-reason response between banks and shadow banks. Vertical bars are 95% confidence intervals based on county-clustered standard errors.

D.7 Connecting Application Denials to Local Market Shares

We estimate the share and denial relationships on matched samples and calculate the change in shadow banks' dollar market share implied by the approval responses to collateral uncertainty. The calculation holds application numbers, the fraction of approvals that become originations, and average originated loan amounts fixed. We measure shadow banks' share relative to mortgage dollars originated by banks, shadow banks and other lenders.

Sample. We use HMDA purchase and refinance applications from 2007 to 2024 for conventional, first-lien mortgages on owner-occupied, site-built properties with one to four units. The sample includes originations, approvals not accepted and denials; it excludes withdrawals, incomplete applications and purchased loans. We require borrower income above \$1,000 and reported loan amounts of at least \$50,000, and apply the annual national one-unit base conforming limit.³⁷

We retain ZIP-years with at least 50 total originations in the original market panel and applications with recorded decisions to both banks and shadow banks. This overlap requirement applies within each purpose for the purchase and refinance analyses, and across both purposes for the pooled analysis. Other lenders are included wherever present.³⁸

The approval calculation also requires originations for every lender group and purpose with

³⁷We use the national base limit for all properties, without adjustments for high-cost counties or the number of units. Before 2018, reported principal must not exceed the limit. From 2018, the lower edge of the published \$10,000 amount bin must not exceed it, so boundary bins can contain loans on either side of the exact limit. This restriction does not establish GSE eligibility.

³⁸We preserve the source classifications, including bank affiliates classified as other lenders. We exclude 612 applications with unusable lender identifiers from both analyses, but retain valid negative identifiers. County assignments are identical across regressions.

applications, so that we can measure conversion rates and average loan amounts. We estimate both the share and denial regressions on the resulting matched ZIP-years within each sample. This additional restriction retains more than 99% of originated dollars (Table A21).

Table A21: Sample Coverage for the Denial–Share Reconciliation

	Pooled	Purchase	Refinance
Full shared ZIP-years	148,130	146,664	147,927
Projection ZIP-years	144,499	144,600	146,365
Counties	1,417	1,417	1,417
Originated dollars retained (%)	99.42	99.83	99.91
Bank applications	28,175,896	8,906,006	19,421,941
Bank approvals	22,735,470	7,954,511	14,893,610
Shadow-bank applications	28,129,814	11,031,367	17,215,404
Shadow-bank approvals	24,139,969	10,267,590	13,969,275
Other-lender applications	13,370,377	4,541,306	8,865,818
Other-lender approvals	11,065,197	3,980,269	7,112,430
Full-support share slope	-1.004 (0.117)	-1.559 (0.163)	-0.672 (0.100)

HMDA, 2007–2024. Application and approval counts refer to the sample used to calculate the lending implied by approvals. Approvals include originations and approved applications not accepted. The full share sample allows a group to have no originations if total lending in the ZIP-year is positive. The calculation sample also requires positive originations for each group and purpose with applications. The retained dollar share compares these two samples. The last row reports the full-sample share coefficient, in percentage points per standard deviation of uncertainty, with county-clustered standard errors in parentheses. Matched-sample coefficients appear in Table A23.

Regressions. We standardize collateral uncertainty once over the original 148,130 eligible ZIP-years, counting each ZIP-year once. We use this measure, $U_{z,t}$, across samples and lender groups, so all coefficients refer to the same increase in uncertainty. The scale also remains fixed across bootstrap draws.³⁹

Both regressions control for log mean income, log mean requested loan amount, mean loan-to-income ratio, mean squared loan-to-income ratio, and race and sex proportions. We include refinance-category proportions where applicable and the refinance application fraction in the pooled sample. These controls, $\mathbf{W}_{z,t}$, are calculated from all applications with recorded decisions within each ZIP-year. White and male are the reference categories; constant or redundant controls are omitted. LTV and DTI are excluded because they are not consistently available over the historical period.

For lender group g (Bank, SB or Other), ZIP z , year t and purpose r (purchase or refinance), we estimate the denial rate in percentage points as

$$d_{gztr} = \beta_{0,gr} + b_{gr}U_{z,t} + \mathbf{W}_{z,t}'\boldsymbol{\gamma}_r + \alpha_{c(z),t,r} + \varepsilon_{gztr}. \quad (16)$$

³⁹The raw mean is 0.30564448 and the standard deviation is 0.10870934.

County-year effects are common across lender groups, while group intercepts and uncertainty slopes differ; $c(z)$ denotes the ZIP's county. For the pooled calculation, we estimate separate purchase and refinance denial relationships on the pooled sample, allowing coefficients and county-year effects to differ by purpose.

We estimate the market-share relationship on the same ZIP-years, with the same controls and county-year effects:

$$100s_{zt} = TU_{z,t} + \mathbf{W}'_{z,t} \boldsymbol{\gamma}^S + \alpha_{c(z),t} + \varepsilon_{z,t}^S, \quad (17)$$

where s_{zt} is shadow banks' share of originated dollars and T is its relationship with uncertainty. Each ZIP-year receives equal weight. In the denial regressions, this weight is divided equally among the lender groups present; within each group, pooled purposes are weighted by application counts.⁴⁰ Standard errors are clustered by county. Table A22 reports the denial estimates. These matched regressions use ZIP-year controls rather than the individual borrower controls and lender-year effects of the main application regressions, and use a different uncertainty scale.

