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NEGLECTED NO MORE:
HOUSING MARKETS, MORTGAGE LENDING, AND SEA LEVEL RISE

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ABSTRACT

In this paper, we explore dynamic changes in the capitalization of sea level rise (SLR) risk in housing and mortgage markets. Our results suggest a disconnect in coastal Florida real estate: From 2013-2018, home sales volumes in the most-SLR-exposed communities declined 16-20% relative to less-SLR-exposed areas, even as their sale prices grew in lockstep. Between 2018-2020, however, relative prices in these at-risk markets finally declined by roughly 5% from their peak. Lender behavior cannot reconcile these patterns, as we show that both all-cash and mortgage-financed purchases have similarly contracted, with little evidence of increases in loan denial or securitization. We propose a demand-side explanation for our findings where prospective buyers have become more pessimistic about climate change risk than prospective sellers. The lead-lag relationship between transaction volumes and prices in SLR-exposed markets is consistent with dynamics at the peak of prior real estate bubbles.

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1 Introduction

Is a U.S. coastal housing bubble bursting? Under most climate forecasts, the question is not if but when property values will reflect expected sea level rise (SLR). A sufficiently forward-looking house price should account for both current heightened risk of extreme weather events, storm surges, and nuisance flooding, as well as future anticipated inundation. On the other hand, if prices do not fully reflect future risk, then unmitigated climate change could cause further large declines in property value. As 42% of the U.S. population resides in a coastal shoreline county (Fleming et al., 2018), whether property and mortgage markets are already responding to climate risk is of crucial importance as homeowners, mortgage lenders, insurers, and policymakers try to predict how coastal real estate markets will evolve in the coming decades.

In this paper, we study the relationship between SLR exposure and changes in housing and mortgage markets from 2001-2020. We focus on the coastal Florida market, where the Union of Concerned Scientists projects that over one million properties are at risk of chronic inundation due to SLR by 2100 (Dahl et al., 2018).[1] Our analysis compares housing markets more exposed to SLR with similar coastal markets with less SLR exposure.[2] Using data on home transactions (both cash and mortgaged), mortgage applications, and flood insurance all linked to sea level rise forecasts at the census tract level, we examine the mechanisms through which the increasing salience of SLR exposure over this period may have affected housing and mortgage markets.

Figure 1 presents the raw trends in home sales volume (top panel) and prices (bottom panel) between less-SLR-exposed and more-SLR-exposed tracts normalized by their 2001-2012 mean. Prior to 2012, the two markets were on essentially identical volume paths. However, we document a sharp decline in transaction volume since 2013 in housing markets most exposed to SLR. Sales in these high-risk tracts have fallen in absolute terms since 2013, while sales in low-risk coastal tracts rose between 2013-2018. In contrast, relative home prices follow volumes with a lag; From 2013-2016 they increase similarly in both groups, with a relative decline in the high-risk tracts only beginning to emerge in 2018.

This lead-lag relationship between real estate volumes and prices was last seen in these SLR-exposed tracts at the start of the housing bust. While sales volumes began a precipitous decline in 2005, prices along the Florida coast remained relatively stable; It was only in 2008, after a decline in annual sales volumes of over 60% from the market peak, that prices started a similarly steep

[1]Dahl et al. (2018) note that Florida has the highest SLR exposure of any state in the U.S, motivating our decision to make it the focus of analysis.

[2]We define "more" and "less" exposed coastal tracts as those where more than 70% or less than 10% of developed land would be inundated at 6 feet of sea level rise, respectively. Figure 2 shows maps of the coastal communities included in the full sample, 771 tracts in all, that are within 1/2 mile of the coast.

decline (see Figure 1). The pattern of volume and prices during the housing market boom and bust demonstrates that prices are not a sufficient statistic for market demand, and that declines in volume may occur well before falling prices.[3]

The staggered declines in sales volumes and prices in more-SLR-exposed markets relative to their less-exposed coastal neighbors, echoing the last housing market cycle, raise our two primary research questions. First, does the relative sales volume slowdown have a direct connection to SLR exposure, or is it more plausibly explained by differences between the markets that are only indirectly correlated with SLR? Second, what are the mechanisms for and implications of this divergence between transaction volumes and home prices in SLR-exposed markets?

To assess whether the housing market trends in Figure 1 reflect a direct relationship with climate risk, we use matching estimators in a difference-in-difference framework to control for observable differences between markets with different SLR exposure. Using 2001-2012 as a baseline period, we examine whether the post-2013 volume and price trends in more-SLR-exposed markets diverged from observationally similar areas less exposed to SLR. To test the robustness of our results, we compare our findings across synthetic control, nearest neighbor, and generalized propensity score matching estimators. Each approach provides intuitive counterfactuals and additional flexibility for further hypothesis testing. Our empirical approach reflects the uncertainty and community-level effects of SLR risk while allowing us to flexibly control for a large number of observable differences and pre-trends across markets.

All three methods produce similar results consistent with the raw trends shown above: After 2013, more-SLR-exposed markets declined in housing transaction volumes but saw comparatively little change in prices relative to observationally similar less-SLR-exposed markets. By 2018, we estimate that the most-SLR-exposed census tracts in Florida had 16-20% lower transaction volumes from their 2001-2012 annual average relative to a counterfactual where these areas continued to follow a matched sample of markets with low SLR exposure. Our estimates imply that approximately 16,500 fewer home transactions took place from 2013-2018 among the 187 census tracts most exposed to SLR relative to counterfactual trends. On the other hand, we find no evidence of a strong relationship between changing home prices and SLR from 2013-2016. However, starting in 2016, prices in more-SLR-exposed tracts began to relatively decline, reaching 5-10% below trend by 2020.

Next, we consider the potential mechanisms behind these changing market trends. First, we

[3]See DeFusco et al. (2017), who describe and theoretically motivate the lead-lag relationship between volumes and prices over the housing boom and bust. A related literature studies the co-movement between prices and volume across housing market cycles (e.g. Stein (1995), Scheinkman and Xiong (2003), Burnside et al. (2016)). See also Case and Shiller (2003) and Case (2008), who discuss inertia and downward rigidity in house prices.

rule out the hypothesis that lender behavior can explain these patterns: We estimate similarly large relative declines in both cash home purchase and home purchase loan volumes. We also document generally small changes in the rate of loan denial, securitization, or refinancing volume with respect to SLR exposure. These findings suggest that it is homebuyers, not lenders, whose demand in SLR-exposed areas began to wane in 2013.

Given the importance of socioeconomic status and climate change beliefs in shaping how buyers might be responding to growing risk, we explore how our results vary with poverty and climate change perceptions.[4] High-poverty, SLR-exposed communities have had larger relative declines in home sale volumes and prices, suggesting a greater housing market decline than their wealthier counterparts. We also find that the volume and price declines are concentrated in SLR-exposed markets located in counties where Yale Climate Opinion Survey data show more residents are worried about climate change.

Notably, transaction volumes begin to diverge in 2013 as a confluence of events focused public attention on climate risk. These events include Hurricane Sandy striking the East Coast in October 2012, the release of the Intergovernmental Panel on Climate Change (IPCC) AR5 report which increased worst-case SLR projections, and the release of the 2014 National Climate Assessment which documented SLR exposure in the United States (Stocker et al., eds, 2013; Georgakakos et al., 2014). These reports spurred local news coverage of climate risk, with headlines like "Florida Communities Prepare for Rising Seas," and an apparent increase in public interest (Gibson, 2014).[5] Google Trends search intensity for the topic "Sea Level Rise" in Florida shows a positive trend break in search interest in 2013 (see Appendix Figure A-1). Pew Research polling data found that the percentage of Americans worried about climate change, after flattening at 40% from 2010-2013, began steadily increasing in 2013 to 60% by 2020 along with a growing partisan gap between Democrats and Republicans on the topic (Kennedy, 2020). We interpret these indicators as evidence that an upward trend in SLR risk salience began in 2013.

Given these changing beliefs around sea level rise, we view our findings as most consistent with a framework where the increased salience of climate change has led prospective buyers to become more pessimistic about future home prices in SLR-exposed areas than current homeowners. As in models of climate belief heterogeneity in Bakkensen and Barrage (2017) or Baldauf et al. (2020), SLR risk may not be fully capitalized into home prices in areas where "climate optimists" are the marginal home buyers.[6] However, these models cannot match the pattern of declining volume but

[4]For a few examples from a large literature exploring interactions between poverty and climate change, see Bakkensen and Ma (2020), Keenan et al. (2018), and Räsänen et al. (2016).

[5]For examples of local media coverage, see Frago (2014), Reiser (2014), and *Elevation zero: Rising seas in South Florida* (2013).

[6]A related point is made by Bunten and Kahn (2017), who model how risk and amenity preference heterogeneity,

stable relative prices that we observe in the most-SLR-exposed areas until 2018.

Instead, our empirical findings are best characterized by the housing market bubble dynamics of DeFusco et al. (2017), where sellers remain optimistic about their home's value at the peak of a housing boom because they overestimate demand by extrapolating from recent price increases. Thus, sellers set prices higher than most prospective buyers are willing to pay, causing transaction volumes to decline before prices. The divergence between volume and prices can be explained by sellers in SLR-exposed areas systematically underestimating the SLR risk discount demanded by increasingly anxious buyers.

Under this framework, our results would suggest that declining volume (a 'quiet' phase for transactions) will precede falling prices in high SLR exposure markets. Both the less-SLR-exposed and more-SLR-exposed tracts in our sample exhibit a lead-lag relationship between home sale volumes and prices over the housing boom-and-bust. However, it was only the more-SLR-exposed tracts that experienced a decline in sale volume from 2013-2018 even as home prices continued to increase in both markets. After a significant lag, home prices have started to follow sale volumes into a relative decline, matching the empirical predictions from DeFusco et al. (2017).

If heightened SLR risk awareness has made prospective homebuyers more wary of at-risk coastal markets, why have lenders been relatively unresponsive? Our interpretation, informed by conversations with multiple lenders and industry participants, is that lenders are protected by federal programs that actively mis-price climate risk. First, for mortgage loans held on balance sheets, the National Flood Insurance Program (NFIP) offers generous coverage at subsidized prices below actuarial fairness (Kousky et al., 2017). Second, for securitized loans, Fannie Mae, Freddie Mac, and the FHA, which insure over half of the U.S. mortgage market, do not price predictable regional variation in default risk, including climate risk (Hurst et al., 2016). Thus, while lenders may have more sophisticated risk assessment capabilities relative to homebuyers, their incentives are not aligned to internalize SLR risk, and if anything may exploit the mis-pricing of risk at the federal level (Ouazad and Kahn, 2020).

Our results, which are apparent in the raw time-series, are robust to a variety of sample restrictions and econometric assumptions regarding the construction of the counterfactual or choice of matching variables. Between our methodologies, we are able to include extensive controls for current flood risk, pre-2013 tract demographics, and county fixed-effects. By subsetting the estimation sample to coastal markets, we compare the dynamic capitalization of SLR exposure across areas with similar coastal amenities and trends over the housing market boom and bust. Our findings are robust to excluding Miami-Dade county, suggesting that our estimates reflect a broader pattern in

independent of beliefs, can attenuate the relationship between climate risk and house prices in a residential sorting model.

the coastal Florida real estate market. The estimated coefficients are also similar when we exclude SLR-exposed tracts that were struck by a large hurricane over the 2013-2020 period, indicating that future, rather than current, flood risk better explains our findings. Finally, changes in flood insurance premiums over this time period cannot explain these divergent patterns in home sales.

Our findings contribute to a rapidly growing literature on climate change, sea level rise, and housing markets. First, our paper uniquely incorporates dynamic market activity alongside home prices rather than examining prices independent of transaction volume.[7] Several papers have found evidence that SLR risk is at least partially capitalized into house prices, with an emphasis on heterogeneity in capitalization between markets with different beliefs.[8] Both Bernstein et al. (2019) and Baldauf et al. (2020) estimate large SLR price discounts after 2013, and are significantly higher in areas with high climate change "worry" as measured in the Yale Climate Opinion Survey. Similarly, Giglio et al. (2015) construct a "Climate Attention Index" from mentions of flood zones and hurricanes in property listings, and find that high Index values are related to greater SLR discounts. Our results suggest that focusing on prices alone can miss important dimensions along which housing markets respond to SLR. The initial divergence between home sale volumes and prices that we document provides the first empirical evidence that increasing salience of SLR risk can first result in a decline in market liquidity rather than being immediately capitalized into home prices.

A notable difference between our approach and the prior literature is that we measure SLR exposure and outcomes at the census tract rather than property level. Thus, our identification strategy compares differentially exposed coastal communities rather than differentially exposed properties in the same community. We adopt this approach for two primary reasons. First, SLR inundation projections are highly uncertain at the property level due to measurement error and model uncertainty (Gesch, 2009). Second, property-level comparisons may be contaminated by localized spillover effects from SLR impacting nearby roads or infrastructure and increasing flood risk for even nominally non-inundated properties (McAlpine and Porter, 2018). Using a continuous community level measure better reflects the uncertainty and spillover effects of SLR exposure.[9]

A second central contribution is our analysis of lender behavior in response to increasing SLR salience. Our results showing sharp declines in both mortgage volumes and cash purchases suggest that buyers' changing risk perceptions are currently of primary importance for understanding hous-

[7]A related literature studies the capitalization of *current* flood risk into housing markets. See, for instance, Bin and Landry (2013), Bin and Polasky (2004), Eichholtz et al. (2019), Kousky (2010), and Muller and Hopkins (2019).

[8]A notable exception is Murfin and Spiegel (2020), who compare elevation price premiums across areas with different relative rates of SLR due to geological subsidence. They find that no difference in the elevation premium between areas with higher versus lower expected relative SLR, indicating that SLR risk is not capitalized into prices.

[9]See Section 2 for more details on the construction of our SLR exposure measure and Section D on the decision to use tract-level measures.

ing market trends in SLR-exposed coastal Florida. Our results are potentially consistent with the findings of Ouazad and Kahn (2020) that lenders increase mortgage securitization in areas struck by large hurricanes that occurred between 2004 and 2012, insofar as they suggest that lenders may have updated their beliefs about climate risk before 2013. However, the fact that lenders have not meaningfully changed their rate of refinancing, loan denial, or securitization in the most-SLR-exposed areas suggests that either their perception of SLR risk has either not changed since 2013, or else they view their balance sheets as sufficiently insulated from climate risk.

Finally, our empirical approach provides a uniquely broad analysis of housing markets' response to SLR risk by incorporating many data sources and emphasizing tract-level variation. The primary analysis covers 20 years of housing market activity with data from over 1,380,000 home sales and 2,650,000 loan applications in coastal Florida. We also collect extensive and novel data on changing policy-level flood insurance premiums and take-up rates. Data on over 320,000 flood insurance policies are used to calculate census tract-level measures of premium increases that followed the 2012 Biggert-Waters (B-W) legislation that reformed the NFIP.[10] Merging these records at the tract-level with rich controls and SLR projections, we are able to estimate the effects of SLR risk salience on not just house prices, but also transaction volumes and lender behavior, as well as study the effects of changing flood insurance premiums. Combining these sources, we are able to conclude that SLR-exposed housing markets are experiencing demand-driven declines in transaction volume and home prices over a period coinciding with increasing climate risk salience, and that cannot be explained by lender behavior, insurance premiums, or other observable factors correlated with SLR exposure. These steep transaction volume declines in at-risk tracts may serve as a leading indicator of further impending price declines.

2 Data

2.1 Data Sources

Our analysis relies on five main data sources merged at the 2010 census tract level: Sea level rise (SLR) projections from the National Oceanic and Atmospheric Administration (NOAA), home sales prices and characteristics from CoreLogic and Zillow, mortgage lending data from the Home Mortgage Disclosure Act (HMDA) database, and data on National Flood Insurance Program (NFIP) premiums, claims, and take-up rates from the OpenFEMA policy and claims database. In this section, we describe how these data, along with several other complimentary sources, are used to

[10] See also Gibson et al. (2019), who study the effect of the 2012 B-W reforms, flood map changes, and the impact of Hurricane Sandy on property values in New York.

construct the sample and variables used to conduct our analysis.

2.2 Sample Selection

To compare SLR exposure within housing markets located near similar coastal amenities, we subset to 2010 Florida census tracts where the 2000 census population centroid from National Historic GIS database (Manson et al., 2019) is within 1/2 mile of the coast. There are 859 tracts that meet this definition. We further exclude tracts with zero Census population or that we identify as completely non-residential (14 tracts) and tracts with insufficient data in CoreLogic and Zillow observations to reliably estimate home price indices (HPIs) (74 tracts).[11] These restrictions lead to a final estimation sample of 771 tracts. Our estimation period is 2001-2018 for our lending and home sale volume data, and 2001-2020 for home prices.

We collect a number of tract-level controls from the 2010 census and geographic data, including population share foreign born residents, population share nonwhite, household poverty rate, age demographics, and the share of tract area occupied by water.

2.3 Sea Level Rise Exposure (NOAA)

Our data on SLR projections come from the National Oceanic and Atmospheric Administration (NOAA) (Marcy et al., 2011).[12] These NOAA projections use hydrological models and elevation data to map how coastal land areas would be inundated under one foot to ten feet of SLR. We use these projections to create our measures of SLR exposure across coastal housing markets at the census tract level.

We calculate a continuous measure of SLR exposure for each tract as the share of developed land that would be inundated at six feet of SLR. Developed land is defined using the 2001 National Land Cover Database and overlaid with the six-foot SLR layer from the NOAA in ArcGIS (Consortium, 2001). From this continuous measure, we construct a binary indicator of "more-SLR-exposed" versus "less-SLR-exposed" tracts, defined as tracts with SLR exposure greater than 70% (187 tracts) or less than 10% (217 tracts) respectively.[13]

Figure 2 maps the geography of SLR exposure across the estimation tract sample. The top panel shows continuous exposure for all estimation tracts and the bottom panel shows the subset of more-SLR-exposed (red) or less-SLR-exposed (green) tracts. Both maps show that SLR exposure

[11] See Section 2.4 for the details of tract-level HPI construction.

[12] See `https://coast.noaa.gov/slrdata/` for NOAA SLR data. Our version was downloaded in August 2018.

[13] Our rationale for choosing these specific thresholds comes from our Generalized Propensity Score (GPS) results (see Section 3.3), which estimate effects as a function of the continuous SLR exposure measure. The GPS results find small and insignificant effects among the less-SLR-exposed group, and that the largest treatment effects are concentrated in the most-SLR-exposed tracts.

tends to be higher on the state's west coast and along the southern edge to Miami. However, the inset maps focused on Tampa Bay and Miami show substantial SLR risk heterogeneity within small geographic areas. Figure 3 plots the distribution of SLR exposure with cutoffs for the more-SLR-exposed and less-SLR-exposed tracts. The density of SLR exposure is greatest at the upper and lower ends of the exposure distribution.

The NOAA's six-foot measure matches the benchmark for SLR exposure used in other research on climate risk and housing markets (Bernstein et al., 2019; Goldsmith-Pinkham et al., 2019). A recent meta-analysis of climate models suggests that six feet of SLR is towards the upper end of likely SLR outcomes under a high emissions scenario (Garner et al., 2018). This measure captures variation in SLR tail risk, an important consideration given that much of the expected costs of climate change occur under such worst-case scenarios (Weitzman, 2011). By construction, the continuous tract-level measure of SLR exposure at six feet will be correlated with relative exposure at other SLR depths.

