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Underwaterwriting: from theory to empiricism in regional mortgage markets in the U.S.

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Abstract
This article provides the theoretical foundation for the concept of "Underwaterwriting," which can be understood as various informational and institutional limitations related to environmental exposure and climate change impacts—specifically flooding and sea level rise inundation—shaping firm participation in mortgage markets. Underwaterwriting suggests that the unevenness of scientific knowledge and local soft information, as well as the institutional barriers for the utilization of that information, could result in determinations of risk that may not accurately reflect long-term asset performance or credit loss. These informational asymmetries may result in assignments of risk that reflect a degree of arbitrariness or inaccuracy that may operate to strand assets and shed or increase market share in ways that are inefficient and may otherwise lead to negative public externalities. Consistent with this theory, this article provides evidence that concentrated local lenders are transferring risk in high-risk coastal geographies in the Southeast Atlantic and Gulf Coasts (U.S.) through increased securitization of mortgages. These findings provide an impetus for supporting more robust analysis of climate-risk in light of forthcoming accounting rules that require an upfront accounting of forward-looking credit losses.

Keywords Climate adaptation · Sea level rise · Climate-risk · Mortgage market · Banking · Housing

1 Introduction

According to the U.S. government, over $1 trillion of privately held coastal real property is at-risk from climate change in the U.S. (USGCRP 2018). Early-stage empirical research suggests

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that current and anticipated impacts of climate change are shaping the behavior of local real estate markets, particularly within coastal property markets (Bernstein et al. 2019; Keenan et al. 2018; McAlpine and Porter 2018; Ortega and Taṣpınar 2018). Research has highlighted that these demand effects by and between buyers and sellers are driven not only by present value determinations of risk and nuisance, as a negative amenity function, but also by the belief systems of market participants (Barrage and Furst 2019). The implications of these emergent market behaviors have begun to be evaluated in terms of the adaptation strategies and capacities of local jurisdictions to protect their property tax base (Conyers et al. 2019), as well as a broader set of considerations relating to municipal credit impairment and issuance costs associated with a realized or anticipated depreciating property tax base (Painter 2018). Even with robust local public investments in adaptation, millions of people along the U.S. coastline are anticipated to be displaced as sea level rise approaches a 1.8 m benchmark at the end of the century (Hauer et al. 2016). In light of this potential shift in demography and demand for coastal real estate (Treuer et al. 2018), it would hold that banks should be sensitive to their mortgage portfolio risk as a function of the circular interdependency of housing demand and mortgage supply (Hott 2011).

Little attention has been paid to how mortgage lenders might engage in autonomous and/or planned adaptation to climate change, and the extent to which uncoordinated, unregulated and/or misinformed individual behavior of mortgage lenders may lead to arbitrary, unidimensional determinations of risk that result in the accrual of negative externalities. This article provides the theoretical foundation for the concept of "Underwaterwriting," which can be understood as various informational and institutional limitations related to environmental exposure and climate change impacts—specifically flooding and sea level rise ("SLR") inundation—shaping firm participation in mortgage markets ("UWW"). UWW suggests that the unevenness of scientific knowledge and locally sourced soft information about the physical exposure of asset collateral, as well as the institutional barriers for the utilization of that information, could result in determinations of risk that may not accurately reflect long-term asset performance or credit loss. These informational asymmetries may result in assignments of risk that reflect a degree of arbitrariness or inaccuracy that may operate to strand assets and shed (or expand) market share in ways that are inefficient and may otherwise lead to negative externalities associated with everything from household capital accumulation to municipal credit.

To highlight the relevance of a theory of UWW, this paper tests the hypothesis that local mortgage lenders with concentrated portfolios retain fewer mortgage assets on the books than larger lenders with diversified portfolios that are collateralized by property in 0.3-m SLR inundation zones in the Southeast Atlantic and Gulf Coasts ("SLR zones") ("Retention Hypothesis"). As will be discussed, a central assumption of the Retention Hypothesis is that local lenders that concentrate their business in a relatively small number of markets have superior locally sourced information about environmental exposure due to their longstanding and diverse relationships in the communities that they serve. This article provides correlative evidence in support of a confirmation of the Retention Hypothesis. In light of these findings, the theory of UWW provides a useful conceptual framing to guide regulatory oversight that balances portfolio exposure, consumer transparency, and standardized metrics for the determination of climate-risk on collateral asset impairment. This article provides an impetus for supporting more robust analysis of climate risk in light of forthcoming accounting rules that require an upfront accounting of forward-looking credit losses (FASB 2016). As such, this article highlights a broad range of economic and institutional considerations that will be central to future asset valuation in coastal mortgage markets in the face of climate change.

1.1 Underwaterwriting and lending behavior

1.1.1 Mapping Pathway

A theory of UWW is based on a simple premise that the non-standardized, unidimensional determinations of credit loss and collateral impairment from climate change based on simple semi-empirical heuristics of physical exposure may result in arbitrary and/or inaccurate spatial determinations of risk. In this sense, when a bank draws a line around any given geography associated with whether to lend or not in a geography, there is an inherent element of arbitrariness, possibly even for the sake of administrative convenience. This arbitrariness is determined by irreducible uncertainty in hazard models, as well as the lack of appropriate granularity in those models to fully capture a range of biophysical and social variables. Together, these actions create formal and informal maps—sometimes referenced as “Bluelining”—that guide investment decision-making that may otherwise be maladaptive to lenders, borrowers, applicants and even property-tax dependent jurisdictions (the “Mapping Pathway”).

In this regard, much flood risk modeling is comparatively coarse in the face of climate change (Buchanan et al. 2016; Moftakhari et al. 2017; Buchanan et al. 2017). Flood risk valuation is largely limited in commercial terms to the catastrophe modeling supporting annual reinsurance pricing and which has limited methodological application to the term of an average mortgage life. Likewise, physical models generally do not capture risk, endogenous mitigation, and adaptation activities that may operate to either increase or indirectly decrease risk in any given geography (Stephens et al. 2017; Sriver et al. 2018). For instance, an adaptation investment to protect one neighborhood may steer water into another neighborhood—or, it may result in the incursion of an opportunity cost for distributive investments that benefit a wider range of exposure reduction opportunities.

Some have argued that these technological and measurement barriers are likely to be resolved in favor of acceptable degrees of uncertainty for purposes of informing investment decision making (Stephens et al. 2018). For instance, low-cost remote sensing and measurement hardware is allowing for external model calibration and validation (Yan et al. 2015). However, assuming perfect information, the institutional diffusion of this information is challenging. The primary barrier is the current mortgage market's reliance on the National Flood Insurance Program’s (“NFIP”) flood insurance rate maps (“FIRMs”) that are widely considered to be flawed given their variable degrees of measurement and their political nature, both of which undermine objective actuarial determinations of risk (Blessing et al. 2017; Kousky 2018). More fundamentally, base flood elevation does not fully capture risks associated with storm or event characteristics, nor does it capture local hazard mitigation efforts.

In light of these scientific, technological and institutional barriers, the degrees of uncertainty and inaccuracy could be exacerbated by the administrative convenience of banks to make determinations of risk on an ad hoc (i.e., loan-by-loan) basis absent precise public or cooperative determinations of risk assessment that would otherwise be integrated into capital, spatial and land use planning. Over time, these ad hoc determinations and the accrual of disparate information could operate to lock-in institutional and management behaviors (Barnes et al. 2004) that create de facto maps that may not take advantage of best available science and/or external information. For instance, these de facto maps may be formed by nominal data aggregated as lists and sorted by zip codes or census tracts that operate to exacerbate the contested boundaries of the ad hoc maps. Accordingly, the direction of bias may dictate that banks not only overcorrect with the withdrawal of capital allocations, but they may also extend additional allocations of capital based on inaccurate information.

Figure 1a highlights the continuum from which the Mapping Pathway would be expected to manifest in light of model resolution and institutional mainstreaming. In hypothetical terms, with a pure overlap between an actionable risk zone and the true risk zone, no UWW would exist. An actionable risk zone being the spatial area of lending operations that is assigned a value—albeit an imperfect value—for flood and SLR risk based on convenience, limited risk models and high institutional barriers for the diffusion of information. As such, it would be anticipated that there would always be some differential between climate change risk—as a moving target—and the science, technology, and institutional capacity to measure and respond.

