Disaster on the Horizon: The Price Effect of Sea Level Rise *

Asaf Bernstein† Matthew Gustafson‡ Ryan Lewis§

Original draft November 18, 2017

This version March 18, 2018

Abstract

Homes exposed to sea level rise (SLR) sell at a 7% discount relative to observably equivalent unexposed properties equidistant from the beach. This discount has grown over time and is driven by sophisticated buyers and communities worried about global warming. Consistent with causal identification of long horizon SLR costs we find no relation between SLR exposure and rental rates, and current SLR discounts are not caused by differential investment, flooding, or views. Overall, we provide the first evidence on how markets price SLR exposure thereby contributing to the literature on how investors price long-run risky cash flows and providing insights for optimal climate change policy.

JEL Classifications: G1, G14 and Q54

Keywords: Climate Change, Asset Prices, Beliefs, Sea Level Rise, Real Estate

*We are extremely grateful toward the folks at Zillow and NOAA for providing critical data. Data provided by Zillow through the Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at `http://www.zillow.com/ztrax`. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group. Thanks to Pontificia Universidad Católica de Chile, CU-Boulder Consumer Financial Decision Making Lab Group, CU Environmental Economics Brown Bag, Richard Thakor, Diego Garcia, Ed Van Wesep, Brent Ambrose, Cloe Garnache, William Mullins, Paul Goldsmith-Pinkham, Randy Cohen, Tony Cookson, Brian Waters, Peter Iliev, Katie Moon, Robert Dam, Stephen Billings, Jaime Zender, David Gross, John Lynch, Nick Reinholtz, Shaun Davies, Brendan Daley, Ralph Koijen, Francisco Gomes, Nils Wernerfelt and Xingtan Zhang for the valuable feedback. All errors are our own.

†University of Colorado at Boulder - Leeds School of Business; asaf.bernstein@colorado.edu

‡Pennsylvania State University; mtg15@psu.edu

§University of Colorado at Boulder - Leeds School of Business; ryan.c.lewis@colorado.edu

1 Introduction

The manner in which investors perceive and discount long-run risky cash flows and disasters is central to a wide range of public policy debates (see e.g. Stern (2006), Nordhaus (2007), Barro (2015), and Gollier (2016)) and to understanding how investors price financial assets (see e.g. Bansal and Yaron (2004), Hansen et al. (2008), and Barro (2006)). Yet, evidence is mixed as to whether market participants correctly anticipate and price long horizon shocks. In particular Hong et al. (2016) shows that, despite the predictable nature of worsening droughts at the country level, equity markets do not anticipate the cash flow effects for agricultural firms until after they materialize. By contrast, Giglio et al. (2014) and Giglio et al. (2015), provide evidence that, when facing certain and complete loss in the form of lease expiration, home buyers demand a significant discount. However, this setting lacks critical features of most types of cash flow: uncertainty and heterogeneity of investor information.[1]

In this paper, we examine how markets price long-run uncertain cash flows as they relate to one of the most salient long-run risks facing today's society, sea level rise (SLR). Answering this question is important because of the key role that markets can play in mitigating this disaster: pricing expected SLR risk today reduces the possibility of wealth transfers between uninformed and sophisticated agents, and reduces the likelihood of extreme price swings in the future.

The scientific community shares a consensus that SLR is a serious risk, but the magnitude and timing of SLR are uncertain. For example, the highly publicized IPCC (2013) report contains worst case predictions from a number of external researchers ranging from less than one meter of global average SLR over the next century to more than two.To put these projections in perspective, Hauer et al. (2016) find that a 1.8 meter SLR would inundate areas currently home to 6 million Americans and work by Zillow suggests nearly one trillion dollars of coastal residential real estate is at risk (see e.g., (Rao, 2017)). This risk is heavily concentrated, leading to potentially disastrous outcomes for exposed communities.[2] The durability of real estate investments, combined with the fact that real estate is by far the largest asset for the median U.S. household (Campbell, 2006), should make these predicted effects of SLR a first-order concern for millions of Americans. Yet, as we discuss above, the long-run uncertain nature of SLR risk makes its pricing an unanswered empirical question. Not only do behavioral biases and bounded rationality appear to affect households' financial decisions (Bernheim et al., 2001), but Bunten and Kahn (2014) and Bakkensen and Barrage (2017) show that heterogeneity in beliefs about SLR can lead to believers selling to non-believers, potentially negating the house price discount via a selection effect of the marginal buyer.

Our first contribution is to show that properties exposed to projected SLR sell at around a 6–7.5% discount relative to otherwise similar properties (e.g. same zip, time, distance to coast, elevation, bedrooms, property

[1] In Giglio et al. (2014) and Giglio et al. (2015) there is no uncertainty about the loss event, since there can be no debate or question that all future housing consumption is lost after lease expiration.

[2] While FEMA provides subsidized insurance in flood zones, premiums are not fixed and, for individual homeowners can increase up to 18% per year according to 2015 guidelines. Thus these contracts cannot effectively insure against long run SLR risk.

and owner type.). This discount implies very similar time horizons for rising sea levels as the medium to highly pessimistic scientific forecasts. Pricing effects are primarily driven by properties unlikely to be inundated for over half a century, suggesting that it is due to investors pricing long horizon concerns about SLR costs. Moreover, the same discount does not exist in rental rates, indicating that this discount is due to expectations of future damage, not current property quality. Second, we provide evidence that the SLR exposure discount is greatest in markets with sophisticated investors (i.e., non-owner occupied properties). Third, we find that community beliefs regarding expected SLR risk affect the pricing of SLR, but only when investors are arguably less sophisticated (i.e., owner occupied properties). Finally, we show that the discount for SLR exposure has increased significantly over the past decade, coinciding with both increased awareness of the issue and more dire SLR projections.

To analyze the impact of SLR exposure on real estate prices we combine the Zillow Transaction and Assessment Dataset (ZTRAX) with the National Oceanic and Atmospheric Administration's (NOAA's) SLR calculator to identify each property's exposure to SLR. In addition, ZTRAX supplies pertinent information about the buyer, seller, and property type, which we join with information on a property's elevation and distance from the coast. Our main test sample contains over 480,000 sales of residential properties within 0.25 miles of the coast between 2007 and 2016. In our baseline analyses, we define any property that would be inundated at highest high tide with a 6 foot global average SLR to be exposed.

Identifying the price effect of SLR exposure requires overcoming a number of obstacles, the most prominent of which is that exposure probability decreases with distance to coast. Properties closer to the coast may be inherently different than those farther away. Our main method to address this identification issue is to compare otherwise observably equivalent properties where the variation between properties is isolated to SLR exposure. In our workhorse specification, we compare exposed and unexposed homes with the same property characteristics (e.g. bedrooms, property type), sold in the same month, within the same zip code, in the same 200 foot band of distance to coast, and in the same 2 meter elevation bucket. Within each fixed effect bucket, some of the variation in SLR exposure is due to very granular changes in elevation (even within a six-foot elevation bin the expected time until inundation can vary by over a century), but directly observable factors like elevation and coastal distance of a property combine to explain at most 45% of the exposure.

In our main specification, we estimate that SLR exposed properties trade at a 7.5% discount relative to comparable unexposed properties. We further break this into exposure buckets, with properties that will be inundated after 1 foot of global average SLR trading at a 19.38% discount, properties inundated with 2-3 feet SLR trading at a 15.85% discount, and properties inundated with a 4-5 and 6 foot SLR trading at 8.45% and 5.55% discounts, respectively.[3] Using the long run discount rate provided by Giglio et al. (2014) and assuming complete loss at the

[3]The majority of our properties are effected at the 5 and 6 foot level, tilting our unconditional exposure coefficient toward the smaller magnitude coefficients.

onset of inundation, these discounts suggest that markets expect 1 foot of sea level rise within 40 years, 2-3 feet within 46 years, 4-5 feet after 67 years, and 6 feet in 83 years. 95% confidence intervals for these estimates are consistent with projections provided in Parris et al. (2012) and utilized by the NOAA in their 2012 report, but are of course also subject to the assumptions used for implying the years till inundation.

In addition to being robust to the inclusion of controls for a wide range of observable property characteristics, this magnitude is not sensitive to the exclusion of areas with recent flood incidents or properties said to have attractive features such as waterfront views. Owners of exposed properties are less likely to remodel their homes in recent periods consistent with work by Bunten and Kahn (2017), but this differential investment is only in areas that have recently flooded and does not drive our observed discount. Moreover, placebo tests using rental properties reveal no relation between SLR exposure and rental prices. Taken together, this evidence suggests that SLR exposure causes a decline in the price of coastal real estate, which is consistent with real estate buyers pricing long-run SLR exposure risk.

Piazzesi et al. (2015) document substantial segmentation and illiquidity in the residential real estate market, raising the possibility that the pricing of SLR exposure may depend on market or investor characteristics. We exploit this possibility to examine whether buyer sophistication is related to the SLR exposure discount. To empirically proxy for buyer sophistication, we build off of existing literature suggesting that non-owner occupiers (e.g. homeowners purchasing for investment or as a second home) tend to have higher income and FICO scores than owner occupiers and investors with these same traits tend to exhibit fewer biases in their investment behavior (see e.g., Robinson (2012), Madrian and Shea (2001), Agnew (2006), Dhar and Zhu (2006), and Chetty et al. (2014)). We further provide evidence consistent with the non-owner occupiers in our sample being more sophisticated: non-owner occupied buyers tend to come from zip codes with higher education levels and income and earn higher returns when transacting with owner occupiers.

When partitioning the sample based on whether the property is owner occupied, we find that the negative relation between SLR exposure and real estate prices is concentrated in the non-owner occupied segment of the market. On average, exposed non-owner occupied properties trade at an 11% discount, relative to comparable non-exposed properties, while exposed and unexposed owner occupied properties trade at similar prices. Additional evidence suggests that some level of housing market illiquidity is necessary for the SLR discount to persist in the non-owner occupied segment of the market. Specifically, there is little evidence of an SLR discount among non-owner occupied transactions when an area's housing market is particularly liquid (i.e., in the top 5% in terms of average sale-to-list price or the bottom 5% in terms of days-on-market or housing inventories).

In our next set of tests, we examine whether the SLR exposure discount is related to a region's beliefs about climate change. If the SLR exposure discount is indeed driven by sophisticated investors, we expect no such relation. Rather, we expect a market price for SLR exposure that is unrelated to a specific region's beliefs. To empirically test this idea, we merge our data with a county-level measure of climate change beliefs obtained from the Yale Climate Opinion Maps. Consistent with the sophistication of non-owner occupied buyers, we find no evidence that the SLR exposure discount applied to non-owner occupied properties is related to local residents' beliefs regarding future climate change or the beliefs of residents in the buyer's home county. However, we do find that such beliefs significantly affect the manner in which SLR exposure is priced in the owner occupied segment of the market. For example, in areas in the 90th percentile of climate change worry owner exposed owner occupied properties sell at a 10% discount, which is similar to the average discount of non-owner occupied properties.

In our final set of tests we examine how new information regarding SLR expectations affects the market for SLR exposed properties. Expectations regarding future SLR have steadily increased over the course of our sample period. Thus, to the extent that the negative relation between SLR and coastal real estate prices represents sophisticated investors pricing the expected effects of future SLR, we expect the SLR exposure discount to increase over time. We find evidence of exactly such pricing behavior, both over the full sample and within the non-owner occupied segment of the market. The discount in the non-owner occupied market is significant from 2007 and 2014, but grows substantially in the last two years of our sample period.

We investigate this post-2014 increase in the SLR discount more closely by conducting a difference-in-differences analysis comparing the transactions of SLR exposed and unexposed properties surrounding a number of events that changed expectations about future SLR. Between 2013 and 2015, a number of scientific sources as well as reputed media outlets reported on the increased risk of rising oceans faced by coastal communities. At least 3 reports released during that time validated the upper bound on SLR established by Parris et al. (2012) in 2012 and dramatically increased the lower bound (see e.g. Rohling et al. (2013), Hinkel et al. (2015), and Grinsted et al. (2015)). In addition, the IPCC released their 2013 climate assessment in early 2014 where they nearly doubled the projection for SLR over the next century. The popular media seized on the issue of glacial collapse in Antarctica and wrote a number of articles in May of 2014. As measured by Google trends search intensity, we see a massive increase in awareness of SLR during this time period which peaks in May 2014. As such, we look around these events (e.g. prior to 2014 and after) and find that the SLR exposure discount appliued to non-owner occupied purchases increased from 8.2% to 13.8% after this flurry of information. We find no post-2014 increase in the SLR exposure discount applied to owner occupied properties, suggesting that the non-owner occupied market, which we argue is more sophisticated, reacts more to changes in SLR projections within the scientific community.

This event study framework also allows us to examine transaction volumes surrounding an influx of new information. The model in Bakkensen and Barrage (2017) as well as work on the relation between beliefs and trading by Frankel and Froot (1990), Shalen (1993), and Buraschi and Jiltsov (2006) motivate the prediction that as beliefs change in response to these reports, we should see an increased volume of believers buying from non-believers. Our results line up with their model in two ways. First, consistent with the idea that as information about SLR risks comes to light, exposed properties should be more likely to transact, we find that the annual probability of turnover is approximately 0.2 percentage points higher for exposed properties between 2011 and 2016 (relative to a base transaction rate of approximately 11% for all properties). This is entirely driven by the period following the IPCC report where we see a 0.8 percentage point increase in the annual probability of an exposed property transacting.

Taken together, our findings suggest that SLR exposure is a first-order consideration for certain segments of the coastal real estate market, but not others. In particular, we consistently find evidence that the observed SLR exposure discount is driven by sophisticated investors, who are not sensitive to local beliefs regarding the effect of climate change and who incorporate new information regarding climate change into their home buying decisions. We find little evidence of SLR exposure discounts in regions less worried about global warming among less sophisticated buyers, even though housing likely constitutes the plurality of their savings (Campbell, 2006). Thus, even if sophisticated investors are perfectly pricing the effects of expected SLR exposure, this absence of a current house price discount in less sophisticated market segments raises the possibility of a large wealth shock to coastal communities unless strategies are undertaken to mitigate the effects of SLR. An important question for future research is whether the observed SLR exposure discount among sophisticated investors correctly incorporates all information. To the extent that it does not, we expect even larger wealth shocks as SLR projections materialize.

These findings contribute to both the broad literature examining the drivers of the returns to real estate investment (see e.g. Lustig and Van Nieuwerburgh (2005), Piazzesi et al. (2007)) and the more targeted literature on the trade-off between imminent flood risks and the amenities associated with coastal living. For instance, Atreya and Czajkowski (2014) argue that amenities outweigh flood risk, while Ortega and Taspinar (2016) argue that extant damage and the perception of future flooding result in significantly lower house prices in the greater New York area. An important difference between our findings and those in the literature is that we find a large price of SLR exposure when focusing on much longer horizon effects and after aggressively controlling for current or recent flood exposure and property amenities.

