NBER WORKING PAPER SERIES

PARTISAN RESIDENTIAL SORTING ON CLIMATE CHANGE RISK

Asaf Bernstein
Stephen B. Billings
Matthew Gustafson
Ryan Lewis

Working Paper 27989
http://www.nber.org/papers/w27989

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020, Revised November 2021

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. We would like to thank seminar participants at the CU Boulder finance lunch, CU Boulder Applied Micro Brownbag, Baruch College, Louisiana State University, Syracuse University, Stanford Institute of Theoretical Economics, 2020 Meeting of the Urban Economics Association, 2021 Western Finance Association, 2021 PRI Academic Network Conference, the 2021 NBER Environmental and Energy Economics meetings, and the 2020 Weimer School for the Advanced Studies of Real Estate for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Partisan Residential Sorting on Climate Change Risk
Asaf Bernstein, Stephen B. Billings, Matthew Gustafson, and Ryan Lewis
NBER Working Paper No. 27989
October 2020, Revised November 2021
JEL No. D10,D72,G1,G5,Q5,Q54,R2,R21,R23,R31

ABSTRACT

Is climate change partisanship reflected in residential decisions? Comparing individual properties in the same zip code with similar elevation and proximity to the coast, houses exposed to sea level rise (SLR) are increasingly more likely to be owned by Republicans and less likely to be owned by Democrats. We find a partisan residency gap for even moderately SLR exposed properties of more than 5 percentage points, which has more than doubled over the past six years. Findings are unchanged controlling flexibly for other individual demographics and a variety of granular property characteristics, including the value of the home. Residential sorting manifests among owners regardless of occupancy, but not among renters, and is driven by long-run SLR exposure but not current flood risk. Anticipatory sorting on climate change suggests that households that are most likely to vote against climate friendly policies and least likely to adapt may ultimately bear the burden of climate change.

Asaf Bernstein
Leeds School of Business
University of Colorado at Boulder
Campus Box 401
Boulder, CO 80309
and NBER
asaf.bernstein@colorado.edu

Stephen B. Billings
University of Colorado
Department of Finance
Leeds School of Business
Boulder, CO 80309
stephen.billings@colorado.edu

Matthew Gustafson
Smeal College of Business
Pennsylvania State University
335 Business Building
University Park, PA 16802
mtg15@psu.edu

Ryan Lewis
Leeds School of Business
995 Regent Street
Leeds School of Business
Boulder, CO 80302
ryan.c.lewis@colorado.edu

In a 2020 Pew survey asking registered U.S. voters about top policy priorities, climate change was the most partisan issue on a list that included immigration, gun policy, health care, terrorism, and race relations. If this partisan divide extends beyond rhetoric, and into substantive economic decisions, these views might be reflected in residential choice. While ex-post migration after climate disasters (Hornbeck 2012; Bohra-Mishra et al. 2014) could help mitigate the costs of climate change (Desmet & Rossi-Hansberg 2014, 2015), anticipatory partisan-based residential sorting would concentrate climate risk among those least likely to take counteracting measures Local climate change mitigation and adaptation actions, which exceed $300 billion annually, highlight the critical role of local investment in addressing climate change.[1]

In this paper we examine partisan residential sorting in anticipation of climate change. This issue lies at the intersection of growing literatures in household finance, asset pricing, and public finance, which all have become increasingly interested in political beliefs (Cookson, Engelberg, & Mullins 2020; McCartney 2021) and climate change risks (Hong, Karolyi, & Scheinkman 2020; Bakkensen & Barrage 2021).[2] We examine this question in the context of sea level rise (SLR) in coastal communities. Worst case SLR projections for the year 2100 range from less than one meter to more than two (e.g., Stocker et al. 2013). The upper bound of these projections exposes approximately six million Americans and nearly one trillion dollars of coastal real estate (Hauer et al. 2016, Rao 2017). There is, however, significant partisan disagreement on the future consequences of SLR with 67% of liberal democrats believe it is very likely climate change would cause SLR to erode shorelines, relative to only 16% of conservative republicans (Pew Survey 2016). A

[1] In 2020, 161 local U.S. governments reported $308 billion in local climate change actions, with the majority (52% for mitigation and 66% for adaptation) funded locally (https://data.cdp.net/).
[2] See also Kempf & Tsoutsoura (2021), Bernstein, Gustafson, & Lewis (2019), Baldauf, Garlappi, & Yannelis (2020), Murfin & Spiegel (2020), and Chan & Marsh (2021).

benefit to this specific setting though is that properties in similarlocations within coastal communities have substantial and easily observable differences in SLR exposure.[3]

We find that registered Republicans (Democrats) are more (less) likely than Independents to own SLR exposed homes relative to otherwise observably equivalent unexposed properties. Specifically, we find a partisan residency gap of more than 5 percentage points for even moderately SLR exposed properties, reflecting an 11 percent higher Republican share in exposed residences. Partisan sorting is substantially larger for houses with more imminent SLR exposure, but, consistent with anticipatory investment changes in the face of these long-run risks, occurs even for houses where concerns are more temporally distant.

Our empirical analyses compare homes that have similar locations and amenities, but differ in SLR exposure. In our baseline model, we accomplish this comparison with fixed effects for zip code interacted with granular distance-to-coast x elevation intervals. Our findings are similar with the inclusion of a broad set of observable controls for property characteristics. Results are unchanged after including flexible controls for the home's actual transaction value. The presence of home values for transacting properties provides a novel opportunity to control for typically unobservable homebuyer perceived amenity value. Moreover, specification curve analyses (Simonsohn et al. 2020) demonstrate robustness across increasingly granular spatial fixed effects as well as sub-sample choices.

We next show that several local factors that expose areas to more significant SLR risks also positively predict the extent of partisan sorting on SLR risks. Sorting is larger in areas with above median relative sea level rise (i.e., areas that are sinking faster relative to the sea level) or tidal variation. This bolsters our previous evidence

[3] SLR exposure is publicly available through the NOAA's SLR viewer (https://coast.noaa.gov/slr/). We match this with nationwide property-level data and the universe of individual voter registrations.

that Democrats are relatively more hesitant to purchase exposed properties in areas exposed to more imminent SLR risks. We also find more sorting in states with Republican majorities in the legislature, which we interpret as evidence that Democrats are more likely to purchase exposed homes when they anticipate intervention from local governments.

Three additional sets of tests indicate that partisan beliefs about long-run SLR risks drive the observed sorting into SLR exposed properties. First, partisan sorting is not driven by sorting on voter age, race, income, or education. Second, partisan sorting does not appear to reflect current flood risk as political affiliation is not correlated with current exposure to storm surges, a primary cause of short-term flood risks. Finally, partisan residential sorting exists among owners, whether they occupy the property or not, but not among renters. This result limits the plausibility that SLR exposed properties have attributes that systematically attract Republicans instead of Democrats but is consistent with Democrats acting on concerns about long-run SLR risks with their housing ownership decisions.

In our final set of tests, we examine the extent to which partisan-based sorting on SLR exposure has changed over time, as future SLR projections have become increasingly dire. We find that between 2012 and 2018, the partisan gap of voters residing in an SLR exposed property has more than doubled, with this increase concentrated between 2016 and 2018 and among those counties where concern about climate change rose the most between 2014 and 2016. To the extent that this trend continues, voting blocks of residents whose party is currently least concerned with climate change risks will emerge and strengthen in coastal communities, potentially affecting local responses to climate change.

These findings contribute to the growing literature on the economic effects of climate change and most directly relate to the set of studies examining how climate change affects coastal communities. This literature includes studies examining the response of housing transaction prices or volumes, mortgage lending, municipal bonds, and insurance premia to current flood risk (Bosker 2019; Atreya and Czajkowski 2019), hurricanes (Bin & Landry 2013; Ortega & Taşpınar 2018; Ouzazd & Kahn 2020), and SLR (Bernstein et al. 2019; Baldauf et al. 2020; Murfin and Spiegel 2020; Keys and Mulder 2020; Painter 2020; Goldsmith-Pinkham et al. 2020).

Although existing evidence that SLR exposure impacts house price supports SLR exposure as an important driver of the future trajectory of coastal economies, such price effects are neither necessary nor sufficient to predict the type of "quantity" response we document. Indeed, Forsythe et al. (1992) shows that market prices, which are set by the marginal investor, say little about the biases of the average asset owner. For example, in contrast to real estate for investment purposes, prior work has not consistently found house price effects of SLR exposure for primary residences in many coastal communities (Bernstein et al. 2019; Baldauf et al. 2020; Murfin and Spiegel 2020). Our findings show that climate change impacts housing markets along quantity dimensions, as is modeled theoretically by Bakkensen & Barrage (2021) and Baldauf et al. (2020).[4]

The systematic sorting on climate-change risks by political affiliation has significant policy implications. For example, Hornbeck (2012) shows that in the decades after the Dust Bowl ravaged the U.S. plains the primary margin of stabilizing adjustment was via migration away from the area, but this (de)stabilizing nature of migration depends on the type of resident migration. Consistent with evidence in modern data on sorting near high-risk flood zones (Bakkensen and Ma 2020), and migration following natural disasters (Boustan et al. 2012; Mahajan & Yang 2020; Spitzer et al. 2020), Hornbeck (2020) shows that Dust Bowl migrants

[4]Bakkensen and Barrage (2021) also conduct a 187-person survey in Rhode Island and find correlations between SLR exposure and beliefs consistent with our nationwide raw data.

were "negatively selected" via lower education and likely lower income.[5] An important difference in our case is that migration is responding to future expectations, which means that it affects future responses to climate change. For instance, adaptation to SLR exposure is often spurred by recent flooding events through higher uptake of flood insurance (Gallagher 2014) that correlates with political affiliation (Ratnadiwakara et al. 2020). Models of the future effects of climate change migration, (e.g., Hauer 2017), though often do so based on migratory patterns and economic effects once inundation or local devastation actually occurs. Our results provide a context where these projections could change substantially if the selection also occurs along partisan lines far in advance of an actual disaster.

Our findings also offer a large-scale example of how heterogeneous beliefs affect financial decisions. Since exposed properties sell at a discounted price and the exact extent of risk to exposed properties is highly uncertain, we cannot discern who the more informed party is. Our findings, therefore, could be consistent with equally-informed voluntary trade, likely to be desirable (e.g., Gilboa et al. 2014, Brunnermeier et al. 2014), or the presence of incorrect or irrational beliefs by Republicans or Democrats (e.g., Yan 2008, Fedyk et al. 2013). Whether rational or not, or findings connect to a broad and growing literature examining how heterogeneous beliefs affect asset prices, volatility, and allocation.[6]

Partisan residential sorting on climate change has implications for understanding how partisan divides are reflected in substantive actions.[7] Prior work

---

[5] See Banzaf, Ma, Timmins (2019) for a recent summary of the environmental justice literature and the dynamics of sorting around environmental disamenities.

[6] See for example Buraschi and Jiltsov (2006), David (2008), Dumas et al. (2009), Xiong and Yan (2010), Kubler and Schmedders (2012), Simsek (2013, Ehling et al. (2018), and Heyerdahl-Larsen and Walden (2021).

[7] One example is an emerging literature on partisan divide in investor sentiment, including in-group effects on economic expectations (Mian et al. 2021) credit ratings (Kempf & Tsoutsoura 2021), and events surrounding COVID-19 (Meeuwis, Parker, Schoar and Simester 2018; Cookson, Engelberg and Mullins 2020).

has argued that political affiliation is a prominent driver of self-reported climate change expectations (e.g., Hamilton 2011; McCright & Dunlap 2011). Whether this divide manifests in differential behavior or is just superficial rhetoric is critically important, but unclear, especially since despite massive partisan divides now, there was no evidence of partisan gaps in stated beliefs about global warming as recently as 1998.[8] Residential real estate and SLR represent an ideal setting to assess significant responses to climate change partisanship: 1) the individual stakes are high since housing is often the largest component of personal wealth (Campbell 2006) and future flooding from SLR would make this investment worthless; 2) low discount rates make it possible that expectations of temporally distant risks could impact decisions today (Giglio et al. 2014). In fact, evidence suggests households act as if they highly value housing amenities even a century in the future, perhaps driven by bequest motives (Giglio et al. 2014). While these low discount rates raise the possibility of partisan sorting on SLR, the extent of such sorting is unclear ex-ante. Afterall, households struggle to plan for temporally distant vital financial decisions like retirement (Chetty et al. 2014).

In that respect, our findings also provide a unique contribution to the evidence on residential sorting as a mechanism people use to "vote with their feet." Our findings provide evidence of anticipatory sorting far in advance of any disamenities. As communities choose whether or not to improve resilience to climate change, this type of sorting could lead to even larger local general equilibrium responses than what we estimate in our partial equilibrium analyses. Theoretically, even relatively modest preferences for proximity to similar residents could cause multiplier effects (Schelling 1969; Sethi & Somanathan 2004; Banzhaf & Walsh 2013). In fact, recent work has found just such effects, where politically similar people are more likely to choose geographically proximate locations

[8] https://news.gallup.com/poll/107593/partisan-gap-global-warming-grows.aspx

(McCartney & Zhang 2020). The presence of partisan-based sorting with respect to SLR exposure is likely to impact climate changes responses as households most likely to vote against climate friendly policies and least likely to adapt to climate change related flooding ultimately bear the burden of SLR. Whether these adjustments are optimal depends on a variety of uncertain factors such as technological development and the future impacts of climate change.

1 Data and Sample

In this section we discuss the data sources we use to obtain information on all individual level voters, properties, and SLR exposure in coastal communities.

1.1 Data Sources

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

Characteristics from the assessor files provide the exact geo-coded location of each property, which allows us to determine the property's distance from the nearest coastline as well as its elevation. The dataset also contains information on a broad set of property information including square footage, the number of bed/bathrooms, and build year. We also see the type of property (e.g., single-family residence, condo, town-home) as well as whether the unit is owner-occupied following the sale, the type of buyer, and the address of the buyer and seller.

To implement our research design, we determine the property-level exposure to SLR for all properties within our sample utilizing NOAA's publicly available SLR viewer (Marcy et al. 2011). 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 SLR exposure. The NOAA provides detailed SLR shapefiles that describe the latitude and longitudes that will be inundated following a up to 10-foot increase in average global ocean level. We utilize geographic mapping software to assess the exposure level of each parcel within a coastal county in the Zillow data. A property's exposure is based on the minimum amount of feet of SLR such that the parcel centroid would be flooded during mean higher high water (MHHW).[9] We find that approximately 3 million homes are exposed to SLR of between 0 (currently exposed) and 10 feet.

To identify political affiliation, we utilize voter registration data from L2, which has information on 190 million voter records. We obtain these data for coastal states and merge them with the Zillow-SLR dataset based on physical address. For additional tests on the transaction sample, we merge the registration data based on buyer's address. For most of our analysis we use L2's political affiliation. For most states, this reflects individual voter registration files, but requires cleaning and mapping from underlying entries into "Democrat", "Republican", and "Independent."[10]

Finally, to control for other potential drivers of SLR exposure such as income, we utilize a smaller matched sample that includes data collected as part of HMDA (Home Mortgage Disclosure Act). Since HMDA does not provide

[9] MHHW is based on the average of the higher high-water height of each tidal day observation over the National Tidal Datum Epoch (~19 years), excluding wind driven tides. Higher high-water height is the highest tide recorded from a tide station each day. See the NOAA's SLR viewer for more details (https://coast.noaa.gov/data/digitalcoast/pdf/slr-faq.pdf).

[10] We show in our robustness analysis that our findings are unchanged excluding states where L2 augments voter registration data with other observables to predict political affiliation. We also show results are robust to using a simple definition based on raw voter registration data, where "D" and "R" are mapped to Democrats and Republicans respectively. This measure in 2012 is >90% correlated with L2's 2018 affiliation at the voter level, once Independents are excluded, confirming the integrity of both the L2 process and the underlying voter registration files.

transaction level identifiers, this merge requires fuzzy matching on transaction period, sales price amount, loan amount, and broad location. Approximately half of our transaction sample merges uniquely with the HMDA data.[11]

1.2 Sample

Our primary analysis is cross-sectional, with each individual appearing once. We use the voter registration and address information in the fall 2018 L2 to define political affiliation. Property-level characteristics are from deeds records for the most recent date (2018 or earlier), while information available only at the time of sale, such as purchase price, as well as details from HMDA, are all taken as of the most recent transaction date.

We restrict the sample to properties in coastal communities, defined as parcels within 2 miles of the coast that are located in counties with at least one property that the NOAA projects would be inundated with 10 feet of SLR.

We can match 26.65 million observations across ZTRAX and NOAA. There are approximately 16 million observations for which we are also able to obtain accurate distance to the coast, elevation, and political affiliation. Our sample is reduced to about 3.9 million observations in specifications where we also require detailed information on the value of the most recent transaction. For some analyses, we further restrict the sample to the approximately 1.5 million observations with a match to HMDA. Neither the inclusion of these additional controls, nor the smaller samples they require, is ever necessary for our analysis or conclusions, but useful for additional robustness checks.

2 Climate Change and Reported Partisanship

[11] See Billings (2019) for HMDA matching procedures and a discussion of matching ZTRAX to HMDA more broadly.

In this section we provide background and simple statistics on the scientific evolution of predictions about climate change and SLR risks, as well as the growing partisan divide in reported beliefs about such risks.

2.1 Scientific Evidence on Climate Change/SLR

Before examining partisan views on climate change, and in particular SLR, it is useful to understand the underlying scientific evidence on historical patterns and future projections for SLR. In Figure 1a we plot the changes in average global mean temperatures and SLR over the 40-year period from 1970-2010. There is a clear upward movement in both time series, as changes in the global climate and temperature have been accompanied by rising seas.

During the first three decades illustrated in Figure 1a, sea levels rose about approximately 20 mm/decade. Over the final 10 years, average global sea levels rose by more than twice this rate, 45.2mm or about 1.78 inches. If that rate continues over the next 80 years it would imply about 14 inches of additional SLR by 2100. This is below even the low-end of most scientific projections over that period, which we depict in Figure 1b.[12] This is because scientific models expect SLR to accelerate over the coming decades, as it has over the past 40 years.