As a measure of contemporaneous flood risk, we measure the share of each tract's developed land designated by FEMA as inside a Special Flood Hazard Area (SFHA), commonly referred to as a floodplain. Data for the floodplain extent comes from the National Flood Hazard Layer provided by FEMA.[14]

2.4 Home Price Index and Market Transaction Volume (Corelogic and Zillow)

We use home purchase records from CoreLogic to measure housing transaction volume from 2001-2018 at the census tract level and by cash versus mortgage purchases. CoreLogic gathers publicly available deeds and tax assessor records on the near-universe of Florida home sales. The deed records include information on sale date, sale price, and whether the sale was a cash or mortgage purchase. Sales records from deeds are consistently available across most geographic areas starting in 2001 and are updated through the end of 2018.

We measure residential property transaction volumes as the annual number of condo or single-family home transactions at the tract level. We assign each transaction to a 2010 census tract using parcel coordinates in CoreLogic. We use the CoreLogic cash purchase field to separately tally cash purchases.

To measure home prices from 2001-2020, we use the Zillow Zip Code level home price index (HPI) crosswalked to 2010 census tracts and standardized to equal one for each tract in 2001 (Missouri Census Data Center, 2014; Zillow, 2020). We take the annual home price measure as

[14]Current data from the National Flood Hazard Layer can be downloaded at https://www.fema.gov/flood-maps/tools-resources/flood-map-products/national-flood-hazard-layer. Our version of the data were downloaded in August 2018, with the shapefile available upon request.

the May 31 estimate of each year, with the exception of 2020 where we use the end-of-February measurement to avoid contamination from the potential housing market effects of COVID-19.

A key advantage of the Zillow HPI is that it provides the most up-to-date measurement of home prices available, whereas the CoreLogic data are available through 2018.[15] We note that our 2001-2018 home price results are extremely similar when we estimate our HPI in CoreLogic instead. Details of this estimation are available upon request.[16]

2.5 Loan Volumes, Denial Rates, and Securitization Rates (HMDA)

Loan applications from the HMDA database allow us to measure credit volume and lender behavior through rates of loan denials and securitization. Passed in 1975 to enforce fair lending laws, the Home Mortgage Disclosure Act requires lenders to submit detailed characteristics of home mortgage or refinance loan applications and subsequent denials or approvals, including data on applicant income and demographics, property census tract, and loan amount if approved.

We measure annual purchase loan volume as the number of approved home purchase loans in HMDA. We crosswalk loans reported at the 2000 census geography in the earlier HMDA samples to 2010 census tracts using the Missouri Census Data Center Geocorr application weighting by housing units (Missouri Census Data Center, 2014).[17] We use reported loan amounts to analogously define dollar-weighted purchase loan volume. In addition, we construct similar measures of refinancing volume. To account for lender heterogeneity, we also separately measure lending volumes by "local" and "non-local" lenders. Following a similar procedure used in Gallagher and Hartley (2017), if a lender makes at least 10% of their total lending value (as measured in the full, national HMDA data) within a given county, they are classified as "local" to that county.

We estimate tract-level annual denial and securitization indices controlling for characteristics in the loan-level HMDA data. The denial and securitization indices are estimated from linear probability models where the outcome is whether a loan application was approved our denied or whether an approved loan below the conforming loan limit (CLL) was marked in HMDA as sold for

[15] With no similar publicly available data on transaction volumes available with the same recency, we study transaction volumes through 2018 with our CoreLogic data.

[16] The Zillow HPI is missing from 2001-2014 in 16 out of the 771 coastal census tracts, whereas there are sufficient observations in CoreLogic to estimate annual tract-level HPIs for the entire estimation sample over that period. We use the relationship between the estimated CoreLogic HPI and the Zillow HPI from 2001-2014 in the non-missing tracts, which have a correlation coefficient around 0.75, to predict and fill in the missing 2001-2014 Zillow HPI values in the 16 tracts with partial data. Our results are almost identical excluding these tracts. We only estimate a replacement HPI in CoreLogic if the tract has an average of twenty transactions per year over the replacement period.

[17] We obtain very similar results measuring purchase loan volume with CoreLogic instead of HMDA. Small discrepancies in loan counts between the two datasets can be explained by measurement error in crosswalking the 2000 census tracts in HMDA and possible geocoding errors in CoreLogic. Reassuringly, the 2010 tract-level loan counts in both datasets have a correlation coefficient greater than 0.9 from 2001-2018.

securitization, respectively. Both estimating equations include flexible controls for loan value, loan type, distance from the CLL, and the borrower's reported loan-to-income ratio. Appendix Section C describes the estimation of these indices in more detail.

2.6 Flood Insurance Premium Changes (NFIP)

The National Flood Insurance Program (NFIP) is a government entity that provides over 95% of flood insurance policies in the United States, with \$1.3 trillion in value insured as of December 2019 (Kousky et al., 2018). To address the program's large debts after Hurricane Katrina, Congress passed the Biggert-Waters (BW) Insurance Reform Act of 2012, which required the NFIP to increase premiums on subsidized policies and other fees. As a result, average premiums increased in our estimation sample from \$833 in 2012 to \$1,243 in 2018.

To account for these changing premiums, we turn to the OpenFEMA policy and claims databases. These data describe the universe of NFIP policies issued since 2009 and claims filed since 1978 (OpenFEMA, 2020a,b).[18] The policy data include the insured home's geography at the 2010 census tract level and detailed policy attributes. The claims data describe every claim submitted by policyholders, including the exact date of loss and the total claim paid, also geocoded at the 2010 census tract. We manually code NFIP rating manuals to construct premiums and fees across 234 distinct policy categories from 2012 – 2018 to measure premium changes over time.[19]

Simply averaging annual observed premiums may be a biased measure of true premium increases if policyholders respond to higher rates by insuring less on the intensive or extensive margin. To address this measurement issue, we instrument for the observed change in premiums with the counterfactual change if the tract's composition of policies had remained fixed in 2012. To construct the instrument, we measure the difference in premium for each 2012 policy under the 2018 versus 2012 rates as if it had maintained the same coverage decisions in both years. We take the inverse hyperbolic sine (IHS) of the mean difference in each tract multiplied by the take-up rate as our measure of premium changes.[20] Appendix Section C.2 describes our construction of tract-level premiums and IV estimation in more detail.

[18] FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and or Data.gov.

[19] The NFIP historical rating manuals can be accessed via `https://www.fema.gov/flood-insurance/work-with-nfip/manuals/archive`.

[20] The IHS is defined as $IHS(y) = ln(y + (1 + y^2)^{1/2})$. Like the standard log transformation, the IHS shares many of the same properties that allow coefficients to be approximately interpreted as elasticities. The function has the added benefit of being defined at $y = 0$ (Bellemare and Wichman, 2020).

3 Methodology

3.1 Estimating Changes in SLR Capitalization after 2013

A challenge of studying the effects of climate risk on housing markets is the lack of exogenous variation in exposure. In particular, SLR exposure is correlated with current flood risk, coastal amenities, income, and demographics. As shown in Table 1, more-SLR-exposed tracts are closer to the coast, have higher flood risk, higher socioeconomic status, and more foreign-born residents relative to less-SLR-exposed tracts.

The purpose of our estimation strategy is to test whether the differential 2013-2020 market trends in tracts with higher SLR exposure persist when we compare them to a group of less-SLR-exposed tracts that are more observationally similar in pre-2013 characteristics. To achieve this, our methodology builds on a difference-in-difference style estimator that controls for differences in outcome levels and differential trends by a large number of observable characteristics. Motivated by the apparent trend break in SLR risk awareness in 2013, which aligns with the break in home sales volume among more-SLR-exposed tracts in the raw data, we estimate changes in housing market outcomes from 2013-2020 relative to a 2001-2012 baseline period.[21] In particular, our estimators compare changes in outcome trends after 2013 in tracts with different SLR exposure by normalizing each outcome variable by its tract-level 2001-2012 average. This transformation adjusts for pre-existing differences in outcome levels across tracts. The units of our estimated coefficients are the relative change between more-SLR-exposed and less-SLR-exposed tracts as a percentage of each tract's 2001-2012 mean.[22]

Under a parallel trends assumption, our estimates can be interpreted as relative changes in the capitalization of SLR into more- versus less-exposed housing markets. In other words, our parallel trends assumption is that in the absence of growing SLR salience in coastal Florida, housing markets with different SLR exposure would have continued on similar paths. If any of the observable or unobservable differences between more-SLR-exposed and less-SLR-exposed tracts is correlated with some other housing market shock around 2013, then we would misattribute different trends to increasing SLR risk salience.[23]

[21]For other examples of research that shows 2013 as a turning point in SLR capitalization, see Baldauf et al. (2020) and Bernstein et al. (2019), who find that the capitalization of SLR into home prices increases after 2013, and Goldsmith-Pinkham et al. (2019), who identify an SLR premium in municipal bond yields that only starts to emerge in 2013. See also the discussion of increasing SLR risk salience in Section 1.

[22]This data transformation also facilitates matching in the synthetic control (SC) method (see Section 3.2 for details on the SC method). We obtain similar results when we define the outcomes as log differences in the nearest neighbor and generalized propensity score estimators.

[23]Our decision to subset to coastal census tracts is motivated in part by the differential trends between coastal and non-coastal housing markets from 2001-2013, as shown in Figure A-2. Florida as a whole had distinct home sale volume and price dynamics, particularly over the housing boom and bust, relative to its coastal areas.

To address this threat to the parallel trends assumption, we employ a series of matching estimators to select a subset of less-SLR-exposed tracts that are observationally similar to the more-SLR-exposed tracts on pre-2013 characteristics and outcome trends. We can be more confident that different relative trends between more- and less-exposed tracts which persist in matched samples are a result of increasing climate risk awareness rather than some unrelated shock. Combining our difference-in-difference framework with matching estimators relaxes our parallel trends assumption; tracts with higher SLR exposure would have continued on similar paths as the *matched sample* of less-exposed tracts in the absence of growing SLR risk salience.[24]

We apply three different estimators to establish the robustness of our results to alternative matching techniques and sets of covariates: synthetic control (SC), generalized propensity score (GPS), and nearest neighbor (NN) matching. Consistent results across these different methods increases our confidence in the conditional parallel trends assumption. We describe each of the three matching estimators in detail below.

3.2 Synthetic Control

For each more-SLR-exposed tract, the synthetic control (SC) estimator constructs a weighted average of less-SLR-exposed that match it as closely as possible on both covariates and pre-period trends. Assuming that the procedure can achieve a close fit, SC results are robust to differences in observable and unobservable characteristics with time-varying effects (Abadie, 2019).

We apply the SC estimator as described in Abadie et al. (2010) and extended into settings with multiple treated units as in Cavallo et al. (2013). Let Y_{it}^M denote the outcome for a tract i in year t that is in the more-SLR-exposed treatment group. The SC method aims to estimate the counterfactual $\widehat{Y_{it}^L}$, the value of Y if tract i were less-SLR-exposed. It accomplishes this by constructing a "synthetic" tract i from the set of less-exposed tracts $j = 1, \ldots, J$:

$$\widehat{Y_{it}^L} = \sum_{j=1}^{J} w_j Y_{jt}^L \tag{1}$$

where w_j are a set of weights estimated over the less-SLR-exposed tracts and restricted to be non-negative and sum to one. They are chosen to create a synthetic tract that will most closely resemble the treated tract along a set of covariates which can include pre-period outcomes. The estimated treatment effect is $\widehat{\tau_{it}} = Y_{it}^M - \widehat{Y_{it}^L}$.

[24]Spillover effects are another important threat to identification as there may be a reallocation of economic activity from areas affected by SLR into nearby, less affected areas. This concern motivates our decision to refer to the comparison group as "less-SLR-exposed" rather than "control" or "unexposed." Our estimated effects include the net impact of any such reallocation.

We construct our set of synthetic tracts by matching on the following set of non-outcome covariates: 2010 population shares nonwhite, foreign born, under age 18, age 18-64, and in poverty, inverse hyperbolic sine (IHS) of flood insurance claims per capita 1995-2005, share of tract area made up of water, and distance-to-coast from tract population center. We also match on the outcome variable as a set of consecutive two-year averages over the pre-period (i.e. the outcome means in 2001-2002, 2003-2004,..., 2011-2012).

Unlike the traditional SC setting in Abadie et al. (2010) with one treated group, we have many treated units (187 more-SLR-exposed tracts). We adopt the implementation in Cavallo et al. (2013) and run the SC procedure over each more-SLR-exposed tract to estimate an average treatment effect in each year.

We also follow Cavallo et al. (2013) to conduct inference by constructing placebo synthetic controls for each of the less-SLR-exposed tracts from the other less-SLR-exposed tracts. For each year, we construct 100,000 bootstrap samples from the set of placebo estimates equal to the number of exposed tracts to construct a distribution of average placebo treatment effects. The two-sided p-value of a treatment effect in year t is the probability that one of the average placebo effects has a larger magnitude than the estimated average treatment effect.

In sum, the SC estimator can flexibly control for a large number of observable covariates as described above. As we show later in our results, with 12 years of pre-period data, the SC method succeeds at constructing a set of synthetic tracts quite similar to the more-SLR-exposed tracts over the pre-2013 period and across our set of outcomes.

3.3 Generalized Propensity Score

The generalized propensity score (GPS) approach is an extension of propensity score matching that estimates the effects of continuous treatments. This feature means that, unlike with our other two matching estimators, we do not need to classify tracts into binary more-versus-less exposure groups while discarding any tract with intermediate exposure. Instead, we are able to estimate dose-response functions and see the changing effects of SLR on housing markets across the full distribution of exposure for all the tracts in our sample.

We follow the GPS method as described in Hirano and Imbens (2004). Rather than estimate a single propensity score, the GPS method models a generalized propensity scores at every point along the distribution of SLR exposure conditional on actual exposure and covariates. The generalized propensity scores are then used to estimate a "dose-response" function between SLR exposure and outcomes. Appendix Section D describes GPS estimation in more detail.

The generalized propensity scores are estimated conditional on deciles of distance-to-coast and share of a tract's developed area in the floodplain (also referred to as "Special Flood Hazard Areas," or SFHAs), county fixed-effects, inverse hyperbolic sine (IHS) of flood insurance claims per-capita 1995-2005, 2010 population share under 18 and share 18 to 64, and quadratic terms of 2010 population shares nonwhite and foreign born, and tract area made up of water. We estimate potential outcomes at 10% intervals of SLR exposure from 0% to 100%, and pool together our data over 2010-2012, 2013-2015, and 2016-2018, and 2019-2020 to present our estimates compactly.[25]

The ability to include county fixed-effects in propensity score estimation is another desirable property of the GPS. These fixed-effects control for differential trends driven by county-level unobservable factors and show that our results can be robustly identified from within-county variation in SLR exposure. This within-county analysis is most feasible with the GPS relative to our other estimators because it draws on the full sample of coastal tracts and uses variation in continuous, rather than binary, SLR exposure.

3.4 Nearest Neighbor Matching

Nearest neighbor (NN) matching pairs each more-SLR-exposed tract with a single less-SLR-exposed tract that most closely resembles it over specified covariates. In addition to using this method to assess the robustness of our results under alternative matching techniques, it is computationally efficient and amenable to including additional regressors in post-matching estimation (Rubin and Thomas, 2000), a feature we use to control for changing NFIP premiums (see Section C.2 for details on this estimation).

The NN procedure matches more-exposed tracts to less-exposed tracts by minimizing the following Mahalanobis distance metric over covariates X:

$$(X_i - X_j)'\Sigma(X_i - X_j) \tag{2}$$

Where Σ is the X covariance matrix. The estimated treatment effect is the mean difference in outcomes between the more-SLR-exposed tracts and matched less-SLR-exposed tracts.

The procedure works best when the number of covariates in X is relatively small. We choose a set of six covariates based on reducing the largest differences in the full estimation sample and prioritizing covariates correlated with primary outcomes. We implement nearest neighbor matching with replacement over: 2010 population shares nonwhite, foreign born, and in poverty, inverse hyperbolic sine (IHS) of flood insurance claims per capita 1995-2005, share of tract area made up of water, and tract distance-to-coast from the population center.

[25] We obtain similar GPS results from year-by-year estimates.

As shown in Table A-1, matching significantly improves the covariate balance between more-SLR-exposed and the matched sample of less-SLR-exposed tracts. The procedure reduces, but does not eliminate, statistically significant differences in distance-to-coast, population share foreign born, and flood insurance claims per-capita. Thus, the NN estimates rely on the parallel trends assumption holding under these remaining observable differences.

4 Results

4.1 Descriptive Statistics

Figure 2 presents a map of Florida coastal census tracts used in our analysis. The top panel shows the share of each tract's developed land that would be chronically inundated at six feet of sea level rise (SLR). The figure includes insets for Tampa Bay and the Miami region, documenting substantial variation in exposure within these coastal metro areas. The bottom panel highlights the subsample of tracts that are categories as either "more-SLR-exposed" or "less-SLR-exposed." We define "more-SLR-exposed" as at least 70% of the tract's developed land exposed to six feet of sea level rise, and those with less than 10% of developed land exposed as "less-SLR-exposed" tracts.

Table 1 provides descriptive statistics of our sample of coastal Florida census tracts. Among these tracts, we examine both continuous and discrete measures of exposure. Using all tracts, we employ a continuous measure of the share of the parcels in the tract exposed to six feet of sea level rise (SLR). The average tract in our sample has 40% of its parcels exposed to six feet of SLR, and, as seen in Figure 3, the density of SLR exposure is greatest at the upper and lower ends of the exposure distribution.

In Columns 2 and 3 of Table 1, we present summary statistics for tracts assigned by our discrete measure to "more-SLR-exposed" and "less-SLR-exposed" coastal tracts (as defined above). These two groups of tracts are substantially different across a range of geographic and demographic attributes. The high exposure tracts are much more likely to be located in a FEMA floodplain, have a larger water area in the tract boundary, and have higher average house transaction prices. These differences motivate our variety of approaches to account for observable differences between the two areas while exploring the effect of sea level rise on the housing and mortgage markets of these tracts.

Figure 1 presents the time series of aggregate housing transactions and mean house price index for our sample of less-SLR-exposed (top panel) and more-SLR-exposed (bottom panel) tracts. As discussed in Section 1, there is a lead-lag relationship between transaction volumes and prices in both the more- and less-exposed tracts over the housing boom and bust. However, while the less exposed tracts see a steady increase in volumes and prices after the 2008 recession, the recovery in more-exposed tracts is interrupted in 2013 with a sudden decline in transaction volumes. In these at-risk tracts, the lead-lag relationship of the boom and bust repeats: While home prices continue to rise until 2016, they begin to level off and see a large relative decline by 2020.[26]

Figure 4 shows that these relationships between SLR, housing transactions, and house prices hold across the continuous distribution of SLR exposure.[27] Comparing changes in 2018 relative to the pre-2013 mean, panel (a) shows a pronounced decline in relative home sales volume for tracts with greater than 60% exposure to six feet of SLR. On the other hand, there is essentially no relationship between SLR and relative changes in 2018 home sale prices as shown in panel (b). However, by 2020, a significant negative relationship between SLR and relative prices emerges in panel (c).

4.2 Synthetic Control Results

Can the lead-lag relationship between home sale volumes and prices across SLR-exposed areas be explained by differences in observable (and potentially unobservable) characteristics or pre-trends? We test whether the divergence between sales volumes and prices in markets with high SLR exposure in the raw data is robust using the synthetic control (SC) estimator. Figure 5 shows the time series of home sales and HPI for the more-SLR-exposed tracts (labeled with squares) and the synthetically constructed control sample (labeled with circles). The home sales volume series (panel (a)) follow each other closely prior to 2012, the period over which we balance pre-event covariates. After 2012, however, the two series diverge sharply, with many fewer home sales in high exposure areas. By 2018, there are relatively 20% fewer home sales being made in more-SLR-exposed tracts than in the synthetic control sample relative to the 2001-2012 mean.

