Pricing Climate Risk in Mortgage Markets: Lender Responses and Regional Redistribution *

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Abstract

The U.S. mortgage market features substantial geographic heterogeneity in local climate risk, while Government-Sponsored Enterprises (GSEs) fund a large share of mortgages at nationally uniform securitization fees. Uniform pricing is consistent with the GSEs' mandate to support broad access to affordable mortgage credit, but it generates cross-regional monetary transfers. Local risk pricing improves risk-based fairness, but may impose substantial welfare losses on borrowers in exposed markets. This paper studies how lenders shape this trade-off in the case of sea-level-rise (SLR) risk. Exploiting the distinction between GSE-eligible conforming loans and jumbo loans that are primarily retained on lenders' balance sheets, I document that lenders respond to differences in mortgage-origination costs along two margins: they adjust mortgage interest rates and reallocate funding between balance-sheet retention and GSE securitization. I then estimate a structural model of mortgage demand, lender competition, and endogenous funding choice. Under uniform pricing, monetary transfers flow from inland to high-risk coastal borrowers. These transfers are concentrated among a small group of exposed borrowers, are regressive across the income distribution, and are larger in more competitive markets. A counterfactual in which the GSEs price local SLR risk eliminates these transfers, but reduces borrower surplus substantially in high-risk coastal areas, while national aggregate effects remain small. Commercial banks partly mitigate the local adjustment by retaining more conforming loans on their balance sheets. The results quantify a central policy tension between regional fairness and local welfare under the GSEs' affordability mandate.

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1 Introduction

The United States is geographically large and diverse, and its mortgage markets differ sharply in their exposure to local climate risk. Yet a large share of mortgages is funded at a nationally uniform cost. This is because the mortgage market relies heavily on public securitization through government-sponsored enterprises (GSEs). Between 2018 and 2022, more than 75 percent of mortgage originations were securitized, and about 71 percent were securitized through the GSEs.[1] A central feature of GSE securitization is that guarantee fees do not vary with local climate exposure, which is referred to as a uniform pricing scheme. This creates a policy trade-off. Uniform pricing can provide a form of geographic risk pooling and is consistent with the GSE mandate to promote broad access to affordable mortgage credit, but it also generates implicit cross-regional transfers from lower-risk inland borrowers to higher-risk coastal borrowers, raising concerns about regional fairness. Local risk-based pricing, instead, would improve risk-based fairness, but it could lead to substantial reductions in credit supply and borrower welfare in exposed markets, potentially disturbing local financial stability.

Lenders and local market structure are central to this trade-off. Uniform GSE pricing changes the relative cost of mortgage funding, but its incidence on borrowers depends on how lenders respond. When uniform pricing changes the cost of mortgage origination, lenders can respond along two margins: they may adjust mortgage interest rates or switch to alternative funding sources. Local market competition further shapes this incidence by affecting the pass-through of funding costs into mortgage rates. In more competitive markets, lenders are likely to pass a larger share of cost changes to borrowers, whereas in more concentrated markets, they may absorb more of the adjustment through their markups. This leads to the central question of the paper: how do lenders' pricing and funding choices, together with local market structure, shape the trade-off between cross-regional monetary transfers under uniform pricing and regional welfare losses under local climate-risk pricing?

In this paper, I study how lender responses shape this trade-off in the case of sea-level-rise (SLR) risk. SLR exposure provides a geographically precise, persistent, and relatively model-independent measure of climate risk in coastal housing markets. Its transparent construction also allows lenders and GSEs to evaluate exposure using a common risk measure, which is important for the counterfactual analysis.[2] I first examine how lenders respond to uniform pricing through their loan-approval, interest-rate, and funding decisions. Motivated by this evidence, I develop a structural model of mortgage demand and supply, building on Buchak et al. (2024), that incorporates lender competition, endogenous funding choices, and SLR exposure in the cost of mortgage origination. I use the estimated model to quantify the regional monetary transfers generated by uniform pricing and the regional welfare consequences of local SLR-risk pricing.

I begin by examining how lenders respond to SLR risk under uniform GSE pricing, focusing on mortgage approvals, interest rates, and funding choices. The key identification exploits the distinction between conforming and jumbo loans. Conforming loans below the regulatory loan limit are eligible for GSE securitization, whereas jumbo loans above the limit are not and are primarily retained on lenders' balance sheets.[3]

[1] Source: Home Mortgage Disclosure Act data, 2018–2022.

[2] See Section 2, subsection 'SLR Risk in Mortgage Markets' and 'Climate Risk and Geographical Data,' for a detailed discussion of the relevance of SLR risk. See Section 2, subsection 'Role of Insurance' for a detailed discussion of the role of insurance.

[3] In my sample, conforming loans account for roughly 88 percent of mortgages and jumbo loans for about 12 percent. In principle, jumbo loans may be privately securitized, but this market has remained small since the collapse of private-label securitization after the 2008 financial crisis. Consistent with Buchak et al. (2024), I therefore treat jumbo loans as primarily

This contrast allows me to compare lender behavior when local SLR exposure can versus cannot be shifted to GSE funding. I find that approval rates decline with SLR exposure for both loan types, but more strongly for jumbo loans. Relative to zero-risk areas, approval probabilities in the highest SLR-risk quartile decline by 2.98 percentage points for conforming loans and by 4.10 percentage points for jumbo loans. Interest-rate responses also differ sharply: conforming rates remain largely flat across SLR-risk quartiles, whereas jumbo rates rise by 5.64 basis points in the highest-risk areas. At the same time, the probability that conforming loans are securitized through the GSEs rises by 4.78 percentage points. Together, these findings show that lenders price SLR risk when they retain the exposure and substitute toward uniformly priced GSE funding when that funding source is available.

The empirical evidence shows that lenders respond to climate-related pricing policies along two margins: they adjust mortgage interest rates and switch among alternative funding sources. Motivated by these findings, I develop a structural model to quantify the trade-off between the cross-regional monetary transfers generated by uniform pricing and the regional welfare consequences of local SLR-risk pricing. A structural model is necessary because mortgage rates, funding choices, market shares, and borrowing decisions are jointly determined in equilibrium. Building on Buchak et al. (2024), the model combines mortgage demand, lender competition in interest rates, and endogenous funding choices. Borrowers decide whether to take out a mortgage based on loan terms and preferences, while lenders set interest rates and choose whether to retain originated loans on their balance sheets or securitize them through the GSEs. A key novelty of the model is that SLR exposure affects balance-sheet funding costs but not GSE securitization costs under uniform pricing. I estimate how local SLR risk affects lenders' marginal costs and its pass-through to mortgage rates, a relationship that has not been quantified in the existing literature. Using the estimated model, I simulate a counterfactual equilibrium in which GSE securitization fees reflect local SLR risk and analyze the resulting adjustments in mortgage pricing, funding choices, and borrowing decisions.

I estimate the model using product-level data from the U.S. mortgage market and recover lenders' marginal costs of mortgage origination. The results show that both SLR exposure and borrower credit risk increase balance-sheet funding costs. The estimated effect of SLR exposure on marginal cost is economically meaningful but modest on average: a one-standard-deviation increase in SLR exposure raises marginal costs by about 0.9 basis points, corresponding to roughly 0.35 percent of the mean marginal cost. In magnitude, the effect of SLR exposure on marginal cost is about 10 percent of the effect of credit risk on marginal cost. This estimate is consistent with the stylized fact that the SLR premium in mortgage rates is about 10 percent of the credit-risk premium. The effects are substantially larger in highly exposed coastal areas and among lenders with greater risk exposure, where SLR risk can increase balance-sheet funding costs by up to 25 basis points. These estimates provide the first quantitative evidence on how exposure to SLR affects lenders' marginal lending costs in mortgage markets.

Using the estimated model, I quantify the regional monetary transfers generated by uniform GSE pricing. I compare the baseline equilibrium interest rate under uniform pricing with a counterfactual equilibrium interest rate in which GSE securitization fees reflect local SLR exposure. The resulting difference in equilibrium mortgage rates measures the implicit transfer created by uniform pricing. I find that transfers flow from lower-risk inland borrowers to higher-risk coastal borrowers and are concentrated in the most exposed

funded on lenders' balance sheets.

counties.[4] Borrowers in these high-risk coastal counties receive an average interest-rate subsidy of 7.7 basis points, corresponding to approximately $1,409 per loan in present value.[5] This subsidy amounts to about 10 percent of the average federal mortgage interest tax deduction. By contrast, inland borrowers face a smaller implicit tax.[6] The transfer also extends to jumbo loans through equilibrium spillovers: changes in the cost and pricing of conforming loans affect demand for jumbo loans and, in turn, their equilibrium rates. Excluding these spillovers would understate the total transfer by about 10 percent. From a deeper fairness view, the transfer is also regressive across the income distribution, as higher-income borrowers are more likely to reside in highly exposed coastal areas. Finally, the transfers are concentrated in highly competitive mortgage markets and decline sharply with market concentration. This pattern is consistent with stronger pass-through in competitive markets, where lenders transmit a larger share of the funding-cost wedge to borrowers, whereas in more concentrated markets they absorb more of the adjustment through markups.

I next quantify the welfare consequences of replacing uniform GSE pricing with local SLR-risk pricing. Because the counterfactual makes securitization fees reflect local SLR exposure, it eliminates the cross-regional monetary transfer generated by uniform pricing, but sharply redistributes surplus across regions. Aggregate surplus changes little within the model, but inland regions gain modestly while highly exposed coastal regions experience substantial losses. High-risk coastal counties experience a 26 percent decline in borrower surplus and a 7 percent reduction in mortgage lending. Lenders also adjust their funding choices: as GSE securitization becomes more expensive in high-risk areas, commercial banks retain a larger share of mortgages on their balance sheets. In the most exposed coastal markets, the balance-sheet retention rate rises by approximately 32 percent. These results show that local risk-based pricing improves regional fairness by eliminating the transfer, but imposes substantial welfare and credit-supply losses on highly exposed coastal markets.

At the last part of the paper, I evaluate how the central trade-off changes under greater SLR exposure and climate-sensitive capital regulation. First, I set a counterfactual scenario that increases SLR exposure by one standard deviation across counties and solve for equilibrium outcomes under both uniform and local GSE pricing. Under uniform pricing, high-risk coastal areas experience an 8 percent decline in borrower surplus and a 2 percent reduction in lending, while the associated cross-regional transfer rises substantially, intensifying the regional fairness concern. When GSE securitization fees also incorporate local SLR risk, the transfer is eliminated, but the regional adjustment becomes much more severe: borrower surplus falls by about 40 percent, lending declines by 11 percent, and lenders shift further toward balance-sheet funding. Greater climate risk therefore sharpens the trade-off between risk-based fairness and the geographic risk-pooling role and the GSE affordability mandate. As an extension, I further introduce SLR-sensitive capital requirements and compare their effects under uniform and local GSE pricing. When GSE fees remain uniform, the climate sensitive capital requirement policy raises balance-sheet funding costs in exposed regions and sharply contracts jumbo lending, but leaves most conforming-loan cross-subsidization intact because the securitization channel remains uniformly priced. When local GSE pricing is introduced simultaneously, both balance-sheet and securitization costs become sensitive to SLR exposure. This eliminates the regional transfer, but produces a substantially larger contraction in borrower surplus and mortgage lending in high-

[4] High-risk coastal counties are defined as the top 10 percent of coastal counties in the SLR-risk distribution.

[5] This amount is economically meaningful relative to other mortgage-pricing margins. For example, the average interest-rate gap between commercial banks and shadow banks is 2.4 basis points (Buchak et al., 2018), while the benefit from searching for one additional lender is about 7 basis points (Bhutta et al., 2020).

[6] The sample includes 29 high-risk coastal counties and 2,219 inland counties.

risk coastal markets.

Related Literature

This paper first contributes to the literature on cross-subsidies and welfare redistribution among borrowers in mortgage markets. Existing work shows that mortgage-market institutions generate cross-subsidies and redistribute welfare across borrowers through refinancing activity (Fisher et al., 2024; Zhang, 2022; Berger et al., 2024) and across regions and income groups through federal housing policies and credit subsidies (Favilukis et al., 2017; Landvoigt et al., 2015; Adelino et al., 2025). Most closely related, Hurst et al. (2016) show that uniform GSE pricing generates cross-regional transfers by charging identical guarantee fees across heterogeneous housing markets. They develop a dynamic structural model of household location and tenure choice to analyze how uniform pricing affects households' lifetime housing decisions, consumption, and equilibrium regional outcomes. A common feature of this literature is that it focuses on borrowers' responses and abstracts from lenders' endogenous pricing and funding adjustments, effectively treating policy-induced changes in funding costs as fully passed through to mortgage rates. I depart from this approach by placing lenders at the center of the incidence analysis. I model how lenders adjust mortgage rates and funding choices in response to uniform GSE pricing and show that pass-through to borrowers is incomplete and varies with local market competition. As a result, the regional redistribution and borrower-welfare effects of mortgage policy depend critically on lenders' responses rather than on the policy rule alone.

This paper also contributes to the growing empirical industrial organization literature on banking, financial intermediation, and mortgage markets, which uses structural models to study borrower demand, lender pricing, market power, and competition (Egan et al., 2017; Lewellen et al., 2017; Xiao, 2020; DeFusco and Paciorek, 2017). It builds most directly on Buchak et al. (2024), who model competition between commercial banks and shadow banks and lenders' endogenous choice between balance-sheet and securitization funding. I extend this framework by introducing geographically heterogeneous SLR exposure into lenders' funding costs and incorporating the nationally uniform pricing of GSE securitization. This extension allows lenders to respond to local climate risk through both mortgage pricing and funding substitution, and it allows local market competition to determine the pass-through of funding-cost changes to borrowers. Using the estimated model, I quantify how these lender responses shape cross-regional transfers and borrower welfare under uniform and local SLR-risk pricing.

This paper also contributes to the literature on climate risk in U.S. housing and mortgage markets. A substantial body of work studies how climate risk affects housing prices and demand. Bernstein et al. (2019, 2022); Giglio et al. (2021) document lower house prices in areas exposed to greater SLR and flooding risk. Keys and Mulder (2020) show that SLR risk can reduce coastal housing demand through buyer pessimism, while Murfin and Spiegel (2020) find that coastal house prices do not fully reflect long-run SLR risk. Related research shows that climate risk is priced more strongly when households believe in it (Baldauf et al., 2020; Bernstein et al., 2022). In mortgage markets, climate risk increases default and prepayment risk (Biswas et al., 2023; Du et al., 2020) and is associated with higher interest rates and lower approval rates (Nguyen et al., 2022; Duan and Li, 2024). I contribute to this literature by showing that the transmission of SLR risk into mortgage outcomes depends on who ultimately bears the exposure. When lenders retain the risk, they price SLR exposure more strongly, whereas access to uniformly priced GSE securitization allows them to respond through funding substitution as well as mortgage pricing. By comparing conforming and jumbo

loans and estimating lenders' marginal costs, I show that climate-related funding-cost changes are not passed through one-for-one to borrowers and that the degree of pass-through depends on lenders' funding choices and local market competition.

Lastly, this paper contributes to the literature on incorporating climate risk into financial regulatory frameworks. A growing body of work examines climate-sensitive capital requirements and climate-adjusted monetary and credit policies (McConnell et al., 2022; Schoenmaker, 2021; Piazessi et al., 2022; Bartocci et al., 2024), as well as whether financial regulation should respond to climate risk and the associated welfare consequences (Bolton et al., 2020; Oehmke and Opp, 2022). While this literature develops theoretical frameworks and evaluates normative trade-offs, there is limited quantitative evidence on how climate-sensitive financial policies operate in equilibrium, partly because many proposed reforms have not yet been implemented. I elaborate the U.S. mortgage market as an empirical setting in which a nationally uniform pricing rule coexists with geographically heterogeneous climate exposure, allowing me to provide quantitative evidence on the equilibrium effects of climate-sensitive financial policies. This setting enables me to study how financial intermediaries respond when climate risk is incorporated into funding prices and how these responses affect pricing, funding substitution, credit allocation, and welfare incidence. I further examine how SLR-sensitive capital requirements interact with uniform and local GSE pricing. The results highlight a broader trade-off between risk-based fairness and the geographic risk-pooling role embedded in financial institutions with affordability mandates.

2 Institutional Background and Data

2.1 Institutional Background

The US Mortgage Market

Public securitization is a defining feature of the U.S. mortgage market. Under the originate-to-distribute model, lenders sell originated mortgages to securitizers, which pool the loans into mortgage-backed securities (MBS) and sell them to investors. The dominant public securitizers are the Government-Sponsored Enterprises, primarily Fannie Mae and Freddie Mac. By purchasing eligible mortgages and guaranteeing the associated mortgage-backed securities, the GSEs allow lenders to transfer most of the mortgage credit exposure and release balance-sheet capacity. In 2020, approximately 72.5 percent of newly originated mortgages were securitized. Following the collapse of private-label securitization during the 2008 financial crisis, the GSEs became the dominant purchasers of newly originated mortgages.

Two types of lenders play a central role in this market: commercial banks and shadow banks. Commercial banks are depository institutions that can fund mortgages either by retaining them on their balance sheets, using deposits and other liabilities, or by selling eligible loans through GSE securitization. Shadow banks are non-depository financial institutions, such as independent mortgage companies, that originate mortgages but do not take deposits. Because they lack deposit funding and have limited balance-sheet capacity, shadow banks rely primarily on securitization to fund their originations. Their lighter regulatory burden and the absence of branch networks may also allow them to operate at lower cost, particularly in refinancing markets. By 2020, shadow banks originated more than half of all mortgage loans. These differences in funding access shape lenders' pricing, origination, and securitization decisions.

Eligibility for GSE securitization depends primarily on whether the loan amount is below the regulatory conforming loan limit. Loans below this threshold are classified as conforming and are eligible for GSE securitization, whereas loans above the threshold are classified as jumbo and are generally ineligible. In principle, jumbo loans may be sold through private-label securitization or to private investors such as insurance companies, but this market has remained small since the financial crisis.[7] Jumbo loans are therefore primarily retained on lenders' balance sheets. The conforming–jumbo distinction changes the set of funding responses available to lenders. For conforming loans, lenders can respond to local climate exposure through both mortgage pricing and the choice between balance-sheet retention and GSE securitization. For jumbo loans, the GSE funding margin is largely unavailable, so lenders must internalize more of the exposure through balance-sheet funding.

GSE Pricing Scheme and Regional Incidence

In the securitization process, the Government-Sponsored Enterprises charge lenders fees that determine the cost of using GSE funding. These fees include a servicing component and a guarantee fee that compensates the GSEs for the credit risk they insure. The guarantee fee consists of a baseline rate and loan-level adjustments based on observable borrower and contract characteristics. These Loan-Level Pricing Adjustments depend on factors such as the borrower's credit score, the loan-to-value ratio, occupancy status, loan purpose, product type, and loan term. Figure 1 provides an example of the Fannie Mae LLPA matrix. GSE pricing is therefore risk-sensitive along several borrower and loan dimensions.

A defining feature of this pricing system is that guarantee fees do not vary with local SLR exposure or other geographic climate risks. Borrowers with the same observable credit and loan characteristics therefore face the same GSE securitization pricing across regions, even when local climate exposure differs substantially. This uniform pricing reflects the GSE mandate to promote broad and affordable access to mortgage credit nationwide and the political sensitivity of differentiating public securitization fees by location. Charging systematically higher fees in exposed regions would make otherwise similar borrowers face different funding costs solely because of where they live, which could raise substantial political concerns. As a result, GSE fees are largely set on a nationwide basis and incorporate borrower and loan characteristics, but not local climate exposure.

The uniform pricing creates a wedge between the cost of GSE securitization and the cost of retaining mortgages on lenders' balance sheets. If local SLR exposure raises balance-sheet funding costs while GSE fees remain uniform, securitization becomes relatively less expensive in exposed markets. Lenders can respond along several margins by changing approval decisions, adjusting mortgage rates, or shifting a larger share of conforming loans toward GSE securitization. Uniform GSE pricing therefore creates a regional funding-cost wedge, but its incidence on borrowers depends on lenders' pricing and funding responses and on local market competition.

This wedge can generate cross-subsidies and welfare redistribution among mortgage borrowers. In principle, lower-risk inland borrowers may bear part of the cost associated with higher-risk coastal borrowers through nationally uniform GSE pricing (Hurst et al., 2016). However, the resulting transfer is not determined mechanically by the difference between uniform and local risk-based fees. Its magnitude and incidence

[7]Some jumbo loans are sold to private investors such as insurance companies, but this market is much smaller than GSE securitization.

Figure 1: Fannie Mae 2024 Loan-Level Pricing Adjustment (LLPA) Matrix

This figure reports an example of the Loan-Level Pricing Adjustment (LLPA) matrix used by Fannie Mae in 2024. The upper panel presents guarantee-fee adjustments for each combination of borrower credit score and loan-to-value (LTV) ratio. The lower panel shows additional adjustments by loan characteristics, including loan type, occupancy, investment property status, and other product features. For any given mortgage, the final guarantee fee equals the baseline rate plus the adjustments indicated in the relevant cells of the LLPA matrix.

Purchase Money Loans – LLPA by Credit Score/LTV Ratio

Credit Score	LTV Range									
	Applicable for all loans with terms greater than 15 years									
	≤ 30.00%	30.01 – 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	>95.00%	SFC
≥ = 780	0.000%	0.000%	0.000%	0.000%	0.375%	0.375%	0.250%	0.250%	0.125%	N/A
760 – 779	0.000%	0.000%	0.000%	0.250%	0.625%	0.625%	0.500%	0.500%	0.250%	N/A
740 – 759	0.000%	0.000%	0.125%	0.375%	0.875%	1.000%	0.750%	0.625%	0.500%	N/A
720 – 739	0.000%	0.000%	0.250%	0.750%	1.250%	1.250%	1.000%	0.875%	0.750%	N/A
700 – 719	0.000%	0.000%	0.375%	0.875%	1.375%	1.500%	1.250%	1.125%	0.875%	N/A
680 – 699	0.000%	0.000%	0.625%	1.125%	1.750%	1.875%	1.500%	1.375%	1.125%	N/A
660 – 679	0.000%	0.000%	0.750%	1.375%	1.875%	2.125%	1.750%	1.625%	1.250%	N/A
640 - 659	0.000%	0.000%	1.125%	1.500%	2.250%	2.500%	2.000%	1.875%	1.500%	N/A
≤ 639[1]	0.000%	0.125%	1.500%	2.125%	2.750%	2.875%	2.625%	2.250%	1.750%	N/A

Additional LLPAs by Loan Attribute Applicable to Purchase Money Loans

Loan Feature	LTV Range									
	Applicable for all loans									
	≤ 30.00%	30.01 – 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	>95.00%	SFC
Adjustable-rate mortgage	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.250%	0.250%	N/A
Condo[2]	0.000%	0.000%	0.125%	0.125%	0.750%	0.750%	0.750%	0.750%	0.750%	N/A
Investment property	1.125%	1.125%	1.625%	2.125%	3.375%	4.125%	4.125%	4.125%	4.125%	N/A
Second home	1.125%	1.125%	1.625%	2.125%	3.375%	4.125%	4.125%	4.125%	4.125%	N/A
Manufactured home[3]	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	235
Two- to four-unit property	0.000%	0.000%	0.375%	0.375%	0.625%	0.625%	0.625%	0.625%	0.625%	N/A
High-balance fixed-rate	0.500%	0.500%	0.750%	0.750%	1.000%	1.000%	1.000%	1.000%	1.000%	808
High-balance ARM	1.250%	1.250%	1.500%	1.500%	2.500%	2.500%	2.500%	2.750%	2.750%	808
Subordinate financing[4]	0.625%	0.625%	0.625%	0.875%	1.125%	1.125%	1.125%	1.875%	1.875%	N/A

depend on how lenders adjust markups, mortgage rates, and funding choices in equilibrium. Because changes in funding costs need not be passed through one-for-one to mortgage rates, the final redistribution among borrowers can differ substantially from the underlying policy-induced cost wedge.

SLR Risk in Mortgage Markets

SLR exposure is particularly useful for studying climate risk in mortgage markets for four reasons. First, it is comparatively less model-dependent. The measure is derived primarily from observable physical geography such as elevation level and distance to coast, whereas forward-looking measures of hurricane risk require additional assumptions about storm formation, intensity, and paths. SLR exposure is therefore less sensitive to differences across forecasting models and may be measured with greater precision. Second, it is persistent. It reflects a stable geographic vulnerability rather than the realization of a particular disaster, making it well suited for studying long-duration mortgage contracts. Third, it can be measured consistently across institutions. The same inundation framework can be applied to commercial banks, shadow banks, and the GSEs, whereas estimates of other disaster risks may vary substantially across lenders and proprietary models. This common measurement is also important for the counterfactual analysis, which compares pricing under a uniform risk measure across lenders and the GSEs. Finally, SLR and related coastal-risk measures are increasingly used by banks in assessing property and mortgage risk.[8]

Although SLR is often viewed as a long-term risk, its relevance for mortgage markets is not limited to eventual permanent inundation. Rising sea levels can increase the frequency and severity of coastal flooding and storm surge (Vousdoukas et al., 2018; Mayo and Lin, 2022; Lockwood et al., 2022). Expectations of future SLR can also affect housing demand, property prices, and therefore the value of mortgage collateral (Bernstein et al., 2019). In addition, SLR exposure is positively correlated with other coastal hazards, including historical hurricane exposure.[9] Therefore, the SLR risk measurement should be interpreted as an indicator of broader local vulnerability to coastal climate risk, rather than as a narrow measure of long-run permanent inundation.