1.1.2 Lender Pathway

Even if banks had updated, near real-time spatially refined maps with lot and block granularity, it would not necessarily address the challenge of what to do with existing mortgage loans within their portfolios where the collateral falls within a zone of risk that is beyond the current risk tolerance of the bank—or any of its competitors. Absent regulatory standardization that would set benchmarks for credit loss impairment of mortgage notes based on uniform

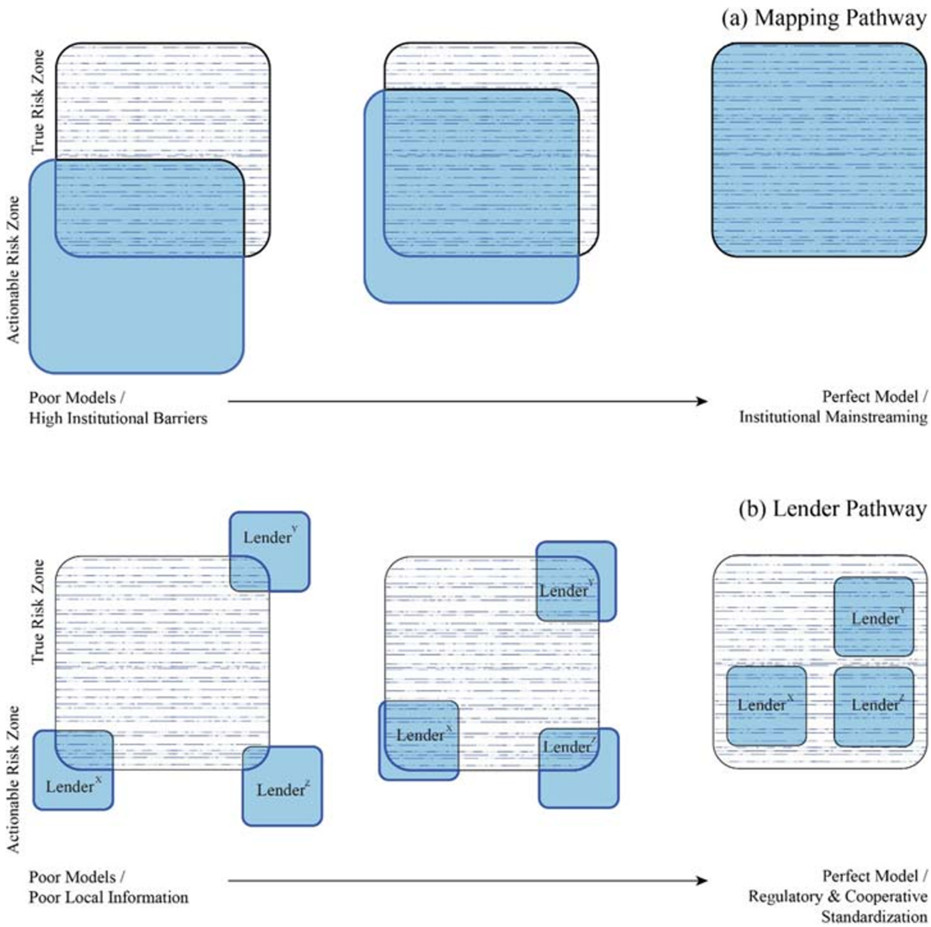


Fig. 1 Pathways to Underwaterwriting

exposure and/or credit loss modeling standards, lenders may not otherwise be incentivized to share information and cooperatively standardize assessment methodologies for a fear of losing market share and/or monopolistic pricing advantages (Gan and Riddiough 2008), particularly as it relates to lucrative jumbo loans in coastal markets. Under this pathway, as highlighted in Fig. 1b, non-cooperative lending behavior would indirectly create imbalances in credit availability in markets that may cloud the mid- to long-term trajectory of either an overall contraction or expansion in mortgage capital (the “Lender Pathway”).

For instance, a consumer may over time have fewer options among competing lenders, as lenders slowly align the actionable risk zone with the true risk zone. However, as long as there is at least one lender willing to lend, consumers may not appreciate that there may be zero lenders to finance the purchase of their home upon their desired intention to sell the home in the future. Of course, housing markets may still operate without a mortgage market and this may benefit renters, high-net worth cash-buyers and private equity firms who invest in high-risk real estate. Indeed, housing markets have been observed to capitalize flood risk and hazard mitigation in limited circumstances (Bin and Landry 2013; Qiu and Gopalakrishnan 2018). The flip side is that uniform and rapid standardization of risk and credit loss impairment assessment and accounting processes may strand large portfolios of assets faster than housing markets can necessarily respond. Therefore, with an increase in modeling and cooperative behavior there would likely be an increase in the number of stranded assets. Lenders may also extend credit based on an overcorrection of a climate signal based on local resilience activities that underestimate the true risk or their capacity to mitigate it. For these reasons, public policy should be prepared to guide what is arguably an inevitable collision course between the measuring, pricing and mitigation of climate-risk in the mortgage markets.

1.2 Lending behavior in the face of climate change

Consistent with the Lender Pathway, it would be expected that banks would gradually—over time—retain fewer mortgages on the books in SLR Zones and other high-risk zones (e.g., forest fire burn zones) with the diffusion of better information. Here, SLR zones are a proxy for a variety of coastal hazards and risks that may or may not be attributable to climate change. This may arise circumstantially based on local information originating from local lenders and/or it may be planned relative to an anticipated credit squeeze. In either case, it would be anticipated that banks would increase the amount of mortgage loans that they pass along to the capital markets (i.e., securitize)—in effect socializing the risk, particularly among the government sponsored entities (“GSEs”) (Christophers et al. 2018). With greater experience with the shocks and stresses of climate change impacts on property markets, it is anticipated that the institutional memory of banks should result in greater risk-averse behavior (Klomp 2014; Bouwman and Malmendier 2015), as has been demonstrated with earthquakes (Bos and Li 2017) and hurricanes (Schüwer et al. 2018).

Research has shown that local concentrated lenders—as opposed to larger diversified lenders—tend to utilize their ability to process soft information, like knowledge about environmental or climate exposure, individual credit-worthiness or construction quality (Stroebel 2016), to their comparative advantage, particularly after natural disasters (Chavaz 2014). A concentrated lender is defined herein as an institution that approves a large portion of their total annual loans in a small number of local markets. A non-concentrated or diversified lender is defined as an institution whose loan portfolio spans across many markets. By example, local lenders may have locally-sourced qualitative knowledge about repetitive loss properties or local topography that may represent unique risks for casualty loss that may not otherwise be aggregated in commercial databases accessible to non-local diversified lenders. They may source this information because of longstanding commercial relationships with local builders, insurance brokers and others members of the local business community. Chavaz (2014) found that in a post-disaster recovery, concentrated lenders not only expand their lending growth in recovery locations, they also—more importantly—sold those loans on secondary markets. Similar research found that local lenders with local branches had a superior advantage over non-local lenders without branches in managing their mortgage portfolio risk—notably through increased utilization of securitization (Cortes 2015). It has been observed that concentrated lenders tend to make greater investments in soft information that allows for a more efficient allocation of mortgage capital relative to diversified competitors (Loutskina and Strahan 2011).

A combination of superior capacity to source and process local, soft information and a capacity to shed risk to the capital markets is precisely the logic supporting the development of the Retention Hypothesis. In theory, local concentrated lenders should be able to source more precise information about pricing signals, local environmental exposures and local hazard mitigation and adaptation efforts. With this information, they should be inclined to manage that risk, *inter alia*, through greater utilization of securitization (Ouazad and Kahn 2019). However, securitization may be an incomplete measure for managing risk.

1.3 Research design and methodology

This article conducts an empirical analysis of historical mortgage market data in the South Atlantic and Gulf Coast regions of the U.S. to test the Retention Hypothesis. Data are retrieved from a nationwide sample of mortgage applications and originations collected and managed by the Federal Reserve Bank and the Consumer Finance Protection Bureau from 2009 to 2017, as mandated by the Home Mortgage Disclosure Act ("HMDA")(FFIEC 2019a). Under the HMDA, all regulated financial institutions with more than $30 million in assets must report a set of variables at the loan-level for all home loans issued—or refinanced—in a given calendar year.

1.4 Data

The HMDA data contain the following loan-level information: (i) year of application, (ii) lending institution, (iii) loan amount, (iv) acceptance decision, and (v) whether or not the lender retained the loan or sold it on the secondary market. In addition, the HMDA data provide information on (vi) the location of the property for which the loan is applied (at the census tract-level), (vii) applicant income, (viii) applicant sex, and (ix) applicant race. It is important to note that the HMDA data do not include any information on the interest rate or term of accepted loans, which limits the ability of this analysis to observe lender responses beyond the acceptance and retention margins.

The HMDA data were culled to include only loans for the purchase of 1–4 family homes.[1] To explore the hypothesized behavior of concentrated lenders with respect to SLR and

[1] Loans not for the purchase of 1–4 family homes are excluded from the sample analyzed herein as these are viewed as materially different from 4 family homes. In particular, multifamily condominiums and manufactured housing are each subject to substantially different flood risk profiles and the market footprint of each of these residence categories is correlated with a number of factors. To maximize homogeneity of the underlying collateral stock, conditional on observables, analysis is limited to 1–4 family homes. Furthermore, the sample is limited to loans for the purchase of 1–4 family homes, excluding refinanced loans.

flooding exposure, a measure of lender diversification is constructed using the HMDA data. The measure of lender diversification is analogous to the Herfindahl-Hirschman index ("HHI") and is calculated as the sum of squared shares of total annual accepted loans in all local markets in which a lender operates, where local markets are defined at the metropolitan statistical area ("MSA") level[2]. A higher HHI value does not necessarily mean that a lender has access to superior local, soft information. Rather, it is a—albeit imperfect, but consistently utilized—proxy for lender diversification. It is plausible that lenders with a high local market share area are in theory better positioned to access local information based on longstanding highly localized operations. Moreover, the HHI measure is shown in the literature to be a robust measure of lender concentration (Loutskina and Strahan 2011). The HHI value for bank b in year t is given as:

$$HHI_{b,t} = \sum_{m=1}^{M} s_{b,m,t}^{2} \tag{1}$$

where $s_{b,m,t}$ is the share of bank b's accepted loans in year t made in market (MSA) m. After the measure of lender diversification is generated using the nationwide pool of accepted loans, the sample is restricted to loans in census tracts within 2 mi. of the coast, as defined by spatial data sourced from the U.S. Geological Survey (USGS 2019).[3]

Bank balance sheet data are obtained from Reports of Condition and Income for commercial banks ("Call Reports") (FFIEC 2019b). Attributes from the Call Report from the fourth quarter of the year prior to the mortgage application are merged to each loan observation. These bank-level attributes include (i) size (log of total assets), (ii) capital-to-asset ratio, (iii) balance-sheet liquidity, (iv) loan volume-to-asset ratio, and (v) net income-to-asset ratio. Matching HMDA data to Call Reports excludes loan applications to non-depository lenders, such as savings institutions, mortgage bankers, and credit unions. Robust data on the primary, conventional measures of borrower default risk are unavailable within the public HMDA data package. To capture borrower default risk, the following measures are constructed using the HMDA loan data; data from the U.S. Census Bureau's American Community Survey: (i) borrower income, (ii) borrower's income-to-loan amount ratio, and (iii) the ratio of the borrower's income to the median income in the property's census tract (Ruggles et al. 2019). Since there exist strong, positive correlations between exposure to SLR and home value and loan acceptance and retention rates and home value, the tract-level median home value is also constructed for each year in the panel using data from the American Community Survey (Ruggles et al. 2019).

