Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise*

Benjamin J. Keys[1] and Philip Mulder[2]

[1]The Wharton School, University of Pennsylvania and NBER

[2]The Wharton School, University of Pennsylvania

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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 2013-2016, home sales volumes in the most-SLR-exposed communities declined 20% relative to less-SLR-exposed areas, even as their sale prices grew in lockstep. Only by 2019 did relative prices in these at-risk markets ultimately decline 5%. Over this period, home sellers accumulated an excess inventory of unsold properties as they maintained high list prices. Lender behavior cannot reconcile these patterns, as both all-cash and mortgage-financed purchases similarly contracted. We propose a demand-side explanation where previously neglected SLR risk became more salient in the home price expectations of prospective buyers than sellers. The lead-lag relationship between transaction volumes and prices in SLR-exposed markets is consistent with dynamics of prior real estate bubbles.

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1 Introduction

How do asset markets incorporate newly salient information about neglected risks? The answer to this question is critically important for coastal housing markets, where climate forecasts project not if but when sea level rise (SLR) will threaten communities. Sufficiently forward-looking house prices should account for both current heightened risk of extreme weather events and future anticipated inundation. If prices today do not fully reflect future risk, then unmitigated climate change could cause larger declines in property value as SLR forecasts become reality. With 42% of the U.S. population residing in coastal counties (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 2001–2019. We focus on coastal Florida, where the Union of Concerned Scientists projects that over one million properties are at risk of chronic inundation due to SLR by 2100, the highest exposure of any state (Dahl et al., 2018). Our analysis considers similar housing markets within 1/2 mile of the coast that are differentially exposed to SLR and compares their transaction price and volume trends before and after 2013 as Hurricane Sandy and increasingly dire climate projections directed public attention towards SLR risk.[1] Using data on home transactions, sales listings, mortgage applications, and flood insurance premiums all linked to SLR 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 (in black) and more-SLR-exposed (in blue) tracts normalized by their 2001-2012 mean.[2] Prior to 2012, the two markets' sales volumes followed essentially identical trends. However, we document a sharp decline in transaction volume after 2013 in the housing markets most exposed to SLR. Sales in these high-risk tracts started to fall in 2013, while sales in low-risk coastal tracts continued to rise. In contrast, relative home prices followed volumes with a lag in more-SLR-exposed markets; From 2013–2016 they increased in line with less-SLR-exposed prices, and only started to relatively decline after 2016.

The staggered declines in sales volumes and prices in more-SLR-exposed markets relative to their less-exposed coastal neighbors motivate our two primary research questions. First, does the

[1] We discuss the specific factors driving increasing climate risk salience around 2013 in more detail in Section 3.

[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.

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 OLS, synthetic control, and generalized propensity score matching estimators.

All three methods produce 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 2019, we estimate that the most-SLR-exposed census tracts in Florida had 19% to 26% 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 22,000 fewer home transactions took place from 2013–2019. On the other hand, we find no evidence of a strong relationship between changing home prices and SLR from 2013–2016. However, from 2016–2019 prices in more-SLR-exposed tracts declined by 5% of their baseline value relative relative to less-exposed markets.

Next, we consider the potential mechanisms behind these changing market trends. First, we compare the behavior of buyers and sellers. We find that even as buyers withdrew from the market, SLR-exposed sellers continued to list their homes in similar numbers as their less-exposed coastal neighbors. As a result, SLR-exposed homes spent more days on the market before selling and accumulated as unsold inventory – echoing trends from the 2007–2009 housing bust. Second, we rule out the hypothesis that lender or insurer behavior can explain these patterns: We estimate similarly large relative declines in both cash home purchase and home purchase loan volumes and small changes in the rates of loan denial, securitization, or refinancing volume with respect to SLR exposure. Neither rising flood insurance premiums nor contemporaneous flood events in exposed markets can explain our results. Finally, we examine heterogeneity in SLR-exposed market declines. Sales of SLR-exposed new homes saw larger transaction volume declines than existing construction, suggesting lower housing supply in at-risk markets. Using a variety of proxies for climate beliefs, we find that SLR-exposed sales volume changes are decreasing in the share of the population worried about climate change. In sum, our analysis suggests that in 2013 buyers in climate pessimistic markets – but not sellers or lenders – began to revise downward their demand for SLR-exposed homes.

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 (2021) 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.[3] However, these models cannot match the pattern of declining volume but stable relative prices that we observe until 2016 or the accumulating inventory of unsold homes.

Instead, our empirical findings are well characterized by a sudden change in the salience of climate risk causing home buyers to stop neglecting future SLR. This "neglected risks" framework best explains the fall in transaction volume, especially among new homes, as indicative of an oversupply of SLR-exposed housing (Gennaioli et al., 2012, 2015). On the other hand, sellers, perhaps extrapolating from recent price increases (Glaeser and Nathanson, 2017), set list prices higher than most prospective buyers are willing to pay. As in DeFusco et al. (2021), optimistic sellers prevent SLR-exposed housing markets from clearing, thereby creating the lead-lag relationship between volume and price declines. By 2019, more-SLR-exposed home prices started to decline but volumes remained substantially below comparable less-SLR-exposed markets, suggesting continued disagreement about SLR risks between buyers and sellers.

Our findings advance a rapidly growing literature on climate change, sea level rise, and housing markets along multiple margins. First, our paper uniquely incorporates dynamic market activity alongside home prices rather than examining prices independent of transaction volume.[4] Both Bernstein et al. (2019) and Baldauf et al. (2020) estimate large SLR price discounts after 2013 that are significantly higher in areas with high climate change "worry" as measured in the Yale Climate Opinion Survey. Similarly, Giglio et al. (2021) 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. On the other hand, Murfin and Spiegel (2020) compare elevation price premiums across areas with different local rates of SLR and observe no SLR price effect.

[3] A related point is made by Bunten and Kahn (2017), who model how risk and amenity preference heterogeneity, independent of beliefs, can attenuate the relationship between climate risk and house prices in a residential sorting model.

[4] 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), Muller and Hopkins (2019), or Zivin et al. (2020).

We find that focusing on prices alone can miss important dimensions along which housing markets respond to SLR. We are the first to document a lead-lag relationship between declining transaction volume and prices after new climate risk information. This is a particularly surprising finding given standard predictions that new information in financial and real estate markets should lead to higher trading volumes, as buyers and sellers adjust their beliefs and pessimists re-sort with optimists (Wang, 1994; Bakkensen and Barrage, 2021; Bernstein et al., 2020). Furthermore, our heterogeneity results suggest that the separation between prices and volumes and rise in the inventory of unsold listings have been largest where residents and prospective buyers are more concerned about climate risk. This divergence between home sale volumes and prices 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 second 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 three reasons. First, SLR inundation projections are noisy 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). Finally, we sought a measure of SLR exposure that is salient to residents through news reporting, as opposed to relying on relatively small differences in elevation between nearby properties. Our alternative SLR exposure measure and absence of a changing SLR price discount until after 2016 may reconcile the different findings in the SLR price discount literature to date.

A third 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 housing market trends in SLR-exposed coastal Florida. Our results are potentially consistent with findings in Ouazad and Kahn (2021) and Bakkensen et al. (2022), who find that lenders relied on mortgage securitization to offload their climate risk before 2013, suggesting they had already updated their climate beliefs. Nguyen et al. (2020) finds that lenders started charging higher rates on SLR-exposed properties in the 2000s, while Sastry (2021) and Blickle and Santos (2022) show that lenders respond to current flood risk by rationing credit.

However, the fact that lenders have not meaningfully changed their rates 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. Our interpretation of these results, informed by conversations with industry participants, is that lenders are protected by federal programs that actively mis-price climate risk. 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). 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).

Finally, our paper extends the literature on price dynamics in real estate and asset markets. Many papers have noted the positive correlation and lead-lag relationship between volume and price changes and have sought to explain this pattern with search models, speculative buyers, bounded rational expectations, and credit conditions (Stein, 1995; Case and Shiller, 2003; Scheinkman and Xiong, 2003; Case, 2008; Han and Strange, 2015; Glaeser and Nathanson, 2015; Burnside et al., 2016). Our results describe a highly localized housing bust along Florida's coast where falling volumes preceded falling prices. Given the rise in unsold SLR-exposed listings, our results suggest that sellers can be slower than buyers to update their beliefs about newly salient climate risk information, leading to delayed price capitalization and less liquidity in at-risk markets (Gennaioli et al., 2012, 2015; Glaeser and Nathanson, 2017; DeFusco et al., 2021).

2 Data

Our analysis relies on sea level rise projections, home sales prices and characteristics, mortgage lending data, detailed information on home listings, and various other supplementary sources aggregated and merged at the 2010 census tract level. In this section, we describe how these data, along with other complimentary sources, are used to construct the sample and variables used to conduct our analysis.

2.1 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 the National Historic GIS database (Manson et al., 2019) is within 1/2 mile of the coast. As shown in Appendix Figure A-1, inland Florida had distinct home sale volume and price dynamics, particularly over the housing boom and bust, relative to its coastal areas. There are 859 tracts that meet this coastal 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 to reliably estimate home price indices (HPIs) (74 tracts). These restrictions produce a final estimation sample of 771 tracts over an estimation period from 2001–2019.

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

2.2 Sea Level Rise Exposure (NOAA)

Our data on SLR projections come from the National Oceanic and Atmospheric Administration (NOAA) (Marcy et al., 2011).[5] These projections use hydrological models and elevation data to identify coastal land areas that would be inundated under one foot to ten feet of SLR.

We construct 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. Our rationale for choosing these specific thresholds comes from our Generalized Propensity Score (GPS) results, described in Section 4.3. We use census tract rather than property-level measures of SLR exposure to reflect the uncertainty and community-level effects of SLR risk.

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 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

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

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.

2.3 Home Price Index and Market Transaction Volume (Corelogic)

We use home purchase records from CoreLogic to measure total housing transaction volume from 2001–2019 at the census tract level and separately 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, whether the sale was a cash or mortgage purchase, and an indicator for sales of newly built homes. Our estimation sample includes over 1.4 million home transactions.

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, we construct a tract-by-year home price index (HPI) from the CoreLogic transactions data, as described in Appendix Section C.

2.4 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. 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. Our estimation sample includes over 2.7 million loan applications.

We measure annual purchase loan volume as the number of approved home purchase loans in HMDA, and similarly define a measure of refinance loan volume. 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).[6] 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.

[6]We obtain similar results measuring purchase loan volume with CoreLogic instead of HMDA. The 2010 tract-level loan counts in both datasets have a correlation coefficient greater than 0.9 from 2001–2019.

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 or denied and whether an approved loan below the conforming loan limit (CLL) was marked in HMDA as sold for 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.

2.5 Home Listings (MLS)

We distinguish between the behavior of buyers and sellers in the housing market using data from the Multiple Listings Service (MLS) provided through CoreLogic. MLS are a collection of databases used by realtors to list homes and search among available homes for sale. The CoreLogic MLS data contains the record of these listings from a sampling of different MLS providers who operate in different regions.

The MLS data show when each property was listed for sale, the price it was listed for, and when it went off the market. We see whether each listing ended as sold versus expired, and its closing price if sold. We subset to listings of single-family homes and condos and geocode each property to its 2010 census tract.

We construct several variables to describe listing activity. First, we measure the total number of new listings each year. In constructing this variable, we account for a common strategy employed by realtors to remove and re-list properties that become "stale" after being on the market for several months. If the same property is listed less than 180 days after expiring, we treat that as part of a single continuous list attempt. Second, we define the average number of days on market for listings that end in sales. We also measure the average number of unsold listings available in each year, calculated as the mean number of unsold listings as of the first of each month in a year. Finally, similar to the home price index, we construct a list price index as described in Appendix Section C.

The MLS data excludes for sale by owner transactions, which typically account for 9-15% of sales (NAR, 2013). In addition, the set of MLS providers CoreLogic has data access from varies over time. Before 2010, there is insufficient listings data to construct a reliable panel. After 2010, we find much higher and more consistent coverage, although still with substantial missing data for some of the 771 estimation sample tracts. We subset to tracts where at least 66% of CoreLogic sales are accounted for in the MLS data. The remaining MLS estimation sample includes 579 of the original 771 census tracts, covering over 800,000 listings and accounting for 84% of the sales in

CoreLogic from 2010 to 2019.

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).[7] 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—2019 to measure premium changes over time on over 350,000 annual NFIP policies (FEMA, 2005-2018b). Appendix Section C.3 describes the construction of our premium change instrument used to address endogeneity between policy composition, take-up, and observed average premiums paid.

The premium changes described above were focused on homes inside the Special Flood Hazard Area (SFHA), commonly referred to as the floodplain. In addition to different premiums, new construction inside the floodplain generally faces higher standards for adaptation and is a source of flood risk information for homeowners and prospective buyers. Although the 2012 BW reforms did not affect floodplain regulations, it is possible that market participants may have reacted differently to floodplain designations over this period separately from the effect of premium changes. We measure the share of each tract's developed land designated by FEMA as inside a SFHA to include as a control for changing perceptions of current flood risk as opposed to future SLR risk (FEMA, 2018a).

2.7 Climate Opinion Proxies

Given the polarizing nature of climate change in U.S. political discourse, we estimate how responses to Sea Level Rise (SLR) risk vary by climate risk beliefs. We gather three proxies for variation in

[7]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.

climate opinions by coastal Florida residents and prospective homebuyers. First, we use data from the 2014 Yale Climate Opinions Survey. The survey uses polling data combined with statistical models to estimate climate change beliefs at the county level (Howe et al., 2015) and has been used in many related studies, including Baldauf et al. (2020), Barrage and Furst (2019), Bernstein et al. (2019), and Goldsmith-Pinkham et al. (2019).

Second, we gather data on the share of buyers in each coastal Florida county between 2010 and 2012 who came from counties in New York or New Jersey that were affected by Hurricane Sandy in October 2012. Given the prominence of Hurricane Sandy in driving the discussion of coastal climate risk after 2013, such buyers might be especially wary of investing in another SLR-exposed market. To construct this measure, we use IRS county-to-county migration tables (IRS Statistics of Income Division, 2010-2012) to calculate the share of migration inflows into Florida counties from New York or New Jersey counties identified as exposed to Hurricane Sandy. New York coastal counties were identified as exposed if they were designated to receive individual and public assistance under FEMA's New York Disaster Declaration (FEMA, 2012); coastal counties in New Jersey were identified as exposed if the were marked as featuring significant Sandy surge extent by USGS (USGS, 2013).

Finally, we use Florida tract-level vote shares for the Democratic candidate in the 2008 U.S. presidential election as a proxy for climate concerns (Tyson, 2021). We obtain Democratic vote shares from the Florida House of Representatives' Redistricting Committee website (Florida House of Representatives Redistricting Commitee, 2011).

3 Methodology

3.1 Estimating Changes in SLR Capitalization

A challenge of studying the effects of climate risk on housing markets is that 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 and higher socioeconomic status relative to less-SLR-exposed tracts.

Rather than make cross-sectional comparisons between more- and less-SLR exposed areas, we instead compare their market dynamics before and after SLR became more salient. A confluence of events around 2013 focused public attention on climate risk, including Hurricane Sandy striking the East Coast, new SLR projections from the Intergovernmental Panel on Climate Change (IPCC) AR5 report, and the 2014 National Climate Assessment which comprehensively documented SLR exposure in the United States (Stocker et al., eds, 2013; Georgakakos et al., 2014). In Florida, these reports spurred local news coverage and google searches for the topic "Sea Level Rise" (see Appendix Figure A-2).[8]

The goal of our estimation strategy is to isolate the effects of this increasing climate salience on the capitalization of risk in SLR-exposed markets. To achieve this, our methodology builds on a difference-in-difference style estimator that compares changes in more-SLR-exposed housing market outcomes from 2013–2019 relative to observationally similar but less-SLR-exposed coastal markets. We measure housing market changes normalizing outcomes by their 2001–2012 tract-level mean.

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. Specifically, our assumption is that in the absence of growing SLR salience, coastal housing markets with different exposure would have continued on similar paths. 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. Different relative trends between more- and less-exposed tracts which persist in matched samples are more likely a result of increasing climate risk awareness rather than some unrelated shock.[9] We apply two different estimators to establish the robustness of our results to alternative matching techniques and sets of covariates: synthetic control (SC) and generalized propensity score (GPS) matching. The fact that the results of these two estimators are consistent with the trends in the raw data increases our confidence in the conditional parallel trends assumption.

3.2 Synthetic Control

For each more-SLR-exposed tract, the synthetic control (SC) estimator constructs a weighted average of less-SLR-exposed tracts that match 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 construct our set of synthetic tracts by matching on the following set of non-outcome covariates: mean 2001-2012 home price index, 2001-2012 share of transactions by non-owner occupied buyers, inverse hyperbolic sine (IHS) of flood insurance claims per capita 1995-2005, 2010 poverty rate, share of tract area made up of water, and distance-to-coast from tract population center. We

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

[9] Spillover effects are another important concern, 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.

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), using the MSCMT package developed by Becker and Klößner (2018), and run the SC procedure over each more-SLR-exposed tract to estimate an average treatment effect in each year.

We conduct inference by constructing placebo synthetic controls for each of the less-SLR-exposed tracts from the other less-SLR-exposed tracts, following Cavallo et al. (2013). For each year, we construct 1,000 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.

3.3 Generalized Propensity Score

The generalized propensity score (GPS) approach extends propensity score matching to estimate the effects of continuous treatments (Hirano and Imbens, 2004). This flexibility means that, unlike with SC, we do not need to classify tracts into binary more-versus-less exposed groups while discarding any tract with intermediate exposure. Instead, we are able to estimate "dose-response" functions and document the changing effects of SLR on housing markets across the full distribution of exposure for all tracts in our sample. Appendix Section D describes GPS estimation in more detail.

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, mean share of 2001-2012 home sales by non-owner occupied buyers, 2010 population share under 18 and share 18 to 64, and quadratic terms of 2010 population shares nonwhite and in poverty, and tract area made up of water. We estimate potential outcomes at 10% intervals of SLR exposure from 0% to 100%, and combine data over 2010-2012, 2013-2015, 2016-2018, and 2019-2020 to present our estimates compactly.[10] The ability to include county fixed-effects in propensity score estimation is another desirable property of the GPS approach. These fixed-effects control for county-level unobservable factors and show that our results can be robustly identified from within-county variation in SLR exposure.

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

4 Results: SLR Exposure and Housing Market Dynamics

4.1 Descriptive Statistics

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. 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 differ substantially across a range of geographic and demographic attributes. High exposure tracts are 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 approaches to account for observable differences between the two areas while exploring the effect of sea level rise on housing and mortgage markets in these tracts.

4.2 Housing Transaction Volumes and Prices

4.2.1 Raw Data Trends and Long-Difference Results

Figure 1 presents the time series of aggregate housing transactions (top panel) and mean house price index (bottom panel) for our sample of less-SLR-exposed and more-SLR-exposed 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 2019.[11]

Figure 4 shows that these relationships between SLR, housing transactions, and house prices hold across the continuous distribution of SLR exposure.[12] Comparing changes in 2016 relative to the pre-2013 mean, panel (a) shows a declining relationship between home sales volumes and SLR. On the other hand, there is little relationship between SLR and relative changes in 2016 home sale

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

[12]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.

prices as shown in panel (b). By 2019, however, a significant negative relationship between SLR and both home sales and relative prices emerges in panels (c) and (d).

As a simple test of the raw trends' robustness to differences in observable characteristics, we estimate linear regressions of the following form:

$$Y_{it} = \alpha_0 + \lambda_t X_i + \beta_t SLR_i + \epsilon_{it} \tag{1}$$

Y_{it} denotes home sales volume or prices of tract i in year $t \in \{2016, 2019\}$ normalized by its tract-level 2001-2012 mean.[13] X_i are tract-level controls for population centroid distance-to-coast and share of 2010 households in poverty. SLR_i is an indicator variable for tract i's exposure, taking distinct values for less-SLR-exposed tracts, medium SLR exposure tracts, and more-SLR-exposed tracts as defined in Section 2.2.

The results of these regressions are shown in Table 2 for home sales volume (panel a) and prices (panel b) in 2016 (columns 1 and 2) and 2019 (columns 3 and 4). The results with no controls suggest a relative decline of 20% in home sales volume relative to 2001–2012 in more-SLR-exposed tracts by 2016, but a small increase in relative prices. By 2019, the volume decline reaches 23% and home prices are 7% lower in more-SLR-exposed areas. The magnitude and lead-lag relationship between the volume and price declines in more-SLR-exposed tracts persist as we introduce controls for distance-to-coast and poverty share in columns (2) and (4).