Insurance and Residual Climate Exposure

In the U.S. mortgage market, insurance is effectively required for most mortgages. If insurance fully covered climate-related losses, remained continuously in force, and paid claims fully and promptly, lenders and the Government-Sponsored Enterprises would have less reason to incorporate local climate exposure directly into mortgage funding costs. In practice, however, insurance provides only partial protection. Coverage limits, incomplete participation, claim underpayment, and insurer fragility can leave borrowers, lenders, and securitizers exposed to residual climate-related losses.

For most climate risks other than flooding, such as hurricanes and wildfires, homeowners insurance is generally required for mortgage origination and is provided by private insurers. However, coverage may be incomplete even when a policy is in place. Biswas et al. (2023) document that nearly 40 percent of wildfire claims in California are under-compensated, with an average shortfall of $122,912, representing approximately 83 percent of total claimed coverage. Insurer quality may also deteriorate in highly exposed

[8] Source to be added.

[9] Historical hurricane exposure is measured using annual hurricane frequency from the National Risk Index. The county-level correlation between SLR exposure and hurricane exposure is 0.62.

markets. Sastry et al. (2023) show that higher-quality insurers tend to exit as climate losses increase, while financially weaker insurers expand their market share. In Florida, Demotech-rated insurers accounted for approximately 50 percent of the market in high-risk areas in 2018, and 19 percent of these insurers became insolvent between 2009 and 2022.[10]

Flood risk is generally excluded from standard homeowners insurance and is primarily covered through the National Flood Insurance Program (NFIP), administered by the Federal Emergency Management Agency (FEMA). Flood insurance is mandatory for federally backed mortgages only in designated Special Flood Hazard Areas, leaving many exposed properties outside these zones without required coverage. [11] Following Hurricane Harvey in 2017, only approximately 40 percent of affected homes had flood insurance (The Economist, 2017). In addition, during my sample period, NFIP premiums were not consistently aligned with borrowers' underlying flood risk, further limiting the extent to which insurance prices reflected local exposure (Carey et al., 2026).[12] Finally, NFIP building coverage is capped at $250,000, which may be substantially below replacement cost in high-value coastal housing markets.

These limitations imply that insurance does not eliminate all climate-related exposure from mortgage markets. Lenders and securitizers may remain exposed through collateral-value losses, default risk, and loan performance. The paper does not separately identify each of these channels, but estimates their combined relationship with mortgage funding costs. The next subsection explains why SLR exposure provides a useful measure of the broader coastal vulnerability underlying this residual exposure.

2.2 Data

This paper combines loan-level mortgage data, lender financial information, and geographic measures of climate exposure. The primary data source is the Home Mortgage Disclosure Act (HMDA), which provides near-universal coverage of U.S. mortgage applications and originations. HMDA reports application outcomes, interest rates, loan amounts, loan purpose, borrower income, lender identity, census-tract location, and whether an originated loan is sold to another institution. I supplement HMDA with Fannie Mae and Freddie Mac loan-level data, the Avery lender file, FDIC Call Reports and Summary of Deposits, NOAA inundation maps, and local demographic and economic data from the U.S. Census Bureau, the Bureau of Labor Statistics and the Fed Reserve Economic Data (FRED). These combined data allow me to observe mortgage approval, pricing, and funding outcomes together with lender characteristics, local market structure, and SLR exposure. The following subsections describe each dataset in detail.

Mortgage Data

The main mortgage data comes from the Home Mortgage Disclosure Act (HMDA). HMDA provides near-universal coverage of U.S. mortgage applications and originations and serves as the primary dataset for both the reduced-form evidence and the structural estimation. HMDA reports applicant and loan characteristics,

[10] Demotech-rated insurers are property insurers whose financial-strength ratings are issued by Demotech, Inc., rather than by traditional rating agencies such as AM Best or S&P. They are empirically more likely to become insolvent (Sastry et al., 2023). Although these insurers are financially more fragile, the GSEs treat them as satisfying insurance eligibility standards comparable to those of traditionally rated insurers.

[11] Special Flood Hazard Areas include inland A-zones and coastal high-risk wave zones, while non-SFHA areas include Zone X and older Zone B/C designations.

[12] Although Risk Rating 2.0 introduced more granular risk-based pricing beginning in 2021, statutory caps caused many existing policies to adjust only gradually toward full-risk rates (Carey et al., 2026).

including borrower income, loan amount, loan purpose, approval status, interest rate, lender identity, and census-tract location. It also identifies whether an originated loan is retained by the lender or sold to another institution, allowing me to construct measures of GSE securitization and balance-sheet retention.[13] HMDA began reporting mortgage interest rates in 2018, so the sample covers 2018–2022. Following Buchak et al. (2024), I restrict the sample to conventional, first-lien mortgages on principal residences. I use the application sample to study lenders' approval decisions and the originated-loan sample to examine interest rates and securitization choices. The data are initially analyzed at the loan level and are subsequently aggregated to construct lender products and market shares for the structural estimation.

I supplement HMDA with loan-level data from Fannie Mae and Freddie Mac. These datasets cover 30-year fixed-rate, single-family mortgages securitized by the Government-Sponsored Enterprises and provide detailed information on interest rates, loan amounts, loan purpose, property location, loan-to-value ratios, debt-to-income ratios, borrower income, and FICO scores. They also report monthly loan performance, including delinquency, default, and prepayment outcomes. The GSE data serve two purposes. First, I use monthly loan performance to construct local mortgage default rates, which are used as instruments for interest rates in the demand estimation. Second, because HMDA does not report borrower credit scores, I use the GSE data to estimate the relationship between FICO scores and borrower and loan characteristics observed in both datasets. I then apply the estimated relationship to HMDA loans to construct predicted FICO scores.[14]

Lender Classification and Banks' Financial Data

I identify lender types using the Avery file, constructed by Robert Avery.[15] The Avery file provides standardized lender identifiers and type classifications for institutions that have filed HMDA reports. I classify lenders as shadow banks when they are identified as independent mortgage banks or independent mortgage banks affiliated with depository institutions.[16] I classify lenders as commercial banks when they are identified as commercial banks, commercial bank subsidiaries, subsidiaries of commercial bank holding companies, liquidated commercial banks, or subsidiaries of liquidated commercial banks.[17] This classification distinguishes shadow banks, which rely primarily on securitization, from commercial banks, which can fund mortgages either by retaining them on their balance sheets or by selling them through securitization.

I obtain commercial banks' financial characteristics from the FDIC Call Reports. These data capture differences in banks' funding structures, balance-sheet composition, and capital positions. The main variables include total assets, total deposits, non-core funding, real estate loans held on balance sheets, total liabilities, Tier 1 capital, and capital ratios. For eligible community banks that elect the Community Bank Leverage Ratio framework, I use the reported CBLR as their measure of capitalization.[18] Finally, I obtain bank

[13] HMDA reports the purchaser type when a loan is sold within the calendar year of origination. Loans not reported as sold during that year are classified as retained. This classification may therefore include some loans sold after the end of the reporting year.

[14] The prediction model uses observable characteristics common to HMDA and the GSE data, including loan-to-value ratios, debt-to-income ratios, borrower income, loan amount, and loan purpose. The detailed specification and validation of the predicted FICO measure are reported in the appendix.

[15] The data are available at `https://sites.google.com/site/neilbhutta/data`.

[16] These institutions correspond to lender types 40 and 41 in the Avery file.

[17] These institutions correspond to lender types 10 through 14 in the Avery file.

[18] The CBLR is a simple leverage ratio based on Tier 1 capital relative to average total consolidated assets, rather than risk-weighted assets. The framework became effective in 2020, during the latter part of the sample period. Detailed information is available at `https://www.fdic.gov/resources/community-banking/docs/cblr-facts.pdf`.

branch locations from the FDIC Summary of Deposits and use them to measure banks' local presence and local banking-market structure.

Climate Risk and Geographical Data

I use sea-level-rise (SLR) exposure as the primary measure of local coastal climate risk. The measure is constructed from inundation maps produced by the National Oceanic and Atmospheric Administration (NOAA). At the census-tract level, SLR exposure is defined as the share of land area projected to be inundated under a 10-foot rise in sea level. County-level exposure is constructed by aggregating the underlying tract-level measures. Figure 2 maps county-level SLR exposure across the United States and provides a detailed illustration of the underlying inundation measure in Southeast Florida. The figure shows substantial geographic variation both across coastal regions and among locations within the same broader coastal area. Again, are mentioned before, the SLR risk measurement should be interpreted as an indicator of broader local vulnerability to coastal climate risk, rather than as a narrow measure of long-run permanent inundation.

I use the 10-foot scenario to create more variation in the cross-sectional measurement of this vulnerability, not because a 10-foot rise is expected during the sample period. The literature commonly uses a 6-foot scenario (Bernstein et al., 2019; Nguyen et al., 2022), but lower scenarios assign little or no inundation exposure to many coastal tracts and therefore provide less differentiation between low-risk coastal locations and inland areas. The 10-foot scenario reveals additional variation in relative exposure among these locations.[19] Accordingly, the estimated coefficients should be interpreted as responses to differences in relative coastal vulnerability, not as the effects of a literal 10-foot increase in sea level.

Because SLR exposure is related to coastal geography, I also control for elevation and distance to the coastline, following Nguyen et al. (2022). Elevation measures the height of the census-tract centroid above sea level, while distance to the coastline measures the tract centroid's proximity to the coast. These variables capture important dimensions of general coastal location, but they are not equivalent to the NOAA inundation measure. Two tracts with similar centroid elevation or coastal distance may differ in the share of their land connected to low-lying inundation pathways. Including these controls therefore helps mitigate the concern that the estimated relationship simply reflects low elevation or proximity to the coast, while preserving the more detailed spatial information contained in the inundation maps.

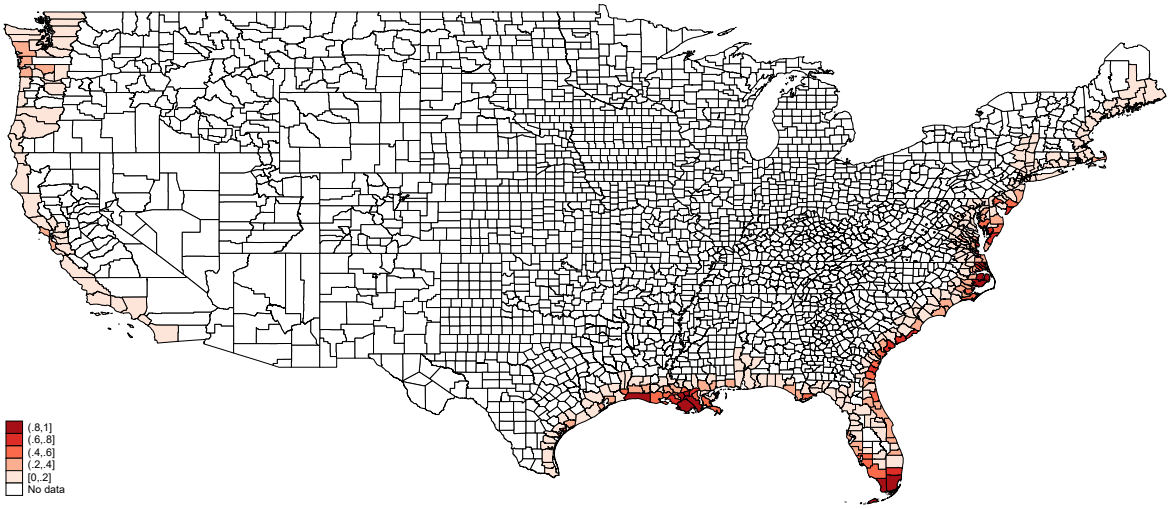
Census Data and FRED Data

I use county-level demographic and economic data from the U.S. Census and the American Community Survey (ACS), including the number of owner-occupied housing units and the total number of households with mortgages. Additional local economic variables, including employment, wages, and population, are obtained from the Bureau of Labor Statistics (BLS). These measures are incorporated as controls in both the stylized facts and the structural model. I also use macroeconomic and financial time series, including GDP, core CPI, inflation, the TED spread, the federal funds rate, and the 10-year Treasury yield, from the Federal Reserve Economic Data (FRED).

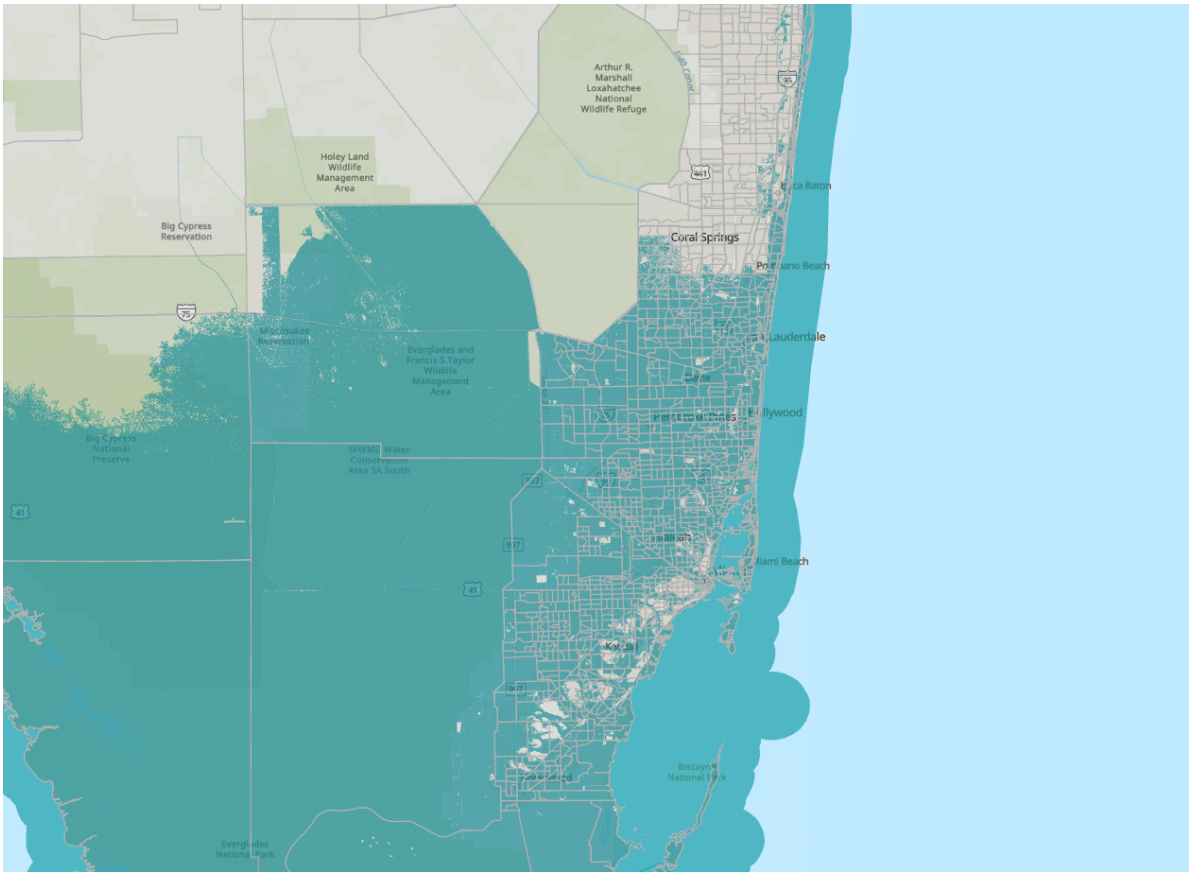
[19] For example, two tracts may each have 30 percent of their land area inundated under the 6-foot scenario, while their inundated shares rise to 50 and 40 percent, respectively, under the 10-foot scenario. The higher scenario therefore differentiates locations that would otherwise receive the same measured exposure. All main results remain qualitatively similar when I use the 6-foot measure, although the estimated magnitudes are generally smaller.

Figure 2: Sea-Level-Rise (SLR) Risk in the United States

Panel A maps county-level exposure to sea-level rise (SLR) across the United States. SLR exposure is measured as the proportion of land area that would be inundated if sea levels rise by ten feet. Counties along the eastern and southern coastlines exhibit the highest levels of exposure. Panel B provides a detailed view of Southeast Florida under the same ten-foot SLR scenario. Blue regions indicate areas projected to be inundated.



Panel A. County-Level SLR Exposure Across the United States



Panel B. Projected Inundation Under a Ten-Foot SLR Scenario in Southeast Florida

3 Reduced-Form Evidence

In this section, I provide reduced-form evidence on how lenders respond to SLR exposure under GSE uniform pricing. The empirical strategy exploits the institutional distinction between conforming loans, which are eligible for GSE securitization, and jumbo loans, which are not and are therefore primarily retained on lenders' balance sheets. [20] If uniformly priced GSE funding changes lenders' exposure to local SLR risk, lender responses should differ across these two segments. SLR exposure should be associated with weaker approval outcomes and higher interest rates for jumbo loans, where lenders retain more of the exposure, but with smaller pricing responses for conforming loans, where GSE securitization is available. At the same time, if lenders use securitization as an adjustment margin, the probability of GSE securitization should increase with SLR exposure among conforming loans, but not among jumbo loans.

Before presenting the results, I introduce the regression framework. For each outcome Y_{ijct}, I estimate a nonlinear specification to account for the skewed distribution of SLR risk, which includes many zero-risk tracts and a small set of highly exposed coastal areas. To allow for differential responses across the risk distribution, I split the SLR measure into indicators for SLR-risk quartiles for groups with SLR risks, and I use zero-risk tracts as the reference group. This approach helps identify whether lenders react more strongly in the highest-risk areas, which is relevant for understanding lending behavior and the distributional implications of GSE uniform pricing.

$$Y_{ijct} = \sum_{q=1}^{4} \beta_q SLRQq_c + X_{ijct}^{'}\Gamma + K_{jt}^{'}\Delta + Z_{ct}^{'}\zeta + \lambda_j + \gamma_t + \varepsilon_{ijct} \tag{1}$$

where Y_{ijct} represents the lending outcome of interest for loan i originated by lender j in census tract c and year t. In the approval analysis, Y_{ijct} is an indicator for loan approval; in the interest rate analysis, it is the loan's interest rate; and in the securitization analysis, it is an indicator for whether the loan is securitized. $SLRQq_c$ is the indicator variable of whether census tract c falls in the qth SLR quartile. The vector X_{ijct} includes loan-level controls such as LTV, DTI, loan purpose, and borrower income; The vector K_{jt} includes lender-year financial controls, including total assets, capital ratios, core deposits, and non-core funding; Z_{ct} includes the county-year economic controls capturing local conditions such as local employment growth, wage growth, and population (Duan and Li, 2024). The term λ_j denotes lender fixed effects and γ_t denotes year fixed effects. [21] I estimated the above specification separately for the conforming and jumbo loan samples. For a robustness check, I also estimate a similar specification using the continuous SLR risk

[20] Jumbo loans may in principle be sold through private-label securitization, but this market has remained negligible since the financial crisis.

[21] Adding state or county FE leads to qualitatively similar results but with a smaller magnitude. I do not include state or county fixed effects in the main specification. The SLR risk has no time-dimensional variation and is highly correlated with location fixed effects. Except for coastal counties, there is no within-county variation of SLR risk. Including state or county fixed effects would absorb meaningful cross-sectional variation and mechanically shrink the coefficient on $SLRQq_c$ toward zero, a pattern confirmed in robustness checks, where coefficients fall substantially while explanatory power (adj R^2) remains almost the same. This differs from settings in which climate-risk variation is rich within a single region. For example, studies of SLR in Florida (Keys and Mulder, 2020; Bernstein et al., 2019), hurricanes in Louisiana (Gallagher and Hartley, 2017; Biswas et al., 2023), or wildfires in California (Calabrese et al., 2024) leverage substantial within-area risk heterogeneity and therefore include location fixed effects. Other work uses fixed effects to account for widespread climate risks, such as extreme temperatures (Duan and Li, 2024). In the national-level SLR context considered here, however, within-state variation is often negligible or nonexistent. In addition, as discussed before, some of the local variables such as housing prices, housing values could serve as channels that SLR risk matters mortgage market, controlling these local effect would absorb the SLR risk effect working with these channels. In these cases, location fixed effects could be inappropriate and potentially misleading.

measurement directly.

$$Y_{ijct} = \beta SLR_c + X_{ijct}^{'}\Gamma + K_{jt}^{'}\Delta + Z_{ct}^{'}\zeta + \lambda_j + \gamma_t + \varepsilon_{ijct}$$

The results are reported in the Appendix Table C1 Table C2. Table 1 reports summary statistics for the main estimation sample, separately for conforming and jumbo loans.

Table 1: Summary Statistics

This table reports the summary statistics of the main variables. *Securitization* is the indicator variable of whether the loan is sold. SLR defines the sea-level-rise risk, which is calculated by the ratio of area that will be inundated in a 10-foot sea-level rise and total area in the census tracts. $SLRQ0$ is the indicator that the census tract has a zero SLR risk. $SLRQq$ is the indicator of whether the census tract is in the qth quartile of all census tracts with $SLR > 0$. DTI is the debt-to-income ratio. LTV is the loan-to-value ratio. *Approval* is the indicator of whether the lender approves the loan application or not. Panels A and B report the sample of granted loans. And Panels C and D report the sample of loan applications, with commercial banks conforming and jumbo loans, respectively.

Panel A: Commercial Bank Loan Applications

	Conforming Loans				Jumbo Loans			
	N	Mean	SD	Median	N	Mean	SD	Median
Approval	8,411,728	0.861	0.346	1	1,143,588	0.882	0.322	1
SLR	8,411,728	0.036	0.154	0.000	1,143,588	0.074	0.220	0.000
SLRQ0	8,411,728	0.893	0.309	1	1,143,588	0.801	0.399	1
SLRQ1	8,411,728	0.031	0.172	0	1,143,588	0.052	0.222	0
SLRQ2	8,411,728	0.028	0.165	0	1,143,588	0.048	0.213	0
SLRQ3	8,411,728	0.027	0.162	0	1,143,588	0.051	0.221	0
SLRQ4	8,411,728	0.021	0.145	0	1,143,588	0.047	0.212	0
DTI	8,411,728	34.371	14.333	33.000	1,143,588	33.738	13.793	33.000
LTV	8,411,728	68.699	20.736	73.409	1,143,588	71.608	15.049	75.000

Panel B: Commercial Bank Granted Loans

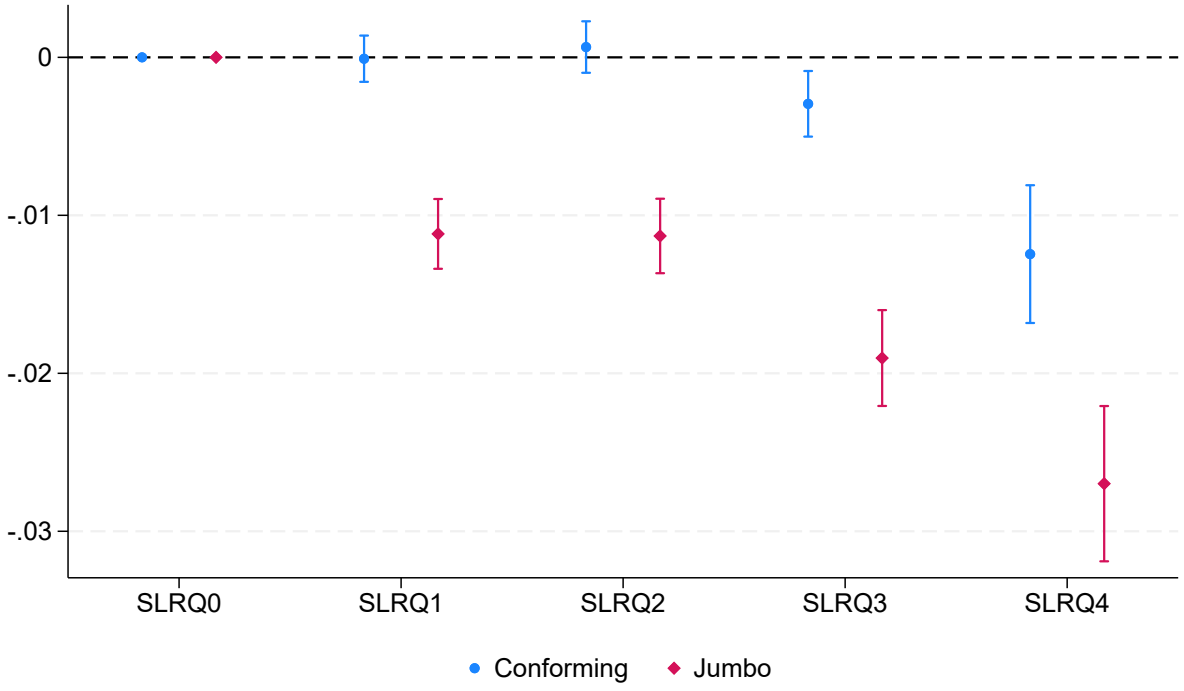
	Conforming Loans				Jumbo Loans			
	N	Mean	SD	Median	N	Mean	SD	Median
Securitization	7,020,227	0.649	0.477	1	981,134	0.054	0.227	0
Interest Rate	7,020,227	3.639	0.979	3.375	981,134	3.366	0.748	3.250
SLR	7,020,227	0.034	0.149	0	981,134	0.073	0.218	0
SLRQ0	7,020,227	0.897	0.305	1	981,134	0.803	0.398	1
SLRQ1	7,020,227	0.030	0.171	0	981,134	0.052	0.222	0
SLRQ2	7,020,227	0.028	0.164	0	981,134	0.048	0.214	0
SLRQ3	7,020,227	0.026	0.160	0	981,134	0.051	0.221	0
SLRQ4	7,020,227	0.020	0.139	0	981,134	0.046	0.209	0
DTI	7,020,227	32.188	11.057	33.000	981,134	31.725	10.553	33.000
LTV	7,020,227	69.029	20.249	73.750	981,134	71.550	14.836	75.000

3.1 SLR Risk and Loan Approval

I begin by examining how lenders' approval decisions respond to SLR exposure under GSE uniform pricing, separately for conforming and jumbo loan applications. Because only conforming loans can be sold to the GSEs, lenders internalize SLR risk for jumbo loans but not for conforming loans. If GSE uniform pricing attenuates lenders' incentives to screen SLR risk on securitizable loans, the effect of SLR risk on approval rates should be smaller for conforming loans. I estimate the earlier quartile specification separately on conforming and jumbo loan samples. Figure 3 plots the standardized coefficients for both loan types. Approval rates decline monotonically with SLR risk for both conforming and jumbo loans, but the magnitude of the decline differs. For conforming loans, only the highest-risk areas exhibit lower approval rates to a meaningful extent. For jumbo loans, all SLR quartiles show substantial declines, and the effect in the highest quartile (SLRQ4) is about 4.10 percentage points, compared with 2.98 percentage points for conforming loans. These patterns indicate that lenders account for SLR risk only when they bear it themselves; uniform GSE pricing substantially reduces their incentive to screen for local climate risk on conforming loans.