Census tract-level exposure to SLR for all loans within the sample is determined using the U.S. National Oceanographic and Atmospheric Administration's (NOAA) Sea Level Rise Viewer, which provides nationwide spatial data on inundation above mean higher high water ("MHHW") resulting from various SLR scenarios (NOAA 2019). This measure is limited to

[2] This is of course not equivalent to the standard definition of the Herfindahl-Hirschman index (HHI) used in the antitrust literature to measure the concentration of a given market. However, given the similarity of our lender diversification measure to the standard HHI, we follow the shorthand of Loutskina and Strahan 2011 and refer to our measure as HHI throughout.

[3] While restricting analysis to loans in census tracts within two miles of the coast significantly reduces the sample size, this does not limit the validity of the analysis described herein. In particular, this paper focuses on the effect of SLR exposure in coastal mortgage markets and uses a convention similar to that found elsewhere in the literature (see Bernstein et al. 2019) to define the geographic extent of coastal markets. Moreover, sufficient variation in SLR exposure still remains when limiting analysis to tracts within two miles of the coast: in the final sample used herein, over half of loans are not exposed to a SLR scenario of 0.30 m.

the extent that it does not account for local topography that may dictate varying degrees of exposure. A continuous measure of SLR exposure is constructed as the share total area of each census tract exposed to inundation above MHHW under different SLR scenarios.[4] A continuous measure of the share of each census tract's total area designated as within FEMA's Special Flood Hazard Area ("SFHA") is constructed to capture static, underlying flood risk levels and existing risk communication pathways (FEMA 2019b).

The final, cleaned panel of coastal loan applications ($n = 1{,}812{,}740$) is used to construct a nationwide panel of coastal lender-tract-year-level observations spanning from 2009 to 2017, averaging relevant borrower and applicant pool measures to the lender-tract-year-level. Thereafter, the nationwide panel is reduced ($n = 645{,}072$) to include only data in the Southeast Atlantic and Gulf Coast regions (the "Subject Regions"). These regions are selected because the Gulf and Atlantic coasts have comparatively high levels of physical exposure to coastal flooding and future SLR (Sweet et al. 2017) and the Subject Regions have high concentrations of vulnerable coastal development in comparison with other regions in the U.S. (Gornitz et al. 1994; Chi and Ho 2018). Table 2 provides descriptions of the variables included in the final panel and Table 3 provides summary statistics for the final panel. The total volume of approved loans collateralized by property exposed to 0.30 m SLR over the period covered in the final panel is approximately \$39.38 billion ($n = 140{,}818$) in 2017 US dollars (USD), which corresponds to an annual average of approximately \$4.67 billion (2017 USD). The total volume of approved loans collateralized by property not exposed to 0.30 m SLR in the final panel is approximately \$34.18 billion ($n = 148{,}376$) (2017 USD), which corresponds to an annual average of approximately \$3.80 billion (2017 USD).

1.5 Empirical analysis of hypothesis

In the absence of a clear causal model, efforts are taken to isolate variation in mortgage market behavior which is associated with variation in SLR exposure. While the results of the empirical analysis herein are viewed as internally and externally valid based on the model described below, it is important to note that these findings are observational in nature. Additional effort is necessary to identify the marginal causal effect of changes in SLR exposure on lender behavior beyond the analysis conducted herein.

The empirical model used to test the Retention Hypothesis is as follows:

$$Reten_{b,c.t} = \beta_1 \cdot Exposure_{\mathrm{c}} \times HHI_{b,t} + \beta_2 \cdot Exposure_c + \beta_3 \cdot HHI_{b,t} + \beta_4 \cdot \boldsymbol{X}_{b,c,t} + \alpha_b + \gamma_c + \delta_{c,t} + \varepsilon_{b,c,t} \tag{2}$$

[4] Note that the SLR exposure field captures exposure to different SLR scenarios based on the share of a census tract which would inundated in each scenario. Importantly, this exposure field is based on inundation modeling and does not take a stance on a particular SLR projection. In other words, this SLR exposure field captures the share of a census tract which would be inundated were there to be, for example, 0.30 m. of global mean SLR. It is therefore a static object based on inundation scenarios. This SLR exposure field does not capture, for example, the share of a census tract which will be inundated by 2100 due to SLR nor does it capture the amount of SLR to which a census tract is exposed over the time period examined in the analysis. With that said, estimates suggest that there is a 90% probability of global mean SLR of between 0.2 and 2.0 m. by 2100 (Parris et al. 2012), which suggests that the results using the 0.30 m. SLR inundation scenario may be interpreted as the estimated effect of exposure to some lower bound of end-of-century SLR.

$Reten_{b, c, t}$ is bank b's retention rate in census tract c in year t. $Exposure_c$ is a continuous variable indicating whether census tract c is exposed to inundation from a selected SLR scenario. $HHI_{b, t}$ is bank b's measure of market concentration in year t as described by Eq. (1). $\boldsymbol{X}_{b, c, t}$ is a vector of bank, tract, and borrower controls, which vary over bank-time, tract-time, and bank-tract-time space, respectively. α_b, γ_c, and $\delta_{c, t}$ are bank-, tract-, and county-by-year fixed effects which are intended to capture time-invariant unobserved heterogeneity at the bank- and tract-levels as well as time-variant unobserved heterogeneity across different sub-markets in the panel. $\varepsilon_{b, c, t}$ is a lender-tract-year-level, heteroskedasticity-robust, normally-distributed error term clustered at the census tract-level with a mean zero and variance of σ^2. Errors are clustered at the census tract-level to account for spatial autocorrelation across lender-tract units. In addition to Eq. (2) above, an identical model with $Accept_{b, c, t}$ as the dependent variable is estimated.

The specification given by Eq. (2) identifies the effect of SLR exposure on census tract-level lender behavior primarily through the inclusion of county-by-year fixed effects. In particular, the inclusion of county-by-year fixed effects throughout the results reported herein identifies the effect of SLR exposure on lender behavior by comparing loan acceptance and retention across lender types in different census tracts within the same county in the same year. Moreover, controlling for a number of relevant, observed lender- and tract-level characteristics as well as unobserved, time-invariant lender- and tract-level characteristics through the inclusion of bank- and census tract-fixed effects mitigates the possibility that SLR exposure relates to some lender-tract-year-level unobservable.

It is important to note that confounding, or omitted variable bias, possibly remains a threat to the internal—and, as a result, external—validity of the model given by Eq. (2). In particular, while care is taken to construct a panel of independent variables which capture meaningful variation in the observed lending behavior (both acceptance and retention rates) and various time-variant and invariant fixed effects are included, it is possible that time-invariant and time-variant unobserved heterogeneity remains. While conventional approaches to address confounding, such as fixed or random effects models, are attractive, they are unavailable in the current setting. Given that a key variable of interest, $Exposure_c$, is time-invariant, inclusion of unit (i.e., bank-by-tract) fixed effects would limit the ability to estimate and conduct inference on the relationship between SLR exposure and lender behavior, which is the purpose of this analysis. Moreover, the assumption of uncorrelated unit-level error that is key to the random effects model is implausible in this setting. Thus, given the unbalanced nature of the lender-tract-year panel used herein, a pooled ordinary least squares (OLS) model is used with time-variant and time-invariant fixed effects.[5] Table 4 compares pooled OLS models with different fixed effects. Given that the time-variant unobserved heterogeneity in lender behavior plausibly varies over the spatial dimension as well, the preferred specification includes bank-, tract-, and county-by-year fixed effects.