In contrast, the house price series (shown in panel (b)) follows a very different pattern, with high exposure tracts' relative prices rising until 2016, peaking at roughly 2% higher prices, and then falling to a level 5% below that of the synthetic control sample's prices by 2020. Note that prices followed similar paths prior to 2012, highlighting the ability of the synthetic control method to balance pre-trends for house prices despite the differences in many observable attributes of these coastal tracts.

Thus, even when the set of less-SLR-exposed tracts are chosen to match the more-SLR-exposed

[26] Figure A-3 plots volumes and prices side-by-side in the more- and less-exposed samples to emphasize their lead-lag dynamics.

[27] Figure A-4 presents a map of the change in home sales volume (panel (a)) and HPI (panel (b)) between 2011-2012 and 2017-2018.

tracts on relevant covariates and outcomes prior to 2013, we see the same divergence between house prices and sale volume emerge in high exposure tracts as shown in the raw data from Figure 1. Cumulating the differences between the exposed and synthetic series and multiplying by the most-SLR-exposed tracts' 2001-2012 mean home sale volume, we estimate that between 2013 and 2018, there were approximately 16,500 fewer home transactions in more-SLR-exposed tracts relative to pre-2013 predicted trends.

Panels (c) and (d) of Figure 5 present the estimated treatment effects (the difference between the two series in panels (a) and (b), respectively) along with the two-sided 95% interval of placebo treatment effects indicated by the shaded gray region.[28] Treatment effects falling outside of the shaded gray region are statistically significant at $\alpha = 0.05$.[29]

The estimated coefficients for housing volume are negative and statistically significant in five out of the six years between 2013-2018, and generally increasing in magnitude over time from a decline of 4% in 2013 to 19% in 2018. The estimated coefficients for HPI are positive and significant from 2012-2016, but then fall into the range of the placebo results in 2017 before becoming a significantly negative 5% relative decline from 2018-2020. Notably, relative to the volume declines which were already significant in 2013, there was not a statistically significant relative decline in prices until 2018.

4.2.1 Sea Level Rise and Mortgage Lending

Does the decline in transaction volume reflect a change in credit supply on the part of lenders, who may recognize the growing risk of a long-term 30-year obligation in SLR exposed markets? Or do these patterns instead represent a negative shift in credit demand due to declining housing demand in exposed areas? In Figure 6, we explore the dynamics of home purchase lending volumes alongside cash purchase volumes. If the patterns we document were a consequence of lenders tightening their credit standards, then we would expect a larger decline in home purchase lending volumes than cash purchase volumes.

Both panels (a) and (b) of Figure 6 show a sharp divergence between more-SLR-exposed tracts and control tracts after 2012, with declines of roughly 20% by 2018 in both mortgage and cash trans-

[28] The placebo treatment effects are calculated first by estimating a placebo synthetic control for each of the less-SLR-exposed tract from the sample of other less-SLR-exposed tracts. Next, we draw 100,000 bootstrap samples of size 187 (i.e. the number of more-SLR-exposed tracts) from the less-SLR-exposed tracts and calculate the placebo treatment effect for each sample as the mean difference between the bootstrap sample and their placebo synthetic controls. This procedure provides a distribution of placebo treatment effects from which we can calculate p-values as the probability of observing a placebo effect greater in magnitude than the estimated treatment effect.

[29] The first column of Table 2 presents the 2018 coefficients from the SC estimator across housing market outcomes with p-values in parentheses.

actions that are consistent with the overall volume results presented above in Figure 5.[30] Thus, the explanation for the decline in transaction volume cannot be solely based on lender behavior. While previous research has focused on lender decision-making, by examining cash purchase transactions where lenders are not involved and nonetheless observing a pronounced contraction in home buying activity, we are able to provide new evidence that the decline in sales volume reflects primarily a housing demand rather than credit supply response.

In Figure 7, we further examine additional indicators of lender behavior. If lenders are differentially tightening their standards in these tracts, we would expect to see a decline in refinancing volume and an increase in loan denials. In panel (a), we observe essentially no change in refinancing activity. Panel (b) of Figure 7 shows that more loan applications are being denied in more-SLR-exposed tracts, with coefficients consistently 4-7% more loan denials (off a base of 25% in the pre-2013 period), but not statistically significant in all years. Thus, we conclude that while lenders may be making small adjustments on the margin, changing loan denials cannot explain a 20% decline in purchase loan volume in more-SLR-exposed tracts.

Although lenders have not meaningfully tightened credit in areas at risk of sea level rise, it is possible they have increased securitization to transfer their climate risk to the housing GSEs. However, Figure 8 shows little support for this hypothesis. The securitization rates of more-SLR-exposed tracts mostly follow their synthetic counterparts (albeit noisily), with the 2018 coefficient close to zero.

While the above patterns suggest a muted lender reaction to SLR risk, it is possible that local lenders with concentrated portfolios may be more exposed and thus more responsive. To test if behavior differs across local and non-local lenders we define a lender within a county for a given year as "local" if it originates at least 10% of its total annual lending in that county. We explore purchase loan volumes across these two types of lenders in Figure 9.

The local lender series (panel (a)) is quite noisy, but by 2018 shows a substantial decline in lending volume. In panel (b), we document that non-local lenders have steadily been differentially decreasing purchase loan volumes since 2012 in more-SLR-exposed markets, reaching roughly a 15% decline by 2018. Both series appear to show a decline, but non-local lenders' decline was earlier and more consistently statistically significant, whereas local lending patterns are considerably noisier. Thus, these results do not support the view that local lenders have differentially responded to climate risk due to superior local information or greater concentrated risk exposure.[31]

[30] Our results also show consistent declines in the aggregate dollar value of purchase loans.

[31] The number of loans originated and applied for with local lenders is too sparse at the tract level to reliably estimate their securitization or denial indices. However, we obtain similar null results for securitization and denials using only non-local lenders. We also find no evidence of changes in volume of refinance loans for local or non-local lenders.

In sum, our results suggest that changing SLR risk salience has not dramatically affected credit supply in coastal Florida. One plausible mechanism behind these results is that lenders were already incorporating climate risk into their practices prior to 2013, as suggested by Ouazad and Kahn (2020) who find that lenders increased mortgage securitization in high-risk areas following large hurricanes from 2004-2012.

Furthermore, federal housing policies, by insulating mortgage balance sheets from disaster risk, could also make lenders less responsive to climate risk. The National Flood Insurance Program (NFIP) offers flood insurance at premiums generally below actuarial rates for the highest risk properties (Kousky et al., 2017). For instance, after Hurricane Katrina, the most flooded parts of New Orleans saw no significant change in loan delinquency, consistent with flood insurance payments protecting lenders from mortgage default (Gallagher and Hartley, 2017). Lenders can also securitize loans with the housing GSEs, Fannie Mae or Freddie Mac, at prices that are completely independent of current or future flood risk. Although the NFIP and mortgage securitization leave taxpayers exposed to climate risk, these programs insulate lenders' balance sheets.

4.3 Examining the Distribution of SLR Exposure

While our synthetic control results highlight different housing market trends between more-SLR-exposed and less-SLR-exposed tracts, they are limited to studying SLR exposure as a binary variable. In reality, we observe a continuous distribution of SLR exposure across our sample in coastal Florida. To study how intermediate levels of SLR risk affect housing markets, we turn to a generalized propensity score (GPS) estimator.

Figure 10 presents results for home sales and the home price index across the sea level rise distribution, with the x-axis representing sea level rise exposure. "0" indicates no exposure, while "1" means the entire tract (100% of developed area) would be inundated at six feet of sea level rise. Panel (a) shows the differential change in home sales by 2013-2015 from the 2001-2012 period relative to tracts with no SLR exposure. There is evidence of a modest and statistically insignificant decline in transaction volume of 5% for tracts with at least 80% SLR exposure. Tracts at lower levels of exposure show no relative difference in volume relative to tracts that are completely unexposed. However, by the 2016-2018 period shown in panel (c), there is a clear downward trend in home sales for tracts with greater than 50% exposure. For tracts that would be fully inundated at six feet of sea level rise, we estimate a relative decline of roughly 20% of the pre-2013 mean in home sales over the 2016-2018 period relative to tracts with no exposure, very similar to our estimated effect for the more-SLR-exposed group using synthetic control methods.

Panel (b) of the figure shows the relative change in home prices in 2013-2015 from the 2001-

2012 period. Similar to our results in Figure 5, we estimate a statistically significant relative increase in prices of around 5-10% for tracts with high SLR exposure over this period. In panel (d), we see that this relative increase has completely disappeared by the 2016-2018 period and that relative price levels have returned to their 2001-2012 baseline or lower among SLR-exposed tracts. Panel (e) shows that, by 2020, tracts with high SLR exposure saw relative home price declines of approximately 10% of their pre-2013 mean prices.

The main advantage of the GPS method is to show changing housing market dynamics across the sea level rise distribution. We observe declining home sales only in tracts with at least 50% sea level rise exposure, with the largest declines in the same tracts from the more-SLR-exposed treatment group used in the synthetic control method. Tracts in the less-SLR-exposed group have uniformly small estimated relative changes.

Our GPS results across other outcomes are summarized in column 2 of Table 2, which shows the point estimates for fully exposed tracts in 2016-2018 for volumes and prices as well as additional outcomes with bootstrapped standard errors in parentheses, and the 2019-2020 price estimates. These results show that the declining pattern in 2018 home sales volume is also present in home purchase loans and cash sales, with relative declines in both around 20% of the pre-2013 mean. We do estimate a statistically significant decline of 6% in refinancing volume and a 9% increase in denials, but no significant change in securitization. In sum, our supplemental findings using the GPS method estimate changing SLR capitalization across the entire distribution of SLR exposure and are consistent with our synthetic control estimates. Seeing that the largest effects are concentrated in the most-SLR-exposed areas, these results support the use of our "high vs. low" binary measure for capturing the relevant treatment effect.

4.4 Nearest Neighbor Matching with Flood Insurance Premium Controls

We turn to a third and final estimator applying nearest neighbor matching to assess the robustness of our results. For each of our more-SLR-exposed tracts, the estimator chooses a single less-SLR-exposed tract that most closely resembles the exposed tract along 2010 population shares nonwhite, foreign born, and in poverty, 1995-2005 flood insurance claims per capita, share of tract area made up of water, and tract distance-to-coast from the population center, under a Mahalanobis distance metric. This set of less-SLR-exposed tracts chosen with replacement forms the comparison group for the more-SLR-exposed tracts.

To first assess whether our synthetic control results are robust under this alternative matching method, we re-examine the home sale volume and home price trends in Figure 11. The figure plots annual treatment coefficients from 2010-2020 with 95% confidence intervals calculated from bootstrapped standard errors indicated by the dashed red lines. Panel (a) shows the home sale volume results, where we see flat trends prior to 2013 but a growing decline starting in 2013 that culminates in a statistically significant relative decline of around 19% of the pre-2013 mean in 2018 for the most-SLR-exposed tracts.

Panel (b) shows the results for relative home prices, which are increasing in the highly exposed tracts through 2016. However, this increasing trend reverses, and by 2020 becomes a statistically significant decline of around 5% of the pre-2013 mean. Together, the figure tells a similar story as the synthetic control and GPS results: A sharp volume decline in tracts with high SLR exposure starting in 2013, but a price decline that only emerges with a significant lag.

The third column of Table 2 summarizes our nearest neighbor matching results over other outcome variables, showing the estimated 2018 coefficients with bootstrapped standard errors in parentheses as well as results for 2020 prices. Once again, we see declines around 20% in both home purchase loans and cash purchases. There is no evidence of an increase in loan denials or securitization, although there is a statistically significant decline of 6% in refinance volume.

While it is reassuring that the nearest neighbor approach finds similar estimates as our synthetic control and GPS methods, the main advantage of this methodology is that we can easily include additional regressors in our estimates after matching. This is particularly useful to control for the effects of flood insurance premium changes induced by 2012 Biggert-Waters (B-W) reforms. As described in Table 1, more-SLR-exposed tracts have significantly more properties in the floodplain than their less-SLR-exposed counterparts. Given that the B-W reforms primarily targeted increases on subsidized properties in these high-risk areas, increasing premiums are a plausible alternative explanation for the observed market trends.

As described in Section 2, we measure premium changes as the inverse hyperbolic sine (IHS) of the difference in per-capita premiums at the tract level for policies active in 2012 versus 2018. A concern is that is that this measure may understate the true magnitude of premium increases if changes in the rates induce a change in flood insurance take-up on the extensive margin or coverage choices on the intensive margin. To address this concern, we construct an instrument for premium changes by calculating the counterfactual change if each tract's policy cohort and take-up rate had remain fixed from 2012 to 2018.[32]

Table 3 shows the results from including the premium change variable in regressions over the matched sample across our main outcomes in 2018 as well as home prices in 2020. Including the controls do not significantly attenuate any of our estimates.[33]

[32] See Section C.2 for more details on the premium change variable construction and estimation.

[33] While useful as controls, we caution against any causal interpretation of the premium change coefficients themselves without a thorough examination of housing market pre-trends for areas differentially affected by the B-W

4.5 Heterogeneity of Capitalization by Climate Opinions

Our results point to a demand-side explanation for the drop in home sales volume in more-SLR-exposed markets. In this section, we examine whether beliefs regarding climate change are associated with the changes in sales volumes and prices documented above. Our beliefs data come from the 2018 Yale Climate Opinions Survey. The Yale Climate Opinions Survey uses polling data combined with statistical models to estimate climate change beliefs at the county level (Howe et al., 2015).[34]

Panel (a) of Figure 12 presents the relationship between the 2018 nearest neighbor matching estimated treatment effect for changes in home purchase volume and the share of the more-SLR-exposed tract's county that says they are worried about climate change in 2018.[35] There is a strong and statistically significant negative relationship: More-SLR-exposed tracts in counties with a larger share of residents worried about climate change have experienced much weaker growth in home sales through 2018. The differences are dramatic, with an additional ten percent of the county worried about climate change associated with an approximately 11 percentage point greater relative decrease in home sales volume.

Panel (b) shows the relationship between the 2018 change in house prices and the share that are worried about climate change. Here we observe only a small and statistically insignificant negative relationship between the relative home price changes and worry about climate change. However, panel (c) shows that by 2020, there is a strong and statistically significant relationship between price declines and the climate worry measure. An additional ten percent of worried residents implies a 7 percentage point greater relative home price decline. Indeed, in the counties with the lowest share of worried residents, there is little evidence of relative price declines.

In sum, the places with the largest transaction volume and price declines since 2013 are in counties where residents are most worried about climate change. Together with the evidence on changing SLR risk salience in Florida since 2013, this pattern suggests that the climate change beliefs among prospective buyers may be affecting how and when SLR risk is capitalized into housing markets. A consistent explanation for these findings is that counties with the most worried potential buyers first saw a decline in transaction volume for SLR-exposed properties as optimistic sellers held out for higher prices. Only more recently have prices finally started to decline with falling demand. On the other hand, counties with fewer worried residents have seen neither volume

reforms and subsequent rate changes.

[34] A partial list of recent studies using the Yale Climate Opinions Survey to estimate the heterogeneity of SLR capitalization include Baldauf et al. (2020), Barrage and Furst (2019), Bernstein et al. (2019), and Goldsmith-Pinkham et al. (2019).

[35] In particular, the x-axis is defined as the estimated percent of adults in the county who would respond "somewhat worried" or "very worried" to the question, "How worried are you about global warming?"

nor price declines in the most-SLR-exposed markets. Thus, our results point to an important role for beliefs as driving market pessimism and housing market outcomes.

4.6 Heterogeneity of Capitalization by Poverty

Not all coastal communities in Florida are wealthy; in fact, poverty rates in our sample of census tracts range from near zero to over 50%. We next explore whether there is any evidence of heterogeneous treatment effects by tract-level poverty. Given that lower-income households may find it more difficult to adjust to climate risks, this is an especially important margin of heterogeneity (Keenan et al., 2018).

As a reduced form assessment of the evidence for such heterogeneity, we plot the difference for 2018 home sales volume and prices and 2020 prices between each more-SLR-exposed tract and its matched less-SLR-exposed tract from the nearest neighbor matching against the more-SLR-exposed tract's 2010 share of households in poverty. Figure A-5 shows these plots as binscatters, where each point represents the mean treatment effect within one of twenty quantiles of population poverty share.

The figure shows that more-SLR-exposed tracts with higher poverty experienced greater home sales volume and prices declines relative to matched less-SLR-exposed tracts. Although the linear relationship between poverty and the relative 2018 sales volume decline is statistically insignificant, both the 2018 and 2020 relative home price declines have a stronger and statistically significant negative relationship with tract-level poverty. Panel (c) suggests that by 2020, more-SLR-exposed tracts with a 10% high poverty rate experienced 7% greater relative price declines.

Taken together, these results suggest that higher poverty communities have seen a faster and larger change in the capitalization of SLR risk since 2013. While difficult to isolate specific mechanisms behind this relationship in our context, one plausible explanation is that these communities may have less resources for adaptation, or sellers may have less flexibility regarding marking their assets to market.

4.7 Other Housing Market Outcomes and Additional Robustness

We use our nearest neighbor matching estimator to explore a wider range of housing market outcomes in more-SLR-exposed tracts relative to the less-SLR-exposed matched sample.[36] In each of the results below, we summarize the 2018 coefficients, which give the relative change in more-SLR-exposed tracts as a percentage of their pre-2013 mean.

[36] The flexible matching and low computational burden of our nearest neighbor method made it the most feasible for analyzing additional outcomes. As noted earlier, we see similar results in our main outcomes across all three methods.

We first examine subcategories of credit market responses to heightened SLR salience. In Table A-2, we explore denials and securitization separately for purchase and refinance loans, where we find no statistically significant changes. Table A-3 analyzes changes in loan volume separately by local versus non-local lenders, purchase loans versus refinances, and loan volume versus value. The results are, in total, similar to our previous findings that use more aggregate measures. There is little evidence of consistent changes in refinancing volumes by local or non-local lenders, but there are consistent declines in purchase loan volumes across local and non-local lenders.

We next examine the sensitivity of our synthetic control results to match quality. The consistency and robustness of the synthetic control estimator is conditional on match quality over pre-period outcomes. In addition, if placebo tracts have poor match quality relative to the treated unit, this can make inference too conservative (Abadie, 2019).

To address these concerns, we re-estimate our transaction volume and home price outcomes, removing any more-SLR-exposed with a 2001-2012 root mean square error (RMSE) above the 90th percentile for calculating treatment effects as well as any less-SLR-exposed tract with a RMSE greater than twice the more-SLR-exposed trimmed mean when calculating the distribution of placebo effects.[37] Figure A-6 shows synthetic control estimates for transaction volume and home prices estimated with the trimmed samples described above. The robustness check shows similar results as in the full sample, suggesting that match quality is not a large source of bias.[38]

Other research has shown that large hurricanes can affect housing markets and lender behavior in impacted areas (Zivin et al., 2020; Ouazad and Kahn, 2020). Over the 2013-2020 period, Florida was struck by major hurricanes in 2017 and 2018. To assess whether our estimates are driven by these storms, we recalculated our point estimates across our three estimators over our main outcomes excluding the 54 more-SLR-exposed tracts that were flooded by at least one of these storms, finding that the sample restriction made little difference to our point estimates.[39]

Finally, given that the metropolitan area of Miami is a poster child for the growing threat of climate change to cities, it is reasonable to wonder how much of these results are driven by Miami-Dade county. To explore this question, we re-estimate the results for home sale volumes and prices across the three methods excluding all census tracts in Miami-Dade county. This removes a

[37]Note that the set of trimmed tracts is specific to each outcome. We remove 8 out of the 217 placebo estimates for the volume estimates, and 4 from home prices. Appendix Table A-4 shows the RMSE between the set of more-SLR-exposed and their synthetic counterparts from 2001-2012.