Table A22: Denial Relationships on the Matched Accounting Samples

	Purpose-specific sample		Pooled sample	
	Purchase	Refinance	Purchase	Refinance
Bank uncertainty slope	0.741 (0.067)	0.230 (0.089)	0.483 (0.065)	0.433 (0.094)
Shadow-bank uncertainty slope	1.042 (0.096)	1.968 (0.143)	0.838 (0.095)	2.175 (0.134)
Other-lender uncertainty slope	0.826 (0.081)	-0.096 (0.095)	0.673 (0.075)	0.159 (0.101)
Shadow bank minus bank	0.302 (0.089)	1.739 (0.159)	0.355 (0.082)	1.741 (0.162)
Group-ZIP-year observations	432,095	438,072	430,381	432,328
Target ZIP-years	144,600	146,365	144,499	144,499
Common county-year effects	Yes	Yes	Yes	Yes
Group intercepts and controls	Yes	Yes	Yes	Yes
Lender-year effects	No	No	No	No
R ²	0.331	0.487	0.357	0.543
Within R ²	0.121	0.204	0.129	0.231

The outcome is the group denial rate in percentage points. Coefficients measure the change per standard deviation of uncertainty. Parentheses contain county-clustered standard errors; the standard error of the shadow-bank-minus-bank difference accounts for covariance between the two estimates. Market controls are defined in the text. The pooled columns use the pooled sample and its controls, weight each group's purposes by their application counts, and allow coefficients and county-year effects to differ by purpose. Observations count group cells, not individual applications. Groups with no applications are omitted rather than assigned a zero denial rate.

⁴⁰The group-purpose weight is $A_{gztr} / [G_{zt} \sum_s A_{gzts}]$, where A counts applications, G counts groups with applications, and the sum covers that column's purposes. For a single purpose, the weight is $1/G_{zt}$. Correspondingly weighted lender-level estimation gives the same coefficients.

From approvals to originated dollars and market shares. For each ZIP-year, lender group g and loan purpose r , let A denote applications, p the approval rate, q the fraction of approvals that become originations, and L the average originated loan amount. Originated dollars satisfy

$$V_{gzt} = A_{gzt} p_{gzt} q_{gzt} L_{gzt}.$$

The denial coefficient b_{gr} measures percentage points per standard deviation of uncertainty. Holding applications, conversion and loan size fixed, the corresponding change in originated dollars is

$$\mathcal{G}_{gzt} = -A_{gzt} q_{gzt} L_{gzt} \frac{b_{gr}}{100} = -\frac{V_{gzt}}{p_{gzt}} \frac{b_{gr}}{100}. \quad (18)$$

We evaluate this local response using each cell's observed values. For the pooled calculation, we sum purchase and refinance dollars and their implied changes within each lender group.

Let $V_{zt} = \sum_g V_{gzt}$ be total originated dollars and $s_{zt} = V_{SB,zt} / V_{zt}$ the shadow-bank share. Approval changes affect both its numerator and denominator. Averaging across the N matched ZIP-years gives the share response in percentage points:

$$I = \frac{1}{N} \sum_{zt} 100 \frac{\mathcal{G}_{SB,zt} - s_{zt} \sum_g \mathcal{G}_{gzt}}{V_{zt}}. \quad (19)$$

The sums include banks, shadow banks and other lenders. Groups without applications contribute zero dollars and zero dollar changes. This extends equation (25) to originated dollars and three groups.

Bootstrap and results. We compare the approval-only projection I with the matched share coefficient T ; I/T is the accounting ratio and $T - I$ the remaining difference. We draw 999 bootstrap samples of counties with replacement, retaining each county's full history. In every draw, we re-estimate both regressions and their fixed effects, then recalculate the approval projection and accounting ratio over the selected ZIP-years. The uncertainty scale remains fixed. We report pointwise 95% percentile intervals using all 999 draws. Ratios retain their signs and are not restricted to zero–100%.

Table A23, Panel A, reports the matched share coefficients, approval-only projections and accounting ratios. The accounting ratio is 28.2% [22.0%, 38.6%] for pooled lending, 3.3% [1.1%, 5.8%] for purchases and 74.0% [57.9%, 108.3%] for refinances. For refinances, the matched share coefficient is -0.665 percentage points [-0.832 , -0.454], compared with an approval-only projection of -0.492 [-0.567 , -0.418]. The remaining difference, $T - I$, is -0.173 percentage

points $[-0.350, 0.039]$.⁴¹

Borrower switching and pricing may affect the application flows, conversion rates and loan amounts held fixed here; the remaining difference does not identify their contribution.

Bank–shadow-bank comparison. We also measure shadow banks’ share relative to banks and shadow banks alone. We retain the same samples and estimated denial coefficients, excluding other lenders only from the dollar calculations. The accounting ratio is 23.6% [18.8%, 30.7%] for the pooled sample, 3.3% [1.3%, 5.8%] for purchases and 57.8% [46.0%, 78.5%] for refinances (Panel B). The refinance interval includes 50%, so this comparison does not establish that approvals account for more than half of the relationship.

