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Sorting over flood risk and implications for policy reform[☆]

Laura A. Bakkensen [a], Lala Ma [b,*]

[a] School of Government and Public Policy, University of Arizona, 315 Social Science Building, Tuscon, AZ 85721, USA
[b] Department of Economics, Gatton College of Business and Economics, University of Kentucky, 550 S. Limestone Street, Lexington, KY 40506, USA

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ABSTRACT

Do individuals sort across flood risk? This paper applies a boundary discontinuity design to a residential sorting model to provide novel estimates of sorting across flood risk by race, ethnicity, and income. We find clear evidence that low income and minority residents are more likely to move into high risk flood zones. We then highlight the overall and distributional implications of proposed price and information reforms to the U.S. National Flood Insurance Program. While such reforms are likely welfare increasing overall, heterogeneous behavioral responses yield significant distributive effects that also alter the composition of residents in harm's way.

1. Introduction

Scholars and policy makers have long been concerned with how individuals locate relative to environmental hazards such as natural disasters. Residential patterns surrounding disaster risk can have critical consequences for many economic outcomes including household finance, economic growth, and migration (Strobl, 2011; Hornbeck, 2012; Cavallo et al., 2013; Gallagher and Hartley, 2017) as well as public programs for emergency management, welfare, and insurance (Michel-Kerjan, 2010; Deryugina, 2017). While a rich literature has estimated household preferences to avoid such risks, a longstanding challenge to empirical identification is the correlation between disaster risk and spatial amenities. In addition, an open question surrounds the potential for sorting based on socioeconomic status that, if present, can lead to unintended and unwanted distributional consequences including from benevolently-intentioned public policies.

This paper provides novel empirical evidence on sorting across disaster risk and highlights implications for policy reform. Using the case of flood risk in South Florida, we first estimate a discrete choice residential sorting model with three innovations on the flood risk literature. Compared with the hedonic price model predominately employed in existing studies, our approach (i) allows for sorting over flood risk by homebuyer race, ethnicity, and income, (ii) accounts for property-specific insurance pricing that could otherwise confound analysis, and (iii) employs a boundary discontinuity identification strategy (Black, 1999) within our sorting model (Bayer et al., 2007) to deal with the endogeneity of disaster risk and spatial attributes. Our results

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* Corresponding author.
E-mail addresses: laurabakkensen@email.arizona.edu (L.A. Bakkensen), lala.ma@uky.edu (L. Ma).

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provide the first estimates of sorting over flood risk by socioeconomic characteristics.

Second, we investigate the potential consequences of sorting for policy reform. We estimate the welfare and distributional consequences of changes in prices and flood risk information faced by households under the U.S. National Flood Insurance Program. In particular, using the structural parameters from our sorting model, we estimate the compensating variation for different race, ethnicity, and income groups from a (counterfactual) removal of the program's three largest insurance price discount schemes, and predict the resulting reallocation of household types across flood risk zones. In addition, we assess the value of risk information using new flood risk maps released by the National Flood Insurance Program. We then compare these benefits to the costs of map revisions.

We find clear evidence that individuals are willing to pay to avoid flood risk, as homes located just inside a high risk flood zone sell at a 6.3 percent discount relative to those just outside. Ignoring correlated amenities and insurance price discounts implies that high risk homes sell at a premium. Second, low income and minority residents are more likely to sort into high flood risk areas. This sorting takes place, even though high income, white residents tend to be concentrated in high risk coastal zones, likely driven by the amenity value associated with flood risk (e.g., Kahn and Smith (2017)).[1] In addition to furthering our understanding of residential location choice around environmental risk, the presence of sorting reaffirms the established result that housing price capitalization effects, estimated from hedonic price models, should be interpreted with care as they may combine preferences to avoid flood risk with changes in the implicit prices of flood risk and other co-existing amenities due to sorting (Kuminoff et al., 2010; Kuminoff and Pope, 2014; Bakkensen and Barrage, 2017).

Policy changes can also have important distributional consequences in the presence of sorting based on socioeconomic status. In our setting, the costs of insurance price reform fall more heavily on low income residents as a fraction of income. Resulting re-sorting would then lead to a greater concentration of low income and minority residents in harm's way. While policy reform may well be a desirable goal, these distributional impacts could have potentially long lasting implications for disaster vulnerability, recovery, and fiscal policy (Arrow et al., 1996; Robinson et al., 2016; Banzhaf et al., 2019).