Figure 3: SLR Risk and Loan Application Approval

This figure plots standardized coefficients from the nonlinear quartile specification in which the dependent variable is the loan approval indicator. SLR risk is measured using quartile indicators, with zero-SLR tracts as the baseline category. Estimates are reported separately for conforming and jumbo loan applications. All regressions include loan-level controls (LTV, DTI, borrower income, loan purpose), lender-year financial controls (assets, capital ratios, core deposits, non-core funding), and county-year economic controls (employment growth, wage growth, population), along with lender and year fixed effects. Standard errors are clustered at the lender × year × state level. Blue circles denote estimates for conforming loans, and red diamonds denote estimates for jumbo loans. Confidence intervals are shown at the 95 percent level.

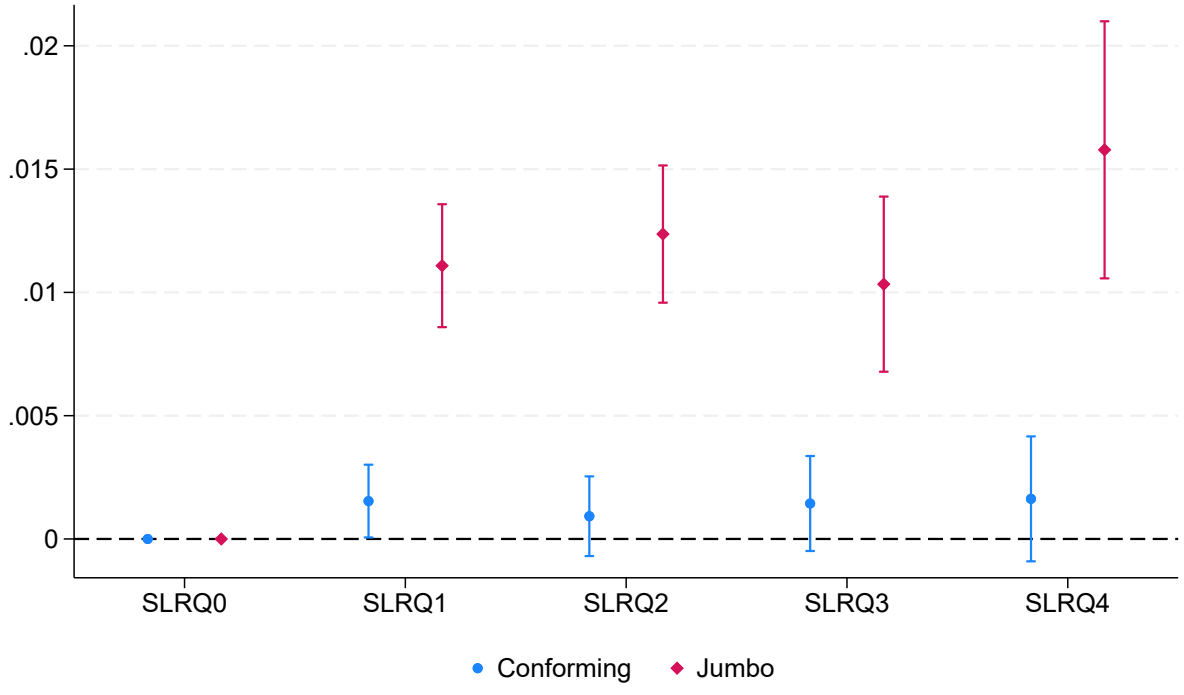


3.2 SLR Risk and Interest Rate

I next examine how mortgage interest rates respond to SLR exposure under GSE uniform pricing. Conforming and jumbo loans again offer a natural comparison: lenders may pass SLR risk into pricing only when they expect to hold the loan. Because conforming loans can be sold to the GSEs at a uniform price, lenders can choose not to price SLR risk on those loans, so the interest rate response should be much weaker than for jumbo loans. Figure 4 plots the standardized coefficients of specification 1 estimated separately by the conforming loan sample and the jumbo loan sample. For conforming loans, interest rates are almost flat across all SLR quartiles, indicating that SLR risk is not priced in. For jumbo loans, interest rates rise monotonically significantly with SLR exposure, with the effect concentrated in the highest-risk areas. In the top SLR quartile (SLRQ4), lenders charge approximately 5.64 basis points more than in zero-risk tracts, more than ten times larger than the effect for conforming loans. These results show that lenders price SLR risk only when they hold the loans themselves. For conforming loans, uniform GSE pricing of SLR risk effectively disincentivizes lenders from passing local climate risk into mortgage rates.

Figure 4: SLR Risk and Mortgage Interest Rates

This figure plots standardized coefficients from the nonlinear quartile specification in which the dependent variable is the mortgage interest rate. SLR risk is measured using quartile indicators, with zero-SLR tracts as the baseline category. Estimates are reported separately for conforming and jumbo loans. All regressions include loan-level controls (LTV, DTI, borrower income, loan purpose), lender-year financial controls (assets, capital ratios, core deposits, non-core funding), and county-year economic controls (employment growth, wage growth, population), along with lender and year fixed effects. Standard errors are clustered at the lender × year × state level. Blue circles denote estimates for conforming loans, and red diamonds denote estimates for jumbo loans. Confidence intervals are shown at the 95 percent level.

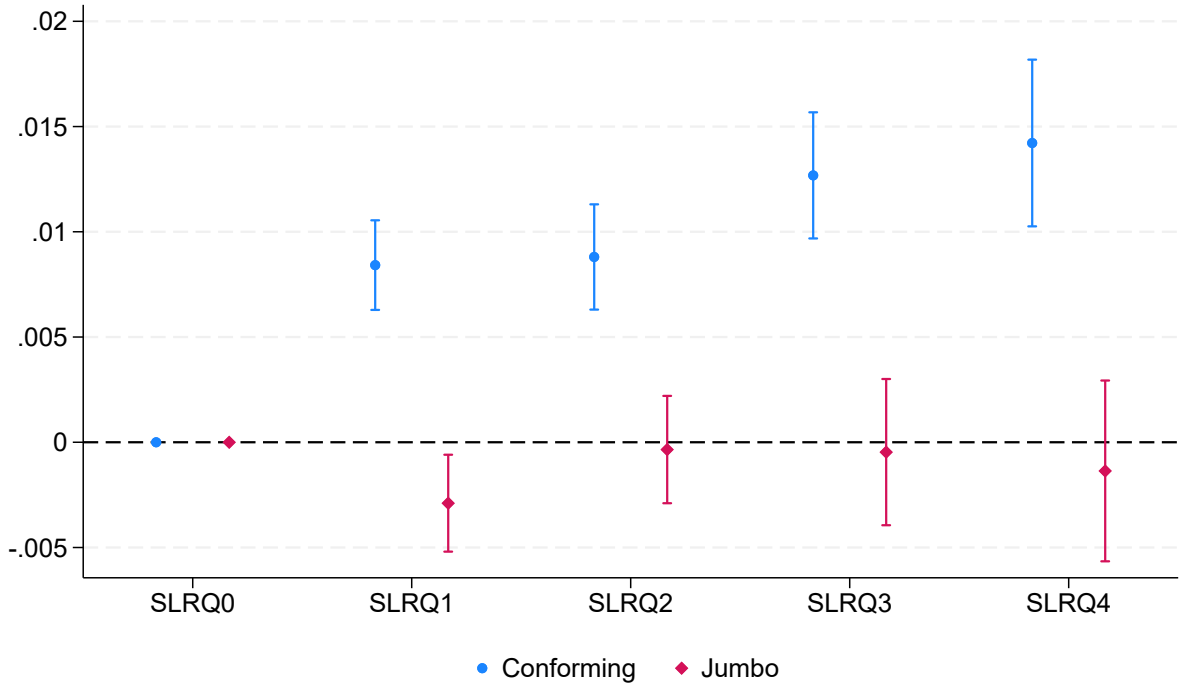


3.3 SLR Risk and Securitization

Finally, I examine how lenders' securitization decisions respond to SLR exposure under GSE uniform pricing. If lenders choose not to screen or price SLR risk on conforming loans, they may instead pass this risk to the GSEs by securitizing more of these loans. Jumbo loans are not GSE-eligible and therefore again provide a valid comparison group: securitization rates for jumbo loans should not respond to SLR risk. Figure 5 plots the standardized coefficients of the quartile specification 1. For conforming loans, securitization rates rise monotonically across SLR quartiles. Relative to zero-risk tracts, the increase reaches about 4.89 percentage points in the highest-risk quartile. For jumbo loans, securitization probabilities remain flat across all SLR quartiles, reflecting the fact that these loans are almost always retained on the balance sheet. Taken together, the evidence shows that lenders respond to higher SLR risk by shifting more conforming loans into GSE securitization. Because GSE pricing does not reflect spatial risk, this mechanism increases the share of high-SLR-risk loans placed into uniform-priced GSE pools, amplifying the underlying redistribution generated by the pricing scheme.

Figure 5: SLR Risk and Securitization

This figure plots standardized coefficients from the nonlinear quartile specification in which the dependent variable is an indicator for whether a granted loan is securitized. SLR risk is measured using quartile indicators, with zero-SLR tracts as the baseline category. Estimates are reported separately for conforming and jumbo loans. All regressions include loan-level controls (LTV, DTI, borrower income, loan purpose), lender-year financial controls (assets, capital ratios, core deposits, non-core funding), and county-year economic controls (employment growth, wage growth, population), along with lender and year fixed effects. Standard errors are clustered at the lender × year × state level. Blue circles denote estimates for conforming loans and red diamonds denote estimates for jumbo loans. Confidence intervals are shown at the 95 percent level.



Overall, the reduced-form evidence indicate that SLR risk matters for lenders only when they bear the risk themselves. For conforming loans, lenders avoid screening or pricing SLR risk and rely more heavily on GSE securitization. These patterns reflect the incentives created by uniform GSE pricing and motivate the structural analysis of welfare and regional redistribution in the next section.

4 Model

The reduced-form evidence points to two margins along which lenders adjust when climate-related policies shift mortgage-origination costs. Lenders may pass changes in origination costs through to borrowers by adjusting mortgage interest rates, or they may alter how loans are funded by switching between balance-sheet retention and GSE securitization. These responses determine how a change in climate-risk pricing affects mortgage allocation, securitization, and borrower welfare. Building on Buchak et al. (2024), I develop a random-coefficients model of mortgage demand, supply, and lender competition that incorporates SLR exposure into lenders' funding costs. On the demand side, borrowers choose among lenders' mortgage offerings or decide not to borrow in order to maximize indirect utility. On the supply side, lenders set interest rates in each market and choose how to fund originated loans in order to maximize profits. A central feature of the model is an explicit representation of marginal funding costs. For conforming loans, commercial banks may retain mortgages on their balance sheets or sell them to the GSEs. Shadow banks, which lack deposit-funding capacity, rely entirely on GSE securitization. GSE funding consists of a baseline guarantee fee and a credit-risk adjustment and is uniform across locations, so it does not reflect local SLR exposure. Balance-sheet funding incorporates banks' deposit costs, capital constraints, and the local climate exposure retained when mortgages are held on balance sheets. The model therefore allows me to quantify the trade-off between the regional transfers generated by uniform GSE pricing and the local welfare consequences of moving to SLR-sensitive pricing.

Demand

A market is defined by the triplet (c, p, r), where c denotes the county, loan purpose $p \in \{purchase, refinance\}$, and credit risk level $r \in \{highFICO, lowFICO\}$. Markets are treated as independent across years. In each market–year (t, m), $i = 1, ..., I_{tm}$ borrowers choose among the mortgage products offered by $j = 1, ..., J_{tm}$ lenders or the outside option of not borrowing to maximize their indirect utility.

Lenders offer differentiated mortgage products k, characterized by observable attributes X_{jmtk}, including whether the loan is conforming, the loan-to-value (LTV) ratio, and the debt-to-income (DTI) ratio. Borrowers may value conforming loans because they are cheaper and require less documentation (Buchak et al., 2018; Fuster et al., 2019). LTV and DTI serve as controls for loan size, which borrowers typically prefer to be higher. The borrower $i's$ indirect utility from selecting mortgage k from lender j in market-year (t, m) is

$$u_{ijtmk} = \alpha_i r_{jtmk} + \gamma_i Conforming_{jtmk} + X'_{jtmk}\Gamma + q_{jt} + \xi_{jtm} + \varepsilon_{ijtmk} \tag{2}$$

where r_{jtmk} is the interest rate. $Conforming_{jtmk}$ is the indicator variable of whether the loan k is a conforming loan or jumbo loan. q_{jt} is the lender type times year fixed effect. ξ_{jtm} is the lender-market-specific unobservable. ε_{ijtmk} is type one extreme shock.

In the utility function, $\alpha_i < 0$ is the disutility from interest rates r_{jtmk}. $\gamma_i > 0$ measures the conforming loan convenience. Again, borrowers also care about loan size, and, in general, larger loans are preferred over smaller ones. Meanwhile, loan size is often positively related to the interest rates. Omitting the loan-size effect would lead to an underestimation of price sensitivity. Here, I include the Loan-To-Value ratio of loan k LTV_{jtmk} and the Debt-To-Income ratio of loan k DTI_{jtmk} in the loan size control X'_{jtmk}. And Γ is the coefficient vector to capture the loan-size effect. Preferences for price and conforming loans are heterogeneous and borrower-specific, with random coefficients. For computational simplicity, I set no borrower-level randomness for loan-size controls, such as LTV and DTI.

Lenders also differ in services. Shadow banks and commercial banks can provide borrowers with different service experiences. For example, commercial banks can provide deposit services to borrowers, allowing borrowers to manage both their loans and deposits in a single account. For some shadow banks, such as FinTech shadow banks, online loan processes offer borrowers the convenience they value. To capture the difference in lenders' services, I included the term $q_{jt} + \xi_{jtm}$. q_{jt}, as the lender-type and year fixed effect, captures the observable service across commercial and shadow banks within the same year. ξ_{jtm} is the lender-year-market specific unobservable. In this case, only q_{jt} is observed by researchers. Finally, the type-I extreme shock term, ε_{ijtmk}, captures borrowers' idiosyncratic preferences.

The demand-side random-coefficient vectors

$$PD_i \equiv (\alpha_i, \gamma_i, \Gamma)$$

is specified as

$$PD_i = \overline{PD} + \Pi \times D_{itm} + \Sigma \times v_i$$

where $\overline{PD}$ is the mean borrower preference vector and Π captures the demographic effect on the borrower preference. D_{itm} is the demographic characteristics of the borrower i in year-market (t, m). Following Buchak et al. (2024), I consider two demographic characteristics: the borrower's income and the borrower's property value. Higher-income borrowers are often less price-sensitive. Borrowers who purchase more expensive houses are more price-sensitive to loan terms, given that housing prices are already very high. The Σ captures the pure random effects of borrowers' preferences. v_i is an i.i.d random shocks with $v_i \sim N(0, I)$. The demand parameter sets to be estimated are then $\theta_d = (\overline{PD}, \Pi, \Sigma)$

Borrowers either select the loan yielding the highest utility or choose the outside option with normalized utility $u_{i0} = 0$. Given the demand parameters θ_d, the sets of borrowers who will choose loan k offered by lender j in year t and market m can be written as

$$B_{jtmk}(\mathbf{r_{.tm}}, \mathbf{X_{.tm}}, \mathbf{q_{.t}}, \xi_{\mathbf{.ct}}; \theta_d) = \{(D_i, \epsilon_{ijtm0}, ..., \epsilon_{ijtmk}) | u_{ijmk} \geq u_{ilmg}, \forall l, g\}$$

Specifically, $\mathbf{r_{.tm}}$ is the price vector of loans provided in market m in year t. $\mathbf{X_{.tm}}$ is the loan characteristics matrix for all loans in market m in year t. $\mathbf{q_{.t}}$ is the vector for all lender-type year observed fixed effects at year t, and $\xi_{\mathbf{.ct}}$ is the vector for all lender-county-year unobservables. Sets B_{jtmk} define the borrowers for whom, given the loan characteristics and demand-side parameter θ_d, the utility of taking loan k from lender j in year-market (t, m) is larger than or equal to the utility of any other loan or the outside option.

Conditional choice probabilities therefore take the standard logit form, and the market share of product loan k provided by lender j in year t and market m to individual i is then

$$s_{jtmk}(D_i, v_i) = \frac{exp\ (u_{ijtmk})}{1 + \sum_{g \in K} exp\ (u_{ijtmg})}$$

Integrating the market shares of each product over the demographic and idiosyncratic variables yields the market share of mortgage k for lender j in the market m and year t

$$s_{jtmk} = \int \frac{exp\ (u_{ijtmk})}{1 + \sum_{g \in K} exp\ (u_{ijtmg})} \hat{P}_D(D_i)\hat{P}_v(v_i)dD_i dv_i$$

The total market share of lender j in year-market (t, m) is then

$$s_{jtm} = \sum_{k \in K_j} s_{jtmk}$$

Supply

On the supply side, lenders choose (i) the interest rate they charge in each market and (ii) the method used to finance originated loans. Commercial banks can finance conforming loans either on their balance sheet or by selling them to the GSEs. Shadow banks, which do not hold deposits and have little balance-sheet capacity, rely exclusively on GSE securitization. Jumbo loans are not GSE-eligible. Given the limited market for private securitization, in the model, I follow Buchak et al. (2024) to assume that jumbo loans can be funded only on the balance sheet by commercial banks. These funding choices imply distinct costs, and lenders set interest rates taking these funding margins into account. I separately describe the two components of lenders' costs that I model: administrative costs and financing costs.

Administrative Cost

Originating a mortgage requires labor and operational resources. This administrative cost varies both by lender type and loan purpose. Consistent with the evidence in Fuster et al. (2019); Buchak et al. (2018), refinance loans involve lower administrative costs because they do not require a new appraisal or title search. Shadow banks also face lower administrative costs for refinance loans due to their greater use of technology. Let w_{jm} denote the per-dollar administrative cost incurred by lender j in market m, and d_{jtm} is the total dollar amount of loans originated by lender j in year-market (t, m). I define four fixed administrative costs: shadow banks' purchase loans, shadow banks' refinance loans, commercial banks' purchase loans, and commercial banks' refinance loans. The total fixed administrative cost for lender j is

$$\sum_p d_{jtm} * w_{jm}$$

Financing Cost

Built on Buchak et al. (2024), for loans sold to the GSEs, the per-dollar financing cost in year t and market m is

$$\sigma_{tm}^{GSE} = \beta^{GSE} Fed\ Rates_t + GSE\ Fees_t + \sigma^{GSE,Risk} Low\ FICO_m \tag{3}$$

a proportion β^{GSE} of the risk-free policy rate, which is the Fed rate, captures the macro level cost of funding; the $GSE\ Fee_t$ captures the additional fees the GSE charges in the securitization process, including the basic guarantee fee and service fee. $Low\ FICO_m$ is the indicator variable of whether the market m is targeted at low-FICO borrowers. Thus, $\sigma^{GSE,Risk}$ captures the additional fee GSE charges for high-risk loans. [22] Because the GSE pricing schedule does not incorporate local risk, σ_{tm}^{GSE} is uniform across locations.

Commercial banks incur a separate cost when they retain loans on their balance sheets. Following Buchak et al. (2024), I define the bank's risk-weighted capital ratio as:

$$\rho_{jt} = \frac{e_{jt}}{\xi_0 d_{jt0}^b + \xi_J d_{jtJ}^b + \xi_C d_{jtC}^b}$$

where e_{jt} is the banks' tier-one equity capital. Banks hold three assets in the balance sheet: the risk-free bonds with a total amount d_{jt0}^b, the jumbo mortgage loans with a total amount d_{jtJ}^b, and the conforming mortgage loans with a total amount d_{jtC}^b. ξ_0, ξ_J and ξ_C are the corresponding regulatory risk weights.

Balance-sheet funding costs take the form:

$$\sigma_{jtm}^b = \beta_j Fed\ Rates_t + \sigma^b(\rho_{jt} - \bar{\rho})^{-1} + \sigma^{b,Risk} Low\ FICO_m + \beta^{SLR} SLR\ Risk_{jtm} \tag{4}$$

Specifically, β_j captures how banks' costs respond to changes in the Fed funds rate, in other words, their market power in deposit markets. Banks do not fully pass through the policy rate, so β_j varies by lender. $\bar{\rho}$ is the risk-adjusted capital ratio required by the regulator, and thus $\rho_{jt} - \bar{\rho}$ is the excess risk-adjusted capital ratio of banks. σ^b captures the effect of the excess capital ratio on banks' costs. A higher excess capital ratio leads to lower funding costs through the balance sheet. $\sigma^{b,Risk}$ is the additional costs for a low-credit borrower. [23] Finally and most importantly, I deviate from Buchak et al. (2024) by including the additional costs associated with SLR risk exposure for banks.

$$SLR\ Risk_{jtm} = \underbrace{Lender\ SLR\ Exposure_{jt}}_{\text{Average SLR exposure of loans held on balance sheet}} \times \underbrace{Market\ SLR\ Risk_m}_{\text{SLR risk of the newly originated loan}}$$

This measure captures two forces: the lender's existing exposure, because banks with substantial coastal portfolios face greater marginal risk when adding another coastal loan; and the exposure from the newly originated loan, because the loan's location directly contributes to the climate risk retained. As a result, balance-sheet funding costs rise more quickly for lenders that already hold many high-risk coastal mortgages.

Let b_{jtm} denote the share of conforming loans that lender j retains on balance sheet in year-market

[22] $Fed\ Rates_t$ and $GSE\ Fees_t$ come from the data, and the only parameter is $\sigma^{GSE,Risk}$.

[23] In this part, $Fed\ Rates_t$, $(\rho_{jt} - \bar{\rho})^{-1}$, $Low\ FICO_m$ and $Climate\ Risk_{jt}$ come from the data. The estimated parameters are β_j, σ^b, $\sigma^{b,Risk}$ and β^{SLR}.

(t, m), then

$$\underbrace{d^b_{jtm} = b_{jtm} d_{jtm}}_{\text{Amount of loans on balance sheet}} \quad , \quad \underbrace{d^{GSE}_{jtm} = (1 - b_{jtm}) d_{jtm}}_{\text{Amount of loans sold to GSE}}$$

The profit function of lender j in year t is

$$\Pi_{jt} = \sum_{m \in M} \{r_{jtm} - w_{jm} - [(1 - b_{jtm})\sigma^{GSE}_{tm} + b_{jtm}\sigma^{b}_{jtm}]\} d_{jtm} \tag{5}$$

Lenders choose $\{r_{jtm}, b_{jtm}\}$ to maximize their profit, taking other lenders' pricing decisions as given. [24] Formally, denoting $\mathbf{r_{jt.}}$ as the interest rate vectors of lender j in year t in all markets, lenders solve the maximization problem

$$Max_{\mathbf{r_{jt.}}, \mathbf{b_{jt.}}} \Pi_{jt} = \sum_{m \in M} \{r_{jtm} - w_{jm} - [(1 - b_{jtm})\sigma^{GSE}_{tm} + b_{jtm}\sigma^{b}_{jtm}]\} d_{jtm} \tag{6}$$

Equilibrium

The equilibrium consists of:,

- **Borrower choice:** Given the demand parameters θ_d, borrowers choose loans to maximize utility, generating market shares s_{jtmk}.
- **Funding decisions:** Commercial banks choose b_{jtm} by comparing balance-sheet and GSE funding costs.
- **Pricing:** Lenders set interest rates r_{jtm} to maximize profits given demand and funding costs.

5 Estimation and Results

I estimate the demand and supply sides of the model separately. The demand estimation recovers how borrowers value interest rates, conforming loan status, and loan-size characteristics by matching observed market shares to the structure of the random-coefficients model. The supply estimation recovers the cost parameters that determine lenders' pricing and funding decisions, including GSE funding, balance-sheet funding, and loan origination costs. The estimation proceeds in two steps. First, I estimate the demand system using the simulated method of moments. Second, I estimate the supply-side parameters using a minimum-distance procedure that matches model-implied marginal costs and funding choices to those observed in the data.

5.1 Demand Side

I estimate the demand side as the standard random-coefficient logit model (Berry et al., 1995; Nevo, 2000). The data are aggregated at the product–lender–market level. A market is defined by a county, a loan purpose (purchase or refinance), and a borrower credit-risk group (high or low FICO, where high credit risk is defined as FICO below 740). Markets are treated as independent across years. For example, high-FICO

[24] Similar to Buchak et al. (2024), by this setting, I avoid solving a two-way first-order condition equation system, which has no analytical solution. Detailed discussion can be found in the appendix.

refinance borrowers in New York County in 2018 and 2019 belong to the same underlying market but are treated as separate market-year observations in the estimation. Following Buchak et al. (2018, 2024), I restrict the sample to newly originated conventional first-lien mortgages for principal residences. Market shares are computed as the lender's total loan counts in a market divided by the corresponding market's size. The market size data comes from American Community Survey measures of local housing markets. For purchase-loan markets, I use ten percent of owner-occupied housing units. For refinance markets, I use ten percent of households with a mortgage. I drop observations with implausible values, such as market shares exceeding 1, resulting in a sample of 305,691 product–lender–market observations.