In doing so, we provide new evidence on how markets price long-horizon uncertain cash flow shocks. While Giglio et al. (2014) show a 2.6% discount rate at the 100 year horizon for freehold vs leased real estate, confirmed by follow-up work by Fesselmeyer et al. (2017) and Bracke et al. (2017), their results are not straightforwardly applied to many real-world settings where investors face different information sets about uncertain outcomes. We contribute to the asset pricing literature by providing evidence that, even under these conditions, SLR risk generates similarly sized discounts in real estate prices. Additionally, we show that heterogeneity in both investor type as well as beliefs about SLR create dramatic variation in the market price of exposed assets.

We also contribute to the macro-finance literature on household balance sheets and optimal household decisions. Campbell (2006) documents that housing wealth provides the plurality of retirement savings and our work provides evidence on the extent to which homeowners identify SLR risk and adjust prices in response. In doing so, we contribute to the literature documenting sub-optimal household decision making across a variety of dimensions often stemming from inattention (see e.g. Andersen et al. (2015); Chetty et al. (2014); Huberman et al. (2007); Stango and Zinman (2009)). We document similar lack of attention to SLR risk among unsophisticated investors, particularly when those investors are not worried about climate change. This provides one example of how optimistic investors can drive real estate prices as in Piazzesi and Schneider (2009).

Finally, we contribute to the literature exploring the potential costs of climate change and value of current interventions. Deschênes and Greenstone (2007) provide evidence that weather changes due to climate change are likely to have significant negative effects for the value of agricultural land. We complement this finding by showing that concerns about climate change among coastal properties are already affecting real estate value. We also build on a broad set of papers trying to understand the present value cost of climate change and the benefit of mitigation strategies (see e.g. Stern (2006); Nordhaus (2007); Becker et al. (2011); Deshpande and Greenstone (2011); Weitzman (2012); Nakamura et al. (2013); Barro (2015); Gollier (2016)). The significant SLR price discounts are consistent with the potential for significant gross benefits of mitigation strategies which can reduce future costs of climate change.

2 Data

2.1 Main Sample

We obtain property-level data from the real estate assessor and transaction data from the Zillow Transaction and Assessment Dataset (ZTRAX). ZTRAX is, to the best of our knowledge, the largest national real estate database of its kind with information for more than 374 million detailed public records across 2,750 U.S. counties. It also includes detailed assessor data including property characteristics, geographic information, and valuations on over 200 million parcels in over 3,100 counties.

Characteristics from the assessor files provide exact geo-coded locations of each property, which allows us to determine the property's distance from the nearest coastline point as well as its elevation. The dataset also contains information on a broad set of property information including the existence of a sea or ocean view, square footage, the number of bedrooms/bathrooms, and build year. We also see the type of property (e.g. single family residence, condo, town-home) as well as whether or not the unit is owner-occupied following the sale, the type of buyer, and the address of the buyer and seller.

We filter the Zillow data in 3 ways. First, we retain only transactions of residential properties for which the price of the transaction is verified by the closing documents as being between \$50,000 and \$10,000,000. Second, we only include transactions that occur within a quarter mile of the beach. Finally, we only include properties with sufficient non-missing property information. This leaves us with a total of 481,321 transactions.

To implement our research design, we determine the property-level exposure to SLR for all properties within our sample. Since tidal variation and other coastal geographic factors affect the impact of global oceanic volume increases on local SLR, we utilize the NOAA's SLR calculator to define each property's exposure to SLR. As exhibited in Internet Appendix Figure A1, the NOAA provides detailed SLR shapefiles that describe the latitude and longitudes that will be inundated following a 1-6 foot increase in average global ocean level.

We utilize geographic mapping software to assess the exposure level of each property within a coastal county in the Zillow data. We find that approximately 1.7 million homes within the assessor file are exposed to SLR of between 0 and 6 feet. Restricting the sample to homes that are within 0.25 miles of the beach leaves 144,880 transactions of exposed properties. Thus, approximately 30% of properties in our test sample are exposed to a 6-foot rise in sea levels. Figure 1 provides a county by county map of the proportion of transactions that involve exposed properties throughout our sample period (constructed using all properties within a county). We can see that the most exposed counties are in the gulf region, Washington state, and along the eastern seaboard.

Panel a of Table 1 provides summary statistics for the transactions in our main sample. In general, exposed and unexposed properties are similar. They are nearly identical in terms of square footage and property age, but exposed properties sell for $643 per square foot on average, which is a 7% premium over unexposed properties. A likely driver for this premium is that exposed properties are typically closer to the coast. Throughout our empirical analysis we control for any observable differences between exposed and unexposed properties. In particular, we include miles-to-coast and elevation bin fixed effects to ensure that we do not misattribute any price differences between exposed and unexposed properties.

2.2 Supplemental Data

2.2.1 Rental Prices

As we discuss below, we replicate our analyses using rental market information. To do so, we collect rental data from Trulia utilizing a python based web scraper. On November 6th 2017, we queried Trulia for rental properties in each zip code appearing in our sample with at least one exposed property. The site returns (in JSON format) pages containing 35 characteristics with detailed information including address, price, square footage, geo-data, number of beds and number of baths. Exactly as with the Zillow data, we identify the SLR exposure status as well as the elevation and distance to coast.

Internet Appendix Figure A2 demonstrates the quality of the rental listing data scrapped from Trulia.com. Panel a is a scatter plot of the relation between median log(rental list price) scraped for individual properties from Trulia.com with the log(rental list price) for aggregate data publicly available by zip code from Zillow.com for

November of 2017. These measures of rental rates from independent sources are very similar with a correlation of 94.8% at the zip code level. Panel b is a scatter plot of the relation between median log(rental list price) scraped on November 2017 for individual properties from Trulia.com with the log(median house price) for all property-level transactions from the proprietary ZTRAX database from 2007-2016 at the zip code level. Again, the relation between these variables is strongly positive (with a correlation of 84.1%), suggesting that the data are of high quality. Panel b of Table 1 shows that exposed and unexposed rental properties are observably similar, as in our Zillow sample. On average, both exposed and unexposed properties rent for approximately $6,000 per month, are approximately 1,500 square feet, and have 2.25 bedrooms.

2.2.2 Climate Change Beliefs

We merge our data with the Yale Climate Opinions map data (Howe et al., 2015). This service provides survey data at the county level regarding perceptions of climate change. In the words of researchers behind the project,

> The model uses the large quantity of national survey data that we have collected over the years — over 13,000 individual survey responses since 2008 — to estimate differences in opinion between geographic and demographic groupings. As a result, we are able to provide high-resolution estimates of public climate change understanding, risk perceptions, and policy support in all 50 states, 435 Congressional districts, and 3,000+ counties across the United States. We validated the model estimates with a variety of techniques, including independent state and city-level surveys.

In particular, we utilize the county level survey data capturing whether the respondents are "worried about global warming." Importantly, we see significant variation in this measure. Moreover, it is negatively correlated with the county-level exposure percentage. While this may be driven by external factors, this negative and significant correlation between worried and exposed is consistent with the model proposed in Bakkensen and Barrage (2017), in which less worried individuals move toward exposed areas.

2.2.3 Market Liquidity

To test the cross sectional impact of market liquidity on the exposure discount we also merge our transaction data with county level market liquidity measures provided by Redfin. The average sales to list ratio, the total inventory and the average days on market are available monthly at the county and MSA level starting in January 2009. Since market characteristics vary heavily by region and through time, we demean all measures by absorbing a month and FIPS fixed effect. To merge these normalized liquidity measures with our data, we manually create a concordance file between Redfin region names and FIPS codes at the county level.

3 Empirical Predictions and Methods

3.1 Main Specification

To the extent that participants in the real estate market foresee and discount the potential losses associated with SLR, SLR exposed properties should trade at a discount relative to equivalent unexposed properties. The goal of our empirical design is to compare properties that transact in the same month and zip code and are observably equivalent (i.e., have the same number of bedrooms, distance to the coast line, owner occupancy status, and 6 foot elevation above sea-level), but vary in the amount of SLR that would cause them to be underwater. The resulting hedonic regression takes the following form:

$$Ln(Price/Sqft)_{it} = \beta\, Exposure_{it} + X_{it}\phi + \lambda_{ztmeopb} + \epsilon_{it} \tag{1}$$

where the dependent variable $Ln(HousePrice/Sqft)_{it}$ is the natural log of property i's transaction price in month t divided by property i's square footage. $Exposure_{it}$, our explanatory variable of interest, is an indicator variable equal to 1 if 6 feet or less of SLR would put the property underwater. X_{it} flexibly controls for property age and square footage using indicators for each property's age and square footage percentile (i.e., we include 100 indicators for both age and square footage), similar to the method used in Stroebel (2016). The key to our identification strategy is $\lambda_{ztmeopb}$, which absorbs variation in house price that is related to the interaction between location, time of sale, and property characteristics, including the distance a property is from the coast and the property's elevation above sea level. Specifically, $\lambda_{ztmeopb}$ is comprised of interacted fixed effects between: zip code (Z), year x month (T), distance-to-coast category (D),[4] 6 foot elevation buckets (E), owner occupancy and out-of-zip buyer indicators (O), condominium indicator (P), and total bedrooms (B). After including this full set of fixed effect interactions, our assertion is that the remaining variation in exposure to SLR is as if randomly assigned and thus a plausible basis for causal interpretation of, β - the effect of SLR exposure on house prices.

Although the inclusion of fixed effects for region x time x property characteristics is common in the housing valuation literature (see e.g., Giglio et al. (2014), Stroebel (2016)), the inclusion of an interaction with categorical dummies for miles to the coastline, which are only approximately 220 feet in size on average, but increase in width farther from the beach, are less common and critical for our identification strategy. Not only does their interaction with zip code improve the granularity of our location control, but they control for ease of beach access. In Internet Appendix Figure A3 Panel a we plot the non-linear relationship between distance to the coast line and the log of house price per square foot, while in Panel b we plot that same relationship, after controlling for zip code x time fixed effects. In both cases, we show that as properties get closer to the coast line the value of the property quickly

[4] There are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16. The average bucket size is 220 feet wide.

increases. These results are not surprising since these properties have improved amenities, such as beach access (see e.g., Atreya and Czajkowski (2014)). Thus, distance to the coast fixed effect interactions are necessary in all specifications intended to identify the causal effect of SLR on home prices.

To better understand this identification strategy, we next examine the variation that is left in SLR exposure after controlling for the myriad of fixed effects in Equation 1. We begin with anecdotal evidence from one bin in our sample. Specifically, Figure 2 plots the elevation and location of all transactions in July of 2014 in zip code 23323 (in Chesapeake, VA) that involve a property that is (1) between 0.16 and 0.25 miles from the coast, (2) elevated between 2 and 4 meters above sea level, (3) four bedrooms, (4) a non-condominium, (5) owner occupied, (6) bought by a non-local buyer. The figure shows that Properties D and E are approximately 0.5 to 1 meter higher in elevation than properties A, B, and C and are unexposed to a 6-foot SLR. Thus, there is variation in SLR exposure within each fixed effect bucket that is due to very granular changes in elevation. Although these granular differences in elevation are unlikely to drive substantial differences in property value they do significantly affect the expected time until inundation due to SLR. Indeed, a one foot differential in SLR exposure corresponds to a several decade delay in expected SLR related flooding.

Figure 2 also shows that some variation in exposure is not monotonically associated with elevation. Comparing properties A, B, and C in the figure shows that property C is actually higher than A and the same distance to the coast, but A has higher elevations between it and the coast (as well as a highway) that appear to reduce the exposure of this property to SLR. Conversations with researchers at NOAA suggest that intense time and effort was spent to incorporate all available information on intervening contours, land type, and features in projecting SLR exposures and that many otherwise low lying properties are insulated from SLR risk by natural and man made features. Anecdotally, Louisiana was the last state rolled out as part of the SLR viewer specifically due to the difficulty of obtaining and incorporating levy data. Thus, much of the within bin variation in SLR exposure is not explained by easily observable factors.[5]

3.2 Robustness Analyses

Even in the presence of this research design, it is still possible that there exist uncontrolled for amenities or dis-amenities that jointly correlate with SLR exposure and house prices, which would compromise our ability to identify the causal effect of SLR exposure. One possibility is that properties with high SLR exposure could be have been recently flooded, causing damage and reducing house value. Although this would be suggestive of a relation between house prices and SLR, it would not reflect long-horizon disaster risk. A second possibility is that higher

[5] In the Internet Appendix Table A1 we show that approximately 4% of the variation in abnormal SLR exposure is explained directly by the inclusion of 0.1 meter elevation bins. Also considering how the relation between elevation and SLR exposure varies by zip code and distance-to-coast (i.e., including the interaction between 0.1 meter elevation bins, zip code fixed effects, and and distance-to-coast fixed effects) explains approxiamtely 35% of the variation in abnormal SLR exposure.

properties have better views, increasing their value relative to lower-lying properties. Finally, SLR exposure could affect house value by changing the value of remodeling or investing in these properties, which could in turn affect property value.

As we discuss in more detail in the following section, we take several steps to mitigate these concerns. First, we interact all other fixed effects with 6 foot elevation above sea level buckets. Although a 6 foot range is unlikely to yield substantially differences in amenities, such as views, it would still lead to substantial differences in future SLR exposure. Second, we rerun all analysis showing results excluding (1) regions that have recently flooded, (2) properties listed as having nice views, or (3) properties in the top 10th percentile of elevation of properties in the same zip code that are the same distance or closer to the coast. Third, we examine whether SLR exposed properties differ on observable co-variates that are not part of their choice function, such as original property age and/or square footage. We also re-run the analysis in equation 1, but with either (1) the probability of being re-modeled as the dependent variable or (2) excluding all re-modeled properties. This lets us ascertain both the extent to which SLR exposure affects investment in a property and how much of any observed price discount could be affected by any change in investment.

Finally, we re-run our primary methodology using rental listing prices, instead of sale prices. Non-causal interpretations of the estimated relation between SLR exposure and house prices would predict a similar effect using rental data. By contrast, if the relation between long horizon SLR costs and house prices is causal (and due to investors pricing the negative cash flow effect of long-run SLR exposure) we expect there to be no significant relation between SLR exposure and rental rates, since rental prices embed only short-term features of living in the property.