4.2.2 Synthetic Control Results

In this section, we examine whether the divergence between sales volumes and prices in markets with high SLR exposure in the raw data is robust to flexibly controlling for differential trends between more and less SLR exposed areas during the housing market recovery using the synthetic control (SC) estimator.

Figure 5 shows the time series of home sales and HPI for the more-SLR-exposed tracts (in blue) and the synthetically constructed control sample (in black). 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 begin to diverge, with fewer home sales in high exposure areas. By 2019, annual home sales are 9% below the "pre-period" 2001–2012 mean in more-SLR-exposed tracts, whereas in the synthetic control sample sales are 10% above their mean, yielding a total sales gap of 19%.[14]

[13] Results are similar when we calculate the long-difference as the change in the log outcome variable from 2012.

[14] We also confirm that our results are not sensitive to the matching endpoint. Appendix Figure A-5 shows that the results remain similar for home sales volumes and prices when we end the matching pre-period in 2010 instead of 2012.

In contrast, the house price series (shown in panel (c)) follows a different pattern, with high exposure tracts' relative prices rising until 2016, peaking at roughly 3% higher prices in 2014, and then falling 6% below that of the synthetic control sample's prices by 2019. Note that prices followed similar paths prior to 2013, 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.[15]

Thus, even when the set of less-SLR-exposed tracts are chosen to match the more-SLR-exposed 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. Summing 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 there were approximately 22,000 fewer home transactions in more-SLR-exposed tracts relative to the synthetic control sample between 2013 and 2019.

Panels (b) 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. Treatment effects falling outside of the shaded gray region are statistically significant at $\alpha = 0.05$. Relative to the statistically significant volume declines from 2013 to 2016, there was not a significant relative price decline until 2017.[16]

4.3 Dynamics Across the Distribution of SLR Exposure

While our synthetic control results highlight divergent housing market trends between more-SLR-exposed and less-SLR-exposed tracts, they are constrained to measure 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 6 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. Panels (a) and (c) show the differential change in home sales by 2013-2016 and 2017-2019

[15] While the future risk of sea level rise should affect house prices, current amenity values and thus rents should be unchanged. Bernstein et al. (2019) find cross-sectional support for this prediction using 2017 rental prices. However, we know of no longitudinal data to test the effect of SLR salience on rents.

[16] We further show in Appendix Figure A-6 that are our results are robust to removing tracts with a poor fit with their synthetic comparison group over the 2001–2012 matching period. See Appendix Table A-1 for the matching period root mean square error distribution. In Appendix Figure A-7 we establish that these results are not driven solely by Miami, despite its prominence in the national discussion around SLR.

from the 2001-2012 period relative to tracts with no SLR exposure. In the 2013-2016 period, tracts with at least 80% exposure experience a statistically significant decline in transaction volume. By the 2017-2019 period, there is a clear downward trend in home sales for tracts with greater than 40% exposure. For tracts that would be fully inundated at six feet of sea level rise, we estimate a relative decline of roughly 25% of the pre-2013 mean in home sales, similar to the estimated effect for the more-SLR-exposed group using synthetic control methods.

Panel (b) of Figure 6 shows the relative change in home prices in 2013-2016 from the 2001-2012 period. Similar to the trends in the raw data, we estimate a statistically significant relative increase in prices of around 5% for tracts with high SLR exposure over this period. In panel (d), we see that this relative increase has completely disappeared by the 2016-2019 period, with more-SLR-exposed tracts instead facing a relative price decline of 5% compared to their pre-2013 mean prices.

In sum, examining changing housing market dynamics across the sea level rise distribution, we observe statistically significant declining home sales by 2017-2019 only in tracts with at least 40% sea level rise exposure. The largest declines are concentrated in the same tracts as the more-SLR-exposed treatment group used in the synthetic control method, supporting the use of our "high vs. low" binary exposure measure for capturing the relevant treatment effect.[17]

5 Separating Buyers' and Sellers' Responses to SLR Risk

Our evidence so far documents a housing market slowdown in more-SLR-exposed areas relative to less-SLR-exposed ones that began with declining transaction volumes in 2013 and then continued with falling sales prices in 2016. These findings are the result of an equilibrium negotiation between buyers and sellers.

To separate buyer and seller responses, in this section we compare the dynamics of home sale listings in more- and less-SLR-exposed markets between 2010 and 2019 using the Multiple Listing Service (MLS) data described in Section 2. If changing seller perceptions of climate risk caused these market declines, we would expect to see a sharp increase in listings as sellers attempted to exit risky properties. In contrast, if buyers are updating their understanding of risk in this market, we would expect listed properties to take longer to sell and ultimately at lower prices.

We find multiple pieces of evidence that while potential buyers adjusted their behavior in 2013, sellers had a delayed reaction to the climate news. First, panel (a) of Figure 7 shows almost no difference in the trends in the number of new listings in more- and less-exposed markets across the

[17]Similar to the synthetic control results, we show in Appendix Figure A-8 that our GPS results hold when excluding all tracts in Miami-Dade county.

entire sample period in the raw data.[18] This similarity in listings stands in sharp contrast to the divergence in home sale volume documented in the top panel of Figure 1.

As a result of the continuing growth in listings but stagnating sales volumes after 2013, we show that the inventory of unsold homes increased in more-SLR-exposed areas even as it continued to decline among less-SLR-exposed properties (Figure 7 panel b). Further, consistent with these trends, panel (c) shows that the days-on-market from listing for homes sold in more-SLR-exposed markets increased from 2013 to 2016 relative to less-SLR-exposed markets.

The listing price trends shown in Figure 7 panel (d) document similar growth from 2010-2016 across the two markets. After 2016, however, more-SLR-exposed list prices declined relative to less-SLR-exposed ones. The timing of this relative decline in list prices aligns with the relative decline in transacted prices documented in the bottom panel of Figure 1. As the growth in more-SLR-exposed prices began to slow, days-on-market declined between 2016 and 2019, although the inventory of unsold homes remained elevated.

Looking across the distribution of SLR exposure, we apply the Generalized Propensity Score (GPS) methodology described in Section 3.3 to the outcomes in Figure 7. The results, shown in Figures 8 and 9 and summarized in Table **??** with accompanying long-difference estimates, are consistent with the trends from the raw data. As sellers continued to list properties in the face of reduced demand, we estimate that unsold inventories were approximately 60% higher in more-SLR-exposed markets than comparable less-SLR-exposed areas over their 2010 mean.

The results from the listings data uniquely clarify the dynamics of supply and demand in the housing market, and suggest that sharp changes in volume and delayed capitalization of climate risk into prices are initially demand-driven. In the next section, we examine potential mechanisms for these patterns.

6 Exploring Mechanisms Driving Market Dynamics

6.1 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? 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

[18] As described in Section 2, the MLS data are only consistently available starting in 2010. Because of this shortened time series, we cannot apply the synthetic control estimator.

than cash purchase volumes.

In Figure 10, we explore the dynamics of home purchase lending volumes alongside cash purchase volumes with the synthetic control estimator. Panels (a) and (b) of Figure 10 show a sharp divergence of both cash and mortgage transactions between more-SLR-exposed tracts and matched control tracts after 2012 that are consistent with the overall volume results presented above in Figure 5. The decline is actually larger for cash than mortgage purchases, with relative declines of 28% and 17% by 2019, respectively. 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 provide new direct evidence that the decline in sales volume reflects primarily a housing demand rather than credit supply response.

In Figure 11, we further examine additional indicators of lender behavior. If lenders were 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 11 shows that approximately 5% more loan applications were denied between 2014 and 2018 in more-SLR-exposed tracts from a base of 25%. Thus, we conclude that while lenders may be making some small adjustments on the margin, changing loan denials cannot explain a nearly 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 government-sponsored enterprises (GSEs). However, Figure 12 shows only modest support for this hypothesis. The securitization rates of more-SLR-exposed tracts are elevated by about 5% of the 2001–2012 mean relative to the synthetic control for most of the 2013–2019 period, with the 2018 and 2019 differences close to zero.[19]

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 (Keenan and Bradt, 2020). 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. Appendix Figure A-9 shows the synthetic control results for local (top row) and non-local (bottom) purchase loan volumes. Although the relative decline by 2019 of 25% for local loans is larger than the corresponding 15% decline of non-local loans in more-SLR-exposed areas, the difference between the two series is noisy. In Appendix Figure A-10, we see no evidence of

[19] In results not shown, estimated responses in volume, denials, and securitization for loans larger than the conforming loan limit (the "jumbo" mortgage market) are not statistically distinguishable from those below the conforming loan limit, but with large error bands given small sample sizes.

a substantial decline in refinance lending for local or non-local lenders. Our results suggest that as SLR risk perceptions changed around 2013, neither local nor non-local lenders substantively responded.

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 (2021) 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 independent of current or future flood risk (Hurst et al., 2016). Although the NFIP and mortgage securitization leave taxpayers exposed to climate risk, these programs insulate lenders' balance sheets.

6.2 Higher Insurance Premiums

One possible explanation for our findings is that higher flood insurance premiums drove the decline in SLR-exposed housing markets over this periods. 2012 and 2014 saw the passage of reforms of the National Flood Insurance Program (NFIP) that began to increase premiums on previously subsidized homes inside floodplains.

These rising premiums are unlikely to explain our findings. First, there is no reason that higher premiums should lead to a decline in transaction volume or its lead-lag relationship with lower transaction prices. Second, our GPS method includes controls for the share of homes inside the FEMA floodplain – the group most affected by premium increases over this period. Notably the floodplain is not perfectly correlated with our measure of sea level rise due to differences in current versus future flood risk and floodmap accuracy.

To directly test the role of higher premiums in driving volume and price outcomes, we control for log per-capita premium changes from 2012–2019 in our long-difference OLS specification, with results described in Appendix Table A-2. The magnitude and lead-lag relationship between the declines remain consistent when we add the premium change variable in columns (1) and (3). The results also remain quantitatively similar when we instrument for premium changes in columns (2) and (4) with the counterfactual premium change if each tract's 2012 policy cohort were held fixed, as described in Appendix Section C.[20]

6.3 New and Old Construction

Next, we compare the changes in SLR-exposed transaction volumes between sales of new and existing homes. While most of the existing coastal housing stock was built well before sea level rise (SLR) was a concern for most housing market participants, changes in newly built home sales reflect housing supply responses to growing SLR awareness after 2013. One might rationalize the decline in volume we observe as driven by a decrease in housing construction in SLR-exposed areas driven by rising flood insurance premia or regulations.

Figure 16 shows the synthetic control estimates for the sales volumes of new homes (top row) and existing homes (bottom row). Noting the difference in the y-axis scales between the top and bottom rows, new home sales were much more elastic over the housing market boom and bust than existing home sales. After 2013, whereas new home sales continued to decline through 2019 in more-SLR-exposed markets, they recovered in the matched synthetic control sample of less-SLR-exposed tracts, reaching their 2001–2012 mean by 2019 (panel a). As a result, new home sales were 90% of the 2001-2012 mean lower in more-SLR-exposed markets relative to their synthetic controls by 2019 (panel b). The bottom row of the figure shows that existing home sales also declined substantially in more-SLR-exposed tracts after 2013 (panel c), falling over 20% of the 2001–2012 baseline by 2019 relative to their synthetic controls (panel d). Generalized propensity score estimates of changes in new and existing home sales across the SLR distribution are consistent with the synthetic control results (Appendix Figure A-16).

Despite the significant decline in new home sales, the magnitude of the decline in existing sales is statistically indistinguishable from the decline estimated for total sales of SLR-exposed homes, unsurprising given that existing home sales comprised nearly 90% of 2001–2012 sales in the estimation sample. Although the decline in new home sales volume is consistent with a strong negative supply response in more-SLR-exposed areas, it alone cannot explain the drop in overall transaction volumes.

[20]We additionally show that our results are not driven by contemporaneous disasters by re-estimating our home prices and sales volumes results excluding tracts in the top quartile of 2001–2018 flood insurance claims per capita. Appendix Figure A-11 shows that this sample restriction excludes essentially all tracts with significant flood insurance claims over the sample period. Appendix Figures A-12 and A-13 present similar synthetic control and GPS estimates for transaction volumes and home prices, respectively, excluding census tracts with high claims as in the full sample.

6.4 Heterogeneity by Climate Opinions

Our results thus 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.

Panel (a) of Figure 13 presents the relationship between the 2019 synthetic control 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 2014. 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?" 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 2019. The differences are dramatic, with an additional ten percent of the county worried about climate change associated with an approximately 27 percentage point greater relative decrease in home sales volume.

Panel (b) shows the relationship between the 2019 change in house prices and the share that are worried about climate change. Here we observe a negative albeit statistically insignificant relationship between the relative home price changes in more-SLR-exposed markets and worry about climate change.

Our other climate opinion proxies show a similar negative relationship between climate pessimism and housing market declines in SLR-exposed markets. SLR-exposed markets where a greater share of 2010–2012 home purchases were by buyers in parts of New York and New Jersey affected by Hurricane Sandy saw greater home transaction volume declines by 2019 (Figure 14), while a higher 2008 Democratic vote is associated with larger volume declines (Figure 15). Greater Sandy-affected migration, or higher Democratic vote share, are associated with larger 2019 home price declines, although the relationships are statistically insignificant. The directional relationships from our heterogeneity tests are consistent with other papers that have found larger price effects of SLR among markets with more climate pessimists (Bernstein et al., 2019; Baldauf et al., 2020). However, we find a much stronger relationship between beliefs and SLR-exposed volume declines than prices.

In sum, the places with the largest transaction volume and price declines are in counties where climate risk is most salient to residents and prospective homebuyers. Together with the evidence on changing SLR risk salience in Florida, this pattern suggests that climate change belief heterogeneity may be affecting how and when SLR risk is capitalized into housing markets. Contrary to prior studies which have focused on the heterogeneity of capitalization of SLR into home prices, we find that the heterogeneity of SLR's effects on transaction volumes is more elastic with respect to climate risk beliefs.

The larger volume declines in markets with more climate pessimists is a puzzle for the usual explanation that segmented markets and re-sorting by beliefs drives heterogeneous SLR capitalization (Bakkensen and Barrage, 2021; Bernstein et al., 2019, 2020). Such a model would predict *higher* housing market turnover as pessimists sell to optimists. We return to possible explanations for this pattern in Section 7.

6.4.1 Heterogeneity by Socioeconomic Status

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 in lower socioeconomic status census tracts. 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).

To assess such heterogeneity, we plot the 2019 synthetic control sales volumes and prices treatment effects by share of households in poverty in Appendix Figure A-14. The figure shows little evidence of differential volume declines (top panel) by poverty, and while higher poverty tracts experienced larger price declines (bottom panel), the relationship is statistically insignificant. In Appendix Figure A-15, we find a negative, but also statistically insignificant, relationship between the share of each SLR-exposed tract's population that is nonwhite and its price and volume declines.

Taken together, these results suggest relatively little heterogeneity in the housing market dynamics or capitalization surrounding SLR risk by socioeconomic status. Although researchers have speculated that higher-income areas will be better equipped to adapt to climate change, we note that investment in adaptation is not guaranteed, as evidenced by debates around the high cost of elevating flood-prone roads in the Florida Keys and recent pushback against a Miami seawall (Harris, 2019; Mazzei, 2021).

7 Discussion

In this section we consider potential mechanisms for our results. Table 3 summarizes the effect of SLR salience on our main 2019 outcomes across the synthetic control, generalized propensity score, and OLS specifications. All three estimators describe consistent and novel trends in SLR-exposed markets: declining volumes and an accumulating inventory of unsold homes preceded falling prices. Our results also show that the relationship between SLR exposure and these market dynamics cannot be easily explained by differences in observable characteristics, pre-trends, behavior by lenders, changes to flood insurance policy, recent flood damage, or changes in new housing supply. We now briefly discuss how existing frameworks of the capitalization of SLR risk into housing markets, or the capitalization of new information into asset prices more broadly, fit the trends we document.

Market Segmentation and Belief Heterogeneity

One approach to market segmentation, proposed by Bakkensen and Barrage (2021), allows for dynamic SLR capitalization when homeowners are climate "optimists" or "pessimists," with optimists sorting over time into the risky coast. As negative climate news arrives, optimists update their beliefs, leading to re-sorting and volatile price changes. As in our results above, a number of papers have found supporting evidence that homes exposed to SLR risk sell at a greater discount in markets where more participants are worried about future climate change (Barrage and Furst, 2019; Bernstein et al., 2019; Giglio et al., 2021).

The Bakkensen and Barrage (2021) framework can potentially explain the price heterogeneity among more-SLR-exposed we observe in the bottom panels of Figures 13–15, where higher climate concern proxies are associated with larger home price declines since 2013. However, sorting and heterogeneous beliefs alone cannot explain the volume decline in more-SLR-exposed markets, or the fact that declines in volume were largest where buyers and sellers were most pessimistic. Instead, the model would predict *higher* home turnover as optimists buy from pessimists on the negative climate news.

Sea Level Rise as a Neglected Risk

Gennaioli et al. (2015) describe how "neglected risks" – potential negative shocks treated by market participants as having a probability of zero – can bring about financial crises when they suddenly become salient with the arrival of bad news. Gennaioli et al. (2012) consider the role of neglected risk in driving financial innovation to produce assets that appear safe only because their underlying risk is neglected.

We argue that sea level rise qualifies as a plausibly neglected risk for many coastal residents, or at least one that became much more salient after the many climate-related events and reports in 2013 (Figure A-2). Under this interpretation, the framework in Gennaioli et al. (2012) can explain the steep decline of new home sales in SLR-exposed markets after 2013 shown in the top panel of Figure 16. Coastal housing appeared relatively safe while SLR risk was neglected during the housing boom, leading to overproduction of SLR-exposed homes. After SLR risk became more salient, the production of SLR-exposed homes collapsed.

However, the neglected risk framework is inconsistent with the decline in existing home sales shown in the bottom panel of Figure 16. This is especially true given the belief heterogeneity noted above, as one would still expect optimists to buy from pessimists in SLR-exposed areas after the arrival of bad climate news.

Extrapolative Beliefs

One of the most striking features of the lead-lag relationship between volume and price declines in SLR-exposed communities is its similarity to the experience of housing markets over the boom-and-bust of the 2003–2007. As shown in Figure A-3, home sales volumes in Florida declined dramatically from 2005 to 2006 even as prices continued to rise.

Building on Glaeser and Nathanson (2017), DeFusco et al. (2021) describe a model that matches these volume and price dynamics. In the model, housing market participants incorrectly believe that current home prices solely reflect demand and neglect buyers' price expectations. Under this "cap rate error," sellers overestimate demand during periods of rapid price growth because they misattribute buyers' expectations of capital gains to higher demand for housing services. In the data, this tendency appears as extrapolative beliefs where market participants over-infer future price changes from past price changes. Over the boom, prices exceed their fundamentals until the boom turns into a "quiet phase," with falling volumes as prices continue to rise, and eventually a bust with falling prices (Glaeser et al., 2014).

A model with extrapolative beliefs can help to explain the lead-lag relationship we observe between volume and price declines in the context of climate risks. The bad climate news represented a looming negative amenity shock in SLR-exposed areas, decreasing housing demand. Nonetheless, sellers continued to post high list prices, believing under the cap rate error that the continuing high flow utility of coastal housing services *today* justify high prices. Buyers, anticipating increasing climate risks over their housing tenure, are less willing to buy, causing falling sales volumes even as prices remain high among those that still transact. With our unique listings data, we are able to verify a key prediction behind this account of a climate-driven housing bust: The rise in unsold home inventories and time on the market before sale in more-SLR-exposed areas (Figures 7–9). These patterns are consistent with SLR-exposed sellers overestimating demand as they try to sell their homes.

Finally, this extrapolative belief framework can parsimoniously explain the climate concern heterogeneity we observe. Even in SLR-exposed markets where both buyers and sellers are pessimists, the cap rate error causes list prices to exceed housing demand, accentuating the decline in home sales. Where buyers and sellers are climate optimists, sales volumes and prices will remain high even in the face of negative climate news. In sum, the patterns that we document in the housing and mortgage markets around the arrival of climate news are consistent with heterogeneous beliefs, previously neglected risks, and expectations formed by extrapolation from recent market performance.

8 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, we show that annual home transaction volumes have fallen in relative terms by 20% in the most-SLR-exposed coastal census tracts. This stark time-series pattern of diverging 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 and with controls for flood insurance premiums and recent disasters, suggesting that demand for at-risk coastal properties has fallen sharply since 2013, above and beyond any adjustments currently being made by lenders or insurers.