To address price endogeneity, I instrument interest rates using the lagged local mortgage default rate following Hurst et al. (2016) and Buchak et al. (2024). The identification exploits an institutional feature of the mortgage market: GSE purchase prices depend on borrower characteristics such as LTV and FICO but do not incorporate geographic risk. As a result, local default risk affects lenders' costs for loans held on the balance sheet but not for GSE-eligible conforming loans, generating variation in mortgage prices that arises from supply-side financing costs rather than borrower demand. For each market, I recover the empirical distributions of log income and log property value, and draw 3000 simulated borrowers to approximate the integrals in the market-share equation.

5.2 Supply Side

The supply side differs from the linear-cost-function setting because lenders choose between two funding methods, resulting in a non-linear cost function. A simple linear regression is therefore not feasible. Following Buchak et al. (2024), I estimate the supply parameters using a minimum distance approach. The parameters to be estimated are grouped into three sets: the administrative cost parameters,

$$\theta_s^f = \{w_{SB,p},\ w_{SB,r},\ w_{CB,p},\ w_{CB,r}\}$$

the GSE funding parameters,

$$\theta_s^g = \{\beta^{GSE}, \sigma^{GSE,Risk}\}$$

and the balance-sheet funding parameters,

$$\theta_s^b = \{\beta_j, \sigma^b, \sigma^{b,Risk}, \beta^{SLR}\}$$

I estimate these objects in several steps. I begin with the GSE funding parameters because shadow banks can only use GSE funding. Their marginal cost is therefore the sum of the GSE funding cost and their administrative cost. I observe the GSE service fee and basic guarantee fee directly from the data. After subtracting these fees from the demand model-implied marginal cost, the remaining variation depends only on the federal funds rate, borrower risk, and the shadow-bank administrative cost. Formally, the marginal

cost of shadow banks can be written as

$$\begin{aligned} MC_{jtm} &= \sigma_{tm}^{GSE} + w_{SB,m} \\ &= GSE\ Fees_t + \beta^{GSE} Fed\ Rates_t + \sigma^{GSE,Risk} Low\ FICO_m + w_{SB,m} \end{aligned}$$

where $w_{SB,m}$ is the fixed origination cost of shadow banks in market m. I retrieve $GSE\ Fee_t$, which captures the service fee and basic guarantee fee for GSE on all loans, from the official GSE data reports. [25] I can back out the marginal cost for shadow banks net of GSE fees, and this net marginal cost depends only on fed fund rates, loan risk and fixed administrative costs. Thus, defining

$$Net\ MC_{jtm} = MC_{jtm} - GSE\ Fees_t$$

I estimate the following regression on all shadow-bank observations to recover β^{GSE} and $\sigma^{GSE,Risk}$ in θ_s^g and the administrative cost parameters for purchase and refinance loans by shadow banks $w_{SB,p}, w_{SB,r}$.

$$Net\ MC_{jtm} = \beta^{GSE} Fed\ Rates_t + \sigma^{GSE,Risk} Low\ FICO_m + \delta Refinance_m + Const + \epsilon_{jtm} \tag{7}$$

$Refinance_m$ is the indicator variable that market m is refinance. The coefficient β^{GSE} captures the GSE's sensitivity to the macro risk-free rate and the fed funds rate. The coefficient $\sigma^{GSE,Risk}$ captures the additional guarantee fee that GSE charges for riskier borrowers. The constant term $Const$ identifies the administrative cost of shadow banks for purchase loans $w_{SB,p}$. The sum of the constant term and refinance coefficient $Const + \delta$ gives the administrative cost of shadow banks for refinance loans $w_{SB,r}$.

Next, I estimate the balance-sheet funding parameters θ_s^b. The sensitivity of a bank's cost to the federal funds rate, β_j, is calibrated following Drechsler et al. (2021). For each commercial bank, I estimate the following time-series specification using data from 1984 to 2017 (prior to my main sample period) and restrict the sample to banks with at least 60 quarterly observations. [26]

$$\Delta DepIntExp_{jt} = \alpha_j + \sum_{\tau=0}^{3} \beta_{j,\tau}^{Dep} \Delta Fed\ Rates_{t-\tau} + \epsilon_{it} \tag{8}$$

where $\Delta DepIntExp_{jt}$ is the change in bank j's deposit rates from year-quarter t to year-quarter $t+1$. $\Delta Fed\ Rates_t$ is the change in the Fed funds rate from t to $t+1$. α_j are bank-specific constants for the bank j. Following Drechsler et al. (2021), I include the contemporaneous change and three lags of the Fed funds rate. Because the data are quarterly, these four coefficients capture the cumulative response of funding costs over a one-year horizon, corresponding to the time required for interest income and expenses to fully adjust to interest rate changes. The sum of the lag coefficients $\sum_{\tau=0}^{3} \beta_{j,\tau}^{Dep}$ is used as the estimate of β_j.

With β_j fixed, I estimate the left parameters σ^b, $\sigma^{b,Risk}$ and β^{SLR} using a generic minimum distance

[25] Here, I use the sum of the yearly average value of the service fee and guarantee fee from Fannie Mae and Freddie Mac as the estimation of $GSE\ Fees_t$. The corresponding service fee data are available at https://selling-guide.fanniemae.com/sel/c2-1.1-05/servicing-fees, and the corresponding guarantee fee data are available at https://www.fhfa.gov/policy/guarantee-fees. Service fees for different loans can vary. For simplicity, I set all service fees to 0.5%.

[26] To capture the heterogeneity of deposit market power among commercial banks, I don't estimate the β_j inside the main supply side of the model. This is because the data include more than 300 commercial banks, which leads to high computational complexity when estimating the β_j for each bank j in the supply side. To reduce computational complexity, I calibrate the parameter β_j prior to the main sample period using linear time-series regressions.

scheme [27]. I start from an initial guess of the parameter vector. Given a guess, I compute the model-implied balance-sheet funding cost for each lender, incorporating the lender's capital ratio, borrower credit risk, and SLR-risk exposure. Comparing the balance-sheet cost to the GSE cost determines whether a lender would use GSE funding or balance-sheet funding in the conforming-loan market. The model-implied share of loans held on the balance sheet is matched to the observed share in the data, which forms the first set of moments.

After determining the funding choice in each conforming-loan market, I recover the administrative cost of commercial banks. For each lender–market observation, the total marginal cost implied by the demand estimates is known, and the model-implied funding cost is computed using the current guess of θ_s^b. The difference between these two objects gives the administrative cost residual [28]. I then regress these residuals on an indicator for refinance loans:

$$MC\ Resid_{jtm} = \delta^b Refinance_m + Const^b + \epsilon_{jtm} \tag{9}$$

The constant term identifies the administrative cost of originating a purchase loan, and the sum $Const^b + \delta^b$ identifies the cost of originating a refinance loan. If the parameters are well identified, the residual of the regression ϵ_{jtm} should be 0. So, the residual ϵ_{jtm} forms the second set of moments.

Additional moments come from jumbo loans. Since jumbo loans are almost exclusively held on the balance sheet, a correct value of θ_s^b should make the model-implied balance-sheet marginal cost match the marginal cost recovered from the demand side. To discipline this condition, I run parallel regressions of the model-implied marginal cost and the observed marginal cost on capital ratios and climate-risk exposure, and include the differences in these coefficients as moments.

The final set of moments is based on covariances. The administrative-cost residuals should not be systematically related to capital ratios or climate-risk exposure. Likewise, the covariance between the model-implied share of conforming loans retained on the balance sheet and these variables should match the covariance observed in the data. I stack all moments and estimate θ_s^b by minimizing the squared distance between model-implied and data-implied moments. Details of the procedure are in the appendix.

5.3 Demand Results

Table 2 reports the estimates from the demand system. The average price sensitivity is $\overline{\alpha} = -3.554$. This is in line with earlier work (DeFusco and Paciorek, 2017; Buchak et al., 2024). The average utility gain from choosing a conforming loan is $\overline{\gamma} = 5.072$. Both estimates are consistent with the idea that borrowers strongly prefer lower interest rates and value the lower costs and simpler documentation of conforming loans.

Borrower characteristics influence these preferences. Higher-income borrowers are less sensitive to interest rates and place less value on conforming loans. This pattern is consistent with the idea that high-income households place greater weight on obtaining a sufficiently large loan than on small price differences. In contrast, borrowers purchasing more expensive homes are more sensitive to loan pricing and value conforming loans more, likely because high house prices tighten budget constraints and make cheaper mortgage terms more valuable.

[27] Here my estimation method relies on micro moments, similar to Conlon and Gortmaker (2025). In this case, the estimator is a generic minimum distance estimator.

[28] By construction, the total marginal cost equals the sum of the non-linear funding cost and the administrative cost. $MC_{jtm} = min(MC\ GSE_{tm}, MC\ BS_{jtm}) + w_{CB,m}$

The random-coefficient estimates show limited extra dispersion in price sensitivity (σ_α is not statistically significant), indicating that most of the random effect of price disutility stems from demographics. Instead, there is a statistically significant heterogeneity in the valuation of conforming loans $\sigma_\gamma = 1.660$. Both $\overline{\Gamma}_{LTV} = 0.034$ and $\overline{\Gamma}_{DTI} = 0.096$ confirm that borrowers prefer larger loans.

Table 2: Estimation Results of Demand Side Parameters

This table reports the estimated parameters from the demand system. Borrowers' utility takes the form

$$PD_i = \overline{PD} + \Pi \times D_{itm} + \Sigma \times v_i,$$

where $\overline{PD}$ captures the mean utility coefficients. Π captures how borrower demographics shift preferences, and Σ captures the random taste variation. Panel A reports the mean utility coefficients, including the coefficient on price disutility, α, the conforming-loan convenience parameter γ, and the loan-size utility parameters Γ_{LTV} and Γ_{DTI}. Panel B reports the demographic coefficients in Π and the random-coefficient standard deviations in Σ. Panel C reports additional model outcomes, including the implied mean interest rate elasticity. Standard errors are shown in parentheses.

Parameter Name	**Parameter Description**	**Parameter Value**
Panel A: Mean Utility Coefficients		
$\overline{\alpha}$	Price Disutility	-3.554
		(0.293)
$\overline{\gamma}$	Conforming Convenience	5.072
		(0.640)
$\overline{\Gamma}_{LTV}$	LTV Utility	0.034
		(0.005)
$\overline{\Gamma}_{DTI}$	DTI Utility	0.096
		(0.006)
Panel B: Random Utility Coefficients		
Σ		
σ^2_α	Price Unobserved Heterogeneity	0.057
		(0.312)
σ^2_γ	Conforming Convenience Unobserved Heterogeneity	1.660
		(0.077)
Π		
α_i (Income)	Price Demo (Log Income)	1.477
		(0.101)
γ_i (Income)	Conforming Convenience Demo (Log Income)	-3.513
		(0.319)
α_i (PV)	Price Demo (Log PV)	-0.646
		(0.057)
γ_i (PV)	Conforming Convenience Demo (Log PV)	1.585
		(0.186)
Panel C: Other Model Outcome		
Interest Rate Elasticity		-7.505

5.4 Supply Results

The supply-side estimation results are reported in Table 3. The estimates indicate that lenders incorporate SLR risk into marginal costs, although the magnitude is modest. The estimated coefficient implies that a one-standard-deviation increase in SLR exposure raises marginal cost by about 1 basis point, or roughly 0.35% of the mean marginal cost.[29] This effect is economically meaningful but smaller than the effect of borrower credit risk, accounting for about 10% of the credit-risk effect. This magnitude is consistent with the reduced-form HMDA evidence, which suggests that SLR-risk pricing in the jumbo-loan market is approximately 12% of credit-risk pricing, reported in Table 4.[30]

Table 4 also evaluates the model fit by comparing other key model outputs with institutional benchmarks. The model matches several important features of the mortgage market. In particular, it predicts that commercial banks hold 36.5% of conforming loans on their balance sheets, which is close to the 33.6% observed in the data. The estimated marginal cost of loan origination is also consistent with institutional evidence. The model implies an average marginal cost of about 272.2 basis points net of the risk-free rate, corresponding to approximately $8,721 per loan.[31] This estimate is close to the approximately $8,000 average cost reported in the Freddie Mac cost-to-originate study.[32]

6 Monetary Transfers under Uniform GSE Pricing

I first use the model estimates to quantify the regional monetary transfer arising from SLR Risk under the GSE uniform pricing. I first compute the counterfactual equilibrium interest rate for loan k, denoted r_k^{fair}, under a scenario in which GSE guarantee fees incorporate local SLR risk. Specifically, I allow the local SLR exposure to enter the GSE securitization cost function in the same way it enters lenders' marginal costs in the estimated model. I then compute the equilibrium interest rates under this counterfactual cost structure. The resulting r_k^{fair} therefore represents the mortgage rate that would prevail if GSE pricing reflected local SLR risk. Then, I calculate the rate gap between the observed rate in the data, r_k, and the fair rate, $r_k^{Gap} = r_k^{fair} - r_k$. The dollar value regional monetary transfer for product k of lender j in county c and market m in the origination year t is then defined by

$$\Delta W_{kjcmt} = r_k^{Gap} \times AveLoanAmt_k$$

where $AveLoanAmt_k$ is the average dollar value of the loan amount for loan product k. Since payments are locked in at origination, the same transfer will continue in subsequent years until the loan is refinanced or matures. In this case, I follow Hurst et al. (2016) to regard this transfer as perpetuity with a discount rate of 15%, so that the present value of the regional transfer is computed as

$$\Delta W_{kjcmt}^{pv} = \frac{W_{kjcm}}{15\%}$$

[29] This analysis is also based on commercial banks' jumbo loans.

[30] Reference value based on SLR-risk effect (0.30%) and its relative size to credit risk effect (12%) in interest-rate regressions for jumbo loans.

[31] This is calculated by averaging the net-of-risk-free-rate marginal cost in percentage points (2.722) times the average loan amount per loan ($ 320368).

[32] The reports can be found at https://sf.freddiemac.com/articles/insights/2024-cost-to-originate-study.

Table 3: Estimation Results of Supply Side Parameters

This table reports the estimation of the supply-side parameters. Panel A reports the fixed administrative costs for commercial banks and shadow banks. Panel B reports the GSE funding cost parameters. The basic GSE fees (g-fee and s-fee) are taken directly from the data. Panel C reports the balance-sheet funding cost parameters for commercial banks. For the deposit market power parameter β_j, the mean across banks is reported as the parameter value, with the standard deviation shown in parentheses. For all other parameters, standard errors are reported in parentheses.

Parameter Name	**Parameter Description**	**Parameter Value**
Panel A: Fixed Administrative Cost		
$w_{CB,p}$	Commercial banks, Purchase	1.555
		(0.002)
$w_{CB,r}$	Commercial banks, Refinance	1.415
		(0.002)
$w_{SB,p}$	Shadow banks, Purchase	1.639
		(0.001)
$w_{SB,r}$	Shadow banks, Refinance	1.352
		(0.001)
Panel B: GSE Funding Cost		
$GSE\ Fee_{2018}$	GSE g-fee + s-fee 2018	1.00
$GSE\ Fee_{2019}$	GSE g-fee + s-fee 2019	1.02
$GSE\ Fee_{2020}$	GSE g-fee + s-fee 2020	1.02
$GSE\ Fee_{2021}$	GSE g-fee + s-fee 2021	1.04
β^{GSE}	GSE Macro Rates Sensitivity	0.496
		(0.001)
$\sigma^{GSE,Risk}$	GSE Credit-Risk Additional Cost	0.783
		(0.002)
Panel C: Balance-Sheet Funding Cost		
β_j	Deposit Market Power (Mean)	0.407
		(0.106)
σ^b	Excess Capital Effect	0.064
		(0.001)
$\sigma^{b,risk}$	Credit-Risk Additional Cost	1.058
		(0.069)
β^{SLR}	SLR-Risk Cost	0.114
		(0.067)

Table 4: Key Moments of Model Fits

This table reports key moments used to evaluate how well the model matches institutional benchmarks. The commercial bank holding share is the fraction of conforming loans retained on commercial banks' balance sheets. Net marginal cost per loan equals the average marginal cost (in percentage points, net of the risk-free rate) multiplied by the average loan size. The fixed administrative cost share measures the fraction of marginal costs attributable to administrative expenses. The GSE credit-risk g-fee captures the additional guarantee fee applied to high-risk borrowers. Deposit market power is summarized by the mean and standard deviation of the parameter β_j. The balance-sheet credit-risk cost measures the additional funding cost for high-risk loans held on banks' balance sheets. The standardized SLR risk effect measures the effect of a one-standard-deviation increase in SLR risk scaled by the mean marginal cost. The SLR-to-credit risk effect ratio compares the standardized climate-risk effect to the standardized credit-risk effect.

Moment	**Model Outcome**	**Reference Value**	**Reference**
Commercial Bank Loan Holding Share	36.5%	33.6%	HMDA (Loan Sales)
Average Net Marginal Cost per Loan ($)	8,721	8,000	FHLMC Cost Study
Fixed Administrative Cost Share	50%–61%	55%–70%	FHLMC Cost Study
GSE Credit-Risk G-Fee	0.78%	0.62%	GSE LLPA Schedule
Deposit Market Power — Mean	0.407	0.350	Drechsler et al. (2021)
Deposit Market Power — Std. Dev.	0.106	0.102	Drechsler et al. (2021)
Balance-Sheet Credit-Risk Cost	1.07%	0.99%	Stylized Fact (Int Rate)
SLR Risk Effect — Standardized	0.35%	0.30%	Stylized Fact (Int Rate)
SLR-to-Credit Risk Effect Ratio	10.02%	12.16%	Stylized Fact (Int Rate)

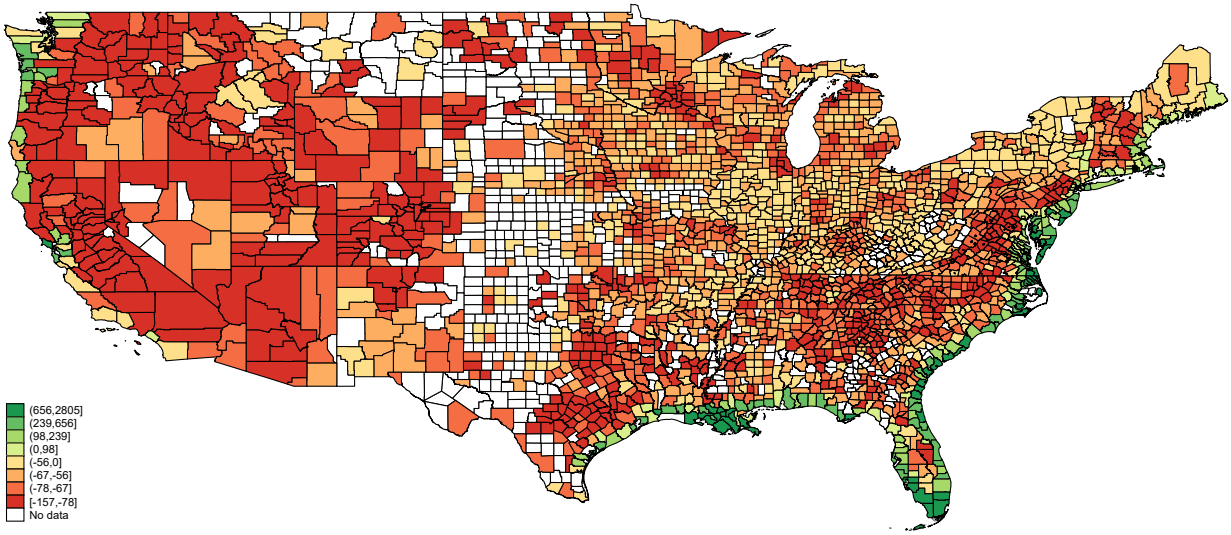
Finally, I calculate the county-level average present value of monetary transfers, weighted by the number of loans for each loan product. Counties with $\Delta W_c^{pv} > 0$ mean that borrowers from county c face a lower-than-fair interest rate regarding their SLR Risk and receive subsidies for mortgages they get. On the other hand, counties with $\Delta W_c^{pv} < 0$ mean that borrowers from county c are charged more than fair interest rates for SLR Risk and are thus being taxed. Figure 6 represents the average dollar value of transmission per loan at the county level.

On average, inland counties subsidize coastal counties, especially those on the southeastern coastline, such as counties in Florida and Louisiana, which face the highest SLR risk. Table 5 provides further details on the regional transfers. Panel A reports the total regional transfer, nationally and separately for inland and low- and high-risk coastal counties. High-risk coastal counties are defined as those whose SLR risk exceeds the 90th percentile of SLR risk among coastal counties. The nationwide total taxes paid by borrowers is $1,361 million, while the total subsidies received by borrowers is $1,446 million. These amounts need not coincide because transfers are computed separately within each market, and markets are independent in the model. As a result, the aggregate subsidies and taxes across markets may differ. Any difference is absorbed by the GSEs' balance sheet. Looking at the detailed regions, borrowers from inland counties contribute 1125 million in taxes, while receiving only 1 million in subsidies. At the same time, borrowers in high-risk coastal counties receive 595 million in subsidies from other borrowers, while they paid a total of 1 million in taxes.

Panel B shows the top 5 counties receiving the most subsidies and the top 5 counties paying the most taxes. The most subsidized counties are counties in the southeast coastal region with high SLR risk. Panel C presents the detailed distribution of transfers among inland counties, low-risk coastline counties, and high-risk coastline counties. It shows that a large number of inland borrowers subsidize a small number of high-risk borrowers in coastal counties. On average, the 29 high-risk coastal counties experience a 7.7 bps

Figure 6: Regional Transfers Across Counties

This figure shows the average transfer per loan, ΔW_c^{pv}, for each county over 2018–2021. $\Delta W_c^{pv} > 0$ indicates that a county receives a subsidy, while $\Delta W_c^{pv} < 0$ indicates that a county pays a tax.



rate gap between the fair rate and the realized rate, meaning that borrowers pay 7.7 bps less than their fair rate due to the GSE uniform-pricing scheme. This 7.7 bps is not negligible compared with the magnitude of effects identified in prior studies examining mortgage loan pricing, such as the average interest rate gap between traditional banks and non-fintech shadow banks (2.4 bps) (Buchak et al., 2018) and interest rate reduction when borrowers apply to more than one bank in search for better loan terms (7 bps) (Bhutta et al., 2020). Translated into dollars, borrowers from high-risk coastal counties receive $1409 in subsidies per loan application. To further illustrate the magnitude, I use the federal tax deduction for the mortgage as the benchmark [33]. On average, these subsidies account for approximately 10.2% of the federal tax deduction, which is not negligible, given that SLR risk is just one of many local risks. For the 309 low-risk coastal counties, the subsidies are relatively small, at $163 per loan, accounting for around 1% of the mortgage federal tax deduction. The 2219 inland counties exhibit a -0.45 bps gap between the fair rate and the realized rate, implying they paid 0.45 bps above their fair rate. In dollar amount, inland borrowers pay $68 more per loan. The average transfer per loan in inland counties is small, but given the number of counties and loans, the total transfer remains non-negligible. Again, the results show that a large number of inland borrowers subsidize a small number of high-risk borrowers in coastal counties.

6.1 Balance-sheet Loan and Securitization Adjusting Margin

The model incorporates two additional lender adjustment margins that shape the monetary transfers generated by uniform GSE pricing: the balance-sheet loan pricing margin and the securitization decision margin. Through competition and substitution across mortgage products, uniform GSE pricing affects not only GSE-securitized conforming loans but also the fair interest rates on non-GSE-eligible jumbo loans and conforming

[33] The federal tax deduction for one loan is calculated as $Marginal\ Tax\ Rate \times Interest\ Rate \times Loan\ Amount$. Similar to the regional transfer, I take it also as a perpetuity with the same discount rate 15%.

Table 5: Regional Monetary Transfer Details

This table reports regional monetary transfers. Panel A reports aggregate taxes and subsidies, in millions of dollars. High-Risk Coastal counties are those above the 90th percentile of SLR risk among coastal counties. Panel B reports the top five subsidized and taxed counties. Panel C reports the distribution of county-level average transfers per loan. Interest Rate is the gap between the fair and realized mortgage rate. Transfer is the present value of the transfer per loan. Tax Deduction is the present value of the federal mortgage tax deduction. Transfer / Tax Deduction reports the transfer as a share of the mortgage tax deduction.