[38]We obtain trimmed results consistent with the full sample estimates for our other main housing market outcomes.

[39]These results are available upon request. We define a tract as "flooded" by a hurricane if its land extent is within or intersected by the 64kt wind radii of the storm and there is at least one flood insurance claim in the tract with the loss dated to the storm's period filed with the National Flood Insurance Program. The 2017 (Hurricane Irma) and 2018 (Hurricane Michael) impact date ranges and paths are pulled from the NOAA Final Best Tracks data (NOAA, 2017-2018).

total of 91 tracts from the estimation sample, 13 of which were less-SLR-exposed and 50 of which are more-SLR-exposed. Appendix Figures A-7, A-8, and A-9 show these results for the synthetic control, GPS, and nearest neighbor matching methods respectively. We find similar results as in our estimation over the full sample.

5 Conclusion

In this paper, we provide new evidence that the "most liquid" parts of Florida (in that they are most likely to be underwater by 2100) have increasingly illiquid housing markets. Since 2013, home transaction volumes have fallen in relative terms by 16-20% in the most-SLR-exposed coastal census tracts. This stark time-series pattern of divergence in sales volumes between more and less-exposed areas is robust to a wide variety of controls, methods, and samples. Notably, this pattern holds for both home mortgage volumes and cash purchases, suggesting that demand for at-risk coastal properties has fallen sharply since 2013, above and beyond any adjustments currently being made by lenders, insurers, or the GSEs.

In contrast, home prices in both more and less-exposed markets rose from 2013-2015, and only in recent years 2018-2020 have prices begun to (relatively) fall. This pattern of declining sales volumes but relatively unresponsive prices points to a phenomenon most recently observed during the housing boom and bust of the 2000s when a strong lead-lag pattern was observed in many markets: Falling sales volumes preceded sharp declines in prices. The most natural explanation for this pattern is the shrinking and eventual departure of "market optimists" from the market. For supply to equal demand, "optimistic" sellers and "pessimistic" buyers would need to agree on how the threat of sea level rise affects the present value of at-risk homes. Agreement might come with continuing changes in beliefs, or else the realization of climate risk in the coming decades (Bakkensen and Barrage, 2017).

Why might some housing market actors have been slower than others to respond to increasingly severe SLR projections? One possibility is that partisan division on climate change has led to durable belief heterogeneity, a premise supported by polling data (Kennedy, 2020). Another explanation is that the behavioral forces of myopia and optimism (among other potential biases) may be causing homeowners in SLR-exposed areas to make irrational assessments of their risk (Meyer and Kunreuther, 2017). In addition, nominal loss aversion relative to their purchase price could also make homeowners slow to accept lower market prices (Genesove and Mayer, 2001). Finally, those living in the places most exposed to SLR might already be the most optimistic about present (and future) flood risk due to housing market sorting (Bakkensen and Barrage, 2017). Documenting the mechanisms and connections between SLR belief heterogeneity and housing market behavior remains a promising direction for future research.

While our empirical approach is not predictive of the future, sharp declines in transaction volume could anticipate further declines in price. The ultimate consequences of perceptions of sea level rise on coastal property values, and the associated mortgages attached to those properties, depends crucially on whether there are buyers willing to hold these properties and at what price. At some later date, in the absence of substantial mitigation and infrastructure efforts, many Florida properties will be underwater. Until then, homeowners and lenders face greater risk of extreme weather events, storm surges, and nuisance flooding. Our results suggest that fewer buyers are willing to bear these risks at current market prices, leading to a sharp fall in transaction volumes.

Finally, it is worth reiterating that these housing market responses to climate risk are not due to the pricing of National Flood Insurance Program (NFIP) premiums or federal mortgage programs; Instead, these responses are *in spite of* federal policies that actively mis-price predictable climate risk. This mis-pricing tends to subsidize coastal property markets at the expense of non-coastal communities, distorting investment into more at-risk regions. Whether these programs will continue to differentially support coastal housing investment in the face of rising costs, and how these markets will respond to changes in these programs that may more accurately acknowledge the current and future costs of climate change, remain crucial topics for future research.

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Tables

	All	More-SLR-Exposed	Less-SLR-Exposed
Share SLR-Exposed	.396	.884	.033
	(.338)	(.091)	(.03)
2001-2012 Mean Annual Sale Volume	122	136	106
	(100)	(117)	(85)
2001-2012 Mean Sale Price	329000	422650	209046
	(289853)	(277285)	(134203)
Population	3461	2921	3838
	(1463)	(1542)	(1270)
Share Nonwhite	.132	.076	.191
	(.146)	(.065)	(.167)
Share Poverty	.129	.107	.155
	(.087)	(.064)	(.098)
Share Foreign Born	.156	.226	.139
	(.148)	(.193)	(.122)
Distance-to-Coast (Meters)	664	427	964
	(458)	(405)	(412)
Share Area Water	.333	.446	.172
	(.259)	(.266)	(.204)
Share in Floodplain	.473	.913	.111
	(.368)	(.192)	(.137)
Observations	771	187	217

Table 1: Tract-level summary statistics of variable means with standard deviation in parentheses. Sample divided into all coastal tracts, more-SLR-exposed tracts (share SLR-exposed > 0.7), and less-SLR-exposed tracts (share SLR-exposed < 0.1).

Outcome	Synthetic Control (P-value)	GPS (SE)	Nearest Neighbor (SE)
Home Sale Volume	-.191***	-.216**	-.187***
	(.000)	(.070)	(.048)
Home Price Index (2018)	-.036***	-0.005	-0.020
	(.000)	(0.023)	(0.017)
Home Price Index (2020)	-.066***	-0.138***	-.067***
	(.000)	(.033)	(.018)
Home Purchase Loan Volume	-.147***	-.262**	-.215***
	(.000)	(.073)	(.055)
Home Cash Sale Volume	-.246***	-.176	-.197**
	(.000)	(.115)	(.075)
Refinance Volume	-.004	-.060**	-.059**
	(.993)	(.023)	(.016)
Denial Index	.033	.091**	-.015
	(.649)	(.040)	(.034)
Securitization Index	-.012	-.035	.031
	(.478)	(.037)	(.022)

Table 2: Coefficients for the relative change by 2018 in SLR-exposed tracts over less-SLR-exposed tracts across the primary outcomes, as well as the relative change for 2020 home prices, for each of the three empirical methodologies. Bootstrap standard errors are in parentheses for the propensity score matching and GPS columns, and p-values in parenthesis for the synthetic control column. The GPS column estimates are from the pooled 2016-2018 period. Outcome variables are standardized by their tract-level 2001-2012 mean.

	Sales	HPI (2020)	Purch Loans	Cash Sales	Refis	Denials	Securitization
SLR-Exposed	-.287***	-.090***	-.382***	-.242**	-.066**	-.025	.091**
	(.071)	(.022)	(.074)	(.093)	(.021)	(.045)	(.035)
Premium Change	.049**	.011	.083***	.022	.003	.005	-.030**
	(.020)	(.008)	(.020)	(.027)	(.007)	(.014)	(.013)

Table 3: Results from nearest neighbor matching showing the relative change in main outcomes for 2018 in SLR-exposed markets relative to matched less-SLR-exposed markets. Includes control for inverse hyperbolic sine of per capita increase in average NFIP premiums between 2013-2018. Outcome variables are measured in 2018 relative to 2001-2012 tract-level mean, except for HPI which is measured in 2020. Bootstrapped standard errors in parentheses.

Figures

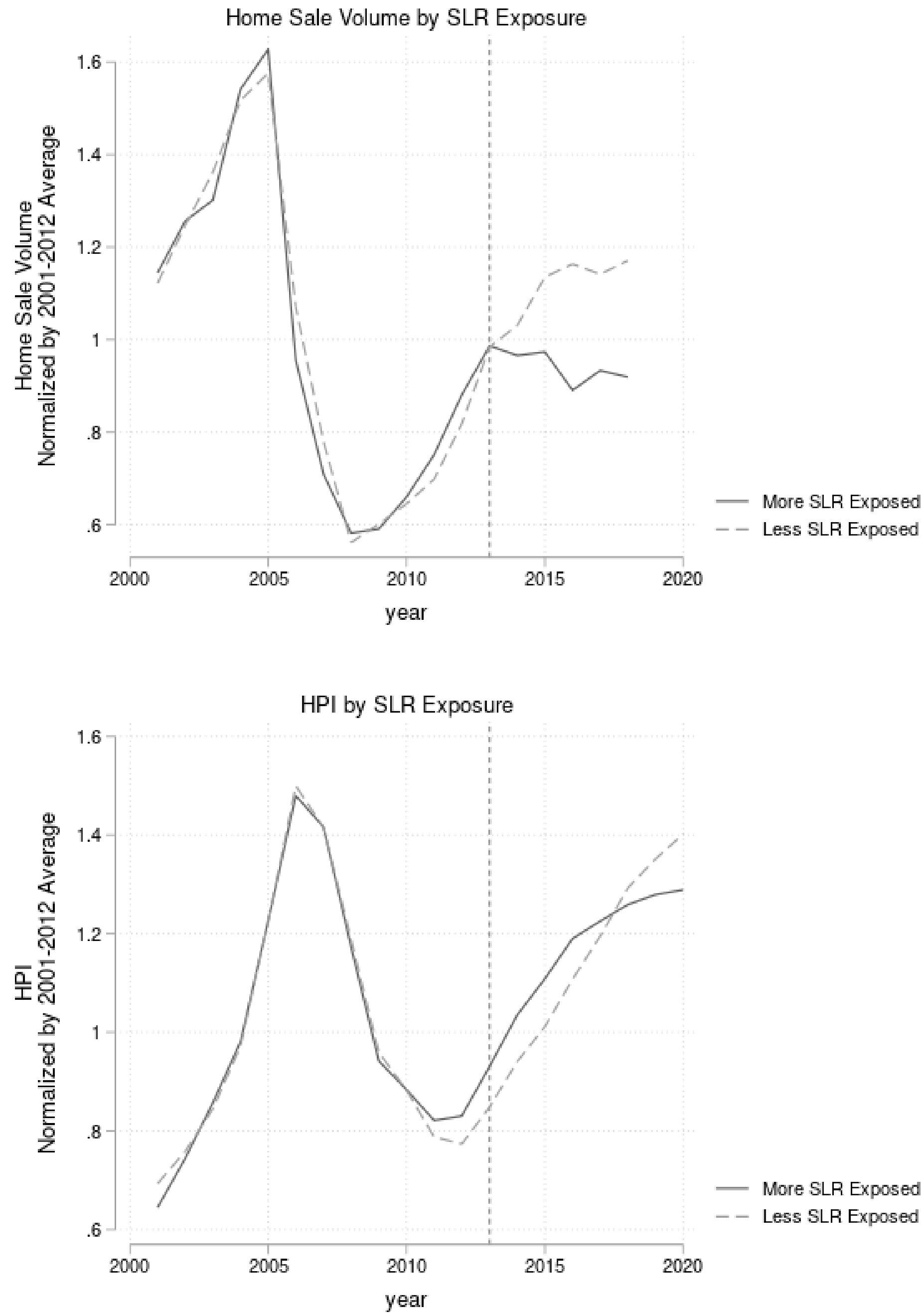


Figure 1: Housing transaction volume (top panel) and home price (bottom panel) trends in coastal Florida census tracts with high versus low SLR exposure. Housing volume and home price index are normalized by their 2001-2012 mean. Sources: Zillow Home Value Index, CoreLogic, Authors' calculations

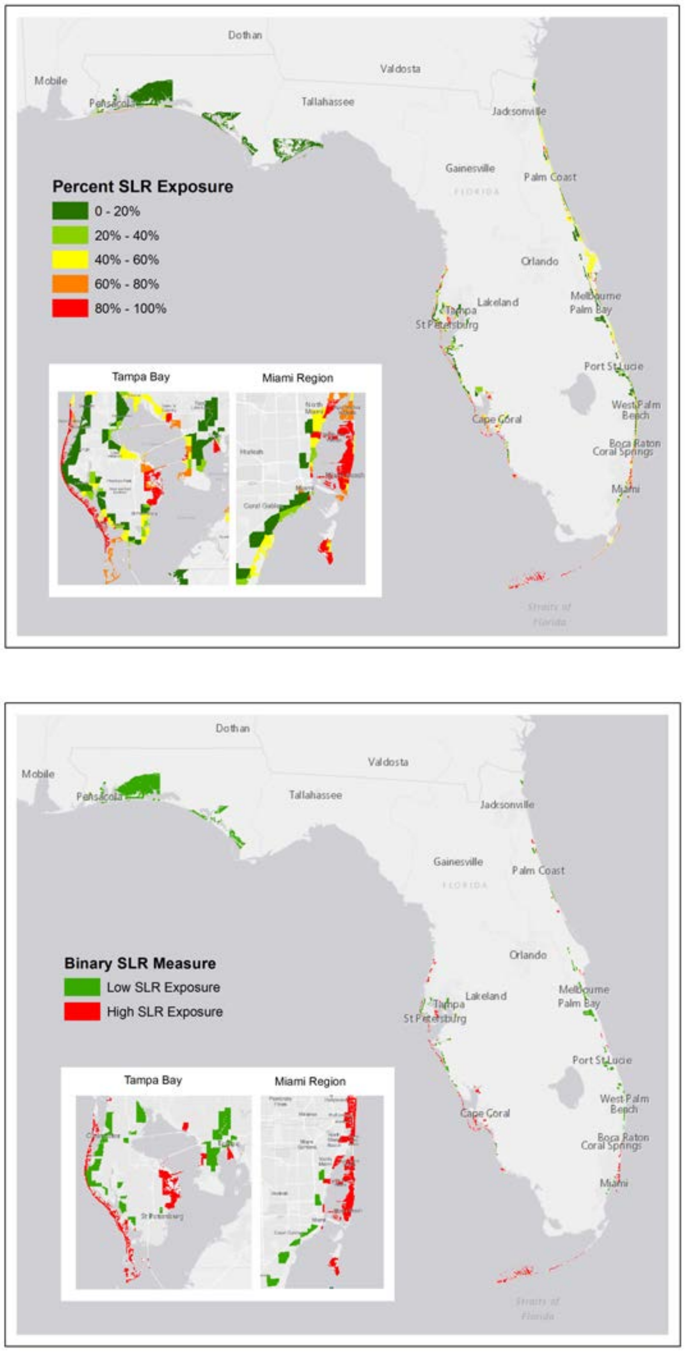


Figure 2: Maps show SLR exposure for the sample of 771 coastal Florida census tracts. The top panel shows the share of each tract's developed land in 2000 that would be chronically inundated at six feet of SLR. The bottom panel shows the subsample of tracts categorized as either "more-SLR-exposed" (> 70% exposure, 187 tracts) or "less-SLR-exposed" (< 10% exposure, 217 tracts).

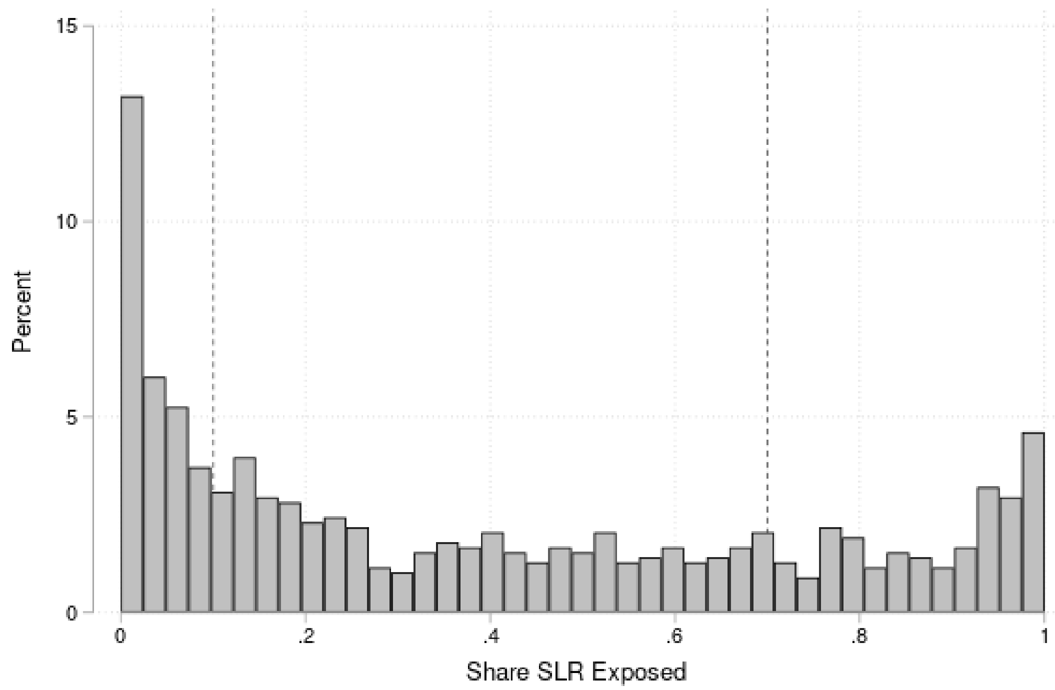


Figure 3: Histogram of tract SLR exposure. The first and second dashed lines indicate the cutoffs for the less-SLR-exposed and more-SLR-exposed tracts, respectively.