In contrast, home prices in both more and less-exposed markets rose from 2013–2015, and only towards the end of our sample did prices begin to fall in relative terms. This lead-lag pattern of declining sales volumes but relatively unresponsive prices was most recently observed around the apex of the housing boom and bust of the 2000s. In another echo to the previous housing market cycle, sellers continued to list their homes in similar volumes regardless of climate risk, leading to a rise in unsold inventories and days-on-market in more-SLR-exposed areas.

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 (Bakkensen and Barrage, 2021). However, belief heterogeneity across buyers alone cannot explain the accumulation of unsold inventory or continuing high list prices of for-sale SLR-exposed homes. These facts suggest that it was primarily buyers and not sellers who first responded to SLR risk.

Why might sellers have been slower than buyers to respond to increasingly severe SLR projections? We suggest that our unique pattern of empirical findings is most consistent with the role of extrapolative beliefs and neglected risk (Gennaioli et al., 2012, 2015; Glaeser and Nathanson, 2017; DeFusco et al., 2021). These frameworks explain the lead-lag relationship between price and volume declines, the direction of our heterogeneity results, and the unsold housing inventory and high list prices in at-risk markets. Homeowners – rather than selling below their expected price – may simply choose to let their listings expire and continue to enjoy the flow utility of their durable housing asset (Genesove and Mayer, 2001). Given the evidence that climate risk is not frictionlessly capitalized into home prices, further documenting the mechanisms and connections between belief heterogeneity and housing market behavior remains a promising direction for research.

While our empirical approach is not an exercise in prediction, 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, depend 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 information signals and investment in adaptation (Mulder, 2021). Whether these programs will continue to differentially support coastal housing investment in the face of rising costs, and how housing and mortgage markets will respond to changes in these programs that incorporate the current and future costs of climate change, remain crucial topics for future research.

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Figures

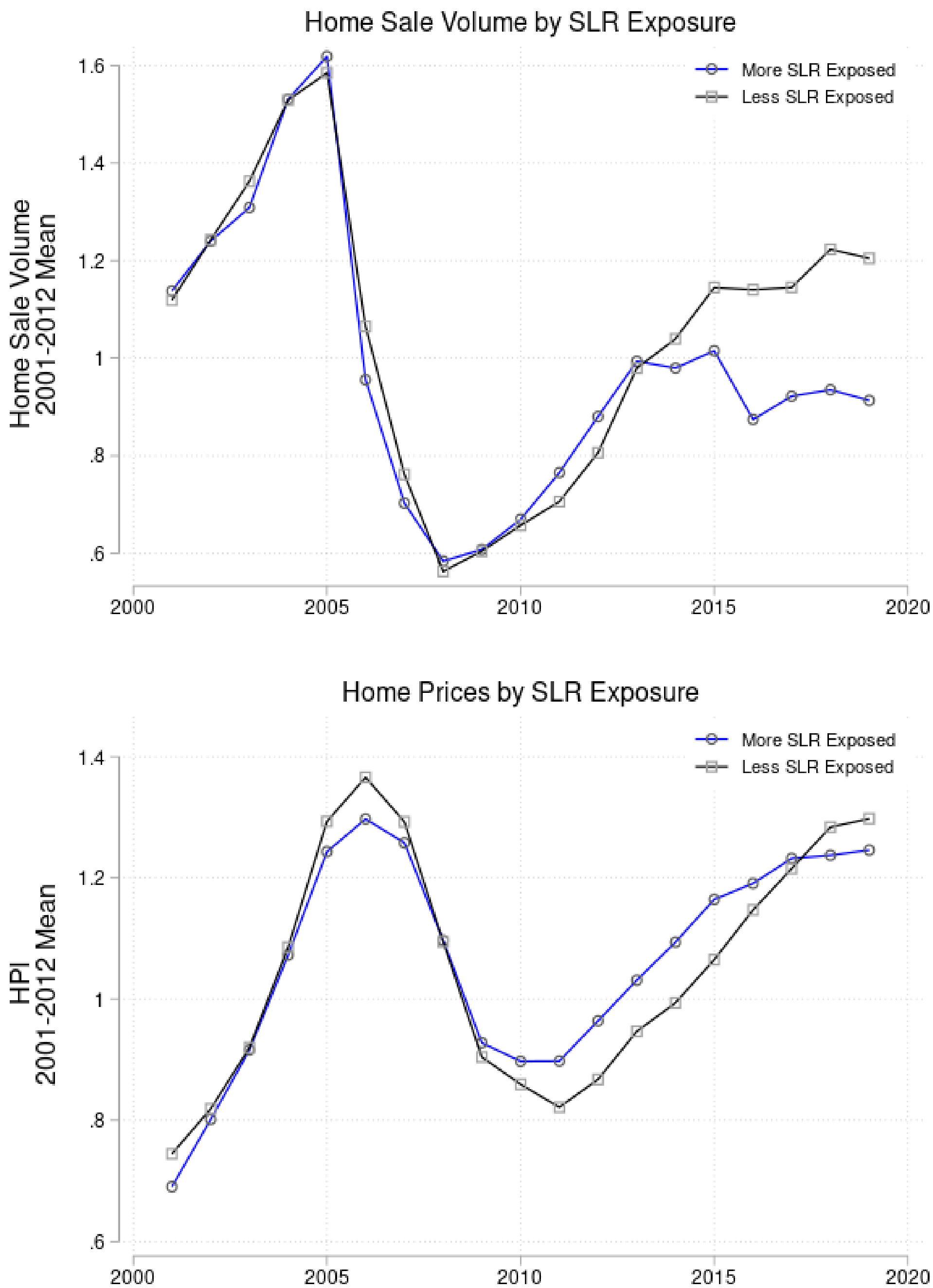


Figure 1: Housing transaction volume (top panel) and home price (bottom panel) trends in coastal Florida census tracts with high (blue) versus low (black) SLR exposure. Housing volume and home price index are normalized by their 2001-2012 mean. Sources: CoreLogic, Authors' calculations.

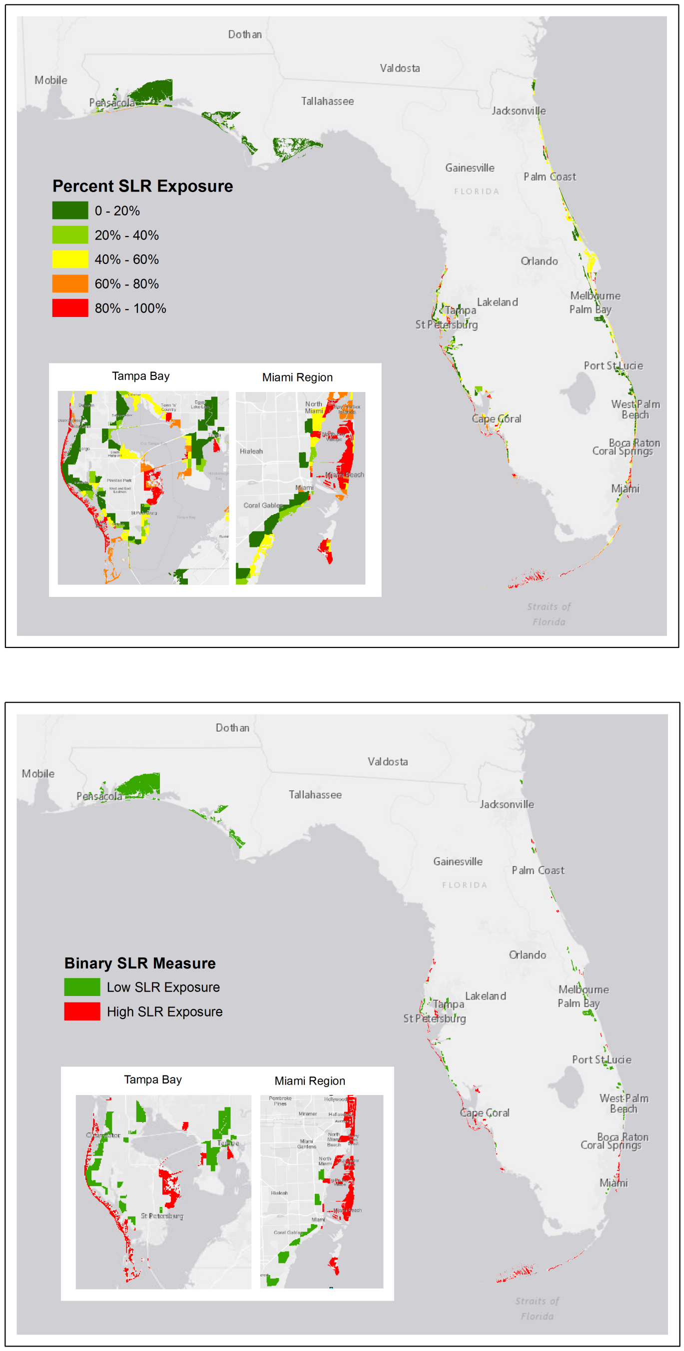


Figure 2: Maps show SLR exposure for the sample of 771 coastal Florida census tracts. The top panel shows the share of each tract's developed land in 2000 that would be chronically inundated at six feet of SLR. The bottom panel shows the subsample of tracts categorized as either "more-SLR-exposed" (>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

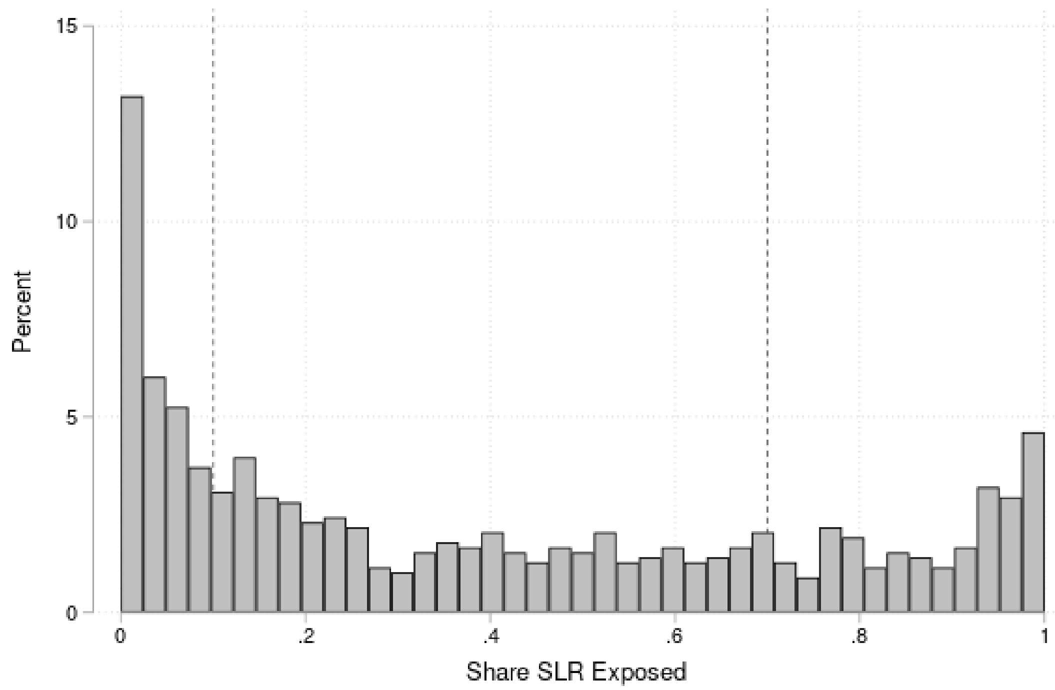
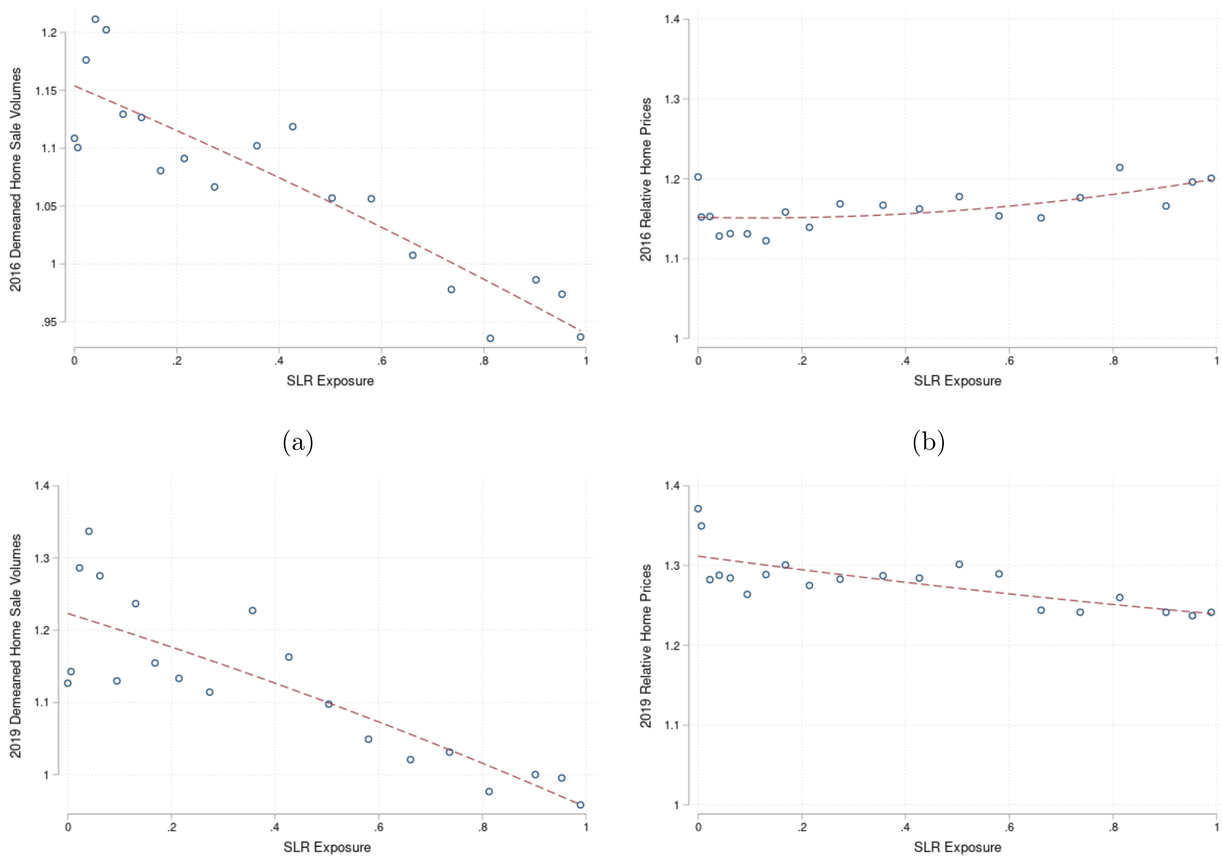


Figure 3: Histogram of tract SLR exposure. The first and second dashed lines indicate the cutoffs for the less-SLR-exposed and more-SLR-exposed tracts, respectively.



(a) (b)

(c) (d)

Figure 4: Relationship between tract-level SLR exposure and 2016 home sale volumes (a), 2016 home prices (b), 2019 home volume (c), and 2019 home prices (d) 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.

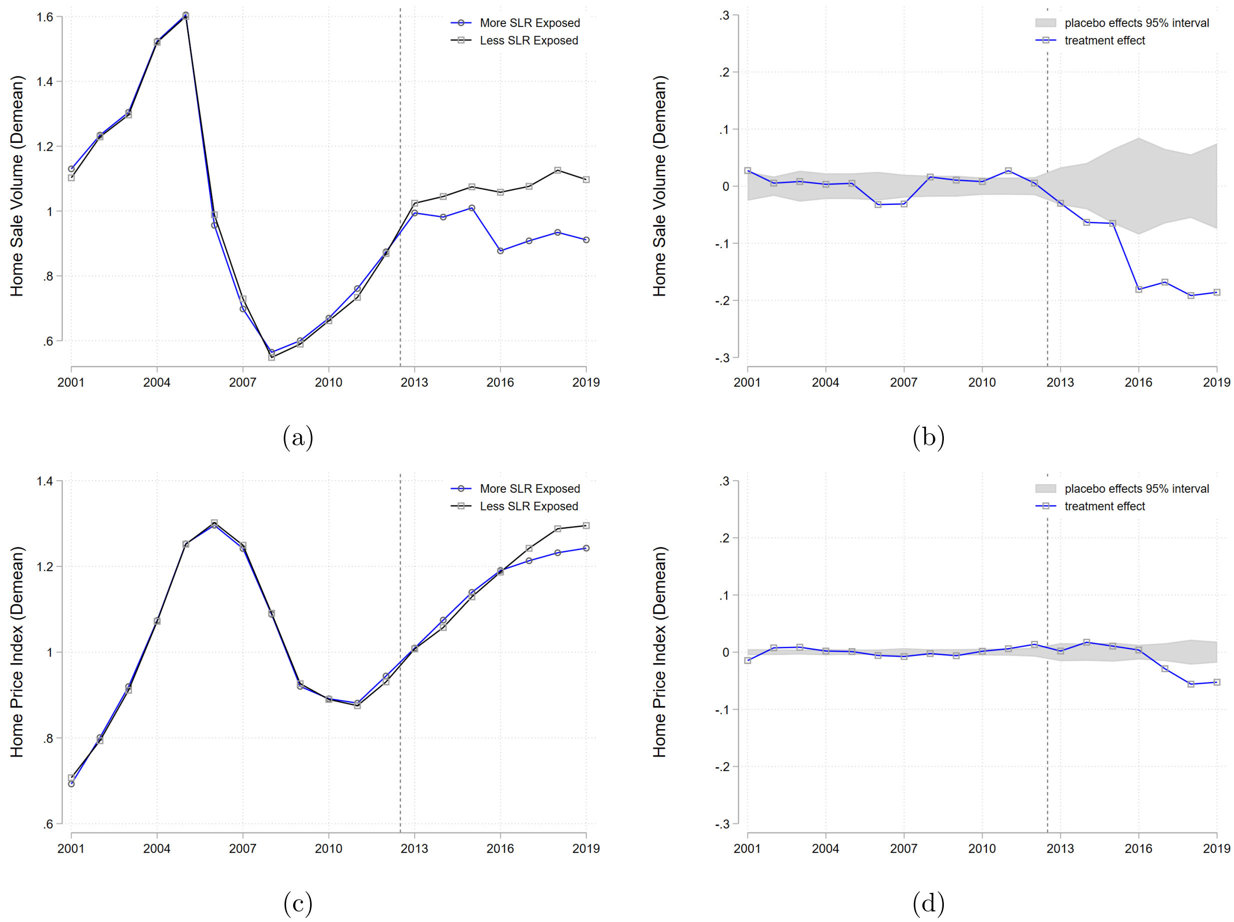
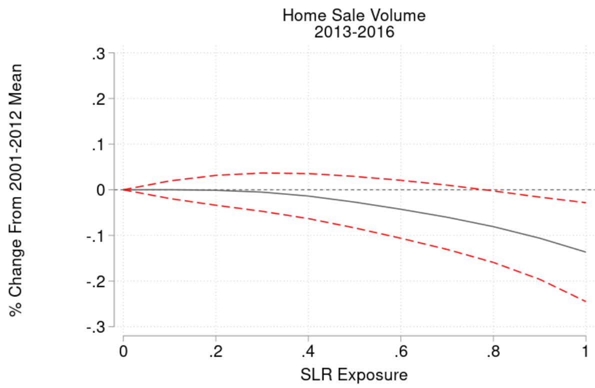
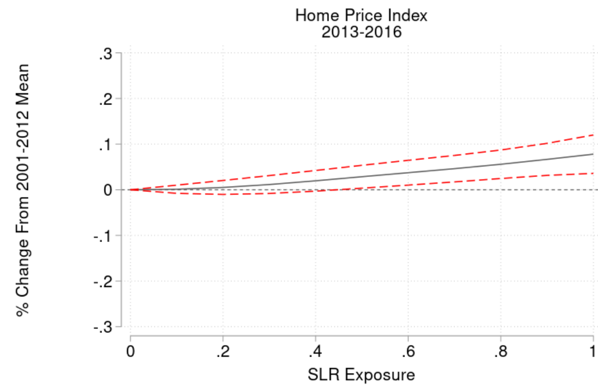


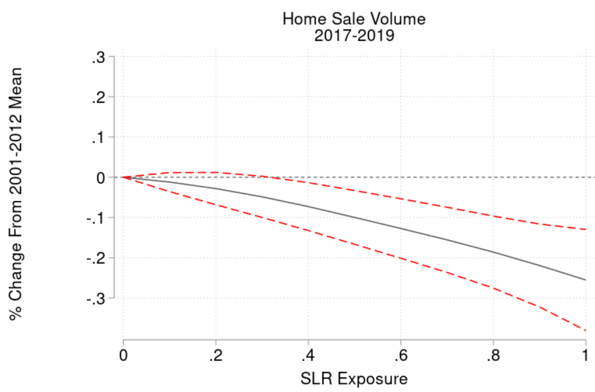
Figure 5: Synthetic control results for home sale volume (panels a and b) and home price index (c and d). Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.