Panel A: Aggregate Transfer ($ millions)

	Taxes	**Subsidies**
National	1,494	1,610
High-Risk Coastal	10	652
Low-Risk Coastal	275	948
Inland	1,209	11

Panel B: Top 5 County Transfers

Subsidized	**County**	**State**	**SLR Risk**	**Transfer ($)**
1	Monroe County	FL	0.972	2,804
2	Poquoson City	VA	0.998	2,277
3	Miami-Dade County	FL	0.863	2,069
4	Broward County	FL	0.795	1,834
5	Dare County	NC	0.812	1,832
Taxed	**County**	**State**	**SLR Risk**	**Transfer ($)**
1	Falls Church City	VA	0	157
2	Loudoun County	VA	0	157
3	San Benito County	CA	0	156
4	Fairfax City	VA	0	151
5	Montgomery County	MD	0	143

Panel C: Transfer per Loan

	N	**Mean**	**p10**	**p25**	**p50**	**p75**	**p90**
High-Risk Coastal							
Interest Rate (bp)	29	7.70	6.01	6.26	7.25	9.14	10.18
Transfer ($)	29	1,409	937	1,076	1,316	1,622	2,069
Tax Deduction ($)	29	14,625	9,272	10,692	12,204	15,217	24,589
Transfer / Tax Deduction	29	10.20%	6.94%	8.50%	9.16%	11.80%	15.00%
Low-Risk Coastal							
Interest Rate (bp)	309	0.86	-0.44	-0.23	0.40	1.29	3.13
Transfer ($)	309	163	-74	-41	74	267	611
Tax Deduction ($)	309	16,526	9,299	11,340	13,955	17,730	28,155
Transfer / Tax Deduction	309	1.11%	-0.57%	-0.28%	0.50%	1.89%	3.81%
Inland							
Interest Rate (bp)	2,219	-0.45	-0.51	-0.49	-0.47	-0.44	-0.38
Transfer ($)	2,219	-68	-90	-79	-68	-57	-47
Tax Deduction ($)	2,219	10,649	7,241	8,402	9,914	11,983	14,526
Transfer / Tax Deduction	2,219	-0.66%	-0.80%	-0.74%	-0.67%	-0.60%	-0.52%

loans retained on lenders' balance sheets. The model also allows lenders' securitization decisions to respond endogenously to the GSE pricing scheme. In particular, moving from uniform pricing to local SLR-risk pricing changes the relative cost of GSE securitization and may induce commercial banks to retain a larger share of conforming loans on their balance sheets. Because GSE securitization and balance-sheet financing have different funding costs, this adjustment in the funding mix changes the implied fair prices of mortgages. By incorporating both product-market competition and endogenous funding choices, the model provides a more complete quantitative measure of regional monetary transfers and allows these transfers to be decomposed into distinct adjustment margins.

Figure 7 illustrates these mechanisms. Panel A shows the contributions of different loan types to monetary transfers in my baseline analysis, allowing both balance-sheet loan pricing and securitization margins to adjust. GSE-securitized conforming loans account for roughly 90% of the total regional redistribution. This dominance is intuitive: conforming loans securitized by the GSEs are directly subject to the constant-pricing scheme, and they constitute the bulk of the mortgage market. In contrast, conforming loans held on the balance sheet contribute little to the aggregate redistribution, reflecting their relatively small market share.[34] Jumbo loans account for the remaining 10% of redistribution. While jumbo loans are not directly affected by the GSE pricing rule, equilibrium spillovers from changes in the cost of conforming loans influence their fair price. Given their larger average loan size, jumbo loans contribute more to redistribution than portfolio-conforming loans, despite their smaller market share.

Panel B examines the importance of these margins. Eliminating the price response of jumbo loans reduces the aggregate transfer to roughly 90% of its full-equilibrium value. Fixing all balance-sheet loan pricing yields a reduction of a similar magnitude. When securitization decisions are held fixed, the decomposition shifts: the total allowance rises slightly, while the tax falls. This pattern is consistent with securitization as a buffer margin. Once the GSE begins pricing local SLR risk, the effective cost of securitizing high-risk, coastal, conforming loans increases. Lenders can mitigate this by retaining more coastal loans on their balance sheets, tempering the associated price increases. Conversely, securitization of inland conforming loans expands as GSE costs decline, amplifying the reduction in those loan prices. Disabling the securitization margin, therefore, leads to sharper price increases in coastal counties and smaller price declines inland, thereby redistributing toward greater allowances and lower taxes.

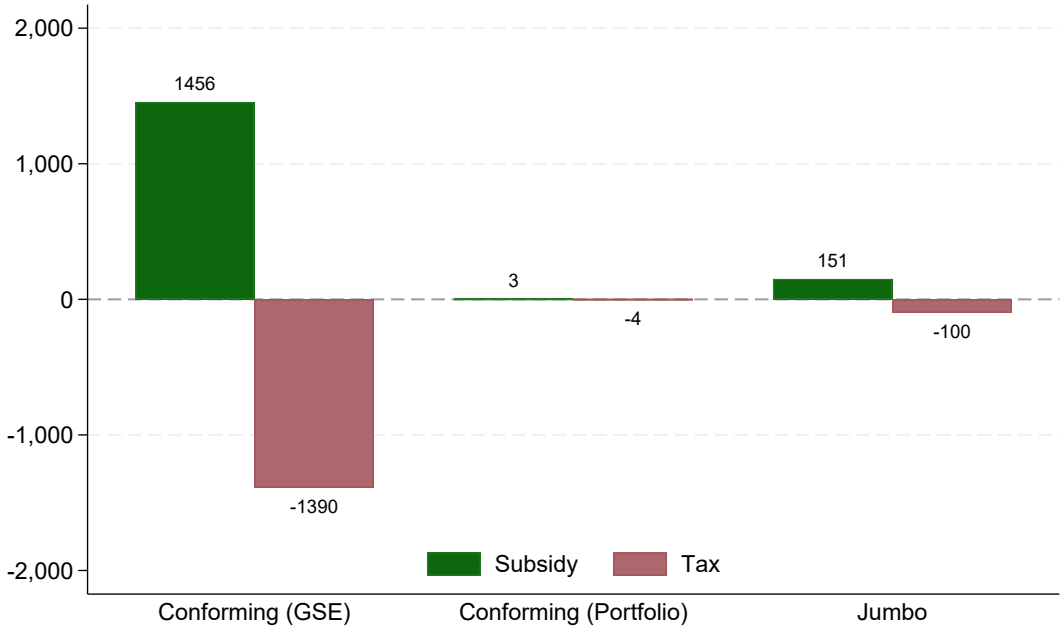
6.2 Regressive Regional Transfers

Evaluating how the monetary transfers generated by uniform GSE pricing of SLR risk are distributed across income groups is important for understanding their distributional and fairness implications. These transfers may reallocate resources between borrowers at different income levels, even when they arise through geographic rather than explicitly income-based pricing. To quantify these effects, I group borrowers into 10 income deciles and, for each decile, aggregate the total subsidies received and the total taxes paid. Figure 8 reports the results. Panel A displays the aggregate subsidies and taxes across income deciles, while Panel B shows the net transfer, defined as the difference between subsidies and taxes. A positive value indicates a subsidy, whereas a negative value represents a tax.

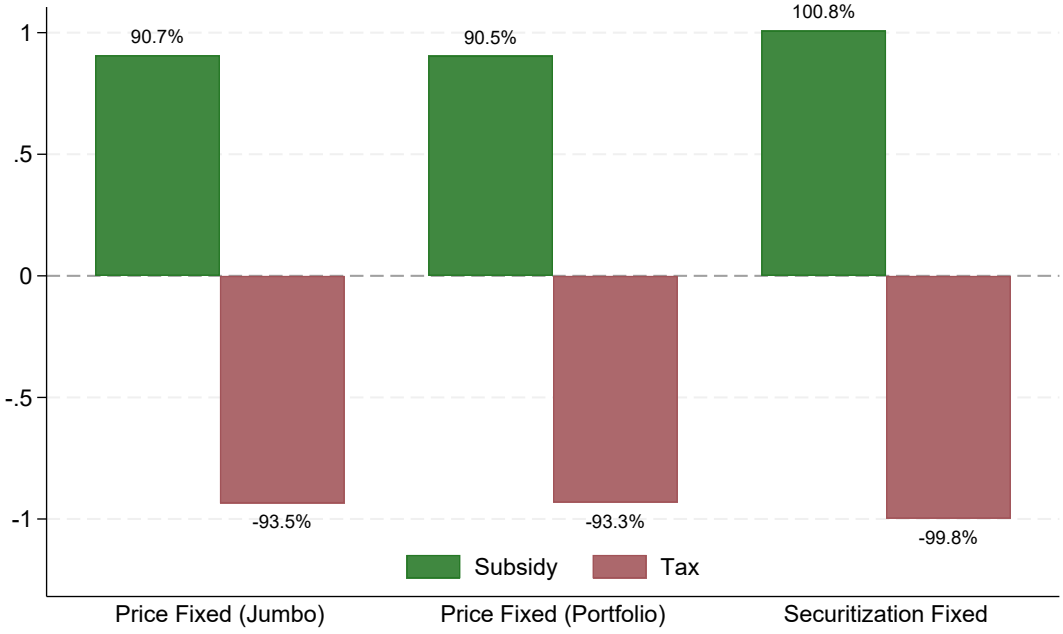
[34] On average, commercial banks retain about 33% of conforming loans on their balance sheet. However, because shadow banks—whose originations are overwhelmingly GSE-eligible—command a significant market share, the aggregate portfolio share of conforming loans remains small.

Figure 7: Monetary Transfers by Loan Type and Adjustment Margins

This figure decomposes monetary transfers under the GSE's constant-pricing scheme by loan type and adjustment margin. Panel A reports total transfers, in millions of dollars, for GSE-securitized conforming, portfolio conforming, and jumbo loans when both the balance-sheet pricing and securitization margins adjust in equilibrium. Panel B shows the percentage of the full-equilibrium aggregate transfer that remains when either the pricing or securitization margin is held fixed, highlighting the relative contribution of each channel to overall redistribution.



(a) Panel A. Contributions of Loan Types under Full Adjustment



(b) Panel B. Aggregate Transfers with Fixed Pricing and Securitization Margins

The results reveal a distinctly regressive pattern. Lower-income borrowers are net taxpayers, while higher-income borrowers are net recipients, with the top decile receiving the largest subsidy. This pattern emerges because higher-income households are more likely to reside in high-amenity coastal areas with higher SLR risk, thereby benefiting more from the existing SLR uniform pricing structure. Moreover, higher-income borrowers typically have larger loan balances, so each subsidy results in a greater total transfer. Together, these factors imply that wealthier borrowers not only face a higher likelihood of receiving a subsidy but also benefit from a larger subsidy amount. Consequently, the overall distribution of transfers is regressive, channeling resources from lower-income inland borrowers to wealthier coastal borrowers and reinforcing existing geographic and income disparities. This pattern contrasts with the policy objective of uniform pricing, which is intended to promote affordability and avoid penalizing higher-risk households. In the presence of climate risk, however, uniform pricing instead redistributes resources toward relatively wealthier borrowers located in high-risk coastal areas.

6.3 Market Competition and Regional Transfers

In this part, I provide further evidence on how market competition interacts with regional transfers. I first aggregate taxes and subsidies separately for each market. To evaluate market competition, I compute the Herfindahl–Hirschman Index (HHI) for each market. Then, I divide all markets into 100 HHI groups and, for each group, calculate the mean of the aggregated taxes and subsidies. Figure 9 plots the relationship between these average regional transfers and the degree of market concentration. Panel A shows that subsidy payments decline sharply with increasing HHI. Markets with low concentration (low HHI) receive substantial subsidies, while those with higher concentration experience little to no subsidy. Panel B presents a similar pattern for taxes: as market concentration rises, the tax per market declines toward zero.

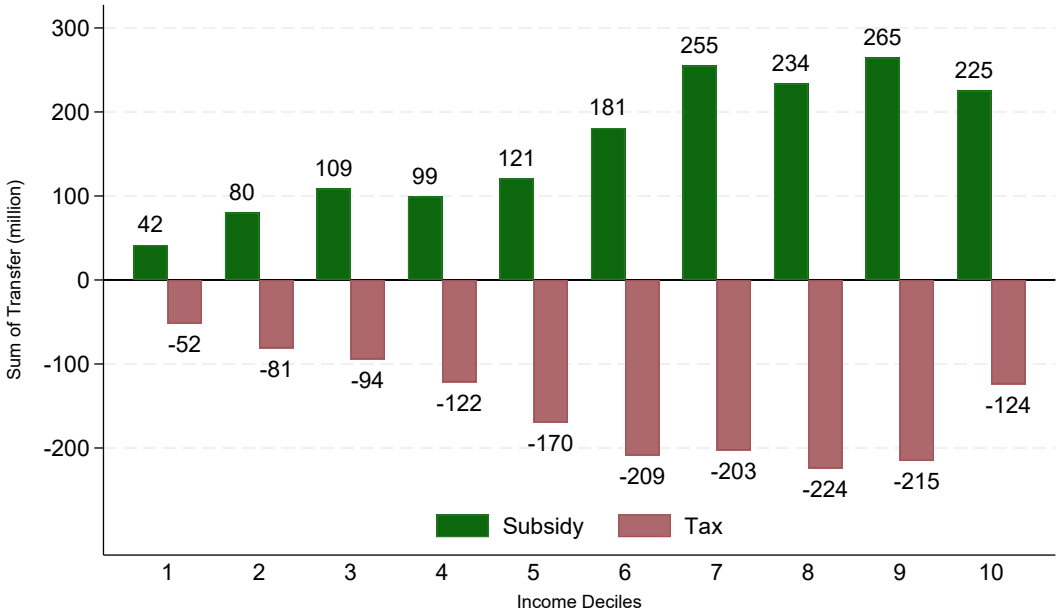
Together, the two panels reveal a clear negative relationship between market concentration and regional transfers. In more competitive markets, lenders are more responsive to changes in funding costs and therefore more likely to pass GSE subsidies or taxes through to borrowers via adjustments in loan rates. In contrast, in highly concentrated markets, limited competition dampens this pass-through. Dominant lenders retain most of the benefits (or absorb most of the costs) rather than adjusting borrowers' rates. As a result, borrowers' realized rates remain close to the fair rates implied by lenders' funding costs and required returns. When this alignment occurs, the gap between the two rates—which defines the size of the transfer—becomes small. Consequently, both subsidies (positive gaps) and taxes (negative gaps) are negligible in concentrated markets, consistent with the near-zero transfers shown in Figure 9.

7 Welfare Effects of Local SLR-Risk Pricing

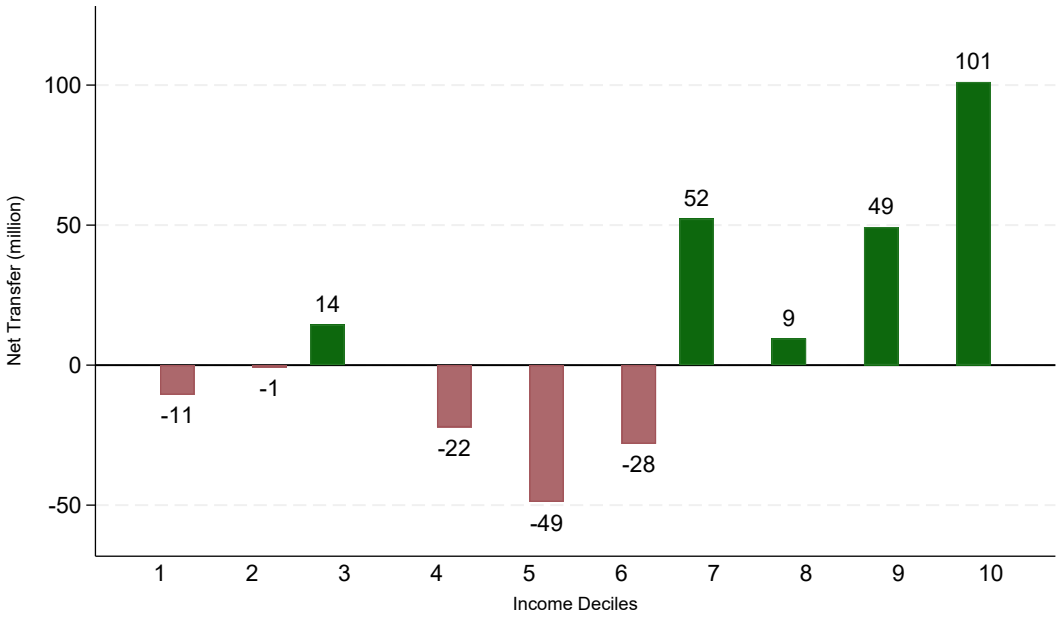
The previous section quantifies the regional monetary transfers generated by uniform GSE pricing of local SLR risk. I now examine the other side of the policy trade-off by considering a counterfactual in which the GSEs price local SLR exposure directly. Using the estimated structural model, I evaluate how this change affects mortgage origination, interest rates, commercial banks' securitization decisions, and borrower and lender welfare across high-risk coastal, low-risk coastal, and inland counties. I report the results separately for these regions because both climate exposure and reliance on mortgage credit are highly localized, and national aggregates would mask substantial differences in incidence. The baseline is the current uniform

Figure 8: Regressive Regional Transfers from GSE Uniform Pricing of SLR Risk

This figure shows the regional transfers generated by the GSEs' uniform pricing of sea-level-rise (SLR) risk across borrowers with different income levels. Panel A reports the aggregate subsidies received and taxes paid by borrowers in each income decile, measured in millions of dollars. Panel B presents the corresponding net transfer, defined as subsidies minus taxes; positive values indicate a net subsidy, and negative values indicate a net tax. Transfers are computed by aggregating borrower-level subsidies and taxes within each income decile, using loan-level estimates of the regional transfer induced by uniform GSE pricing of SLR risk.



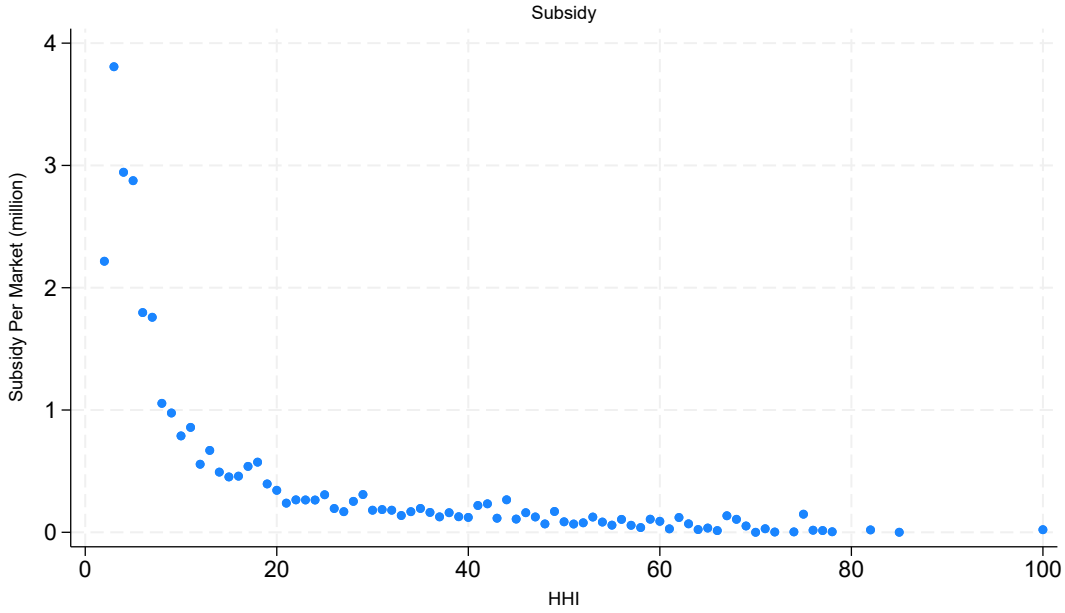
(a) Panel A. Aggregate Subsidies and Taxes by Income Decile



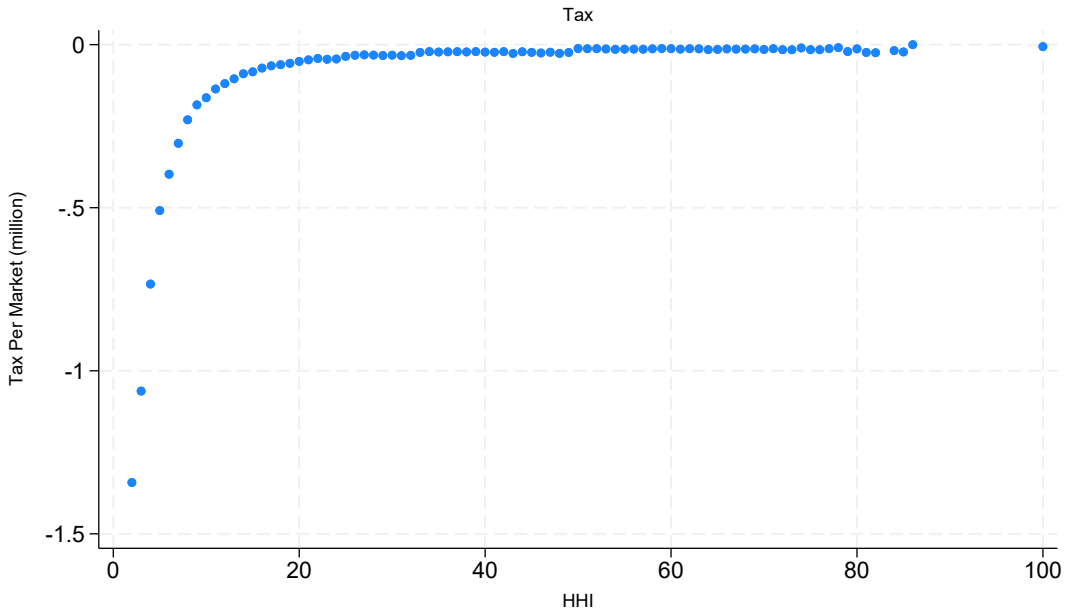
(b) Panel B. Net Transfers by Income Decile

Figure 9: Regional Transfers and Market Concentration

This figure shows the relationship between regional transfers induced by GSE uniform pricing of sea-level-rise (SLR) risk and market concentration. The Herfindahl–Hirschman Index (HHI) is used to measure market concentration, and total subsidies and taxes are aggregated separately at the market level. Markets are grouped into 100 HHI bins, and the average transfer within each bin is reported. Panel A plots the mean subsidy per market against HHI, and Panel B plots the mean tax per market against HHI. Transfers are expressed in millions of dollars.



(a) Panel A. Subsidy per Market and HHI



(b) Panel B. Tax per Market and HHI

GSE pricing scheme, under which securitization fees do not vary with local SLR exposure.

The counterfactual reveals a sharp regional trade-off. Local SLR-risk pricing removes the cross-regional monetary transfers brought by uniform GSE pricing, but it also raises mortgage costs and reduces credit and borrower welfare in the most exposed coastal markets. National aggregate effects are negligible, while high-risk coastal counties experience a 25.9% decline in borrower surplus and a 6.8% reduction in lending. Commercial banks partly offset the higher cost of GSE securitization by retaining more conforming loans on their balance sheets, with the retention rate increasing by 32.4%. Inland counties, in contrast, experience modest gains. These results show that the consequences of local risk pricing are primarily distributional across regions: it improves risk-based fairness by eliminating implicit geographic transfers, but imposes substantial welfare and credit costs on borrowers in high-risk coastal areas.

Using the current uniform GSE pricing scheme as the baseline, I simulate a counterfactual in which the GSEs price local SLR exposure in the same way as commercial banks. Specifically, I assume that the GSEs apply the estimated balance-sheet SLR-cost coefficient to local SLR exposure when setting securitization fees. Under the baseline, GSE fees reflect the national average level of SLR risk and do not vary across locations, generating monetary transfers from inland to coastal areas. In the counterfactual, I replace this national-average SLR component with the corresponding local exposure for high-risk coastal, low-risk coastal, and inland counties. This changes lenders' marginal securitization costs, after which I resolve the model for the new equilibrium in mortgage prices, market shares, funding choices, and welfare. Detailed numerical results are reported in Table C3 in the Appendix.

Figure 10 reports percentage changes relative to the baseline. National aggregates remain largely unchanged, indicating that the policy primarily redistributes credit and welfare across regions. High-risk coastal counties experience the largest adjustments: borrower surplus declines by 25.9%, lender profits increase by 4.5%, and total lending volume declines by 6.8%. The balance-sheet retention rate rises by 32.4%, reflecting higher securitization costs under risk-based pricing. As GSE fees increase in high-risk areas, lenders substitute away from securitization and retain a larger share of loans on their balance sheets.

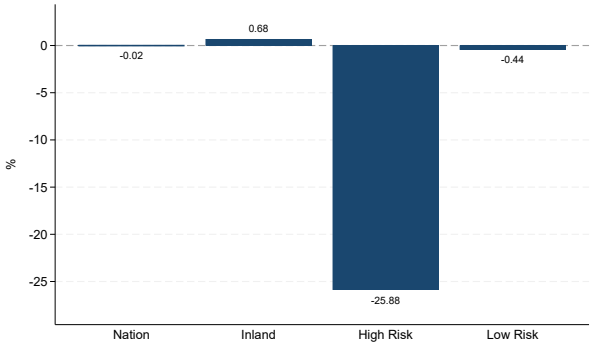
Table 6 shows the regional welfare transfers that GSE pricing of local SLR risk would unwind, providing a detailed breakdown by loan type and region that complements the earlier results on the overall magnitude and direction of these transfers. The results highlight that the current uniform GSE pricing redistributes resources from inland to coastal counties, with most of the transfer occurring through conforming loans. Inland areas contribute the majority of implicit taxes, while both high- and low-risk coastal areas receive substantial subsidies. Transfers associated with jumbo loans are small, reflecting their limited role in GSE securitization, but their prices are mainly influenced by market equilibrium when the cost of GSE-eligible loans changes. Together, these results clarify that the cross-subsidy embedded in uniform pricing operates primarily through conforming loans concentrated in coastal markets.

8 Additional Counterfactual Analysis

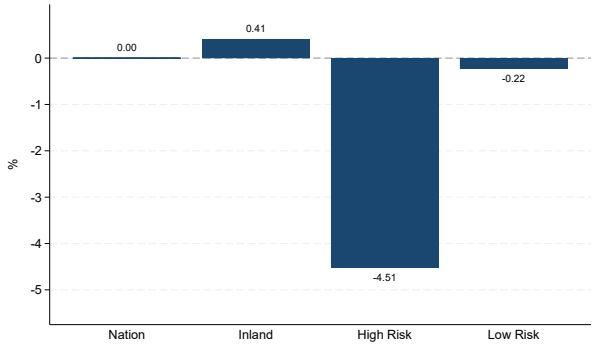
This section extends the baseline counterfactual analysis in two directions. First, I examine how the trade-off between regional monetary transfers under uniform pricing and local welfare effects under SLR-sensitive pricing changes as coastal risk becomes more severe. Second, I consider an alternative policy instrument that operates through commercial banks' balance-sheet costs rather than through GSE securitization fees.