Improved scientific understanding of mechanisms driving these increasing rates of SLR have led to substantial increases in SLR projections and uncertainty about SLR acceleration. This can be seen in Figure 1b. In the 2001 Intergovernmental Panel on Climate Change (IPCC) report, the expected SLR by the end of the century was about 1 foot under a medium emissions scenario and around 1.5 feet for the high emissions scenario, with 1.5-2 feet of uncertainty within

[12] Following the same approach as Goldsmith-Pinkham et al. (2020) we include all studies highlighted in Garner et al. (2018) which have both medium and high emission scenarios, are semi-parametric, probabilistic, or part of the IPCC or NOAA analysis papers, include sufficient information for computation of a mean and variance of global SLR by the end of the century, and don’t impose explicit constraints on projection variables or use non-standard temperature projections.

an approximate 95% confidence interval. By 2017, the average expected SLR by the end of the century across the studies presented is 3 feet and 5 feet for the medium and high emissions scenarios, respectively. Notably, uncertainty about these projections has risen as well. Ninety-five percent confidence intervals for 2017 projections were on average 3 feet and 3.8 feet for the medium and high emissions scenarios, respectively. The high end of the 95% confidence intervals for the three studies in the high emissions scenario is 8 feet, while the low end in the medium emissions scenario is under 2 feet.[13] This widening uncertainty in SLR projections by scientific reports could cause reasonable disagreements about the degree of climate-change-induced future SLR.

2.2 The Reported Partisan Divide on Climate Change

Political affiliation affects the way people interpret uncertain information. For instance, there is growing evidence that education has divergent effects on climate change beliefs by political party (McCright 2011; Hamilton 2011; McCright & Dunlap 2011), while Kahan et al. (2012) and Drummond and Fischhoff (2017) show that even experts' interpretation of new information about climate change is heavily mediated by partisan affiliation. This lens of partisanship may, in part, reflect the way in which prior perceptions mediate how one acquires and processes information (Alesina et al 2018; Stantcheva 2020; Alesina et al 2020).

Figure 2 depicts the results of a 2020 Pew Research Center survey that directly examines the relationship between partisanship and climate change beliefs. The survey asked U.S. adults whether they agree that a given topic should be a "top priority for President Trump and Congress." Of all 18 topics raised, "climate

[13] While even high-end confidence intervals for SLR projections over the next century don't exceed 8 feet, it is hard to know ex-ante whether even longer time periods could matter for current housing decisions, nor whether individual uncertainty exceeds those reported by the studies themselves. This is inevitable an empirical question and one we explore explicitly in our non-linear analysis later in the paper.

change” was the one least agreed with by Republicans. By contrast, along with the environment, health care, and education, it was one of the most agreed upon topics by Democrats. Perhaps not surprisingly then, this meant it was the topic with the largest partisan gap, even though the other topics mentioned included “gun policy”, “immigration”, “military, and “race relations” – all considered to highly partisan topics in the U.S.

This variation in stated concerns about climate change does not simply represent differential geographic exposure. The 2018 Yale Climate Study asked participants “Do you think that global warming is happening?” In Figure 3 we plot the % of Democrats who answer yes in a county minus the % of Republicans who answer yes. Overall, only 45% of conservative Republicans report believing in global warming, relative to 95% of liberal Democrats. Moreover, there is a positive Democrat-Republican partisan gap of at least 20 percentage points in every single one of the 435 congressional districts in the country.

In Table 1 we descriptively examine the partisan divide on climate change by looking at cross-county correlations. We find that counties with more SLR exposure have a higher proportion of Republicans (and less Democrats). This is also summarized by a measure we construct, and use throughout the paper, *Pol. Conservative*, which is 1 for Republicans, 0 for Independents, and -1 for Democrats. Using this measure, we see that more conservative counties have more SLR exposure, but are less worried about climate change. Specifically, *Pol. Conservative* has a -60% correlation with the % who are worried about climate change according to the 2016 Yale Climate survey, and a -55% correlation with concerns it will affect them personally. Therefore, Republicans are in more exposed areas and are much less worried about climate change compared to Democrats.

In Table 2 we find that across the whole sample of SLR exposed counties, 23% of properties are owned by Republicans, 50% are owned by Democrats, and the remaining 27% by Independents. Restricting attention to SLR exposed homes, the percentage owned by Republicans increases to 31%, while the percentage of Democrats drops to 41%. SLR exposed properties are about 2% less expensive, but are more likely to be purchased by higher income and older individuals. Exposed and unexposed properties both have approximately the same number of voters per household and are similarly distributed across ethnicity with approximately 55% of properties owned by Whites, 16% owned by Hispanics, and 13% owned by Blacks.

To the extent these descriptive results are driven by Republicans (Democrats) who are less (more) concerned about climate change risks being more (less) willing to buy properties with SLR exposures, this would have broader economic implications. A Democrat who is aware and concerned about climate change in an SLR exposed property might vote in favor of adaptation efforts, while if that same voter moved to a property already insulated from SLR, even if it is physically proximate, might feel little need to finance adaptations that are no longer necessary to protect them. If a Republican was the new owner of the SLR exposed property just vacated, and they were either unaware or unconcerned about climate change, they may be unlikely to support paying for local adaptation efforts. Therefore, any systematic sorting, even just within a local jurisdiction, could have important implications for spending on local adaptation efforts.[14] Moreover, it would suggest partisan views on climate change are strongly held enough that people are willing to bet significant portions of their wealth on them. Of course, given all the potential confounds with such aggregate analysis it is hard to say, thus supporting the need for the more well-identified analysis carried out in the remainder of the paper.

[14] For example, in November 2020 Key Biscayne, FL approved a $100 million bond issue to deal with effects of climate change that passed by only 801 votes, with support heavily divided along political party lines (https://www.islandernews.com/news/updated-leaders-react-to-go-bond-referendum-passing-with-56-percent-of-the-vote/article_5eed85fe-1e51-11eb-a01e-2bafd4edcc98.html).

3 Empirical Method

While the large differential between Republican and Democrat in exposure to SLR risk is suggestive of partisan-based sorting on beliefs about long-run SLR risks, a number of other explanations may be at play (as evidenced by the differences in age of home and homebuyer income). We use a number of identification methods to mitigate the concern of confounding variables along three dimensions: 1) differences in amenity sets driven by coastal proximity, 2) unobserved heterogeneity in buyer and property types, and 3) differences in appetite for current flood risk that is reflected in SLR exposure.

We address the first issue in a similar way as Bernstein, Gustafson, and Lewis (2019): we control for the property's zip code interacted with flexible non-linear controls for its distance to the coast and its elevation. We create flexible non-linear controls for coastal proximity and elevation by taking continuous measures of elevation and distance to the coast for each parcel and assigning them to intervals. Distance-to-the-coast is split up into intervals of 1/5th of a mile, while elevation is split into 2-meter intervals.[15] By interacting these fixed effects with zip code, we reduce the comparison group to homes in the same neighborhood with a very similar coast-related amenity set, but potentially quite different SLR exposure. As discussed in more detail in Bernstein, Gustafson, and Lewis (2019), this design appears to eliminate coastal amenity differences between properties, while still leaving substantial variation in SLR exposure. As they note, this SLR exposure variation comes both from within interval variation in elevation and the topology of the terrain surrounding the property. Several foot differences in elevation are unlikely to substantially alter amenity values on average, but can change the timing of SLR-induced inundation by half a century. The same is true of the topology

[15] As we discuss in Section 4, much finer distance-to-coast bins yield qualitatively similar results.

surrounding a given property, since small inclines or structures may substantially alter the exposure to SLR without altering the amenities of the property.

Equation 1 below presents our benchmark regression:

$$Pol.Cons_{izde} = \beta\ Exposure_{izde} + \lambda_{zde} + \boldsymbol{X}_{izde}\phi_1 + \boldsymbol{Z}_{izde}\phi_2 + \varepsilon_{izde} \qquad (1)$$

where for property i, $Pol.Cons_{izde}$ takes a value of 1 if the voter registered at the property is Republican, 0 if they are Independent, and -1 if they are a registered Democrat. Independents are defined to be any registered voter who is neither a likely Democrat nor a likely Republican based on L2's mapping of voter registration fields into affiliations, and so includes primarily registered unaffiliated voters, but also those registered outside the two major parties. We also estimate Equation 1 on a sample excluding either Republicans or Democrats to see whether effects are consistent with what we would expect for each party relative to Independents.

Exposure is an indicator that takes a value of 1 if the property will experience chronic tidal flooding at the highest seasonal high tides with up to 10 feet of global average SLR and zero otherwise. Given that scientists project that it will be at least 100 years before ten feet of SLR manifests, this measure captures any property with a chance of being inundated this century, ensuring that our control group consists of properties that will remain free of chronic flooding for the foreseeable future.[16] λ_{zde} is the set of zip, distance and elevation fixed effects discussed above.

An important aspect of our identifying assumption is that after including our primary set of fixed effects any remaining association between SLR exposure and political affiliation is not due to correlated omitted variables related to

[16] In robustness analyses, we find similar results using a 6-foot cutoff and excluding properties exposed to 7-10 feet of SLR.

amenities or disamenities. To examine this, we also include specifications with $\boldsymbol{X}_{izde}$, $\boldsymbol{Z}_{izde}$, which is a set of property attributes and buyer demographics that varies depending on the analysis. For property characteristics these include third order polynomials of building age and lot size square footage, linear controls for the number of bedrooms and bathrooms, as well as fixed effects for the number of stories, assessed building quality, and presence of a garage or pool.[17] For buyer demographics in the most saturated model these include fixed effects for age, race, income at origination deciles from HMDA, and estimated years of education.

A remaining concern is the possibility that there are buyer or property characteristics that we do not observe or adequately control for that are correlated with political affiliation and the choice to own an SLR exposed property. For example, if SLR exposed homes offered an unexamined set of amenities that Republicans happened to enjoy, we would show a positive β coefficient that would be unrelated to SLR risk. One novel feature of our setting is that for the subset of properties with observable transactions, we typically have the transaction price, which captures the net value of amenities. Therefore, for much of our analysis we consider a slightly augmented version of Equation 1:

$$\begin{aligned} Pol.Cons_{izdep} = \beta\, Exposure_{izdep} + \lambda_{zdep} + \gamma_{ip} + \boldsymbol{X}_{izdep}\phi_1 \\ + \boldsymbol{Z}_{izdep}\phi_2 + \varepsilon_{izdep} \end{aligned} \tag{2}$$

where we restrict the sample to properties for which we have transaction prices. In this specification, we also include γ_{ip} to control for the time period upon which the homebuyer purchased a given property.[18] We also include λ_{zdep}, where the subscript p denotes a flexible non-linear control for the value of the property, based off the most recent transacted price. We implement this non-linear control, by

[17] We do not drop observations for missing values of these covariates. Rather, we set the value to zero and include an indicator for the missing value.
[18] γ_{ip} indicates a dummy for each year by quarter of most recent property sale of value p between 2007 and 2017 for a given property i.

computing common price intervals used in housing searches ($50,000 bins up to properties of $1M and $100,000 bins for properties greater than $1M), adjusted for price appreciation at the state-level to make transactions comparable over time.[19] Not only does the inclusion of these flexible price controls help alleviate concerns about unobserved correlated (dis)amenities, but a comparison between the estimated coefficients in Equations 1 and 2 provides useful information on the relevance of such unobserved factors.

Since our models include granular fixed effects to control for locational attributes such as elevation, zip code and distance to beach as well as property attributes and prices, it is important to confirm that there exists enough residual variation in SLR exposure for us to identify partisan sorting. To this end, Appendix Table A1 estimates Equations 1 and 2 without any voter attributes and increasingly granular fixed effects. The results show that even in our most restrictive price models, we explain at most 89% of SLR exposure.

4 Results

We begin in Section 4.1 by analyzing the relation between the SLR exposure of properties and the political affiliation of their residents. We rely on variation that remains after including the flexible set of property controls in the primary specifications outlined in Equations 1 and 2. In Section 4.2, we then provide additional evidence that observed sorting comes from partisan sorting on long-run SLR risk, not selection on other demographics, short-term flood risk, or current amenities.

[19] In particular, we estimate state house price indices (normalized to 2007) by regressing time fixed effects on the transaction values for all properties in our primary sample, after including the aforementioned controls for property characteristics, state-by-state. We then take each observed housing transaction in our dataset and subtract this state house price index to put transactions within each state at different times on more comparable footing and increasing the dispersion of prices across both price intervals and time/regions.

4.1 Partisan Residential Sorting on SLR

In our primary analysis we estimate Equations 1 and 2 to identify the relation between political affiliation and the propensity to live in a property that is exposed to SLR. Table 3 presents our main findings.

In Panel A Column 1, we regress indicators for Republican residents on an indicator for a property being SLR exposed, along with zip code x distance-to-coast bin x elevation bin fixed effects. This fixed effect structure controls for the location as well as the proximity to coastal amenities. The coefficient on SLR exposure is identified from variation in SLR exposure that is driven by either small (i.e., within 6-foot elevation bin) differences in elevation or in topography, which can channel water towards or away from specific parcels. We find that properties inundated with ten or fewer feet of SLR are on average 1 percentage point more likely to have a Republican resident. The dependent variable mean, after controlling for effects of exposure, is 22.5 percentage points, suggesting that SLR exposure is associated with a 4 percent higher Republican share.

In the next columns we examine to the extent to which this relation is continuous across the political spectrum. We continue to include the same set of controls, but restrict the sample to Independents and either Republicans (Column 2) or Democrats (Column 3). Because we exclude registered Democrats (Republicans) from the sample in Column 2 (3), these coefficients estimate the effect that a property being SLR exposed has on the likelihood that the resident is Republican (Democrat) as opposed to Independent. The coefficient on *Exposed* is positive in Column 2 and negative in Column 3, indicating that Republicans are more likely than Independents to reside in SLR exposed properties, while Democrats are less likely. Taken together these results provide evidence of a monotonic relationship between partisan sorting and SLR exposure which are consistent with survey evidence on climate change beliefs.

Column 4 uses the full sample and our $Pol.Cons$ measure, which aggregates political affiliation, equaling 1 for Republican, 0 for an Independent, and -1 for a Democrat, as the dependent variable. The estimated effect of this variable, 0.02, corresponds to a Republican-Democrat gap in SLR exposed properties that is 2 percentage points higher than is seen in otherwise comparable properties. In other words, in an area with a 50/50 split between Republicans and Democrats residing in unexposed homes, our estimate would predict similar exposed homes to exhibit a 51/49 split in favor of Republicans.[20] We employ this aggregated measure of political affiliation as our dependent variable for most of our subsequent analyses since it provides a more parsimonious way of capturing political leaning.

In Column 5 we augment the empirical specification with additional controls for property characteristics. These additional controls have little effect on the estimated relation between political affiliation and SLR exposure. Column 6 further limits our sample to only voters in properties that have a property sale since 2007 (i.e., the price sample). Here, we add price bins to the interacted fixed effects and separate fixed effects for the time at which the property transacted. The additional inclusion of flexible interval-based fixed effects for housing transaction prices provides a control for the combined value of all housing amenities.[21] The inclusion of price controls has little effect on the relation of interest. After controlling for property characteristics and zip code x distance-to-coast bin x elevation bin x price bin fixed effects the magnitude of the coefficient only barely changes to 0.023.

[20] $Pol.Cons$ is agnostic about how redistribution occurs along the political spectrum, so 40/20/40 for republican/independents/democrats becoming 40/22/38 would also be consistent with this coefficient.

[21] For instance, price controls will capture the net effect of amenities such as the view, other benefits of proximity to the beach, costs associated with current flooding risk, etc.

In Table 3 Panels B and C, we examine how partisan sorting varies with the degree of SLR exposure. Properties requiring lower levels of future SLR change to be flooded would be flooded much sooner based on climate change projections, and so we anticipate beliefs about SLR projections to be more relevant for these properties. By contrast, properties requiring 9 or 10 feet of SLR to be flooded would not likely be underwater for significantly more than a century, so we would expect less partisan sorting.

In Table 3 Panel B, we replicate all the specifications from Panel A, but exclude properties that would require 7-10 feet of SLR to be inundated. This result lets us compare our least exposed properties with properties that would be inundated with 6 feet or less of global SLR. In all specifications, we find statistically significant coefficients that qualitatively match those seen in Panel A but are larger in magnitude.

In Panel C of Table 3 we reintroduce the full sample and include a dummy variable equal to 1 if a property would be inundated if sea levels were to rise by 10 feet or less as well as one if they were to rise by 6 feet. Since any property flooded at 6 feet would also be flooded at 10 feet the second exposure variable ("Exposed (≤6ft)") captures the incremental sorting for more highly exposed properties and provides a formal test for statistical significance of that difference. Across all columns the larger sorting among more exposed properties is positive and statistically significant. This is consistent with our expectation that more exposed properties will experience more sorting, combined with the evidence in Appendix Figure A1 that less exposed properties are predominant in our sample and thus substantially attenuate estimates. For example, in Column 1, the effect on the Republican share goes from 1 to 2.5 percentage points, while for Column 6 we can see that the effect on the Republican-Democrat residency gap grows from 2.3 to 5.3 percentage points. Taken together, our results suggest that the Republican-Democrat residency gap is 4.2-5.4 percentage points, reflecting a 11.5 percent higher Republican share (0.025/0.217), for homes that may be inundated by SLR this century.

In Figure 4, we more closely examine how political affiliation changes non-linearly with categorical dummies representing intervals of SLR needed to flood the property (ex. 0-1, 1-2, 2-3 feet, etc.). Figure 4 Panel B breaks down the effect in Panel A by splitting the political affiliation measure to separately examine the effect of being Democrat or Republican relative to Independent.[22] Here, the red and blue lines represent coefficients on Republican and Democrat indicators when regressed on these separate indicators for SLR exposure. Each point estimate reflects Republicans' or Democrats' preference for a property with the exposure denoted on the x-axis relative to a property that is not exposed to 10 feet of SLR.