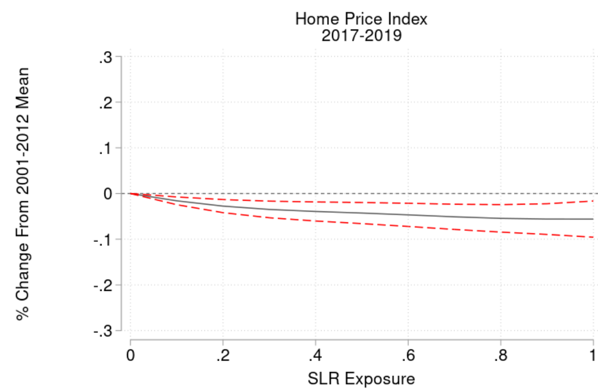
(a)



(b)

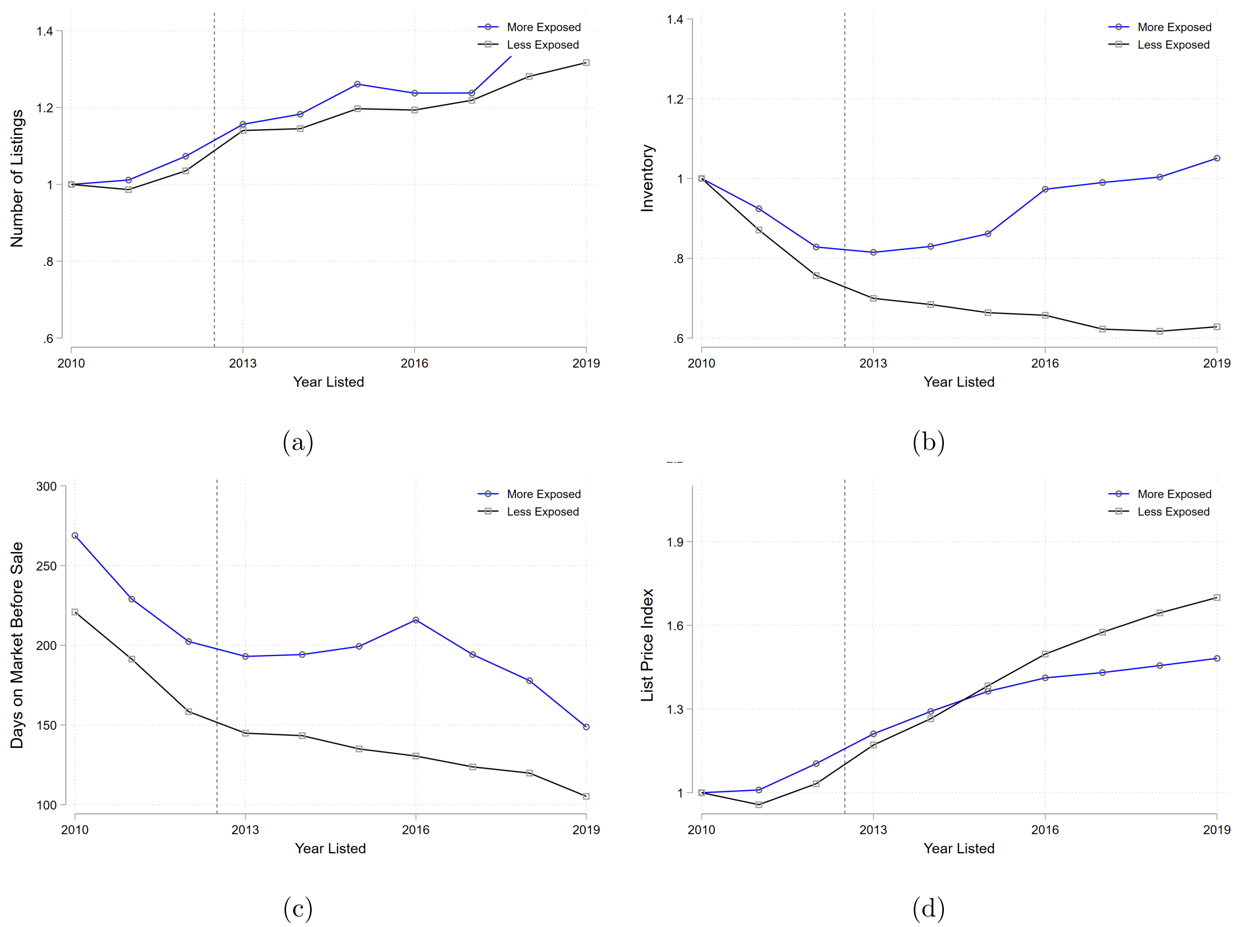


(c)



(d)

Figure 6: 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 for 2013-2016 (top row) and 2017-2019 (bottom row).



(a) (b) (c) (d)

Figure 7: MLS home listings data comparing trends in more-SLR-exposed (blue) and less-SLR-exposed (gray) markets. Shows raw data trends for total number of listings (a), unsold inventory (b), days on the market before sale (c), and list price index (d). Panels (a), (b), and (d) are normalized by their 2010 mean.

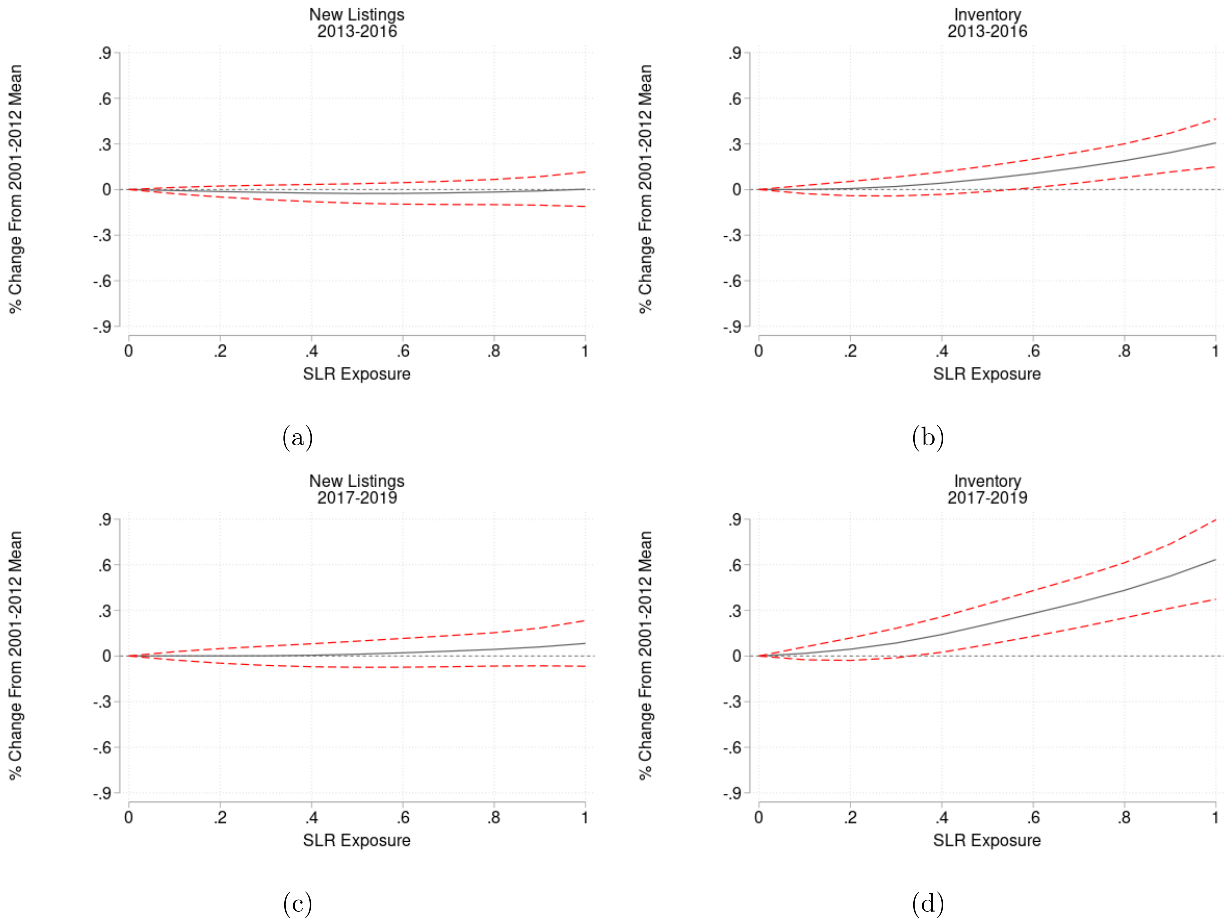
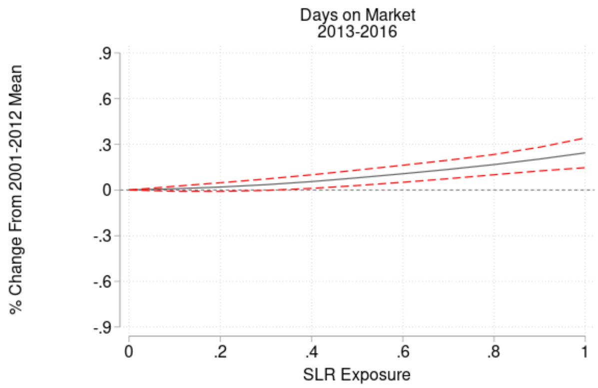
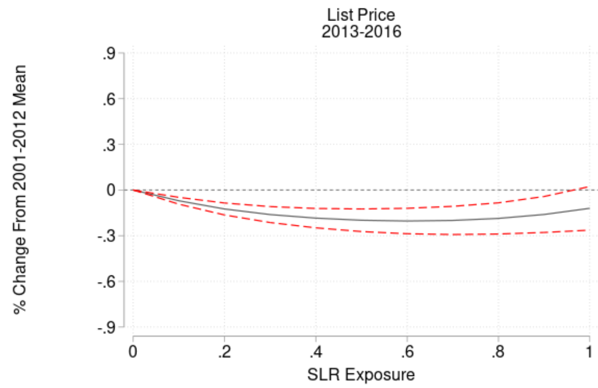


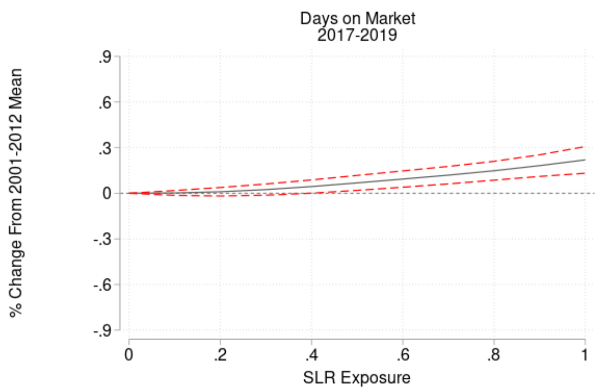
Figure 8: Generalized propensity score results for listing volume (left) and unsold inventory (right). Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean for 2013-2016 (top row) and 2017-2019 (bottom row).



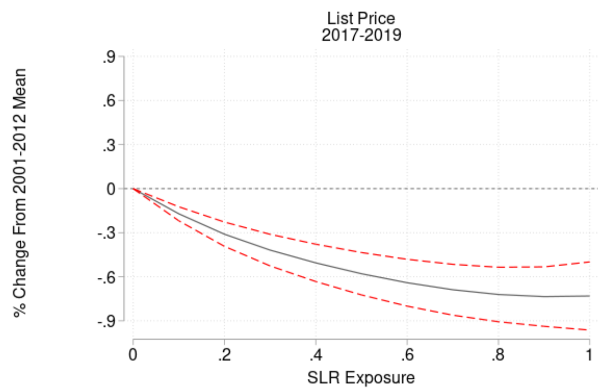
(a)



(b)



(c)



(d)

Figure 9: Generalized propensity score results for days on market before sale (left) and list price index (right). Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean for 2013-2016 (top row) and 2017-2019 (bottom row).

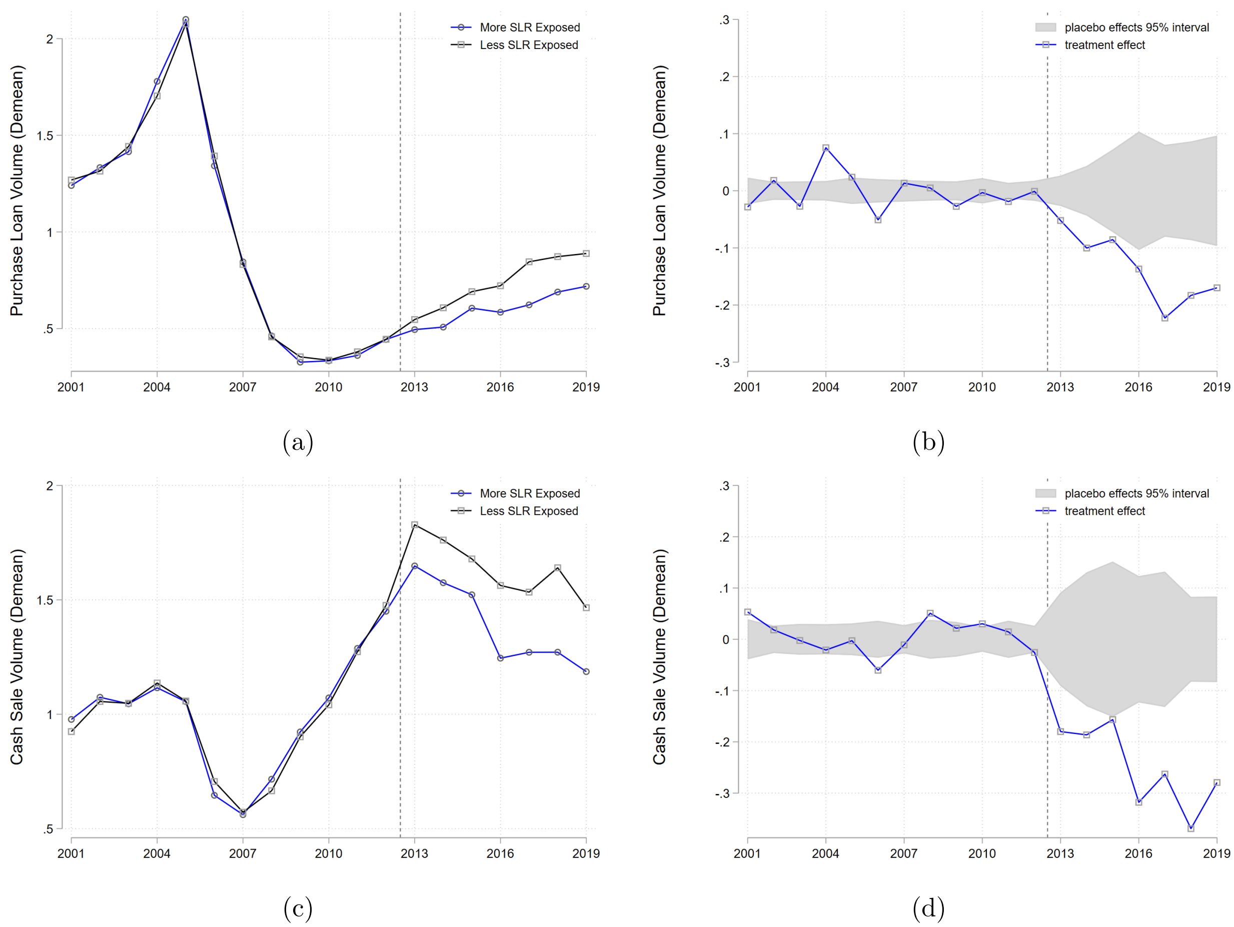


Figure 10: Synthetic control results for housing purchase loan and cash sale volumes. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

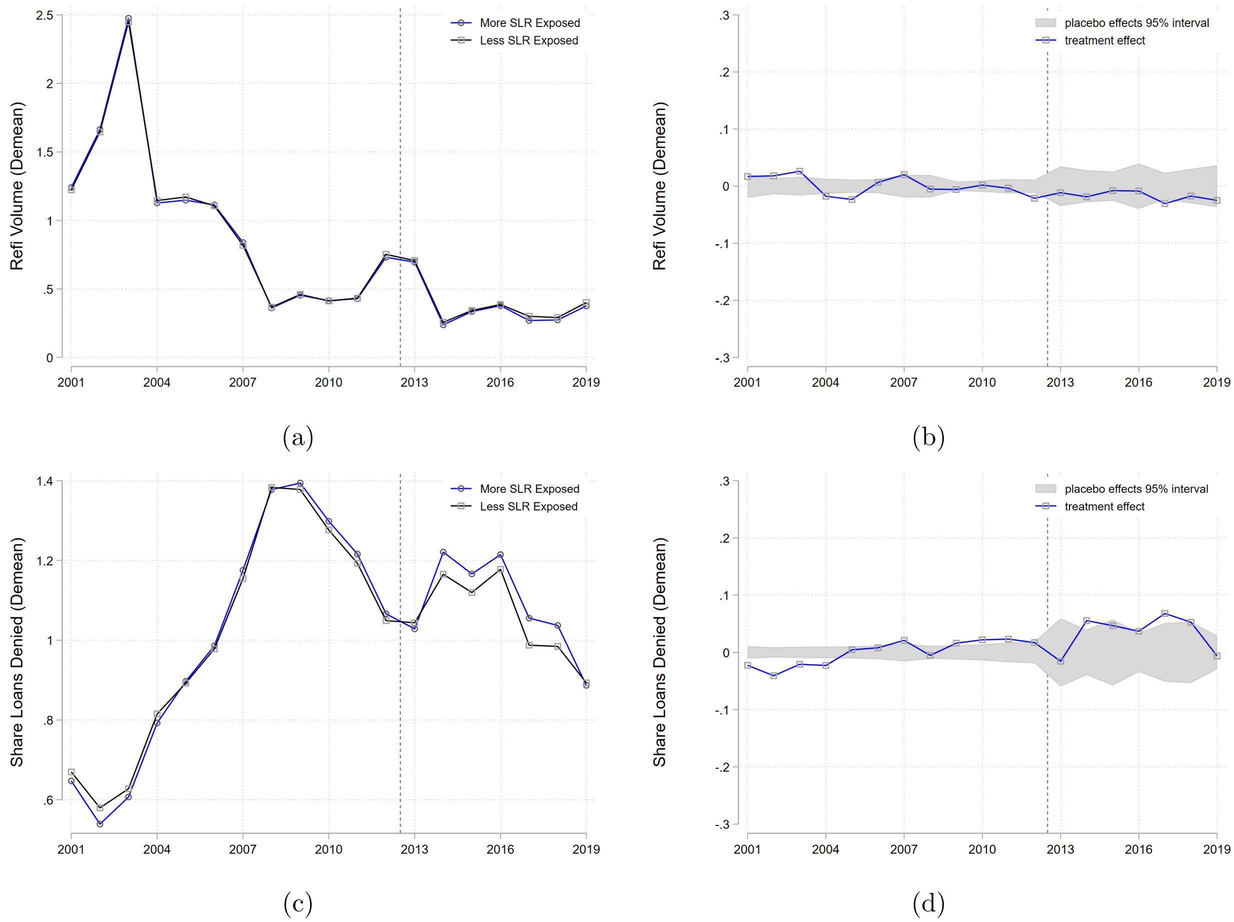


Figure 11: Synthetic control results for refinancing volume and loan denial index. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