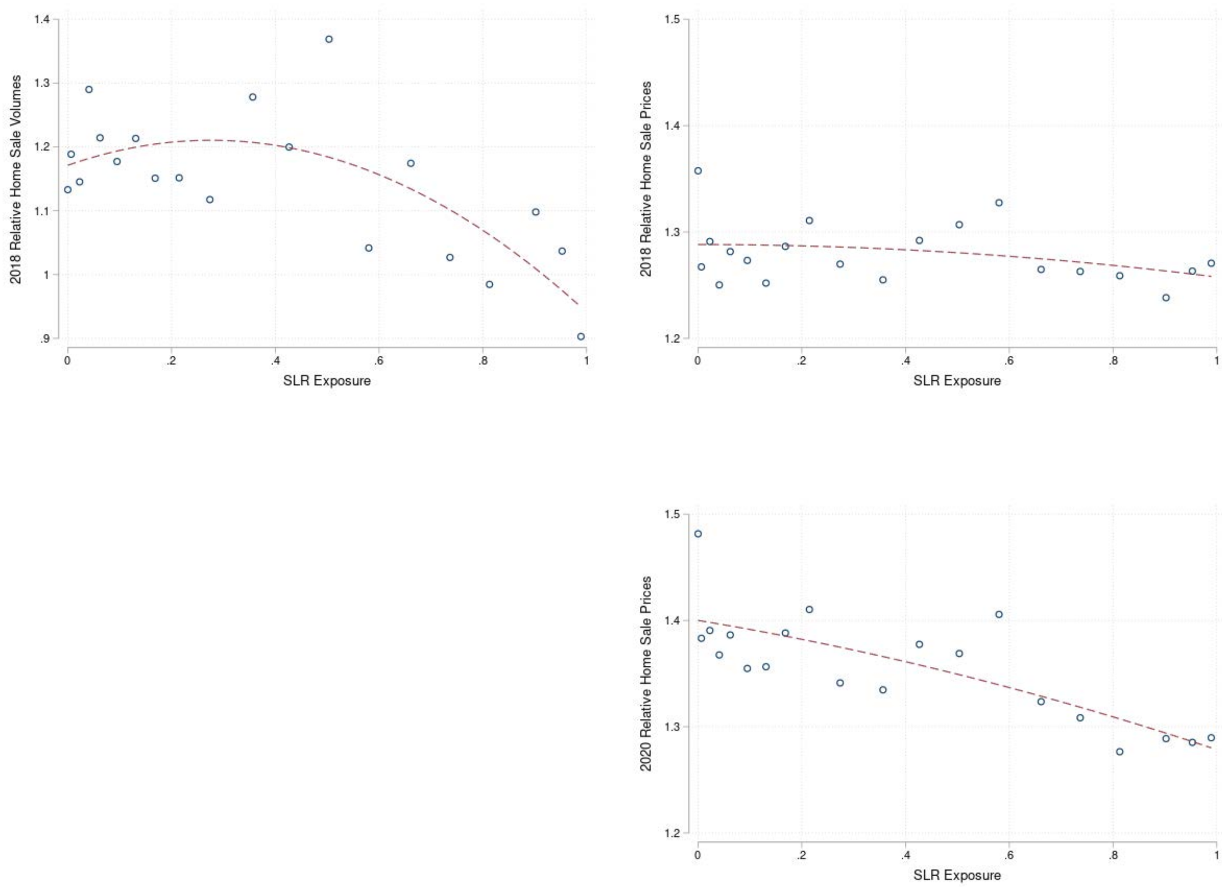


Figure 4: Relationship between tract-level SLR exposure and 2018 home sale volumes (top left), 2018 home prices (top right), and 2020 home prices (bottom right) relative to their 2001-2012 mean. The plot divides tracts into twenty quantiles of SLR exposure and fits a quadratic curve to the resulting scatterplot.

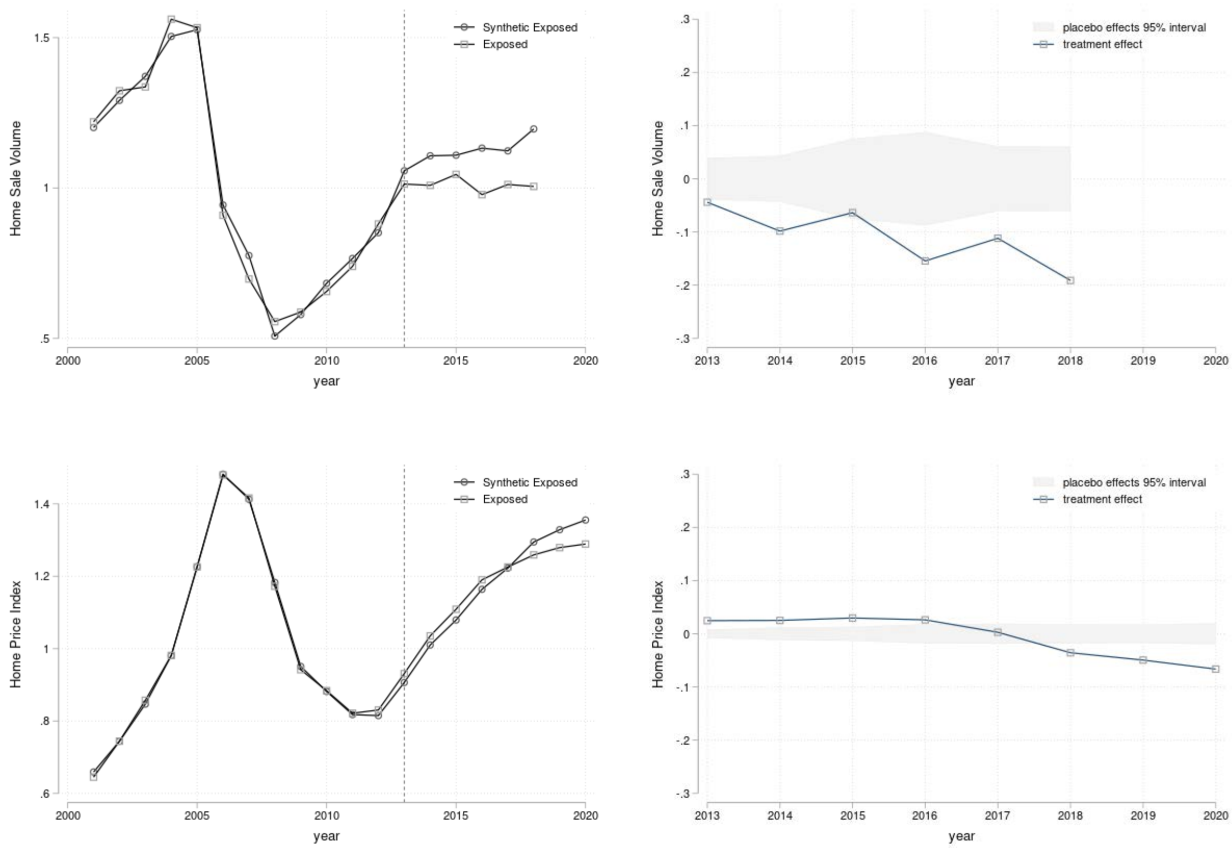


Figure 5: Synthetic control results for housing transaction volume and home prices. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

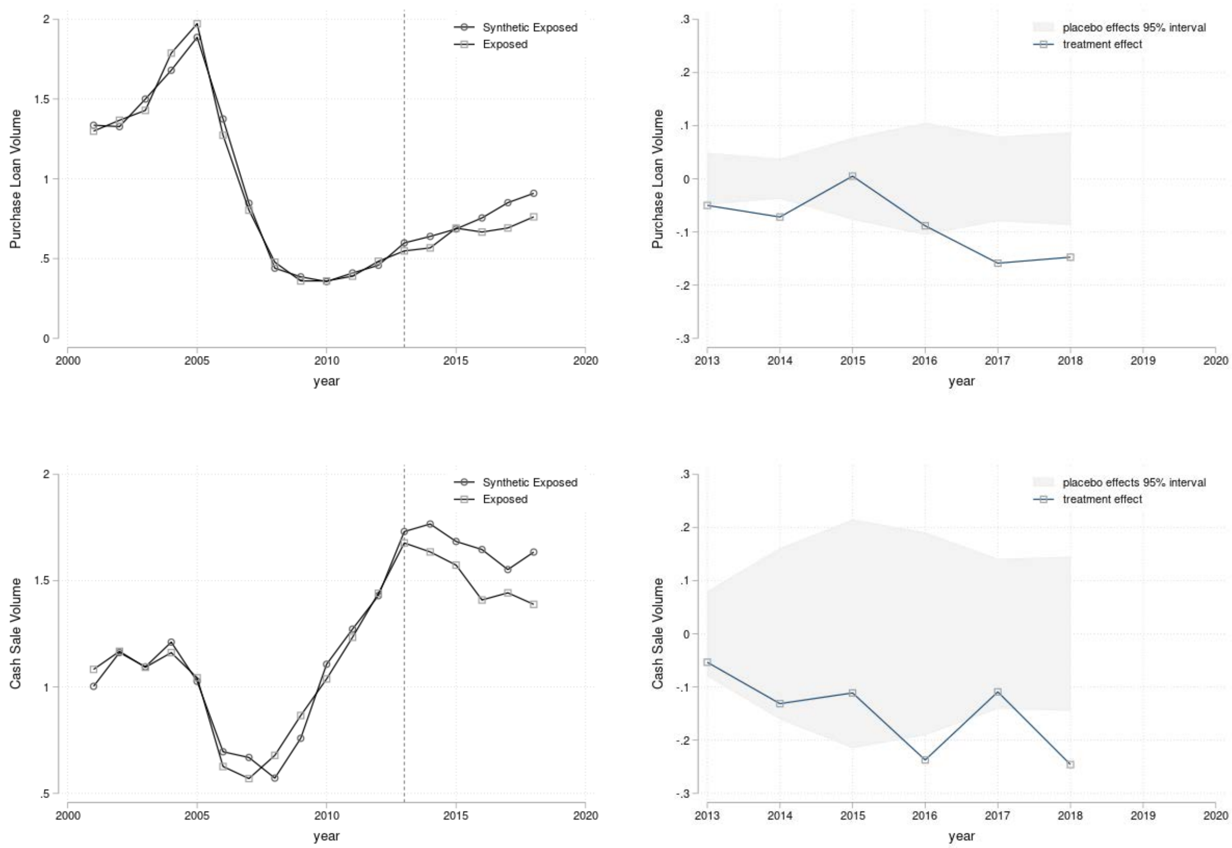


Figure 6: Synthetic control results for housing transaction loan and cash purchase volumes. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

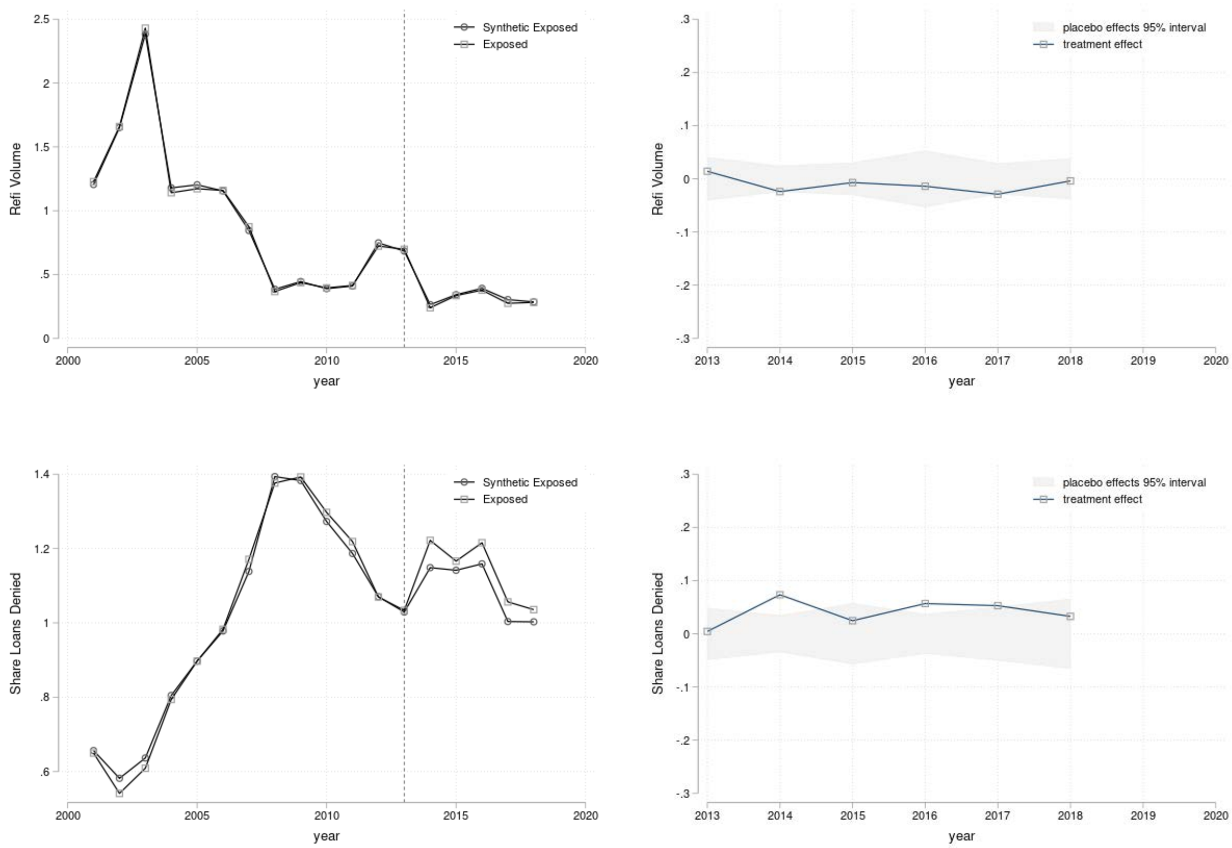


Figure 7: Synthetic control results for refinancing volume and loan denial index. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

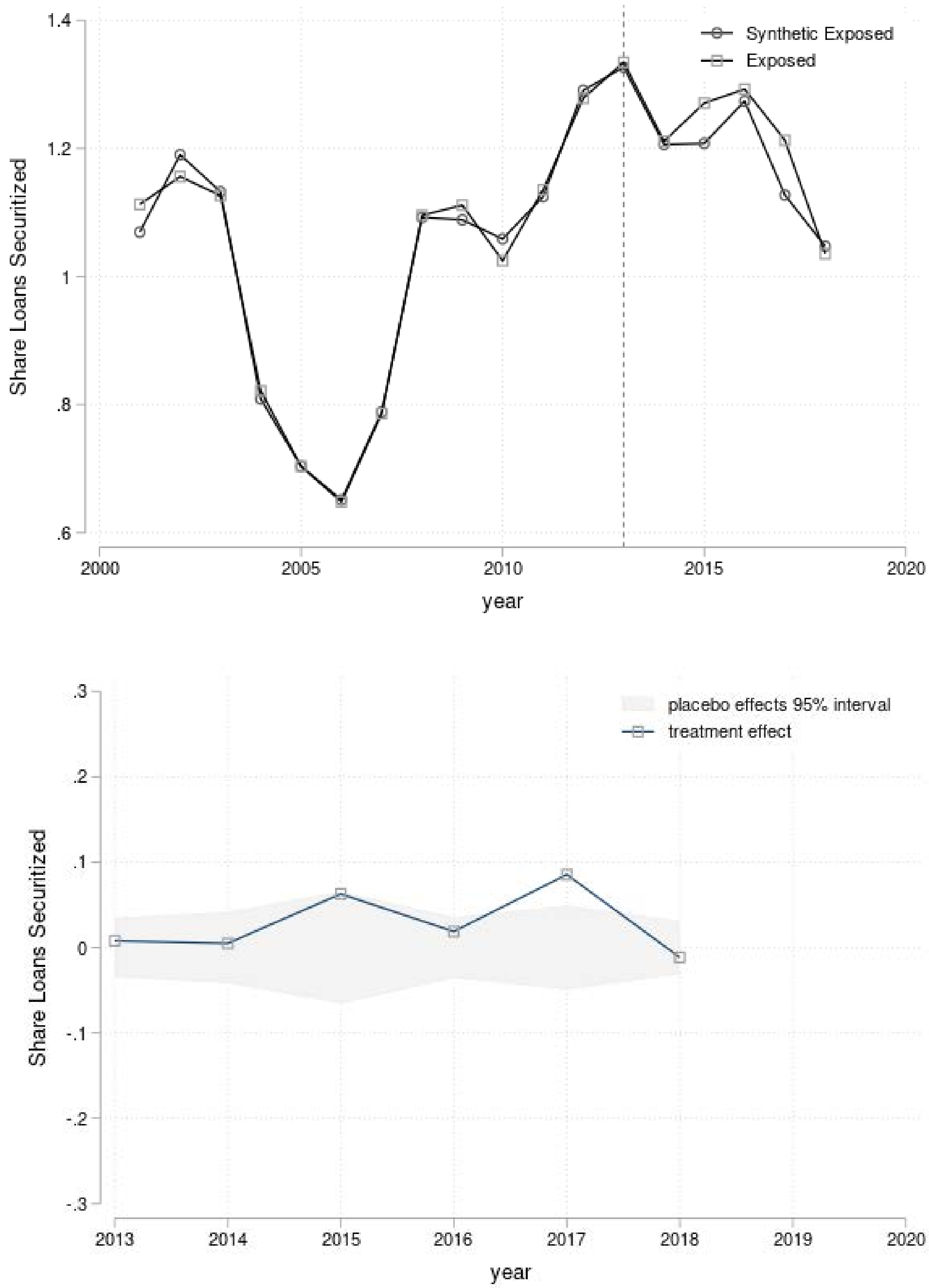


Figure 8: Synthetic control results for securitization index. Top row shows outcome for SLR-exposed tracts alongside synthetic counterparts, bottom shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

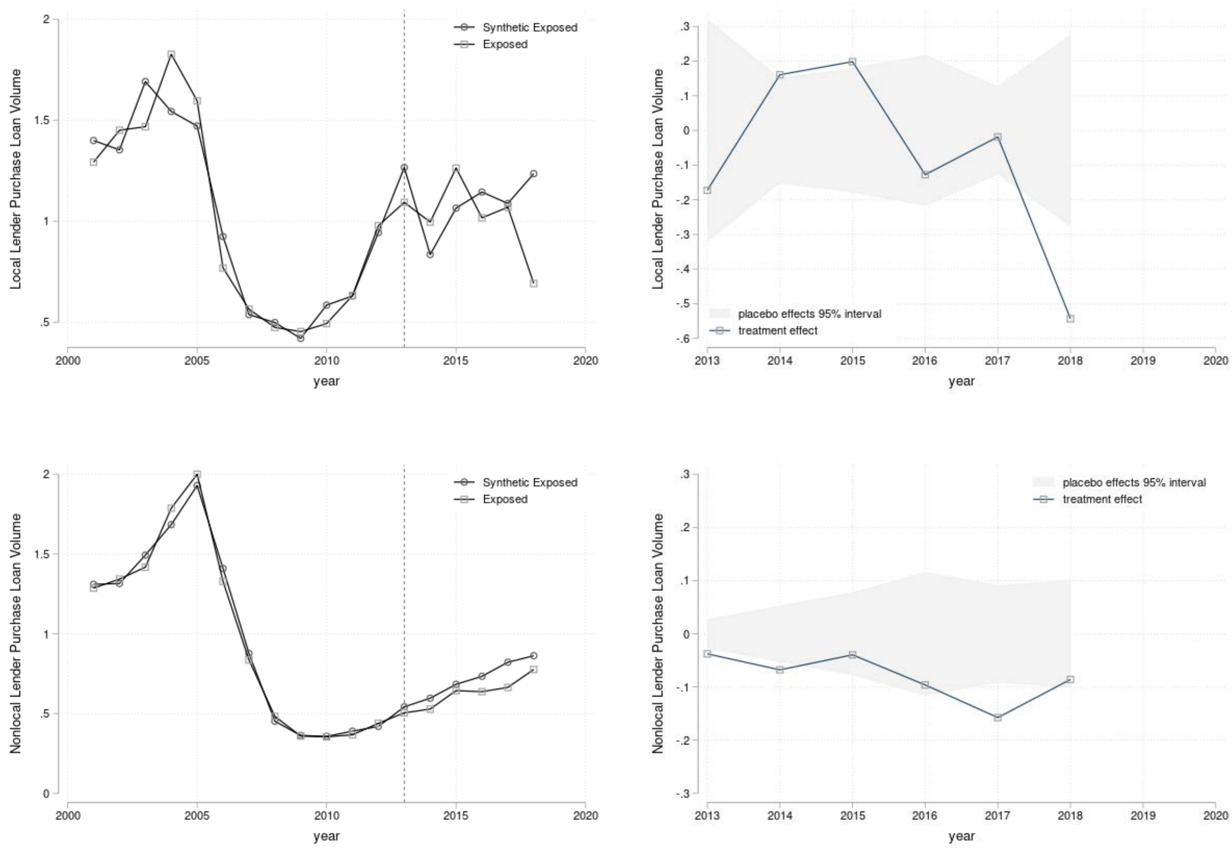


Figure 9: Synthetic control results for local and non-local lender purchase loan volume. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