3.3 Exploring Heterogeneity

The segmentation and illiquidity in the residential real estate market (see e.g., Piazzesi et al. (2015)) raise the possibility that the SLR discount may depend on both investor and market characteristics. Thus, we extend our analysis by examining whether buyer sophistication or community climate change beliefs affect the SLR exposure discount. Although we have no ex-ante prediction regarding the magnitude of any investor's discount, we do expect the SLR discount that sophisticated investors apply to be less sensitive to regional beliefs regarding future climate change. Rather, we expect sophisticated investors to apply a single market price for SLR exposure.

To examine this, we regress $Ln(HousePrice/Sqft)_{it}$ on SLR exposure and its interaction with empirical proxies for buyer sophistication and a region's climate change beliefs as in Equation 2 below.

$$Ln(Price/Sqft)_{it} = \beta_1\, Exposure_{it} + \beta_2\, Interaction_{it} + \beta_3 Exposure_{it}\, x\, Interaction_{it} + X_{it}\phi + \lambda_{ztmeopb} + \epsilon_{it} \quad (2)$$

To separately identify the role of beliefs on more and less sophisticated buyers, we also partition this analysis on our proxy for buyer sophistication, which we discuss in Section 4.2.1.

In addition, we also use this specification in our final set of tests to examine how new information regarding SLR expectations affects the market for SLR exposed properties. Here, we interact Exposure with measures of time to see whether the effect of exposure varies over the course of our sample period, as expectations regarding future SLR have steadily increased. Perhaps the most comprehensive SLR projections are released periodically by the Intergovernmental Panel on Climate Change (IPCC). In their 2007 report, the IPCC projected that sea level would rise by only 0.18 to 0.59 meters by the end of the century,[6] but in 2013, the IPCC updated its own projections, approximately doubling SLR expectations. As of 2013, the NOAA supplied an upper bound SLR projection of 2 meters, which was increased to 2.5 meters in January 2017. Over this same period between 2013 and 2015 three reports were released substantiating these higher predictions for SLR over the next century (e.g. Rohling et al. (2013), Hinkel et al. (2015), and Grinsted et al. (2015)). To the extent that the negative relation between SLR and coastal real estate prices represents sophisticated investors pricing the expected effects of future SLR, we expect the negative relation to be increasing over time, along with projected SLR. Notably, alternative explanations for the relation between SLR exposure and house prices would not make such a prediction. For instance, since short-horizon flood risk projections have not increased over our sample period so we would not expect the SLR discount to change to the extent that it is driven by the risk of flooding in the near future.

4 Results

4.1 Effect of SLR Exposure on Coastal Real Estate Prices

Evidence from the scientific community suggests that SLR will become a first-order concern for millions of Americans over the next century (see e.g., Hauer et al. (2016)). The durability of real estate investments, combined with the fact that real estate is by far the largest asset for the median U.S. household (Campbell (2006)), should lead investors to discount properties in accordance with their SLR exposure. However, the extent to which investors actually perform such discounting remains an unanswered empirical question.

On the one hand, the financial markets do not always accurately price predictable long-run risks (see e.g., Hong et al. (2016)). This seemingly irrational investment behavior is even more striking when considering personal finance decisions, such as retirement saving (see e.g., Chetty et al. (2014)). Piazzesi and Schneider (2009) show that such behavioral biases (in the form of investor beliefs) can affect real estate market prices, though as Bakkensen and Barrage (2017) theoretically show, simple selection where those who believe in climate change sell to those who

[6] Other sources released between 2007 and 2009 projected higher SLR (see e.g., Pfeffer et al. (2008)) however there is substantial variation in the projections across studies.

do not can delay the price response. On the other hand, there is evidence that market prices do reflect long-run and disaster risks at times (see e.g. Bansal and Yaron (2004), Hansen et al. (2008), and Barro (2006)). Furthermore, Giglio et al. (2014) finds that very long-run cash flows are an important driver of real estate value as investors discount fairly certain cash flows arriving in 100 years at an annual rate of only 2.6%. This evidence coupled with the fact that real estate prices often reflect flood risks (see e.g., Bin and Landry (2013)), raises the possibility that expected future SLR materially affects the prices of exposed real estate.

In Table 2 we present baseline regression results that provide the first evidence on this empirical question. In Column 1, we naively regress the natural log of sale price per square foot on an indicator for SLR exposure controlling only for age and square foot percentiles. The significantly positive coefficient on exposure indicates that SLR exposure is associated with higher prices, consistent with evidence in Atreya and Czajkowski (2014). This result is not surprising, given that on average exposed properties are more proximate to the beach, which tends to be highly desirable. In Column 2, we show that a correlation between SLR exposure and proximity to the coast drives the observed positive unconditional relation between SLR exposure and sale price in Column 1. After controlling for the interaction between zip code, distance-to-coast bin, and two meter elevation bin fixed effects, the relation between SLR exposure and sale price becomes significantly negative, as would be expected if investors are pricing the expected long-run effects SLR. Although this negative relation between SLR exposure and coastal real estate prices is consistent with market participants pricing long-run SLR risks, there are several potential alternative explanations.

In Columns 3 and 4, we begin to address one such alternative, which is that the SLR exposed properties sold during our sample period are different from unexposed properties, even after controlling for the distance from the coast. To this end, we add property-level controls to make the SLR exposed and unexposed properties more similar. In Column 3, we interact the zip code, distance-to-coast and elevation fixed effects with fixed effects for the the total number of bedrooms in the property and whether the property is a condo. In Column 4 we further interact the fixed effects with information about the transaction—year-month and an indicator for an owner occupied property or a property sold to a non-local buyer. We continue to find a significantly negative relation between SLR exposure and sale price. Notably, the magnitude is similar across the two different fixed effects structures, even though the number of non-singleton observations is over three times as large in Column 3 compared to Column 4.[7] To alleviate concerns that the full suite of fixed effects overly narrows the sample, we relax the time variable to year-qtr in Column 5. We continue to find an SLR exposure discount of comparable magnitude after this change in fixed effect structure, which increases the number of non-singleton observations by over 50%.

The SLR Exposed coefficients of -0.075 and -0.060 in Columns 4 and 5, respectively, suggest that exposed properties sell for 6% to 7.5% lower prices relative to unexposed properties sold in the same zip code at the same

[7]Throughout the paper we will utilize the full array of fixed effects in Column 4 as our primary specification.

time that are a similar distance from the beach and have the same number of bedrooms. A natural question is, after controlling for the fixed effects structure used in Column 4 of Table 2, what type of variation in SLR exposure drives the observed discount. Internet Appendix Table A1 shows that the interaction between very granular 0.1 meter elevation bins and zip code x distance-to-coast fixed effects explains approximately 35% of the variation in abnormal SLR exposure. Internet Appendix Table A2 further shows that both this explained variation in SLR exposure and variation in SLR exposure that remains unexplained (perhaps due to unique features of the local landscape, such as highways or other construction) are significantly negatively related to home prices.

Another potential driver of the price difference between exposed and unexposed properties is current flood risk. Bin and Landry (2013) find that flood risk is only priced when a flood has recently occurred in the area, so we begin by excluding properties in counties that have recently experienced flooding. This has the added benefit of eliminating all properties that may be less valuable due to past flood damage, which are likely to be disproportionately exposed properties. To this end, Column 1 of Table 3 excludes properties that experience flooding in the current year or have experienced flooding in the past 3 years. Similarly, Column 2 excludes all counties that have received FEMA assistance through the individuals and households program (this is triggered when homes are damaged in FEMA flood zones and dates to 2000). Neither of these sample restrictions, which reduce our sample by approximately 30% and 60% respectively, eliminate the significant negative relation between SLR exposure and sale prices. Moreover, the 95% confidence interval on the estimated effect includes the -0.075 point estimate from our baseline model in Column 4 of Table 2. Thus, past flood exposure is an unlikely driver for the observed negative relation between SLR exposure and coastal real estate prices. Finally, Column 3 of Table 3 excludes all properties with a designated lot site appeal—this field has an indicator for water views and being considered waterfront —and excludes any properties in the top 90% of elevation within the zip code. Again, the coefficient remains virtually unchanged meaning the discount is unlikely to be related to view or other property features. This is also consistent with evidence in Internet Appendix Table A5 where we show that after including our full set of controls there is relationship between elevation and water views.

It is also possible that a portion of the SLR exposure discount is due to owners of exposed properties investing less in their property. In Internet Appendix Table A3 we examine this possibility by regressing remodeling rates on SLR exposure.[8] Column 1 indicates that the probability of remodeling is lower for exposed properties, while Column 2 reveals no significant difference between the differential remodeling rates of owner and non-owner occupiers. Column 3 further shows that the differential remodeling rate of exposed properties becomes statistically insignificant (and less than one-third the magnitude) after dropping recently flooded properties. Since our main results all holds after

[8]We utilize a remodeling indicator provided by ZTRAX. This is based on assessor and deeds records where any variation over time in square footage, number of bedrooms, number of bathrooms, number of kitchens, number of stories, roofing, air conditioning, foundation type, fireplace, exterior wall type (ex. wood, brick, stone), garage type, heating system, interior flooring, interior wall, or pool indicated in those records would lead to the year of that remodeling recorded each time.

excluding flooded properties, this supports our general assertion that variation in pricing is driven by differential expectations about future loss, not current investment.[9]

The stability of the relation between SLR exposure and real estate prices suggests that a causal interpretation of the SLR coefficient is reasonable. However, we cannot completely rule out the possibility that unobserved characteristics that are correlated with both SLR exposure and sale price contribute to the estimated effect. To mitigate such a possibility we next conduct a series of placebo tests. Columns 1 and 2 of Internet Appendix Table A6 conduct the first two such tests regressing the natural log of property age and square footage on SLR exposure and our full set of fixed effects. To the extent that our fixed effects absorb property-level information (i.e., SLR's effect on price is causal), we expect no relation between SLR exposure and property characteristics that are not directly affected by expected SLR. Consistent with this, we find no significant relation between SLR exposure and either property age or square footage. Thus, our fixed effect structure appears to absorb enough property- and deal-level information such that there is no relation between SLR exposure and other observable property characteristics, which may be correlated with price.

Our next set of placebo tests examines the relation between rental prices and SLR exposure. These tests are predicated on the idea that both renters and buyers care about property quality, but, unlike buyers, renters do not care about long-run SLR risk. Thus, if the relation between SLR exposure and sale prices that we observe is causal, we expect no significant relation between rental prices and SLR exposure. If instead the relation between exposure and sale prices that we observe is due to omitted property characteristics, amenities, or short-run costs, then we expect a negative relation between SLR exposure and rental prices. Table 4 presents estimates for regressions of rental prices on SLR exposure. Columns 1 and 2 replicate the first specification of Table 2 (Column 1) with and without controls for property square footage. As in the purchase market, we find a large positive effect of exposure likely arising from the high amenity value from living near the coast. However, once we control for the suite of fixed effects such as distance to the coast, elevation, and property characteristics in Columns 3 and 4, we find no significant discount in rental rates for exposed properties. Importantly, our result is not driven by an overly conservative clustering level as we use only robust standard errors in all specifications presented.

Taken together, the evidence presented thus far indicates a robust negative relation between SLR exposure and coastal real estate prices. This negative relation does not appear to be driven by exposed properties having different property characteristics, past flood exposure, or remodeling rates. Placebo tests further support a causal

[9] The similarity between the observed remodeling of exposed and unexposed properties (after excluding flooded properties) also makes it unlikely that unobserved remodeling differs substantially across exposed and unexposed properties in a manner that drives the observed SLR exposure discount. Although we view this alternative as unlikely, we empirically examine its plausibility building off the idea in Plaut and Plaut (2010) that remodeling is much more likely among older properties that have not been recently remodeled. Column 1 of Internet Appendix Table A4 confirms this association. In columns 2-4 we show that our main results on SLR discounts remain statistically significant and of similar magnitude when restricting the sample to properties less than 10 years old, 5 years old, and 5 years old and not recently flooded. Although we cannot completely rule out the possibility that some unobserved differential investment into exposed properties contributes to our SLR discount, such an alternative is unlikely because we observe a similar discount within a sample of properties that are unlikely to derive much value from past remodeling.

interpretation of the effect of SLR exposure on coastal real estate prices. The magnitude of the effect is relatively persistent across the various specifications. SLR exposed properties sell at a 6% to 8% discount relative to comparable non-exposed properties. We next examine whether the long-run effects of SLR are likely drivers of the observed discount by partitioning SLR exposure into 1-2 foot bins. To the extent that the SLR discount is present in homes with exposure to only 5 or 6 foot SLR, it is unlikely that the discount is driven by concerns relating to the immediate future. Indeed, even pessimistic SLR projections do not expect these properties to be inundated for approximately 80 years.

Figure 3 illustrates the effect of SLR exposure on house prices using this more continuous measure of SLR exposure. We include all fixed effects and controls specified in equation 1, but include categorical dummies for the amount of SLR that would put the property underwater. This allows us to look at the non-linear relationship between SLR exposure and house prices. Across all interactions we see a statistically negative effect of SLR exposure, meaning that any amount of exposure is related to a price discount relative to unexposed properties (i.e., those with >6 feet SLR required to be underwater). The fact that properties requiring exactly 6 feet of SLR to be inundated still trade at a significant discount lends credibility to the idea that much of the estimated relation between SLR exposure and home value is due to long-horizon risk, not more immediate concerns. Also consistent with this idea, exposure effects are monotonically increasing as less SLR is required to put properties underwater. In particular, for properties imminently at risk, such as those that would be underwater with 1 foot of SLR, we find that exposure reduces those property values by 19.38%. By contrast properties that require 6 feet of SLR to become underwater experience only a 5.55% discount relative to unexposed properties. These findings contribute to the growing literature on how investors price long-run risks (see e.g., Bansal and Yaron (2004); Hansen et al. (2008); Giglio et al. (2014, 2015); Piazzesi et al. (2015)). Our findings that investors price long-run SLR risk is also relevant from a policy perspective because it suggests that on average investors believe that SLR will materially affect coastal economies over the coming decades and that such costs have significant effects on current property values.

Although determining whether the magnitude of our estimated SLR exposure discount is correct is beyond the scope of this paper, it is worth noting that the estimate is plausible. By making two simplifying assumptions, we can interpret Figure 3 to assess the market expectation of the timing SLR risk. First, we assume that when sea levels rise to the point where a property becomes exposed the property is immediately unlivable and worthless.[10] Second, we assume a 2.6% discount rates on coastal housing properties, following the 100 year discount rate on residential properties detailed in Giglio et al. (2014).[11]

[10]Likely, SLR would begin to impact a property prior to rendering it uninhabitable, however it is also possible that the property will retain some value even after it is expected to be flooded.