Figure 4 indicates that the differential preference of Republicans for SLR exposed properties is largest for the most exposed properties. Republicans' preference for SLR exposed properties monotonically drops for properties with less than 1 foot through 3 feet of exposure. In fact, for these most at-risk properties the Republican-Democrat partisan gap increases to over 10 percentage points. According to scientific projections, these properties are at risk of being inundated within the next 50 years. The difference between Republican and Democratic preference continues to be statistically significant for properties with between 4 and 8 feet of SLR until inundation. Upper end SLR projections would have these properties inundated within the next 100 years. Notably, Republicans and Democrats treat properties that will be inundated by 10 feet of SLR similarly to each other and similarly to unexposed properties, which is consistent with the lower risk of exposure at more than 8 feet of SLR.

We perform a number of analyses to ensure that our specification of fixed effects and sample choice is not driving our findings. In particular, in a number of

[22] All models in Figure 4 includes zip code x distance-to-coast bin x elevation bin fixed effects.

Appendix tables we show that results are robust to the choice of clustering of standard errors (Table A2), the sub-samples with matching observations across all data sources (Table A3), exclusion of states where L2 predicts some voter affiliations from non-voter registration data and dropping "likely independents" which are more difficult to discern from voter registration details (Table A4), the exclusion of any particular state (Table A5), and the choice of even more granular geographic region fixed effects (Table A6). We also show in Appendix Table A7 that our findings are not driven by properties likely to have atypically high or low amenity values, by showing very similar findings excluding properties right near the beach (Column 1), that are unusually high/low elevation for their zip code (Columns 2 and 4) and those with atypically high/low property value for their area (Columns 5 and 6).

Figure 5 and Appendix Figure 2 further provide specification curves (Simonsohn et al. 2020) for models that vary in how we specify distance to coast fixed effects, the choice of sample, and how we incorporate price controls. This provides a parsimonious presentation of a broad range of possible robustness tests and specifications. In Figure 5, we provide all iterations of fixed effects and other controls for our three main data samples and compare them to our main results for all voters and those that are limited to our properties with prices. Results are consistent and show that the choice of controls generates some variation in magnitudes, but results are consistently around 0.02 and always statistically significant. Even in models with quite restrictive fixed effects (price by elevation by distance to coast by zip and year by quarter of sale bins) or distance to the coast bins of only 0.05 miles, we still find similar coefficients that are statistically significant. Appendix Figure 2 provides a specification curve for two additional samples, limiting properties to only those within 1 mile of the coast as well as excluding properties with SLR exposure at less than 1 feet (in essence, already exposed to SLR). Again, we find consistent effects across these alternative samples.

4.2 Exploring Heterogeneity in Partisan Sorting

If local factors exacerbate (mitigate) the future damage caused by SLR are known to homebuyers, then they may increase (attenuate) the degree of partisan sorting. We examine whether three such local factors—the extent of relative sea level rise, volatility in high tides, and the political ideology of the state legislature—positively predict sorting.

To test these predictions, we employ a series of heterogeneity tests that build off our primary empirical design to examine these questions. Specifically, we estimate the following model:

$$Pol.Cons_{izdep} = \beta\ Feet\ Inundated_{izdep} \times H_i + \lambda_{zdep} + \gamma_{ip} + \boldsymbol{X}_{izdep}\phi_1 + \varepsilon_{izdep} \qquad (2)$$

The explanatory variable of interest is the interaction between the heterogeneity dimensions of interest, H_i, and a continuous measure of SLR exposure, which we denote *Feet Inundated*. *Feet Inundated* captures how far under water a property would after 10 feet of global SLR. The measure ranges from 0 for properties that would not be inundated with 10 feet of global SLR to 10 for properties inundated with 1 foot of SLR.

We choose a continuous exposure measure when conducting heterogeneity tests for two reasons: First, the result illustrated in Figure 4 suggest that partisan sorting is correlated with the extent of SLR exposure, even within the set of exposed properties. Thus, any correlation between a given dimension of heterogeneity and this intensive margin exposure will complicate the interpretation of heterogeneity tests. Second, to the extent that some of the heterogeneity factors may be more relevant over a short horizon (e.g. extrapolation of historic local SLR changes or the political makeup of a region) the interaction may me stronger for more exposed properties. Note, in Equation 2, we include ten separate one-foot

SLR exposure buckets, γ_i, to absorb the baseline effect SLR exposure. We also control for the baseline effect of the various dimensions of heterogeneity, to the extent that they vary within a Zip Code, but the lack of within zip code variations makes the coefficient estimates difficult to interpret. As in our primary analysis, we include the same flexible set of controls and fixed effects that allow us take advantage of properties with variation in SLR exposure, but are otherwise similar.

The first two dimensions of heterogeneity that we examine are Relative SLR (RSLR) and tidal variation. Both measures capture the idea that the global measure of SLR may differentially impact areas since SLR is not happening at a uniform pace and the immediacy of SLR risks depend on the extent of tidal variations. To examine whether our findings vary based on the extent of RSLR, which reflects the extent to which a locality is rising or sinking relative to the sea level, we collect data on RSLR from the NOAA (Sweet et al. 2017). The report details the historic adjustment to baseline SLR for a number of major cities and for a range of locations around the globe. To connect our data with Sweet et al. (2017) we first find the closest city or location from the report to each of the properties in our sample and extract the "baseline SLR" value , which we will call the Relative SLR or RSLR. The median property on which we estimate Equation 2 has a RLSR of 0.48, with an interquartile range of -0.07 to 1.27. The distribution is left skewed with the 5th percentile of -2.77 and a 95th percentile of 1.68 and contain several large negative outliers. Thus, we use an indicator for above median RSLR as our primary variable of interest.[23]

Columns 1 (larger sample) and 2 (additional price controls) of Table 4 present estimates of Equation 2 where the interaction between SLR exposure and

[23] In unreported tests, we find similar results using a measure that equals zero for properties that are rising (i.e., have negative RSLR) and then is continuous for properties that are sinking. Aside from having fewer extreme values, one reason that positive variation is RSLR matters more than negative variation could be that sinking land is more salient.

an indicator for above median RSLR is the explanatory variable of interest. In both cases we find an estimate on the interaction that is positive and borderline statistically significant at conventional levels (T-statistics of 1.77 & 1.87 respectively). These findings are consistent with SLR exposure inducing more partisan sorting when a local area faces more SLR risk due to its high RSLR.

We next conduct a similar analysis with an interaction between SLR exposure and an indicator for a location's tidal variation. Our global SLR measure classifies properties as exposed based on its elevation relative to the mean higher high-water mark (MHHW), which reflects the average high tide in the area. The more variation there is around this mean, the sooner properties with a given global SLR exposure will begin to flood. We employ a similar methodology as discussed with respect to RSLR above to obtain a measure of tidal variation for each property. We use a list of tidal stations in the US and their unique ID information to query the NOAA Tides and Currents API. We obtain the time series of monthly MHHW, the mean water level of the highest high tide for each day of that month, for each station. To construct a measure of tidal variation we begin by taking the standard deviation of MHHW for all available monthly data at each tidal gauge. Unlike RSLR described above, this measure is agnostic to the trend in sea levels over time and simply captures the extent to which tides vary heavily in an area. There is substantial positive skew to this measure, which has a median of 0.66 and an interquartile range of 0.57 to 0.78, but a 1st percentile (minimum) of 0.47 (0.37) and a 99th percentile (maximum) of 8.44 (23.46). In our regression analyses we convert this to an indicator for Tidal Variation that equals one for areas with above median tidal variation and zero otherwise. Notably, the Spearman correlation between the RLSR and Tidal Variation indicators is less than 0.1.

We employ the same identification strategy we did when looking at RSLSR, but in Columns 3 and 4 of Table 4 report the estimate on the interaction between SLR exposure and an indicator for above median high tide variation. In both specifications, the point estimate is positive as well as similar to each other and the RSLR interaction in Columns 1 and 2, but, not surprisingly, we have more power when we allow for the larger sample without price controls in olumn 3. These findings suggest that partisan sorting is larger in regions with higher tidal variation, consistent with concerns about rising sea levels being more imminently relevant in these areas.

The final dimension of heterogeneity we consider is the political ideology of the state legislature, which we obtain from the National Conference of State Legislatures (ncls.org). The motivation for this test is the possibility that Democrats living in Republican areas may be more likely to shift away from exposed properties since they expect less SLR mitigation strategies to be implemented. The positive interaction between having a majority of Republicans in the state legislature and SLR exposure in Columns 5 and 6 of Table 3 is consistent with this idea and indicates that our main effects grow in areas that are perceived to be less likely to adapt to climate change. [24]

Taken together, the results in this section are consistent with the extent of partisan-based SLR sorting increasing in the immediacy of an area's local exposure to SLR and the perceived probability that politicians will support remediation efforts in the coming years.

4.3 Evidence of a Partisan Long-Run Risk Channel

The evidence thus far suggests that Republicans are more frequently owning SLR exposed properties than Democrats, all else equal. In this section, we conduct three additional analyses that all suggest that the observed sorting is driven by partisan beliefs about long-run SLR risks. First, we show that our findings are not

[24] We also show in appendix Figure 3 that while sorting is fairly ubiquitous across states, there is some evidence consistent with bigger effects in regions with more republicans and a faster pace of local sea level rise. In unreported tests, we find mixed evidence of less partisan sorting in condominiums where adaptions costs may be lower due to the possibility of risk sharing.

driven by correlated individual demographics. Second, we show that partisan sorting occurs in response to long-run SLR-related exposures, but not in response to current flood risk. Third, we show that this partisan sorting exists with respect to property ownership, but does not exist for property renters, mitigating the likelihood that differences in current amenities drive our findings.

4.3.1 Addressing selection on other resident characteristics

We next examine the relation between SLR exposure and our Pol. Conservative (%) measure after controlling for, age, race, income, and estimates of education levels.[25] We estimate this model in Table 5 using our sample of voters in properties that contain information on prices, homebuyer income, age and race and employ zip code x distance-to-coast bin x elevation bin x price bin fixed effects.[26] Column 1 estimates the effect of exposure on political affiliation after controlling for measures of age, race, and household income. There is some correlation between political affiliation and both ethnicity and gross income, but this has little effect on the estimated effect of SLR exposure on political affiliation, which is very similar to the estimates obtained in Table 3. The small change in magnitude of our measure of partisanship highlights the strong influence of this variable even when controlling for other voter attributes that correlate with political affiliation. In the remainder of the table, we use non-linear controls for these correlated characteristics. The most saturated specification in Column 5 includes zip code x distance-to-coast bin x elevation bin x Price Bin, year-quarter, age bin, race, income bin, and education years fixed effects.

[25] We only have an imputed measure of education levels based on Census data that has been estimated by L2. Income is limited to our sample of mortgage-holders that can be matched to sold properties and race is a mix of actual race given on voter registration forms in some states and imputed race based on full name. We also verify race through HMDA variables for race and ethnicity. Age is measured accurately since voter registration forms all require some age verification based on birth date.

[26] This restriction generates a substantially smaller sample size but in Appendix Table A3, column 5 we show that this does not impact our main conclusions.

The main takeaway from Table 5 is that the inclusion of other personal characteristics has little effect on the estimated relation between political affiliation and residing in SLR exposed properties. The evidence in Table 5 relates to Bakkensen and Ma (2020) who find that low income and minority residents are more likely to move into high-risk flood zones. Taken together, this evidence suggests that there may be differential sorting with respect to short- and long-run flood risk.[27]

Also, our finding that proxies for education do not negate the effects of partisan residential sorting on climate change is consistent with prior work based on self-reported beliefs. Existing evidence on partisanship differences in beliefs about climate change consistently suggest that education is not the primary driver of this divide (Kahan et. al 2012; Drummond & Fischhoff 2017; Bolsen & Druckman 2018) but rather "a distinctive conflict of interest: between the personal interest individuals have in forming beliefs in line with those held by others with whom they share close ties and the collective one they all share in making use of the best available science to promote common welfare" (Kahan et. al 2012). This adherence to group beliefs is quite evident in the short-run as shown by large differences in hurricane evacuation behavior along partisan lines (Long, Chen & Rohla 2020) as well as the role of politics in shared time with family during the holidays (Chen & Rohla 2018) and responses to COVID-19 (e.g. Makridis & Rothwell 2020; Green et al. 2020; Grossman et al. 2020).

4.3.2 Ruling out Short-Term Flood Risk

Our finding of sorting along political dimensions is consistent with survey-based beliefs regarding climate change, but could also reflect short-run flood risk

[27] The Bakkensen and Ma (2020) result is consistent with a larger environmental justice literature (e.g. Kahn 2000; Banzaf & Walsh 2008; Davis 2011; Bento, Freedman & Lang 2015; Lavaine 2019; Banzaf, Ma, Timmins 2019) that provides evidence of low-income and minority households sorting into areas with higher environmental disamenities like industrial sites, air quality and flooding.

concerns. To more formally test the role of current flood risk, Table 6 repeats our main test (i.e., Column 5 of Table 3) including controls for *stormsurge*, which proxies for current flood risk.[28] The highly correlated relation between SLR and storm surge does require enough variation to separately identify how both relate to partisan sorting. Appendix Figure 4 provides an illustration that although storm surge is positively correlated with SLR exposure, this correlation is substantially less than 1. For instance, approximately 35% of properties expected to be hit with ten feet of storm surge should the area be hit by a category III hurricane are not expected to be inundated by ten feet of SLR. Assuming that we have the statistical power to separately identify the effect of political affiliation on SLR exposure and storm surge exposure, we expect that if the driver behind the partisan sorting into SLR exposed properties is Republicans having more appetite for current flood risk in owning a property, then the coefficient on political affiliation should attenuate upon the inclusion of storm surge exposure controls.

Moving from Column 1 to Column 2 of Table 6 reveals no evidence for this as the coefficient on *Exposure* does not move out to three decimals after the inclusion of storm surge bin fixed effects. Column 3 shows that this is not due to the inclusion of the west coast, which exhibits little storm surge risk due to its lack of hurricanes. Columns 4 and 5 further support the lack of partisan-based sorting into storm surge exposed properties as *Pol. Conservative* is not significantly related to either an indicator for or a continuous measure of storm surge exposure. These findings strongly support the idea that the partisan sorting we observe is due to differential beliefs about long-run SLR exposure risk.

[28] NOAA conducts a series of simulation exercises using past storm data for Atlantic hurricanes and tropical storms and creates storm surge maps to highlight current flood risk for coastal areas. In particular, they simulate 100,000 hypothetical storms. They then take the maximum possible height the water reaches at a given location across all simulations (and assuming the highest possible tide) and that is the feet of storm surge we use in our analysis. Many locations never experience any storm surge related flooding across all simulations, which we use for our extensive margin analysis.

4.3.3 Owners Not Renters Exhibit Partisan SLR Sorting

Thus far we have controlled for home characteristics in a variety of ways, some of which (such as sale price) even partially address unobservable differences between exposed and unexposed properties. In our final set of tests, we further address the possibility that our findings are driven in part by unobservable differences between exposed and unexposed properties that differentially attract Republicans, but are not captured by our controls. Here, we separately identify the political orientation of the owner and renter of non-owner-occupied properties and run a similar analysis.[29] If our main results capture sorting by political affiliation over some amenity from living at non-owner-occupied properties with SLR exposure, we expect conservatives to be not only more likely to own them, but also rent there.

In our prior analysis the inclusion of price controls helps adjust for (dis)amenities that alter the value of a given property overall, but what they don't necessarily let us control for completely are (dis)amenities that may not alter house values (or alter them very little), but still lead to systematic sorting along political lines. To address this possibility, we identify $Pol.Cons$ as the political orientation of the buyer of the home for non-owner-occupied properties and run a similar analysis. If unobservable amenities that appeal to conservative buyers are an important driver of our results, we should find a similar effect on the occupier political orientation (either renter or owner) of SLR exposure and no effect on owner political orientation for non-owner-occupied homes. We also include a

[29] ZTRAX allows for this distinction based on tax records which provide a property and mailing address. These two addresses are the same unless the owner lives at another location. For these non-owner-occupied homes, we use L2 voting data to determine the political affiliation of the renter (current resident at the property address) and the owner (the current resident at the mailing address). Even though the number of properties that fit this definition are smaller, this model allows for us to capture a unique distinction, the renter and owner associated with the same home.

measure of owner and renter political orientation to control for political ideological preferences in tenancy relationships.

Columns 1 through 5 of Table 7 show that the politically driven residential sorting only exists among owners, whether they occupy the property or not, but not among renters. This result is similar using two definitions of renters: i) a property listed as non-owner occupied, and ii) same as (i) but also considers a resident a renter if the mailing address for the owner is in a different zip code than the property. Using either of these definitions, we consistently find significant positive impacts of SLR exposure on the political orientation of the owner, but small and imprecise effects on renters. Since we focus on the same property, the limited impacts of the political affiliation of renters as it relates to SLR suggests that amenities do not differ based on SLR exposure, after the inclusion of our fixed effects and property controls. Owners do have reason to care about SLR beyond correlated current amenities as it impacts future property values and rental incomes. Again, these findings are consistent with partisan-based sorting into SLR exposed properties being primarily due to difference in beliefs regarding long-run SLR across the political spectrum.

4.4 Evolution in Partisan-based SLR Sorting

In our final set of tests, we examine the extent to which partisan-based sorting on SLR exposure has changed over time, as future SLR projections have become more dire. Our analysis thus far examines property owners as of 2018. As we discuss in Section 2.1., there was a substantial increase in scientific projections of SLR as well as popular attention to the issue in the years leading up to 2018.