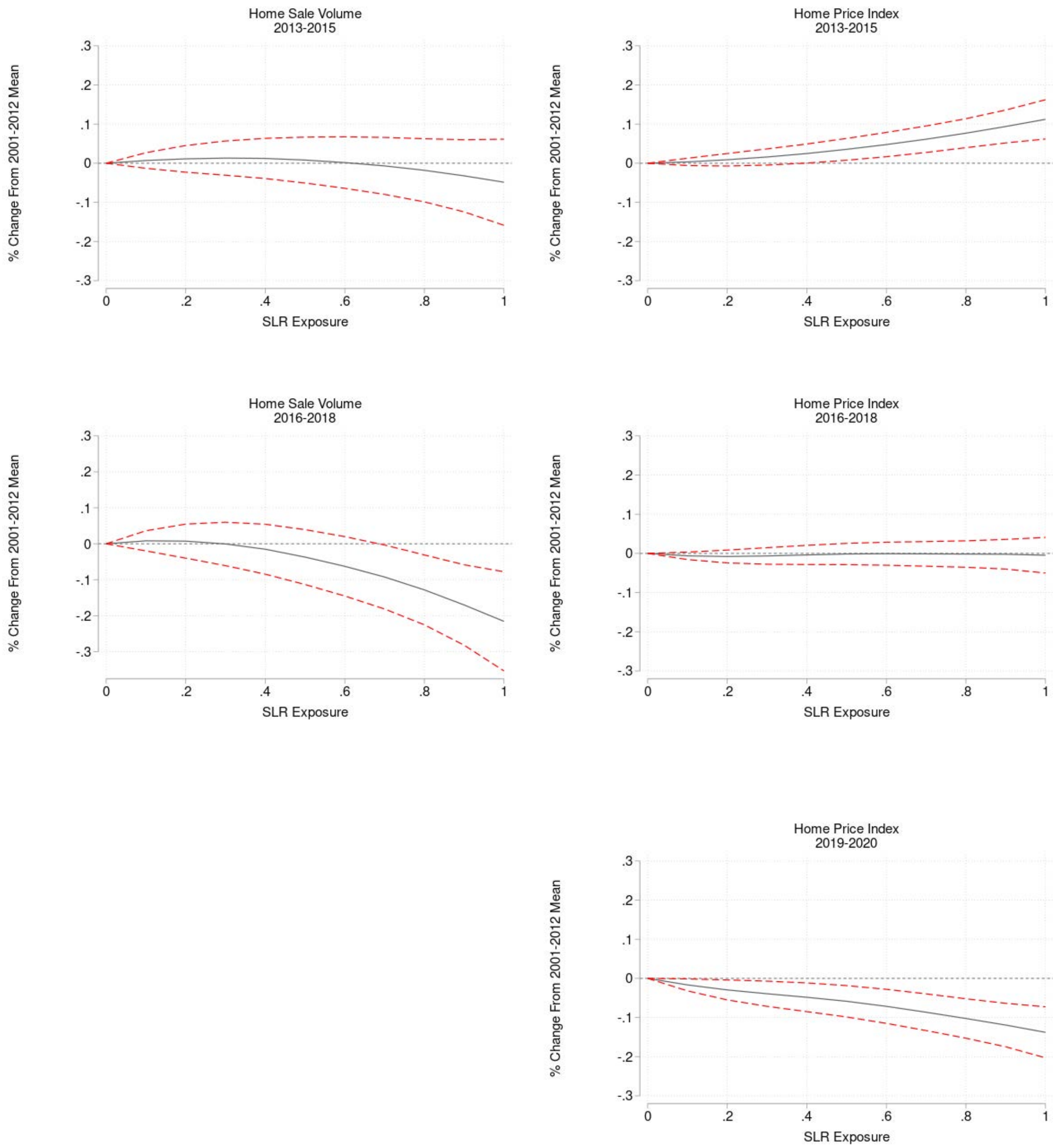


Figure 10: Generalized propensity score results for housing transaction volume and home prices. Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean by 2013-2015 (top row) and 2016-2018 (bottom row).

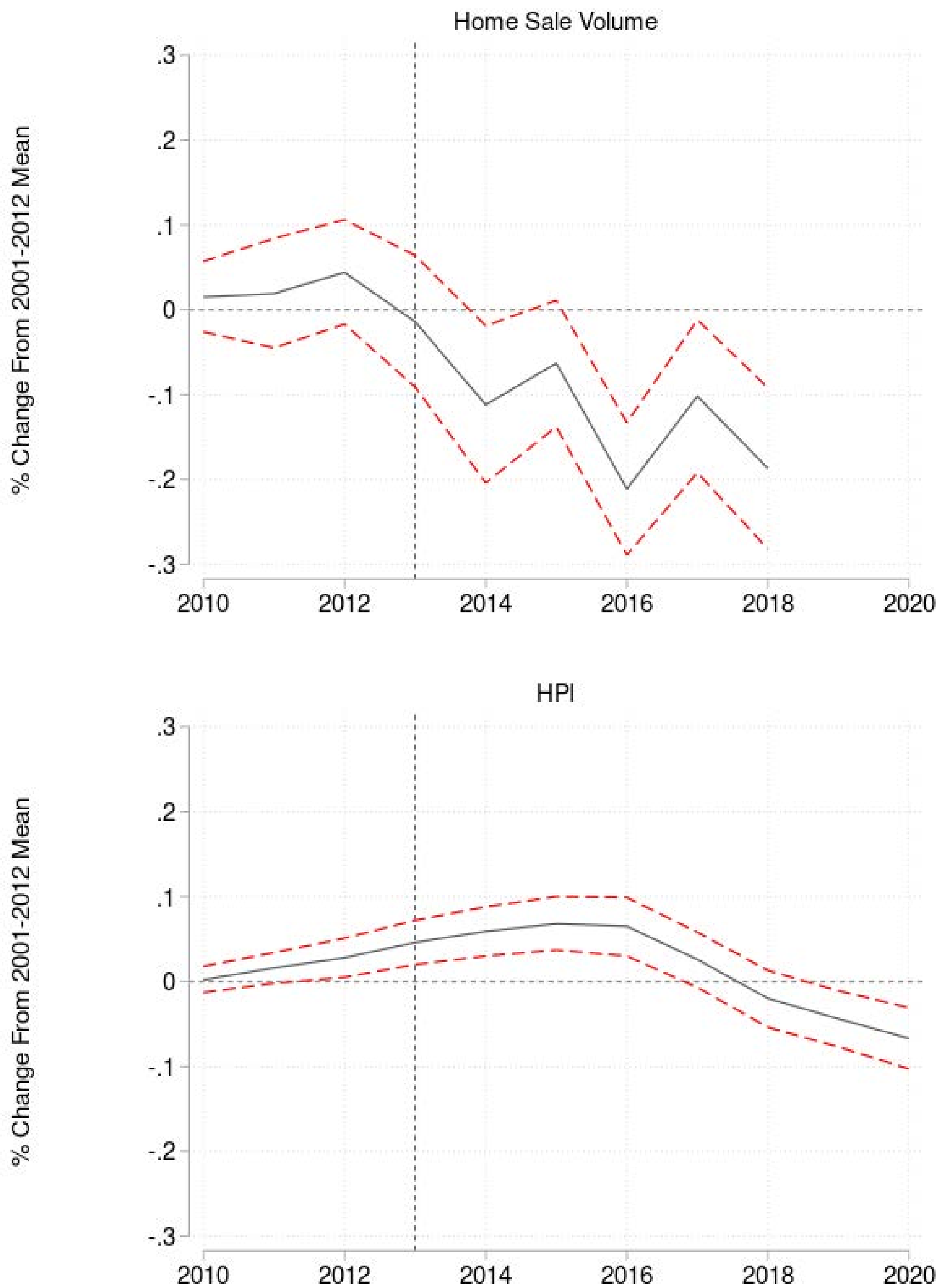


Figure 11: Annual coefficients from nearest neighbor matching for housing transaction volume (top panel) and home prices (bottom panel). Units matched with replacement on the inverse hyperbolic sine of flood insurance claims per capita 1995-2005, share of tract area made up of water, tract distance-to-coast from the population center. Dashed lines indicate 95% confidence interval.

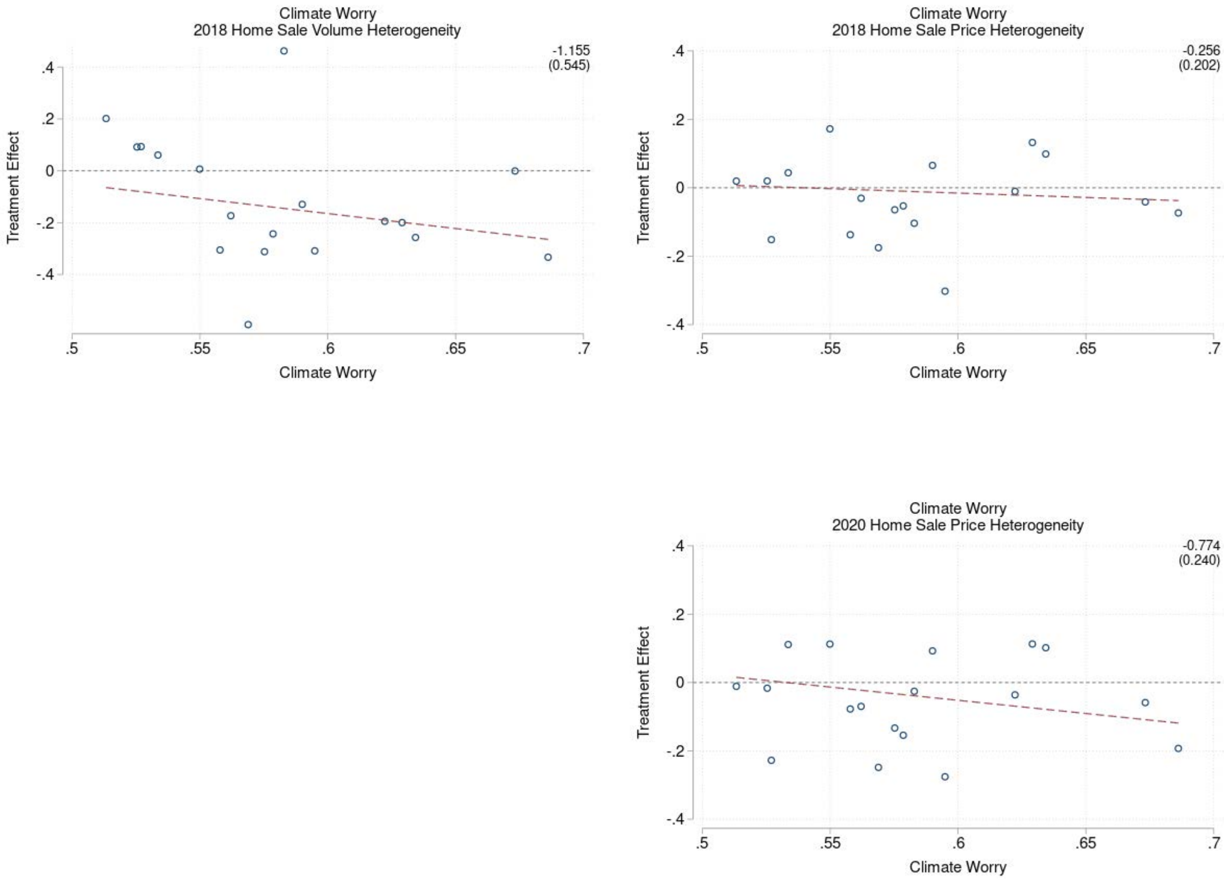


Figure 12: Summarizes treatment effect heterogeneity from nearest neighbor matching estimator for 2018 home sale volume (top left), 2018 home prices (top right), and 2020 home prices (bottom right) by county-level concern about climate change. Each point is a county with the average treatment effect of its more-SLR-exposed on the y-axis and the estimated share of adults in the county worried about climate change from the 2018 Yale Climate Opinion Survey on the x-axis. The dashed red line indicates the best-fit linear line through the points, with the coefficient and standard error from the tract-level regression of the worry measure over the estimated treatment effects indicated in the upper-right corner. Outcomes are normalized by the tract-level 2001-2012 mean. See Figure 11 for description of matching covariates.

A Appendix Tables

Covariate	Sample	More Exposed	Less Exposed	% Diff	t-stat
Tract Distance-to-Coast (Meters)	Unmatched	427	964	-131.4	-13.16
	Matched	427	626	-48.7	-4.85
Share Pop. Nonwhite	Unmatched	0.076	0.191	-90.5	-8.83
	Matched	0.076	0.080	-3.0	-0.59
Share Pop. Foreign	Unmatched	0.226	0.139	53.9	5.49
	Matched	0.226	0.174	32.2	2.81
Share Pop. Poverty	Unmatched	0.108	0.155	-57.8	-5.71
	Matched	0.108	0.101	7.6	0.98
Log Flood Claims Per-Capita	Unmatched	4.71	3.76	32.1	3.22
	Matched	4.71	4.59	4.3	0.41
Tract Share Water	Unmatched	0.446	0.172	115.5	11.69
	Matched	0.446	0.373	30.6	2.56

Table A-1: Covariate balance before (unmatched) and after (matched) nearest neighbor matching. See text for specific covariate definitions. Flood claims per-capita are calculated by dividing the total single-family flood insurance payments made in the designated Tract from 1995-2005 and dividing by the 2000 Census count of single-family housing units.

Outcome	Relative Change from 2001-2012 2018 Coefficient
Denials - Purchase Loans	-.044
	(.051)
Denials - Refis	.033
	(.047)
Securitization - Purchase Loans	.025
	(.032)
Securitization - Refis	.059
	(.038)

Table A-2: Results from nearest neighbor matching showing the relative change in denial and securitization indices separated by purchase and refinance loans in SLR-exposed markets relative to matched less SLR-exposed markets. Outcome variables are measured as changes relative to 2001-2012 tract-level mean with the second column showing the relative change coefficient in 2018. Bootstrapped standard errors in parentheses.

Outcome	Relative Change from 2001-2012 2018 Coefficient
Purch Loan Volume - Local	-.408**
	(.159)
Value Purch Loan - Local	-.549**
	(.201)
Purch Loan Volume - Non-local	-.183***
	(.055)
Value Purch Loan - Non-local	-.288***
	(.068)
Refi Volume - Local	.081
	(.073)
Value Refi - Local	.322**
	(.132)
Refi Volume - Non-local	-.062***
	(.016)
Value Refi - Non-local	-.024
	(.020)

Table A-3: Results from nearest neighbor matching showing the relative change in purchase and refinance loan lending separated by local and non-local lenders in tracts exposed to sea level rise relative to less-exposed tracts. See Figure 11 for description of matching covariates. Outcome variables are measured as changes relative to 2001-2012 tract-level mean with the second column showing the relative change coefficient in 2018. Bootstrapped standard errors in parentheses.

Percentile	Transaction Volume	Home Price Index
10th	0.0875	0.0094
25th	0.1108	0.0139
50th	0.1466	0.0189
75th	0.2056	0.0257
90th	0.3578	0.0561

Table A-4: Distribution of root-mean-square error (RMSE) for transaction volume (second column) and home price index (third column) outcome variables between more-SLR-exposed tracts and their constructed synthetic counterparts from 2001-2012.

B Appendix Figures

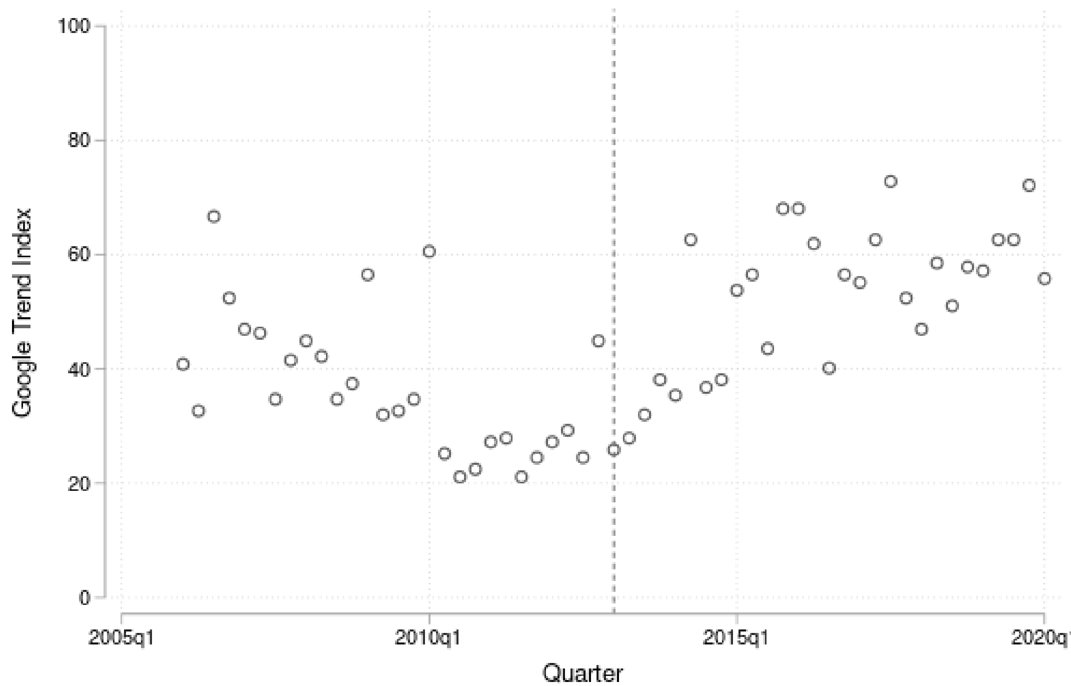


Figure A-1: Quarterly Google Trends search intensity for topic "Sea Level Rise" in Florida from 2006 to 2020. Dashed line is at the first quarter of 2013.