Figure 10: Effects of GSE Pricing of Local SLR Risk

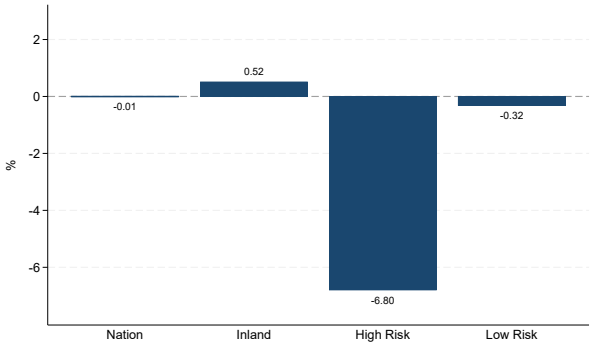
This figure shows percentage changes in borrower surplus (Panel A), lender profit (Panel B), total lending volume (Panel C), and the balance-sheet retention rate (Panel D) under GSE pricing of local sea-level-rise (SLR) risk relative to the baseline uniform pricing. Results are reported for national, inland, and coastal counties by SLR risk level.



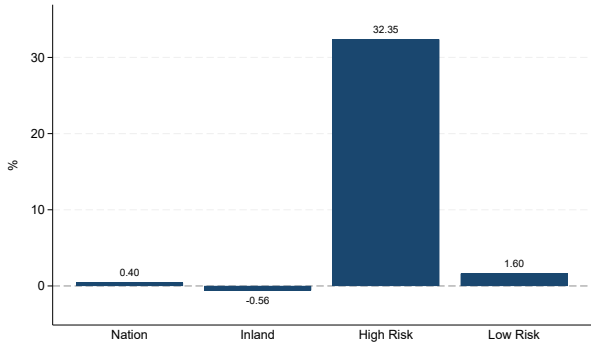
(a) Panel A. Borrower Surplus



(b) Panel B. Lender Profit



(c) Panel C. Total Lending Volume



(d) Panel D. Balance-Sheet Retention Rate

Table 6: Monetary Transfers from Uniform GSE Pricing of SLR Risk

This table reports the regional monetary transfers created by the current uniform GSE pricing of sea-level-rise (SLR) risk that would be unwound by GSE pricing of local SLR risk. Transfers are reported separately for national, inland, and coastal counties, with coastal areas further divided into high- and low-SLR-risk groups. Results are shown by loan type (conforming and jumbo) and report aggregate subsidies, taxes, and net transfers in billions of dollars.

	Regional Transfer ($ billions)			
	National	**Inland**	**High-Risk Coastal**	**Low-Risk Coastal**
	(1)	(2)	(3)	(4)
All Subsidy	1.610	0.011	0.652	0.948
All Tax	-1.494	-1.209	-0.010	-0.275
Jumbo Subsidy	0.151	0.009	0.067	0.074
Jumbo Tax	-0.100	-0.055	-0.010	-0.036
Conf. Subsidy	1.459	0.001	0.584	0.874
Conf. Tax	-1.394	-1.154	0.000	-0.240

Specifically, I introduce SLR-sensitive capital weights that vary across high-risk coastal, low-risk coastal, and inland counties. Together, these exercises show how the incidence of climate-risk pricing depends both on the severity of local exposure and on the margin through which policy changes lenders' funding costs.

The results show that higher SLR exposure magnifies the regional trade-off identified in the baseline analysis. Under uniform GSE pricing, lenders respond to increasing coastal risk partly by shifting exposed conforming loans toward GSE securitization, which limits the contraction in mortgage supply in high-risk areas but increases the monetary transfers embedded in uniform pricing. Under local SLR-risk pricing, the same increase in exposure produces much larger declines in lending and borrower welfare in high-risk coastal markets, while inland areas experience modest gains. SLR-sensitive capital weights operate through a different margin. By increasing the cost of retaining exposed mortgages, they reduce balance-sheet lending, particularly for jumbo loans, and induce lenders to substitute toward securitization when uniform GSE pricing remains available. When combined with local GSE pricing, however, both balance-sheet retention and securitization become more costly in high-risk areas, producing a substantially stronger contraction in local credit and welfare.

8.1 An Increase in SLR Risk

I first evaluate how a one-standard-deviation increase in SLR exposure affects mortgage market outcomes under both the GSEs' current uniform pricing scheme and a counterfactual in which the GSEs price local SLR risk. The increase is defined relative to the distribution of positive SLR exposure across coastal counties, with adjusted values capped at one. Inland counties remain at zero exposure. Table C4 in the Appendix reports the results.

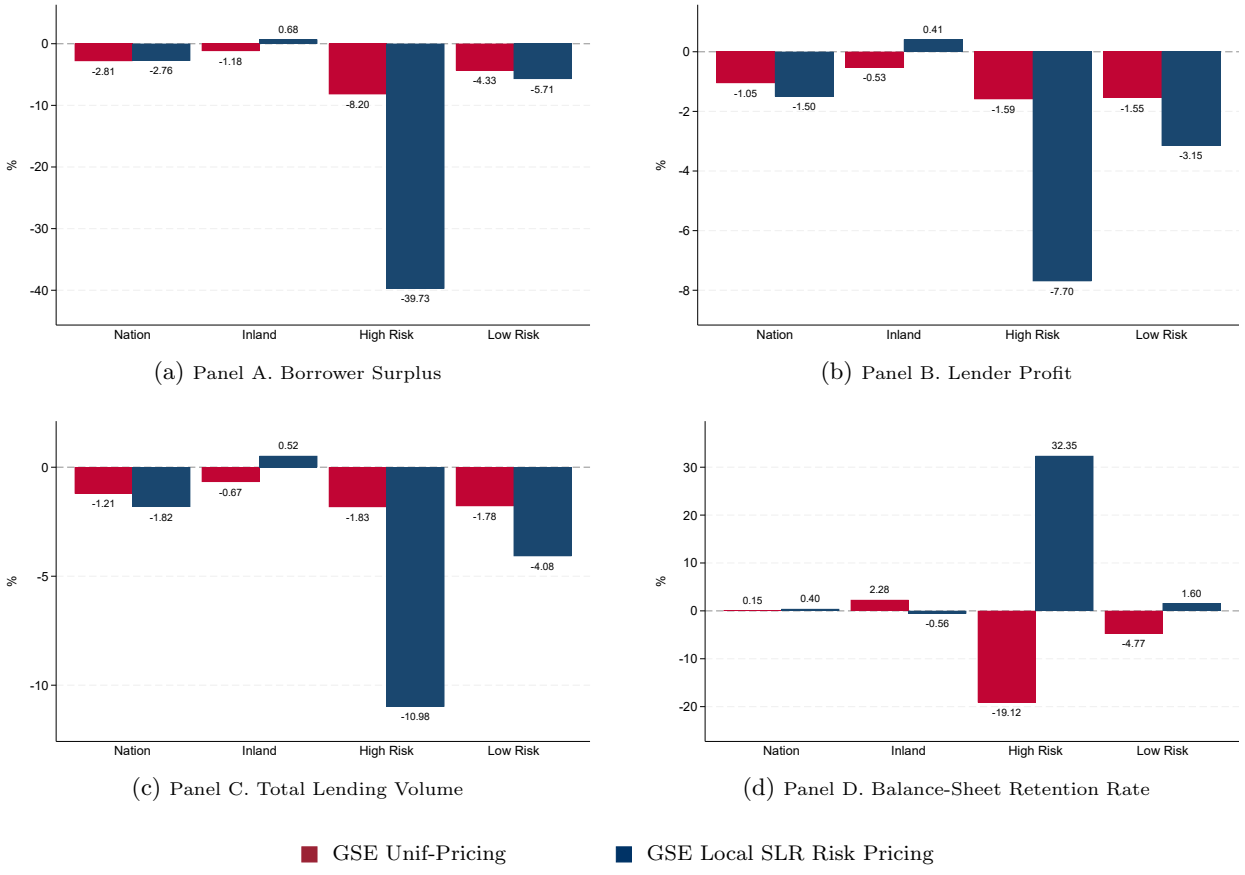
Figure 11 reports percentage changes in key outcomes relative to the baseline. National effects remain small under both pricing regimes, but higher SLR exposure widens regional differences. Under uniform GSE pricing, borrower surplus declines by approximately 8.2% in high-risk coastal counties and 4.3% in low-risk coastal counties. Inland counties also experience a smaller decline of 1.2% because the increase in coastal exposure raises the national-average SLR component embedded in GSE guarantee fees. Despite the increase in risk, mortgage supply contracts only modestly in high-risk coastal counties, declining by approximately 1.8%. Because GSE fees continue to reflect national-average rather than local exposure, securitization becomes relatively more attractive than balance-sheet retention for coastal loans. Commercial banks therefore reduce their retention of coastal mortgages and transfer a larger share of the exposure to the GSEs. Uniform pricing consequently limits the local contraction in credit, but spreads part of the higher cost of coastal SLR exposure across borrowers in other regions.

Under local GSE pricing, the effects of higher SLR exposure become substantially more concentrated in coastal markets. Borrower surplus falls by 39.7% and mortgage origination declines by 11.0% in high-risk coastal counties. Because GSE securitization fees now reflect local exposure, lenders can no longer offset the higher cost of coastal risk by increasing securitization. Instead, the balance-sheet retention rate rises by approximately 32.3%. Relative to the roughly 20% decline in retention under uniform pricing, the difference in lender funding responses across the two pricing regimes exceeds 50 percentage points. Low-risk coastal counties also experience larger declines in lending and welfare under local pricing, whereas inland counties experience modest gains.

These results show that higher SLR exposure sharpens the trade-off between uniform and local risk

Figure 11: Effects of GSE Pricing of Local SLR Risk under an Increased Risk Level

This figure shows percentage changes in borrower surplus (Panel A), lender profit (Panel B), total lending volume (Panel C), and the balance-sheet retention rate (Panel D) in response to an increase in sea-level rise (SLR) risk relative to the baseline. Results are reported for national, inland, and coastal counties by SLR risk level, comparing outcomes under the GSE's uniform and local SLR risk pricing schemes. The increase in SLR risk is defined as a one-standard-deviation increase based on the distribution of positive SLR risk across coastal counties; if the adjusted value exceeds 1, it is capped at 1. Inland counties remain at zero SLR risk.



(a) Panel A. Borrower Surplus

(b) Panel B. Lender Profit

(c) Panel C. Total Lending Volume

(d) Panel D. Balance-Sheet Retention Rate

pricing. Uniform pricing cushions the contraction in credit and borrower welfare in high-risk coastal markets by allowing lenders to transfer more exposed loans to the GSEs. However, it also spreads the cost of increasing coastal risk across regions. Local pricing concentrates that cost in the markets where the exposure originates, reducing lending and borrower welfare more sharply in high-risk areas while shifting credit toward less-exposed inland regions.

Table 7: Monetary Transfers from Uniform GSE Pricing of SLR Risk under Higher Risk

This table reports the regional monetary transfers created by the current uniform GSE pricing of sea-level-rise (SLR) risk that would be unwound by GSE pricing of local SLR risk when SLR risk increases by one standard deviation. Transfers are reported separately for national, inland, and coastal counties, with coastal areas further divided into high- and low-SLR-risk groups. The one-standard-deviation change is defined from the distribution of positive SLR risk across coastal counties; adjusted values above one are capped at one. Only coastal counties are affected by this adjustment, while inland counties remain at zero SLR risk. Results are shown by loan type (conforming and jumbo) and report aggregate subsidies, taxes, and net transfers in billions of dollars.

	Regional Transfer ($ billions)			
	National	**Inland**	**High-Risk Coastal**	**Low-Risk Coastal**
	(1)	(2)	(3)	(4)
All Subsidy	6.092	0.023	0.899	5.171
All Tax	-2.922	-2.791	-0.017	-0.114
Jumbo Subsidy	0.568	0.020	0.092	0.456
Jumbo Tax	-0.239	-0.127	-0.016	-0.096
Conf. Subsidy	5.525	0.003	0.807	4.715
Conf. Tax	-2.682	-2.664	-0.001	-0.017

Table 7 reports the monetary transfers embedded in uniform GSE pricing under the higher-SLR-risk scenario. The total amount transferred increases by approximately 40% relative to the baseline scenario with current SLR exposure. Inland counties remain net contributors, while high- and low-risk coastal counties remain net recipients. The increase in transfers is more heavily concentrated in low-risk coastal counties because the cap on adjusted SLR exposure compresses the upper tail of the risk distribution. As in the baseline analysis, most transfers operate through conforming loans, reflecting the central role of GSE securitization in spreading local SLR costs across regions.

Taken together, the results show that increasing SLR exposure amplifies both sides of the policy trade-off. Under uniform pricing, larger monetary transfers help limit reductions in mortgage supply and borrower welfare in exposed coastal markets. Moving to local SLR-risk pricing unwinds these transfers, but the associated credit and welfare losses in high-risk coastal counties become substantially larger as SLR exposure increases.

To examine how this trade-off evolves under more severe climate exposure, I also consider an extreme-SLR-risk scenario. I raise the exposure of coastal counties below the 90th percentile of the positive SLR distribution to the 90th-percentile level, while leaving counties already at or above that threshold unchanged. Inland counties remain at zero exposure. The results, reported in Table C5, Figure C2, and Table C7 in the Appendix, reinforce the baseline findings. More severe SLR exposure increases the monetary transfers generated by uniform pricing and further widens the regional welfare effects of moving to local risk pricing, with sharper contractions in high-risk coastal markets and larger gains in inland counties.

8.2 SLR-Sensitive Capital Weights

Lastly, I examine an alternative policy that incorporates local SLR exposure into banks' risk-adjusted capital weights and evaluate its effects on mortgage market outcomes under both uniform and local GSE pricing of SLR risk. This counterfactual reflects a potential regulatory reform in which bank supervisors modify Tier 1 capital requirements to account for regional SLR risk exposure. Under current regulations, capital risk weights are uniform across all mortgages, implicitly treating inland and coastal loans as equally risky. In the SLR risk–adjusted framework, risk weights vary across high-risk coastal, low-risk coastal, and inland counties, thereby linking capital requirements to local SLR exposure.

I assume that SLR risk accounts for approximately 10% of total mortgage credit risk. Accordingly, the baseline capital weights, which embed both general credit risk and the national-average SLR component, are divided into 11 equal components. One component represents the contribution of national-average SLR risk to the effect of capital requirements on lenders' marginal costs. For inland counties, I remove this component to reflect their zero SLR exposure. For coastal counties, I replace it with a local component scaled by the ratio of the group's average SLR exposure to the national mean. This procedure produces lower capital weights in inland counties and higher weights in coastal counties, with the largest increases occurring in high-risk coastal areas. In the baseline, the capital weights for conforming and jumbo loans are 0.2 and 0.5, respectively.[35] Under the counterfactual, the SLR-sensitive capital weights for conforming loans are 0.12 in inland counties, 0.22 in low-risk coastal counties, and 0.50 in high-risk coastal counties. The corresponding weights for jumbo loans are 0.45, 0.56, and 1.25. Table C6 in the Appendix reports the detailed numerical results.

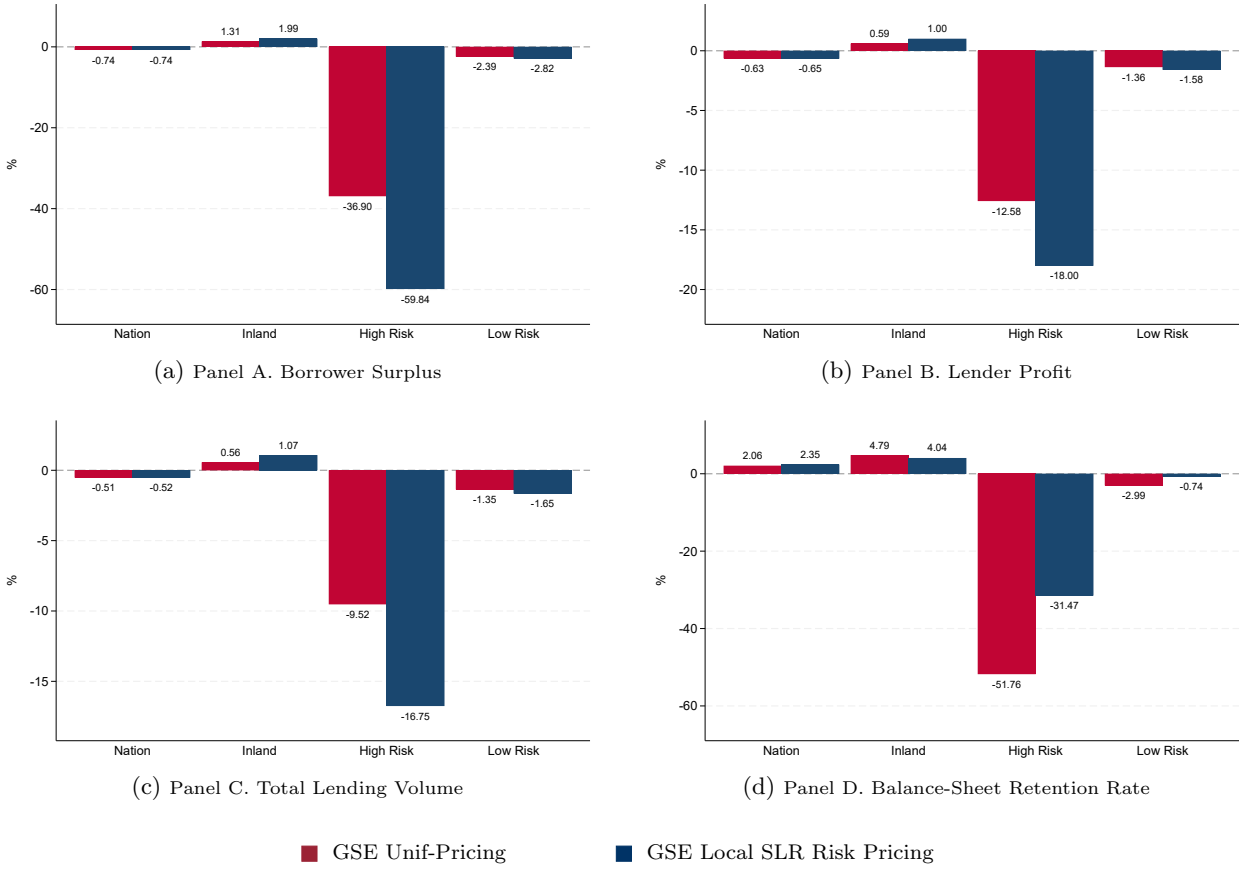
Figure 12 reports percentage changes in key outcomes under SLR-sensitive capital weights. Under uniform GSE pricing, the policy generates small aggregate effects but substantial regional reallocation in credit and welfare. National lending and borrower surplus decline slightly because the increase in capital requirements in coastal markets raises commercial banks' marginal funding costs. The effects are concentrated in high-risk coastal counties, where total lending declines by nearly 10% and borrower surplus falls by approximately 37%. The policy operates primarily through the balance-sheet lending margin. Because the higher capital weights directly raise the cost of retaining exposed mortgages, the contraction is especially pronounced among jumbo loans, which cannot be securitized through the GSEs. Jumbo interest rates in high-risk coastal counties rise by approximately 50 basis points, while conforming rates remain comparatively stable because lenders can continue to fund conforming loans through uniformly priced GSE securitization. Consistent with this mechanism, the balance-sheet retention rate in high-risk coastal counties falls by approximately 51.8% as commercial banks substitute from retention toward securitization. Low-risk coastal counties experience smaller declines in lending and borrower welfare because their SLR exposure, and therefore the increase in their capital weights, is more limited. Inland counties benefit from lower capital requirements, with modest increases in lending and borrower surplus, small declines in mortgage rates, and a slight increase in balance-sheet retention. Shadow banks' market share also rises because they are not directly subject to the new bank capital requirements.

When SLR-sensitive capital weights are combined with local GSE pricing of SLR risk, the aggregate effects remain small, but the contraction in high-risk coastal markets becomes substantially larger. The two policies affect different funding margins. SLR-sensitive capital weights increase the cost of retaining exposed

[35] The values come from Buchak et al. (2024).

Figure 12: Effects of SLR Risk–Adjusted Capital Weights

This figure shows percentage changes in borrower surplus (Panel A), lender profit (Panel B), total lending volume (Panel C), and the balance-sheet retention rate (Panel D) under a counterfactual scenario in which bank regulators incorporate sea-level-rise (SLR) exposure into risk-adjusted capital weights used to calculate Tier 1 capital requirements. Results are reported for national, inland, and coastal counties by SLR risk level, comparing outcomes under the GSE's uniform and local SLR risk pricing schemes. Under baseline regulations, risk weights are uniform across all mortgages regardless of geographic exposure. In this counterfactual, new SLR-sensitive capital weights are introduced to reflect regional climate exposure, assuming SLR risk accounts for about 10 percent of total credit risk. Baseline risk weights for conforming and jumbo loans are divided equally into 11 components, with one component representing the contribution of the national average SLR risk currently embedded in regulation. Inland counties have their risk weights reduced by one component to reflect zero SLR exposure. For coastal counties, SLR-sensitive weights are determined by scaling one component with an adjustment factor specific to high- and low-risk groups, where each group's factor equals the ratio of its average SLR risk to the national mean minus one. Reported results show percentage deviations relative to outcomes under the baseline uniform capital-weight regime.



(a) Panel A. Borrower Surplus

(b) Panel B. Lender Profit

(c) Panel C. Total Lending Volume

(d) Panel D. Balance-Sheet Retention Rate

mortgages on commercial banks' balance sheets, while local GSE pricing raises the cost of securitizing conforming loans from the same markets. As a result, both jumbo and conforming lending contract in high-risk coastal counties, and borrower surplus falls further. Conforming mortgage rates increase by approximately 12.5 basis points.

The funding response also differs from that under uniform GSE pricing. Although balance-sheet retention continues to decline, the reduction is approximately 31.5% smaller under local GSE pricing because the higher securitization cost narrows the cost advantage of GSE funding relative to balance-sheet retention. Thus, SLR-sensitive capital weights primarily constrain balance-sheet lending, especially jumbo lending, while local GSE pricing extends the contraction to conforming loans by increasing securitization costs. Together, the two policies produce a substantially larger tightening of mortgage credit in high-risk coastal markets.

Table 8: Monetary Transfers from Uniform GSE Pricing of SLR Risk under SLR-Adjusted Capital Weights

This table reports the regional monetary transfers created by the current uniform GSE pricing of sea-level-rise (SLR) risk that would be unwound by local SLR risk pricing when bank regulators incorporate SLR exposure into risk-adjusted capital weights used to calculate Tier 1 capital requirements. Under baseline regulations, risk weights are uniform across mortgages regardless of geographic exposure. In this counterfactual, SLR-sensitive capital weights are introduced, assuming that SLR accounts for approximately 10 percent of total credit risk. Baseline risk weights are divided into 11 components, with one component representing the contribution of the national average SLR risk currently embedded in regulation. Inland counties have their risk weights reduced by one component to reflect zero SLR exposure. For coastal counties, SLR-sensitive weights are determined by scaling this component with an adjustment factor based on the ratio of group-level average SLR risk to the national mean. Transfers are reported separately for national, inland, and coastal counties, with coastal areas further divided into high- and low-SLR-risk groups. Results are shown by loan type (conforming and jumbo) and report aggregate subsidies, taxes, and net transfers in billions of dollars.

	Regional Transfer ($ billions)			
	National	**Inland**	**High-Risk Coastal**	**Low-Risk Coastal**
	(1)	(2)	(3)	(4)
All Subsidy	1.682	0.010	0.709	0.963
All Tax	-1.641	-1.203	-0.032	-0.406
Jumbo Subsidy	0.242	0.009	0.141	0.092
Jumbo Tax	-0.250	-0.055	-0.030	-0.165
Conf. Subsidy	1.440	0.001	0.568	0.871
Conf. Tax	-1.391	-1.148	-0.002	-0.241

Table 8 reports the monetary transfers embedded in uniform GSE pricing when SLR-sensitive capital weights are in place. Relative to the baseline transfer estimates in Table 6, the aggregate magnitude of the transfers changes only modestly: total subsidies increase by approximately 4.5%, while total taxes increase by approximately 10%. Most of the transfers continue to operate through conforming loans, for which the subsidy amount declines by only about 1%. The overall regional transfer structure generated by uniform GSE pricing therefore remains broadly unchanged. The largest change occurs in the jumbo-loan component. Jumbo subsidies increase from $0.151 billion to $0.242 billion, an increase of approximately 60%, while jumbo taxes increase in magnitude from $0.100 billion to $0.250 billion. This amplification arises because SLR-sensitive capital weights raise balance-sheet funding costs most sharply in high-risk coastal counties.

Since jumbo loans must be retained on lenders' balance sheets, the policy substantially tightens jumbo credit supply in these markets.

When local GSE pricing is introduced, the higher cost of conforming loans shifts some borrower demand toward jumbo products. However, the jumbo segment is already constrained by the higher capital requirements and cannot accommodate this additional demand without substantial increases in mortgage rates. The resulting equilibrium response enlarges the jumbo-loan component of the monetary transfers that local GSE pricing would unwind. The regional pattern remains similar to the baseline. Inland counties continue to be net contributors under uniform GSE pricing, while high- and low-risk coastal counties remain net recipients. However, because the capital-weight policy produces especially large distortions in high-risk jumbo markets, a somewhat larger share of the total transfer is directed toward high-risk coastal counties.