Table A23: *Application Decisions and Local Market Shares*

	Pooled	Purchase	Refinance
<i>A. All-group dollar denominator</i>			
Matched share coefficient T	-0.985	-1.540	-0.665
	[-1.186, -0.731]	[-1.813, -1.196]	[-0.832, -0.454]
Approval-only projection I	-0.278	-0.051	-0.492
	[-0.330, -0.227]	[-0.085, -0.016]	[-0.567, -0.418]
Discrepancy $T - I$	-0.707	-1.489	-0.173
	[-0.901, -0.456]	[-1.762, -1.154]	[-0.350, 0.039]
Accounting ratio I/T (%)	28.2	3.3	74.0
	[22.0, 38.6]	[1.1, 5.8]	[57.9, 108.3]
<i>B. Bank-plus-shadow-bank dollar denominator</i>			
Matched share coefficient T	-1.216	-1.765	-0.846
	[-1.397, -0.996]	[-2.010, -1.443]	[-1.029, -0.643]
Approval-only projection I	-0.287	-0.059	-0.489
	[-0.344, -0.234]	[-0.098, -0.022]	[-0.569, -0.410]
Discrepancy $T - I$	-0.929	-1.706	-0.357
	[-1.110, -0.709]	[-1.943, -1.388]	[-0.536, -0.148]
Accounting ratio I/T (%)	23.6	3.3	57.8
	[18.8, 30.7]	[1.3, 5.8]	[46.0, 78.5]

Panels A–B use common county-year effects in the matched share and denial regressions. Changes are in percentage points per standard deviation of uncertainty. Brackets contain pointwise 95% percentile intervals from 999 county bootstrap samples, with the same draws used for all regressions and calculations. Ratios retain their signs and can exceed 100%. Both panels use the same ZIP-years; Panel B excludes other lenders only from the dollar calculation. The approval-only projection holds application counts, approval-to-origination conversion rates and average loan amounts fixed.

⁴¹The all-group refinance contrast $-I + T/2$ is 0.160 percentage points, with a 95% interval of [0.062, 0.280].

E Model and Supporting Mechanism Evidence

This appendix provides the model's accounting and proofs, the institutional distinctions relevant to loan sales, and the supporting empirical results. The framework is a conditional lending-choice model, not an equilibrium model of purchaser pricing, lender entry, or borrower search.

E.1 Accounting and Model Assumptions

Fix an application type, including principal L , purpose p , borrower characteristics, and contract terms. Suppress purpose subscripts where convenient below. Normalize principal disbursement to L , expected retained principal receipts to $L - h(a)$, and base sale proceeds to $L - c_0(a)$, all at a common valuation date. Then the payoffs in (4) are $-L + m + L - c_0 - C$ and $-L + m + L - h - \kappa_\ell$. This is a principal-only normalization, not a valuation of a full amortizing mortgage. Common costs and receipts included in m are not counted again. Interest and servicing receipts may enter the common baseline only with consistent accounting.

One representation of the incremental expected sale cost is

$$C(a, U) = \mathbb{E} \left[K_{\text{rem}} + \int_0^T D_v b_v dv + \sum_j D_{T_j} J_j \mid a, U, p, \text{sale route} \right]. \quad (20)$$

Here K_{rem} is remaining verification expense, T the execution time, D_v the discount factor, b_v net incremental carrying expense, and J_j a net contractual remedy at date T_j . Carrying expense subtracts interim receipts and excludes costs already reflected in the base sale proceeds. For a repurchase, net liability subtracts the returned mortgage's continuation value from the payment and additional expenses. Future losses already reflected in that value are not charged twice. Costs, duration, and remedies may be correlated; the model does not multiply unconditional event rates by assumed constant costs.

We assume finite payoffs, $C \geq 0$, and $C_U \geq 0$ over the comparison. These restrictions apply to the aggregate expectation; individual net components need not be positive. Expenses already incurred at final funding are sunk. An earlier processing decision would instead compare expected lending profits with a still-avoidable processing cost. The baseline assumes an executable sale route conditional on eligibility and summarizes subsequent expenses. Failed delivery and contingent fallback are not separately modeled.

The retention-cost parameter follows the financing-choice logic of Buchak et al. (2024). For a lender with total capacity cost $H_\ell(B)$ and retained exposure B , a local approximation is $\kappa_\ell = wLH'_\ell(B)$, where wL is the loan's incremental exposure. If $H(B) = Bq(B)$, the marginal cost is $q(B) + Bq'(B)$, not just $q(B)$. We do not solve for B or equate a lender-type label with this parameter.

E.2 Choice Sets and Comparative Statics

Let $\mathcal{E} = [L/\lambda, \infty)$, $\mathcal{Q}_S(U) = \{a \in \mathcal{E} : \Pi^S(a, U) > 0\}$, and $\mathcal{Q}_R(\kappa) = \{a \in \mathcal{E} : \Pi_\kappa^R(a) > 0\}$. The approval set is their union. Infeasible routes have payoff $-\infty$; rejection has payoff zero. A strictly positive tie is routed to sale.