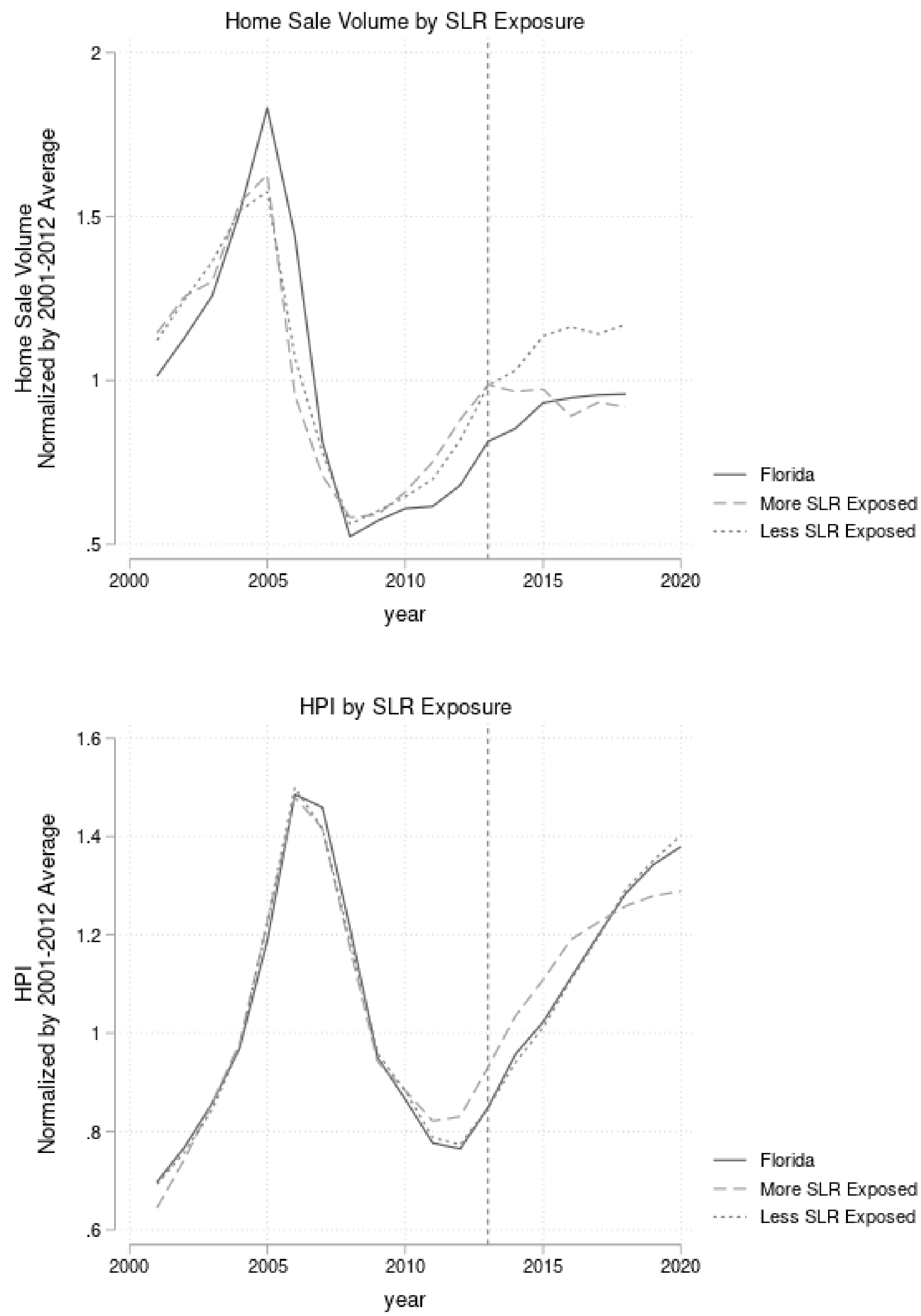
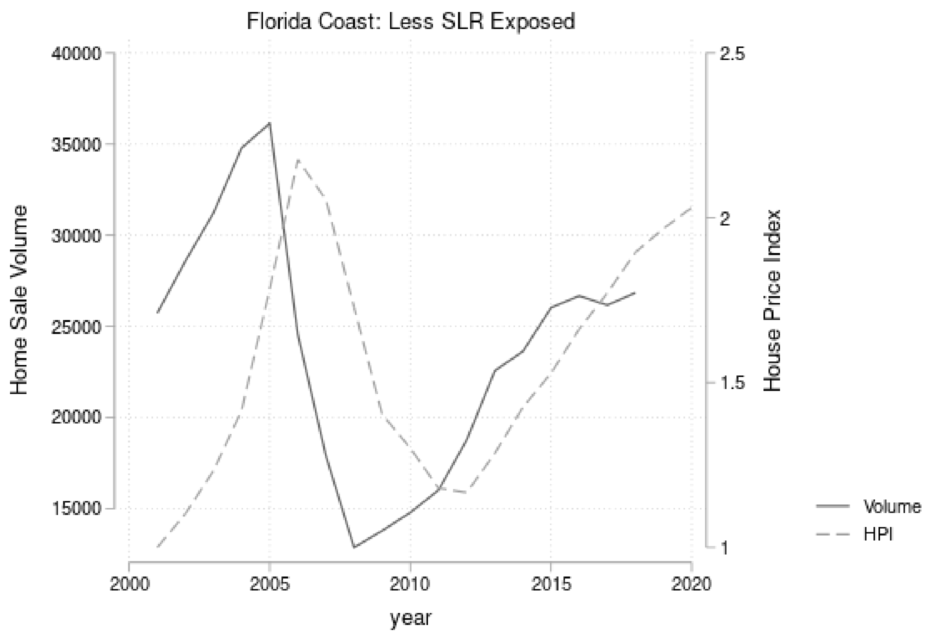


Figure A-2: Housing transaction volume (top panel) and home price (bottom panel) trends across all of Florida (solid lines) and coastal Florida census tracts with high versus low SLR exposure (dashed and dotted lines, respectively). Housing volume and home price index are normalized by their 2001-2012 mean.



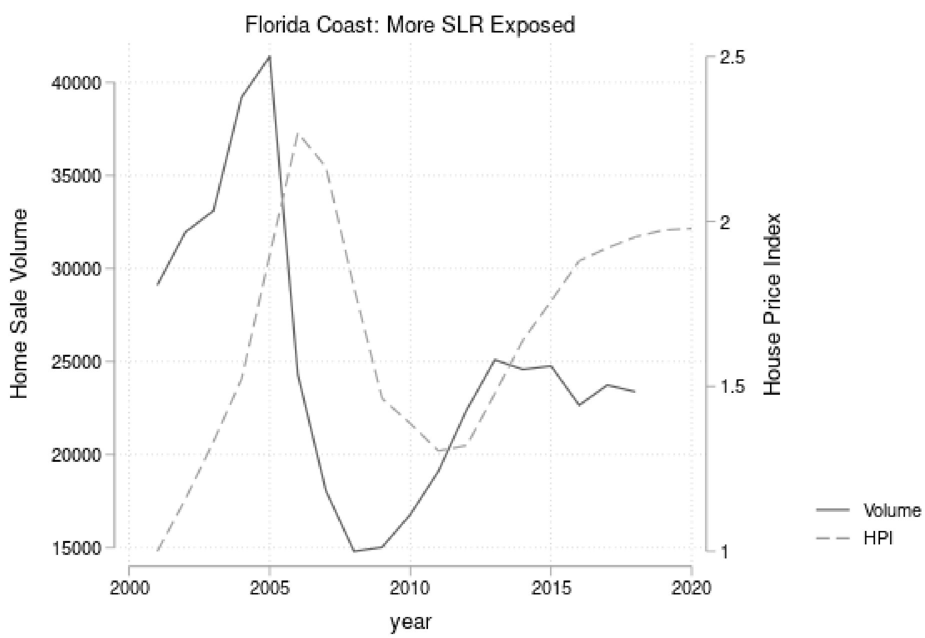
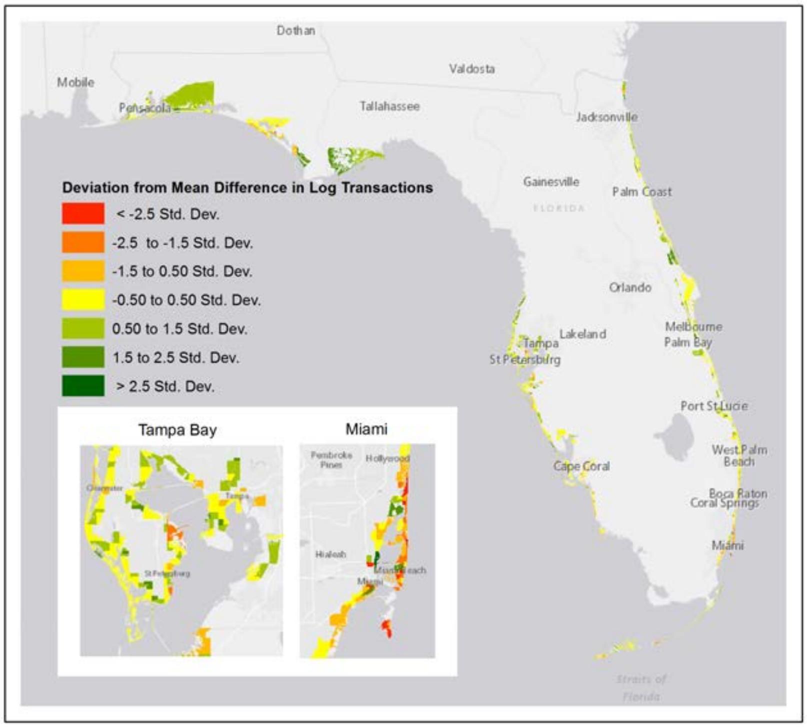


Figure A-3: Annual aggregate housing transactions (left axis) and mean house price index (right axis) for coastal Florida census tracts with either less-SLR-exposure (top panel) or more-SLR-exposure (bottom panel). See Data and Methodology sections for data sources and definitions of coastal and SLR exposure.



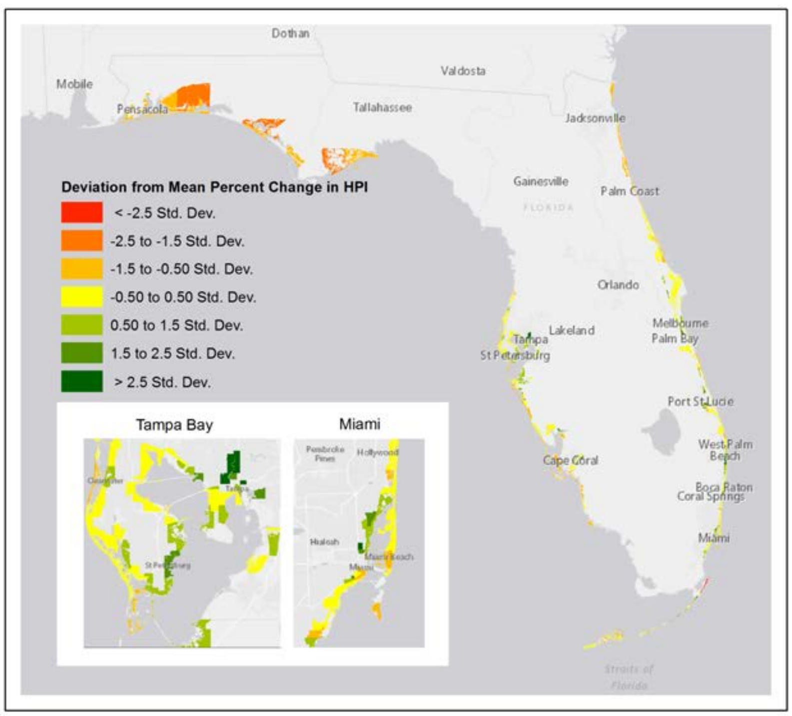


Figure A-4: Maps show change in log home transactions (top panel) and home price index (bottom panel) by coastal tract between 2011-2012 and 2017-2018. Tracts are colored by relative change, with red indicating larger relative to declines and green larger relative increases.

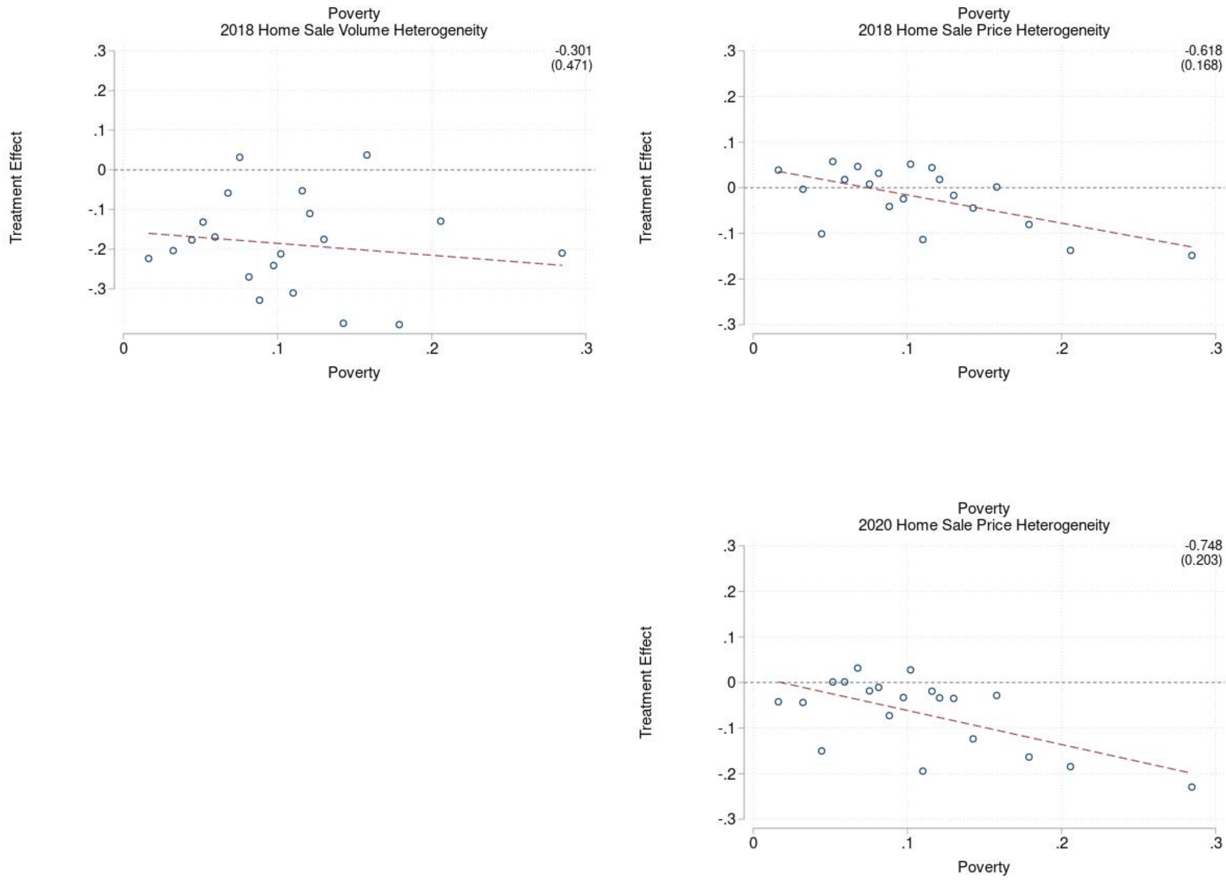


Figure A-5: Summarizes treatment effect heterogeneity from nearest neighbor matching by tract-level poverty for 2018 home sale volume (top left), 2018 home prices (top right), and 2020 home prices (bottom right). Points indicate the average treatment effect (y-axis) within twenty quantiles of more-SLR-exposed tracts grouped by 2010 census estimate of the share of residents in poverty (x-axis). The dashed red line indicates the best-fit linear line through the points, with the coefficient and standard error from the tract-level regression of poverty over the estimated treatment effects indicated in the upper-right corner. Outcomes are normalized by the tract-level 2001-2012 mean. See Figure 11 for description of matching covariates.

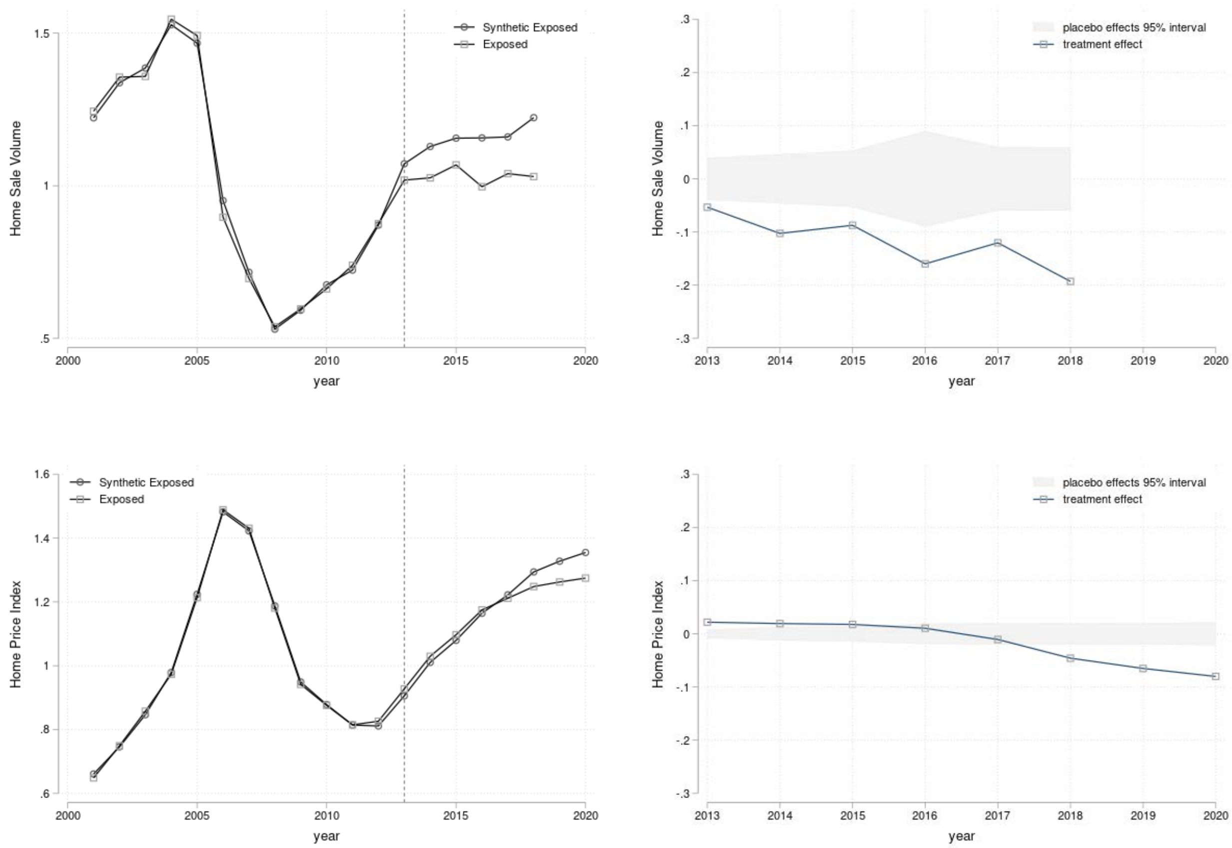


Figure A-6: Synthetic control results for housing transaction volume and home prices, excluding more-SLR-exposed tracts with root mean square error (RMSE) above the 90th percentile by outcome. Placebo tracts with RMSE greater than double the more-SLR-exposed trimmed RMSE are also removed for inference.