Overall, SLR-sensitive capital weights alter the composition of regional monetary transfers more than their aggregate magnitude. The policy operates primarily through the cost of balance-sheet lending and therefore has its largest effects on jumbo loans in high-risk coastal counties. Local GSE pricing operates through the securitization margin and affects conforming lending more directly. The interaction of these two policies illustrates how the incidence of climate-risk regulation depends on the funding margin through which it is implemented.

9 Conclusion

This paper studies how lenders shape the trade-off between uniform and local pricing of sea-level-rise (SLR) risk in the U.S. mortgage market. Lenders respond to shifts in mortgage-origination costs along two margins: they adjust mortgage interest rates and reallocate funding between balance-sheet retention and GSE securitization. I develop and estimate a structural model of mortgage demand, lender competition, and endogenous funding choice to quantify how these responses affect regional monetary transfers and local welfare.

Under the current uniform GSE pricing scheme, monetary transfers flow from inland to coastal borrowers. These transfers are concentrated among a small group of highly exposed borrowers, are regressive across the income distribution, and vary with local market competition. Moving to local SLR-risk pricing unwinds these transfers, but produces substantial reductions in mortgage credit and borrower welfare in high-risk coastal areas, while aggregate national effects remain small. This trade-off becomes more pronounced as SLR exposure increases.

The results highlight a central policy tension. Uniform pricing supports geographic risk sharing and limits local credit contractions, but creates cross-regional transfers and fairness concerns. Local risk pricing improves the alignment between mortgage funding costs and local climate exposure, but may conflict with the GSEs' mandate to support broad access to mortgage credit in exposed regions. More broadly, the findings show that the consequences of climate-risk pricing depend critically on lenders' pricing and funding responses and on the structure of local mortgage markets.

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A Model

A.1 Marginal Cost of Balance-Sheet Funding

Again, for simplicity of writing, I denote m as any other market dimension other than year t. So, the market in year t, county c, loan type p, and credit risk r can be denoted by market tm. In this case, m denotes a combination of cpr.

The per-dollar cost of balance-sheet funding for lender j in market tm is

$$\sigma^p_{jtm} = \beta_j Fed\ Rates_t + \sigma^b(\rho_{jt} - \bar{\rho})^{-1} + \sigma^{b,Risk} Low\ FICO_m + \beta^{Climate} Climate\ Risk_{jtm}$$

where

$$\rho_{jt} = \frac{e_{jt}}{\xi_0 d^b_{jt0} + \xi_J d^b_{jtJ} + \xi_C d^b_{jtC}}$$

Specifically, $Fed\ Rates_t$ is the Fed fund rate. ρ_{jt} is the capital ratio of the bank. $\bar{\rho}$ is the capital ratio requirements. Thus $(\rho_{jt} - \bar{\rho})$ measures the excess capital ratio. $Low\ FICO_m$ is the indicator variable that market m is a market target for low-FICO (high-risk) borrowers. $Climate\ Risk_{jt}$ is the climate risk exposure of banks. All of the above variables are derived from data.

The marginal cost to originate one additional dollar of jumbo loans is

$$\begin{aligned} MC\ Portfolio^j_{jtm} &= \frac{\partial(\sigma^p_{jtm} \times (d^b_{jtJ} + d^b_{jtC}))}{\partial d^b_{jtJ}} \\ &= \sigma^p_{jtm} \times \frac{\partial(d^b_{jtJ} + d^b_{jtC})}{\partial d^b_{jtJ}} + (d^b_{jtJ} + d^b_{jtC}) \times \frac{\partial \sigma^p_{jt}}{\partial d^b_{jtJ}} \\ &= \sigma^p_{jtm} + d^b_{jt} \times \frac{\partial \sigma^p_{jtm}}{\partial d^b_{jtJ}} \end{aligned}$$

where

$$d^b_{jt} = d^b_{jtJ} + d^b_{jtC}$$

Since only ρ_{jt} contains d^b_{jtJ}

$$\begin{aligned} \frac{\partial \sigma^p_{jt}}{\partial d^b_{jtJ}} &= \frac{\partial \sigma^b(\rho_{jt} - \bar{\rho})^{-1}}{\partial d^b_{jtJ}} \\ &= \sigma^b(\rho_{jt} - \bar{\rho})^{-2} \frac{\xi_J e_{jt}}{(\xi_0 d^b_{jt0} + \xi_J d^b_{jtJ} + \xi_C d^b_{jtC})^2} \\ &= \sigma^b \xi_J ((\rho_{jt} - \bar{\rho})^{-2} \rho^2_{jt}) \frac{1}{e_{jt}} \end{aligned}$$

Plugging the above calculation and σ^p_{jtm} into the $MC\ Portfolio^j_{jtm}$, I have

$$\begin{aligned} MC\ Portfolio^j_{jtm} = \beta_j Fed\ Rates_t + \sigma^b(\rho_{jt} - \bar{\rho})^{-1} + \sigma^{b,Risk} Low\ FICO_m \\ + \beta^{Climate} Climate\ Risk_{jtm} + \sigma^b \xi_J ((\rho_{jt} - \bar{\rho})^{-2} \rho^2_{jt}) \frac{d^b_{jt}}{e_{jt}} \end{aligned}$$

Reorganize the terms I have

$$MC\ Portfolio^{j}_{jtm} = \beta_j Fed\ Rates_t + \sigma^b[(\rho_{jt} - \bar{\rho})^{-1} + \xi_J((\rho_{jt} - \bar{\rho})^{-2}\rho^2_{jt})\frac{d^b_{jt}}{e_{jt}}]$$
$$+\sigma^{b,Risk} Low\ FICO_m + \beta^{Climate} Climate\ Risk_{jtm}$$

Similarly, the marginal cost to originate one additional conforming loan is

$$MC\ Portfolio^{c}_{jt} = \beta_j Fed\ Rates_t + \sigma^b[(\rho_{jt} - \bar{\rho})^{-1} + \xi_C((\rho_{jt} - \bar{\rho})^{-2}\rho^2_{jt})\frac{d^b_{jt}}{e_{jt}}]$$
$$+\sigma^{b,Risk} Low\ FICO_m + \beta^{Climate} Climate\ Risk_{jtm}$$

A.2 Lenders' Maximization Problem

Given the actions of other lenders, lenders maximize their profits. Lenders' profit can be written as below

$$\Pi_{jt} = \sum_{m \in M} [(r_{jtm} - w_{jm})d_{jtm} - (d^{GSE}_{jtm}\sigma^{GSE}_{tm} + d^{b}_{jtm}\sigma^{b}_{jtm})]$$

where r_{jtm} is the interest rates for lender j in year t and market m. w_{jm} is the fixed origination cost of lender j in market m. d_{jtm} is total loan originated by lender j in market tm. d^{GSE}_{jtm} is the total number of loans originated via GSE funding by lender j in market tm. d^{b}_{jtm} is the total number of loans originated via balance-sheet funding by lender j in market tm. Note here $d_{jtm} = d^{GSE}_{jtm} + d^{b}_{jtm}$. σ^{GSE}_{tm} is the per-dollar cost of GSE funding for market tm and σ^{b}_{jtm} is the per-dollar cost of balance-sheet funding of lender j in market tm. Assuming that the holding percentage of lenders of conforming loans is $b_{jtm}\%$ so that $d^{b}_{jtm} = b\%d_{jtm}$ and $d^{GSE}_{jtm} = (1 - b_{jtm}\%)d_{jtm}$. In this case, the lenders' profit can be rewritten as

$$\Pi_{jt} = \sum_{m \in M} \{r_{jtm} - w_{jm} - [(1 - b_{jtm})\sigma^{GSE}_{tm} + b_{jtm}\sigma^{b}_{jtm}]\}d_{jtm} \tag{10}$$

Lenders' first order condition with respect to interest rates is then

$$\frac{\partial \Pi_{jt}}{\partial r_{jtm}} = d_{jtm} + \sum_{l \in J}\{\ r_{ltm} - w_{lm} - [(1 - b_{jtm})\sigma^{GSE}_{tm} + b_{jtm}\sigma^{b}_{ltm}]\}\frac{\partial d_{ltm}}{\partial r_{jtm}} \tag{11}$$

This equation is a standard BLP-style maximization solution, and the marginal cost can be calculated. The assumption here is that the holding percentage b is determined independently of the interest rates. In this case, in each market, commercial banks first assess their balance-sheet condition, monetary policy rates, and climate-risk exposure, determine the cost of funding, and choose the minimum between GSE funding and balance-sheet funding. Then lenders maximize their profits by choosing interest rates. Under this assumption, each commercial bank will choose a single funding method for all loans in that market. The holding percentage is then calculated at the market level. When considering the market-average holding percentage, this assumption poses no issue.

Without this assumption, the lenders' maximization problem would become a non-linear two-way first-order condition equation system. In this case, the problem has two variable vectors to maximize

$$Max_{\mathbf{r_j}_\cdot, \mathbf{b_j}_\cdot} \Pi_{jt}$$

The corresponding first-order condition system is then

$$\frac{\partial \Pi_{jt}}{\partial r_{jtm}} = d_{jtm} + \sum_{l \in J}\{\ r_{ltm} - w_{lm} - [(1 - b_{jtm})\sigma^{GSE}_{tm} + b_{jtm}\sigma^{b}_{ltm}]\}\frac{\partial d_{ltm}}{\partial r_{jtm}} \tag{12}$$

$$\frac{\partial \Pi_{jt}}{\partial b_{jtm}} = (\sigma^{GSE}_{tm} - \sigma^{b}_{jtm} - b_{jtm}\frac{\partial \sigma^{b}_{jtm}}{\partial b_{jtm}})d_{jtm} \tag{13}$$

Since σ^{b}_{jtm} is a non-linear function of b_{jtm}, this equation system has no analytical solution. Follow Buchak et al. (2024), to avoid using numerical methods and reduce the complexity of calculation, I don't use this

method and use the first method to estimate.

B Supply Side Estimation

The supply side of the model deviates from the standardized BLP. I derive the marginal cost from the demand side, where lenders maximize their profits by setting prices. Then, I use different settings to estimate parameters separately.

Recall from the model that lenders have a fixed administrative cost to originate different types of loans, which varies among banks and shadow banks. I denote the fixed cost sets as θ_s^f and θ_s^f is defined as

$$\theta_s^f \coloneqq \{w_{SB,p}, w_{SB,r}, w_{CB,p}, w_{CB,r}\}$$

The per-dollar cost of GSE funding in the year market tm is

$$\sigma_{tm}^{GSE} = \beta^{GSE} Fed\ Rates_t + GSE\ Fees_t + \sigma^{GSE,Risk} \times Low\ FICO_m$$

The per-dollar cost of balance-sheet funding for lender j in market tm is

$$\sigma_{jtm}^{p} = \beta_j Fed\ Rates_t + \sigma^b(\rho_{jt} - \bar{\rho})^{-1} + \sigma^{b,Risk} Low\ FICO_m + \beta^{Climate} Climate\ Risk_{jtm}$$

where $Climate\ Risk_{jtm} = Bank\ Climate\ Exposure_{jt} \times Market\ Climate\ Risk_m$

I sum up all the parameters to be estimated as below

$$\theta_s^g = \{\beta^{GSE}, \sigma^{GSE,Risk}\}$$

$$\theta_s^b = \{\beta_j, \sigma^b, \sigma^{b,Risk}, \beta^{Climate}\}$$

$$\theta_s = \{\theta_s^f, \theta_s^g, \theta_s^b\}$$

B.1 Estimation of θ_s^g and fixed cost of shadow banks

I start by estimating the parameters that determine the GSE funding cost, θ_s^g, and the administrative costs of shadow banks, $w_{SB,p}$ and $w_{SB,r}$. Considering that GSE funding is the only funding method for shadow banks, the marginal cost of shadow banks should be fully determined by the GSE funding cost parameters. Together with the fixed origination administrative cost, the marginal cost for the shadow bank j in the market mt should be

$$\sigma_{tm}^{GSE} = \beta^{GSE} Fed\ Rates_t + GSE\ Fees_t + \sigma^{GSE,Risk} Low\ FICO_m + w_{SB,m}$$

Since $GSE\ Fees_t$ comes from the data [36], a linear function can estimate the marginal cost net of GSE fees. In this case, I estimate the following linear regression specification on all shadow bank samples

$$Net\ MC_{jtm} = \beta^{GSE} Fed\ Rates_t + \sigma^{GSE,Risk} Low\ FICO_m + \delta Refinance_m + Const + \epsilon_{jtm}$$

where

$$Net\ MC_{jtm} = MC_{jtm} - GSE\ Fees_t$$

In this case, the coefficient of $Fed\ Rates_t$, β^{GSE} captures the GSE's sensitivity to macro risk-free rates, which is the Fed funds rate. The coefficient of $Low\ FICO_m$, $\sigma^{GSE,Risk}$ captures the additional cost for the high credit risk market $\sigma^{GSE,Risk}$. The constant term $Const$ captures the fixed cost of shadow banks to originate purchase loans, which is denoted by $w_{SB,p}$. The coefficient of the Refinance indicator measures the additional fixed cost borne by shadow banks for refinance loans, relative to the fixed administrative cost of purchased loans. So, $\delta + Const$ captures the fixed administrative cost of shadow banks to originate refinance loans $w_{SB,r}$.

B.2 Estimation of θ_s^b and fixed cost of commercial banks

Then, I estimate the parameters that determine the balance-sheet funding cost and the fixed administrative cost of originating loans for commercial banks. Since banks choose the funding type based on their cost, a linear specification is not feasible. Following Buchak et al. (2024), I apply a generic minimum-distance scheme to estimate the left-hand parameters θ_s^b. Overall, the guess values of the parameters are used to calculate the model's implied cost of balance-sheet funding. For conforming loans, commercial banks' funding cost is then the minimum of the GSE funding cost, calculated in the previous period, and the balance-sheet funding cost implied by the guess values. Commercial banks' securitization decisions are then influenced by the type of cost they choose. I can calculate the market-level average percentage of loans held on the balance sheet (the holding percentage in the later text) implied by the model and the guess values, and minimize the difference between this estimate and the holding percentage in real data. The fixed administrative cost then captures the residual part of the marginal cost, as determined by the data and the model-implied marginal cost.

Formally, to reduce computational complexity, I first estimate the banks' deposit market power parameter β_j separately, following Drechsler et al. (2021), from the other part of the model. With quarterly-level data from the bank call report, for each bank, I estimate the following time series regression

$$\Delta DepIntExp_{jt} = \alpha_j + \sum_{\tau=0}^{3} \beta_{j,\tau}^{Dep} \Delta Fed\ Rates_{t-\tau} + \epsilon_{it}$$

where $\Delta DepIntExp_{jt}$ is the change in bank j's deposit rates from year-quarter t to year-quarter $t+1$. $\Delta Fed\ Rates_t$ is the change in the Fed funds rate from t to $t+1$. α_j are the bank fixed effects and η_t are the year-quarter fixed effects. Again, following Drechsler et al. (2021), I define $\beta_j^{Dep} = \sum_{\tau=0}^{3} \beta_{j,\tau}^{Dep}$ and use it as the estimation of β_j in the model. Here, I used quarterly-level bank call report data prior to 2018, which is before the start point of the structure analysis estimation. Additionally, I require the bank to have at least

[36] The corresponding guarantee fee data can be found at https://www.fhfa.gov/policy/guarantee-fees.
The corresponding service fee data are available at https://selling-guide.fanniemae.com/sel/c2-1.1-05/servicing-fees.
Service fees for different loans can vary. For simplicity, I take all service fees as 0.5%

60 quarters of data to ensure the number of observations is sufficient for precise estimation.

Then, I start the generic minimum-distance scheme to estimate the left-hand parameters σ^b, $\sigma^{b,Risk}$, and $\beta^{Climate}$. I minimize the model-implied value of the calculated moments against the real data value. I start with initial guesses for the three parameters. Using the initial guess, I compute the model-implied funding cost for balance-sheet funding. Commercial banks choose the lower of the balance-sheet funding cost and the GSE funding cost. The funding cost part of the marginal cost of conforming loans can then be written as

$$MC\ Funding_{jtm} = min(MC\ Balance\ Sheet_{jtm}, MC\ GSE_{tm})$$

Examining the funding method banks use for the conforming loan sample, I can calculate the holding percentage at the market level. If the GSE funding cost is lower, then I assume the bank securitizes all of its loans. If the balance-sheet funding cost is lower, then banks hold everything. [37] At the market level, I calculate the average model-implied holding percentage, compare it with the market-level average holding percentage observed in the data, and use the difference as one of the moments to be minimized in the optimization problem.

The total marginal cost of a commercial bank j in market tm can then be determined by the funding cost plus the fixed cost

$$MC_{jtm} = MC\ Funding_{jtm} + w_{CB,m}$$

With each guess value, I calculate the residual part of the marginal cost net of the marginal funding cost. The administrative cost should capture the residual part. Define the administrative cost part of the marginal cost as

$$MC\ Fixed_{jtm} = MC_{jtm} - MC\ Funding_{jtm}$$

I estimate the following linear specification to retrieve the fixed administrative cost.

$$MC\ Fixed_{jtm} = \delta Refinance_m + Const + \epsilon_{jtm}$$

In this case, the value of $Const$ captures the fixed administrative cost of commercial banks to originate purchased loans, and δ is the additional fixed administrative cost of commercial banks to originate refinance loans compared with purchased loans. Thus, the fixed administrative cost of commercial banks $w_{CB,p}$ is captured by $Const$, and $w_{CB,r}$ is captured by $Const + \delta$. If all parameters are correctly estimated, the regression residuals should be zero. Thus, I use the regression residual ϵ_{jtm} as an additional moment to be minimized.

To better identify the parameters, I include the moment sets along with a few additional moments. One set of additional moments to be minimized comes from the jumbo loans data. Note that jumbo loans can only be funded from the balance sheet; they should depend on both the capital ratio and the bank's

[37] Following Buchak et al. (2024), I don't calculate the holding percentage at the bank level. This requires solving a two-way first-order conditional equation system, which has no analytical solution, resulting in high computational complexity when using numerical methods.

climate risk exposure. In this case, I run regressions of the model-implied marginal cost of jumbo loans on banks' capital ratio and climate exposure, and also a regression with the same independent variables, but using the real marginal cost from the demand side as the dependent variable. If θ_s^b is correctly estimated, the coefficients of the two regressions should be the same. In this case, I use the differences between the corresponding coefficients as a set of moments to be minimized. Specifically, I run the following regression on the commercial banks' jumbo loan sample

$$MC_{jtm}^{mi} = \delta_1^m Capital\ Ratio_{jt} + \delta_2^m Climate\ Risk_{jtm} + \epsilon_{jtm}$$

$$MC_{jtm}^{d} = \delta_1^d Capital\ Ratio_{jt} + \delta_2^d Climate\ Risk_{jtm} + \epsilon_{jtm}$$

where MC_{jtm}^{mi} is the model-implied marginal cost and MC_{jtm}^{d} is the marginal cost from real data demand side. The differences of the corresponding coefficients such as $\delta_1^m - \delta_1^d$ and $\delta_2^m - \delta_2^d$ are then be used as the moments.

The second set of additional moments comes from the covariance. I elaborate on the differences between the covariance of the holding percentage and the capital ratio in the model and in real data, as well as between the covariance of the holding percentage and climate risk exposure in the model and in real data. Also, if the model is correctly estimated, the final residual ϵ_{jtm} should be uncorrelated with both the capital ratio and the climate exposure. Thus, I explore the covariance between the residual ϵ_{jtm} and the capital ratio or climate exposure as additional moments to be minimized. By minimizing the sum of the moments mentioned above, I can estimate the parameters governing the balance-sheet funding and fixed administrative costs of commercial banks.

B.3 Supply Results

In this section, I provide further details on the interpretation and model fitness of the supply-side estimation results, in addition to the SLR coefficients.

Administrative Costs

Panel A of Table 4 reports fixed administrative costs. For each dollar of mortgage originations, commercial banks incur administrative costs of 1.555 percentage points for purchase loans and 1.415 percentage points for refinance loans. Shadow banks face costs of 1.639 and 1.352 percentage points for purchase and refinance loans, respectively. Consistent with Buchak et al. (2018); Fuster et al. (2019), refinance loans are cheaper to process because they require less documentation. Shadow banks have the lowest refinance cost, reflecting their operational advantage in digital processing.

These estimates line up well with institutional references. Freddie Mac reports that fixed administrative costs account for 55%–70% of total origination cost net of the risk-free rate. In my data, fixed administrative costs represent 50% (commercial banks) and 61% (shadow banks) of total marginal costs, well within the institutional range. Table 5, row 3, reports the comparison.

GSE Funding Costs

Panel B of Table 4 shows the estimated GSE funding parameters. The pass-through of the federal funds rate is $\beta^{GSE} = 0.496$, meaning the GSE incorporates about half of the change in the policy rate into its pricing. This is slightly higher than the average for commercial banks $\beta_j = 0.407$, consistent with deposit-rate stickiness that lowers banks' funding sensitivity.

The GSEs charge an additional fee for high-risk borrowers, which is $\sigma^{GSE,risk} = 0.783$ percentage points. This result is comparable to the GSE g-fee LLPA matrix, which shows that the loan-level adjustment for loans with FICO scores > 740 is about 0.41%, while for loans with FICO between 680 and 740 [38] is about 1.03 % [39]. According to the LLPA matrix, the additional charge for high-risk loans is approximately 0.62 percentage points. Table 5 shows the comparison.

Balance-Sheet Funding Costs

Panel C of Table 4 reports the balance-sheet funding estimates for commercial banks. The average deposit beta is 0.407, with a standard deviation of 0.106, consistent with Drechsler et al. (2021, 2023). This means banks fund themselves at roughly 40% of the macro risk-free rate due to imperfect pass-through to deposit rates. Rows 5-6 in Table 5 present the comparison. The excess-capital coefficient $\sigma^b = 0.064$ implies that a one-standard-deviation tightening in excess capital ratio increases marginal cost by 0.519 percentage points, about 20% of the mean marginal cost. This is consistent with findings in Buchak et al. (2024) that balance-sheet capacity is a key driver of mortgage pricing. [40] High-credit-risk borrowers add 1.058 percentage points to balance-sheet funding costs. This is consistent with the institutional evidence that credit risk affects balance-sheet costs more strongly than GSE costs. Based on HMDA, the credit-risk premium is approximately 1.5 times larger for balance-sheet loans than for GSE-eligible loans, implying a reference value of 0.99 percentage points, which is very close to my estimate. Table 6, row 7, shows the comparison. [41]

[38] In my sample, the minimum FICO score is 669, while the 1% of FICO scores is 723. Almost all high-risk borrowers have a FICO score between 723 and 740.

[39] The LLPA matrix can be found at https://www.fanniemae.com/content/pricing/llpa-matrix.pdf

[40] Here I consider the jumbo loans originated by commercial banks to eliminate the confounding effect of GSE funding, since the jumbo loans' marginal cost purely depends on balance-sheet funding.

[41] The calculation is based on HMDA data. In the HMDA data, I regress interest rates on the Low FICO indicator using the conforming loan and jumbo loan samples. $IntRate_{ijct} = \beta Low\ FICO_{ijct} + \gamma_{jt} + \delta_{ct}$ The relative credit risk effect of jumbo loans to conforming loans is calculated by the ratio of the two coefficients β_j/β_c. Since conforming loans can be sold to GSEs at any time, whereas jumbo loans cannot, the ratio can reflect the relative credit risk impact on the cost of the balance sheet and on GSE funding. $\beta_j = 1.555$ and $\beta_c = 0.971$. The reference value equals the relative ratio times the reference effect of credit risk on GSE funding cost (0.62%), which is $\beta_j/\beta_c * 0.62\% = 0.99\%$

C Additional Results

C.1 Reduced -form Evidence

Table C1: SLR Risk and Loan Approval, Interest Rates, and Securitization

This table reports the relationship between sea-level-rise (SLR) risk and lenders' approval, pricing, and securitization decisions. The table estimates the following specification:

$$Y_{ijct} = \beta\, SLR_c + X'_{ijct}\Gamma + K'_{jt}\Delta + Z'_{ct}\zeta + \lambda_j + \gamma_t + \varepsilon_{ijct}.$$

Columns (1) and (2) present approval regressions, columns (3) and (4) present interest-rate regressions, and columns (5) and (6) present securitization regressions. Panel A contains estimates for conforming loans, and Panel B contains estimates for jumbo loans. SLR risk is measured at the census-tract level as the share of land inundated under a 10-foot rise in sea level. All specifications include loan-level controls (LTV, DTI, loan purpose, borrower income), lender-year financial controls (assets, capital ratios, deposits, non-core funding), and county-year economic controls (employment growth, wage growth, population). Columns (1), (3), and (5) include lender and year fixed effects. Columns (2), (4), and (6) include lender × year fixed effects. The bottom rows report the mean of the dependent variable Y and the standard deviation of SLR risk within each estimation sample. Standard errors are clustered at the lender × year × state level.