[11]This discount rate is also in line with a survey conducted byDrupp et al. (2015) of 197 researchers views of long run discount rates where 90% were comfortable with a range of 1% to 3%.

To translate our estimates into the market expected timing of SLR risk, we start with the assumption that the value of a property is the discounted sum of future cash flows. For unexposed properties (u), we assume these cash flows in perpetuity, while exposed properties (e) cease providing income at some date T.

$$V_u = \sum_{s=1}^{\infty} \frac{CF_u}{(1+r)^s} = \frac{CF_u}{r} \tag{3}$$

$$V_e = \sum_{s=1}^{T} \frac{CF_e}{(1+r)^s} = \frac{CF_e}{r} - \frac{CF_e}{r(1+r)^T} \tag{4}$$

Our estimated coefficients presented in Figure 3 indicates the impact on log price of a property for being exposed at certain levels of exposure. Thus we can interpret the inverse of this coefficient as the log ratio of prices for exposed and unexposed homes.

$$\log\left(\frac{V_e}{V_u}\right) = \beta_e \tag{5}$$

Since our properties are observably equivalent, and we know that from our placebo test the rental cash flows are effectively the same for exposed and unexposed properties, we set $CF_u = CF_e$. Inserting equations 3 and 4 above and rearranging yields the following expression which expresses the observed discount as a function of the T.

$$\log\left(1 - \frac{1}{(1+r)^T}\right) = \beta_e \tag{6}$$

Plugging in our point estimates from Figure 3, we observe the following market expectations for the timing of SLR impact. According to this equation, the prices of exposed homes suggest a window of 40 years before homes which will be exposed to one foot of SLR are worthless, 46 years for homes exposed with 2-3 feet of SLR, 67 years for the 4-5 foot homes and 83 years for those homes that will be exposed with 6 feet of average SLR. These estimates fall between the intermediate and high scenarios prepared by Parris et al. (2012) for the NOAA and are generally more pessimistic than the median scenario used by the IPCC. It appears these market projections are consistent with scientific projectons, but the wide range in the 95% confidence interval of our estimates makes it is difficult to say with certainty.[12]

[12] In addition to standard statistical uncertainty in the estimated house price discounts due to SLR exposure, the method used in mapping these SLR-related price discounts into implied probabilities rely on assumptions about future loss and discount rates that are also estimated with uncertainty. For example, the discount rate from Giglio et al. (2014) is based on a situation with no uncertainty with respect to timing or magnitude of dollar loss, that is unlikely to be correlated with future economic conditions. By contrast losses due to SLR have the potential to occur during future periods when global economic conditions are under duress and consequently discount rates are high. If this is true current prices could be more sensitive to future cash flow shocks if they are driven by SLR, which could imply more optimistic projections for SLR than are suggested by our analysis.

4.2 When do Coastal Real Estate Markets Price SLR risk?

Illiquidity and constraints to shorting individual properties in the residential real estate market create limits to arbitrage that allow market segmentation and differential prices between buyer types to persist. Piazzesi et al. (2015) provides evidence that such segmentation can affect market prices. This raises the possibility that the SLR discount may depend on both investor and market characteristics.

In this section, we examine heterogeneity in the relation between SLR exposure and coastal real estate prices. Our first two sets of tests examine which types of markets most aggressively discount SLR exposure. Specifically, we examine the extent to which buyer sophistication or local individuals' beliefs influence the discount due to SLR exposure risk. Next, we examine how new information regarding expected SLR affects the market for SLR exposed properties. These tests provide evidence on the joint hypothesis that our findings are due to investors pricing SLR exposure and that investors have increased their beliefs regarding expected SLR over the course of our sample period, along with the scientific community.

4.2.1 Is the SLR Exposure Discount related to Buyer Sophistication?

Our primary proxy for buyer sophistication is whether the buyer occupies the property. Robinson (2012) supports this proxy, showing that non-owner occupiers have higher income and better credit scores and arguing that non-owner occupiers are more likely to treat home purchases as financial transactions. This type of investor (i.e., high-income, wealthy, or employed in professional occupations) is also less subject to behavioral biases when making financial investments (see e.g., Madrian and Shea (2001), Agnew (2006), Dhar and Zhu (2006), and Chetty et al. (2014)). Although we do not observe a wide range of buyer-level characteristics, we find evidence consistent with the sophistication of non-owner occupiers in our sample, which we discuss in detail in Appendix B. In short, non-owner occupiers come from wealthier and more educated zip codes (relative to that of the purchased property) and owner-occupier to non-owner occupier sales earn higher returns than non-owner-occupier to owner occupier transactions. One buyer level characteristic that we do observe is that approximately 85% of the non-owner occupied purchases in our sample are made by individuals purchasing properties for investment purposes, not second home buyers or companies. The repeated nature of non-owner occupier purchases provides an additional channel through which non-owner occupiers are likely to be more sophisticated buyers. For instance, Feng and Seasholes (2005) show that experience helps sophisticated investors improve their financial decisions.

An important determinant of whether or not the SLR discount will depend on buyer sophistication is the extent to which the coastal real estate market is segmented along this dimension. We exmine this in Internet Appendix Table A8 and find evidence of significant segmentation by owner occupancy status. Specifically, non-owner occupied sellers are more than 6 times more likely to sell a property to a non-owner occupier than an owner-occupier even though the majority of buyers are owner-occupiers. Thus, given the evidence in Piazzesi et al. (2015) that segmentation can lead to differential pricing, it is plausible that the SLR discount may depend on buyer sophistication. Ex-ante, we expect that more sophisticated buyers will demand a discount for SLR risk and that, ceterus paribus, this discount will depend less on beliefs and more on the scientific community's projections regarding SLR risks.

To test whether non-owner occupiers more heavily discount SLR exposed properties, Column 1 of Table 5 regresses the natural log of sale price per square foot on an indicator for SLR exposure and its interaction with an indicator for a non-owner occupied property. The majority of the negative relation between SLR exposure and real estate prices is in the approximately 42% of properties that are non-owner occupied. The main SLR Exposed effect drops to -0.020 and is statistically insignificant, suggesting that SLR exposure has little effect on the price of the average owner occupied property. By contrast, the SLR Exposed x Non-Owner Occupied interaction is highly significant, with a point estimate of -0.092. Summing this interaction with the main SLR Exposed coefficient of -0.020, suggests that exposed non-owner occupied properties trade at an 11.2% discount, relative to comparable non-exposed properties.[13]

In Columns 2 and 3 of Table 5 we introduce two additional proxies for the information set of the buyer, which may be related to different dimensions of buyer sophistication. First, we look at buyers in different zip codes than the purchase property since they also may be more likely to be engaging in more sophisticated transaction. Second, we examine whether condominiums—a more homogeneous real estate product for which the public price signal is likely to be more reflective of the average investor's willingness to pay—are more or less sensitive to exposure. The interactions between SLR exposure and both non-local buyers and condominium sales are negative, although the condominium interaction is statistically insignificant. Column 4 simultaneously includes all three interactions, and shows that only the Exposed x Non-Owner Occupied interaction remains statistically, and economically, significant.

The results in Table 5 suggest that SLR exposure affects the average price of SLR exposed real estate in the non-owner occupied market, but not the owner occupied market. These findings contribute to and support the literature on segmented real estate markets. In particular, Piazzesi et al. (2015) shows that segmented search markets can lead to differential pricing depending on participant characteristics. Although we cannot definitively say whether the SLR exposure discount is correct in either market segment, segments that we argue are dominated by more sophisticated investors are pricing SLR exposure in a manner that is more consistent with the scientific community's projections regarding the expected effects of SLR. These results also strengthen the validity of our placebo test with rental listings. Since non-owner occupied properties are also those that are rented, the fact that

[13] In Internet Appendix Table A7 we examine whether different types of non-owner occupiers pay different discounts. We see no significant difference between the discounts paid second home buyers, company buyers, or non-second home individual buyers, which comprise the majority of our sample. However, the fact that we have only 715 non-singleton observations involving a company buyer, combined with the fact that we estimate a 6% larger discount for company buyers (with a t-statistic of -1.23), raises the possibility that this null result is due to a lack of statistical power.

exposure effects are largest among these properties suggests that the absence of an effect of exposure on rental rates is not driven by differential property types.

Despite the evidence of segmentation discussed above, the question remains: why would a non-owner occupier who demands an SLR exposure discount ever outbid an owner occupier that does demand such a discount for an exposed property? If housing markets were highly liquid with enough transactional buyers, then such a transaction may not occur frequently. However, recent evidence indicates that housing markets are highly illiquid. As shown by Piazzesi et al. (2015) the illiquidity premium in housing can be substantial with a median discount of 14% and a 90th percentilediscount of 24%, even in markets as liquid as the Bay Area. The high degree of illiquidity in this real estate and practical constraints in shorting individual properties create substantial limits to arbitrage which allow market segmentation and differential prices between buyer types to persist. For instance, among RedFin real estate agents from 2014-2017, 49.9-51.4% of housing transactions each year involve only a single bidder and if that bidder is not an owner occupier they could win by default.[14] Even in the presence of multiple bidders, some of which may be owner occupiers, heterogeneity in beliefs about SLR and more generally about the property-specific match mean that a non-owner occupier can supply a winning bid.

A possible exception arises in "hot" housing markets where each seller has a huge number of bids. In that setting, we might expect an SLR-related discount driven more by non-owner occupiers to dissipate. So to further validate our interpretation of our findings, we examine the relation between market liquidity and the SLR exposure discount associated with non-owner occupied properties by interacting exposure with three indicators of high market liquidity—average sale price to list ratio, inventories, and days on marketThe above argument suggests that the coefficient on the interaction term between exposure and periods of extremely high liquidity will be positive, negating the SLR exposure discount in these settings.

Table 6 presents the results from interacting the SLR exposure discount in non-owner occupied transactions with indicators for a market in the top 5% in terms of liquidity. In Column 1 we see a base coefficient consistent with our findings from Table 6, non-owner occupiers pay approximately 10% less for exposed properties. However, the coefficient on the interaction between exposure and 95th percentile of normalized sales to list is positive, significant, and of a similar economic magnitude, suggesting that SLR discounts for non-owner occupying buyers disappears in the most liquid markets. We confirm this by constraining our sample to just markets in the 95th percentile of liquidity and see a coefficient near zero. Columns 3 through 6 repeat this analysis with two additional normalized measures of liquidity with similar results. Sophisticated buyers do not pay discounted prices for SLR exposed properties in highly liquid markets. We obtain similar results using the top 10% most liquid markets, although the interaction terms diminish in magnitude and the partitioned regressions have economically smaller but statistically significant SLR discounts. This suggests that the SLR discount we document over the full sample is economically

[14] https://www.redfin.com/blog/2017/12/redfin-ranks-2017s-most-competitive-neighborhoods-for-homebuyers.html

meaningful in all but the most liquid markets.

4.2.2 Beliefs and the SLR discount.

In our next set of tests, we examine whether community beliefs regarding expected climate change affect market prices. Piazzesi and Schneider (2009) show that such an effect is possible and most likely when prices are set via bilateral negotiation, which we posit is more likely in the owner occupied market segment. If prices in the owner occupied housing market are indeed driven by the opinions of investors, then we expect the community's beliefs about the effects of climate change to affect the relation between SLR exposure and real estate prices. In contrast, we expect no such relation in the non-owner occupied market, to the extent that properties are priced based on sophisticated investors' expectations regarding future cash flows. To empirically investigate this idea, we merge our data with the Yale Climate Opinion Maps, which provides an aggregate measures of a residents' answer to the question "Are you worried about climate change?."

In Table 7, we regress property sale prices on SLR Exposed and its interaction with Worried. Column 1 shows that a county's reported level of concern over future SLR does not significantly affect the average effect of SLR on exposed real estate prices. In Column 2, which restricts the sample to non-owner occupied properties, we continue to find a negative relation between SLR exposure and a property's price, but no evidence that this relation is sensitive to an area's beliefs. This is consistent with the non-owner occupied property market establishing a price that incorporates SLR risk. In Column 3 we interact the Yale survey worry about global warming with not just the location of the property, but also the mailing address of the buyer. We find no evidence that climate change worry in either the property's or buyer's county is significantly related to the SLR discount. Thus, the lack of a relation between climate change worry and the SLR discount within the non-owner occupied sample is not due to buyers living farther away, and therefore having beliefs that are less correlated with those measured near the property. Instead, it is more consistent with a level of sophistication in the transaction that is less sensitive to local beliefs or information.

Column 4 shows that beliefs play a significant role in the pricing of owner occupied coastal properties. Although the prices of owner occupied properties are not significantly related to SLR exposure on average, SLR exposure does affect prices when an area is sufficiently worried about SLR. For example, at the 90th percentile of Worried, which corresponds to a Worried z score of 1.36, exposed owner-occupied properties sell at an 8% (1.36*0.042+0.020) discount.

Taken together, the results in Tables 5 through 7 suggest that the effect of SLR exposure on coastal real estate prices critically depends on the market structure. The market for non-owner-occupied properties consistently prices SLR risk, except for periods of extremely high liquidity. In contrast, the market for owner-occupied properties only prices SLR risk to the extent that area residents are worried about SLR. These findings are consistent with non-owner occupied property purchases being based more directly on the market's expectations regarding expected future cash flows, as opposed to bilateral negotiations dictated in part by personal preferences and beliefs.

4.2.3 Does new information about expected SLR affect exposed properties?

As we have noted, over time SLR projections have steadily increased. Thus, if the negative relation between SLR and home prices represents sophisticated investors pricing long-run SLR exposure, the discount should increase over time. In Table 8, we empirically examine this by regressing sale price per square foot on SLR Exposed and its interaction with the natural log of months since the beginning of our sample. The statistically insignificant SLR Exposed coefficient in Column 1 suggests that under the assumption of a log-linear change in the discount over time, the SLR exposure had little effect on coastal real estate prices at the beginning of our sample in 2007. Rather, the significantly negative Exposed x Time interaction suggests that the negative relation between SLR exposure and prices has emerged throughout our sample period. Given that the logged time trend maxes out at 4.79 at the end of our sample period, the coefficient of -0.024 suggests that by the end of 2016 exposed properties were selling at an approximate 10% discount. These findings are robust to interacting exposure with a linear (instead of logged) time trend or an indicator for the second half of our sample period.

Columns 2 and 3 partition the sample by owner occupancy to see whether this inter-temporal increase in the relation between SLR exposure and property values is more pronounced in the non-owner occupied market, which we argue is more sophisticated. We find that the trend toward more aggressive pricing of SLR risk is concentrated in the non-owner occupied market. The negative and significant Exposed x Time interactions in Column 2 suggests that exposed non-owner occupied properties are priced approximately 13.0% below comparable unexposed properties by the end of our sample period. In contrast, the prices for exposed owner occupied properties do not respond to the increases in SLR projections that occur throughout our sample period.