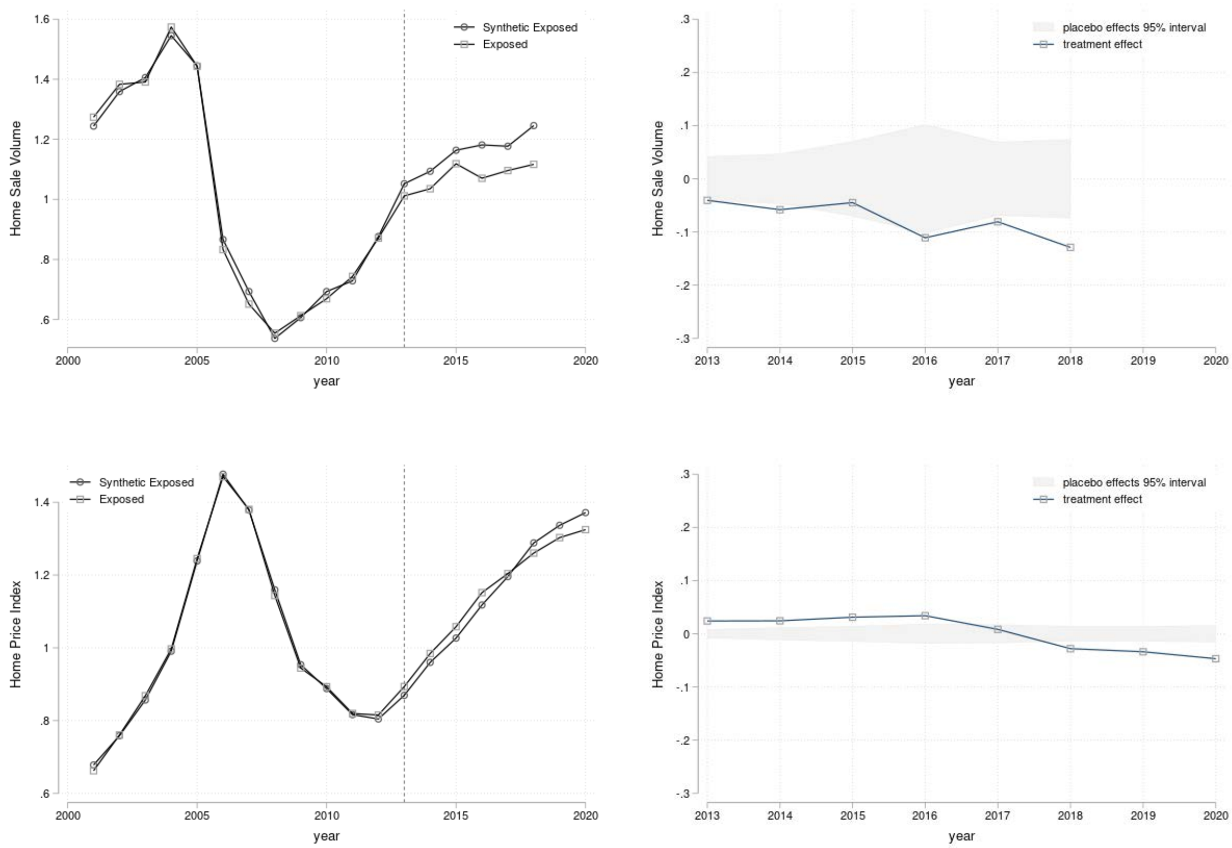


Figure A-7: Synthetic control results for housing transaction volume and home prices, excluding all tracts in Miami-Dade County. Top row shows outcome for SLR-exposed tracts alongside synthetic counterparts, bottom shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

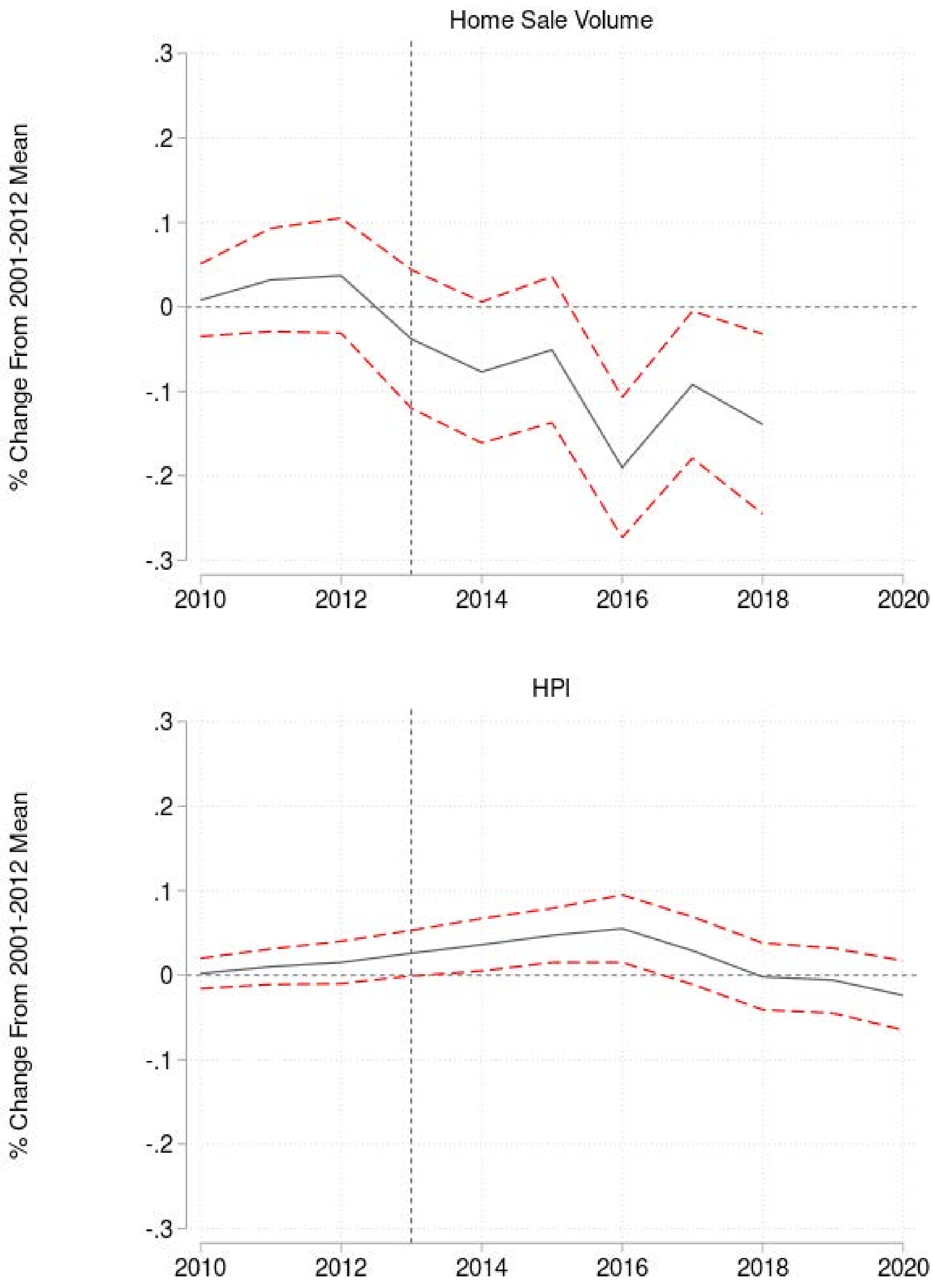


Figure A-8: Annual coefficients from nearest neighbor matching for housing transaction volume (top panel) and home prices (bottom panel) excluding observations in Miami-Dade county. See Figure 11 for description of matching covariates. Dashed lines indicate 95% confidence interval.

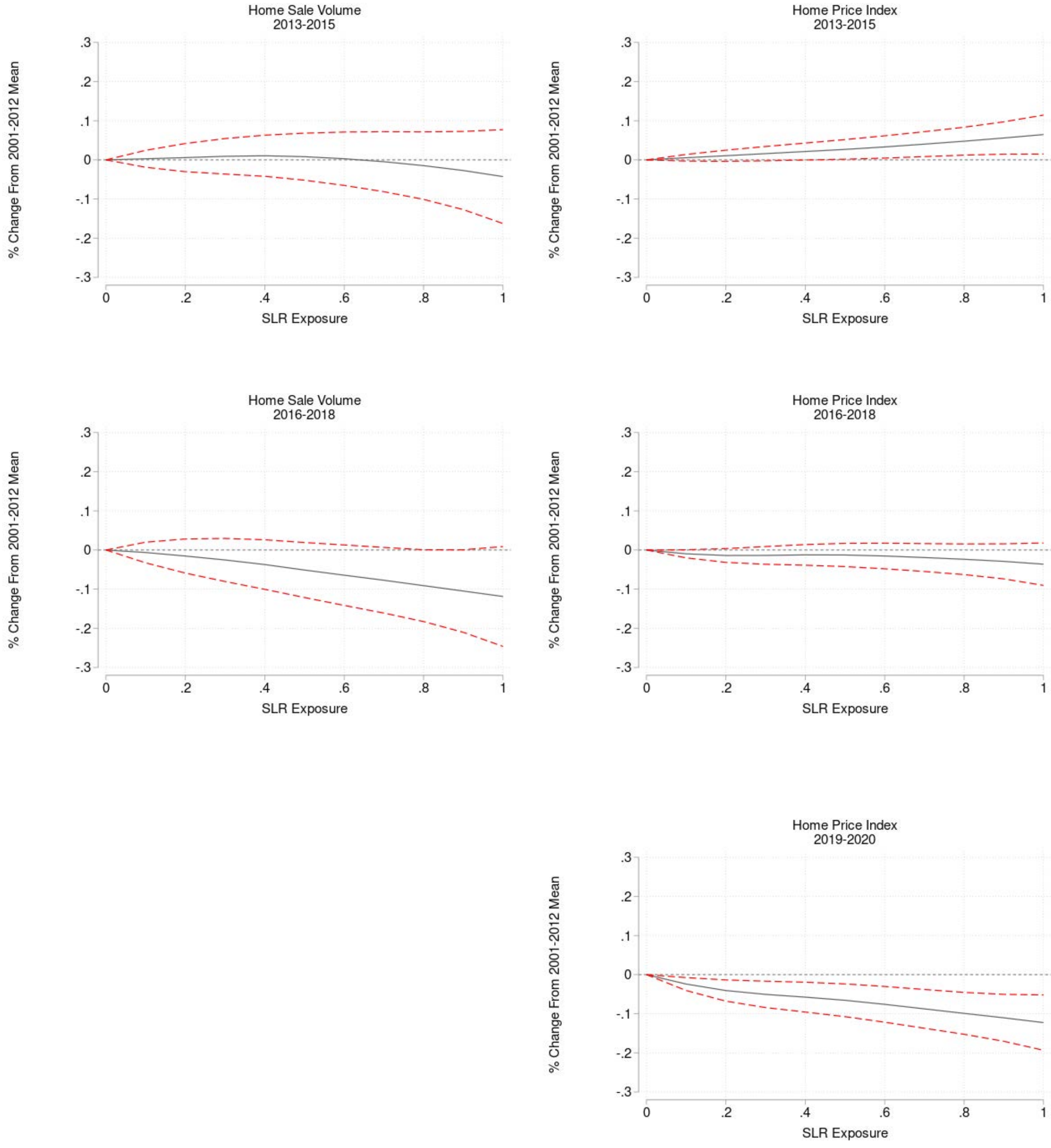


Figure A-9: Generalized propensity score results for housing transaction volume and home prices excluding all observations in Miami-Dade county. Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean by 2013-2015 (top row) and 2016-2018 (bottom row).

C Data Appendix

C.1 Denials and Securitization Index Estimation

This section describes the estimation of our tract-by-year indices for loan denial and securitization using loan-level data in HMDA. To define the securitization index, we subset to approved purchase or refinance loans below the conforming loan limit (CLL) in the estimation sample of tracts. To construct a tract-level securitization index, using all approved loans i of type $l \in \{Refi, Purchase\}$ for a property in tract j in year t, we estimate a linear probability model:

$$s_{iljt} = \alpha^l + \beta_t^j Year_t + \beta_0^l \sum_{n=1}^{2} VALUE_i^n + LTI_i^n + \beta_1^l \sum_{m=1}^{3} (CLL_{jt} - VALUE_i)^m + \beta_2^l X_{ij} + \epsilon_{iljt} \quad (3)$$

where s_{iljt} is an indicator variable for whether loan application j was marked in HMDA data as sold to one of the housing GSEs (Fannie/Ginnie Mae or Freddie/Farmer Mac) or to a private securitization entity. $Value_i$ is defined as the inverse hyperbolic sine (IHS) of loan value and LTI_i is the loan-to-income ratio derived from reported borrower income and loan value. Both of these variables enter as second-order polynomials in the estimating equation. $(CLL_{jt} - VALUE_i)$ is the IHS of the difference between the CLL and loan value and enters as a third-order polynomial. Finally, X_{ij} contains binary indicators for whether the borrower is reported as nonwhite, whether the property is owner-occupied, and whether the lender is local. The constant term α, as well as each of the β slope coefficients, vary by whether the loan is a refinance or purchase loan, as indicated by the l superscripts.

Equation (3) is estimated from 1,575,345 observations. The tract-by-year securitization index is constructed by adding each of the β_t^j terms to the overall mean securitization rate in the estimation data such that the index values fall between zero and one. The final index values are winsorized by year at the 99th and 1st percentiles.

The denials index is estimated similarly over the sample of applications for purchase or refinance loans. Because the denials index includes both conforming and non-conforming loans, l now indexes four categories of loans by whether they are purchase or refinance and conforming or non-conforming. In addition, the term $|CLL_{jt} - Value_i|$ is the IHS of the *absolute* difference between the loan value and conforming loan limit. The estimating equation is written:

$$d_{iljt} = \alpha^l + \lambda_t^j Year_t + \lambda_0^l \sum_{n=1}^{2} VALUE_i^n + LTI_i^n + (|CLL_{jt} - VALUE_i|)^n + \lambda_1^l X_{ij} + \epsilon_{iljt} \quad (4)$$

where d_{iljt} is an indicator for whether loan application i was denied. Equation (4) is estimated from 2,650,018 observations.

C.2 Calculation of Flood Insurance Premium Controls

This section describes how we construct tract-level controls for changes in National Flood Insurance Program (NFIP) premiums from 2013-2018. To movtivate our approach, consider the tract-level regression described below:

$$Y_{j,2018} - Y_{j,2012} = \alpha + \beta(P_{j,2018} - P_{j,2012}) + \epsilon_j \tag{5}$$

where $Y_{j,t}$ is some tract-level outcome (say Home Price Index) in tract j in year t, and $P_{j,t}$ is some measure of the cost of flood insurance.

One way to define P is by taking a simple mean of the premiums we observe for the policies in each tract in the corresponding years. The problem with this approach is that the observed premiums are a function of the rates and fees that households face. When premiums increase between 2012 and 2018, some households may choose to insure less or not buy flood insurance altogether, attenuating our measure of premium changes. Thus, estimation of β in Equation 5 would be biased. This is a similar source of endogeneity as in other literatures where prices are a function of consumption (see e.g. Gruber and Saez (2002) or Ito (2014)).

To address this issue, we adopt a standard approach by instrumenting for the observed premium change from 2012 to 2018 with the counterfactual change in premiums if insurance uptake were exactly the same in 2018 as it was in 2012. To define these measures precisely, define $p_{ijr,2012}$ as the premium paid by policy i in tract j that is part of rate class r in 2012, and let $p_{njr,2018}$ index the corresponding set of policies in 2018.[40] Let N_{jt} be the number of homes eligible for flood insurance in tract j in year t, and I_{jt} the number of flood insurance policies.[41] We calculate the observed change in flood insurance premiums as:[42]

$$P_{j,2018} - P_{j,2012} = \frac{I_{j,2018}}{N_{j,2018}} \sum p_{njr,2018} - \frac{I_{j,2012}}{N_{j,2012}} \sum p_{ijr,2012}$$

As described above, this measure may be biased because the composition of observed policies and $\frac{I_{jt}}{N_{jt}}$, the take-up rate, may change in response to the premium changes. We construct our instrument by measuring 2018 premiums under the 2012 policy cohort. This means using the 2012

[40] Rate class refers to the set of attributes (e.g. property elevation relative to the floodplain, number of floors in the home) that determines a policy's flood insurance rates and fees.

[41] We subset to 1-4 family homes and NFIP policies, excluding mobile homes and condos. This sample forms the large majority of policies and price variation over the period.

[42] We scale premiums by the take-up rate to match the tract-level definition of our outcome variables.

instead of 2018 take-up rate, and calculating the 2018 premiums as if the same exact policies written in 2012 formed the set of insured in 2018. This measure is defined:

$$\frac{I_{j,2012}}{N_{j,2012}} * (\sum p_{ijr,2018} - p_{ijr,2012})$$

Using this instrument, we can estimate Equation (5) via two-stage least squares.

D Methodology Appendix

D.1 Census Tract Versus Property Level Estimation

A notable difference between our approach and the papers described above is that we measure SLR exposure and outcomes at the census tract rather than property level. In this section, we describe in further detail our rationale for this decision. As described in Section 2, our SLR measure is constructed from the share of a tract's developed land[43] that would be inundated under six feet of SLR whereas other studies relate property level exposure to property level sales prices.

We opt for the tract-level approach for several reasons. First, the NOAA SLR model's inundation projections are highly uncertain on a property-by-property basis (Gesch, 2009). In addition to fundamental uncertain from climate models, there is extra uncertainty from measurement error in local geography, changes from construction or erosion over time, and the climate itself. We view our continuous and community-level measure as better reflecting this uncertainty. Second, there will likely be many local spillover effects from SLR that negatively impact even nominally non-inundated properties, such as roadway flooding, which has been shown to erode property value (McAlpine and Porter, 2018), or flooding of other critical infrastructure. Properties at a lower elevation due to rising seas will also be exposed to increased flood risk due to their lower elevation. Estimating SLR capitalization by comparing neighborhoods with different exposure, rather than properties with nominally different exposure in the same neighborhood, avoids contamination from these localized spillovers.

D.2 Generalized Propensity Score Estimation

This section describes the technical details behind the estimation of our generalized propensity score (GPS) model. Let tract j have continuous SLR exposure R_j between 0 and 1. The first stage of the GPS models R_j as a function of tract covariates. We use a tobit model censored at 0 and 1 with the following underlying linear model:

$$\begin{aligned} R_j =& \alpha + \beta_0 Dist_j + \beta_1 SFHA_j + \beta_2 Claims_j + \beta_3 Pop^{18} + \beta_4 Pop^{64}_{18} \\ &+ \beta_5 \sum_{n=1}^{2} Nonwhite^n_j + Foreign^n_j + Water^n_j + \epsilon_j \end{aligned} \tag{6}$$

Where the covariates are, in order, deciles of distance-to-coast and share of a tract's developed area in a FEMA Special Flood Hazard Area (SFHA), IHS of flood insurance claims per-capita 1995-

[43] In particular, developed land includes roads and non-residential buildings

2005, 2010 population share under 18 and share 18 to 64, and quadratic terms of 2010 population shares nonwhite and foreign born, and tract area made up of water.

In the second stage, we estimate each tract's generalized propensity score, $\widehat{p_j}$, as the probability density of observing the tract's actual SLR exposure from a normal distribution with mean $\widehat{R_j}$ and variance from Equation (6). Next, we fit the outcomes Y_j as a flexible model of the generalized propensity score and actual SLR exposure using a quadratic model:

$$E[Y_j|R_j, \widehat{p_{Rj}}] = \alpha_0 + \alpha_1 R_j + \alpha_2 R_j^2 + \alpha_3 \widehat{p_j} + \alpha_4 \widehat{p}_j^2 + \alpha_5 T_j * \widehat{p_j} \tag{7}$$

Finally, we estimate the average potential outcome at any level of SLR exposure, r. Let $\widehat{p(r, X_j)}$ be the generalized propensity score for tract j at counterfactual exposure r. $p()$ is the same function used to calculate the generalized propensity score $\widehat{p_j}$ from the results of equation (6), but calculated from the counterfactual exposure r rather than the tract's actual exposure R_j. Then, the average potential outcome at exposure r is:

$$E[\widehat{Y(r)}] = \frac{1}{J}\sum_{j=1}^{J} \alpha_0 + \alpha_1 r_j + \alpha_2 r_j^2 + \alpha_3 \widehat{p(r, X_j)} + \alpha_4 \widehat{p(r, X_j)}^2 + \alpha_5 T_j * \widehat{p(r, X_j)} \tag{8}$$

By calculating Equation (8) across the full distribution of SLR exposure, we can estimate the effects of SLR risk over time as a series of dose-response functions relative to tracts with no SLR exposure. We estimate potential outcomes at 10% intervals of SLR exposure from 0% to 100%, and calculate standard errors from 2,000 panel bootstrap samples.