Despite distributional costs, society may still realize large efficiency gains from reforms overall. We find that household welfare costs from insurance price reforms are significantly lower relative to costs estimated from an analysis that assumes no re-sorting, with expected welfare loss experienced by these households to be, on average, only 18.5 percent of the price discount that was removed. Importantly for disaster resilience and recovery, we find that higher insurance prices would lead to fewer individuals living in high risk zones, highlighting that migration will likely be an important (albeit costly) channel to mitigate climate risks. In addition, we find that flood risk map updates are valuable sources of information and are appealing from both a distributional and efficiency perspective. Depending on the quality of old versus new maps, we estimate a benefit cost ratio of 7.3 from map revisions, and find benefits more greatly concentrated among low income individuals. Understanding sorting over flood risk and the implications for policy is critical as flooding remains one of the costliest and deadliest types of natural disasters around the world, and impacts are expected to increase significantly under a changing climate (Hallegatte et al., 2013; Smith and Katz, 2013).

The paper proceeds as follows. Section 2 reviews relevant literature, highlighting where our work contributes to existing knowledge. In Section 3, we describe our data, research setting, and empirically motivate some important sources of heterogeneity that we capture in our empirical model. We then present our residential sorting model in Section 4 and describe our estimation strategy in Section 5. Section 6 discusses our sorting results. Sections 7 and 8 present and discuss our policy counterfactuals, and Section 9 concludes.

2. Literature

Ever since Tiebout's observation that heterogeneous individuals sort across varied landscapes (Tiebout, 1956), rich literatures have emerged to understand how individuals locate relative to spatial (dis)amenities. First, an active residential sorting literature has developed to estimate preferences for spatial characteristics (Sieg et al., 2004; Bayer et al., 2007, 2016; Walsh, 2007; Klaiber and Phaneuf, 2010; Tra, 2010; Klaiber and Kuminoff, 2013; Fan and Davlasheridze, 2016; Ma, 2019), including climate variables (Timmins, 2007; Albouy et al., 2016; Fan et al., 2018; Sinha et al., 2018).[2] More generally, a growing literature, known as environmental justice, is concerned with understanding why environmental risk is often correlated with higher concentrations of lower income and minority residents (GAO, 1983; Taylor, 2000; Mohai et al., 2009).

Second, a large empirical literature utilizes hedonic property value models to estimate the capitalization of disamenities such as flood risk into home prices (Rosen, 1974). While results are mixed, the literature generally finds a price discount for residences in high risk flood zones, identified using both long run flood risk and also recent flood events (Hallstrom and Smith, 2005; Bin et al., 2008; Bernstein et al., 2019).[3] However, growing evidence surrounding the heterogeneous impacts of disasters on, for example, migration (Smith et al., 2006; Strobl, 2011) and income or debt (Gallagher and Hartley, 2017; Deryugina et al., 2018) highlights the potential for (ex-ante) sorting across underlying disaster risk, which has largely been overlooked in the hedonic literature. Moreover, the parameters from hedonic models, while aimed at estimating marginal willingness to pay, are

[1] We note, but cannot tease apart, mechanisms that could give rise to this heterogeneity including, e.g., tastes (Banzhaf and Walsh, 2008), beliefs (Bakkensen and Barrage, 2017), access to information (Hausman and Stolper, 2019), or housing discrimination (Christensen and Timmins, 2018)).

[2] See comprehensive overviews by Klaiber and Kuminoff (2013) and Kuminoff et al. (2013).

[3] See review by Beltrán et al. (2018).

typically not suitable for recovering the effects of counterfactual policy changes (Kuminoff et al., 2013).

A long standing challenge to empirical estimation in both sorting and hedonic models is that the spatial attributes of interest are often correlated with other (unobserved) spatial characteristics. In our setting, flood risk is often highly correlated with access to desirable water amenities. Without an approach to disentangle these collinearities, the positive (and potentially incompletely observed) amenity value may cause an upward bias in the effects of flood risk on price (Bin et al., 2008). Also relevant for the U.S. flood risk context is that prices for flood insurance under the National Flood Insurance Program, the nation's leading flood insurance provider accounting for more than 95 percent of all policies (Dixon et al., 2006), can be heavily discounted. In some cases, the subsidized premium can be more than 85 percent below the risk-based premium (Kousky et al., 2016). As only the non-subsidized portion of flood insurance premiums is expected to be capitalized into house prices by attentive homebuyers (Shilling et al., 1989; Harrison et al., 2001; Bin et al., 2008), preferences to avoid flood risk could be biased downward if insurance discounts are not accounted for.