Approval-set inclusion. Increasing κ lowers retention profit at every appraisal without changing sale profit or eligibility. Thus $\mathcal{Q}_R(\kappa_H) \subseteq \mathcal{Q}_R(\kappa_L)$, and taking unions with the common sale set preserves inclusion. Define $\mathcal{B} = \mathcal{Q}_R(\kappa_L) \setminus \mathcal{Q}_R(\kappa_H)$. With continuous density $f_A(a; U, p)$,

$$d_H - d_L = \int_{\mathcal{B}} \mathbf{1}\{\Pi^S(a, U) \leq 0\} f_A(a; U, p) da. \quad (21)$$

At fixed appraisal distribution and retention payoffs, lowering sale profit expands this set weakly. The change is strict only if a positive-probability subset of $\mathcal{B}$ loses profitable sale. The argument does not require monotone payoff schedules or a particular appraisal distribution. $\square$

For the cutoff representation, let $q(a, U) = c_0(a) + C(a, U)$ and suppose q and h are continuous and decreasing in a , strictly so at interior zero-profit roots. Let $b_S(U)$ solve $q(b_S, U) = m$ and $b_R(\kappa)$ solve $h(b_R) = m - \kappa$, allowing boundaries zero or infinity when a route is everywhere profitable or unprofitable. Then

$$t(U) = \max\{L/\lambda, b_S(U)\}, \quad r_\ell = \max\{L/\lambda, b_R(\kappa_\ell)\}, \quad \tau_\ell = \min\{t, r_\ell\}. \quad (22)$$

At interior roots, $b'_S = -q_U/q_a \geq 0$ and $\partial_\kappa b_R = -1/h_a > 0$. The eligibility floor can make the effective threshold locally constant. Isolated zero-profit points have zero mass; flat zero-profit intervals require the set formulation above.

Application-weighted lender groups. Let E_g average across lenders using fixed application weights conditional on application type. Assume A and $r_{\ell p}$ are independent conditional on that type. Thus $D_{g,p} = E_g[F_A(\min\{t_p, r_{\ell p}\}; U, p)]$ and $\chi_{g,p} = \Pr_g\{r_{\ell p} > t_p\}$. These weights describe applications, not the distribution of lenders or originated loans. With a continuous appraisal distribution and no mass at $r_{\ell p} = t_p$, the denial gap also satisfies

$$\Delta_p = \int_{e_p}^{t_p} f_A(a; U, p) \left[\Pr_{\text{SB}}\{r_{\ell p} > a\} - \Pr_{\text{Bank}}\{r_{\ell p} > a\} \right] da. \quad (23)$$

Below e_p , both groups reject. Above t_p , both can originate for sale. Between these boundaries, rejection requires $r_{\ell p} > a$, giving the integral.

Proof of Proposition 1. At fixed appraisal distribution and retention thresholds, an increase in t_p changes approval only for lenders with $r_{\ell p} > t_p$. Their denial derivative is $f_A(t_p; U, p)t_{p,U}$; it is zero for lenders with $r_{\ell p} < t_p$. Averaging with fixed application weights gives $D'_{g,p}|_{\text{financing}} = f_A(t_p; U, p)t_{p,U}\chi_{g,p}$. Subtracting the bank response proves (6). The derivative of (23) gives the same result. Positive boundary density, a rising cutoff, and greater shadow-bank marginal sale dependence make the product strictly positive. At ties or eligibility-floor transitions, use one-sided derivatives or finite changes. $\square$

When U also changes the appraisal distribution, while retention thresholds remain fixed, differentiation yields

$$\begin{aligned} D'_{g,p} &= f_A(t_p; U, p)t_{p,U}\chi_{g,p} + J_{g,p}, \\ J_{g,p} &= E_g [\partial_U F_A(\tau_{\ell p}; U, p)]. \end{aligned} \quad (24)$$

The partial derivative in $J_{g,p}$ holds its appraisal argument fixed. The total denial-gap derivative adds $J_{\text{SB},p} - J_{\text{Bank},p}$ to (6). The distribution contribution is not signed by a mean-preserving spread alone.

Derivation of the lending-share response. Let $\mathcal{A}_{g,p}$ be comparable application flows and $v_{g,p}$ the fraction of approvals converted into originations. Then $O_{g,p} = \mathcal{A}_{g,p}(1 - D_{g,p})v_{g,p}$ and $\sigma_p = O_{\text{SB},p}/(O_{\text{SB},p} + O_{\text{Bank},p})$. At fixed positive flows and conversion rates,

$$\frac{\partial \sigma_p}{\partial U} = -\sigma_p(1 - \sigma_p) \left[\frac{D'_{\text{SB},p}}{1 - D_{\text{SB},p}} - \frac{D'_{\text{Bank},p}}{1 - D_{\text{Bank},p}} \right]. \quad (25)$$

This follows by differentiating the log ratio of originations and multiplying by $\sigma_p(1 - \sigma_p)$. Substituting the pure financing derivatives proves (7). The full response instead uses (24). Equal denial-gap derivatives need not imply equal proportional approval losses when approval levels differ.

Changing application flows or conversion rates adds their log relative derivative inside this accounting relation. Dollar shares additionally depend on changes in relative mean loan amounts. The main-text comparison holds these terms fixed and uses a bank-plus-shadow-bank denominator. Neither its three quantities nor a reduced-form interaction coefficient identifies a share of aggregate credit rationing. The more general empirical accounting exercise requires aligned samples, denominators, and lender-specific denial levels and slopes.

The total uncertainty response. When uncertainty changes the appraisal distribution as well as sale costs, differentiation gives

$$\frac{d(d_H - d_L)}{dU} = \int_{\tau_L}^{\tau_H} \partial_U f_A(a; U, p) da + f_A(\tau_H; U, p) \tau'_H - f_A(\tau_L; U, p) \tau'_L. \quad (26)$$

The boundary contribution is nonnegative under the maintained common sale cost and fixed retention payoffs. It equals $f_A(t; U, p)t'(U)$ when $r_L < t < r_H$ and zero in the two outer regions. The distribution contribution need not be positive. A sufficient condition is $\partial_U f_A \geq 0$ throughout the interval between approval thresholds. A positive boundary contribution can also outweigh a negative distribution contribution. Use one-sided derivatives or finite changes at regime boundaries.