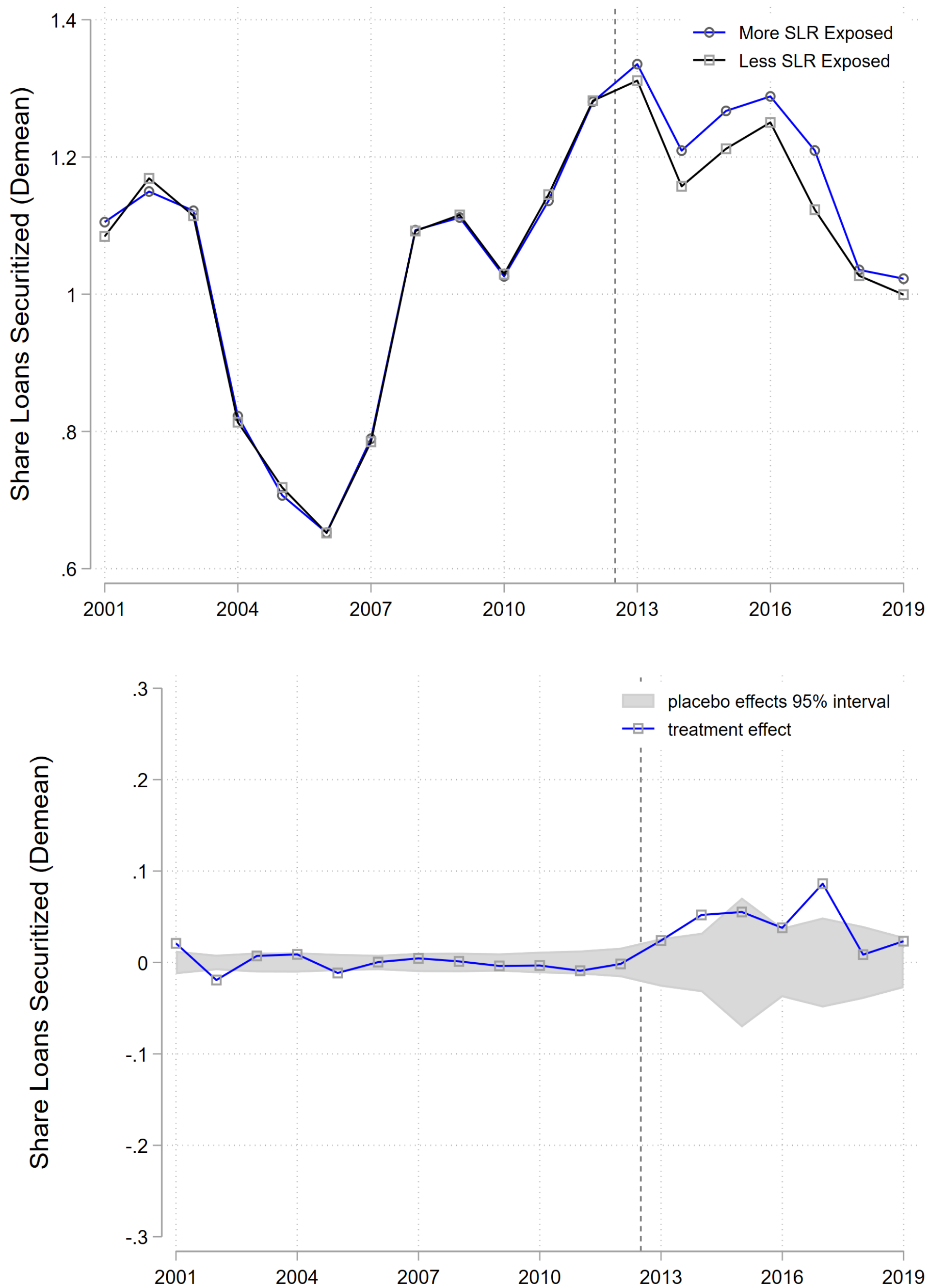


Figure 12: Synthetic control results for securitization index. Top row shows outcome for SLR-exposed tracts alongside synthetic counterparts, bottom shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

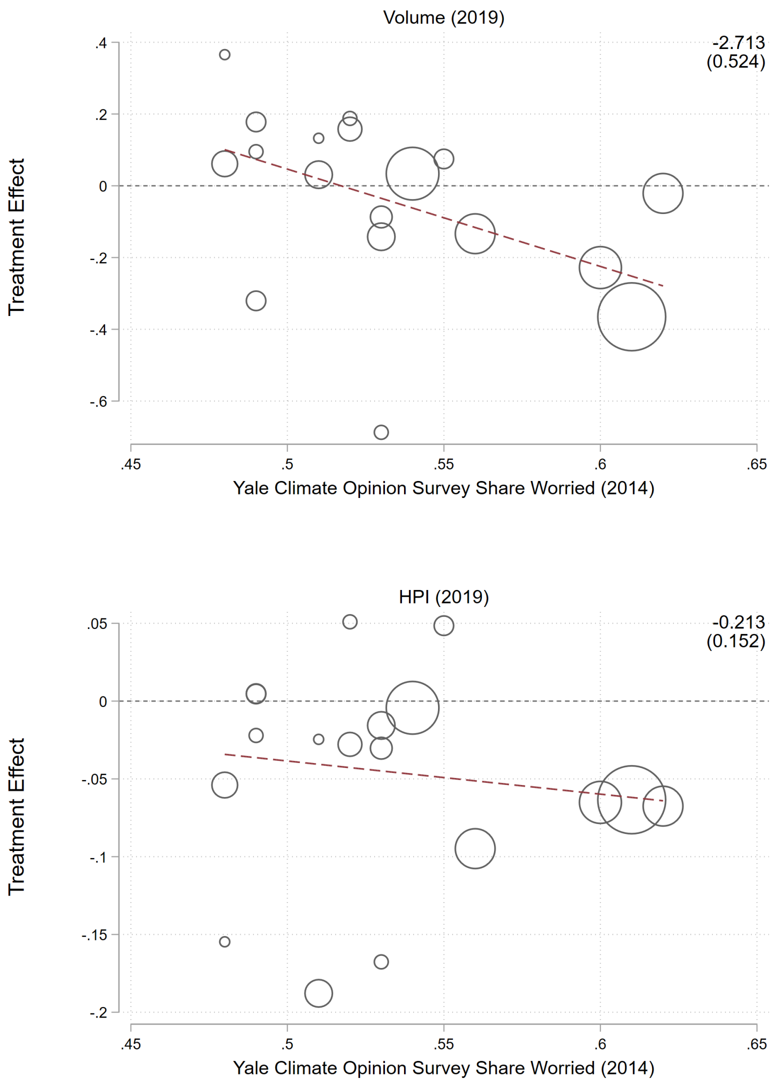
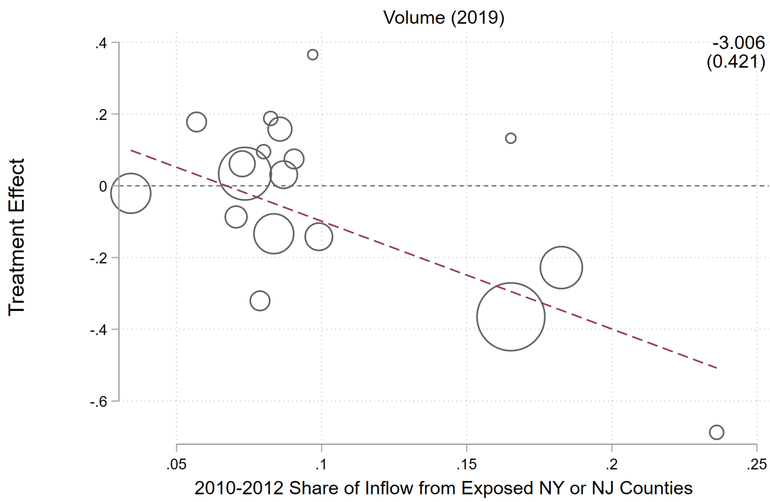


Figure 13: Summarizes treatment effect heterogeneity from synthetic control estimator by climate change concern for 2019 home sale volume (top) and 2019 home prices (bottom). Each point is a county with the average treatment effect of its more-SLR-exposed census tracts on the y-axis and the estimated share of adults in the county worried about climate change from the 2014 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 robust 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.



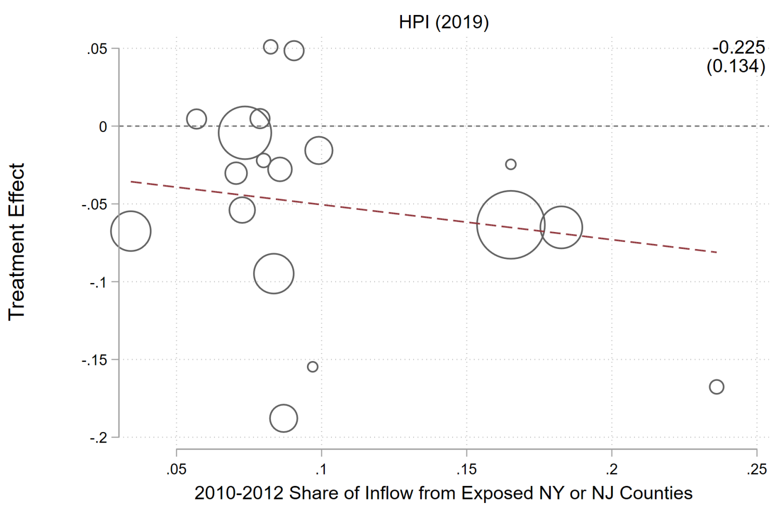


Figure 14: Summarizes treatment effect heterogeneity from synthetic control estimator by share of 2010-2012 home sales made by New Jersey or New York residents affected by hurricane Sandy for 2019 home sale volumes (top) and 2019 home prices (bottom). Each point is a county with the average treatment effect of its more-SLR-exposed census tracts on the y-axis and the share of migration inflows from New Jersey or New York residents affected by Hurricane Sandy on the x-axis. The dashed red line indicates the best-fit linear line through the points, with the coefficient and robust standard error from the tract-level regression of the share of migration inflows over the estimated treatment effects indicated in the upper-right corner. Outcomes are normalized by the tract-level 2001-2012 mean.

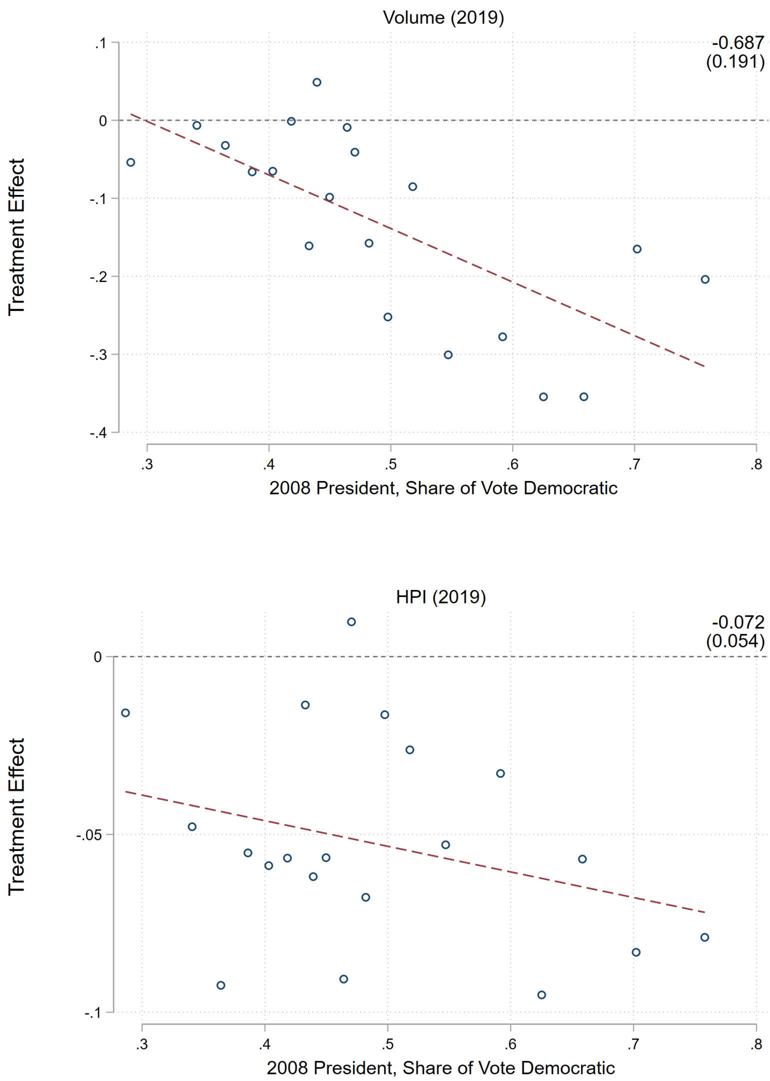


Figure 15: Summarizes treatment effect heterogeneity from synthetic control estimator by 2008 Democratic presidential vote share for 2019 home sale volumes (top) and 2019 home prices (bottom). The binscatter plot shows the average treatment effect of more-SLR-exposed census tracts on the y-axis binned by quantiles of the 2008 Democratic Presidential candidate vote share on the x-axis. The dashed red line indicates the best-fit linear line through the points, with the coefficient and robust standard error from the tract-level regression of the share voting Democratic in 2008 over the estimated treatment effects indicated in the upper-right corner. Outcomes are normalized by the tract-level 2001-2012 mean.

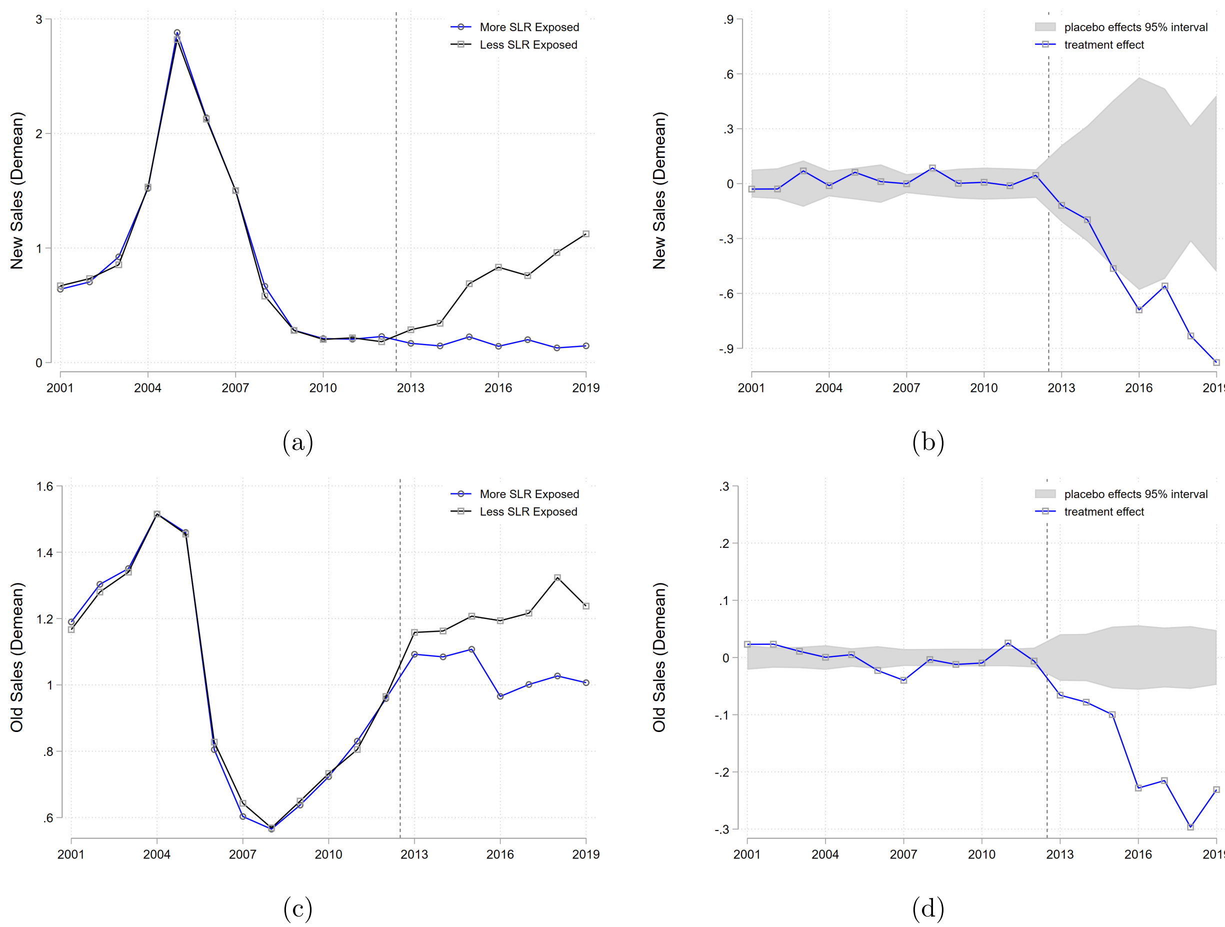


Figure 16: Synthetic control results for transaction volume of new (top row) and existing (bottom row) homes. Left column shows outcomes for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

Tables

	All	More-SLR-Exposed	Less-SLR-Exposed
2001-2012 Annual Sale Volume	120	134	104
	(70)	(83)	(61)
2001-2012 Median Sale Price	259778	334526	172982
	(201914)	(187615)	(101215)
2010 Population	3436	2921	3838
	(1481)	(1273)	(1545)
2010 Share Nonwhite	0.132	0.076	0.191
	(0.146)	(0.065)	(0.167)
2010 Poverty Share	0.129	0.107	0.155
	(0.087)	(0.063)	(0.098)
2001-2012 Share Owner-Occupied Buyers	0.626	0.557	0.679
	(0.168)	(0.167)	(0.156)
Meters-to-Coast	664	427	964
	(458)	(405)	(412)
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).

Panel (a)

	2016 Home Sales Volume		2019 Home Sales Volume	
	(1)	(2)	(3)	(4)
More-SLR-Exposed	-0.196***	-0.197***	-0.231***	-0.215***
	(0.027)	(0.030)	(0.031)	(0.034)
Medium-SLR-Exposed	-0.076***	-0.076***	-0.087***	-0.076***
	(0.022)	(0.023)	(0.026)	(0.028)
Constant	1.156***	1.190***	1.220***	1.219***
	(0.017)	(0.032)	(0.021)	(0.038)
Observations	771	771	771	771
R-squared	0.067	0.090	0.069	0.084

Panel (b)

	2016 Home Prices		2019 Home Prices	
	(1)	(2)	(3)	(4)
More-SLR-Exposed	0.036***	0.039***	-0.069***	-0.039***
	(0.010)	(0.011)	(0.010)	(0.011)
Medium-SLR-Exposed	-0.000	0.002	-0.028***	-0.009
	(0.008)	(0.008)	(0.009)	(0.009)
Constant	1.154***	1.151***	1.311***	1.242***
	(0.007)	(0.012)	(0.007)	(0.012)
Observations	771	771	771	771
R-squared	0.026	0.027	0.061	0.127

Controls	No	Yes	No	Yes

Robust standard errors in parentheses

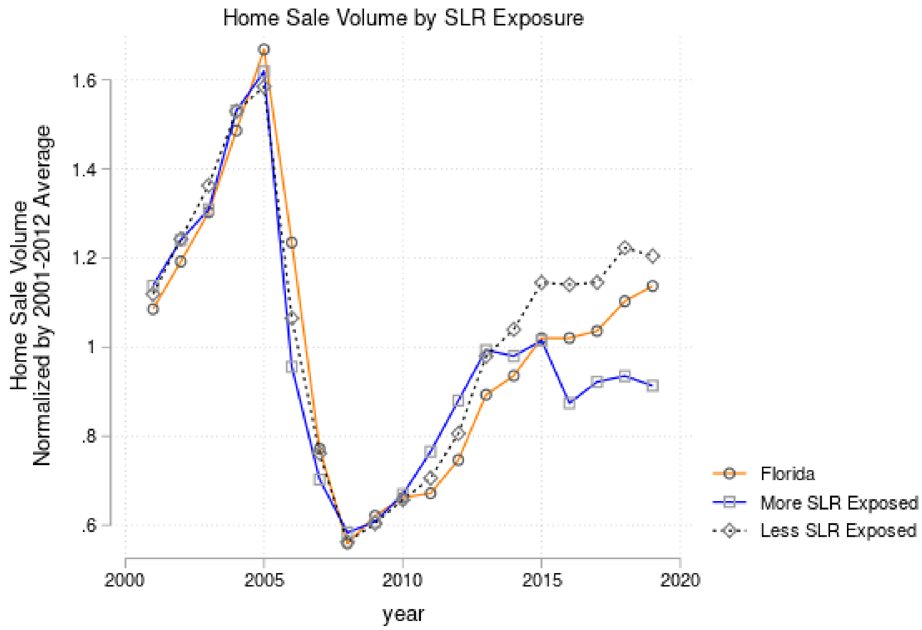
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Results from long-difference OLS regressions showing the relative change in home sales volumes (top panel) and prices (bottom panel) in 2016 (columns 1-2) and 2019 (columns 3-4) in more-SLR-exposed and medium-SLR-exposed markets relative to less-SLR-exposed markets. Columns 2 and 4 include controls for tract population centroid distance-to-coast and 2010 share of households in poverty.