Although precisely estimating which reports are causing the cumulative growth of the discount over time is beyond the scope of this paper, a number of scientific reports and popular media articles released between 2013 and 2015 documented the increasingly dire prognosis for global coastlines. First, in April of 2014, the relatively conservative IPCC released its 2013 report on sea levels nearly doubling its expectation for SLR before the end of the century. This was accompanied by a sequence of peer reviewed articles (e.g. Rohling et al. (2013), Hinkel et al. (2015), and Grinsted et al. (2015)) that confirmed the 2 meter upper bound established by Parris et al. (2012) while providing substantially higher lower bounds (as high as 1.2 meters) on end of century expected SLR. Moreover Joughin et al. (2014) raise the specter of Antarctic ice shelf instability and the possibility that the Thwaites Glacier will collapse before the end of the century. This article sparked fears of accelerating sea level rise in popular media outlets and was released near the time google search intensity for "sea level rise" peaked as documented in Appendix Figure A4. Finally, in late 2014 the NOAA's SLR viewer, previously relegated to a flash application buried on their website, was relaunched providing complete US coverage in an easy to use map interface.

While real estate prices are unlikely to react instantly to new information (in part due to the selection effects documented in Bakkensen and Barrage (2017)), we predict that the deluge of information around this time period should increase the SLR discount in subsequent years. For simplicity we will utilize the IPCC report as our event, though these findings are robust to altering the exact date of the "event." Table 9 Panel a conducts an analysis similar to that in Table 8, except that we replace the Exposed x Time interaction with an Exposed x Post-IPCC interaction, which equals one for exposed properties after April of 2014 and zero otherwise. We also restrict the sample to periods after 2010, which leaves approximately three years in the pre- and post-IPCC samples. We find that the relation between SLR exposure and property prices is more negative following the 2013 IPCC report release, but only within the non-owner-occupied sample. Again, this result fits squarely with the narrative that the impact of new information is likely to move prices when sophisticated investors are the marginal purchasers.

Figure 4 delves deeper into how the SLR discount changes over time and relaxes our previous linearity assumption. Panel A restricts the sample to non-owner occupied purchases and shows that the SLR discount ranges from 5% to 13% over the first 8 years of our sample period and grows substantially during 2015 and 2016, the last two years of our sample. This significant increase in the SLR discount coincides with the significant increases in both SLR projections and awareness discussed above. Thus, the timing of the increase in the SLR discount of non-owner occupied properties suggests that non-owner occupiers pay attention to new information regarding SLR projections. In contrast, Panel B provides little evidence that the insignificant SLR discount applied to owner occupied properties increases over time.

Finally, examining market activity in the period following a major event allows us to examine any changes in transaction volumes accompanying an influx of new information. Again, the model in Bakkensen and Barrage (2017) provides some guidance: as beliefs, and in particular the extent of heterogeneity about future SLR, changes in response to these reports, we should see an increased volume of believers buying from non-believers. As shown in Table 9 Panel b, our results line up with their model in two ways. First, consistent with the idea that exposed properties should be more likely to transact as new information about SLR is released, Column 1 indicates that the annual probability of turnover is approximately 0.2% higher for exposed properties between 2011 and 2016 (relative to a base transaction rate of approximately 11% for all properties). This is entirely driven by the period following the IPCC report where we see a 0.8% increase in the annual probability of an exposed property transacting as evidenced in Column 2. Columns 3 and 4 partition the sample on owner occupancy. Here, we see the more precise and larger coefficient in the owner occupied buyer group—exactly the subset of agents where we find belief heterogeneity matters and where we would expect to find optimistic buyers selecting into exposed properties.

Taken together, our findings are consistent with non-owner occupied home purchases being conducted by sophisticated investors who actively discount properties based on the SLR exposure. Within the non-owner occupied market the SLR discount is (1) not affected by a community's beliefs about climate change, and (2) increasing over time, along with SLR projections in the scientific community. In contrast, the average owner occupied property experiences a significantly smaller discount for SLR exposure, which is increasing in community beliefs and not increasing over time.

5 Conclusion

We show that home buyers look to the distant horizon when bidding on coastal properties that scientists project will be affected by sea level rise. We find average discounts of approximately 7% of the home value during our 2007 - 2016 sample period, with properties not projected to be inundated for almost a century experiencing more than a 5% discount. Our evidence further suggests that this discount is driven by non-owner occupiers, who we argue and provide evidence are more sophisticated investors. Within this market segment, the average SLR exposure discount is approximately 11% and has increased over time, coinciding with the release of new scientific evidence on the extent and timing of ocean encroachment. Among buyers who we argue are less sophisticated (i.e., owner occupiers), we find that the SLR exposure discount varies at the county level by the degree to which inhabitants are worried about the effects of climate change: with more worried areas impounding a significant discount and unworried areas demanding no concessions for SLR exposure. These results are robust to a wide range of specifications, but do not hold in our placebo test sample of non-owner occupied rental properties rates, suggesting our effects are driven by concerns about long horizon SLR risks.

In his 2015 state of the union, President Barack Obama named climate change as the single greatest challenge facing humanity. Like many challenges, capitalist societies look toward markets to provide guidance and solutions. Our research represents an important step in understanding the relation between financial markets and climate change by establishing and characterizing the real estate price discount due to sea level rise. Where these risks are priced, there is less scope for wealth transfer between homeowners and less chance of significant and destabilizing downward price volatility in the future. Our research, by documenting the role of information distribution and increased attention in steepening the discount, also suggests that policy interventions, requiring increased risk disclosure for coastal property transactions, may affect the prices of residential real estate.

References

Agnew, J. R., 2006. Do behavioral biases vary across individuals? evidence from individual level 401 (k) data. Journal of Financial and Quantitative Analysis 41, 939–962.

Andersen, S., Campbell, J. Y., Nielsen, K. M., Ramadorai, T., 2015. Inattention and inertia in household finance: Evidence from the danish mortgage market. Tech. rep., National Bureau of Economic Research.

Atreya, A., Czajkowski, J., 2014. Is flood risk universally sufficient to offset the strong desire to live near the water. Risk Management and Decision Processes Center, The Wharton School of the University of Pennsylvania .

Bakkensen, L. A., Barrage, L., 2017. Flood risk belief heterogeneity and coastal home price dynamics: Going under water? Tech. rep., National Bureau of Economic Research.

Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. The Journal of Finance 59, 1481–1509.

Barro, R. J., 2006. Rare disasters and asset markets in the twentieth century. The Quarterly Journal of Economics 121, 823–866.

Barro, R. J., 2015. Environmental Protection, Rare Disasters and Discount Rates. Economica 82, 1–23.

Becker, G. S., Murphy, K. M., Topel, R. H., 2011. On the Economics of Climate Policy. The B.E. Journal of Economic Analysis & Policy 10.

Bernheim, B. D., Skinner, J., Weinberg, S., 2001. What Accounts for the Variation in Retirement Wealth among U.S. Households? American Economic Review 91, 832–857.

Bin, O., Landry, C. E., 2013. Changes in implicit flood risk premiums: Empirical evidence from the housing market. Journal of Environmental Economics and management 65, 361–376.

Bracke, P., Pinchbeck, E. W., Wyatt, J., 2017. The Time Value of Housing: Historical Evidence on Discount Rates. The Economic Journal .

Bunten, D., Kahn, M. E., 2014. The Impact of Emerging Climate Risks on Urban Real Estate Price Dynamics. Working Paper 20018, National Bureau of Economic Research.

Bunten, D., Kahn, M. E., 2017. Optimal real estate capital durability and localized climate change disaster risk. Journal of Housing Economics 36, 1–7.

Buraschi, A., Jiltsov, A., 2006. Model uncertainty and option markets with heterogeneous beliefs. The Journal of Finance 61, 2841–2897.

Campbell, J. Y., 2006. Household finance. The journal of finance 61, 1553–1604.

Chetty, R., Friedman, J. N., Leth-Petersen, S., Nielsen, T. H., Olsen, T., 2014. Active vs. passive decisions and crowd-out in retirement savings accounts: Evidence from denmark. The Quarterly Journal of Economics 129, 1141–1219.

Deschênes, O., Greenstone, M., 2007. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. American Economic Review 97, 354–385.

Deshpande, M., Greenstone, M., 2011. Comment on "On the Economics of Climate Policy": Is Climate Change Mitigation the Ultimate Arbitrage Opportunity? Berkeley Electronic Press .

Dhar, R., Zhu, N., 2006. Up close and personal: Investor sophistication and the disposition effect. Management Science 52, 726–740.

Drupp, M., Freeman, M., Groom, B., Nesje, F., 2015. Discounting disentangled: an expert survey on the determinants of the long-term social discount rate. Tech. rep., Grantham Research Institute on Climate Change and the Environment.

Feng, L., Seasholes, M. S., 2005. Do investor sophistication and trading experience eliminate behavioral biases in financial markets? Review of Finance 9, 305–351.

Fesselmeyer, E., Liu, H., Salvo, A., 2017. How Do Households Discount Over Centuries? Evidence from Singapore's Private Housing Market. Tech. rep.

Frankel, J. A., Froot, K. A., 1990. Chartists, Fundamentalists, and Trading in the Foreign Exchange Market. The American Economic Review 80, 181–185.

Giglio, S., Maggiori, M., Stroebel, J., 2014. Very long-run discount rates. The Quarterly Journal of Economics 130, 1–53.

Giglio, S., Maggiori, M., Stroebel, J., Weber, A., 2015. Climate change and long-run discount rates: Evidence from real estate. Tech. rep., National Bureau of Economic Research.

Gollier, C., 2016. Evaluation of long-dated assets: The role of parameter uncertainty. Journal of Monetary Economics 84, 66–83.

Grinsted, A., Jevrejeva, S., Riva, R. E., Dahl-Jensen, D., 2015. Sea level rise projections for northern europe under rcp8. 5. Climate Research 64, 15–23.

Hansen, L. P., Heaton, J. C., Li, N., 2008. Consumption strikes back? measuring long-run risk. Journal of Political economy 116, 260–302.

Hauer, M. E., Evans, J. M., Mishra, D. R., 2016. Millions projected to be at risk from sea-level rise in the continental united states. Nature Climate Change 6, 691–695.

Hinkel, J., Jaeger, C., Nicholls, R. J., Lowe, J., Renn, O., Peijun, S., 2015. Sea-level rise scenarios and coastal risk management. Nature Climate Change 5, 188.

Hong, H., Li, F. W., Xu, J., 2016. Climate risks and market efficiency. Tech. rep., National Bureau of Economic Research.

Howe, P. D., Mildenberger, M., Marlon, J. R., Leiserowitz, A., 2015. Geographic variation in opinions on climate change at state and local scales in the usa. Nature Climate Change 5, 596–603.

Huberman, G., Iyengar, S. S., Jiang, W., 2007. Defined contribution pension plans: determinants of participation and contributions rates. Journal of Financial Services Research 31, 1–32.

IPCC, 2013. Summary for Policymakers, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, book section SPM, p. 1–30.

Joughin, I., Smith, B. E., Medley, B., 2014. Marine ice sheet collapse potentially under way for the thwaites glacier basin, west antarctica. Science 344, 735–738.

Lustig, H. N., Van Nieuwerburgh, S. G., 2005. Housing collateral, consumption insurance, and risk premia: An empirical perspective. The Journal of Finance 60, 1167 – 1219.

Madrian, B. C., Shea, D. F., 2001. The power of suggestion: Inertia in 401 (k) participation and savings behavior. The Quarterly Journal of Economics 116, 1149–1187.

Nakamura, E., Steinsson, J., Barro, R., Ursúa, J., 2013. Crises and Recoveries in an Empirical Model of Consumption Disasters. American Economic Journal: Macroeconomics 5, 35–74.

Nordhaus, W. D., 2007. A Review of the Stern Review on the Economics of Climate Change. Journal of Economic Literature 45, 686–702.

Ortega, F., Taspinar, S., 2016. Rising sea levels and sinking property values: The effects of hurricane sandy on new york's housing market .

Parris, A. S., Bromirski, P., Burkett, V., Cayan, D. R., Culver, M. E., Hall, J., Horton, R. M., Knuuti, K., Moss, R. H., Obeysekera, J., Sallenger, A. H., Weiss, J., 2012. Global sea level rise scenarios for the united states national climate assessment. NOAA Technical Report .

Pfeffer, W. T., Harper, J., O'Neel, S., 2008. Kinematic constraints on glacier contributions to 21st-century sea-level rise. Science 321, 1340–1343.

Piazzesi, M., Schneider, M., 2009. Momentum traders in the housing market: Survey evidence and a search model. The American Economic Review 99, 406–411.

Piazzesi, M., Schneider, M., Stroebel, J., 2015. Segmented housing search. Tech. rep., National Bureau of Economic Research.

Piazzesi, M., Schneider, M., Tuzel, S., 2007. Housing, consumption and asset pricing. Journal of Financial Economics 83, 531 – 569.

Plaut, P. O., Plaut, S. E., 2010. Decisions to renovate and to move. The Journal of Real Estate Research 32, 461–484.

Rao, K., 2017. Climate Change and Housing: Will a Rising Tide Sink All Homes?

Robinson, B. L., 2012. The performance of non-owner-occupied mortgages during the housing crisis. Economic Quarterly 98, 111–138.

Rohling, E. J., Haigh, I. D., Foster, G. L., Roberts, A. P., Grant, K. M., 2013. A geological perspective on potential future sea-level rise. Scientific reports 3, 3461.

Shalen, C. T., 1993. Volume, Volatility, and the Dispersion of Beliefs. The Review of Financial Studies 6, 405–434.

Stango, V., Zinman, J., 2009. Exponential growth bias and household finance. The Journal of Finance 64, 2807–2849.

Stern, N., 2006. What is the economics of climate change? World Economics-Henley on Thames 7, 1.

Stroebel, J., 2016. Asymmetric information about collateral values. The Journal of Finance 71, 1071–1112.

Weitzman, M. L., 2012. Rare Disasters, Tail-Hedged Investments, and Risk-Adjusted Discount Rates. Working Paper 18496, National Bureau of Economic Research.

Figure 1: Sea Level Exposures by County

Figure 1 Displays the proportion of exposed transactions in coastal counties within the continental United States. Exposure is measured as an indicator variable that takes a value of 1 if a property will be effected by 0-6 feet of sea level rise. (No Data) refers to any counties without any transacting properties with exposure to SLR of 6 feet or less.