For a positive-support illustration, set

$$A = \mu \exp\{s_p(U)Z - s_p(U)^2/2\}, \quad Z \sim N(0, 1), \quad s'_p(U) \geq 0. \quad (27)$$

The mean is μ and variance is $\mu^2(\exp(s^2) - 1)$. This mean-preserving lognormal family is our simplification of the appraisal-risk margin, not the exact noisy-appraisal model or borrower problem of E. X. Jiang and Zhang (2025). With $\rho = \log(\mu/a)$ and $s = s_p(U)$,

$$\frac{\partial f_A(a; s)}{\partial s} = \frac{f_A(a; s)}{s} \left(\frac{\rho^2}{s^2} - 1 - \frac{s^2}{4} \right). \quad (28)$$

Thus a sufficient lower-tail condition for a nonnegative distribution term is

$$\tau_H < \mu \exp\{-s\sqrt{1 + s^2/4}\}. \quad (29)$$

This is a local sufficient condition, not something established by the IV, an observed denial rate, or the empirical sale-share measure. A larger dispersion can otherwise shrink the denial gap.

Loan Purpose and Appraisal Information. Purchase transactions provide a contemporaneous price that can inform collateral valuation. Refinances lack this price and rely more heavily on comparable sales and other property information. This motivates allowing the appraisal distribution $F_A(a; U, p)$ and its response to collateral uncertainty to vary with loan purpose, following the appraisal-based collateral requirement of E. X. Jiang and Zhang (2025).

A low appraisal can make the requested mortgage fail the collateral requirement or become unprofitable to sell or keep. The absence of a current transaction price therefore provides a reason to compare purchase and refinance approvals. Figure 4 presents this comparison; the purpose pattern is evidence to explain, not by itself a test of the financing mechanism.

Greater appraisal dispersion does not automatically increase denials or widen the shadow-bank-minus-bank gap. Its contribution depends on how probability moves relative to approval thresholds and on lenders' retention alternatives, as equation (26) shows. Proposition 1 instead isolates the selling-cost channel while holding the appraisal distribution fixed. A stronger refinance response therefore requires the relevant costs, thresholds and retention alternatives, rather than the refinance label alone.

Sale dependence. At fixed application composition, uncertainty, and sale opportunities, a sale chosen at κ_L remains profitable and dominates retention at any $\kappa_H \geq \kappa_L$. Sale probability therefore weakly increases, whereas origination probability weakly decreases. Their ratio, the sale share among originations, weakly increases whenever originations have positive probability. This need not imply a strict ordering: lenders that are already sale-only can have identical approval thresholds. Heterogeneous sale costs or application composition can invalidate the empirical ordering.

Scope and extensions. With route-specific collateral caps, replace L/λ in t and r_ℓ by L/λ_S and L/λ_R . If every eligible sale is profitable and the caps are equal, approvals coincide across lenders. If retained credit loss also rises with U , an interior retention threshold moves at $r_{\ell,U} = -h_U/h_a$, potentially reversing the differential response. Complete compensation through sale prices can remove the sale-cost channel. A common borrower charge must enter both financing payoffs.

For purchases, a rule using $\min(P, a)$, where P is the transaction price, reduces to the displayed constraint only for requested contracts satisfying $L \leq \lambda P$. Refinancing lacks P , but loan purpose can also change s_p , C , leverage, and program eligibility. No universal refinance, cash-out, or LTV ranking follows. Allowing a common set of alternative loan amounts preserves approval-set inclusion in κ , but does not determine average LTV among originated loans.

With fixed application flows n_ℓ , originations are $O_\ell = n_\ell(1 - d_\ell)$. For the high-cost lender's two-group share ω_H ,

$$\omega'_H = \omega_H(1 - \omega_H) \left[-\frac{d'_H}{1 - d_H} + \frac{d'_L}{1 - d_L} \right]. \quad (30)$$

The share weakly falls if $d_H \geq d_L$ and $d'_H \geq d'_L \geq 0$. Borrower switching and other lenders lie outside this fixed-flow comparison. If a refinancing incentive B only scales common flows, $n_\ell = a_\ell N(B)$, then $O_{\ell,UB} = -a_\ell N'(B)d'_\ell$ but $(\log O_\ell)_{UB} = 0$ and $\omega_{H,B} = 0$. Stronger share or log-volume responses during refinancing waves require additional state dependence. The separate prepayment-and-retention framework is not imposed here.

E.3 Eligibility and Responsibilities in Secondary Markets

Sale eligibility, valuation acceptance, relief from representations and warranties, and profitable execution are different conditions. The originator, purchaser, guarantor, issuer, and servicer can also be different entities. The model's sale option represents an executable distribution route, not necessarily a direct sale to a GSE. HMDA loan sales are not synonymous with securitization.

Fannie Mae and Freddie Mac. The GSE route involves borrower and property eligibility, leverage limits, acceptable valuation documentation, seller approval, and delivery requirements. Appraisal-based constraints in the model summarize one part of these requirements, not an exhaustive eligibility rule. FHFA's December 2020 review explains how standardized property data and collateral tools inform appraisal review and waiver offers. It distinguishes an offer from its exercise by the lender and borrower.⁴²

Current Fannie Mae guidance similarly distinguishes eligibility for Value Acceptance from actual use. Freddie Mac's guidance states that a poor collateral score alone does not trigger repurchase; significant defects identified in quality-control review matter. Additional documentation and review can therefore have value. Neither common GSE tools nor predetermined scoring rules imply that lenders have no incentive to acquire information.⁴³

Representations and warranties can leave contractual exposure after delivery. Applicable relief and exceptions must be distinguished from loan eligibility. Fannie Mae's guide describes both repurchase and make-whole remedies.⁴⁴ These rules motivate expected liability in C, but do not identify its size or establish that every valuation error produces a remedy.