Returning to the preferred model presented in Eq. (2), the interaction term $Exposure_c \times HHI_{b, t}$ identifies whether banks of differing degrees of diversification have different acceptance rates across SLR-exposed and non-SLR-exposed markets. A negative estimate for β_2 when Eq. (2) is estimated with the proportion of accepted loans retained by originating institutions as the dependent variable suggests that an increase lender concentration is associated with the acceptance and retention of fewer loans in SLR-exposed census tract, which

[5] While the lender-tract-year panel is unbalanced, the number of tracts remains relatively constant and the number of lenders increases slightly over the time period included in the final panel. Thus, attrition is not of major concern. Though balancing the panel is considered, this approach is sub-optimal given that a large number of unbalanced units (bank-tracts with missing observations for certain years in the final panel) are highly concentrated lenders. Exclusion of these observations would bias the results given the important role of lender concentration.

would be suggestive of a possible validation of the Retention Hypothesis. Note that the primary results reported herein focus on a 0.30 m. (i.e., 1 ft.) SLR inundation scenario; however, the results are robust to different inundation levels up to 1.83 m. (i.e., 6 ft.) SLR inundation scenario, as referenced in Table 5.

2 Results

Figure 2 shows non-parametric estimates of the conditional expectation functions of lender-tract-year acceptance rate and retention rate for (a) concentrated ($n = 34{,}514$ lender-tract-year observations) and (b) non-concentrated ($n = 75{,}445$ lender-tract-year observations) lenders conditional on the proportion of a census tract's area exposed to 0.30 m SLR inundation for all census tracts with non-zero exposure to SLR under this scenario. Figure 2 suggests that SLR exposure and lender acceptance and retention exhibit a positive relationship; however, this is likely due to confounding: areas with greater SLR exposure are likely to have higher

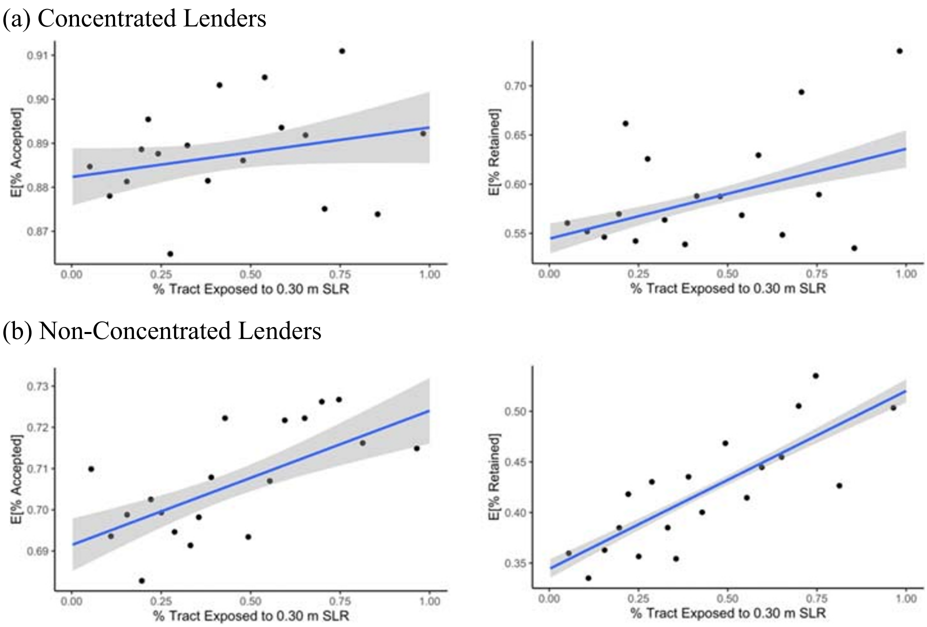


Fig. 2 Lender behavior for loans collateralized by SLR-exposed property. **a** Concentrated lenders. **b** Non-concentrated lenders. Binned scatterplots showing non-parametric estimates of the conditional expectation functions of lender-tract-year acceptance rate and retention rate for concentrated ($n = 34{,}514$ lender-tract-year observations) and non-concentrated ($n = 75{,}445$ lender-tract-year observations) lenders conditional on the proportion of a census tract's area exposed to 0.30 m SLR inundation for all census tracts with non-zero exposure to SLR under this scenario. Concentrated lenders are identified in each year in the sample as those lenders with HHI values greater than 0.25, which approximately corresponds to the mean HHI value. The best linear estimates of the conditional expectations are overlaid (blue line) with 95% confidence intervals shown in the shaded area. These estimates suggest subtle differences in the relationship between acceptance/retention rates and SLR exposure for concentrated and non-concentrated lenders: the marginal effect of SLR exposure on both the acceptance and retention rates for concentrated lenders is smaller than that for non-concentrated lenders as predicted by the simple linear fits of the conditional expectation functions. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017

amenity value and therefore are more likely to have higher value collateral. All else equal, lenders may be more likely to accept and retain loans in these areas as higher collateral value is positively correlated with conventional measures of default risk. Thus, Fig. 2 demonstrates the importance of controlling for confounding variables. Moreover, comparing Fig. 2a and b, a best linear fit of the non-parametric estimates of the conditional expectation functions reveals that the positive relationship between SLR exposure and lender acceptance and retention behavior is stronger for non-concentrated lenders than for concentrated lenders. This is suggestive of an increase in liquidity among concentrated lenders in SLR-exposed areas, which provides an early indication that the Retention Hypothesis may hold.

Table 1 displays the primary results estimating the reduced form of the pooled OLS model given in Eq. (2). All standard errors are clustered at the census tract-level. Column (1) of Table 1 reports the results regressing the lender-tract-year acceptance rate on $Exposure_c$ and a set of controls. The estimated coefficient on $Exposure_c$ is negative yet statistically-insignificant. Column (2) of Table 1 reports the results regressing the lender-tract-year acceptance rate on $Exposure_c \times HHI_{b,t}$ and a set of controls. The estimated coefficient on the interaction term suggests that concentrated lenders decrease their acceptance rate in SLR-exposed tracts ($p < 0.01$, $n = 109{,}959$ lender-tract-year observations). Comparing columns (1) and (2), it is clear that lender concentration plays an important role in this setting.

Column (3) of Table 1 reports the results regressing the lender-tract-year retention rate on $Exposure_c$ and a set of controls. The estimated coefficient on $Exposure_c$ is again negative and statistically-insignificant. Column (4) of Table 1 reports the results regressing the lender-tract-year retention rate on $Exposure_c \times HHI_{b,t}$ and a set of controls. The estimated coefficient on the interaction term suggests that concentrated lenders retain fewer loans that they originate in tracts exposed to SLR ($p < 0.01$, $n = 109{,}959$ lender-tract-year observations). Again, comparing columns (3) and (4), it is clear that accounting for lender concentration is important when examining the relationship between SLR exposure and lender loan retention.

Figure 3 uses the results regressing the lender-tract-year retention rate on $Exposure_c \times HHI_{b,t}$ and a set of controls reported in column (4) of Table 1 to estimate the marginal effect of SLR exposure on loan retention. Figure 3 a plots the marginal effect of exposure to inundation under a 0.30 m SLR scenario as a function of HHI. The clustered variance-covariance matrix from the regression reported in column (4) of Table 1 is used to construct standard errors and a 90%-confidence interval for the marginal effect of SLR exposure as a function of HHI. Figure 3a suggests that for lenders with high HHI values (lenders in the 90% HHI quantile or higher), the marginal effect of SLR exposure is statistically-significant and negative, providing a validation of the Retention Hypothesis. Figure 3b shows the average estimated marginal effect of SLR exposure by county in the Subject Regions.[6]

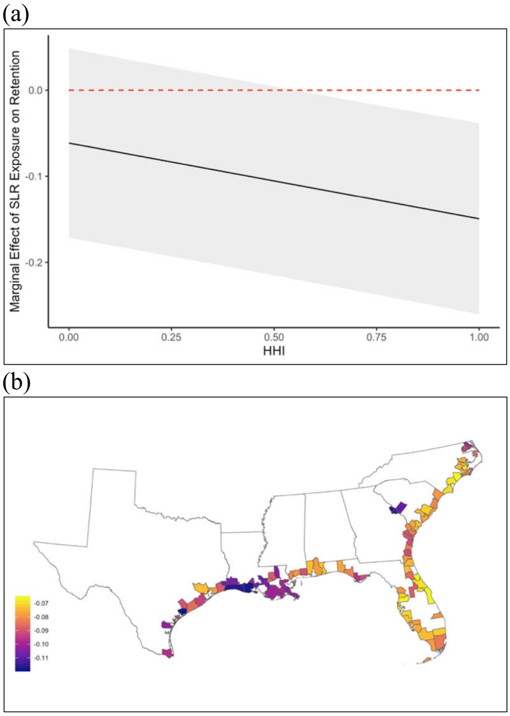
The marginal effect of exposure to inundation under a 0.30 m SLR scenario is estimated for each county in the Subject Regions as an average of annual estimated marginal effects. The annual estimated marginal effect of exposure to inundation under a 0.30 m SLR scenario is estimated for each county-year as the sum of estimated marginal effects for all lenders in a county, with each lender's estimated marginal effect weighted by the share of total accepted loans in the county-year. Figure 3c reports the top and bottom ten counties in the Subject Regions by average estimated marginal effect of SLR exposure on retention along with the associated 90%-confidence intervals.

[6] Note that counties are supersets of census tracts, so aggregating lender-tract-year marginal effects to county marginal effects is feasible.