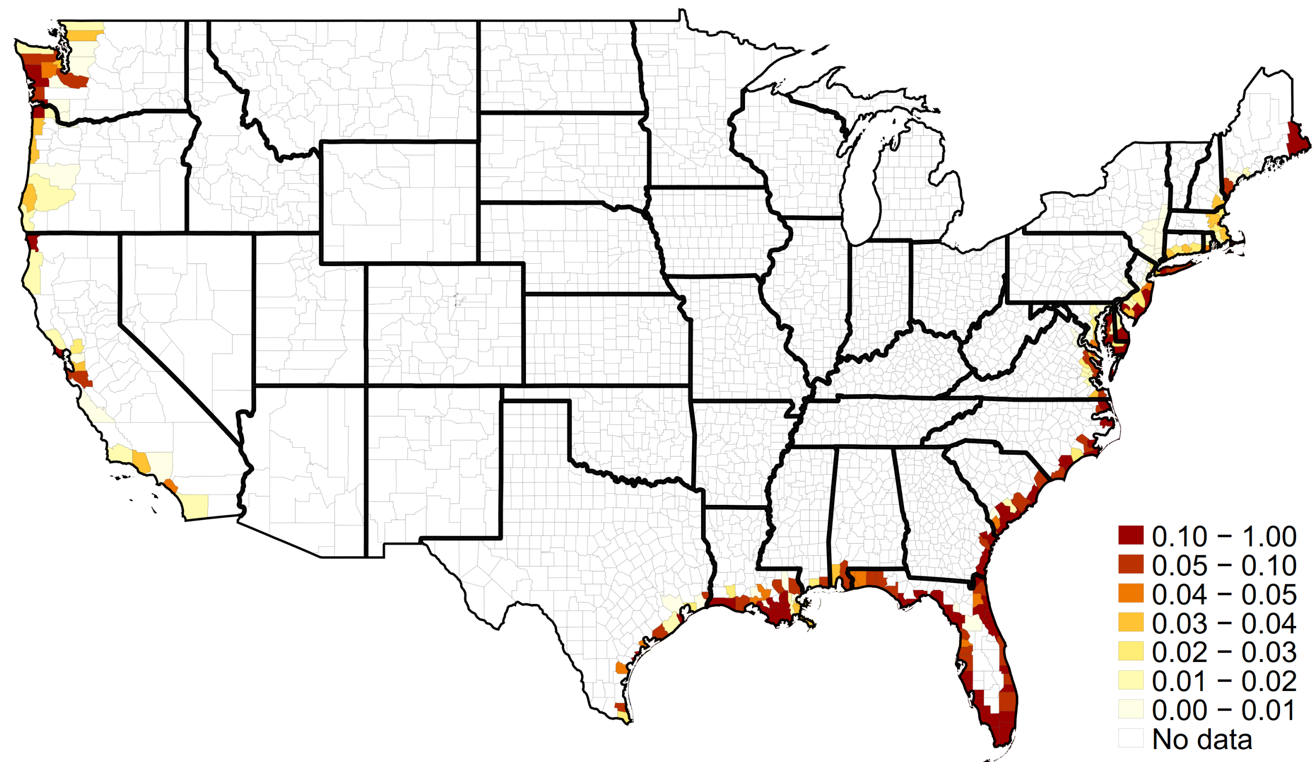


Figure 2: Example of within bin variation in SLR exposure

Figure 2 displays five transactions in zip code 23323 (in Chesapeake, VA) during July of 2014, each of which involves a property that is (1) between 0.16 and 0.25 miles from the coast, (2) elevated between 2 and four meters above sea level, (3) four bedrooms, (4) a non-condominium, (5) owner occupied, (6) bought by a non-local buyer. Properties are labeled A-E, with elevation in meters above the property label. The olive contour lines represent 2 foot elevation contours. The dark blue area is the NOAA 0 foot SLR layer indicating the point of the highest high tide today while the light blue is the 6 foot layer indicating the highest high tide after 6 feet of global average sea level rise.

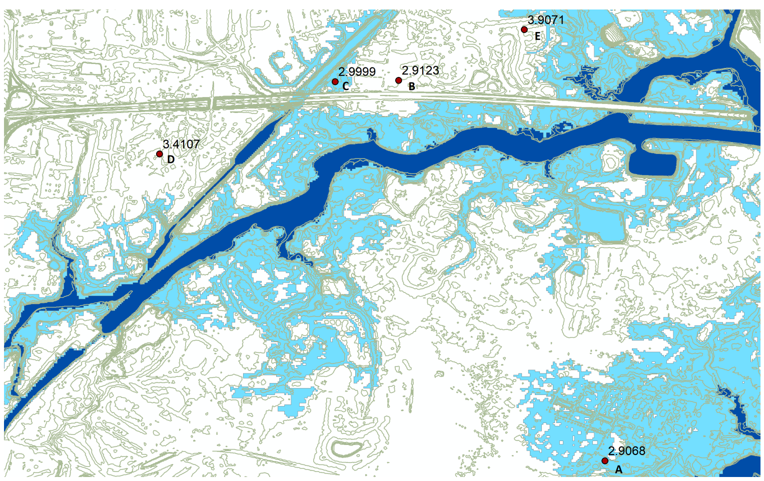


Figure 3: SLR Exposure & House Price Effects

Figure 3 demonstrates the relationship between the % change in house price of exposed properties (relative to unexposed properties), partitioned by the amount of SLR required to make the property underwater. These coefficients are based on a regression of log house price per square foot on categorical dummies for feet of SLR until inundation after including zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. The regression also includes fixed effects for property age and square footage percentiles. 95% confidence intervals based on standard errors that are clustered by zip code are included as bands in the figure.

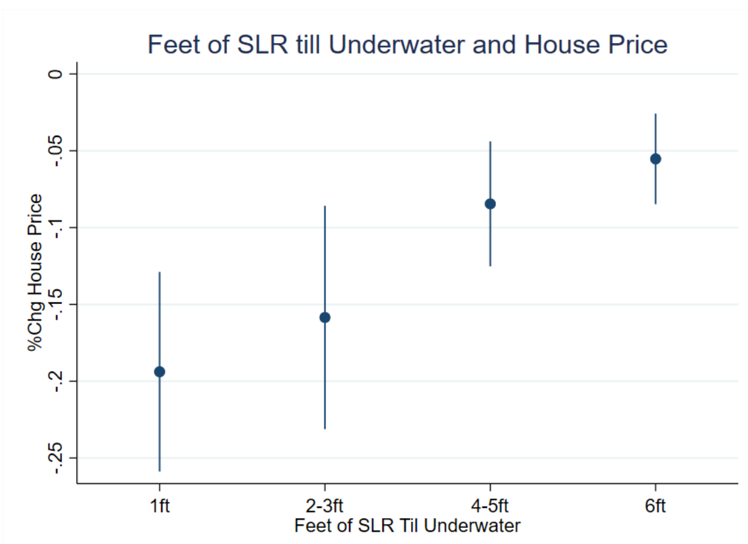
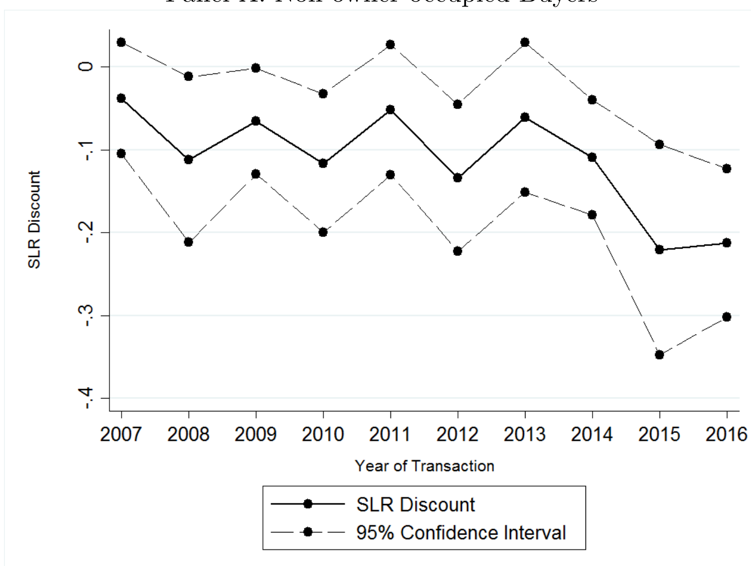


Figure 4: SLR Exposure & House Price Effects over Time

Figure 4 demonstrates the relationship between the % change in house price of exposed (relative to unexposed properties) by year, partitioned by whether the buyer is a non-owner occupier (Panel A) or an owner occupier (Panel B). These coefficients are based on a regression of log house price per square foot on categorical dummies for feet of SLR to be exposed after including zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. The regressions also control for indicators for square footage and property age percentiles and exclude recently flooded properties. 95% confidence intervals based on standard errors that are clustered by zip code are included as bands in the figure.

Panel A: Non-owner-occupied Buyers



Panel B: Owner-occupied Buyers

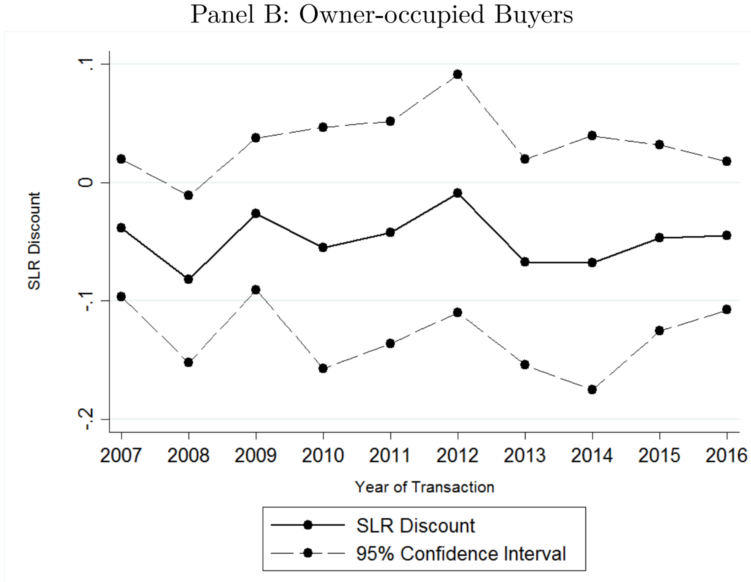


Table 1: Summary Statistcs

This table includes summary statistics from ZTRAXX from 2007 to 2017 (Panel a) and Trulia rental data for November 2017 (Panel b). Properties are restricted to those with 0.25 miles of the beach with all household characteristics and transactions during these time periods. The first group in each panel includes price and price per square foot, while the second group details property and buyer characteristics for both the full sample and exposed properties.

Panel (a)

	Full Coastal Sample			***Exposed=1***		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
House Price($1000s)	458.85	584.76	481321	466.23	563.11	144880
House Price ($/Sq. Ft, Winsor 1%)	603.11	1347.90	481321	642.82	1456.66	144880
ZTRAX Housing Property Characteristics						
Building Sq. Ft.	1702.95	3122.54	481321	1669.65	2408.42	144880
# Bedrooms	1.55	1.64	481321	1.20	1.54	144880
Property Age (log)	3.31	1.10	463039	3.26	1.02	140606
Owner Occupied	0.61	0.49	481321	0.51	0.50	144880
Miles-to-coast (miles)	0.12	0.07	481321	0.08	0.07	144880
Elevation Above Sea Level (meters)	7.09	9.37	481320	2.23	1.82	144880
Exposed (underwater w/ <=6ft SLR)	0.30	0.46	481321	1.00	0.00	144880
Feet of SLR til Property Underwater	7.62	2.23	481321	4.42	1.37	144880

Panel (b)

	Full Coastal Sample			***Exposed=1***		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
Trulia Rental Listing Data						
Rental Listing Price/Mo($)	6127.84	11242.73	17678	5984.80	10820.81	3821
Rental Listing Rate($)/Sq. Ft	4.54	5.84	10830	4.68	6.06	2166
Trulia Rental Listing Property Characteristics						
Sq. Ft.	1543.88	1054.67	10846	1479.61	982.33	2169
# Bedrooms	2.25	1.33	17706	2.26	1.31	3827
Miles-to-coast (miles)	0.13	0.07	17706	0.10	0.07	3827
Elevation Above Sea Level (meters)	7.69	8.92	17706	2.29	0.99	3827
Exposed (underwater w/ <=6ft SLR)	0.22	0.41	17706	1.00	0.00	3827
Feet of SLR til Property Underwater				4.62	1.29	3827

Table 2: Main Regression Results

This table presents ordinary last squares estimates where the dependent variable is Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. Column 1 presents the results including only indicators for square footage and property age percentiles. Column 2 includes zip code (Z) x distance-to-coast bin (D) x 2 meter property elevation bins (E) fixed effects to control for geographic features. There are seven distance-to-coast bins, corresponding to the following miles to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16. Column 3 interacts these fixed effects with fixed effects for the the number of total bedrooms (B) and whether the property is a condominium (P). Column 4 further interacts the fixed effects with transaction characteristics: year-month fixed effects (T), and indicators for occupancy status and different zip of buyer (O). Finally, Column 5 relaxes the time dimension to year-quarter, thereby reducing the number of singleton observations. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
SLR Exposed	0.076***	-0.047***	-0.055***	-0.075***	-0.060***
	(2.66)	(-5.01)	(-5.60)	(-5.20)	(-4.33)
Sqft Pctls	Y	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y	Y
Z x D x E	N	Y	N	N	N
Z x D x E x B x P	N	N	Y	N	N
Z x T x D x E x O x P x B	N	N	N	Y	N
Z x QTR x D x E x O x P x B	N	N	N	N	Y
R^2	0.578	0.835	0.868	0.933	0.923
R^2 Adjusted	0.578	0.828	0.856	0.890	0.884
N	462776	456400	440524	130277	200643

Table 3: Robustness to Flooding

This table presents ordinary last squares estimates where the dependent variable is Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. Column 1 further restricts the sample by excluding properties in counties that have been flooded in the current or past three years. Column 2 makes a similar restriction, excluding counties where FEMA triggered the individuals and household damage aid program (available since 2000). All columns include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the property elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
SLR Exposed	-0.080***	-0.055***	-0.078***
	(-4.92)	(-2.92)	(-3.75)
Sample Constraint	No Curr Flood	No Hist IH	No View/Appeal
Sqft Pctls	Y	Y	Y
Age Pctls	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y
R^2	0.941	0.951	0.933
Adjusted R^2	0.905	0.921	0.889
N	91967	52515	94496