If these developments have made Democrats increasingly more worried about SLR exposure compared to Republicans, then we expect the partisan-based sorting to be expanding. Alternatively, the opposite could be true – even if

Democrats are more worried about SLR and climate change compared to Republicans, the gap in concern could be closing over time. Whether either of these possibilities is occurring is important from a policy perspective because it determines the type of voting blocks that are emerging in coastal communities, which in turn impacts local responses to climate change.

We examine this question by incorporating voter registration data from 2012 to 2016, to go along with the 2018 data used throughout our previous analyses. Our first empirical test splits the sample into 2012 and 2018 observations. For each group we regress the 2018 political affiliation of the resident on whether the property is exposed to 6-feet of SLR. For this analysis, we restrict the sample to properties that enter our sample in both 2012 and 2018, and drop observations exposed to between 6 and ten feet of SLR. In Table 8, columns 1 and 2 both indicate that political affiliation is significantly related to the property's SLR exposure. Comparing the two coefficients, suggests that this relation has almost tripled in magnitude between 2012 and 2018.

To examine this trend more formally, we combine the two samples and add an Exposed x '18 interaction, which estimates the differential relation between exposure and the 2018 resident's political affiliation to the 2012 resident's political affiliation. The estimate on this interaction term in Column 3 is 0.026 and statistically significant showing that the differential sorting has more than doubled from 2012 to 2018. Column 4 shows that the result in Column 3 is robust to an alternative definition of political affiliation, where we match the listed voter registration in a given year to the modal L2 affiliation definition. This alleviates concerns that our findings are influenced by the use of current, rather than historical voter affiliation.

Columns 5 and 6 show that the results again remain significant after the inclusion of parcel fixed effects, or the inclusion of properties with between 6 and ten feet of SLR exposure. Across the columns the estimate remains similar in magnitude, except for predictably decreasing in magnitude after we introduce less exposed properties into the definition of Exposure in Column 6. The similarity of the estimates using within property variation directly supports a migration of more conservative residents replacing less conservative residents in SLR exposed homes, when compared to unexposed homes.

In Column 7 we then explore when this growing partisanship occurred by also including data on party affiliation in 2014 and 2016 and interacting those years with exposure, all relative to 2012. Interestingly, it appears that while there is already partisan sorting in 2012, this remains relatively similar until at least 2016, at which point there is an increase prior to 2018. While there could be any number of explanations, one key event over this period is the presidential election of Donald Trump in 2016. Such an event could plausibly lead to rising pessimism of democrats and perhaps, subsequently a rise in sorting.

We explore this potential source of the rising partisan sorting in Table 9 by seeing whether rising Republican presence or rising climate change concerns relate to the 2016-2018 increase in partisan sorting. Since this analysis involves heterogeneity, we will again use our continuous measure of exposure, *Feet Inundated*, as in Section 4.2. In Columns 1 and 2 we confirm the same pattern we observe with our discrete measure of exposure in the prior table – sorting exists from 2012-2016, but appears to rise from 2016-2018. In Columns 3 and 4 we explore regional heterogeneity in this rise. If this rise is driven by pessimism about future adaptation in the face of Republican political power, we might expect it to be concentrated in counties where the Republican party presidential nominee performed better in 2016 (Trump) than 2012 (Romney).[30] Column 3 provides little support for this idea. Instead, in Column 4 we find that growing sorting is larger in

[30] For example, Bonaparte, Kumar, and Page (2017 JFM) show that people become more optimistic about the economy and investments when their preferred party is in control of the White House, and that this optimism/pessimism affects their financial investment decisions.

counties that had an increase in those reported being worried about climate change from 2014-2016. It may still be that concerns about the possibility of Donald Trump's election in 2016, could have driven up worry about climate change in some regions even in earlier parts of 2016, as well as subsequent sorting. Disentangling these alternatives is outside the scope of this paper, but an interesting question for future work. In the meantime, what we can say is that partisan sorting on SLR risk appears to have escalated from 2016-2018, driven by regions with growing concern about climate change over the prior two years.

Taken together, our findings suggest that partisanship-based sorting over temporally distant climate change risks is reflected in current residential ownership choice. Moreover, the extent of this partisan-divide is expanding over time. This is an important consideration for policymakers because it may impact the response of local residents to climate change threats. Whether the reduction in future local spending on climate change remediation that is suggested by our estimates is optimal is a question for future research.

5 Conclusion

In this paper we show that climate change partisanship is reflected in residential choice. We use detailed nationwide data on all individual voters and properties in coastal communities to compare homes in the same zip code that are a similar elevation and proximity to the coast, but have differing sea level rise (SLR) exposures. After including these controls, Democratic (Republican) voters in coastal communities are less (more) likely than Independents to own properties at risk of becoming worthless because of rising sea levels caused by climate change. Even moderately exposed properties have a 4-5 percentage point Republican-Democrat residency gap, relative to otherwise similar properties. Moreover, this gap more than doubled between 2012 and 2018 and is as large as 10 percentage points for the most highly exposed homes.

These differential choices appear to reflect partisan differences in beliefs regarding the long-run effects of climate change. Results are unchanged controlling flexibly for a broad set of observable property characteristics and individual demographic information. Our findings also hold after including flexible controls for house values, suggesting sorting is not driven by differential selection on valuable amenities. Moreover, partisan-based sorting does not exist with respect to measures of immediate flood risk, and exists among the owners, but not renters, of non-owner-occupied properties.

Our findings have important implications for academics and policymakers in climate finance, political science, real estate, urban economics, environmental economics, and geography. Our results suggest that partisan rhetoric about climate change is more than just talk; residents are "voting with their feet" for salient risks or disamenities that are forward looking. The anticipatory sorting and systematic differences in the pattern of residential movement that we document have important implications for models in environmental economics and geography projecting future migration in response to climate change. Models rarely consider the implications of shifts in residential choice decades in advance of any actual climate change-induced damage or that this earlier shift in migrants may differ systematically based on beliefs. In fact, we find that climate change-induced residential choice is already occurring along political party lines. This may be especially important for policymakers since the growing share of those bearing the burden of future climate change, may also be those least concerned and perhaps unlikely to support adaptation/mitigation efforts.

References

Alesina, Alberto, Stefanie Statcheva, and Edoardo Teso. 2018. “Intergenerational Mobility and Preferences for Redistribution”. *American Economic Review* 108(2): 521-554.

Alesina, Alberto, Stefanie Statcheva, and Edoardo Teso. 2020. “The Polarization of Reality”. *AEA Papers and Proceedings* 110:324-328.

Atreya, Ajita, and Jeffrey Czajkowski. 2019. "Graduated flood risks and property prices in Galveston County." *Real Estate Economics* 47(3): 807-844.

Bakkensen, Laura A., and Lint Barrage. 2021. “Flood risk belief heterogeneity and coastal home price dynamics: Going under water?” *Review of Financial Studies, Forthcoming*.

Bakkensen, Laura A. and Lala Ma. 2020. “Sorting over flood risk and implications for policy reform.” *Journal of Environmental Economics and Management,* 104.

Bakker, A. M. R., Wong, T. E., Ruckert, K. L., & Keller, K. 2017. “Sea-level projections representing the deeply uncertain contribution of the West Antarctic ice sheet.” *Nature Scientific Reports,* 7:3880.

Baldauf, M., Garlappi, L., & Yannelis, C. 2020. “Does climate change affect real estate prices? Only if you believe in it.” *The Review of Financial Studies*, 33(3), 1256-1295.

Banzhaf, Spencer, Lala Ma, and Christopher Timmins. 2019. "Environmental justice: The economics of race, place, and pollution." *Journal of Economic Perspectives* 33(1): 185-208.

Banzhaf, H. Spencer, and Randall P. Walsh. 2013. “Segregation and Tiebout Sorting: The Link Between Place-based Investments and Neighborhood Tipping.” *Journal of Urban Economics* 74: 83–98.

Banzhaf, H. Spencer, and Randall P. Walsh. 2008. "Do people vote with their feet? An empirical test of Tiebout." *American Economic Review* 98(3): 843-863.

Bento, Antonio, Matthew Freedman, and Corey Lang. 2015. "Who benefits from environmental regulation? Evidence from the Clean Air Act Amendments." *Review of Economics and Statistics* 97(3): 610-622.

Bernstein, A., Gustafson, M. T., & Lewis, R. 2019. “Disaster on the horizon: The price effect of sea level rise.” *Journal of Financial Economics*, 134(2), 253-272.

Billings, Stephen. 2019. “Technical Summary - Merging Home Mortgage Disclosure Data to Property Records from Zillow (Ztrax) 1995-2016.” https://sites.google.com/a/colorado.edu/stephen-billings/code

Bin, Okmyung, and Craig E. Landry. 2013. "Changes in implicit flood risk premiums: Empirical evidence from the housing market." *Journal of Environmental Economics and management* 65(3): 361-376.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang. 2014. “Nonlinear permanent migration response to climatic variations but minimal response to disasters.” *PNAS*, 111(27): 9780–9785

Bolsen, T., & Druckman, J. N. 2018. “Do partisanship and politicization undermine the impact of a scientific consensus message about climate change?” *Group Processes & Intergroup Relations*, 21(3), 389-402.

Bonaparte, Yosef, Alok Kumar, and Jeremy Page. 2017. “Political climate, optimism, and investment decisions.” *Journal of Financial Markets*, 34: 69-94.

Boustan, Leah Platt, Matthew E. Kahn, and Paul W. Rhode. 2012. “Moving to Higher Ground: Migration Responpse to Natural Disasters in the Early Twentieth Century.” *American Economic Review P&P*, 102(3): 238–244.

Bosker, Maarten, Harry Garretsen, Gerard Marlet, and Clemens van Woerkens. 2019 "Nether Lands: Evidence on the price and perception of rare natural disasters." *Journal of the European Economic Association* 17(2): 413-453.

Brunnermeier, M. K., Simsek, A., & Xiong, W. 2014. A welfare criterion for models with distorted beliefs. *The Quarterly Journal of Economics 129*(4): 1753-1797.

Buraschi, A., and Jiltsov, A. 2006. Model uncertainty and option markets with heterogeneous beliefs. *The Journal of Finance*, *61*(6): 2841-2897.

Campbell, J. Y., 2006. “Household finance.” *The Journal of Finance* 61, 1553–1604.

Carleton, T. A., & Hsiang, S. M. 2016. “Social and economic impacts of climate.” *Science*, *353*(6304).

Chan, Kam Fong, and Terry Marsh. 2021. “Asset prices, midterm elections, and political uncertainty”. *Journal of Financial Economics*.

Chen, M. K., & Rohla, R. 2018. “The effect of partisanship and political advertising on close family ties.” *Science*, *360*(6392), 1020-1024.

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.” Q*uarterly Journal of Economics* 129, 1141–1219

Cookson, J. A., Engelberg, J., & Mullins, W. 2020. “Does Partisanship Shape Investor Beliefs? Evidence from the COVID-19 Pandemic.” *Review of Asset Pricing Studies.*

David, A. 2008. Heterogeneous beliefs, speculation, and the equity premium. *The Journal of Finance*, *63*(1): 41-83.

Davis, Lucas W. "The effect of power plants on local housing values and rents." *Review of Economics and Statistics* 93.4 (2011): 1391-1402.

Dell, M., Jones, B. F., & Olken, B. A. 2014. “What do we learn from the weather? The new climate-economy literature.” *Journal of Economic Literature*, *52*(3), 740-98.

Desmet, K., Rossi-Hansberg, E., 2014. “Spatial development.” *American Economic Review* 104 (4), 1211–1243.

Desmet, Klaus, and Esteban Rossi-Hansberg. 2015. “On the Spatial Economic Impact of Global Warming.” *Journal of Urban Economics*, 88: 16–37.

Drummond, C., & Fischhoff, B. 2017. “Individuals with greater science literacy and education have more polarized beliefs on controversial science topics.” *Proceedings of the National Academy of Sciences*, *114*(36), 9587-9592.

Dumas, B., Kurshev, A., and Uppal, R. 2009. Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility. *The Journal of Finance*, *64*(2): 579-629.

Edlund, L., & Pande, R. 2002. “Why have women become left-wing? The political gender gap and the decline in marriage.” *Quarterly Journal of Economics*, 117(3), 917-961.

Ehling, P., Gallmeyer, M., Heyerdahl-Larsen, C., and Illeditsch, P. 2018. Disagreement about inflation and the yield curve. *Journal of Financial Economics*, *127*(3): 459-484.

Fedyk, Y., Heyerdahl-Larsen, C., and Walden, J. 2013. Market selection and welfare in a multi-asset economy. *Review of Finance*, *17*(3): 1179-1237.

Forsythe, R., Nelson, F., Neumann, G. R., & Wright, J. 1992. “Anatomy of an experimental political stock market.” *American Economic Review*, 1142-1161.

Gallagher, Justin. 2014. "Learning about an infrequent event: evidence from flood insurance take-up in the United States." *American Economic Journal: Applied Economics* 206-233.

Garner, Andra J., Jeremy L. Weiss, Adam Parris, Robert E. Kopp, Radley M. Horton, Jonathan T. Overpeck, and Benjamin P. Horton. 2018. “Evolution of 21st century sea level rise projections.” *Earth’s Future* 6, 1603–1615.

Gilboa, I., Samuelson, L., and Schmeidler, D. 2014. No-Betting-Pareto Dominance. *Econometrica 82*(4): 1405-1442.

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

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., Weber, A., 2018. "Climate change and Long-Run Discount Rates: Evidence from Real Estate." Working Paper.

Green, Jon, Jared Edgerton, Daniel Naftel, Kelsey Shoub, Skyler J. Cranmer. 2020. "Elusive consensus: Polarization in elite communication on the COVID-19 pandemic." *Science Advances* 6(28).

Grossman, Guy, Soojong Kim, Jonah M. Rexer, and Harsha Thirumurthy. 2020. "Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States". *PNAS*. 117 (39) 24144-24153.

Hamilton, Lawrence C. 2011. "Education, Politics, and Opinions about Climate Change: Evidence for Interaction Effects." *Climatic Change.*

Hauer, M. E., Evans, J. M., and Mishra, D. R. 2016. Millions projected to be at risk from sea-level rise in the continental United States. *Nature Climate Change*, *6*(7): 691-695.

Hauer, M.E., 2017. "Migration Induced by Sea Level Rise could Reshape the U.S. Population Landscape." *Nature Climate Change*, 7:321-325.

Heyerdahl-Larsen, C., and Walden, J. 2021. Distortions and Efficiency in Production Economies with Heterogeneous Beliefs. *The Review of Financial Studies, Forthcoming*.

Hornbeck, R. 2012. "The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe." *American Economic Review*, 102(4), 1477-1507.

Hornbeck, Richard 2020. "Dust Bowl Migrants: Identifying an Archetype." Working paper.

Hong, Harrison, Andrew Karolyi, and Jose A Scheinkman. 2020. "Climate Finance". *Review of Financial Studies*, 33(3):1011-1023.

Hsiang, S. M., Burke, M., & Miguel, E. 2013. "Quantifying the influence of climate on human conflict." *Science*, 341(6151).

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., & Mandel, G. 2012. "The polarizing impact of science literacy and numeracy on perceived climate change risks." *Nature climate change*, *2*(10):732-735.

Kahn, Matthew E. 2000. "Smog reduction’s impact on California county growth." *Journal of Regional science* 40(3): 565-582.

Kempf, E., & Tsoutsoura, M. 2021. “Partisan professionals: Evidence from credit rating analysts” *Journal of Finance, Forthcoming*.

Keys, Benjamin and Philip Mulder. 2020. “Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise.” National Bureau of Economic Research Working Paper 27930.

Kleven, Henrik, Camille Landais, Mathilde Munoz, and Stefanie Stantcheva. 2020. “Taxation and Migration: Evidence and Policy Implications”. *Journal of Economic Perspectives* 34(2): 119-142.

Kopp, R. E., DeConto, R. M., Bader, D. A., Hay, C. C., Horton, R. M., Kulp, S., et al. 2017. “Evolving understanding of Antarctic ice-sheet physics and ambiguity in probabilistic sea-level projections.” *Earth’s Future*, 5(12):1217–1233.

Kubler, F., and Schmedders, K. 2012. Financial innovation and asset price volatility. *American Economic Review*, *102*(3): 147-51.

Lavaine, Emmanuelle. 2019. "Environmental risk and differentiated housing values: Evidence from the north of France." *Journal of Housing Economics* 44: 74-87.

Le Bars, D., Drijfhout, S., & de Vries, H. 2017. “A high-end sea level rise probabilistic projection including rapid Antarctic ice sheet mass loss.” *Environmental Research Letters*, 12(4).

Long, E. F., Chen, M. Lavaine K., & Rohla, R. 2020. “Political storms: Emergent partisan skepticism of hurricane risks.” *Science Advances*, 6(37).

Mahajan, Parag, and Dean Yang. 2020. “Taken by Storm: Hurricanes, Migrant Networks, and US Immigration.” *American Economic Journal: Applied Economics*, 12(2): 250–277.

Makridis, Christos and Jonathan Rothwell. 2020. “The Real Cost of Political Polarization: Evidence from the COVID-19 Pandemic.” Working Paper.

Marcy, D., Herold, N., Waters, K., Brooks, W., Hadley, B., Pendleton, M., Schmid, K., Sutherland, M., Dragonov, K., McCombs, J., Ryan, S., 2011. “New mapping tool and techniques for visualizing sea level rise and coastal flooding impacts.” In Proceedings of the 2011 Solutions to Coastal Disasters Conference, Anchorage, Alaska 474–490.

McCartney, W Ben, and Calvin Zhang. 2020. “’Sort Selling’: Political Affiliation and Households’ Real Estate Decisions”. Working Paper.

McCartney, W Ben. 2021. “Does Household Finance Affect the Political Process? Evidence from Voter Turnout During a Housing Crisis”. *Review of Financial Studies* 34(2): 949-984.

McCright, A. M. 2011. “Political orientation moderates Americans’ beliefs and concern about climate change.” *Climatic Change*, 104(2), 243-253.