Table 1 Regression results for acceptance and retention behavior

Dependent variable				
	Acceptance $rate_{b,c,t}$		Retention $rate_{b,c,t}$	
	(1)	(2)	(3)	(4)
$Exposure_c \times HHI_{b,t}$		− 0.033***		− 0.088***
		(0.010)		(0.016)
$Exposure_c$	− 0.037	− 0.030	− 0.081	− 0.062
	(0.037)	(0.037)	(0.066)	(0.067)
HHI $_{b,t}$		0.045***		0.065***
		(0.008)		(0.013)
Bank controls				
Log(Total $assets_{b,t}$)	− 0.040***	− 0.037***	−0.021***	− 0.018**
	(0.000)	(0.005)	(0.008)	(0.008)
(Liquid assets/assets)$_{b,t}$	− 0.123***	− 0.123***	0.194***	0.193***
	(0.005)	(0.026)	(0.044)	(0.043)
(Capital assets/assets)$_{b,t}$	0.209***	0.236***	0.278***	0.308***
	(0.026)	(0.058)	(0.094)	(0.904)
(Loans/assets)$_{b,t}$	− 0.108***	− 0.102	− 0.106**	− 0.098**
	(0.059)	(0.026)	(0.045)	(0.405)
(Income/assets)$_{b,t}$	− 0.142***	− 0.119	− 0.403**	− 0.372**
	(0.026)	(0.112)	(0.174)	(0.174)
Borrower controls				
(Loan amount/income)$_{b,c,t}$	− 0.001	− 0.001**	− 0.004***	− 0.004***
	(0.112)	(0.0004)	(0.001)	(0.001)
Sex $_{b,c,t}$	− 0.004**	− 0.004**	− 0.029***	− 0.029***
	(0.0004)	(0.002)	(0.003)	(0.003)
Race $_{b,c,t}$	− 0.008**	− 0.008***	0.031***	0.031***
	(0.002)	(0.003)	(0.006)	(0.006)
Tract controls				
$SFHA_{c,t}$	0.007**	0.007	0.007	0.007
	(0.003)	(0.025)	(0.048)	(0.048)
Log(Median HH $income_{c,t}$)	0.005	0.005	0.022	0.022
	(0.025)	(0.008)	(0.014)	(0.014)
Log(Median home $value_{c,t}$	− 0.001	− 0.0003	0.007	0.007
	(0.008)	(0.004)	(0.006)	(0.006)
Poverty $rate_{c,t}$	− 0.017	− 0.018	− 0.024	− 0.025
	(0.004)	(0.023)	(0.037)	(0.037)
Minority $percentage_{c,t}$	0.021	0.021	0.038	0.038
	(0.023)	(0.021)	(0.034)	(0.034)
Tract FE	X	X	X	X
Bank FE	X	X	X	X
County-year FE	X	X	X	X
Observations	109,959	109,959	109,959	109,959
Adjusted R^2	0.422	0.422	0.415	0.416
Residual std. error	0.216	0.216	0.343	0.343
	(df = 104,640)	(df = 104,638)	(df = 104,640)	(df = 104,638)

Results regressing acceptance rate and retention rate on $Exposure_c$ and a set of controls (columns (1) and (3)) and on $Exposure_c \times HHI_{b,t}$ and a set of controls (columns (2) and (4)). $Exposure_c$ is a continuous variable measuring the share of a census tract c's total area that is exposed to inundation under SLR of 0.30 m. Note: p values are calculated using a two-sided t-test and heteroskedasticity-robust standard errors clustered at the census tract-level; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Heteroskedasticity-robust standard errors clustered at the census tract-level are reported in parentheses. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include tract-, bank-, and county-by-year fixed effects. For information on the robustness of these results, see Tables 4, 5, 6, 7, and 8 and Fig. 5



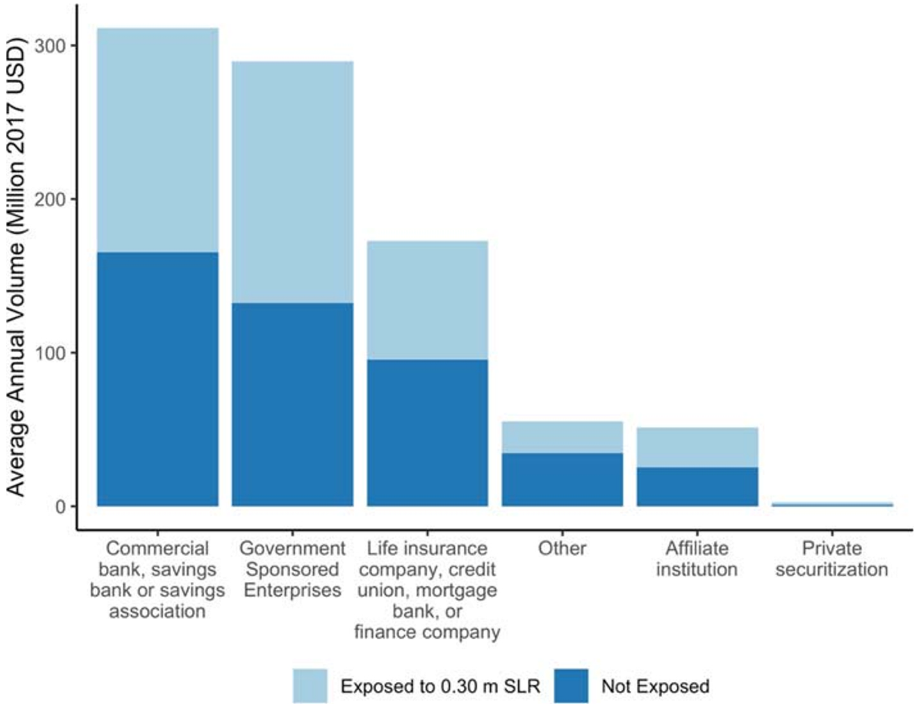
(c)

	County	State	Estimated Marginal Effect
1	Calhoun County	Texas	-0.119 [-0.229, -0.008]
2	Vermilion Parish	Louisiana	-0.118 [-0.229, -0.007]
3	Cameron Parish	Louisiana	-0.116 [-0.227, -0.006]
4	Columbia County	Georgia	-0.116 [-0.226, -0.005]
5	Richmond County	Georgia	-0.114 [-0.224, -0.004]
6	Aiken County	South Carolina	-0.109 [-0.22, 0.001]
7	Orange County	Texas	-0.108 [-0.218, 0.002]
8	Assumption Parish	Louisiana	-0.108 [-0.218, 0.003]
9	Iberville Parish	Louisiana	-0.108 [-0.218, 0.003]
10	Iberia Parish	Louisiana	-0.107 [-0.218, 0.003]
	⋮		
78	Manatee County	Florida	-0.071 [-0.181, 0.039]
79	Brunswick County	North Carolina	-0.07 [-0.18, 0.04]
80	Seminole County	Florida	-0.07 [-0.18, 0.04]
81	Pender County	North Carolina	-0.069 [-0.179, 0.041]
82	Volusia County	Florida	-0.069 [-0.179, 0.041]
83	Pamlico County	North Carolina	-0.069 [-0.179, 0.041]
84	Pasco County	Florida	-0.067 [-0.177, 0.042]
85	Flagler County	Florida	-0.067 [-0.177, 0.043]
86	Onslow County	North Carolina	-0.067 [-0.177, 0.043]
87	Brevard County	Florida	-0.066 [-0.176, 0.044]

Fig. 3 Estimated marginal effect of exposure to inundation under a 0.30 m SLR scenario on loan retention behavior. **a** Marginal effect of exposure to inundation under a 0.30 m SLR scenario as a function of HHI based on the results reported in column (4) of Table 1. Shaded 90% confidence interval is constructed using standard errors calculated via the delta method using the clustered variance-covariance matrix estimated in column (4) of Table 1. **b** Estimated annual average marginal effect of exposure to SLR for all counties included in the main specifications reported in Table 1. The estimated annual average marginal effect of exposure is based on the results reported in column (4) of Table 1. The marginal effect of exposure to inundation under a 0.30 m SLR scenario is estimated for each county as an average of annual estimated marginal effects. The annual estimated marginal effect of exposure to inundation under a 0.30 m SLR scenario is estimated for each county-year as the sum of estimated marginal effects for all lenders in a county, with each lender's estimated marginal effect weighted by the share of total accepted loans in the county-year. **c** Top- and bottom-10 counties by magnitude of the estimated annual average marginal effect of exposure to inundation under a 0.30 m SLR scenario, which is estimated using the same method as in **b**. Ninety percent confidence intervals are reported in brackets and are constructed using standard errors calculated via the delta method using the clustered variance-covariance matrix estimated in column (4) of Table 1. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include tract-, bank-, and state-by-year fixed effects. For information on the robustness of these results, see Tables 4, 5, 6, 7 and 8 and Fig. 5

To examine whether this relationship is observed outside of the Subject Regions, the specification reported in column (4) of Table 1 is run using analogous panels from other regions in the Continental U.S., including coastal markets in the Mid-Atlantic, Northeast, and West Coast regions. Results are reported in Table 6. While results regressing lender-tract-year retention rate on $Exposure_c \times HHI_{b,\,t}$ and a set of controls for different regional subsamples suggest similar relationships between SLR exposure, lender concentration, and loan retention behavior, the results are not statistically significant in these other regions. Thus, it appears as though the observed relationship is at present limited to coastal mortgage markets in the Subject Regions.