Table 4: Rental Placebo Test

This table presents ordinary least squares estimates where the dependent variable is Ln(Rental Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise. The sample is restricted to residential properties within 0.25 miles of the coast and all listings are scraped in November of 2017. Columns 3 and 4 regressions include zip code (Z) x distance-to-coast bin (D) x 2 meter elevation bucket (E) fixed effects. All columns also include indicators for square footage percentiles. Property ages are not available for this sample. We use seven distance-to-coast bins, corresponding to the following miles to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16. All columns display T-statistics based on robust standard errors. Columns 2 and 4 include percentile buckets for square feet. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
SLR Exposed	0.034***	0.041***	-0.003	-0.014
	(4.61)	(5.72)	(-0.14)	(-1.22)
Sqft Pctls	N	Y	N	Y
Z x D x E x B	N	N	Y	Y
Cluster Level	Robust	Robust	Robust	Robust
R^2	0.001	0.055	0.804	0.823
Adjusted R^2	0.001	0.052	0.758	0.780
N	36535	36535	28672	28672

Table 5: Exposure and Market Segmentation

This table presents ordinary last squares estimates where the dependent variable is Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise, along with its interaction with an indicator for a non-owner occupied property (Columns 1 and 4), a property sold to a non-local buyer (Columns 2 and 4), and a condominium property (Columns 3 and 4). The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. All columns include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the propertys elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
SLR Exposed	-0.020	-0.026*	-0.049**	-0.017
	(-1.34)	(-1.81)	(-2.53)	(-1.21)
Exposed x Non-Owner Occupied	-0.092***			-0.087***
	(-4.76)			(-2.78)
Exposed x Non-Local Buyer		-0.070***		-0.012
		(-4.05)		(-0.51)
Exposed x Condo			-0.047	0.006
			(-1.64)	(0.14)
Sqft Pctls	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y	Y
R^2	0.933	0.933	0.933	0.933
Adjusted R^2	0.890	0.890	0.890	0.890
N	130279	130279	130279	130279

Table 6: Exposure Discount In Highly Liquid Market

This table presents ordinary least squares estimates where the dependent variable is either Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise, along with its interaction with measures of liquidity at the zip code level. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2011 and 2016. In all regressions we include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects, and In Panel a Column 2 (3) and Panel b column 3 (4) restricts the sample to non-owner occupied (owner-occupied) properties. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposed	-0.103***	0.002	-0.104***	-0.046	-0.107***	-0.032
	(-5.24)	(0.05)	(-5.41)	(-1.52)	(-5.42)	(-1.00)
Exposed x High Sale to List	0.149***					
	(3.89)					
Exposed x Low Inventories			0.091**			
			(2.27)			
Exposed x Low Days on Market					0.096***	
					(2.78)	
Occupancy						
Sqft Pctls	Y	Y	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y	Y	Y	Y
R^2	0.880	0.930	0.877	0.809	0.877	0.818
Adjusted R^2	0.808	0.849	0.804	0.647	0.804	0.679
N	26260	1325	25200	1614	25260	2152

Table 7: Beliefs and the Price of Exposure

This table presents ordinary last squares estimates where the dependent variable is Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise, along with its interaction with Worried, a standardized measures of the level of concern regarding SLR in the county housing the property. Column 3 also interacts SLR Exposed with Worried Mailing FIPS, which is the same measure as Worried, except that it reflects the worry in county associated with the buyer's mailing address. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. Column 2 and 3 (4) further restricts the sample to non-owner occupied (owner-occupied) properties. All columns include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the property elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
SLR Exposed	-0.074***	-0.098***	-0.102***	-0.020
	(-5.28)	(-5.24)	(-5.25)	(-1.43)
Exposed x Worried	-0.007	0.011	0.009	-0.042***
	(-0.40)	(0.38)	(0.31)	(-2.72)
Exposed x Worried Mailing FIPS			0.002	
			(0.33)	
Occupancy	All	Non-OO	Non-OO	OO
Sqft Pctls	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y	Y
R^2	0.934	0.897	0.894	0.957
Adjusted R^2	0.892	0.842	0.839	0.926
N	130276	55096	45527	75180

Table 8: Price of SLR Over Time

This table presents ordinary last squares estimates where the dependent variable is Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise, along with its interaction with Time, measured as the natural log of the number of months passed since the beginning of our sample in January of 2007. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. Column 2 (3) further restricts the sample to non-owner occupied (owner-occupied) properties. All columns include zip code (Z) x time (T) x miles-to-coast bin (D) x elevation bin (E) x owner occupied property and non-local buyer (P) x condominium (C) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the property elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
SLR Exposed	0.010	0.008	-0.001
	(0.32)	(0.20)	(-0.02)
Exposed x Time	-0.022***	-0.029***	-0.006
	(-2.87)	(-2.81)	(-0.67)
Occupancy	All	Non-OO	OO
Sqft Pctls	Y	Y	Y
Age Pctls	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y
R^2	0.933	0.895	0.956
Adjusted R^2	0.890	0.839	0.923
N	130279	55099	75180

Table 9: Prices and Trading Following the 2013 IPCC Report

This table presents ordinary least squares estimates where the dependent variable is either Ln(Price/Sq. Foot)—Panel a—or an indicator if a particular property transacted in a given year—Panel b. The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise, along with its interaction with Post-IPCC, which equals one for transactions occurring after April of 2014 and zero otherwise. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2011 and 2016. In all regressions we include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects, and In Panel a Column 2 (3) and Panel b column 3 (4) restricts the sample to non-owner occupied (owner-occupied) properties. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel (a) Price

	(1)	(2)	(3)
SLR Exposed	-0.068***	-0.082***	-0.021
	(-3.58)	(-4.17)	(-0.79)
Exposed x Post-IPCC	-0.024	-0.056**	0.002
	(-0.93)	(-2.07)	(0.07)
Occupancy	All	Non-OO	OO
Sqft Pctls	Y	Y	Y
Age Pctls	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y
R^2	0.924	0.881	0.952
Adjusted R^2	0.874	0.814	0.915
N	68992	31072	37920

Panel (b) Trading Volume

	(1)	(2)	(3)	(4)
SLR Exposed	0.002*	-0.002	-0.002	-0.002
	(1.96)	(-1.10)	(-0.68)	(-1.03)
Exposed x Post-IPCC		0.008**	0.007	0.008**
		(2.56)	(1.57)	(2.40)
Occupancy	All	All	Non-OO	OO
Sqft Pctls	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y	Y
R^2	0.198	0.198	0.228	0.182
Adjusted R^2	0.050	0.050	0.067	0.040
N	1616358	1616358	577578	1038780

Internet Appendix

A Supplementary Tables and Figures

Figure A1: NOAA Sea Level Rise Calculator

Figure A1 displays a sample screenshot from the NOAA Sea Level Rise (SLR) viewer of the New York Metropolitan area. The viewer provides an online portal to access the underlying SLR shapefiles which describe, for each coastal area in the Continental USA, detailed data on the properties that will inundated following a 1-6 foot increase in average global ocean level. In this case, the light blue regions of the figure represent properties that will become chronically inundated following a 2 foot increase in global average sea levels.

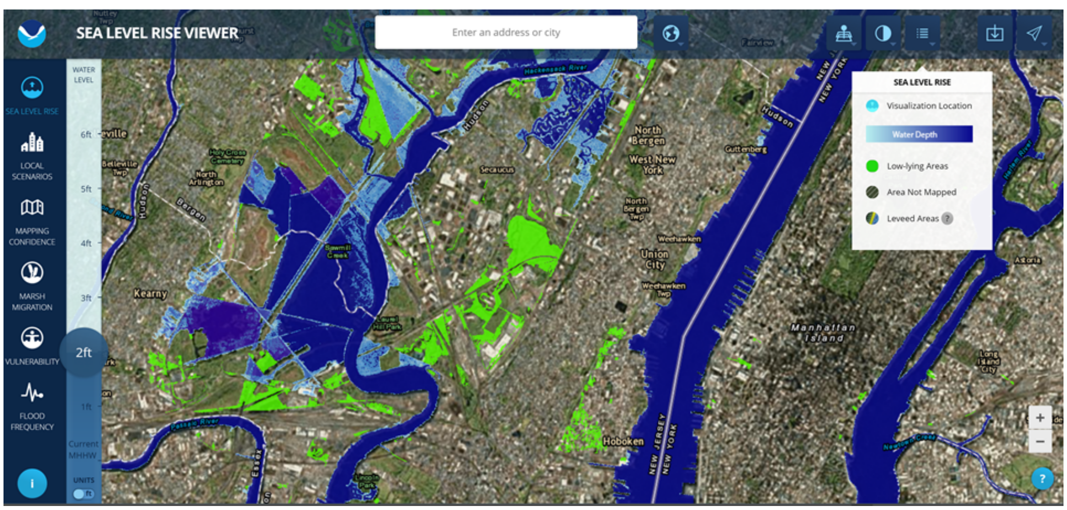
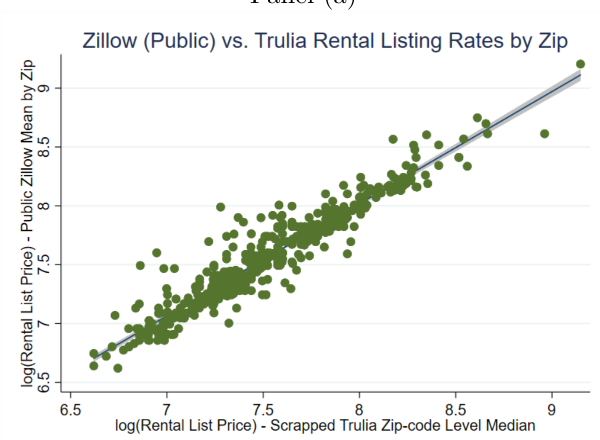


Figure A2: House Prices vs. Rental Rates (Public vs. Private Data) by Zip Code

Figure A2 demonstrates the quality of the rental listing data scrapped by the authors from Trulia.com. Panel a is a scatter plot of the relationship between median log(rental list price) scrapped for individual properties from Trulia.com with the log(rental list price) for aggregate data publicly available by zip code from Zillow.com for November of 2017. Panel b is a scatter plot of the relationship between median log(rental list price) scrapped on November 2017 for individual properties from Trulia.com with the log(median house price) for all property-level transactions from the proprietary ZTRAX database from 2007-2016 at the zip code level.

Panel (a)



Panel (b)

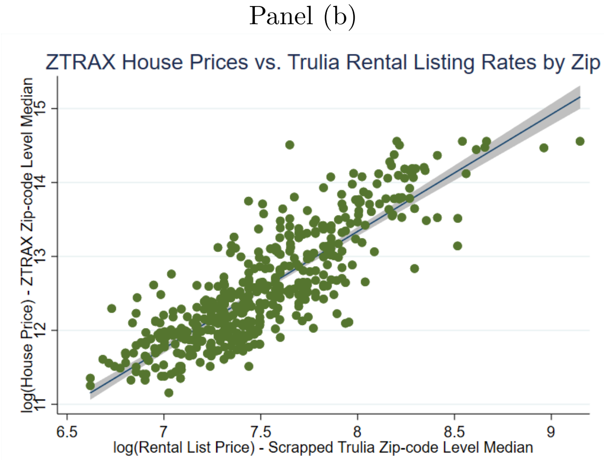
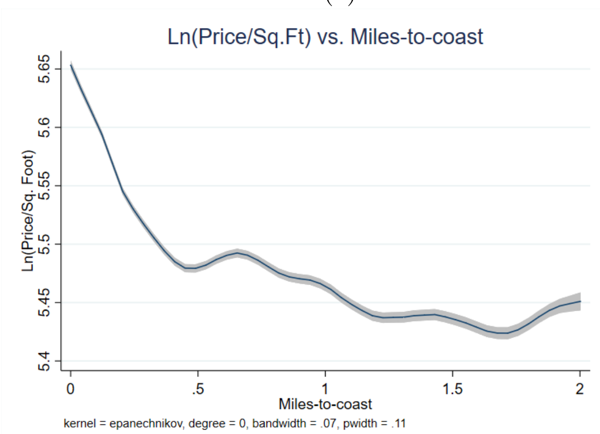


Figure A3: Importance of Distance-to-coast Fixed Effects

Figure A3 demonstrates the importance of controlling for distance to the coast, when trying to evaluate the effect of SLR on home value. Panel a depicts the non-linear relationship, via a smoothed moving average, between the log price per square foot of housing transactions as a function of miles to the coastline without any controls. Panel b is the same as the first, but includes the residual log price per square foot of housing transactions after including fixed effects for zip code interacted with time (monthly).

Panel (a)



Panel (b)

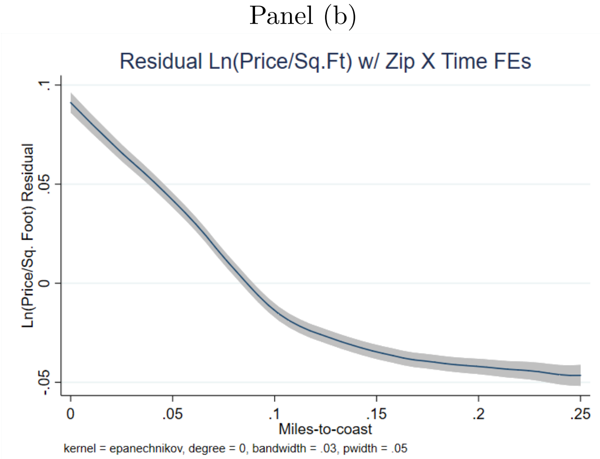


Figure A4: Google Search Trend for "Sea Level Rise"

This Figure displays the Google search intensity for the term *sea level rise* within the United States from 2004-2017. The vertical axis is normalized by the maximum search activity during the period. The vertical green line indicates the release window for parts 2 and 3 of the 2013 IPCC report on climate change.