2019 Outcome	Synthetic Control (P-value)	GPS (SE)	OLS (SE)
Home Sale Volume	-.186***	-.255***	-.215***
	(.000)	(.035)	(.034)
Home Prices	-.053***	-0.056**	-0.039***
	(.000)	(0.020)	(0.011)
Home Purchase Loan Volume	-.170***	-.273***	-.221***
	(.000)	(.070)	(.038)
Home Cash Sale Volume	-.279***	-.147	-.236***
	(.000)	(.102)	(.052)
Refinance Volume	-.025	-.082**	-.093***
	(.281)	(.025)	(.017)
Denial Index	-.006	.085**	.042**
	(.679)	(.038)	(.021)
Securitization Index	-.023	-.030	.025
	(.102)	(.033)	(.020)
Inventory	N/A	0.635***	0.421***
	(N/A)	(0.133)	(0.058)
New Listings	N/A	0.083	0.124**
(N/A)	(.077)	(.045)	

Table 3: Coefficients for the relative change by 2019 in more-SLR-exposed tracts over less-SLR-exposed tracts across the primary outcomes for synthetic control, generalized propensity score (GPS), and methodologies. OLS specifications include distance-to-coast and 2010 share of residents in poverty. Standard errors are in parentheses for the OLS and GPS columns, and p-values in parenthesis for the synthetic control column. The GPS column estimates are from the pooled 2017-2019 period. Synthetic control estimates are unavailable for inventory because the MLS data start in 2010. Outcome variables are standardized by their tract-level 2001-2012 mean.

A Appendix Figures



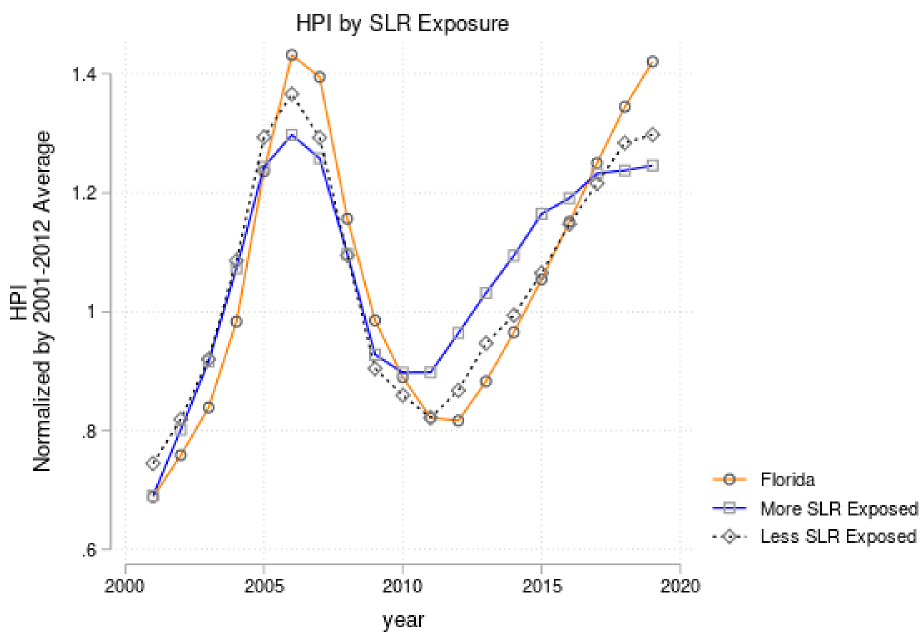


Figure A-1: Housing transaction volume (top panel) and home price (bottom panel) trends across all of Florida (solid lines) and coastal Florida census tracts with high versus low SLR exposure (dashed and dotted lines, respectively). Housing volume and home price index are normalized by their 2001-2012 mean.

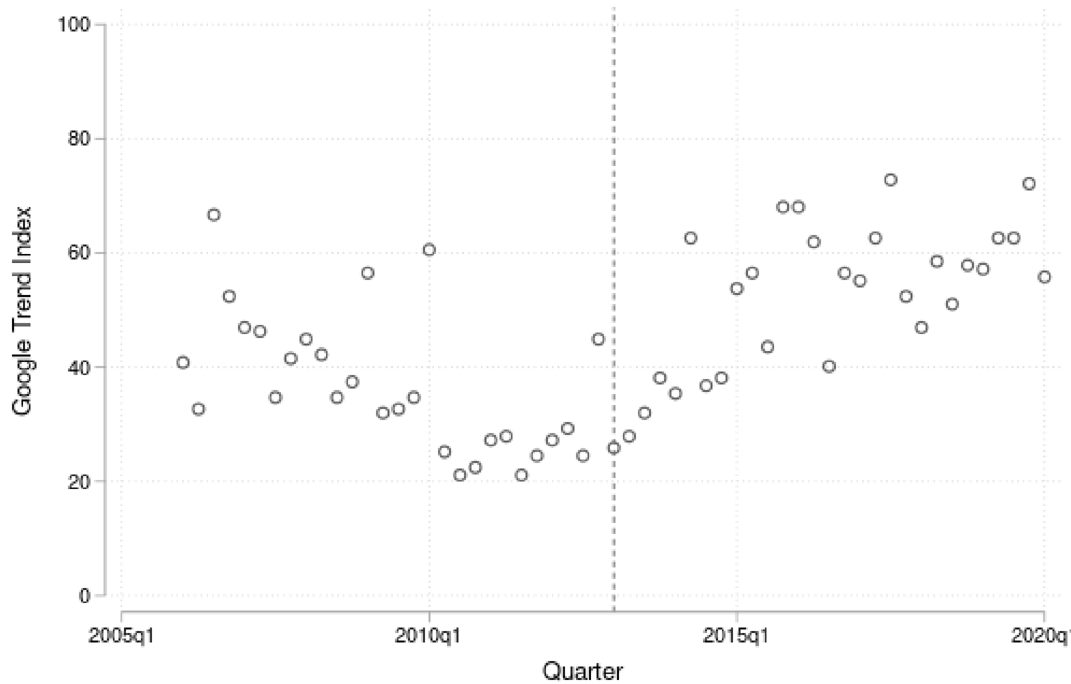


Figure A-2: Quarterly Google Trends search intensity for topic “Sea Level Rise” in Florida from 2006 to 2020. Dashed line is at the first quarter of 2013.

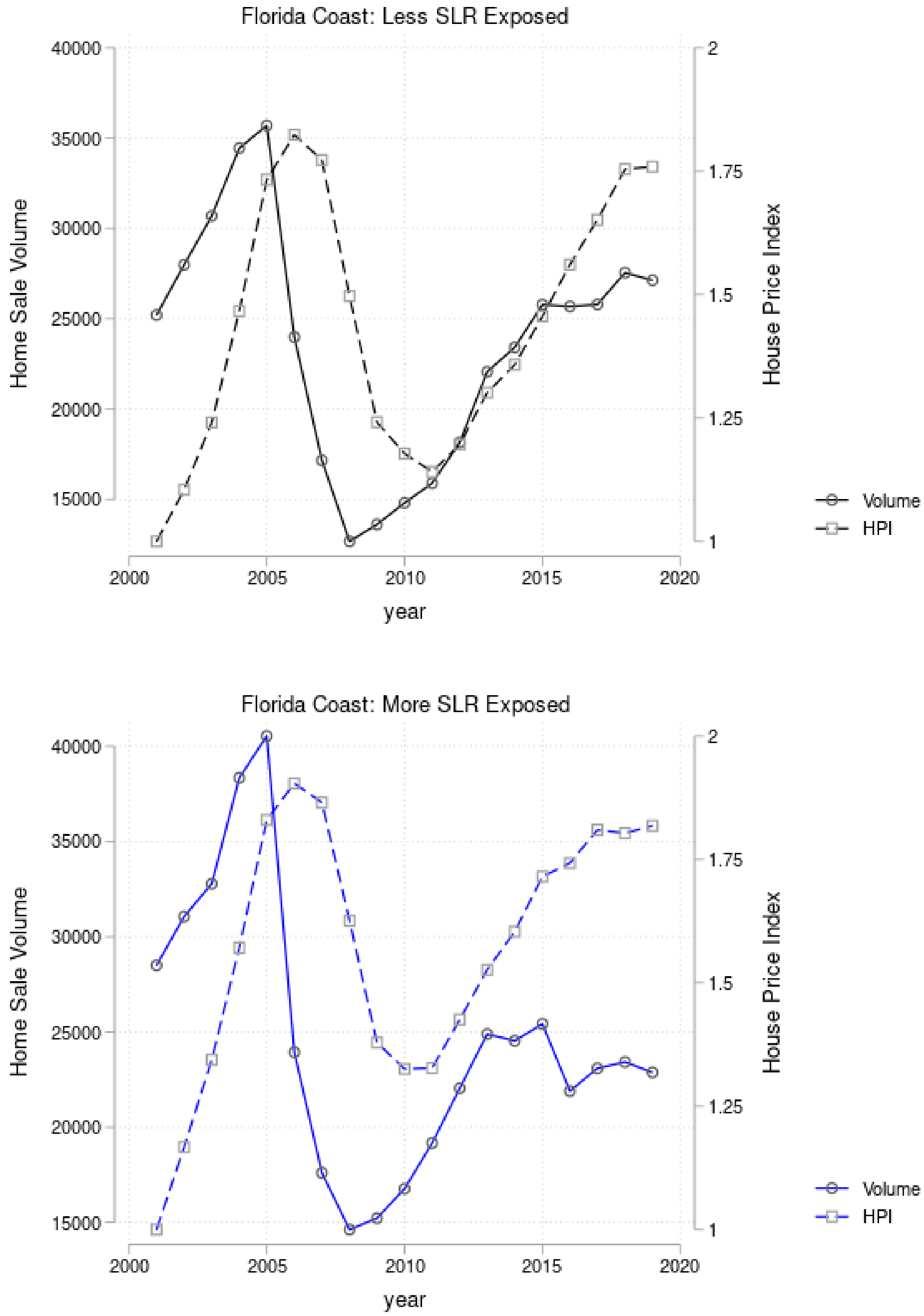
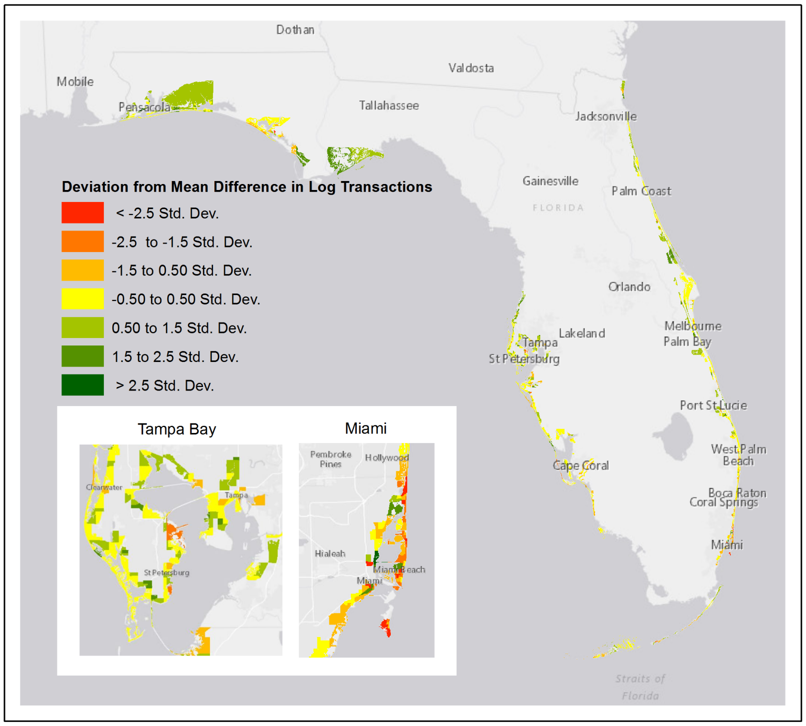


Figure A-3: Annual aggregate housing transactions (left axis) and mean house price index (right axis) for coastal Florida census tracts with either less-SLR-exposure (top panel) or more-SLR-exposure (bottom panel). See Data and Methodology sections for data sources and definitions of coastal and SLR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



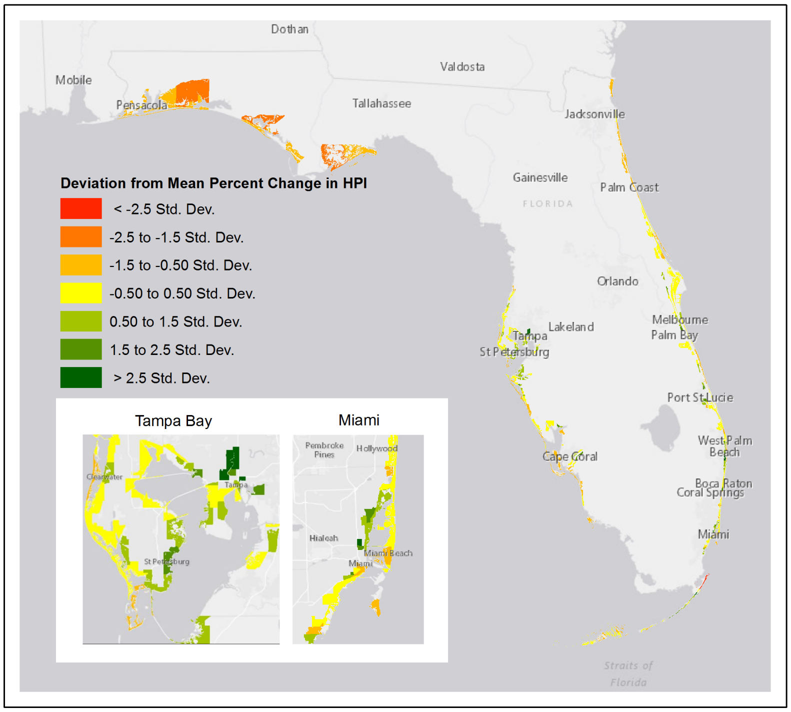
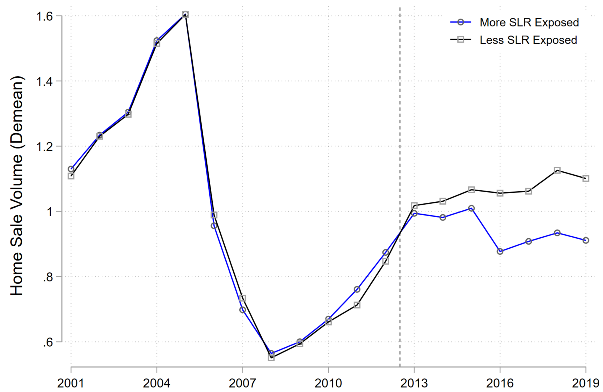
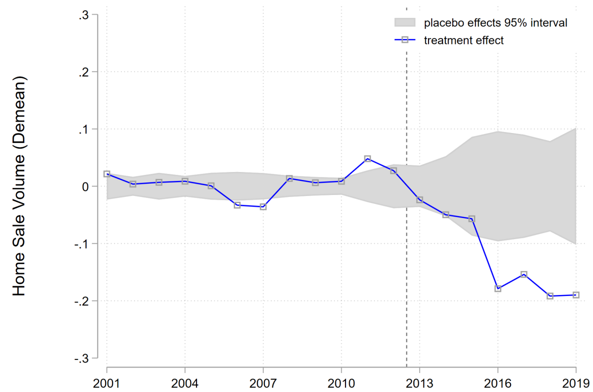


Figure A-4: Maps show change in log home transactions (top panel) and home price index (bottom panel) by coastal tract between 2011-2012 and 2017-2018. Tracts are colored by relative change, with red indicating larger relative to declines and green larger relative increases.



(a)



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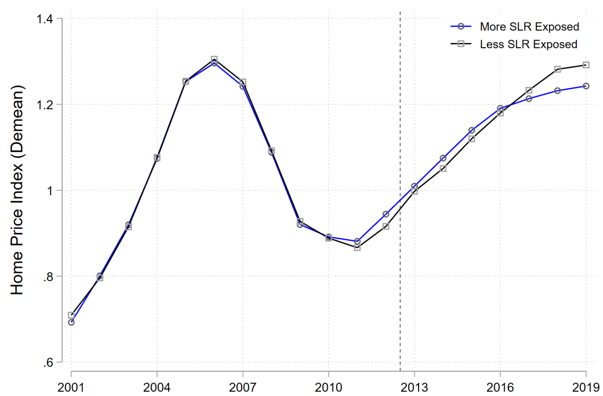

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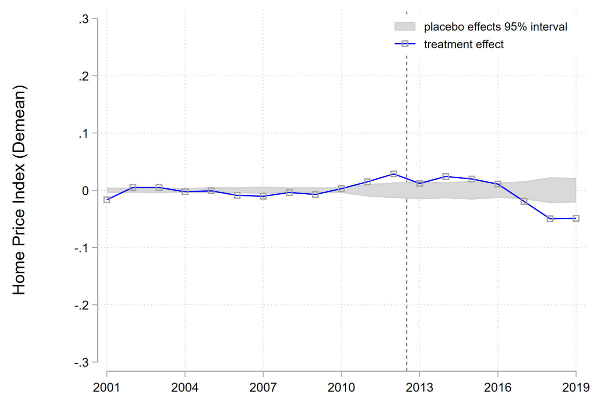
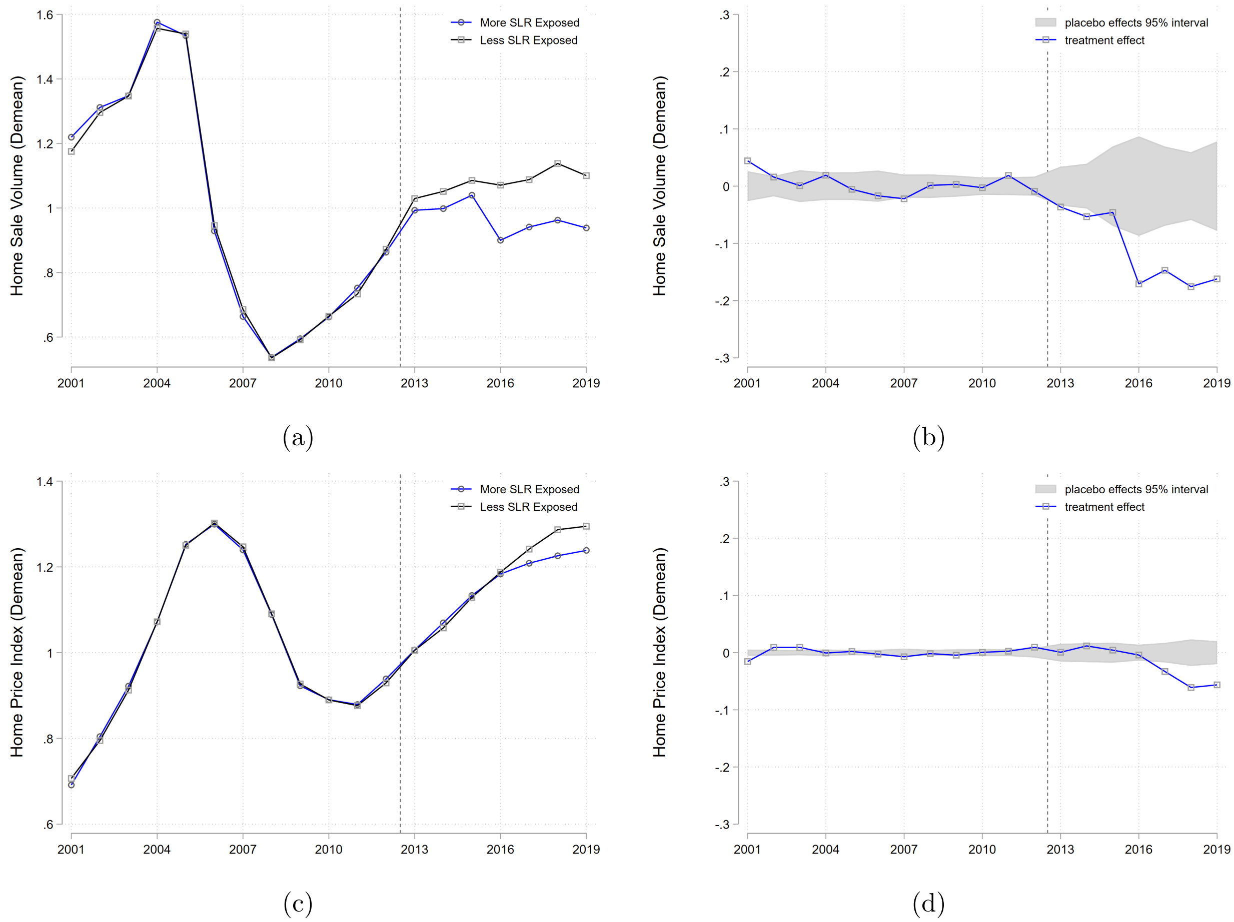


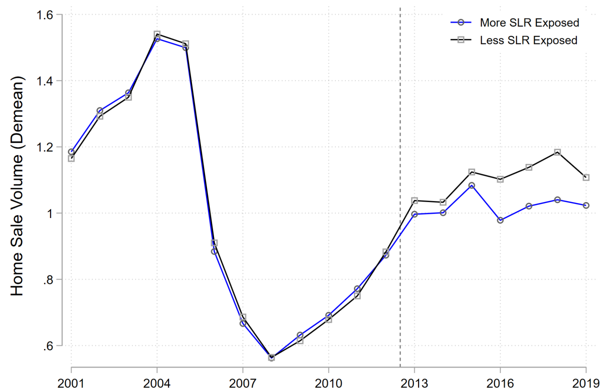
(d)

Figure A-5: Synthetic control results for housing transaction volume and home prices only matching from 2001-2010 instead of 2001-2012 as the pre-period. Top row shows outcome for more-SLR-exposed tracts in blue alongside synthetic counterparts in gray, bottom shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

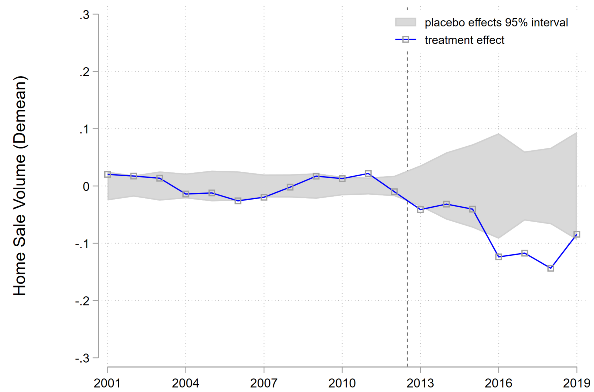


(a) (b) (c) (d)

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.