(a)



(b)

	Commercial bank, savings bank or savings association	Government Sponsored Enterprises	Life insurance company, credit union, mortgage bank, or finance company	Affiliate institution	Other	Private securitization
Not Exposed	165.251	132.283	95.492	25.250	34.559	0.932
Exposed to 0.30 m SLR	146.052	157.394	77.243	26.096	20.805	1.590
Total	311.303	289.677	172.735	55.364	51.346	2.522

Fig. 4 Secondary loan market volumes of loans collateralized by SLR-exposed and non-exposed property for concentrated lenders. **a** Average annual volume in millions of dollars (2017 USD) of loans accepted and sold on the secondary market by concentrated lenders in the same year by purchaser type. Concentrated lenders in a given year are identified as those lenders with HHI values greater than 0.25, which corresponds to mean HHI value in the sample. Annual average volumes are broken down by loans collateralized by SLR-exposed properties (under SLR of 0.30 M) and non-exposed properties. "Government sponsored enterprises" ("GSEs") include Fannie Mae ("FNMA"), Freddie Mac ("FHLMC"), Ginnie Mae ("GNMA"), and Farmer Mac ("FAMC"). "Private securitization" refers to loans sold on the secondary market to a non-GSE purchaser that is then securitized by the institution purchasing the loan; all non-GSE purchasers that either retain or dispose the purchased loan by non-securitization means will fall under one of the remaining applicable categories. The purchaser type "affiliate institution" refers to purchasers that are subsidiaries of the institution originating the loan, but do not fall under the category of a commercial bank, savings bank, savings association, life insurance company, credit union, mortgage bank, or finance company. The purchaser type "other" refers to non-securitized loans purchased by a non-GSE institution that does not fall into one of the remaining applicable categories. **b** Same average annual volume data for loans accepted and sold on the secondary market by concentrated lenders in the same year by purchaser type (2017 USD). Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017

Additional checks of the robustness of the primary results are conducted. To test the identification strategy discussed in the previous section, the primary relationships of interest are examined over the time period covered in the final sample. This test exploits the fact that general awareness of SLR has increased over the period covered by the sample, which implies that a general increase in the effect of SLR on lender behavior should be observed (Bernstein et al. 2019). Figure 5 reports year-by-year coefficient estimates on $Exposure_c \times HHI_{b,\,t}$ from regressions of acceptance rate and retention rate on this interaction term of interest and the same set of controls and fixed effects as in the results reported in Table 1.[7] Results are suggestive of an increase in the effect of SLR exposure on the retention behavior of concentrated lenders over the time period, but not acceptance behavior, which is in line with the primary results reported herein. To further test whether a SLR exposure effect has indeed been identified, the primary results in Table 1 are replicated in a sample excluding those census tract-year observations which experienced a flood-related federal disaster declaration in the current or previous year (FEMA 2019a). Results reported in Table 7 suggest that past flood exposure is likely not driving the observed negative relationship between loan retention behavior among concentrated lenders, but rather some signal of exposure to future flooding due to SLR. As a final robustness check, the primary results are replicated at the loan-level using the analogous linear probability models of the probability of acceptance and retention, with results reported in Table 8 verifying the main findings of this analysis.

2.1 Analysis

The results provide evidence that concentrated lenders are managing coastal environmental hazards and collateral exposure by passing along those risks (and uncertainties) to the capital markets through greater securitization. An affirmation of the Retention Hypothesis intuitively makes sense, as it can be argued that local concentrated lenders have superior information about very localized hazards, exposure and mitigation that may not be well represented in formal risk-assessment models and data sets. In theory, with knowledge of this behavior of concentrated lenders, capital market purchasers would be inclined to impose a climate-risk premium to account for undisclosed non-standard risk. Likewise, consistent with the results in Table 6, the effects have been observed to be strongest among all regions in the U.S. in the Subject Regions where exposure to SLR and experience with coastal hazards are comparatively more severe. This is exactly where one would expect the results to be most robust in that greater experience with flooding and storms would arguably be translated into more local soft information as it relates to the unique exposure of collateral properties.

This information disconnect between local soft information and national assessment data further highlights the challenge delineated with UWW. Absent more resolute and standardized assessment data and techniques, this market advantage for concentrated lenders could become more robust with the advancement of SLR and coastal flooding. Under this scenario, there may be unevenness of mortgage availability and pricing that may cloud short-term perceptions of risk. In addition, the results also highlight evidence of credit constraints in some SLR-exposed zones. Credit availability is perhaps one of the most significant anticipated byproducts of climate-risk pricing exacerbated by UWW. With greater information sharing and risk modeling by and between concentrated and diversified lenders, it would be anticipated that credit availability would be increasingly constrained. For instance, diversified lenders might be inclined to impose greater interest rates to account for concentrated lender's ability to cherry pick the highest credit worthy borrowers. At present, it is very likely that upfront yields from points and servicing fees, as well as considerations for market share, trump any kind repricing

[7] Annual interaction term coefficients are obtained by interacting a set of binary variables indicating the year in which a lender-tract-year observation occurs with the main interaction term of interest.

that might account for the informational advantage of concentrated lenders. Overtime, it would be anticipated that diversified lenders would also decrease their retention rates. Nevertheless, given concentrated lenders demonstrated behavior, it can be argued that the mismatch in spatial determinations of risk by and between concentrated and diversified lenders is evidence of the early stages of the Mapping and Lender Pathways of UWW.

The findings highlight observed behavior associated with SLR zones. However, these zones should be conceptualized as proxies for a variety of coastal hazards and risks that may or may not otherwise be exacerbated by SLR. This does not mean that the behavior of concentrated lenders is a function of their cognitive attribution of environmental risk to SLR or climate change. Indeed, some measure of experience may have little to no attribution to climate change at all. Likewise, there may be alternative explanations for this behavior, such as housing development trends in areas where land costs are cheap, infrastructure is sparse, and non-climatic environmental exposure is high. This new development in more rural areas may be understood locally as having a greater market risk, as opposed to an environmental risk. Nonetheless, the empirical strategy employed herein and the robustness of the findings across the subject region suggests a potentially widespread recognition of environmental risks, including those scientifically attributable to climate change.

To provide some perspective, Fig. 4 shows the total loan volumes sold in millions of 2017 USD by concentrated lenders on the secondary market by purchaser type in an average year in the final sample (2009 to 2017) of Subject Region loans. The figure breaks down average loan volumes further by loans collateralized by SLR-exposed properties (under a SLR scenario of 0.30 m.) and non-exposed properties for each purchaser type. In the Subject Regions, the average annual volume of SLR-exposed loans in the final sample is roughly equal to the volume of non-exposed loans, representing on average around 47% of the total loan volume sold to the secondary market by concentrated lenders in a given year in the final sample of loans collateralized by coastal property. Moreover, GSEs purchase a large portion of loans collateralized by SLR-exposed property sold by concentrated lenders. In an average year in the final sample of coastal properties, GSEs account for around 24% of the total volume of exposed loans sold to the secondary market by concentrated lenders. It should be noted that the final sample is restricted to loans collateralized by property within 2 mi. of the coast in the Subject Regions and only includes loans originated or sold by depository institutions. However, it is still apparent from the analysis of this sample that concentrated lenders tend to pass on the risk associated with loans exposed to coastal flooding and SLR to institutions participating in the secondary market for loans and GSEs account for a significant portion of those institutions purchasing these assets.

This socialization of risk through the GSEs likely represents a major challenge for federal regulators and policymakers going forward (Ouazad and Kahn 2019). It can be argued that if the GSEs were to significantly over- or undercorrect, this observed risk transfer of environmental risk, it could exacerbate and lead to inefficiencies consistent with the Lender Pathway. Conversely, if the private market moves without coordination of the GSEs, a similar market distortion may be realized. These market distortions may operate to exacerbate existing environmental justice inequalities among low-to-moderate households with potentially stranded residential assets. Indeed, sufficiently priced climate-risk premiums may attract high-risk capital market investors to fill a void from the exit of conventional mortgages and this may operate to additionally constrain the affordability and accessibility of housing.

Given the aforereferenced modification of accounting rules to require forward-looking losses, all capital market participants may be inclined to take action to coordinate risk predication and valuation (FASB 2016). The question remains as to what extent coordination may be undertaken to mitigate market inefficiencies and distortions in a manner consistent with a theory of UWW. A necessary pre-condition to coordinated behavior relates to the technological and institutional challenge of developing a scientifically defensible system for making property-specific determinations of risk and exposure that are able to supplant the existing (mis)reliance on FIRMs.

3 Conclusions

UWW highlights that the information asymmetry stemming from a combination of limitations in spatial risk analysis and observational data, irreducible model uncertainty and lending behavior may exacerbate the challenge of accurately responding to climate risks in the mortgage and housing markets. The empirical results provide evidence to suggest that local, concentrated lenders are already taking action to transfer risk and to limit exposure in SLR zones in the Subject Regions. These local lenders are likely taking these actions based on their ability to collect superior, soft information. While these findings provide evidence of a validation of the Retention Hypothesis, it is important to note that these are simply observational results. Future research could focus on identification of the causal effect of soft information in driving these behaviors among concentrated lenders in markets exposed to SLR. In particular, while the empirical analysis described herein effectively isolates variation in lender behavior resulting from SLR exposure and lender concentration, future work could use exogenous variation in market concentration or some exogenous shock to local, soft information as a means of testing this mechanism. One implication is that the disconnect between local concentrated lenders and regional and national lenders may be exacerbating the negative distortions associated with UWW. While a determination and pricing of “true” risk is arguably the long-term goal of many market participants, it is the interim challenges of a lack of data, a lack of regulatory oversight, and strong disincentives for coordinated underwriting behavior that are likely working against the informational transparency necessary to guide risk-adjusted consumer behavior.