McCright, A. M., & Dunlap, R. E. 2011. “The politicization of climate change and polarization in the American public's views of global warming, 2001–2010.” *The Sociological Quarterly*, *52*(2), 155-194.

Meeuwis, M., Parker, J. A., Schoar, A., & Simester, D. I. 2018. “Belief disagreement and portfolio choice”. National Bureau of Economic Research Working Paper 25108.

Mian, A. R., Sufi, A., & Khoshkhou, N. 2021. “Partisan bias, economic expectations, and household spending.” *The Review of Economics and Statistics, Forthcoming*.

Murfin, Justin, and Matthew Spiegel. 2020. "Is the risk of sea level rise capitalized in residential real estate?" *The Review of Financial Studies* 33(3): 1217-1255.

Nauels, A., Meinshausen, M., Mengel, M., Lorbacher, K., & Wigley, T. M. L. 2017. “Synthesizing long-term sea level rise projections—The MAGICC sea level model v2.0.” *Geoscientific Model Development*, 10, 2495–2524.

Ortega, Francesc, and Süleyman Taṣpınar. 2018. "Rising sea levels and sinking property values: Hurricane Sandy and New York’s housing market." *Journal of Urban Economics* 106: 81-100.

Ouazad, A., & Kahn, M. E. 2019. “Mortgage finance in the face of rising climate risk” National Bureau of Economic Research Working Paper 26322.

Rao, K. 2017. “Climate change and housing: will a rising tide sink all homes?”. Residential Research Quarterly.

Ratnadiwakara, Dimuthu and Venugopal, Buvaneshwaran. 2019. “Climate Risk Perceptions and Demand for Flood Insurance”. Working Paper.

Sethi, Rajiv, and Rohini Somanathan. 2004. “Inequality and Segregation.” *Journal of Political Economy* 112(6): 1296–1321.

Simsek, A. 2013. Belief disagreements and collateral constraints. *Econometrica*, *81*(1): 1-53.

Simonsohn, Uri, Joseph P. Simmons, and Leif D. Nelson. 2020. “Specification curve analysis.” *Nature Human Behavior*.

Spitzer, Yannay, Gaspare Tortorici, and Ariell Zimran. 2020. “International Migration Responses to Natural Disasters: Evidence from Modern Europe’s Deadliest Earthquake.” National Bureau of Economic Research Working Paper 27506.

Stantcheva, Stefanie. 2020. “Understanding Economic Policies: What Do People Know and How Can They Learn?” Harvard University Working Paper.

Stern, Nicholas. 2007. “The Economics of Climate Change: The Stern Review.” Cambridge University Press.

Stocker T., Qin D. , . Plattner G., Tignor M., Allen S. , Boschung J., Nauels A. , Xia Y., Bex V., Midgley P. 2013. “Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change”, Cambridge University Press, New York. Book Section SPM (2013), pp. 1-30

Sweet, William, Robert Kopp, Christopher Weaver, Jayantha Obeysekera, Radley Horton, Robert Thieler, and Zervas. 2017. “Global and Regional Sea Level Rise Scenarios for the United States.” NOAA Technical Report NOS CO-OPS 83.

Wong, T. E., Bakker, A. M. R., & Keller, K. 2017. “Impacts of Antarctic fast dynamics on sea-level projections and coastal flood defense.” *Climatic Change*, 144(2), 347–364.

Xiong, W., and Yan, H. 2010. Heterogeneous expectations and bond markets. *The Review of Financial Studies*, *23*(4): 1433-1466.

Yan, H. 2008. Natural selection in financial markets: Does it work?. *Management Science*: *54*(11), 1935-1950.

Figure 1. Historical Sea Level Rise and Projections for the Future

These figures depict historical changes in sea level rise and scientific projections for the future. Figure 1a plots the change in global mean temperature (Celsius) and sea level rise (feet) over the 40 years from 1970 to 2010 (https://climate.nasa.gov/). Figure 1b plots projected future sea level rise (feet) by 2100 for medium and high emission scenarios for all studies with both scenarios considered and mentioned in Goldsmith-Pinkham et al. (2020). Points represent the mean SLR, while bars represent 95% confidence intervals from reported standard deviations in estimates and the assumption of normality.

Figure 1a. Historical Changes in Global Mean Temperature and Sea Level Rise Since 1970

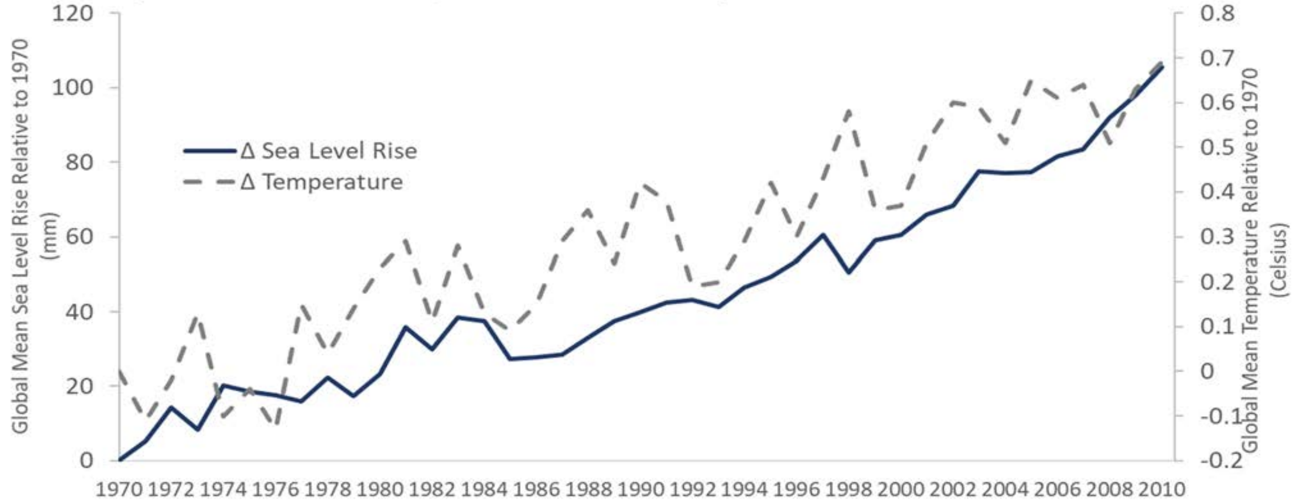


Figure 1b. Future Projections for Sea Level Rise (Feet by 2100) in '01 vs. '17

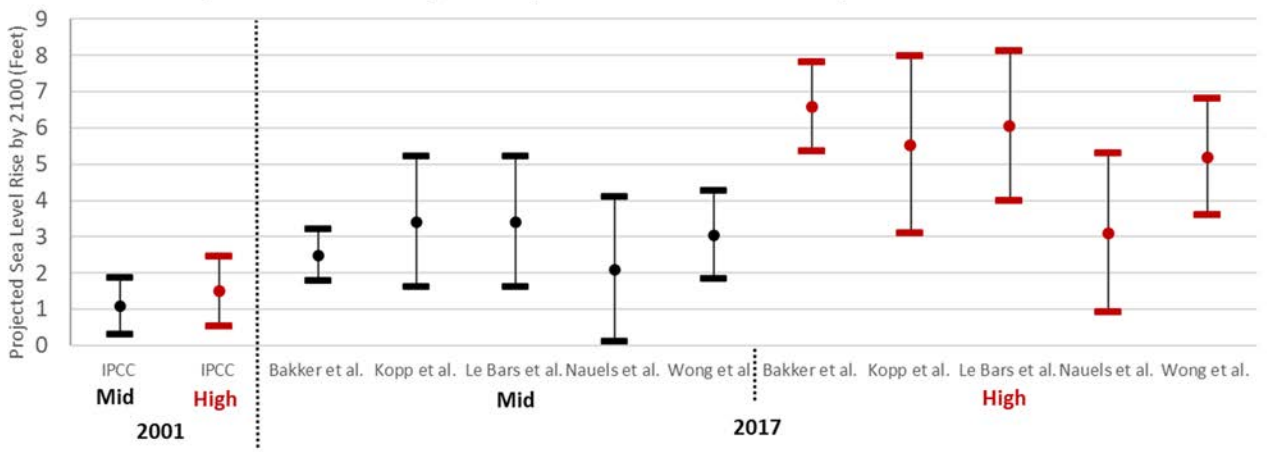


Figure 2. Pew Survey: % who say the issue is a top priority in 2020

This figure depicts the % of participants in a Pew Research Center survey of U.S. adults conducted Jan. 8-13, 2020 who say that "__ should be a top priority for President Trump and Congress", by stated political affiliation (red circles = republicans; blue diamonds = democrats) and the partisan gap between them in order of that gap (largest on the left and smallest on the right). For more details see www.pewresearch.org/.

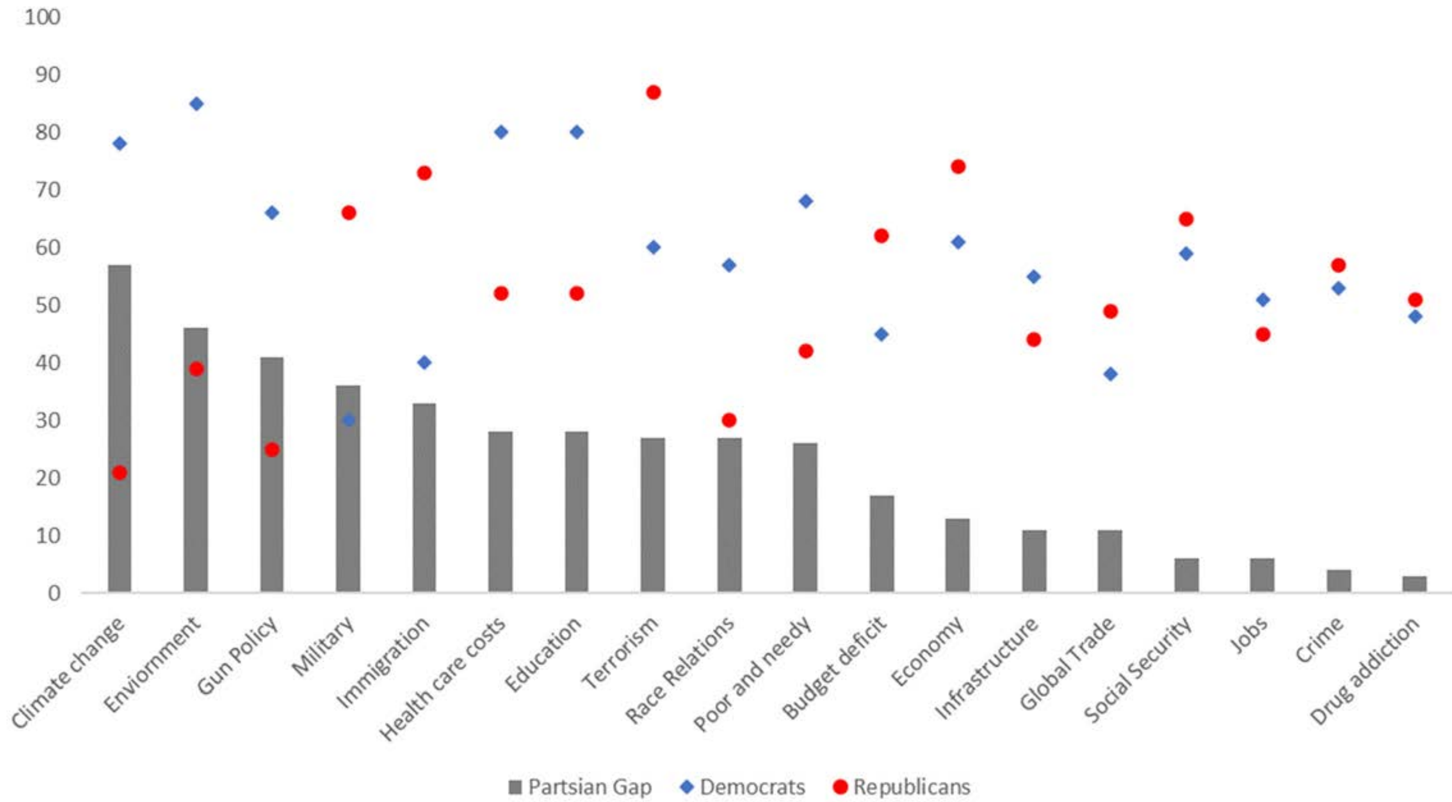
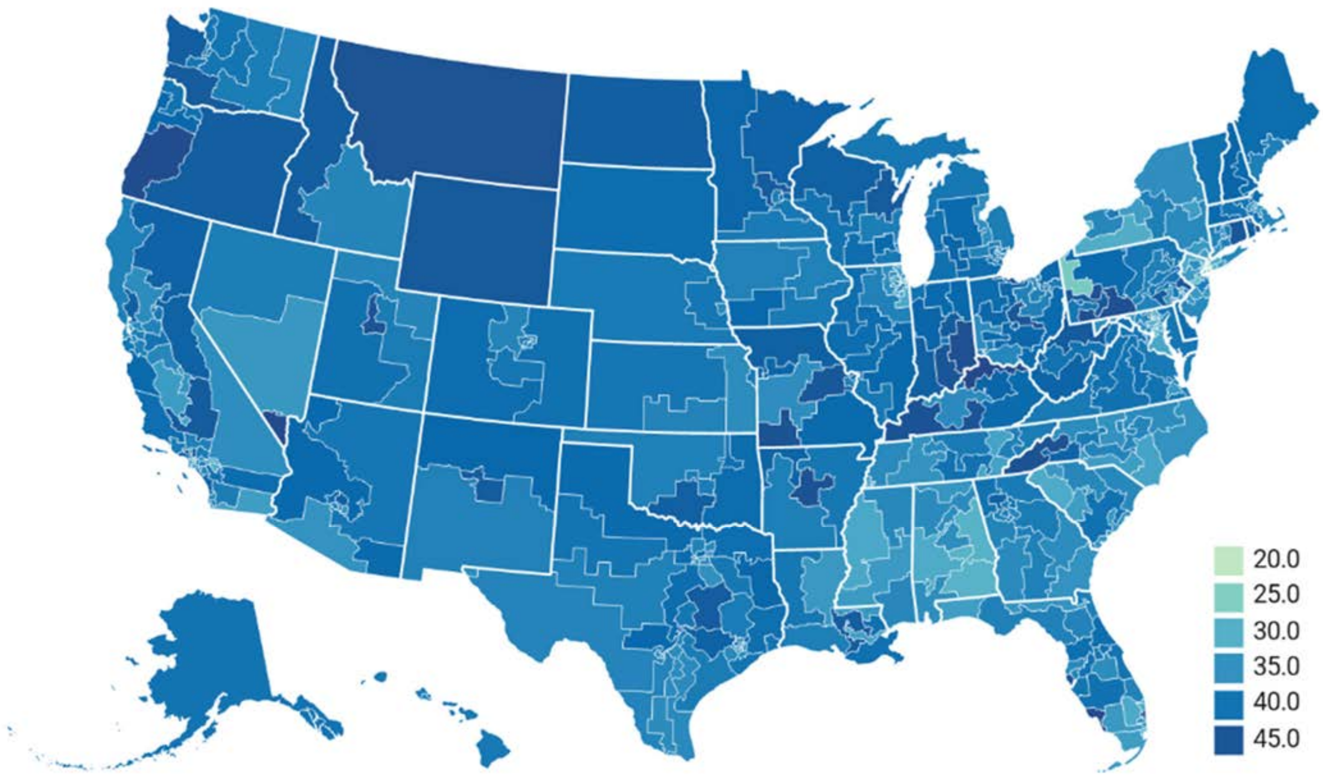


Figure 3. 2018 Yale Climate Survey: % that “think that global warming is happening” by Congressional District

The 2018 Yale Climate Survey (details here: https://climatecommunication.yale.edu), which asked participants “Do you think that global warming is happening?”. This figure depicts the % of democrats in a given congressional district who answered yes minus the % of republicans who answered yes. Darker blue indicates a larger gap between these groups in the answer to this question.



Partisan Gap (% Dems - % Reps):
Believe in Global Warming

Figure 4. Political Affiliation and Feet of SLR Until Inundated

This table shows that controlling for other property observables, residents of properties with more exposure to future rises in sea levels are more likely to be registered Republicans and less likely to be registered Democrats, and this is true even for properties unlikely to inundated without substantial increases in future sea level rise (SLR). In Panel A, the dependent variable is *Pol. Conservative* which takes the value of 1 if the owner is a registered republican, 0 if they are independent, and -1 if they are a democrat. In Panel B, the dependent variable is either 1 if the resident is a Democrat (in blue) or Republican (in red) relative to the omitted group (Independents – so in each regression the other party isn't included at all). These dependent variables are regressed on a dummy variables equal to 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by "X" feet after including property zip code x distance-to-the-coast quantiles x elevation quantile as well as the property characteristic controls outlined in Table 3. The coefficients on feet until SLR exposed are plotted, as well as 95% confidence intervals. Standard errors are clustered at the same level as the primary fixed effects.