(a)



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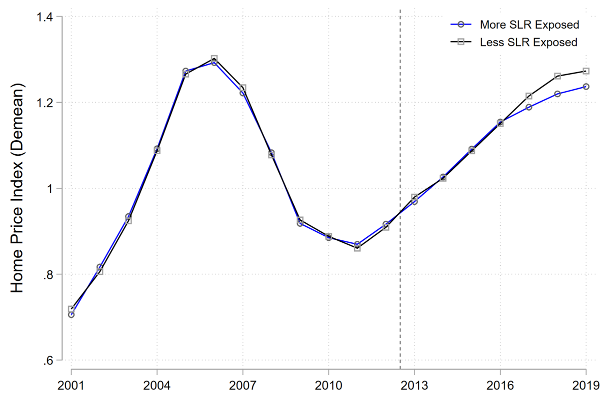

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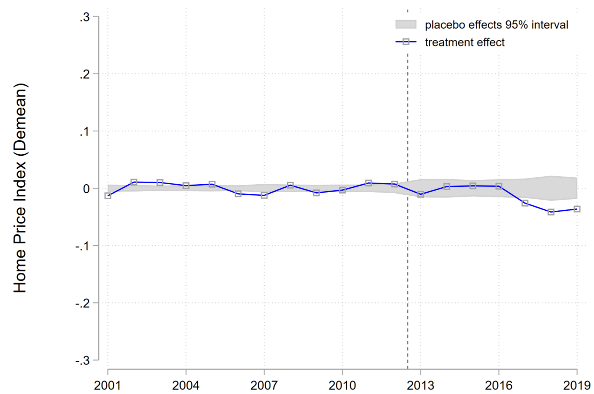


(d)

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.

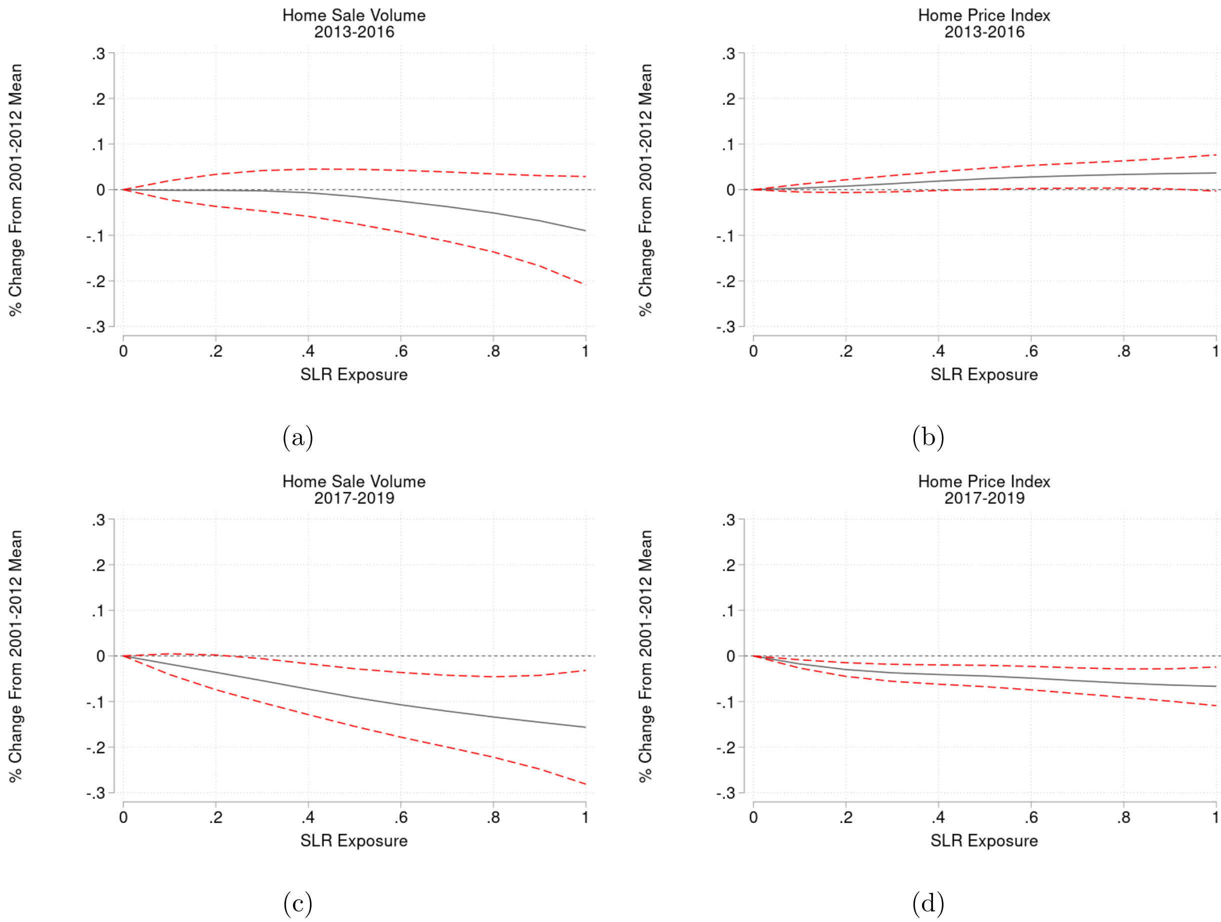
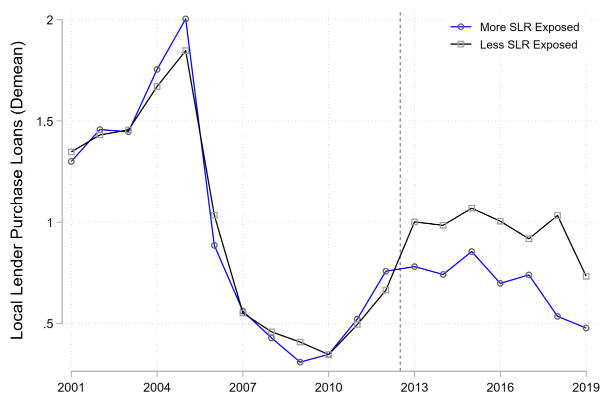
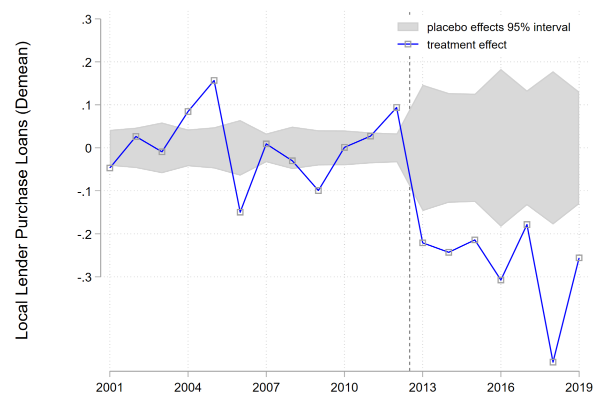


Figure A-8: Generalized propensity score results for housing transaction volume and home prices excluding all observations in Miami-Dade county. Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean for 2013-2015 (top row) and 2016-2019 (bottom row).



(a)



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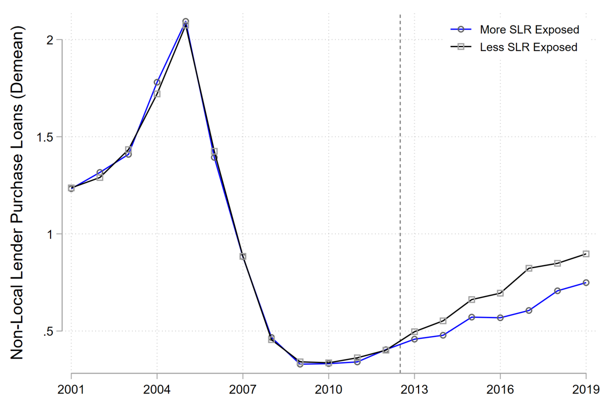

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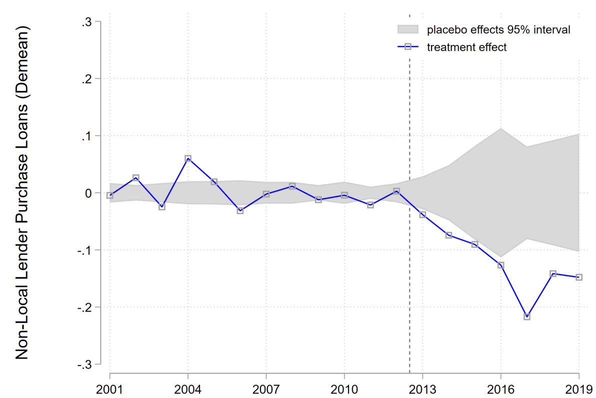


(d)

Figure A-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.

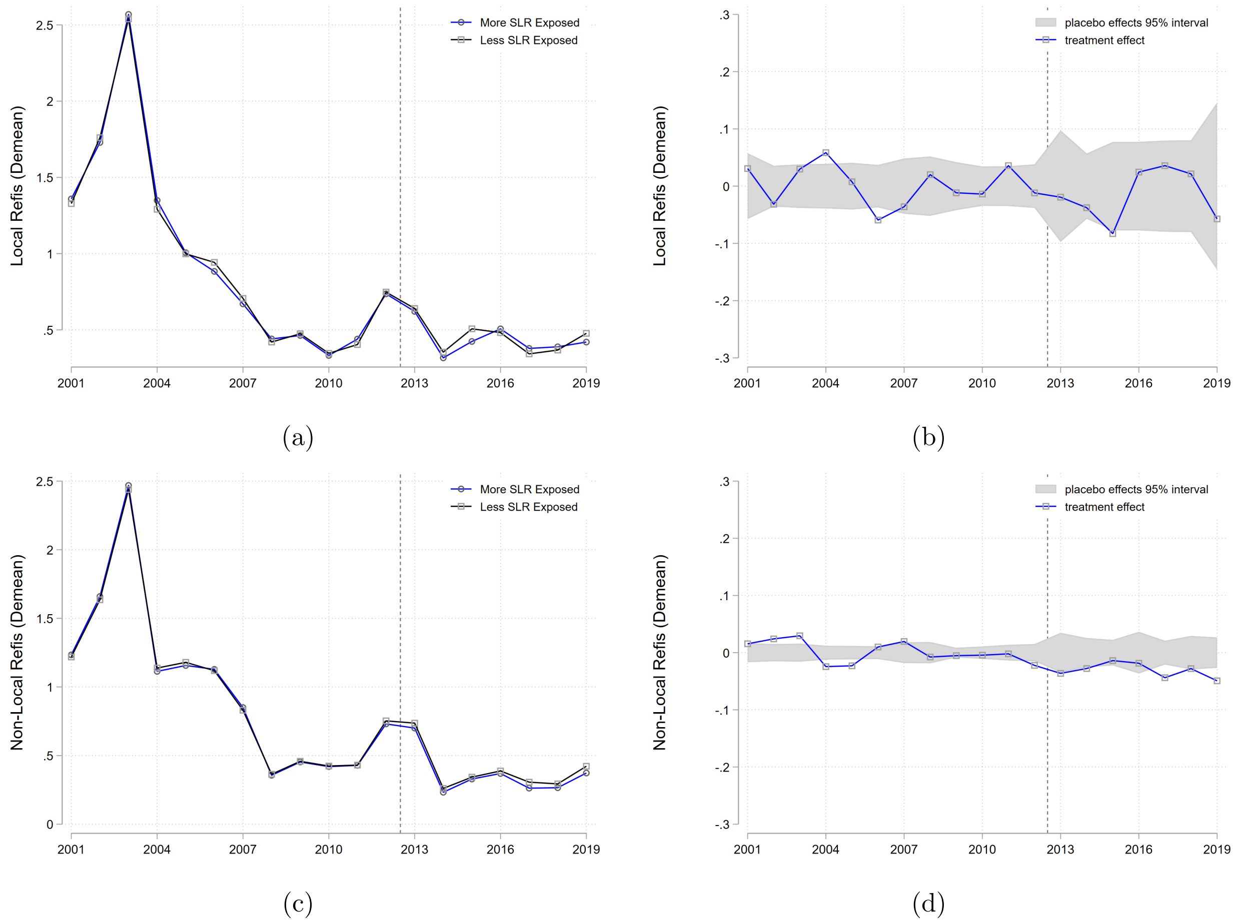


Figure A-10: Synthetic control results for local and non-local refinancing volume. Left column shows outcome for SLR-exposed tracts alongside synthetic counterparts, right column shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.

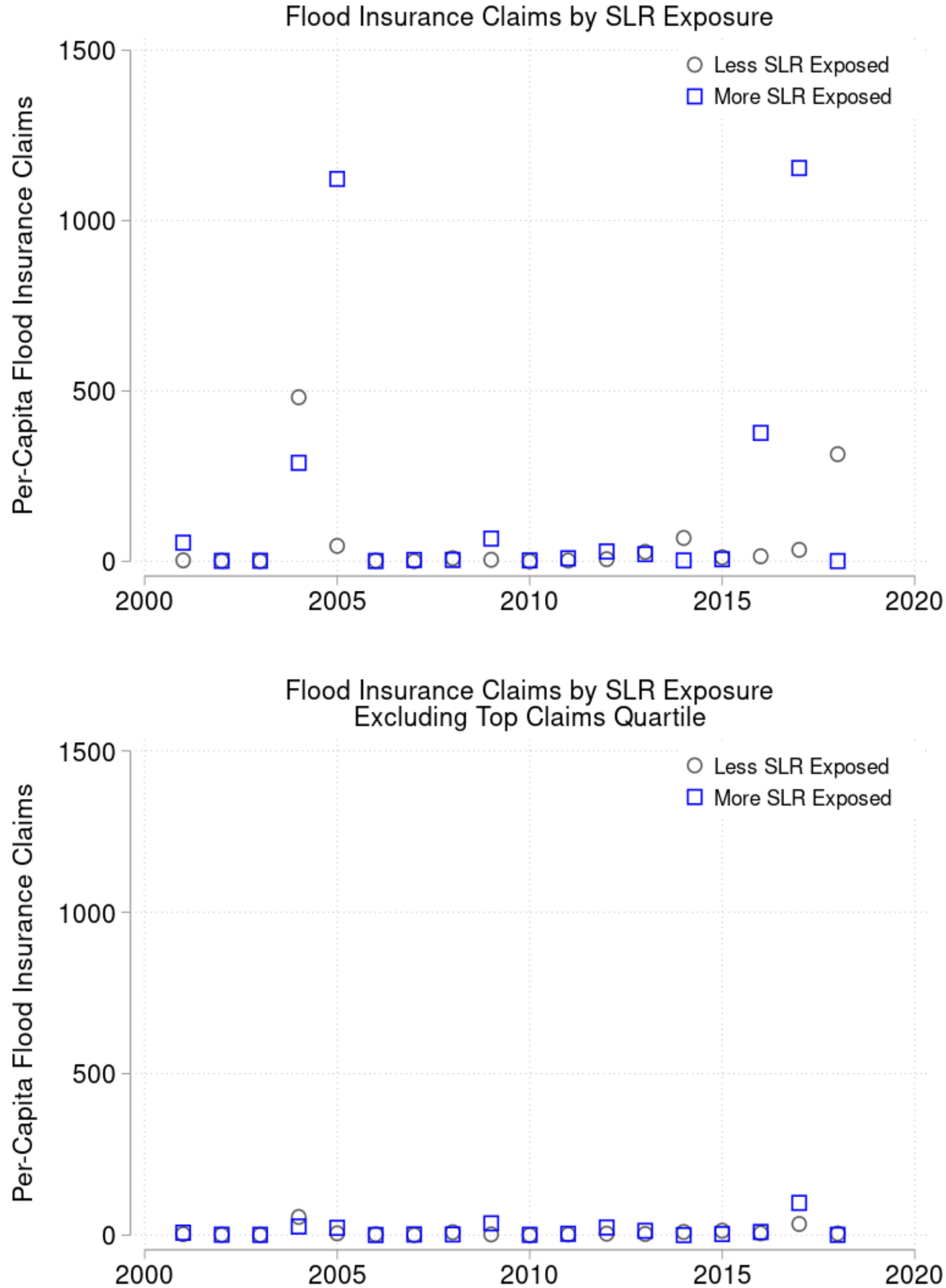


Figure A-11: Annual flood insurance claims per-capita of more-SLR-exposed (blue squares) and less-SLR-exposed (black circles) census tracts. The top panel is calculated from the full estimation sample while the bottom panel excludes census tracts in the top quartile over total 2001-2018 claims per-capita. Claims per-capita calculated from the NFIP claims database and decennial census housing unit estimates.