In light of these findings and a theory of UWW, the most fundamental question relates to which households will be holding stranded residential assets. The longer the music plays, the more people there are that want to play the game. For many people, they may not even know that they are playing the game. The challenge facing policymakers is what to do with the households who are going to be trapped when the music stops. A policy purview may also extend over regulated lenders whose climate exposed assets challenge their underlying stability. The good news is that local concentrated lenders may very well be ahead of the curve. Addressing the challenges delineated in UWW is arguably an important step to minimizing the economic losses that are likely on the horizon in the face of climate change. A failure to understand these challenges will likely operate to further delay the hard decisions that face coastal households as they buy, sell and finance housing. This article highlights that in a game of musical chairs, it is likely the market that will start and stop the music sooner than people might realize.

Appendix

Table 2 Description of variables in final panel

Variable	Description
Acceptance rate$_{b,c,t}$	Proportion of loan applications accepted by bank *b* in census tract *c* in year t.
Retention rate$_{b,c,t}$	Proportion of accepted loan applications retained by the originating bank b in census tract *c* in year *t*.
Exposure$_c$	Proportion of total area of census tract *c* exposed to inundation from a selected SLR scenario.
Bank controls	
HHI$_{b,t}$	Measure of lender loan portfolio diversification for bank *b* in year *t* based on the Herfindahl-Hirshman index (see Sect. 1.4)
Total assets $_{b,t}$	Total assets of bank *b* in the fourth quarter prior to year *t*
(Liquid assets/assets)$_{b,t}$	Ratio of capital assets to total assets of bank *b* in the fourth quarter prior to year *t*.
(Loans/assets)$_{b,t}$	Ratio of total loans to total assets of bank b in the fourth quarter prior to year *t*.
(Income/assets) $_{b,t}$	Ratio of net income to total assets of bank b in the fourth quarter prior to year *t*.
Borrower controls	
(Loan amount/income)$_{b,c,t}$	Average ratio of loan amount to applicant income for loans accepted by bank *b* in census tract *c* in year *t*.
Sex$_{b,c,t}$	Proportion of accepted loans to female borrowers for bank *b* in census tract *c* in year *t*.
Race$_{b,c,t}$	Proportion of accepted loans to minority borrowers for bank *b* in census tract *c* in year *t*.
Tract controls	
SFHA$_{c,t}$	Proportion of total area of census tract c within the special flood hazard area in year *t*.
Disaster declarations$_{c,t}$	Total number of statewide and county-level federal disaster declaration in census tract *c* in year *t*.
Median HH income$_{c,t}$	Median household income in census tract *c* in year *t*.
Median home value$_{c,t}$	Median home value in census tract *c* in year *t*.
Minority percentage$_{c,t}$	Percentage of minority residents in census tract *c* in year *t*.
Poverty rate$_{c,t}$	Percentage of residents living below the poverty level in census tract *c* in year *t*.

This table provides descriptions of the primary dependent and independent variables of interest used in the analysis

Table 3 Summary statistics for final panel

Variable	Panel 1: all lenders		Panel 2: concentrated lenders		Panel 3: diversified lenders	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Acceptance rate$_{b,c,t}$	0.759	0.284	0.89	0.199	0.699	0.296
Retention rate$_{b,c,t}$	0.454	0.448	0.575	0.47	0.399	0.426
Exposure$_c$	0.158	0.257	0.163	0.26	0.155	0.254
Bank controls						
Log (Total assets $_{b,t}$)	13.739	1.929	13.177	1.285	16.357	2.246
(Liquid assets/assets)$_{b,t}$	0.257	0.134	0.262	0.135	0.23	0.125
(Capital assets/assets)$_{b,t}$	0.109	0.048	0.108	0.051	0.114	0.027
(Loans/assets)$_{b,t}$	0.647	0.14	0.649	0.142	0.636	0.131
(Income/assets)$_{b,t}$	0.005	0.015	0.005	0.016	0.007	0.011
HHI$_{b,t}$	0.644	0.338	0.753	0.264	0.133	0.071
Borrower controls						
(Loan amount/income)$_{b,c,t}$	2.133	2.134	2.023	1.274	2.184	2.43
Sex$_{b,c,t}$	0.284	0.368	0.266	0.385	0.292	0.36
Race$_{b,c,t}$	0.104	0.272	0.114	0.293	0.099	0.262
Tract controls						
SFHA$_{c,t}$	0.325	0.364	0.331	0.368	0.319	0.361
Disaster declarations$_{c,t}$	0.517	0.809	0.505	0.802	0.526	0.814
Median HH income$_{c,t}$	52,525.72	23,268.03	53,659.63	23,841.07	51,648.09	22,776.56
Median home value$_{c,t}$	186,545.08	162,578.27	194,463.84	166,945.58	180,416.02	158,849.56
Minority percentage$_{c,t}$	0.248	0.25	0.248	0.254	0.248	0.247
Poverty rate$_{c,t}$	0.159	0.108	0.156	0.109	0.161	0.107

This table reports summary statistics of the primary dependent and explanatory variables of interest across the entire sample of lenders (panel 1), concentrated lenders (panel 2), and diversified lenders (panel 3). Concentrated lenders are defined as those lenders with a Herfindahl-Hirschman index value of 0.25 or greater, whereas diversified lenders are defined as those lenders with a Herfindahl-Hirschman index value less than 0.25. This cutoff corresponds to the mean HHI value in our sample. *Acceptance Rate*$_{b,c,t}$ and *Retention Rate*$_{b,c,t}$ are the proportion of loan applications accepted and proportion of accepted loans retained by bank *b* in census tract *c* in year *t*, respectively. *Exposure*$_c$ is a binary variable indicating whether census tract *c* is exposed to inundation from a 0.30 m SLR scenario. Bank controls are indexed over bank-year observations. *HHI*$_{b,t}$ is the Herfindahl-Hirschman index (see Sect. 1.4). Borrower controls are indexed over bank-year-tract observations. (*Loan Amount/Income*)$_{b,c,t}$ is the average ratio of loan amount to borrower income. *Sex*$_{b,c,t}$ is the proportion of accepted loan applications from a female borrower. *Race*$_{b,c,t}$ is the proportion of accepted loan applications from a minority borrower. Tract controls are indexed over tract-year observations. *SFHA*$_{c,t}$ is a binary variable indicating whether census tract *c* falls within a Special Flood Hazard Area (SFHA). *Disaster Declarations*$_{c,t}$ is a count of the number of federal disaster declarations—both statewide and county-specific declarations

Table 4 Model Selection

Dependent variable: (1-3) Acceptance rate $_{b,c,t}$ (4-6) Retention rate$_{b,c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
$Exposure_c \times HHI_{b,t}$	− 0.017	− 0.037***	− 0.033***	− 0.032	− 0.096***	− 0.088***
	(0.040)	(0.010)	(0.010)	(0.040)	(0.016)	(0.016)
$Exposure_c$	0.006***	− 0.032	− 0.030	0.043**	− 0.045	− 0.062
	(0.015)	(0.040)	(0.037)	(0.020)	(0.068)	(0.067)
$HHI_{b,t}$	− 0.097***	0.053***	0.045***	0.185**	0.075***	0.065***
	(0.004)	(0.007)	(0.008)	(0.084)	(0.013)	(0.013)
Controls	X	X	X	X	X	X
Tract FE	X	X	X	X	X	X
Bank FE		X	X		X	X
Year FE	X	X		X	X	
County-Year FE			X			X
Observations	109,959	109,959	109,959	109,959	109,959	109,959
Adjusted R^2	0.266	0.421	0.422	0.121	0.412	0.416
Residual std. error	0.243	0.216	0.216	0.420	0.344	0.343
	(df = 109,942)	(df = 105,366)	(df = 104,638)	(df = 109,942)	(df = 105,366)	(df = 104,638)

Results regressing acceptance and retention rate on $Exposure_c \times HHI_{b,t}$ under different model specifications. $Exposure_c$ is a continuous variable measuring the share of a census tract c's total area that is exposed to inundation under SLR of 0.30 m. Three models are estimated and examined for both the acceptance and retention rate dependent variables: pooled ordinary lease squares (OLS) with tract- and year-fixed effects (columns (1) and (4)); pooled OLS with tract-, bank-, and year-fixed effects (columns (2) and (5)); and pooled OLS with tract-, bank-, and county-year-fixed effects (columns (3) and (6)). The pooled OLS specifications with tract-, bank-, and county-year-fixed effects (columns (3) and (6)) are identified as the preferred specifications as they address potential bias due to omitted time-varying spatial autocorrelation. While a two-way fixed effects specification would be ideal, given the lack of temporal variability in the SLR exposure variable, this approach is unavailable. Moreover, the primary assumption of the random effects model is plausibly invalid in this setting: there are certainly omitted variables which are correlated with the observed control variables. Note: p values are calculated using a two-sided t-test and heteroskedasticity-robust standard errors clustered at the census tract-level; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Heteroskedasticity-robust standard errors clustered at the census tract-level are reported in parentheses. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include the same lender, borrower, and census tract controls as those included in the specifications in Table 1