Figure 4a. Combined Measure of Political Affiliation - Pol. Conservative

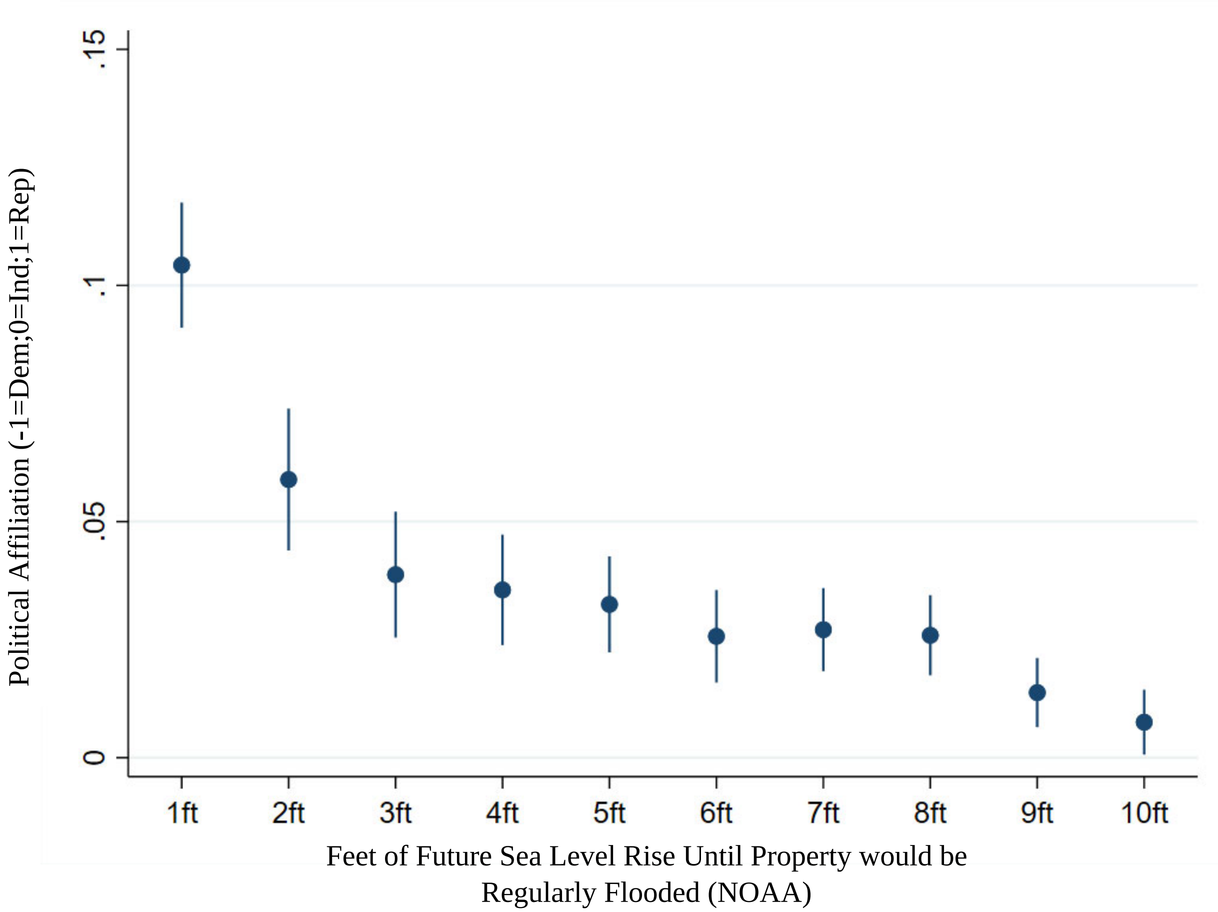
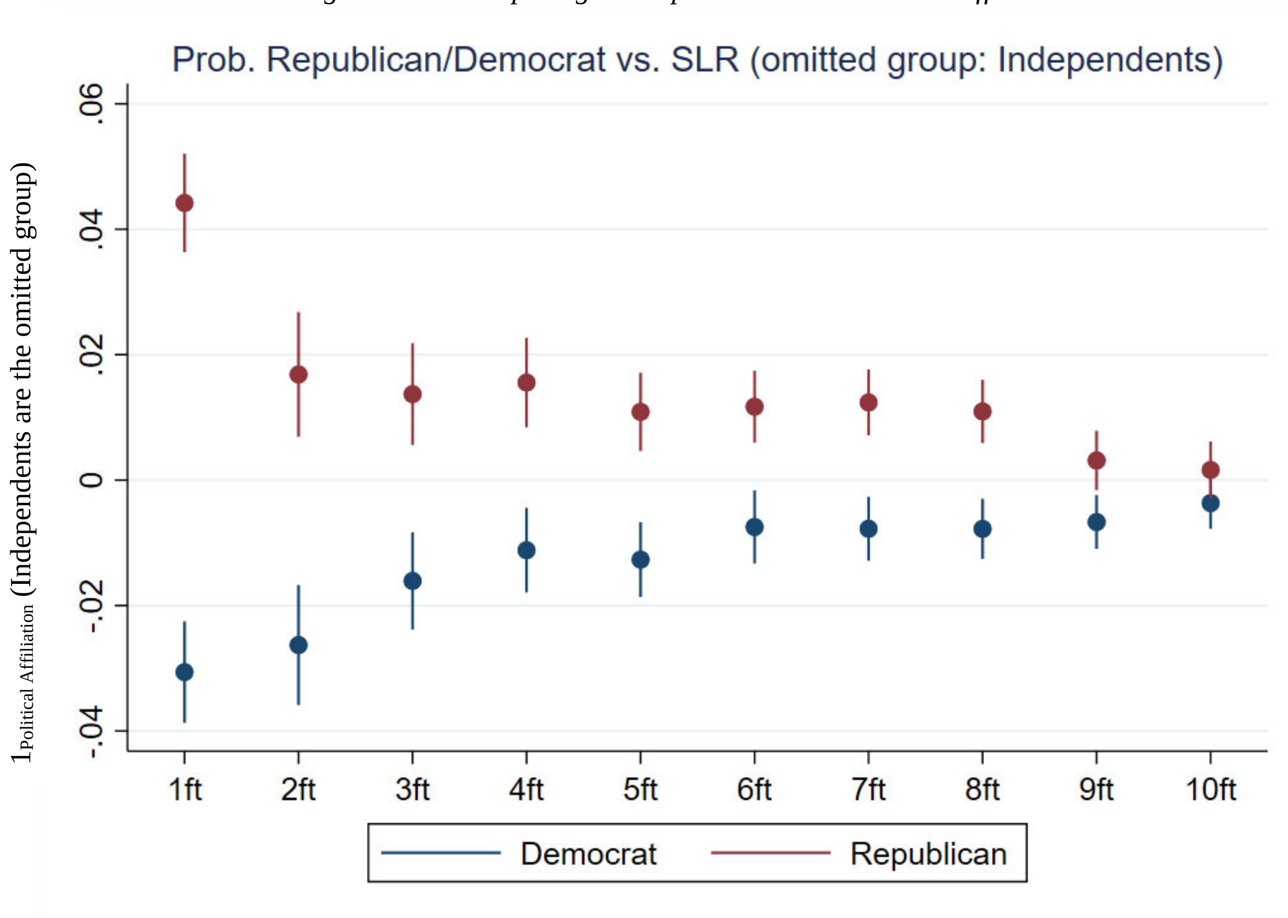


Figure 4b. Decomposing the Republican and Democrat Effects



Feet of Future Sea Level Rise Until Property would be Regularly Flooded (NOAA)

Figure 5. Specification Curve

This figure provides a number of specifications that vary our sample and how we define our controls for distance to coast as well as the inclusion/exclusion of property covariates in the spirit of Simonsohn et al. (2020). We focus on the three main samples used throughout the paper – all voters, voters in properties that sold since 2007 and voters with matched HMDA data. Our specification also varies by changing the distance to coast intervals used in our fixed effects as well as a model incorporating raw (not inflation adjusted) prices. We also provide some models that provide the most restrictive fixed effects – price by zip by distance to coast by elevation by year by quarter property was last sold. This limits identifications to properties sold nearby for similar prices in the same quarter with similar elevation. These restrictive fixed effects generate slightly larger and nosier estimates. Our two primary approaches used in the paper are highlighted in blue.

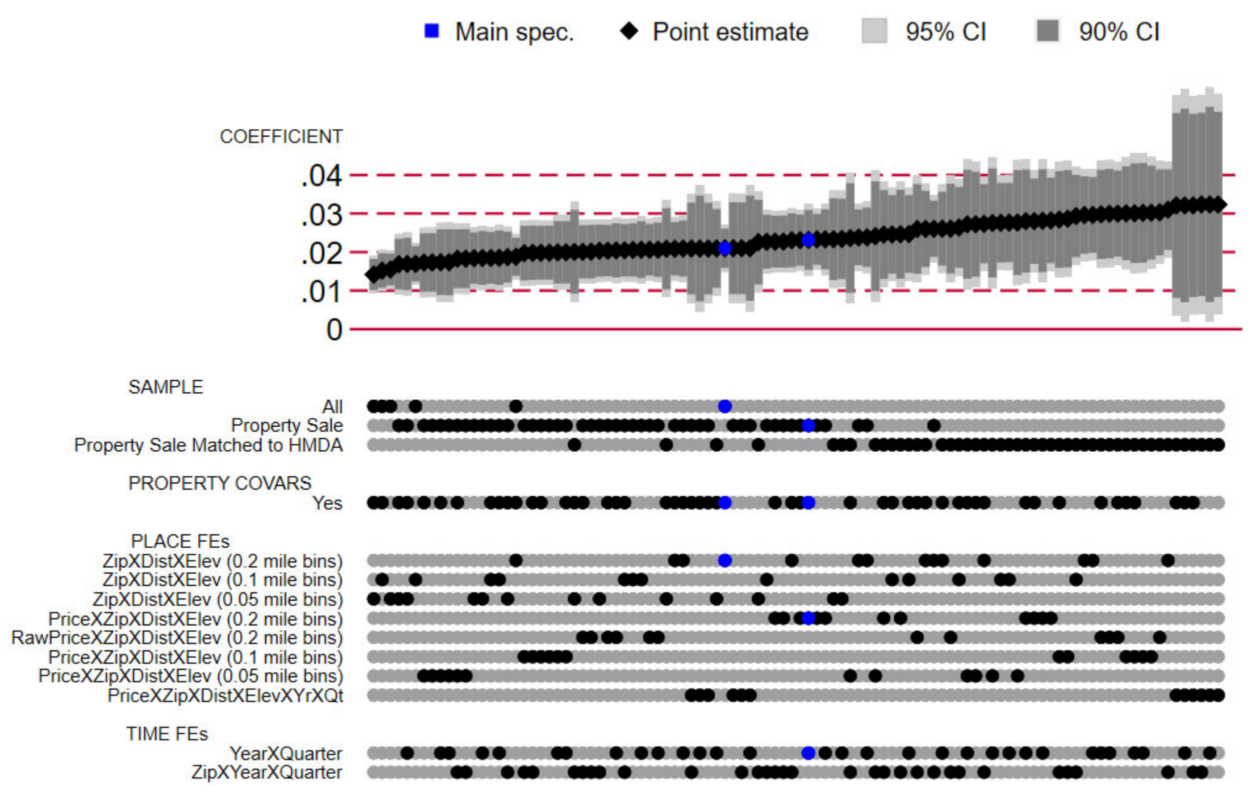


Table 1. County-Level Correlations: Political Affiliation, Sea Level Rise Exposure, and Concern about Climate Change

For the main sample of counties and properties/voters analyzed in our paper this table depicts the county-level correlations in the % of properties with exposure to up to 10 feet of future SLR (*% SLR)*, the % who are registered republicans (*% Republican*), the % who are registered democrats (*% Democrat*), the % who are independents (*% Independent*), the mean of our measure of political conservatism where -1 is for republican, 0 is for independents, and 1 is for democrats (*Avg Pol. Conservative*), the % of respondents who are worried about climate change based off the 2016 Yale Climate Survey (*% Worried*), and the % of respondents who think climate change will personally affect them based off the 2016 Yale Climate Survey (*% Personal*).

	% SLR	% Republican	% Democrat	% Independent	Avg Pol. Conservative	% Worried	% Personal
% SLR	1.00						
% Republican	0.09	1.00					
% Democrat	-0.05	-0.81	1.00				
% Independent	0.04	-0.28	-0.08	1.00			
Avg Pol. Conservative	0.07	0.95	-0.95	-0.10	1.00		
% Worried	-0.26	-0.59	0.56	0.12	-0.60	1.00	
% Personal	-0.18	-0.47	0.57	-0.05	-0.55	0.88	1.00

Table 2 – Descriptive Statistics

This table includes summary statistics from ZTRAX from 2007 to 2017 for properties matched to voters in the L2 database for coastal communities, and when available HMDA data with mortgage based buyer's income. Properties are restricted to those with 2 miles of the coast in counties where at least one property would be regularly inundated with 10 feet of future sea level rise based on projections from NOAA. Characteristics of properties and demographics/political affiliation are shown for all properties in our sample (column 1), those with exposure to 10 feet of SLR (column 2), and those not exposed even to 10 feet of SLR (column 3).

	(1) Full Sample		(2) Voters - SLR Properties		(3) Voters - No SLR Properties	
	Mean	*Std Dev*	*Mean*	*Std Dev*	*Mean*	*Std Dev*
Voter Attributes						
Republican	0.23		0.31		0.21	
Democratic	0.50		0.41		0.52	
Independent/Non-major	0.27		0.27		0.27	
White	0.55		0.55		0.55	
Hispanic	0.16		0.18		0.16	
Black	0.13		0.13		0.13	
Asian	0.05		0.03		0.05	
Age of Voter	49.89	(18.74)	51.74	(18.88)	49.41	(18.68)
# of Voters HH	2.03	(0.99)	2.04	(0.97)	2.02	(0.99)
Housing Attributes						
Sales Price (2008)	565,819	(683,926)	554,481	(674,973)	565,192	(683,379)
Homebuyer Income ($000s)	134.9	(192.2)	149.8	(240.8)	130.2	(174.4)
Age of Home	14.68	(29.24)	10.47	(21.75)	15.68	(30.67)
Living Sq Ft	2,936	(5,509)	2,435	(4,163)	3,050	(5,782)
Condominiums	0.05	(0.22)	0.06	(0.23)	0.05	(0.22)
Bedrooms	1.52	(1.95)	1.61	(1.86)	1.50	(1.97)
Bathrooms	1.09	(1.51)	1.27	(1.62)	1.04	(1.48)
Height of Building	1.62	(2.75)	1.29	(2.24)	1.70	(2.85)
Garage	0.01	(0.09)	0.01	(0.10)	0.01	(0.08)
Pool	0.07	(0.25)	0.16	(0.37)	0.04	(0.20)
Observations	16,149,268		2,957,275		13,073,881	

Table 3. Political Affiliation and Sea Level Rise Exposure

This table shows that controlling for other property observables, residents of properties with more exposure to future rises in sea levels are more likely to be registered republicans and less likely to be registered democrats. Panel A, B, and C are identical specifications, but panel B excludes properties with exposure to 7-10 feet of SLR to focus on effects for more exposed properties, while C tests for statistically significant differences for more exposed properties. The dependent variable in Column 1 is an indicator for being a republican. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. The specification includes property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. Column 2 is the same as column 1, but drops all residents identified as democrats. Column 3 is the same as column 1, but drops all residents identified as republicans and the dependent variable is an indicator for being a democrat. Column 4 is the same as column 1, but the dependent variable takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. Column 5 is the same as column 4, but adds controls for property characteristics including third order polynomials of building age and lot size square footage, as well as fixed effects for the number of bedrooms, bathrooms, building height, assessed building quality, and presence of a garage or pool. Column 6 limits the sample to properties that had an arm's length market transaction with prices. We then add year-quarter of transaction fixed effects and interact the primary fixed effects with most recent transaction price quantile fixed effects, to flexibly control for potential unobservable differences. Throughout the table standard errors are clustered at the level of the fixed effects structure (ZipxDistxElev in Columns 1-5 and double clustered at year-quarter and PricexZipxDistxElev in column 6) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

Panel A. Inundated w/ 10 feet SLR

	Rep		Dem	Rep-Dem Gap ("Pol. Cons.")		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.010***	0.008***	-0.007***	0.021***	0.019***	0.023***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)
ZipxDistxElev FEs	Y	Y	Y	Y	Y	-
Dropped	-	dem	rep	-	-	-
Property Controls	-	-	-	-	Y	Y
PricexZipxDistxElev FEs	-	-	-	-	-	Y
Year-Quarter FE	-	-	-	-	-	Y
Dep Var (mean)	0.225	-	-	-	-	-
R-sq	0.184	0.165	0.123	0.220	0.221	0.407
Obs	16,109,407	8,096,529	12,435,875	16,109,407	16,109,407	4,065,858
Obs (drop singletons)	16,092,264	8,076,984	12,417,740	16,092,264	16,092,260	3,949,439

Panel B. Inundated w/ 6 feet SLR (7-10 feet excluded)

	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.025***	0.020***	-0.015***	0.048***	0.042***	0.054***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.006)	(0.009)
Dep Var (mean)	0.217	-	-	-	-	-
R-sq	0.186	0.170	0.126	0.221	0.222	0.425
Obs	14,600,469	7,243,302	11,369,882	14,600,469	14,600,469	3,631,220

Panel C. Inundated w/ 10 feet SLR vs. 6 feet						
Exposed (≤10ft)	0.009***	0.007***	-0.006***	0.019***	0.017***	0.022***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)
Exposed (≤ 6ft)	0.009***	0.007***	-0.006***	0.017***	0.013***	0.012***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)
R-sq	0.184	0.165	0.123	0.220	0.221	0.407
Obs	16,109,407	8,096,529	12,435,875	16,109,407	16,109,407	4,065,858