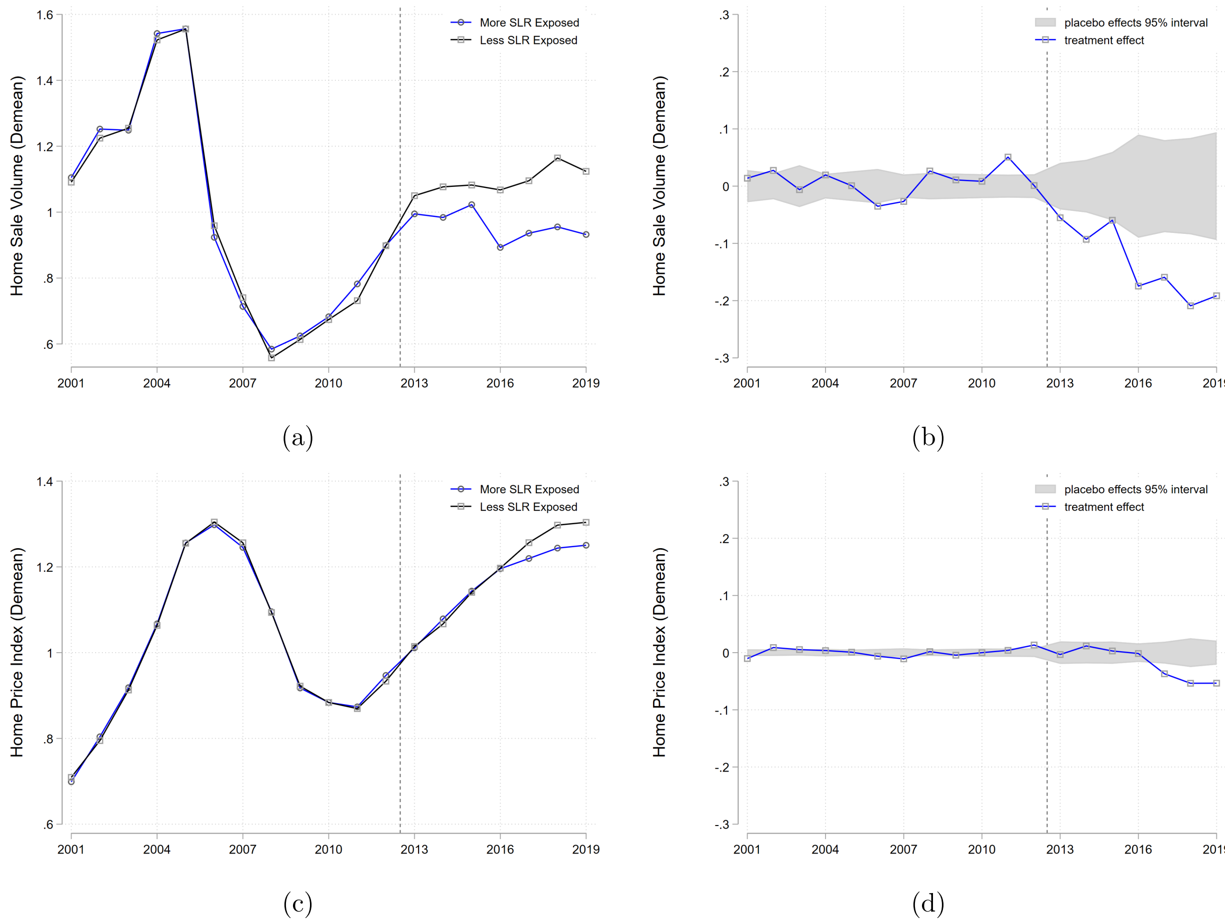
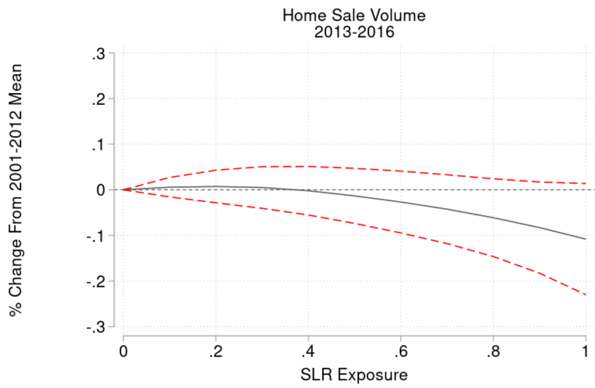


Figure A-12: Synthetic control results for housing transaction volume and home prices, excluding all tracts in the top quartile of 2001-2018 flood insurance claims per-capita. Top row shows outcome for more-SLR-exposed tracts in blue alongside synthetic counterparts in gray, bottom shows treatment effects with two-sided 95% interval of placebo effect estimates in gray.



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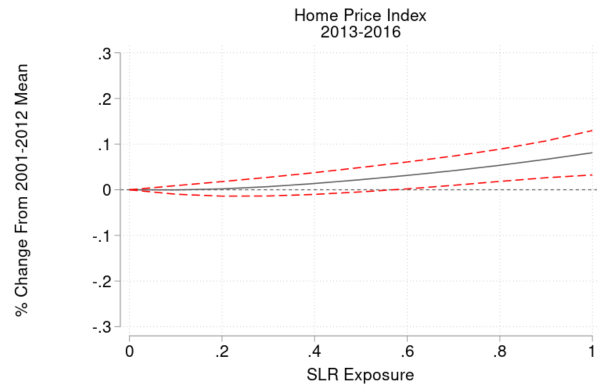

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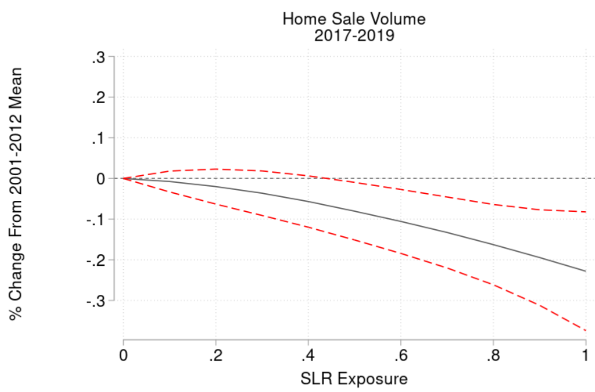

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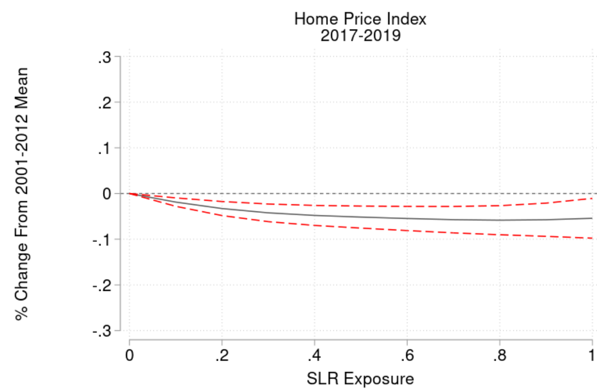
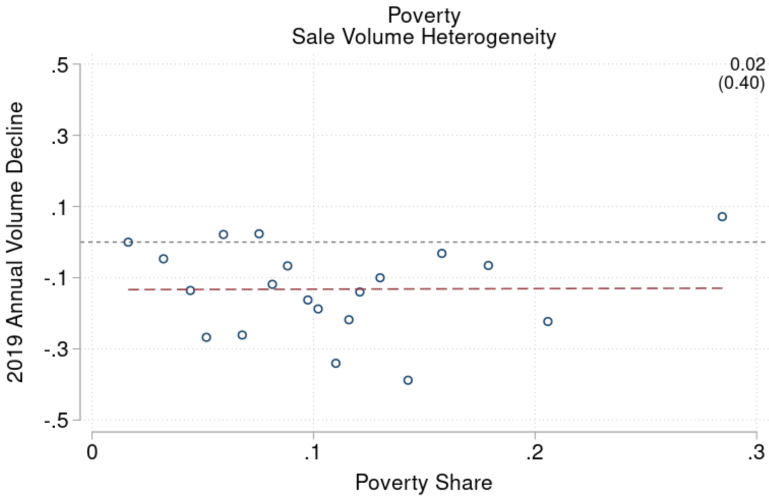


(d)

Figure A-13: Generalized propensity score results for housing transaction volume and home prices excluding all tracts in the top quartile of 2001-2018 flood insurance claims per-capita. Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean for 2013-2015 (top row) and 2016-2019 (bottom row).



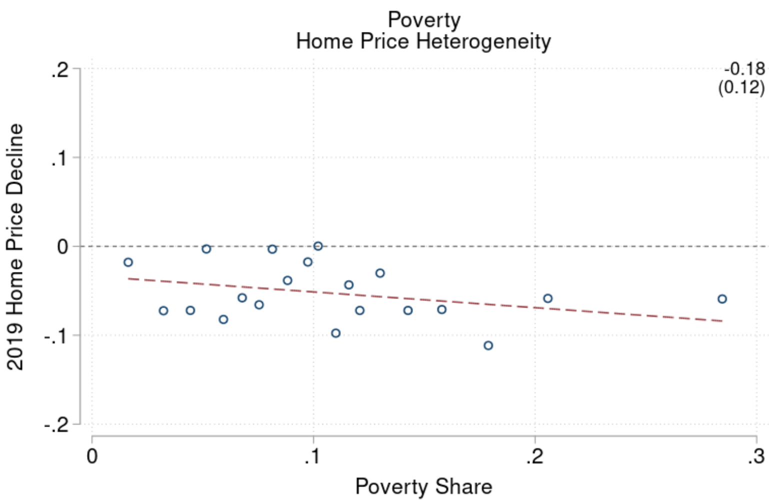
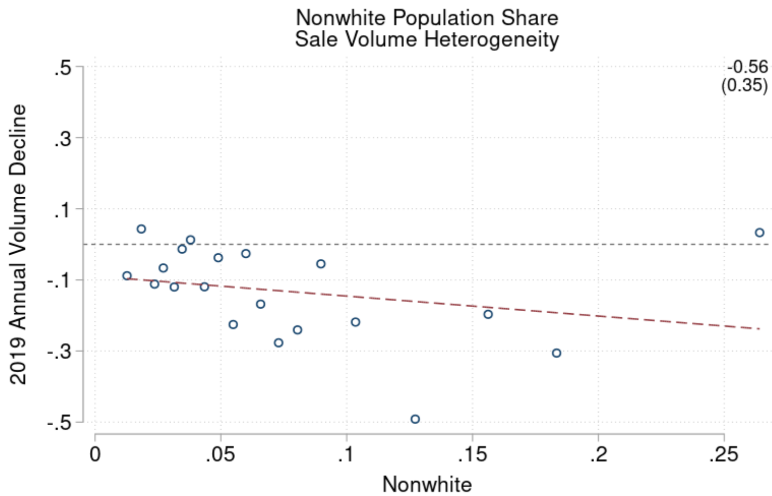


Figure A-14: Summarizes treatment effect heterogeneity from synthetic control estimator by tract-level poverty for 2019 home sale volume (top) and 2019 home prices (bottom). Points indicate the average treatment effect (y-axis) within twenty quantiles of more-SLR-exposed tracts grouped by 2010 census 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.



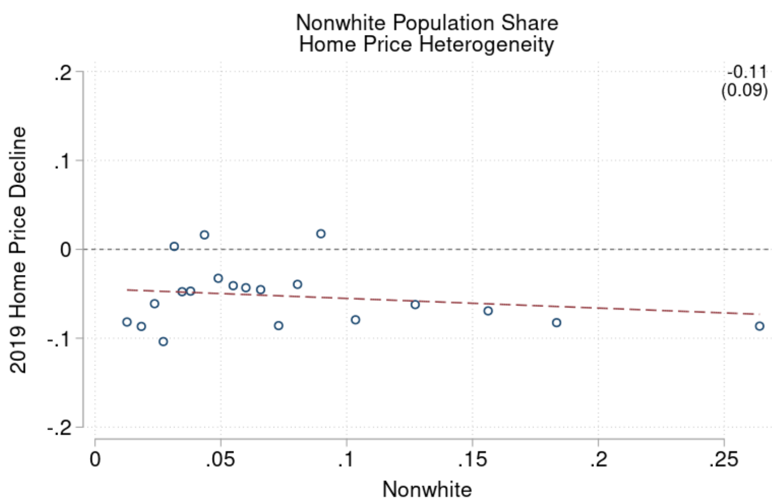
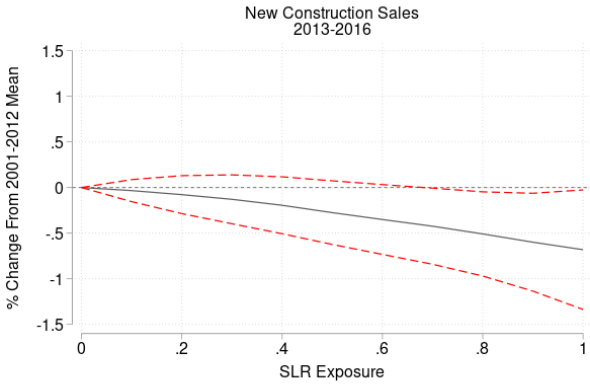


Figure A-15: Summarizes treatment effect heterogeneity from synthetic control estimator by tract-level nonwhite population share for 2019 home sale volume (top), 2019 home prices (bottom). Points indicate the average treatment effect (y-axis) within twenty quantiles of more-SLR-exposed tracts grouped by 2010 census estimate of the share of residents who are nonwhite (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 nonwhite population share over the estimated treatment effects indicated in the upper-right corner. Outcomes are normalized by the tract-level 2001-2012 mean. covariates.



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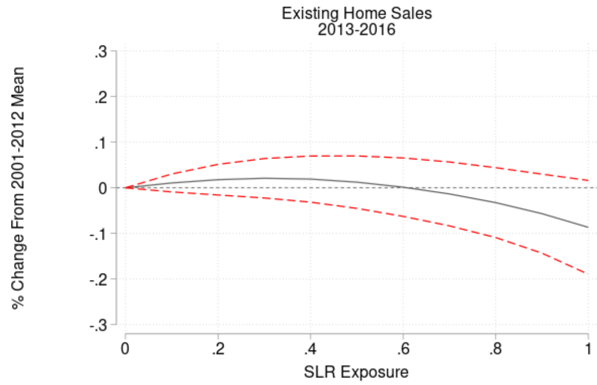

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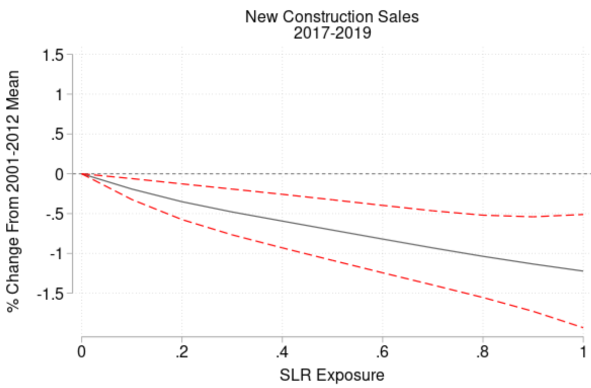

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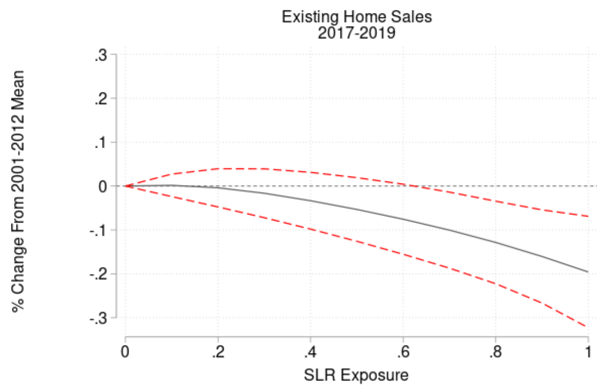

(d)

Figure A-16: Generalized propensity score results for transaction volumes of new (left column) and existing (right column) homes. Results show the relative change in the outcome variable normalized by the tract-level 2001-2012 mean by 2013-2016 (top row) and 2017-2019 (bottom row).

B Appendix Tables

Percentile	Transaction Volume	Home Price Index
10th	0.0319	0.0104
25th	0.0455	0.0140
50th	0.0670	0.0192
75th	0.1090	0.0284
90th	0.1759	0.0429

Table A-1: 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.

Panel (a)

	2016 Home Sales Volume		2019 Home Sales Volume	
	(1)	(2)	(3)	(4)
More-SLR-Exposed	-0.201***	-0.262***	-0.227***	-0.288***
	(0.030)	(0.037)	(0.035)	(0.041)
Medium-SLR-Exposed	-0.078***	-0.107***	-0.082***	-0.111***
	(0.023)	(0.029)	(0.028)	(0.033)
Log Premium Change	0.004	0.059***	0.010***	0.065***
	(0.003)	(0.011)	(0.004)	(0.012)
Constant	1.177***	0.976***	1.181***	0.980***
	(0.034)	(0.056)	(0.040)	(0.062)
Observations	771	771	771	771
R-squared	0.091	-0.248	0.093	-0.155

Panel (b)

	2016 Home Prices		2019 Home Prices	
	(1)	(2)	(3)	(4)
More-SLR-Exposed	0.039***	0.056***	-0.038***	-0.030**
	(0.011)	(0.012)	(0.011)	(0.012)
Medium-SLR-Exposed	0.002	0.010	-0.009	-0.005
	(0.008)	(0.010)	(0.009)	(0.010)
Log Premium Change	-0.000	-0.016***	-0.001	-0.008**
	(0.001)	(0.004)	(0.001)	(0.003)
Constant	1.152***	1.209***	1.246***	1.273***
	(0.013)	(0.019)	(0.014)	(0.018)
Observations	771	771	771	771
R-squared	0.027	-0.197	0.128	0.082
Premium Instrument	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-2: Results from long-difference OLS regressions showing the relative change in home sales volumes (top panel) and prices (bottom panel) in 2016 (columns 1-2) and 2019 (columns 3-4) in more-SLR-exposed and medium-SLR-exposed markets relative to less-SLR-exposed markets. All specifications include controls for tract population centroid distance-to-coast, 2010 share of households in poverty, and log per-capita flood insurance premium changes between 2012 and 2019. Columns 2 and 4 instrument for premium changes with the counterfactual change if the number and composition of flood insurance policies were held fixed at their 2012 base. Outcomes are normalized by their 2001-2012 tract-level mean.

C Data Appendix

C.1 Home Price and List Price Indices Estimation

This section describes the estimation of the tract-by-year home price index (HPI). To construct the HPI, we run the following regression,

$$Y_{hjt} = \alpha_0^{jt} + \alpha_1 X_{ht} + \epsilon_{hjt} \tag{2}$$

where Y_{hjt} is the log transaction price, winsorized at the 1st and 99th percentiles by year, of property h in census tract j transacted in year t. X_{ht} are the following fixed effects: square footage decile, number of bedrooms, number of bathrooms, building age since construction, effective building age, and month sold.[21]

α_0^{jt} are a set of tract-by-year fixed effects that give the HPI. We normalize each tract's HPI to equal 1 in 2001.

We also estimate a list price index for the MLS data using a similar approach as in Equation (2). We observe the same X_{ht} controls in the MLS data, with the exception of the effective building age.

C.2 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:

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

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

[21] The effective building age is constructed using CoreLogic's "effective year built" variable which accounts for renovations and maintenance.

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:

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

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

C.3 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 2013-2019.[22] To motivate our approach, consider the tract-level regression described below:

$$Y_{j,2019} - Y_{j,2012} = \alpha + \beta(P_{j,2019} - P_{j,2012}) + \epsilon_j \tag{5}$$

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

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

between 2012 and 2019, 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 2019 with the counterfactual change in premiums if insurance uptake were exactly the same in 2019 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 $p_{njr,2019}$ index the corresponding set of policies in 2019.[23] Let N_{jt} be the number of homes in tract j in year t, and I_{jt} the number of flood insurance policies.[24] We calculate the observed change in flood insurance premiums as:[25]

$$P_{j,2019} - P_{j,2012} = \frac{I_{j,2019}}{N_{j,2019}} \sum p_{njr,2019} - \frac{I_{j,2012}}{N_{j,2012}} \sum p_{ijr,2012} \tag{6}$$

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 2019 premiums under the 2012 policy cohort. This means using the 2012 instead of 2019 take-up rate, and calculating the 2019 premiums as if the same exact policies written in 2012 formed the set of insured in 2019. This measure is defined:

$$\frac{I_{j,2012}}{N_{j,2012}} * (\sum p_{ijr,2019} - p_{ijr,2012}) \tag{7}$$

Using this instrument, we can estimate Equation (5) via two-stage least squares in our long-difference specifications.

We use the inverse hyperbolic sine (IHS) premium change and its instrument in equations 6 and 7. The IHS is defined as $IHS(y) = ln(y + (1 + y^2)^{1/2})$. Like the log transformation, the IHS transformation allows coefficients to be interpreted as approximate elasticities, but with the added benefit of being defined at $y \leq 0$ for the 115 census tracts in our estimation sample where observed average flood insurance premiums decline between 2012 and 2019 (Bellemare and Wichman, 2020).[26]

[23]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.

[24]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.

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

[26]Holding policy characteristics fixed, the pricing reforms between 2012 and 2019 would have caused premiums to increase in all census tracts. We treat the premium change instrument as zero in the five census tracts with no active flood insurance policies in 2012.

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[27] 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 uncertainty in climate models, there is additional noise 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:

$$\begin{aligned} R_j =& \alpha + \beta_0 Dist_j + \beta_1 SFHA_j + \beta_2 Claims_j + \beta_3 Pop^{18} + \beta_4 Pop^{64}_{18} \\ &+ \beta_5 \sum_{n=1}^{2} Nonwhite^n_j + Foreign^n_j + Water^n_j + \epsilon_j \end{aligned} \tag{8}$$

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-

[27]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 (8). Next, we fit the outcomes Y_j as a flexible model of the generalized propensity score and actual SLR exposure using a quadratic model:

$$E[Y_j|R_j, \widehat{p_{Rj}}] = \alpha_0 + \alpha_1 R_j + \alpha_2 R_j^2 + \alpha_3 \widehat{p_j} + \alpha_4 \widehat{p}_j^2 + \alpha_5 T_j * \widehat{p_j} \tag{9}$$

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 (8), 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:

$$E[\widehat{Y(r)}] = \frac{1}{J}\sum_{j=1}^{J} \alpha_0 + \alpha_1 r_j + \alpha_2 r_j^2 + \alpha_3 \widehat{p(r, X_j)} + \alpha_4 \widehat{p(r, X_j)}^2 + \alpha_5 T_j * \widehat{p(r, X_j)} \tag{10}$$

By calculating Equation (10) 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.