We address the above concerns when examining sorting across flood risk zones. First, our use of a discrete choice residential sorting model allows for observable heterogeneity based on individual socioeconomic status. Second, we account for relevant insurance-premium discounts in our calculation of housing costs. Of relevance, properties in high risk flood zones that carry a federally backed, regulated, or insured mortgage are required to purchase flood insurance (Flood Smart, 2016b), and compliance with this mandate is above 90 percent for homes within three years of purchase (Dixon et al., 2006). These institutional details increase our confidence that we can recover salient net values of required flood insurance premiums from housing transactions data that include mortgage information. Importantly, this also improves our measurement of the portion of flood risk that is financially internalized by the homeowner. Lastly, we employ a boundary discontinuity design to deal with the endogeneity of disaster risk and spatial attributes (Black, 1999; Bayer et al., 2007). We show that observable factors do not change precipitously across floodplains within a certain distance of floodplain boundaries. Restricting our attention to homes on either side of a flood boundary, we apply boundary fixed effects to our sorting model. These features of our analysis – individual observable heterogeneity, information on price discounts, and the application of a boundary discontinuity design – allow us to derive novel estimates of sorting over flood risk.

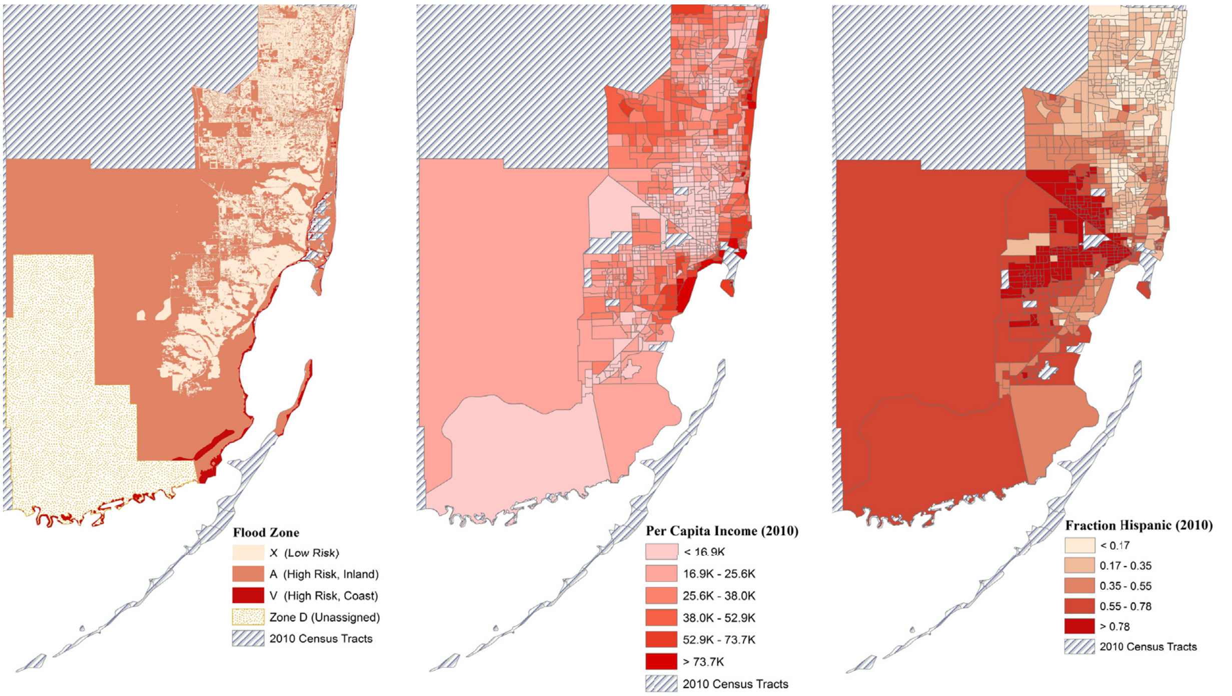
3. Empirical overview

We examine the question of sorting over flood risk by using property sales data from 2009 to 2012 across Florida's Miami-Dade-Ft. Lauderdale-Port St. Lucie Combined Statistical Area (CSA). This CSA represents approximately 2.3 million households and has total property valued at more than $1 trillion. Flood risk in this area is expected to increase over time and Miami is one of the top twenty cities across the world at highest risk for future flood losses due to sea level rise (Hallegatte et al., 2013). This region also contains significant heterogeneity in terms of who is exposed to flood risk. Fig. 1 displays (a) floodplains in South Florida, (b) 2010 Census tract-level average per capita income, and (c) the fraction of residents who are Hispanic in 2010. It provides suggestive evidence of the correlation between (coastal) flood risk and income as well as (inland) flood risk and ethnicity, motivating the potential for sorting. In addition, Fig. 1 shows a high degree of granular variation in flood risk, which necessitates property location information at a fine geographic resolution.