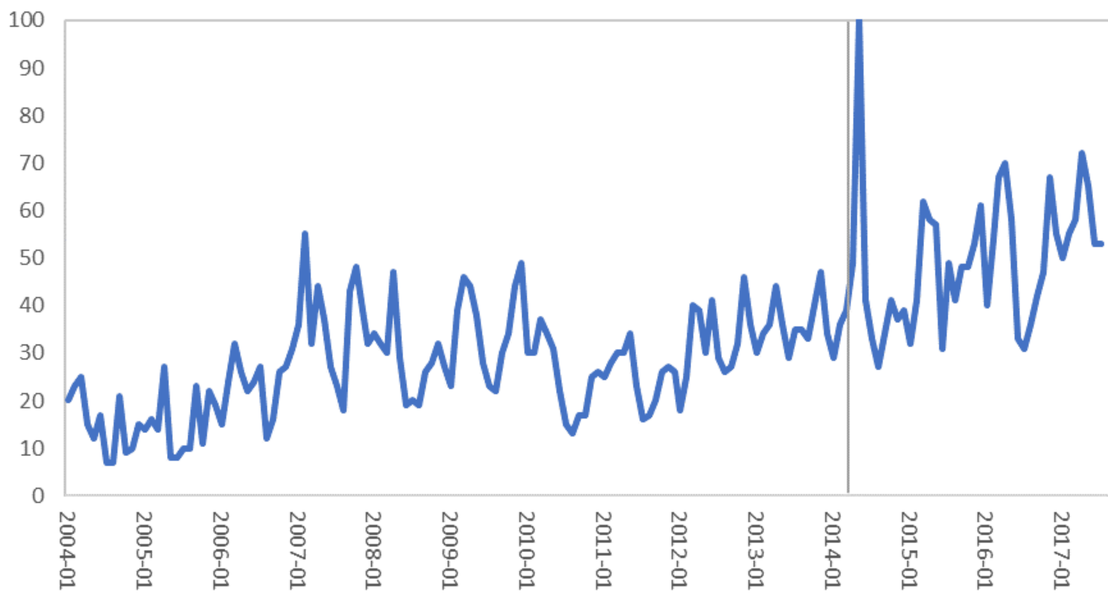


Table A1: Decomposing Variation in SLR exposure

This table conducts a variance decomposition of abnormal SLR exposure, defined as the residual from regressing SLR exposure on the control variables used in our main analysis (i.e., zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects, and indicators for square footage and property age percentiles. Column 1 presents the R-squared from regressing abnormal exposure on 0.1 meter elevation bins, Column 2 does the same using 0.1 meter elevation bins x zip code fixed effects, whicle Column 3 further interacts these fixed effects with our seven distance-to-coast bin fixed effects.

	(1)	(2)	(3)
0.1M Elevation x	Y	Y	Y
Zip Code x	N	Y	Y
Miles-to-Coast	N	N	Y
R^2	0.042	0.236	0.344
Adjusted R^2	0.037	0.116	0.199
N	130162	116204	108798

Table A2: Variance Decomposition of SLR Exposure and Price Discount

This table presents ordinary last squares estimates where the dependent variable is Ln(Price/Sq. Foot). The explanatory variables of interest are Explained and Unexplained Residual SLR Exposure. These measures are constructed using the residual from a regression of SLR Exposed, an indicator for a property that would be inundated with a 6 foot SLR, on indicators for square footage and property age percentiles and zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the property's elevation above sea level. Explained Residual SLR Exposure is the portion of the residual exposure that is predicted by 0.1 meter x zip code x distance-to-coast bin fixed effects. Unexplained Residual SLR Exposure is the remainder of the residual SLR exposure. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Explained Res. Exposure (0.1 Meter Bin)		-0.144***	-0.120***
		(-4.42)	(-3.65)
Unexplained Res. Exposure (0.1 Meter Bin)	-0.077***		-0.055***
	(-4.40)		(-3.19)
Sqft Pctls	Y	Y	Y
Age Pctls	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y
R^2	0.932	0.932	0.932
Adjusted R^2	0.891	0.891	0.891
N	102951	102951	102951

Table A3: Property Investment

This table presents ordinary least squares estimates where the dependent variable is a dummy for whether the property was remodeled after 2006. Our remodeling indicator is provided by ZTRAX, and is an indicator for any variation over time in square footage, number of bedrooms, number of bathrooms, number of kitchens, number of stories, roofing, air conditioning, foundation type, fireplace, exterior wall type (ex. wood, brick, stone), garage type, heating system, interior flooring, interior wall, or pool. The explanatory variable of interest in Columns 1, 3 and 4 is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise. Column 2 also includes the interaction of owner occupancy and SLR Exposed, OOxExposed. Column 1 inclues all properties within 0.25 miles of the coast between 2007 and 2016. Column 2 includes only properties in counties without any significant flooding the year of the transaction or any of the preceeding three years. Column 3 by contrast includes only properties in counties with such flooding. All columns include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the property's elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
SLR Exposed	-0.003**	-0.002	-0.001	-0.004
	(-2.04)	(-1.27)	(-0.94)	(-1.50)
OOxExposed		-0.002		
		(-0.88)		
Sample	All	All	No Recent Flood	Had Recent Flood
Sqft Pctls	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y	Y
R^2	0.740	0.740	0.791	0.674
Adjusted R^2	0.574	0.574	0.664	0.439
N	130277	130277	91965	38312

Table A4: Property Investment, Age, and SLR Discount

This table presents ordinary last squares estimates where the dependent variable is an indicator for a remodeling (Column 1) and Ln(Price/Sq. Foot) (Columns 2 through 4). Our remodeling indicator is provided by ZTRAX, and is an indicator for any variation over time in square footage, number of bedrooms, number of bathrooms, number of kitchens, number of stories, roofing, air conditioning, foundation type, fireplace, exterior wall type (ex. wood, brick, stone), garage type, heating system, interior flooring, interior wall, or pool. In Column 1, the explanatory variable of interest is an indicator for a transacting property that was built within the past ten years. In Columns 2 through 4, the explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise. The sample is restricted to sales of residential properties within 0.25 miles of the coast between 2007 and 2016. Columns 2 through 4 include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the propertys elevation above sea level. All columns also include indicators for square footage and property age percentiles. Column(s) 2 (3 and 4) restricts the sample to properties that were built in the last 10 (5) years. Column 4 also excludes recently flooded properties. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Remodel Rate	Ln(Price//Sqft)		
	(1)	(2)	(3)	(4)
<=10YrsOld	-0.065***			
	(-3.99)			
SLR Exposed		-0.090***	-0.077**	-0.088**
		(-2.95)	(-2.33)	(-2.12)
Age	All	< 10 Years	< 5 Years	< 5 Years
Includes Flooded	Y	Y	Y	N
Sqft Pctls	Y	Y	Y	Y
Age Pctls	Y	Y	Y	Y
Z x T x D x E x O x P x B	N	Y	Y	Y
R^2	Y	Y	Y	Y
Adjusted R^2	0.856	0.966	0.966	0.966
N	0.765	0.945	0.948	0.948
N	130274	23898	16208	13679

Table A5: View and Amenity Placebos

This table presents evidence that after including the set of fixed effects from our primary specification there is no significant relationship between elevation and views. The results are based on ordinary least squares estimates where the dependent variable is dummy variable equal to 1 if a property is listed as having a "water views". The sample contains all properties in Column 1, non-owner occupied properties in Column 2, and owner-occupied properties in Column 3. The explanatory variable of interest is elevation of the property above sea level in feet. The sample is restricted to sales of residential properties within 0.25 miles of the coast and includes zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Elevation	0.000	0.000	0.000
	(0.47)	(0.87)	(0.29)
Occupancy	All	Non-OO	OO
Sqft Pctls	Y	Y	Y
Age Pctls	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y
R^2	0.838	0.836	0.841
Adjusted R^2	0.734	0.748	0.725
N	130276	55097	75179

Table A6: Age and Square Footage Placebos

This table presents ordinary least squares estimates where the dependent variable is the natural log of one plus property age and property square footage in Columns 1 and 2, respectively. The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise. The sample is restricted to sales of residential properties within 0.25 miles of the coast and only includes non-owner occupiers. In all regressions we include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Ln(Age)	Ln(Sqft)
	(1)	(2)
SLR Exposed	-0.017	-0.020
	(-0.41)	(-0.97)
Z x T x D x E x O x P x B	Y	Y
R^2	0.812	0.591
Adjusted R^2	0.693	0.332
N	130279	130279

Table A7: Buyer Type and SLR Discount

This table presents ordinary least squares estimates where the dependent variable is either Ln(Price/Sq. Foot). The explanatory variable of interest is SLR Exposed, which equals one for a property that would be inundated with a 6 foot SLR and zero otherwise, along with its interaction with the type of purchaser. The sample is restricted to sales of residential properties within 0.25 miles of the coast and only includes non-owner occupiers. In all regressions we include zip code (Z) x time (T) x distance-to-coast bin (D) x Elevation Bin (E) x owner occupied property and non-local buyer (O) x condominium (P) x total bedrooms (B) fixed effects, and In Panel a Column 2 (3) and Panel b column 3 (4) restricts the sample to non-owner occupied (owner-occupied) properties. Time is measured on a monthly basis, there are seven miles-to-cost bins, corresponding to the following miles-to coast cutoffs: 0.01, 0.02, 0.04, 0.08, and 0.16, and elevation bins are defined in six foot increments based on the elevation above sea level. All columns also include indicators for square footage and property age percentiles. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
SLR Exposed	-0.113***	-0.101***	-0.100***
	(-5.11)	(-5.10)	(-5.02)
Second Home Waiver		0.075***	
		(8.14)	
Exposed x Second Home		-0.004	
		(-0.25)	
Company Buyer			0.109***
			(4.20)
Exposed x Company Buyer			-0.066
			(-1.32)
Occupancy	Second Home	Non-OO	Non-OO
Sqft Pctls	Y	Y	Y
Age Pctls	Y	Y	Y
Z x T x D x E x O x P x B	Y	Y	Y
R^2	0.849	0.897	0.872
Adjusted R^2	0.744	0.842	0.800
N	7141	55098	39240

Table A8: Market Segmentation

This table presents the transistion probability matrix between owner occupied properties and non-owner occupied properties.

	Owner Occupied Before Transaction		
Owner Occupied After Transaction	Non-Owner Occupied	Owner Occupied	Total
	%	%	%
Non-Owner Occupied	86.2	14.4	49.7
Owner Occupied	13.8	85.6	50.3
Total	100.0	100.0	100.0

Table A9: Buyer Education and Income

This table presents ordinary last squares estimates where the dependent variable captures either education or income levels at the buyer's zip code. In column (1) the dependent variable is percentage of bachelor attainment, column (2) is the natural log of income, column (3) is the percentage bachelor attainment at the buyer zip minus that at the property zip and column (4) is the log ratio of incomes between buyer and property zip. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
OO	-0.033***	-0.053***		
	(-5.80)	(-3.32)		
Constant	0.417***	11.161***	0.039***	0.145***
	(74.35)	(713.71)	(7.59)	(7.74)
R^2	0.008	0.005	0.000	0.000
Adjusted R^2	0.008	0.005	0.000	0.000
N	435947	434952	195608	194511

Table A10: Sophisticated Returns

This table presents ordinary last squares estimates where the dependent variable is annualized holding period return for an oberserved real estate transaction. The explanatory variable of interest is whether the transaction moved from owner occupied to non-owner occupied or vise versa. Columns (2)-(5) include fixed effects at the property zip, purchase year and sale year in various combinations and interactions. T-statistics based on standard errors that are clustered at the zip code level are presented below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
OO to Non-OO	0.012	0.017***	0.009**	0.007**	0.007***
	(1.12)	(3.78)	(2.20)	(2.48)	(3.70)
Non-OO to OO	-0.012**	-0.010***	-0.007***	-0.005***	-0.005***
	(-2.21)	(-4.99)	(-3.29)	(-5.41)	(-6.49)
Include Remodels	Y	Y	N		
Min Holding Period	1 year	1 year	2 years	2 years	2 years
Fixed Effects	-	Z | SY | PY	Z | SY | PY	Z x SY | Z x PY	Z x SY x PY
R^2	0.000	0.021	0.033	0.091	0.138
Adjusted R^2	0.000	0.018	0.030	0.039	0.006
N	1830755	1830319	1556139	1537693	1462947

B Buyer Sophistication

Evidence in Robinson (2012) indicates that individuals purchasing properties that they will not occupy tend to have better credit scores and higher incomes than owner-occupied buyers, consistent with those households being more likely to engage in sophisticated transactions. In this Appendix, we provide two types of empirical evidence consistent with the non-owner occupiers in our sample being more sophisticated buyers. First, we utilize the zip code of the purchaser to link our transactions database with the education and income data from the American Community Survey from Census. Table A9 provides a simple univariate analysis of the education and income differentials between owner occupiers and non-owner occupiers. Column (1) displays the results of a regression with the percentage of bachelor achievement at the buyer's mailing address on the left hand side and a dummy variable that takes a value of 1 if the purchaser is an owner occupier on the right hand side. Here, we see that owner occupiers are likely to have mailing addresses associated with 4% less bachelor degree attainment than non-owner occupiers. A similar gap exists in income as seen in column (2) where owner occupiers as associated with areas that have 11% lower income than non-owner occupiers. In addition, we compare the education and income levels of non-owner occupiers with those at the zip of the property in columns (3) and (4). We see similar magnitude differentials between education and income, suggesting that non-owner occupying buyers appear to come from areas that are more educated and have higher income per capita than the properties they purchase.

To augment the evidence on buyer sophistication, we examine annualized holding period returns as an ex-post measure of investor performance. For all coastal counties we find any properties with repeat transactions utilizing the same screening criteria as described in section 2.1. We then cross-reference transactions with the historical tax records provided in Ztrax to identify the occupancy status prior to and after purchase. Our hypothesis is that, if non-owner occupiers are more sophisticated then they will benefit at the expense of owner occupiers. In particular, transactions where an owner occupier purchases a house from a non-owner occupier should be associated with lower holding period returns, and transactions where a non-owner occupier purchases from an owner occupier should have higher holding period returns. Table A10 displays the results from a regression following the specification in equation 7 below.

$$AnnRet_{it} = \beta_1 OOtoNOO_{it} + \beta_2 NOOtoOO_{it} + \lambda_{z,ty,py} + \epsilon_{it} \tag{7}$$

Column (1) provides a bivarate analysis with no control variables for all properties held for longer than one year. A positive β_1 and a negative and significant β_2 are consistent with the hypothesis of non-owner occupying buyers being more sophisticated. To tighten our analysis, we include zip, purchase year and sale year fixed effects. Here, both β_1 and β_2 are indicate that non-owner occupiers earning higher returns. Flippers—investors that purchase a property, quickly improve it, then sell it–may play a role in our finding, particularly in biasingβ_1 upward. In column (3) we extend the minimum holding period to 2 years, and eliminate any transactions where a remodeling has occurred. Consistent with flippers playing a role in the positive returns accruing in OO to Non-OO transactions, the magnitude of β_1 drops from nearly 2% per year to around 90bps, while β_2 drops by only approximately 25%. Finally, in columns (4) and (5) we include zip interacted with year of purchase and zip interacted with year of sale fixed effects, and the triple interaction of zip, year of purchase and year of sale fixed effects, respectively. Across models (3)-(5) the coefficients remain relatively stable, declining in magnitude only slightly as we absorb more variation with fixed effects. Column (5) implies that the higher returns are not coming from location or timing of purchase, but perhaps the opportunistic buying and selling of properties, consistent with a sophisticated investor.