Government-insured and guaranteed mortgages. FHA insurance and VA guarantees differ from Ginnie Mae's guarantee of securities. Ginnie Mae does not act as a GSE whole-loan purchaser. Issuer and servicer obligations can remain, so government backing should not be treated as eliminating every originator cost. The 2024 FSOC report describes liquidity obligations and repurchases in these channels, but does not establish a collateral-specific origination effect.⁴⁵

Program-specific exceptions also matter for refinancing. Some streamlined refinance routes do not require a fresh appraisal. The July 2021 FHA handbook and VA's July 2022 circular provide dated examples; these cannot be generalized to all refinance products.⁴⁶

⁴²FHFA, [Appraisal-Related Policies, Practices, and Processes](#), December 28, 2020, especially pp. 3–4 and 13–18.

⁴³Fannie Mae, [Selling Guide B4-1.4-10: Value Acceptance](#); Freddie Mac, [Loan Collateral Advisor FAQ](#). Current explanatory guidance accessed September 17, 2026, not a reconstructed rule series for the sample.

⁴⁴Fannie Mae, [Selling Guide A2-3.2-01: Loan Repurchases and Make Whole Payments](#), accessed September 17, 2026.

⁴⁵FSOC, [Report on Nonbank Mortgage Servicing](#), May 2024, Sections 5–6.

⁴⁶HUD, [FHA Handbook 4000.1](#), July 20, 2021, Section II.A.8.d; VA, [Circular 26-22-13](#), July 27, 2022, including the IRRRL exception.

Private purchasers and securitizers. An aggregator or private-label execution can impose its own documentation, underwriting, valuation diligence, and contractual remedies. A transaction-specific illustration is Clayton Services' November 2024 review for MFA 2024-NQM3, which includes valuation diligence.⁴⁷ This is evidence of requirements in one transaction, not a universal private-market rule. The framework does not assume that alternative purchasers remove all valuation costs.

These institutional descriptions clarify the model's interpretation. Quantitative eligibility comparisons or identification using rule changes would require date-, product-, and route-specific criteria. We do not apply current rules retrospectively to the entire 2007–2024 sample.

⁴⁷Clayton Services, [MFA 2024-NQM3 Due Diligence Narrative Report](#), November 21, 2024, SEC ABS-15G exhibit.

E.4 Additional Results: Section Mechanism Evidence

Additional results for empirical mechanism subsection 4.2

E.4.1 OTD-Dependence

This section provides supplementary tables supporting the OTD-dependence mechanisms discussed in subsection 4.2.1.

Table A24: Lender OTD Reliance, Collateral Uncertainty, and Loan Rejection Rates (2009 - 2024)

	Dependent Variable: $\text{Pr}(\text{Rejection}) \times 100$					
	All Loans		Purchase		Refinance	
	(1)	(2)	(3)	(4)	(5)	(6)
OTD Share	-8.629* (4.520)	-9.127** (4.164)	-6.475* (3.379)	-6.618** (3.326)	-19.766*** (6.266)	-20.109*** (5.719)
Collateral Uncertainty	0.288*** (0.073)	0.211*** (0.072)	0.435*** (0.068)	0.316*** (0.071)	0.520*** (0.099)	0.476*** (0.101)
OTD Share x Uncertainty	0.643*** (0.086)	0.577*** (0.089)	0.222*** (0.072)	0.218*** (0.076)	0.510*** (0.106)	0.417*** (0.113)
County-Year FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓		✓		✓
Gete & Reher (2021)		✓		✓		✓
Clustered SE	County	County	County	County	County	County
Sample Avg. OTD Measure	0.845	0.845	0.829	0.829	0.860	0.860
# of Counties	1901	1247	1878	1241	1899	1247
# of ZIPs	13243	7759	13202	7759	13231	7759
# of Lenders	1184	1180	1173	1168	1162	1157
# of Shadow Banks	1184	1180	1173	1168	1162	1157
Observations	42154605	37858919	20674123	18574826	21479698	19283747

Note: This table reports linear probability model estimates based on HMDA loan applications from 2009 to 2024, restricted to shadow banks. OTD share is defined as a lender's 3-year moving average fraction of loans sold, calculated by leaving out the application county. Columns 1–2 use the full sample (all loans), columns 3–4 restrict to purchase loans, and columns 5–6 restrict to refinance loans. For each sample, the first column presents within-lender estimates (with County-Year and Lender-Year fixed effects), and the second column presents the results additionally controlling for the regulatory shocks by Buchak et al. (2018) and Gete and Reher (2021). All specifications include loan and borrower controls (log income, log loan amount, LTI, LTI squared, conforming loan indicator, loan type, loan purpose, race, and sex). Collateral uncertainty is standardized. Standard errors are clustered at the county level and are reported in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

Table A25: Heterogeneous Effects by Lender Refinance Specialization (2009 - 2024)