Important to modeling environmental risk in this context is an understanding of the public institutions surrounding flood risk in the United States. In response to flood threats and due to a lack of private insurance, Congress enacted the National Flood Insurance Act of 1968 that created the National Flood Insurance Program (NFIP), a federal flood insurance program. The NFIP also produced publicly available flood risk maps, known as Flood Insurance Rate Maps (FIRMs), which are periodically updated. FIRMs assign locations to one of several flood risk categories including: Zone A, with a freshwater flood risk of at least 1 percent per year; Zone V, with a coastal saltwater flooding risk of at least 1 percent per year; and Zone X, with a flood risk of less than 1 percent per year. Zones A and V are designated as Special Flood Hazard Areas (SFHA), and structures in these areas are required to purchase insurance if they have a federally backed, regulated, or insured mortgage. Thus, during the mortgage application process, homebuyers are notified of flood risk and required to purchase flood insurance.[4] Program premiums are set according to the dollar value of coverage purchased, the specific property's structural attributes, as well as its location with respect to a FIRM flood zone, and, for a subset of locations (approximately nine percent in our sample), the Base Flood Elevation, which represents the level to which floodwater is anticipated to rise during a 100-year flood.

NFIP premiums are priced to reflect underlying flood risk, but price supports of several types reduce premium rates to below actuarially fair levels. The program's three largest price discount schemes include preferential rates to (i) pre-FIRM properties that were built before the first flood insurance rate map was released in their community; (ii) residents of locations in the Community Rating System, who may receive a price reduction of up to 45 percent as determined by flood activities at the community level; and (iii) grandfathered properties with pre-existing flood insurance policies that can maintain preferential

[4] Flood risk disclosure may also occur earlier in the home search process, but disclosure laws vary by state. In Florida, flood risk disclosure, while not specifically required, should be covered by Florida Statute Section §475.278 (and upheld by the Florida Supreme Court in Johnson vs. Davis), stating "where the seller of a home knows of facts materially affecting the value of the property which are not readily observable and are not known to the buyer, the seller is under a duty to disclose them to the buyer" (https://www.floridarealtors.org/law−ethics/library/florida−real−estate−disclosure−laws). Potential buyers can also access the flood zone of any property by address at the FEMA Flood Map Service Center. Insurance and subsidies are also available for properties in Zone X but purchase is not mandatory and uptake is generally low.



(a) Flood Zone (b) Per Capita Income (c) Fraction Hispanic

Fig. 1. Flood zones and neighborhood demographics.
Source. Generated by authors using NFIP Digitized Flood Insurance Rate Maps and 2010 Census data for South Florida.

rates after new flood maps are released.[5] These discounts are intended to encourage uptake, ensure affordability, and eliminate some of the financial pressure on public post-disaster aid programs (Kousky and Shabman, 2014).

3.1. Data

We categorize our data into four main groups: 1) housing transactions in Florida from Dataquick, Inc., 2) digitized Flood Insurance Rate Maps and insurance premium rate tables, 3) mortgage applications collected under the Home Mortgage Disclosure Act, and 4) information on various other spatial attributes. We provide a brief overview of our process to construct the final dataset and refer readers to Appendix for a detailed description of our data sources and the data construction process.

We begin with all arms-length sales of owner-occupied residential properties from the Miami-Dade, Port St. Lucie, Fort Lauderdale Combined Statistical Area from 2009 to 2012. The data include information on selling price, date of sale, numbers of bedrooms and bathrooms, and mortgage information. We calculate a property's flood-insurance premium based on its flood zone (assigned using Flood Insurance Rate Maps (FIRMs)), structural characteristics, and the year built. This information is sufficient to determine the effective insurance premium rate (per $100 of building coverage) for most properties.[6] We then multiply this rate by the amount of building coverage, set as either the recorded loan amount or $250,000 (whichever is lower) (NFIP, 2016). We note that the pre-FIRM discount is already embedded in the NFIP premium rate based on the year that a house was built. We then calculate a property's final insurance premium by incorporating the Community Rating System (CRS) program discount if a property belongs to a participating community as designated by the NFIP. We do not include the price for contents coverage as this type of coverage is not mandatory and should not impact home price. We also map each property to the closest flood zone boundary using Geographic Information Systems: we first split FIRM flood map polygon boundaries into segments, which are assigned a unique identifier, and then we find the closest segment (in terms of distance) to each house.