Table 5 Robustness to different SLR scenarios

Dependent variable: Retention rate$_{b,c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
SLR scenario	0.30 m SLR	0.61 m SLR	0.91 m SLR	1.22 m SLR	1.52 m SLR	1.83 m SLR
Exposure$_c$ × HHI$_{b,t}$	− 0.088***	− 0.083***	− 0.084***	− 0.085***	− 0.085***	− 0.081***
	(0.016)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)
Exposure$_c$	− 0.062	− 0.038	− 0.044	− 0.068	− 0.012	0.042
	(0.067)	(0.069)	(0.068)	(0.071)	(0.071)	(0.088)
HHI$_{b,t}$	0.065***	0.065***	0.067***	0.070***	0.073***	0.074***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Controls	X	X	X	X	X	X
Tract FE	X	X	X	X	X	X
Bank FE	X	X	X	X	X	X
County-year FE	X	X	X	X	X	X
Observations	109,959	109,959	109,959	109,959	109,959	109,959
Adjusted R^2	0.416	0.416	0.416	0.416	0.416	0.416
Residual std. error	0.343	0.343	0.343	0.343	0.343	0.343

Results regressing retention rate on $Exposure_c \times HHI_{b,\ t}$ for different SLR scenarios. $Exposure_c$ is a binary variable indicating whether tract c will be inundated under SLR of (1) 0.30 m (1 ft), (2) 0.61 m (2 ft), (3) 0.91 m (3 ft), (4) 1.22 m (4 ft), (5) 1.52 m (5 ft), and (6) 1.83 m (6 ft). Note: p values are calculated using a two-sided t-test and heteroskedasticity-robust standard errors clustered at the census tract-level; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Heteroskedasticity-robust standard errors clustered at the census tract-level are reported in parentheses. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include the same lender, borrower, and census tract controls as those included in the specifications in Table 1

Table 6 Regional analysis of loan retention

Dependent variable: Retention rate$_{b,c,t}$

Region	(1) Southeast/Gulf Coast	(2) Mid-Atlantic	(3) Northeast	(4) West Coast
Exposure$_c$ × HHI $_{b,t}$	− 0.088***	− 0.023	− 0.035	− 0.099***
	(0.016)	(0.022)	(0.029)	(0.040)
Exposure$_c$	− 0.062	0.082	0.044	0.043
	(0.067)	(0.087)	(0.078)	(0.099)
HHI$_{b,t}$	0.065***	− 0.017	0.100***	0.078***
	(0.013)	(0.015)	(0.020)	(0.020)
Controls	X	X	X	X
Tract FE	X	X	X	X
Bank FE	X	X	X	X
County-year FE	X	X	X	X
Observations	109,959	117,651	49,817	48.226
Adjusted R^2	0.416	0.406	0.418	0.484
Residual std. error	0.343 (df = 104,638)	0.348 (df = 112,295)	0.348 (df = 48,121)	0.316 (df = 46,305)
States:	AL, FL, GA, LA MS, NC, SC, TX	DE, MD, NJ NY, PA, VA	CT, MA, ME NH, RI	CA, OR, WA

Results regressing retention rate on $Exposure_c \times HHI_{b,\ t}$ for different regions of the coastal US: (1) Southeast/Gulf Coast, (2) Mid-Atlantic, (3) Northeast, and (4) West Coast. $Exposure_c$ is a continuous variable measuring the share of a census tract c's total area that is exposed to inundation under SLR of 0.30 m. Note: p values are calculated using a two-sided t-test and heteroskedasticity-robust standard errors clustered at the census tract-level; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Heteroskedasticity-robust standard errors clustered at the census tract-level are reported in parentheses. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in each region for the years 2009–2017. Specifications include the same lender, borrower, and census tract controls as those included in the specifications in Table 1

Table 7 Robustness to past flooding exposure

Dependent variable	Acceptance rate$_{b,c,t}$ (1)	Retention rate$_{b,c,t}$ (2)
Exposure$_c$ × HHI $_{b,t}$	− 0.036***	− 0.063***
	(0.012)	(0.018)
Exposure$_c$	− 0.028	− 0.035
	(0.051)	(0.068)
HHI$_{b,t}$	0.067***	0.203***
	(0.013)	(0.022)
Controls	X	X
Tract FE	X	X
Bank FE	X	X
County-year FE	X	X
Observations	63,723	63,723
Adjusted R^2	0.432	0.442
Residual std error (df = 59,259)	0.216	0.333
Sample:	No flooding	No flooding

Results regressing (1) acceptance rate and (2) retention rate on $Exposure_c \times HHI_{b,\,t}$ where the sample is restricted to census tracts which did not experience a flood-related federal disaster declaration in either the current or previous year. $Exposure_c$ is a continuous variable measuring the share of a census tract c's total area that is exposed to inundation under SLR of 0.30 m. Note: p values are calculated using a two-sided t-test and heteroskedasticity-robust standard errors clustered at the census tract-level; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Heteroskedasticity-robust standard errors clustered at the census tract-level are reported in parentheses. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include the same lender, borrower, and census tract controls as those included in the specifications in Table 1

Table 8 Linear probability model of acceptance and retention behavior

Dependent variable	Pr[Acceptance $_{i,c,b,t}$ |X $_{i,c,b,t}$]		Pr[Retention $_{i,c,b,t}$| X $_{i,c,b,t}$]	
	(1)	(2)	(3)	(4)
Exposure $_c$ × HHI$_{b,t}$		− 0.057***		−0.059***
		(0.015)		(0.015)
Exposure$_c$	0.012	0.023	− 0.056	− 0.045
	(0.037)	(0.038)	(0.036)	(0.037)
HHI$_{b,t}$		0.012		0.014
		(0.012)		(0.011)
Controls	X	X	X	X
Tract FE	X	X	X	X
Bank FE	X	X	X	X
County-year FE	X	X	X	X
Observations	497,706	497,133	497,706	497,133
Adjusted R^2	0.193	0.193	0.235	0.235
Residual std. error	0.449 (df = 492,206)	0.449 (df = 491,666)	0.362 (df = 492,206)	0.362 (df = 491,666)

Results from a loan-level linear probability model estimating the probability of loan acceptance and retention conditional on $Exposure_c$ and a set of controls (columns (1) and (3)) and on $Exposure_c \times HHI_{b,\,t}$ and a set of controls (columns (2) and (4)). $Acceptance_{i,\,c,\,b,\,t}$ is a binary variable indicating whether loan application i in census tract c received by bank b in year t is accepted. $Retention_{i,\,c,\,b,\,t}$ is a binary variable indicating whether accepted loan i in census tract c originated by bank b in year t is retained. $Exposure_c$ is a continuous variable measuring the share of a census tract c's total area that is exposed to inundation under SLR of 0.30 m. Note: p values are calculated using a two-sided t-test and heteroskedasticity-robust standard errors clustered at the census tract-level; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Heteroskedasticity-robust standard errors clustered at the census tract-level are reported in parentheses. Observations are at the loan-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include tract-, bank-, and county-by-year fixed effects. Specifications include the same lender and census tract controls as those included in the specifications in Table 1 and include the analogous loan-level borrower controls as those borrower controls included in the specifications in Table 1

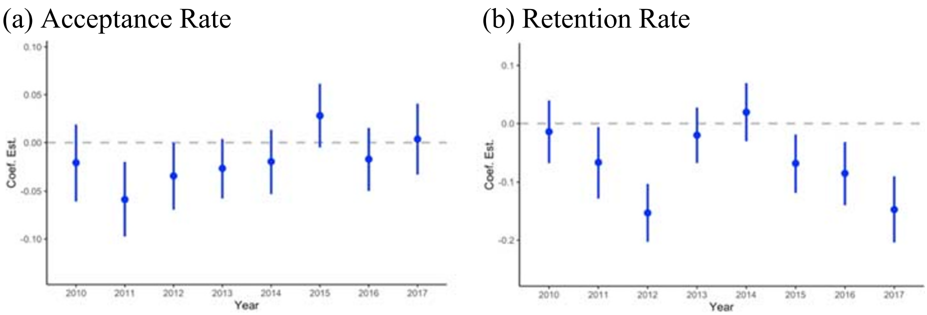


Fig. 5 Loan acceptance and retention behavior over time. Year-by-year coefficient estimates and 95% confidence intervals on $Exposure_c \times HHI_{b,\ t}$ from regressions of **a** acceptance rate and **b** retention rate on the interaction term of interest and a set of controls. Annual interaction term coefficients are obtained by interacting a set of binary variables indicating the year in which a lender-tract-year observation occurs with the main interaction term of interest. $Exposure_c$ is a continuous variable measuring the share of a census tract c's total area that is exposed to inundation under SLR of 0.30 m. Heteroskedasticity-robust standard errors clustered at the census tract-level are used to construct reported confidence intervals. Observations are at the lender-tract-year-level and include all coastal lender-tract-year observations in the Gulf Coast and Southeast states (AL, FL, GA, LA, MS, NC, SC, TX) for the years 2009–2017. Specifications include the same lender, borrower, and census tract controls as those included in the specifications in Table 1 as well as lender-, census tract-, and county-by-year fixed effects

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