Refinance Specialization:	Dependent Variable: $\text{Pr}(\text{Rejection}) \times 100$					
	Low (< 33)		Medium (33–66)		Top (> 66)	
	(1)	(2)	(3)	(4)	(5)	(6)
OTD Share	10.262* (5.427)	8.377 (5.753)	-15.931*** (4.402)	-16.998*** (4.308)	-28.671** (14.072)	-26.555** (12.680)
Collateral Uncertainty	0.223*** (0.086)	0.156 (0.097)	0.450*** (0.086)	0.355*** (0.086)	0.618*** (0.154)	0.490*** (0.169)
OTD Share × Uncertainty	0.230** (0.092)	0.229** (0.105)	0.184** (0.091)	0.163* (0.094)	0.660*** (0.171)	0.603*** (0.180)
County-Year FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓		✓		✓
Gete & Reher (2021)		✓		✓		✓
Clustered SE	County	County	County	County	County	County
# of Counties	1,799	1,216	1,869	1,239	1,895	1,246
# of ZIPs	12,996	7,742	13,181	7,757	13,224	7,759
# of Lenders	617	615	906	901	628	625
# of Shadow Banks	617	615	906	901	628	625
Observations	8777557	7909183	16552134	14957133	16822364	14991456

Note: This table reports OLS regression results examining application rejection rates (multiplied by 100) across shadow bank subsamples sorted by lender refinance specialization (Low: < 33%, Medium: 33%–66%, Top: > 66% of originations) from 2009 to 2024. OTD share is defined as a lender's 3-year moving average fraction of loans sold, calculated by leaving out the application county. Refinance share is similarly defined as the fraction of originated refinance mortgages. For each sample, the first column presents within-lender estimates (with County-Year and Lender-Year fixed effects), and the second column presents the results additionally controlling for the regulatory shocks by Buchak et al. (2018) and Gete and Reher (2021). All specifications include loan and borrower controls (log income, log loan amount, LTI, LTI squared, conforming loan indicator, loan type, loan purpose, race, and sex). Collateral uncertainty is standardized. Standard errors are clustered at the county level and are reported in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

Table A26: Heterogeneous Effects by Refinance Types (2018 - 2024)

	Dependent Variable: Pr(Rejection) × 100					
	Refinance Sample		Non-Cashout Sample		Cashout Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
OTD Share	-14.334 (10.713)	-14.455 (11.095)	-11.363 (9.608)	-11.069 (9.775)	-19.550 (12.833)	-20.209 (13.528)
Collateral Uncertainty	0.333*** (0.126)	0.283* (0.145)	0.637*** (0.145)	0.595*** (0.167)	-0.226 (0.166)	-0.272 (0.189)
OTD Share × Uncertainty	0.566*** (0.114)	0.394*** (0.124)	-0.010 (0.136)	-0.170 (0.151)	1.386*** (0.181)	1.203*** (0.207)
County-Year FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓		✓		✓
Clustered SE	County	County	County	County	County	County
Sample Avg. OTD Measure	0.852	0.852	0.840	0.840	0.865	0.865
# of Counties	1775	1208	1740	1196	1771	1206
# of ZIPS	12762	7715	12662	7713	12745	7715
# of Lenders	826	822	814	809	764	759
# of Shadow Banks	826	822	814	809	764	759
Observations	11620653	10522319	6170693	5624488	5449309	4897372

Note: This table reports linear probability model estimates based on HMDA refinance applications from 2018 to 2024, restricted to shadow banks. OTD share is defined as a lender's 3-year moving average fraction of loans sold, calculated by leaving out the application county. Columns 1–2 use the full sample (all refinance), columns 3–4 restrict to non-cashout applications, and columns 5–6 restrict to cashout loans. For each sample, the first column presents within-lender estimates (with County-Year and Lender-Year fixed effects), and the second column presents the results additionally controlling for the regulatory shocks by Buchak et al. (2018). All specifications include loan and borrower controls (log income, log loan amount, DTI and LTV bins, LTI, LTI squared, conforming loan indicator, loan type, loan purpose, race, and sex). Collateral uncertainty is standardized. Standard errors are clustered at the county level and are reported in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

E.4.2 Retention Capacity

This section provides a supplementary table supporting the bank retention capacity discussed in subsection 4.2.2.

Table A27: Collateral Uncertainty and Loan Retention: Banks versus Shadow Banks (2007 - 2024)

	Dependent Variable: Pr(Loan Retention) × 100					
	All Loans		Purchase Loans		Refinance Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral Uncertainty	1.068*** (0.130)	0.988*** (0.141)	1.422*** (0.134)	1.348*** (0.159)	0.804*** (0.138)	0.730*** (0.135)
Shadow Bank × Uncertainty	-1.278*** (0.175)	-1.283*** (0.203)	-1.594*** (0.173)	-1.592*** (0.202)	-1.015*** (0.184)	-1.058*** (0.213)
County-Year FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓	✓	✓
Borrower Controls	✓	✓	✓	✓	✓	✓
Buchak et al. (2018)		✓		✓		✓
Gete & Reher (2021)		✓		✓		✓
Clustered SE	County	County	County	County	County	County
# of Counties	1913	1254	1911	1253	1911	1253
# of ZIPS	13272	7766	13263	7766	13260	7766
# of Lenders	6910	6741	6571	6375	6426	6188
# of Shadow Banks	1896	1886	1857	1842	1826	1813
Observations	68646551	61252173	33460973	29876198	35178038	31368651

Notes: This table reports OLS regression results examining loan retention rates (multiplied by 100) across traditional banks and shadow banks from 2007 to 2024. Columns (1) and (2) present estimates for the full sample, while columns (3)–(4) and (5)–(6) restrict the sample to purchase and refinance mortgages, respectively. For each sample, the first specification includes county-by-lender type-by-year and lender-by-year fixed effects, whereas the second specification additionally incorporates the regulatory shock controls of Buchak et al. (2018) and Gete and Reher (2021). All models include comprehensive loan- and borrower-level controls (including log income, log loan amount, LTI, LTI squared, conforming loan indicators, loan types, loan purposes, race, and sex). Collateral uncertainty is standardized to a mean of zero and standard deviation of one. Standard errors clustered at the county level are reported in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

E.4.3 Secondary-Market Evidence and Measurement

This section provides supplementary tables supporting the loan-sale frictions discussed in subsection 4.2.3.