Table 4: Heterogeneity in SLR-induced partisan sorting

Each coefficient represents the interaction between a continuous SLR exposure measure that ranges from 0 for unexposed properties to 10 for properties exposed to one or less feet of SLR. In Columns 1 through 4 we interact this measure with indicators for areas with above median relative sea level rise (Column 1 and 2) or above median variation in high tides (Column 3 and 4). Columns 5 and 6 interact exposure with a dummy if the state legislature is majority Republican as of 2016. All models include eleven fixed effects for properties that are exposed to zero to ten feet of SLR as well as year-quarter and property zip code x distance-to-the-coast quantiles x elevation quantile. For even columns (2, 4, and 6) we interact the primary fixed effects with most recent transaction price quantile fixed effects, to flexibly control for potential unobservable differences. We also control in all columns for property characteristics including third order polynomials of building age and lot size square footage, as well as fixed effects for the number of bedrooms, bathrooms, building height, assessed building quality, and presence of a garage or pool. Throughout the table standard errors are clustered at the level of the fixed effects structure (ZipxDistxElev in Columns 1, 3, and 5, and double clustered at year-quarter and PricexZipxDistxElev in columns 2, 4, and 6) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	(1)	(2)	(3)	(4)	(5)	(6)
Feet Inundated x RSLR>Median	0.0023*	0.0028*				
	(0.0013)	(0.0015)				
Feet Inundated x Tidal Variation > Median			0.0029**	0.0023		
			(0.0013)	(0.0015)		
Feet Inundated x (Rep. Leg. Majority)					0.0071***	0.0037**
					(0.0012)	(0.0018)
SLR Exposure Bins	Y	Y	Y	Y	Y	Y
Property Controls	Y	Y	Y	Y	Y	Y
ZipxDistxElev FEs	Y	-	Y	-	Y	-
PricexZipxDistxElev FEs	-	Y	-	Y	-	Y
Year-Quarter FE	-	Y	-	Y	-	Y
R-sq	0.222	0.407	0.222	0.407	0.222	0.407
Obs	16,109,407	4,065,858	16,109,407	4,065,858	16,109,407	4,065,858

Table 5. Controlling for Other Demographics

This table shows that controlling for other resident observables, residents of properties with more exposure to future rises in sea levels are more likely to be registered Republicans. The dependent variable is *Pol. Conservative*, which takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. Column 1 controls for year-quarter fixed effects and zip code x distance-to-the-coast quantiles x elevation quantile x transaction price quantile fixed effects as well as voter age, whether the resident is non-white, and household gross income (aggregate income of all buyers on a mortgage). Column 2 is the same as column 1, but instead of any linear controls includes fixed effects for voter age, to more flexible control for any potential non-linear effects. Column 3 is the same as column 2, but also adds fixed effects for black, Hispanic, and Asian ethnicities. Column 4 is the same as column 3, but includes fixed effects for income deciles. Column 5 is the same as column 4, but includes fixed effects for years of education. All models contain less observations than Table 3 because we require observations to contain HMDA based measures of income which are not available for cash purchases as well as some transactions that are not-matchable to property records (see Billings (2019) for HMDA matching procedures and a discussion of matching ZTRAX to HMDA more broadly). Standard errors are clustered at the same level as the primary fixed effects (i.e., double clustered at year-quarter and PricexZipxDistxElev) and are shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")				
	(1)	(2)	(3)	(4)	(5)
Exposed	0.027***	0.028***	0.024***	0.024***	0.024***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Voter Age (yrs)	-0.000				
	(0.000)				
Non-white	-0.186***				
	(0.003)				
HH Gross Inc ($000s)	0.00022***				
	(0.00002)				
PricexZipxDistxElev FEs	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y
Age FE	-	Y	Y	Y	Y
Race FE	-	-	Y	Y	Y
Income Bkt FE	-	-	-	Y	Y
Educ Yrs FE	-	-	-	-	Y
Included Exposure	All	All	All	All	All
R-sq	0.476	0.469	0.486	0.486	0.485
Obs	1,653,999	1,654,002	1,654,002	1,653,999	1,644,959

Table 6. Future vs. Current Flood Risk

This table shows that controlling for other property observables, properties with more exposure to future rises in sea levels, not just higher current flood risk, are more likely to be registered republicans. The dependent variable is *Pol. Conservative*, which takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat. *Exposed* equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. Column 1 provides a baseline and is identical to Column 6 of Table 3. Column 2 is the same as column 1, but includes fixed effects for highest expected feet of storm surge flooding based on NOAA simulations for that parcel. Column 3 is the same as column 2, but excludes properties in the west coast of the united states, which don't have hurricanes or NOAA storm surge projections. Columns 4 and 5 remove the storm surge fixed effects and include an indicator for the presence of any storm surge and a continuous measure of storm surge exposure, respectively. Standard errors are clustered at the same level as the primary fixed effects (i.e., double clustered at year-quarter and PricexZipxDistxElev) and are shown in parentheses. P-Values: * 10%; ** 5%; ***1%

	Rep-Dem Gap ("Pol. Cons.")				
	(1)	(2)	(3)	(4)	(5)
Exposed	0.023***	0.024***	0.025***		
	(0.005)	(0.005)	(0.005)		
Exposed to storm surge				-0.003	
				(0.003)	
Expected storm surge inundation (ft)					-0.000
					(0.000)
Property Controls	Y	Y	Y	Y	Y
PricexZipxDistxElev FEs	Y	Y	Y	Y	Y
Storm Surge FEs	-	Y	Y	-	-
Year-Quarter FE	Y	Y	Y	Y	Y
Exclude West Coast	-	-	Y	-	-
Included Exposure	All	All	All	All	All
R-sq	0.407	0.407	0.394	0.407	0.407
Obs	4,065,858	4,065,858	3,212,262	4,065,858	4,065,858

Table 7. Rental Properties: Owners vs. Renters

This table shows that controlling for other property observables, owners (rather than renters) of non-owner-occupied properties with more exposure to future rises in sea levels are more likely to be registered Republicans. The dependent variable in columns 1 through 3 is *Owner Pol. Cons.* which takes the value of 1 if the owner is a registered republican, 0 if they are independent, and -1 if they are a democrat. In Columns 4 and 5 the dependent variable, *Renter Pol. Cons*, is the same, but looks at voter registration of the residents of non-owner-occupied properties (aka the renters), not the owners. We employ two rental definitions. In Columns 1, 2, and 4 we define a renter as a resident in a property listed as non-owner occupied. In Columns 3 and 5, we expand the definition to also include instances where the mailing address for the owner is in a different zip code than the property. The explanatory variable of interest is *Exposed*, a dummy variable equal to 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. All columns control for property zip code x distance-to-the-coast quantiles x elevation quantile and year-quarter fixed effects as well as property controls (i.e. third order polynomials of building age and lot size square footage, as well as fixed effects for the number of bedrooms, bathrooms, building height, assessed building quality, and presence of a garage or pool). Column 4 is the same as column 3, but includes both renter and owner (conservative) political affiliation. Standard errors are clustered at the same level as the primary fixed effects (i.e., double clustered at year-quarter and PricexZipxDistxElev) and are shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")				
	Owners			Renters	
	(1)	(2)	(3)	(4)	(5)
Exposed	0.032**	0.031**	0.029**	0.013	0.012
	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
Renter Pol Cons		0.073***	0.076***		
		(0.002)	(0.002)		
Owner Pol Cons				0.191***	0.195***
				(0.006)	(0.006)
Property Controls	Y	Y	Y	Y	Y
PricexZipxDistxElev FEs	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y
Rentals	Y	Y	Y	Y	Y
Rental Proxy	1	1	2	1	2
Included Exposure	All	All	All	All	All
R-sq	0.707	0.711	0.711	0.498	0.498
Obs	581,273	581,273	594,302	581,273	594,302

Table 8. Growing Partisan Sorting on Climate Change Risk

This table shows that partisan-based sorting into SLR exposed properties has increased between 2012 and 2018. The dependent variable is Pol. Cons. which takes the value of 1 if the owner is a registered republican, 0 if they are independent, and -1 if they are a democrat. The explanatory variable of interest is Exposed, a dummy variable equal to 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. All columns control for property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. Column 1 looks at the 2018 political affiliation of people associated with a property in 2012. Column 2 is the same as column 1, but looks at people associated with a property in 2018. Column 3 is the same as column 1, but includes both people's 2012 and 2018 affiliations and looks at the interaction between a exposure and the year being 2018 (rather than 2012) when the people are associated with a given property. Column 4 is the same as column 3, but uses 2012 instead of 2018 voter affiliation based on a mapping from observed voter registration strings to the modal values of those strings in L2. Column 5 is the same as column 3, but includes property fixed effects. Column 6 is the same as column 5, but exclude properties that would be inundated with between 6 and 10 feet of SLR. Column 7 is the same as column 6, but includes political affiliations in the same properties in 2014 and 2016 as well, and includes the interaction of all year dummies with exposure (with 2012 as the omitted year as in column 6). Standard errors are clustered at ZipxDistxElev level and are shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed	0.017**	0.043***	0.017**	0.019**			
	(0.008)	(0.008)	(0.008)	(0.008)			
Exposed x '18			0.026***	0.024***	0.026***	0.015***	0.027***
			(0.007)	(0.009)	(0.007)	(0.004)	(0.007)
Exposed x '14							0.000
							(0.002)
Exposed x '16							-0.001
							(0.003)
ZipxDistxElev FEs	Y	Y	-	-	-	-	-
ZipxDistxElevxTime FE	-	-	Y	Y	Y	Y	Y
Property FE	-	-	-	-	Y	Y	Y
Included Exposure	<=6ft	<=6ft	<=6ft	<=6ft	<=6ft	All	<=6ft
Included Year(s)	'12	'18	'12&18	'12&18	'12&18	'12&18	'12-18
'12 Pol Affiliation Measure	1	-	1	2	1	1	1
R-sq	0.247	0.217	0.228	0.190	0.752	0.754	0.702
Obs	2,472,507	3,624,233	6,096,740	6,644,567	6,096,740	6,461,533	11,646,888

Table 9. Growing Partisan Sorting on Climate Change Risk and the 2016 Election

This table examines whether rising partisan sorting could be related to outcome of the 2016 election. The dependent variable is Pol. Cons. which takes the value of 1 if the owner is a registered republican, 0 if they are independent, and -1 if they are a democrat. The explanatory variable of interest is Feet Inundated, a continuous SLR exposure measure that ranges from 0 for unexposed properties to 11 for properties exposed to zero foot of SLR. All columns control for property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. Column 1 includes the political affiliation of all members of property in 2012, 2014, 2016, and 2018 and includes the interaction of all year dummies with Feet Inundated (with 2012 as the omitted year). Column 2 is the same as column 1, but includes property fixed effects. Column 3 is the same as column 2, but drops the interactions of years in 2014 and 2016, and interacts Feet Inundated x ’18 with the change in the republican presidential candidates share in 2016 (Trump) from 2012 (Romney) in a given county normalized by subtracting the mean and dividing by the standard deviation. Column 4 is the same as column 3, but the key interaction is with change in the percent of those in the Yale survey who say they are worried about climate change in a county from 2014 to 2016. All columns include the full set of all interactions, but some are withheld for simplicity of presentation. Standard errors are clustered at ZipxDistxElev level and are shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap (“Pol. Cons.”)			
	(1)	(2)	(3)	(4)
Feet Inundated	0.0038***			
	(0.0008)			
Feet Inundated x '14	-0.0004	0.0001		
	(0.0003)	(0.0002)		
Feet Inundated x '16	-0.0002	-0.0001		
	(0.0004)	(0.0003)		
Feet Inundated x '18	0.0032***	0.0039***	0.0039***	0.0044***
	(0.0008)	(0.0007)	(0.0007)	(0.0008)
Feet Inundated x '18 x Trump Rep ΔShare (Z)			0.0007	
			(0.0008)	
Feet Inundated x '18 x ΔWorried ’16-‘14 (Z)				0.0019***
				(0.0006)
ZipxDistxElevxTime FE	Y	Y	Y	Y
Property FE	-	Y	Y	Y
Included Year(s)	’12-‘18	'12-‘18	'12-‘18	'12-‘18
Pol Affiliation Measure	1	1	1	1
R-sq	0.227	0.704	0.704	0.704
Obs	12,314,677	12,314,677	12,314,677	12,314,677

Appendix

Figure A1. Distribution of Observations by SLR Feet Until Inundation

This histogram depicts the proportion of observations among properties that would be inundated with 10 feet of SLR, by the minimum feet of SLR necessary to regularly flood them according to the NOAA.

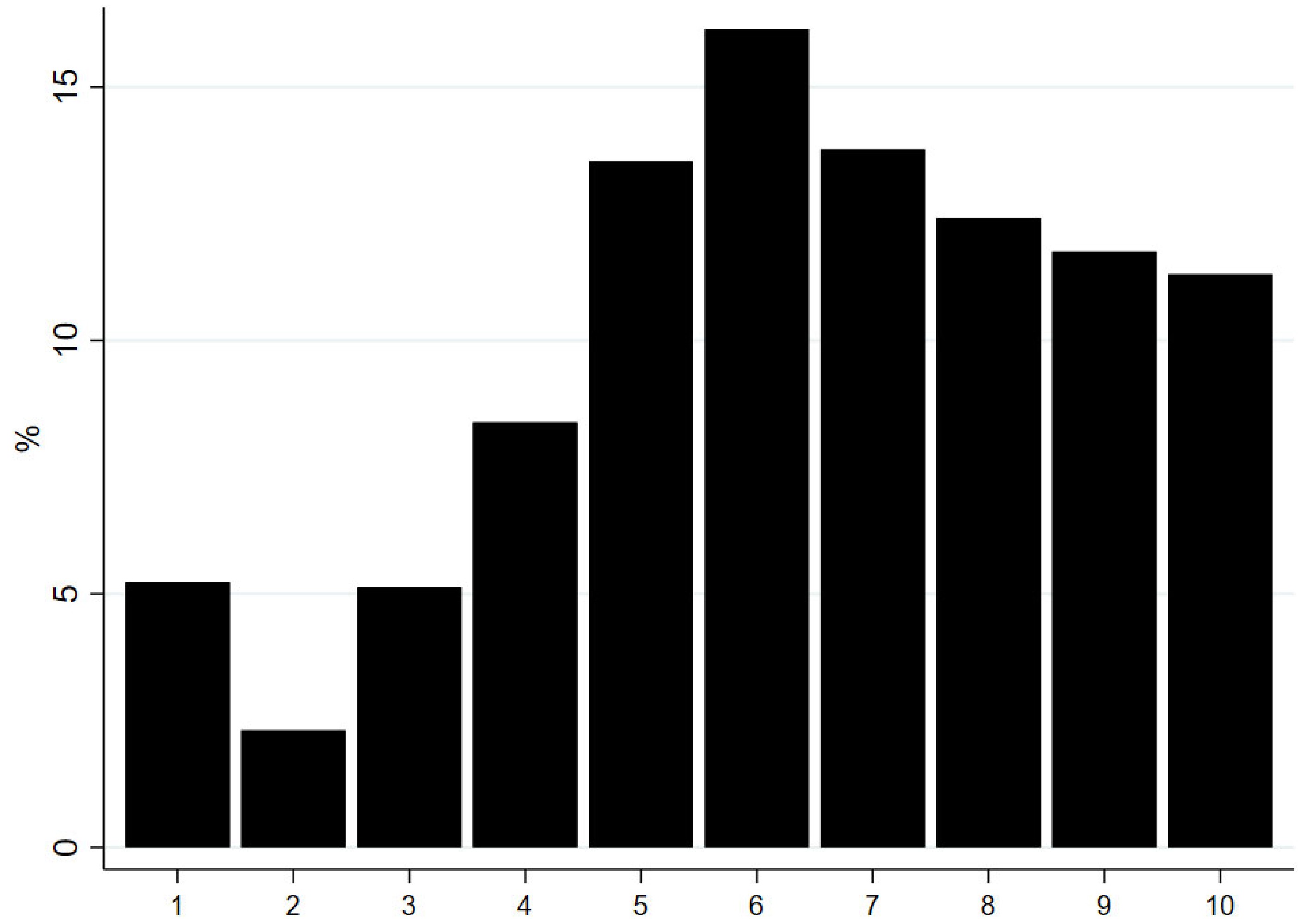


Figure A2. Additional Specification Curve

This figure provides results for two additional samples, properties only within 1 mile of the coast and the exclusion of properties with exposure at less than 1 foot of SLR. We also include our main results from earlier as comparison.

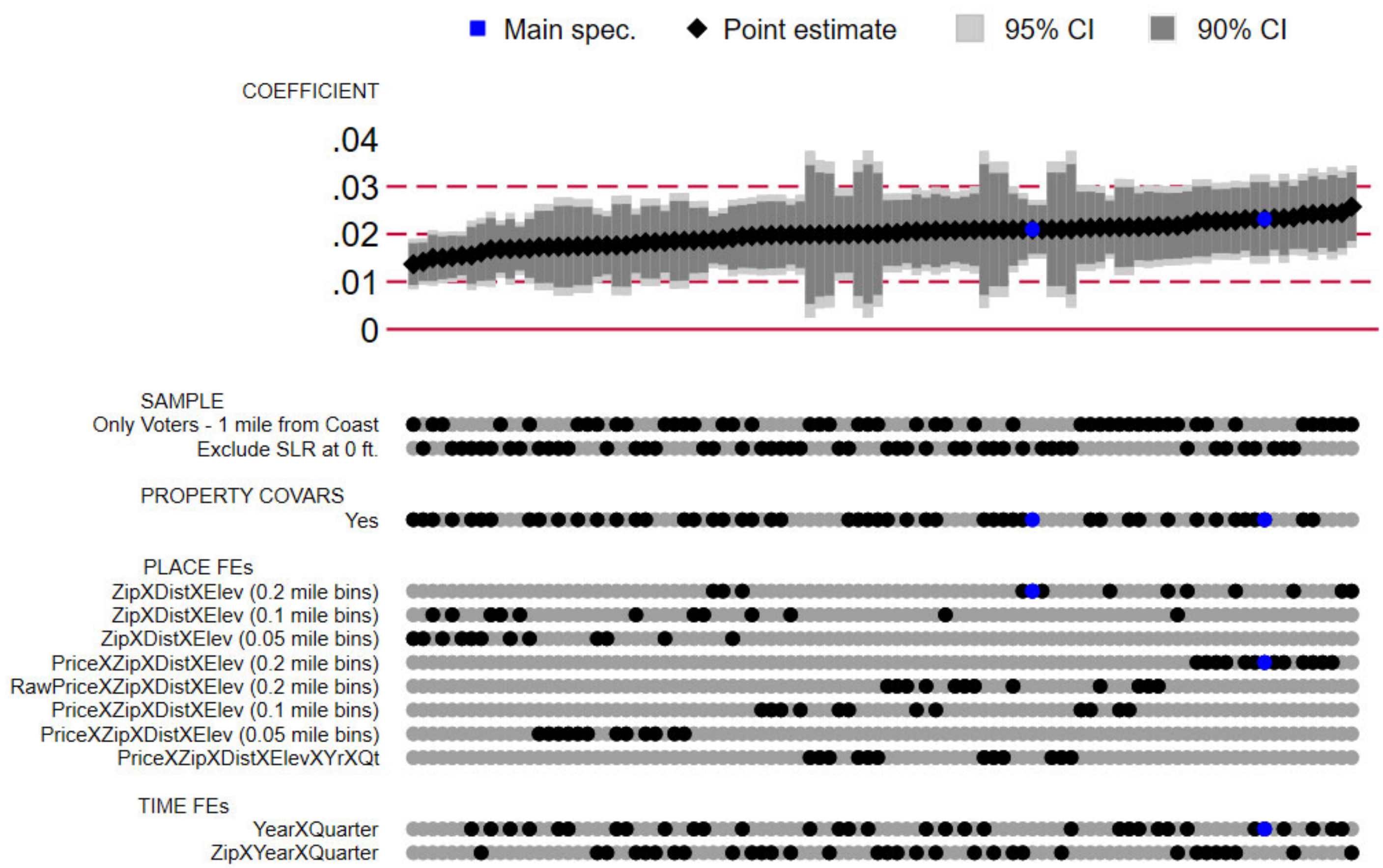


Figure A3. Partisan Sorting on SLR Risk State-by-State

We rerun our primary analysis from Table 3 Column 4 Panel A, but using the continuous measure of exposure (“Feet Inundated”) we focus on when examining heterogeneity to avoid variation in sorting coming from degree of exposure, conditional on any exposure, rather than other sources of variation. We look at partisan sorting on SLR risk state-by-state and plot the coefficients on “Feet Inundated” in order from lowest to highest. The bars represent 95% confidence intervals.