Commercial Banks - National

Panel A: Conforming Loans

	Approval		Interest Rate		Securitization	
	(1)	(2)	(3)	(4)	(5)	(6)
SLR	-0.0297***	-0.0298***	0.0115	0.0105	0.0507***	0.0494***
	(-5.679)	(-6.201)	(1.229)	(1.530)	(7.066)	(10.150)
Control	Y	Y	Y	Y	Y	Y
Lender FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Lender × Year FE	N	Y	N	Y	N	Y
N	8,411,728	8,411,728	7,020,227	7,020,227	7,020,227	7,020,227
Adj R2	0.194	0.199	0.544	0.562	0.296	0.330
Mean (Y)	0.861		3.639		0.649	
Std (SLR)	0.154		0.149		0.149	

Panel B: Jumbo Loans

	Approval		Interest Rate		Securitization	
	(1)	(2)	(3)	(4)	(5)	(6)
SLR	-0.0411***	-0.0403***	0.0513***	0.0453***	-0.0014	0.0005
	(-10.778)	(-11.246)	(5.417)	(6.076)	(-0.572)	(0.279)
Control	Y	Y	Y	Y	Y	Y
Lender FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Lender × Year FE	N	Y	N	Y	N	Y
N	1,143,588	1,143,588	981,134	981,134	981,134	981,134
Adj R2	0.175	0.178	0.548	0.569	0.403	0.463
Mean (Y)	0.882		3.366		0.054	
Std (SLR)	0.220		0.218		0.218	

Table C2: SLR Risk Quartiles and Loan Approval, Interest Rates, and Securitization

This table reports the effect of SLR risk on lending decisions using the regression specification

$$Y_{ijct} = \sum_{q=1}^{4} \beta_q SLRQq_c + X'_{ijct}\Gamma + K'_{jt}\Delta + Z'_{ct}\zeta + \lambda_j + \gamma_t + \varepsilon_{ijct}.$$

$Y_{ijct} \in \{Approval_{ijct}, IntRate_{ijct}, Securitization_{ijct}\}$ denotes lending outcomes. $SLRQ0$ indicates zero SLR risk, while $SLRQq$ indicates the qth quartile of census tracts with $SLR > 0$. Panel A contains estimates for conforming loans, and Panel B contains estimates for jumbo loans. SLR risk is measured at the census-tract level as the share of land inundated under a 10-foot rise in sea level. All specifications include loan-level controls (LTV, DTI, loan purpose, borrower income), lender-year financial controls (assets, capital ratios, deposits, non-core funding), and county-year economic controls (employment growth, wage growth, population). Columns (1), (3), and (5) include lender and year fixed effects. Columns (2), (4), and (6) include lender × year fixed effects. Standard errors are clustered at the lender × year × state level.

Commercial Banks – National

Panel A: Conforming Loans

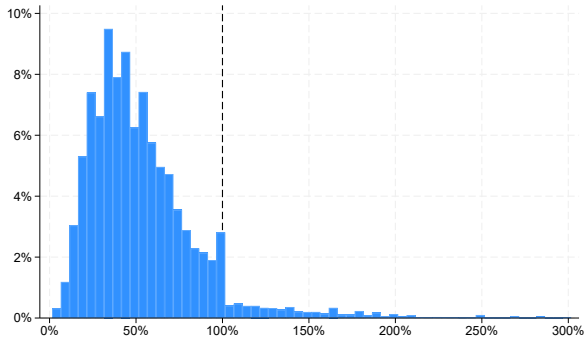
	Approval		Interest Rate		Securitization	
	(1)	(2)	(3)	(4)	(5)	(6)
SLRQ1	-0.0002	-0.0002	0.0088**	0.0080**	0.0236***	0.0237***
	(-0.117)	(-0.149)	(2.043)	(2.268)	(7.750)	(10.289)
SLRQ2	0.0014	0.0014	0.0055	0.0042	0.0257***	0.0250***
	(0.782)	(0.872)	(1.120)	(1.078)	(6.901)	(8.732)
SLRQ3	-0.0063***	-0.0064***	0.0088	0.0079*	0.0379***	0.0370***
	(-2.777)	(-3.105)	(1.465)	(1.654)	(8.294)	(10.865)
SLRQ4	-0.0298***	-0.0298***	0.0115	0.0105	0.0489***	0.0478***
	(-5.600)	(-6.113)	(1.259)	(1.580)	(7.038)	(10.112)
Controls	Y	Y	Y	Y	Y	Y
Lender FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Lender×Year FE	N	Y	N	Y	N	Y
N	8,411,728	8,411,728	7,020,227	7,020,227	7,020,227	7,020,227
Adj. R^2	0.194	0.199	0.544	0.562	0.297	0.330

Panel B: Jumbo Loans

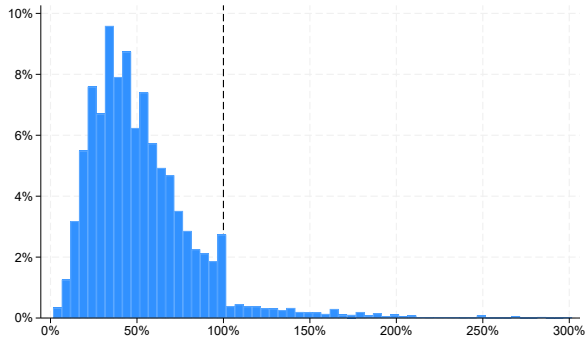
	Approval		Interest Rate		Securitization	
	(1)	(2)	(3)	(4)	(5)	(6)
SLRQ1	-0.0162***	-0.0157***	0.0374***	0.0324***	-0.0030**	-0.0010
	(-9.922)	(-9.773)	(8.714)	(8.337)	(-2.465)	(-1.020)
SLRQ2	-0.0171***	-0.0166***	0.0433***	0.0372***	-0.0004	0.0014
	(-9.399)	(-9.472)	(8.710)	(8.956)	(-0.267)	(1.166)
SLRQ3	-0.0278***	-0.0270***	0.0350***	0.0301***	-0.0005	0.0009
	(-12.299)	(-12.949)	(5.704)	(6.237)	(-0.265)	(0.608)
SLRQ4	-0.0410***	-0.0402***	0.0564***	0.0494***	-0.0015	0.0008
	(-10.764)	(-11.211)	(5.935)	(6.367)	(-0.622)	(0.463)
Controls	Y	Y	Y	Y	Y	Y
Lender FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Lender×Year FE	N	Y	N	Y	N	Y
N	1,143,588	1,143,588	981,134	981,134	981,134	981,134
Adj. R^2	0.175	0.178	0.548	0.569	0.403	0.463

Figure C1: Loan-Size Distributions across SLR-Exposure Groups

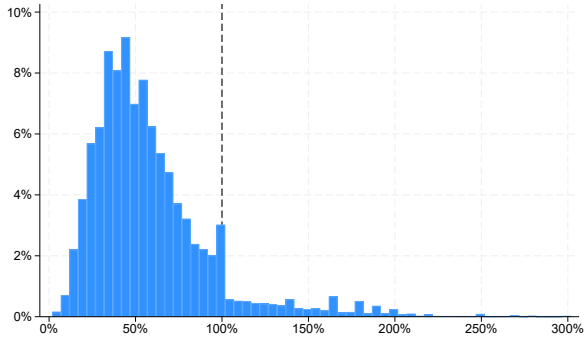
This figure presents the distribution of mortgage loan amounts relative to the conforming loan limit across the five SLR-exposure groups. The vertical dashed line marks the conforming loan limit. Values below 100% correspond to conforming loans, while values above 100% correspond to jumbo loans.



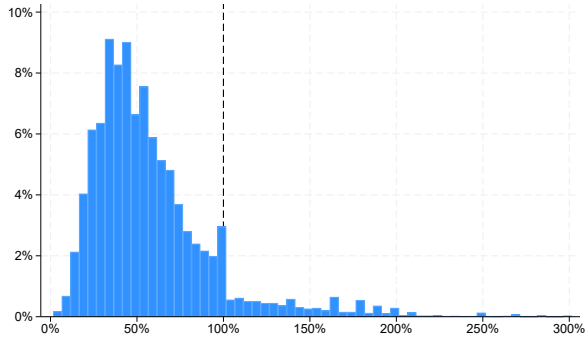
(a) Panel A. Full Sample



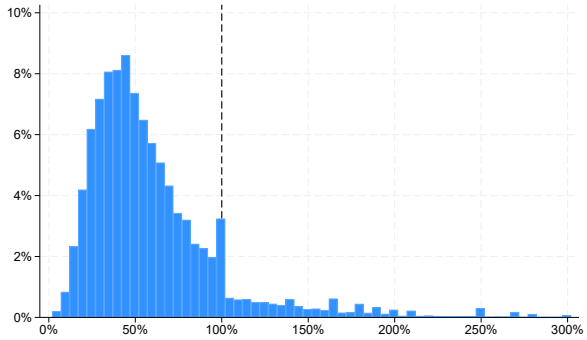
(b) Panel B. Zero SLR Exposure



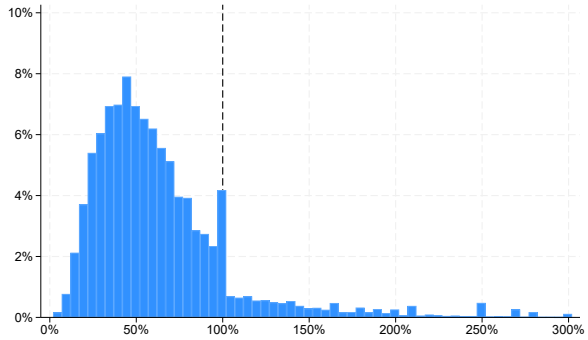
(c) Panel C. SLR Quartile 1



(d) Panel D. SLR Quartile 2



(e) Panel E. SLR Quartile 3

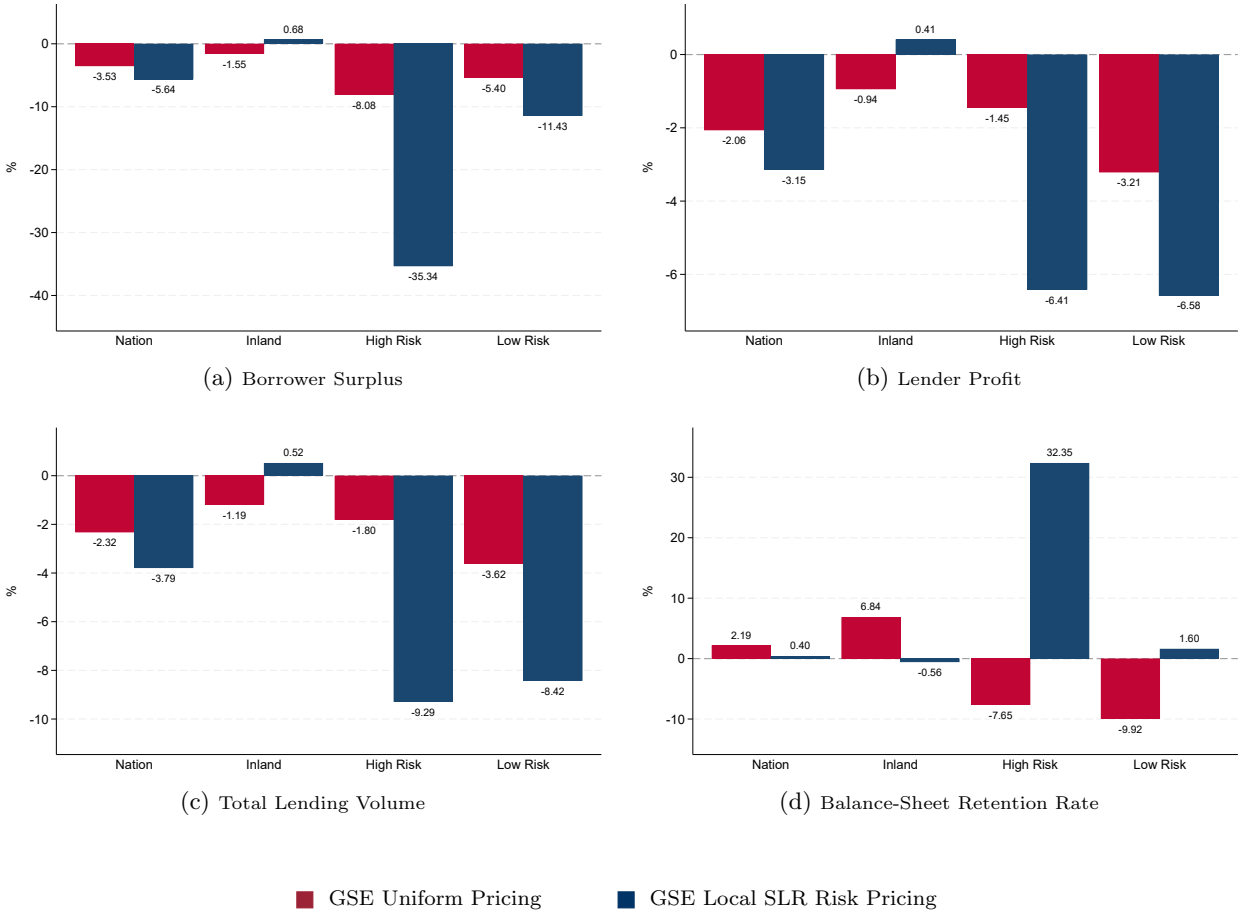


(f) Panel F. SLR Quartile 4

C.2 Counterfactual: Extreme SLR Risk

Figure C2: Effects of GSE Pricing under Extreme SLR Risk

This figure shows percentage changes in borrower surplus (Panel A), lender profit (Panel B), total lending volume (Panel C), and the balance-sheet retention rate (Panel D) under an extreme sea-level-rise (SLR) risk scenario relative to the baseline. Results are reported for national, inland, and coastal counties by SLR risk level, comparing outcomes under the GSE's uniform and local SLR risk pricing schemes. The extreme SLR risk is defined such that, for coastal counties with SLR risk below the 90th percentile of the positive SLR risk distribution across coastal counties, risk values are raised to the 90th percentile level, while counties already at or above this threshold remain unchanged. Only coastal counties are affected by this adjustment, while inland counties remain at zero SLR risk.



(a) Borrower Surplus

(b) Lender Profit

(c) Total Lending Volume

(d) Balance-Sheet Retention Rate

Table C3: Market Outcomes of GSE Pricing of Local SLR Risk

This table reports market outcomes under the baseline uniform GSE pricing and a scenario with GSE pricing local sea-level-rise (SLR) risk. Panel A presents results for national and inland counties, and Panel B reports results for coastal counties divided into high- and low-SLR-risk areas. Reported statistics include lending volumes by loan type, funding composition, interest rate changes, and welfare effects for borrowers and lenders (in billions).

Panel A: National and Inland Counties

	National		**Inland**	
	Baseline	SLR Pricing	Baseline	SLR Pricing
Lending Volumes (billion)				
All Loans	7,900	7,900	4,108	4,130
Conforming Loans	6,380	6,379	3,648	3,669
Jumbo Loans	1,520	1,521	461	460
Funding Source (billion)				
CB Balance Sheet (Conf.)	741	744	383	379
CB–GSE Funding (Conf.)	1,124	1,121	785	792
Shadow Bank Loans	4,830	4,828	2,607	2,625
CB Retention Rate (%)	29.32	29.44	28.00	27.85
Interest Rate Change (bp)				
All Loans		0.00		-0.50
GSE Conforming		0.00		-0.50
Balance-Sheet Conforming		-0.10		-0.30
Jumbo Loans		0.10		-0.20
Welfare Effects (billion)				
Borrower Surplus	2,688	2,688	1,304	1,314
Lender Profit	4,387	4,387	2,152	2,161

Panel B: Coastal Counties

	High SLR Risk		**Low SLR Risk**	
	Baseline	SLR Pricing	Baseline	SLR Pricing
Lending Volumes (billion)				
All Loans	149	139	3,643	3,632
Conforming Loans	105	94	2,628	2,616
Jumbo Loans	44	44	1,016	1,016
Funding Source (billion)				
CB Balance Sheet (Conf.)	7	10	351	355
CB–GSE Funding (Conf.)	17	13	322	316
Shadow Bank Loans	89	79	2,134	2,123
CB Retention Rate (%)	22.58	29.88	34.10	34.65
Interest Rate Change (bp)				
All Loans		7.90		0.50
GSE Conforming		9.00		0.50
Balance-Sheet Conforming		1.80		0.20
Jumbo Loans		3.40		0.10
Welfare Effects (billion)				
Borrower Surplus	11	7	1,373	1,367
Lender Profit	90	86	2,145	2,141

Table C4: Market Outcomes under an Increase in SLR Risk

This table reports market outcomes when sea-level-rise (SLR) risk increases by one standard deviation relative to current levels. The Uniform columns report outcomes under uniform GSE pricing with higher SLR risk, whereas the Local SLR Risk columns report outcomes under GSE pricing that reflects the higher local SLR exposure. The one-standard-deviation change is defined from the distribution of positive SLR risk across coastal counties; adjusted values above one are capped at one. Only coastal counties are affected, while inland counties remain at zero SLR risk. Reported statistics include lending volumes, funding composition, interest rate changes, and borrower and lender welfare (in billions).

Panel A: National and Inland Counties

	National			**Inland**		
	Baseline	**Uniform**	**Local SLR Risk**	**Baseline**	**Uniform**	**Local SLR Risk**
Lending Volumes (billion)						
All Loans	7,900	7,805	7,757	4,108	4,081	4,130
Conforming Loans	6,380	6,320	6,269	3,648	3,620	3,669
Jumbo Loans	1,520	1,485	1,488	461	461	460
Funding Source (billion)						
CB Balance Sheet (Conf.)	741	710	729	383	393	379
CB–GSE Funding (Conf.)	1,124	1,126	1,107	785	770	792
Shadow Bank Loans	4,830	4,798	4,742	2,607	2,584	2,625
CB Retention Rate (%)	29.32	29.37	29.44	28.00	28.64	27.85
Interest Rate Change (bp)						
All Loans		0.80	1.20		0.60	-0.50
GSE Conforming		0.60	1.20		0.60	-0.50
Balance-Sheet Conforming		2.10	1.30		0.40	-0.30
Jumbo Loans		2.10	2.40		0.20	-0.20
Welfare Effects (billion)						
Consumer Surplus	2,688	2,639	2,614	1,304	1,293	1,314
Lender Profit	4,387	4,341	4,321	2,152	2,140	2,161

Panel B: Coastal Counties

	High SLR Risk			**Low SLR Risk**		
	Baseline	**Uniform**	**Local SLR Risk**	**Baseline**	**Uniform**	**Local SLR Risk**
Lending Volumes (billion)						
All Loans	149	146	133	3,643	3,578	3,495
Conforming Loans	105	104	90	2,628	2,596	2,510
Jumbo Loans	44	42	43	1,016	982	984
Funding Source (billion)						
CB Balance Sheet (Conf.)	7	5	10	351	312	339
CB–GSE Funding (Conf.)	17	19	12	322	338	302
Shadow Bank Loans	89	89	75	2,134	2,125	2,042
CB Retention Rate (%)	22.58	18.26	29.88	34.10	32.47	34.65
Interest Rate Change (bp)						
All Loans		1.20	12.00		1.30	3.90
GSE Conforming		0.50	13.10		0.70	3.90
Balance-Sheet Conforming		8.30	6.10		4.30	3.80
Jumbo Loans		3.50	8.00		3.30	4.10
Welfare Effects (billion)						
Consumer Surplus	11	10	6	1,373	1,336	1,294
Lender Profit	90	88	83	2,145	2,112	2,078

Table C5: Market Outcomes under Extreme SLR Risk

This table reports mortgage market outcomes under a counterfactual scenario in which SLR risk rises to an extreme level. For coastal counties with SLR risk below the 90th percentile of the positive SLR risk distribution across coastal counties, risk values are raised to the 90th percentile level, while counties already at or above this threshold remain unchanged. The Uniform columns report outcomes under the existing GSE pricing scheme, and the Local SLR Risk columns report outcomes when pricing reflects local SLR exposure. Inland counties remain at zero SLR risk. Reported statistics include lending volumes, funding composition, interest rate changes, and borrower and lender welfare (in billions).

Panel A: National and Inland Counties

	National			**Inland Counties**		
	Baseline	**Uniform**	**Local SLR Risk**	**Baseline**	**Uniform**	**Local SLR Risk**
Lending Volumes (billion)						
All Loans	7,900	7,717	7,601	4,108	4,059	4,130
Conforming Loans	6,380	6,270	6,151	3,648	3,598	3,669
Jumbo Loans	1,520	1,447	1,450	461	461	460
Funding Source (billion)						
CB Balance Sheet (Conf.)	741	686	711	383	411	379
CB–GSE Funding (Conf.)	1,124	1,123	1,093	785	748	792
Shadow Bank Loans	4,830	4,776	4,651	2,607	2,565	2,625
CB Retention Rate (%)	29.32	29.97	29.44	28.00	29.92	27.85
Interest Rate Change (bp)						
All Loans		1.60	2.60		1.10	-0.50
GSE Conforming		1.10	2.40		1.10	-0.50
Balance-Sheet Conforming		4.20	3.00		0.50	-0.30
Jumbo Loans		4.40	5.20		0.40	-0.20
Welfare Effects (billion)						
Consumer Surplus	2,688	2,639	2,614	1,304	1,293	1,314
Lender Profit	4,387	4,341	4,321	2,152	2,140	2,161

Panel B: Coastal Counties

	High SLR Risk			**Low SLR Risk**		
	Baseline	**Uniform**	**Local SLR Risk**	**Baseline**	**Uniform**	**Local SLR Risk**
Lending Volumes (billion)						
All Loans	149	146	135	3,643	3,511	3,336
Conforming Loans	105	103	92	2,628	2,569	2,390
Jumbo Loans	44	43	44	1,016	943	946
Funding Source (billion)						
CB Balance Sheet (Conf.)	7	6	10	351	269	321
CB–GSE Funding (Conf.)	17	18	12	322	357	288
Shadow Bank Loans	89	88	77	2,134	2,122	1,949
CB Retention Rate (%)	22.58	20.85	29.88	34.10	30.72	34.65
Interest Rate Change (bp)						
All Loans		1.40	10.20		2.60	7.90
GSE Conforming		1.10	11.20		1.20	7.70
Balance-Sheet Conforming		4.20	4.50		9.80	8.20
Jumbo Loans		2.20	6.00		7.30	9.00
Welfare Effects (billion)						
Consumer Surplus	11	10	6	1,373	1,336	1,294
Lender Profit	90	88	83	2,145	2,112	2,078

Table C6: Market Outcomes under SLR-Adjusted Capital Weights

This table reports mortgage market outcomes when regulators incorporate sea-level-rise (SLR) exposure into risk-adjusted capital weights used for Tier 1 capital requirements. SLR is assumed to account for 10 percent of total credit risk. Inland counties have lower risk weights because their SLR exposure is zero. Coastal risk weights are adjusted by group-level SLR exposure. The Uniform columns report outcomes under uniform GSE pricing, while the Local SLR Risk columns report outcomes when GSE pricing reflects local SLR risk. Reported statistics include lending volumes, funding composition, interest rate changes, and borrower and lender welfare (in billions).

Panel A: National and Inland Counties

	National			**Inland Counties**		
	Baseline	**Uniform**	**Local SLR Risk**	**Baseline**	**Uniform**	**Local SLR Risk**
Lending Volumes (billion)						
All Loans	7,900	7,860	7,859	4,108	4,131	4,152
Conforming Loans	6,380	6,381	6,380	3,648	3,651	3,672
Jumbo Loans	1,520	1,478	1,479	461	480	480
Funding Source (billion)						
CB Balance Sheet (Conf.)	741	743	748	383	405	401
CB–GSE Funding (Conf.)	1,124	1,121	1,116	785	770	778
Shadow Bank Loans	4,830	4,834	4,833	2,607	2,602	2,620
CB Retention Rate (%)	29.32	29.93	30.01	28.00	29.34	29.13
Interest Rate Change (bp)						
All Loans		0.10	0.10		-0.30	-0.70
GSE Conforming		-0.20	-0.20		-0.30	-0.80
Balance-Sheet Conforming		1.10	0.80		0.60	0.40
Jumbo Loans		2.30	2.30		-3.60	-3.80
Welfare Effects (billion)						
Consumer Surplus	2,734	2,713	2,713	1,333	1,351	1,360
Lender Profit	4,387	4,359	4,358	2,152	2,165	2,173

Panel B: Coastal Counties

	High SLR Risk			**Low SLR Risk**		
	Baseline	**Uniform**	**Local SLR Risk**	**Baseline**	**Uniform**	**Local SLR Risk**
Lending Volumes (billion)						
All Loans	149	135	124	3,643	3,594	3,583
Conforming Loans	105	105	95	2,628	2,625	2,613
Jumbo Loans	44	29	29	1,016	969	970
Funding Source (billion)						
CB Balance Sheet (Conf.)	7	3	4	351	335	343
CB–GSE Funding (Conf.)	17	21	17	322	330	320
Shadow Bank Loans	89	91	82	2,134	2,141	2,131
CB Retention Rate (%)	22.58	10.89	15.47	34.10	33.08	33.85
Interest Rate Change (bp)						
All Loans		4.80	12.50		0.60	1.00
GSE Conforming		0.50	8.60		0.10	0.60
Balance-Sheet Conforming		4.50	11.80		1.30	1.00
Jumbo Loans		49.60	54.10		4.50	4.50
Welfare Effects (billion)						
Consumer Surplus	13	8	5	1,388	1,355	1,349
Lender Profit	90	78	73	2,145	2,116	2,111

Table C7: Welfare Transfers from Uniform GSE Pricing of SLR Risk under Extreme Risk

This table reports regional welfare transfers created by uniform GSE pricing of sea-level-rise (SLR) risk when SLR risk rises to an extreme level. For coastal counties with SLR risk below the 90th percentile of the positive SLR risk distribution across coastal counties, risk values are raised to the 90th percentile level, while counties already at or above this threshold remain unchanged. Transfers are reported separately for national, inland, and coastal counties, with coastal counties divided into high- and low-risk groups. Only coastal counties are affected by this adjustment, while inland counties remain at zero SLR risk. Results are shown by loan type (conforming and jumbo) and report aggregate subsidies and taxes in billions of dollars.

Regional Transfers ($ billions)				
	National	**Inland**	**High-Risk Coastal**	**Low-Risk Coastal**
	(1)	(2)	(3)	(4)
All Subsidy	11.820	0.031	0.730	11.060
All Tax	-4.262	-4.023	-0.011	-0.228
Jumbo Subsidy	1.118	0.027	0.077	1.015
Jumbo Tax	-0.397	-0.184	-0.010	-0.203
Conf. Subsidy	10.702	0.004	0.653	10.045
Conf. Tax	-3.865	-3.839	0.000	-0.026