Table A28: Collateral Uncertainty and the Probability of Appraisal Waiver

	Dependent Variable: Probability of Appraisal Waiver					
	Full Sample		Non-Refinance		Refinance	
	(1) OLS	(2) PPML	(3) OLS	(4) PPML	(5) OLS	(6) PPML
Collateral Uncertainty	−3.086*** (0.966)	−0.104*** (0.028)	−0.952*** (0.250)	−0.139*** (0.030)	−4.186*** (1.281)	−0.099*** (0.028)
Mean Dependent Variable	29.21	29.41	7.67	8.28	44.08	44.3
SD Dependent Variable	45.48	45.57	26.6	27.55	49.65	49.67
C-Zone x Qtr-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Commuting Zones	297	297	297	295	297	296
# of 3-digit ZIPs	608	608	608	606	608	607
Observations	9117811	9056393	3721734	3447269	5396065	5369317

Notes: This table reports OLS and Poisson pseudo-maximum-likelihood (PPML) estimates of the probability of an appraisal waiver, multiplied by 100, for Fannie Mae loans originated from 2017 to 2024. Columns (1)–(2) report estimates for the full sample, columns (3)–(4) restrict the sample to refinance mortgages, and columns (5)–(6) restrict the sample to nonrefinance mortgages. All specifications include loan- and borrower-level controls, and commuting-zone-by-quarter-year fixed effects. Controls include log loan amount, log loan maturity, FICO, FICO squared, loan-to-value and debt-to-income bins, refinance status, and first-time homebuyer status. Collateral uncertainty is standardized to have a mean of zero and a standard deviation of one. Standard errors clustered at the commuting-zone level are reported in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

Table A29: Collateral Uncertainty and the Probability of Putback

	Dependent Variable: Probability of Putback					
	Full Sample		Non-Refinance		Refinance	
	(1) OLS	(2) PPML	(3) OLS	(4) PPML	(5) OLS	(6) PPML
Collateral Uncertainty	0.017*** (0.006)	0.103*** (0.033)	0.015** (0.007)	0.087** (0.034)	0.016*** (0.005)	0.103*** (0.035)
Mean Dependent Variable	0.16	0.16	0.18	0.18	0.15	0.15
SD Dependent Variable	4.02	4.02	4.26	4.26	3.88	3.88
C-Zone x Qtr-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Commuting Zones	302	302	302	302	302	302
# of 3-digit ZIPs	621	621	621	621	621	621
Observations	18742625	14754594	6765104	4137391	11977476	8686730

Notes: This table reports OLS and Poisson pseudo-maximum-likelihood (PPML) estimates of putback risk, multiplied by 100, for Fannie Mae loans originated from 2007 to 2024. The baseline specifications report estimates for the full sample and separately for refinance and nonrefinance mortgages. All specifications include loan- and borrower-level controls, and commuting-zone-by-quarter-year fixed effects. Controls include log loan amount, log loan maturity, FICO, FICO squared, loan-to-value and debt-to-income bins, refinance status, and first-time homebuyer status. Collateral uncertainty is standardized to have a mean of zero and a standard deviation of one. Standard errors clustered at the commuting-zone level are reported in parentheses.

Table A30: Collateral Uncertainty and the Time to Sale

	Time to Sale (Months)			Pr(Time to Sale ≥ 3 Months) * 100	
	Full Sample	Non-Refinance	Refinance	Refinance	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) PPML
Collateral Uncertainty	0.007 (0.005)	0.005 (0.005)	0.009* (0.005)	0.178*** (0.066)	0.042*** (0.015)
Mean Dependent Variable	1.11	1.11	1.11	3.97	4.01
SD Dependent Variable	0.93	0.93	0.93	19.51	19.62
C-Zone × Qtr-Year FE	Yes	Yes	Yes	Yes	Yes
# of Commuting Zones	302	301	302	302	302
# of 3-digit ZIPs	621	620	621	621	621
Observations	18,742,622	6,765,103	11,977,474	11,977,474	11,838,155

Notes: This table reports OLS and Poisson pseudo-maximum-likelihood (PPML) estimates of time to sale, measured in months, for Fannie Mae loans originated from 2007 to 2024. The baseline specifications report estimates for the full sample and separately for refinance and nonrefinance mortgages. All specifications include loan- and borrower-level controls, and commuting-zone-by-quarter-year fixed effects. Controls include log loan amount, log loan maturity, FICO, FICO squared, loan-to-value and debt-to-income bins, refinance status, and first-time homebuyer status. Collateral uncertainty is standardized to have a mean of zero and a standard deviation of one. Standard errors clustered at the commuting-zone level are reported in parentheses.

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