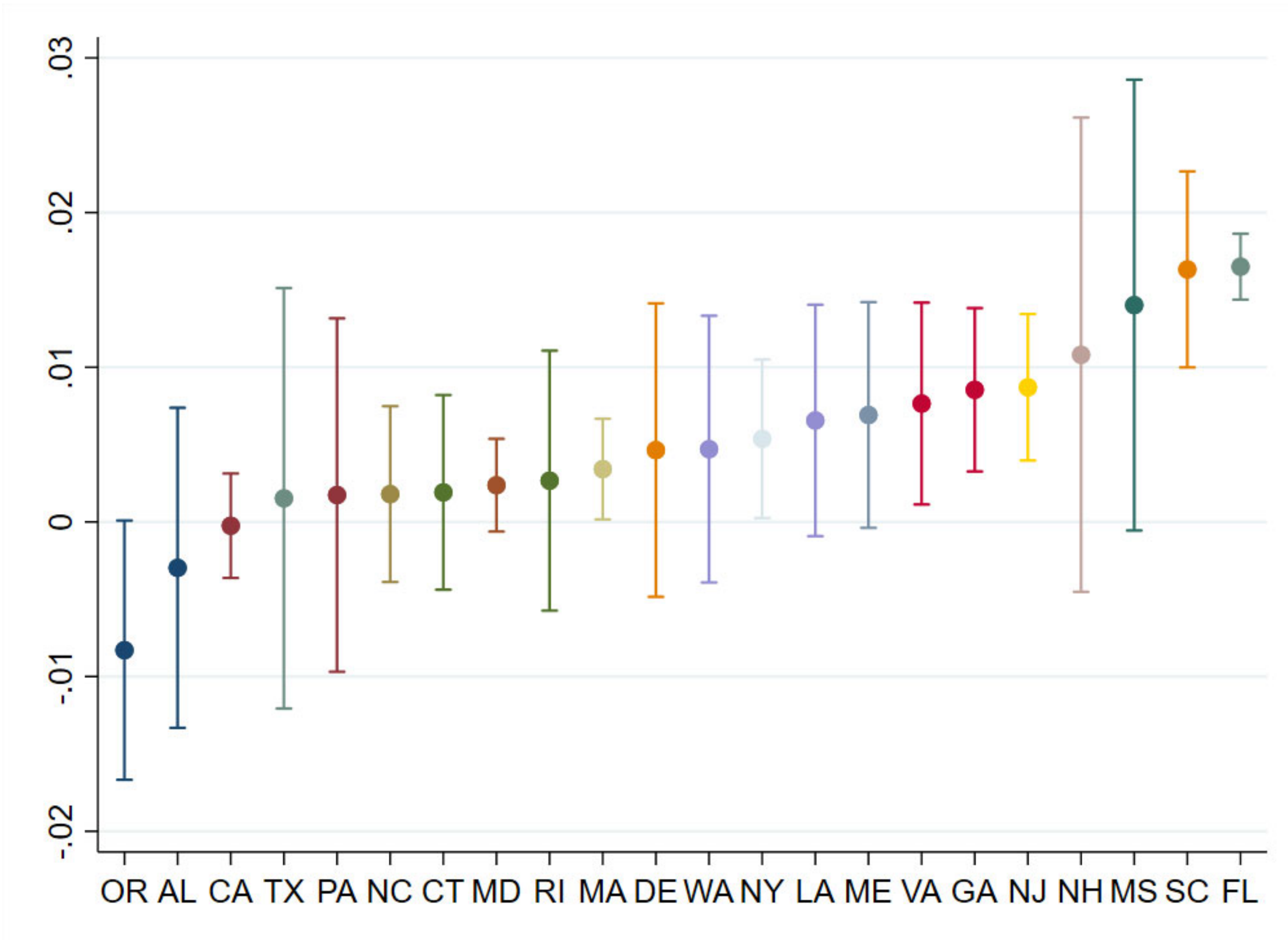


Figure A4. Storm Surge vs. Future Sea Level Rise Exposure

This figure shows for a given properties expected maximum feet of flooding due to storm surge, the probability it would be exposed to regular flooding with 10 feet of future sea level rise exposure.

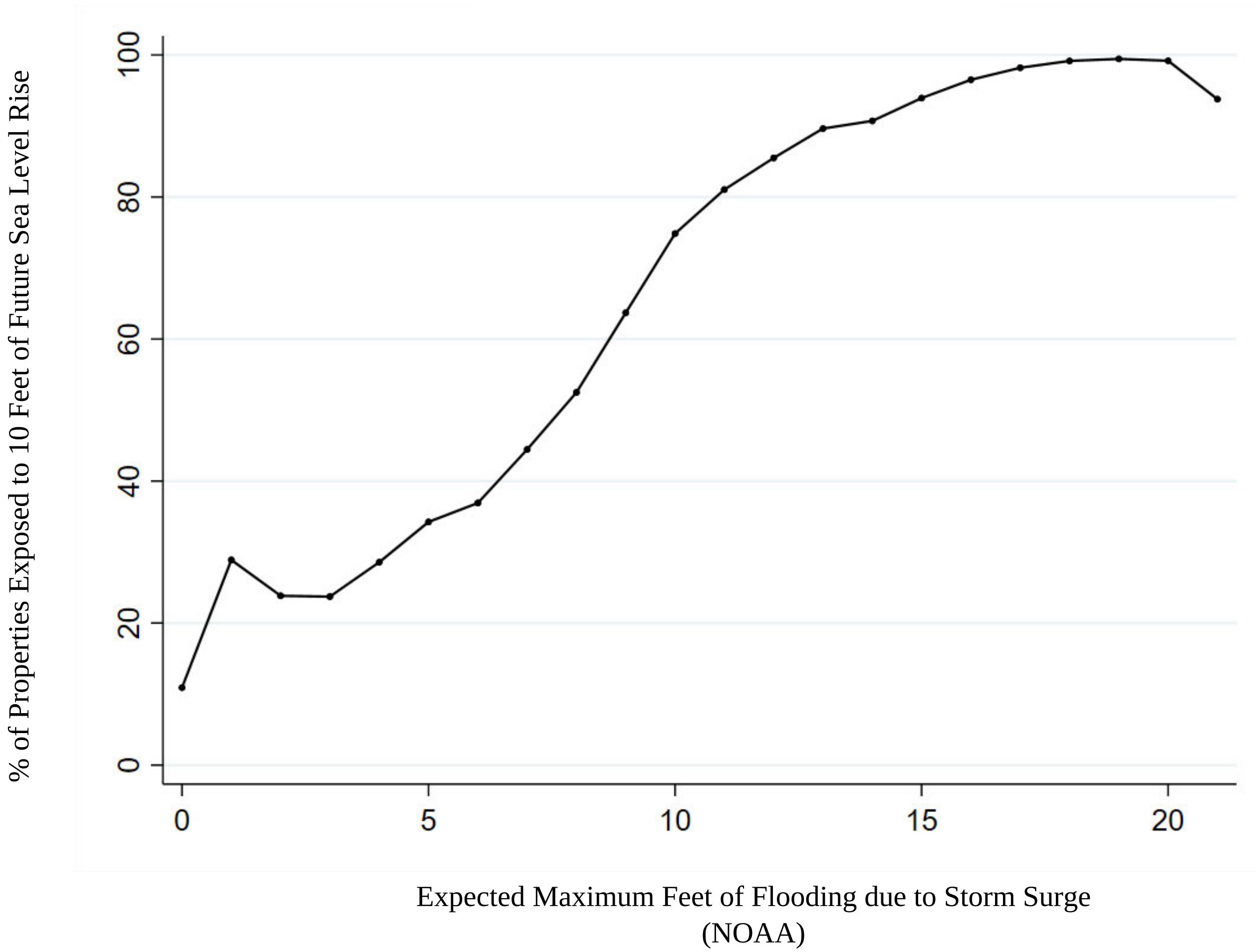


Table A1. Identifying Variation

This table shows how much of SLR exposure is unexplained after the inclusion of different controls and fixed effects. This represents our main sets of fixed effects that control for location and helps to determine how much variation is left using more granular fixed effects for the full sample in columns 1 through 3 as well as just the sample of voters that lived in properties that had a recent property sales transaction.

	Exposed			
	(1)	(2)	(3)	(4)
Explained Variation (R^2)	0.71	0.85	0.85	0.89
Property Controls	-	-	Y	Y
ZipxDist FEs	Y	-	-	-
ZipxDistxElev FEs	-	Y	Y	-
PricexZipxDistxElev FEs	-	-	-	Y
Obs	16,109,407	16,109,407	16,109,407	4,065,858

Table A2. Robustness to Method of Computing Standard Errors

This table shows that our primary findings are not sensitive to the choice of clustering when computing standard errors. The dependent variable in Column 1 takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. The specification includes property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. Standard errors are clustered at the zip code level. Column 2 is the same as column 1, but clustering is at the county level. Column 3 is the same as column 1, but clustering as the zip x distance to the coast quantile level. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap (“Pol. Cons.”)		
	(1)	(2)	(3)
Exposed	0.0210***	0.0210***	0.0210***
	(0.0042)	(0.0043)	(0.0033)
ZipxDistxElev FEs	Y	Y	Y
Clustering	Zip	County	ZipxDist
R-sq	0.220	0.220	0.220
Obs	16,109,407	16,109,407	16,109,407

Table A3. Robustness to Matching Sub-samples

This table shows that our primary findings are not sensitive to the choice of sub-sample or specification. The dependent variable in Column 1 takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. The specification includes property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. The sample is restricted to properties where we observe transaction prices. Column 2 is the same as column 1, but adds controls for property characteristics including third order polynomials of building age and lot size square footage, as well as fixed effects for the number of bedrooms, bathrooms, building height, assessed building quality, and presence of a garage or pool. Column 3 and 4 are the same as columns 1 and 2, respectively, but further limits our sample to voters in properties for which we can match HMDA records to property transactions. Column 5 is the same as column 4, but also adds year-quarter fixed effects and interacts the primary fixed effects with most recent transaction price quantile fixed effects, to flexibly control for potential unobservable differences. Throughout the table standard errors are clustered at the level of the fixed effects structure (ZipxDistxElev in Columns 1-4 and double clustered at year-quarter and PricexZipxDistxElev in column 5) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")				
	(1)	(2)	(3)	(4)	(5)
Exposed	0.0238***	0.0209***	0.0296***	0.0260***	0.0280***
	(0.0044)	(0.0042)	(0.0061)	(0.0060)	(0.0079)
Property Controls	-	Y	-	Y	Y
ZipxDistxElev FEs	Y	Y	Y	Y	-
PricexZipxDistxElev FEs	-	-	-	-	Y
Year-Quarter FE	-	-	-	-	Y
Price Sample	Y	Y	Y	Y	Y
Income Sample	-	-	Y	Y	Y
Included Exposure	All	All	All	All	All
R-sq	0.243	0.245	0.265	0.267	0.469
Obs	4,065,858	4,065,858	1,658,518	1,658,518	1,658,518

Table A4. Robustness to Political Affiliation Measurement

This table shows that our primary findings are not sensitive to the measurement of political affiliation. The dependent variable in Column 1 takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. The specification includes property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. In this analysis we exclude all properties in states where L2 predicts political affiliation also based on other observables besides voter registration, because in those states voter registration affiliation is unavailable or limited. Omitted states are Alabama, Georgia, Missouri, Texas, Virginia, and Washington. Column 2 is the same as column 1, but includes all states and omits all independents. Throughout the table standard errors are clustered at the level of the fixed effects structure (ZipxDistxElev) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")	
	(1)	(2)
Exposed	0.0225***	0.0280***
	(0.0032)	(0.0040)
ZipxDistxElev FEs	Y	Y
Excluded	States w/ Modeled Po. Afil	Ind
Included Exposure	All	All
R-sq	0.219	0.282
Obs	14,213,443	11,686,410

Table A5. Robustness to Excluding Largest States by Observation Count

This table shows that our primary findings are not sensitive to removing any particular state. The dependent variable in Column 1 takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. The specification includes property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. In columns 1-5 we remove all observations from individual states. They are ordered from left-to-right from most to least observations in our sample, among the top 5 most sampled states. Those are, in order, New York, Florida, California, New Jersey, and Massachusetts. Throughout the table standard errors are clustered at the level of the fixed effects structure (ZipxDistxElev) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")				
	(1)	(2)	(3)	(4)	(5)
Exposed	0.0200***	0.0135***	0.0232***	0.0214***	0.0219***
	(0.0032)	(0.0039)	(0.0033)	(0.0032)	(0.0032)
ZipxDistxElev FEs	Y	Y	Y	Y	Y
Excluded	NY	FL	CA	NJ	MA
Included Exposure	All	All	All	All	All
R-sq	0.205	0.212	0.228	0.224	0.224
Obs	12,663,051	13,027,532	14,107,331	15,044,672	15,209,770

Table A6. Robustness to Choice of Geographic Region Fixed Effects

This table shows that our primary findings are not sensitive to choice of geographic region controls. The dependent variable in Column 1 takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. Column 1 has property census tract x distance-to-the-coast quantiles x elevation quantile fixed effects, Column 2 has census block group x distance-to-the-coast quantiles x elevation quantile fixed effects, Column 3 has census block and distance-to-the-coast quantiles x elevation quantile fixed effects. Throughout the table standard errors are clustered at the level of the fixed effects structure (including double clustering in column 4) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")		
	(1)	(2)	(3)
Exposed	0.0069***	0.0071***	0.0081***
	(0.0024)	(0.0025)	(0.0023)
TractxDistxElev FEs	Y	-	-
BlockGroupxDistxElev FEs	-	Y	-
Block FEs	-	-	Y
DistxElev FEs	-	-	-
Included Exposure	All	All	All
R-sq	0.270	0.298	0.259
Obs	15,883,558	15,883,558	15,883,558

Table A7. Robustness to Excluding Likely Unusual High/Low Amenity Value Properties

This table shows that our primary findings are not sensitive to removing properties likely to have unusually high or low difficult to measure amenity values. The dependent variable in Column 1 takes the value of 1 if the resident is a registered Republican, 0 if they are an Independent, and -1 if they are a Democrat, reflecting the republican-democrat partisan gap. The explanatory variable of interest, *Exposed*, equals 1 if the property would be, according to the NOAA, regularly inundated if sea levels were to rise by 10 feet. The specification includes property zip code x distance-to-the-coast quantiles x elevation quantile fixed effects. For all columns the specification remains the same, but the choice of which properties are omitted from the analysis. In Column 1 we remove all properties within 1/10th of a mile of the coast. In Column 2 we remove the 1/4th highest elevation properties in each zip code. In Column 3 we remove the 1/4th highest elevation properties in a given zip code and quantile distance from the coast. In Column 4 we remove the 1/4th highest and lowest elevation properties in a given zip code. In Column 5 we remove the 1/4th highest and lowest value properties in a given zip code. In Column 6 we remove the 1/4th highest and lowest adjusted value properties in a given zip code. Adjusted value is discussed in the methods section of the paper, but adjust for variation in the time since the available price we observed occurs. Throughout the table standard errors are clustered at the level of the fixed effects structure (ZipxDistxElev) and shown in parentheses. P-Values: * 10%; ** 5%; ***1%.

	Rep-Dem Gap ("Pol. Cons.")					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.0150***	0.0214***	0.0178***	0.0233***	0.0199***	0.0208***
	(0.0035)	(0.0032)	(0.0032)	(0.0045)	(0.0053)	(0.0055)
ZipxDistxElev FEs	Y	Y	Y	Y	Y	Y
Excluded	<0.1MilesToCoast	Hi Elev	Hi Elev	Hi/Lo Elev	Hi/Lo Value	Hi/Lo Adj. Value
	-	(Zip)	(ZipxDist)	(Zip)	(ZipxDist)	(ZipxDist)
Ptile Excluded	-	25%	25%	25%/75%	25%/75%	25%/75%
Included Exposure	All	All	All	All	All	All
R-sq	0.216	0.219	0.219	0.215	0.271	0.271
Obs	14,839,402	11,881,773	11,756,970	7,878,418	2,120,333	1,953,666