Next, to characterize the neighborhoods in which houses are located, we map each house to nearby spatial amenities. These include (1) distances to the nearest park, river, and coast, (2) number of Institutional Controls Registry (ICR) sites within 3 km (a

[5] Preferential rates (e.g., grandfathering) can be passed on to future owners if a policy is continually held.
[6] See Appendix for assumptions used to calculate property-specific premiums for a small number of properties with missing data.

Table 1
Summary statistics for housing (full sample).

A. Structural and Neighborhood Characteristics					
Variable	Mean	Median	St. Dev.	Min.	Max.
Price (in 2010 $'s)	219,841	171,985	168,702	9,625	1,399,301
# of Bathrooms	1.83	2.00	0.84	0.00	12.00
Year Built	1975	1978	16	1900	2010
Any Basement	0.0004	0	0.02	0	1
Enviro. Nuisances	0.60	0.00	1.43	0.00	15.00
School Quality	270	265	16	202	313
B. Flood-Related Characteristics					
Variable	Mean	Median	St. Dev.	Min.	Max.
Dist. to River	218.5	227.9	50.5	33.6	294.8
Dist. to Park	14.4	12.4	11.5	0.0	90.9
Dist. to Coast	10.4	10.2	7.4	0.0	68.2
Surface Elevation	2.4	2.1	1.4	−1.3	20.8
Zone X (low risk)	0.405	0.000	0.491	0.00	1.00
Zone A (high risk)	0.593	1.000	0.491	0.00	1.00
Zone V (high risk)	0.002	0.000	0.041	0.00	1.00
Pre-FIRM	0.62	1.00	0.49	0.00	1.00
BFE Assigned	0.09	0.00	0.28	0.00	1.00
Relative BFE	−7.88	−8.00	1.69	−15.00	0.00
C. Homebuyer Characteristics					
Variable	Mean	Median	St. Dev.	Min.	Max.
White	0.47	0.00	0.50	0.00	1.00
Asian	0.02	0.00	0.15	0.00	1.00
Black	0.12	0.00	0.32	0.00	1.00
Hispanic	0.39	0.00	0.49	0.00	1.00
Income (in 2010 $1000's)	90.42	63.53	122.23	4.81	9745.98

Note. "BFE" refers to base flood elevation and "Relative BFE" is the surface elevation minus the BFE. "Enviro. Nuisances" refers to the number of sites listed on Florida's Institutional Controls Registry and "School Quality" evaluates achievement in the categories of reading, mathematics, science and writing, with a maximum score of 400 points (see Appendix for details). All distances to spatial amenities are in kilometers. Surface elevation and BFE are measured in meters. The number of observations for all variables is 48,174, with the exception of the "Relative BFE," which only has 4,212 observations since not all areas are assigned a base flood elevation.

proxy for local environmental quality),[7] (3) test scores as a proxy for public school quality, and (4) tract-level per-capita income and race/ethnicity population shares from the 1990 Census.[8] Lastly, we follow the procedure outlined in Bayer et al. (2016) to recover the race and income of buyers in our sales data using mortgage information from the Home Mortgage Disclosure Act. This is so that we can categorize households into different "types," defined by race and income, where income is categorized into bins based on quintiles of the observed income distribution.[9]

Our final sample includes 48,174 individual house sales between 2009 and 2012 across six counties and 953 census tracts in Florida.[10] Table 1 provides summary statistics for property and household characteristics. Each house is described by its structural attributes and neighborhood characteristics, such as the distance to various spatial (dis)amenities. At the time of each sale, we know the race/ethnicity (white, Black, Hispanic, or Asian) and income of the primary buyer involved, and the flood zone and premium that the buyer faces. The average sales price is $219,841, where prices are normalized to January 2010 dollars using the Consumer Price Index for All Urban Consumers in the South region for the expenditure category of "Housing" (BLS, 2012). The majority of the properties are either in an X or an A zone, with less than 1 percent of our sample belonging to the V zone.[11]

Regarding flood insurance premiums and discounts, approximately 60 percent of sales qualify for the pre-FIRM premium discount, and 40 percent would be affected by grandfathering. Most of our sample (99 percent) is located in areas that are

[7] Information on environmental nuisances (e.g. brownfields, Superfunds, and solid waste sites) comes from Florida's Institutional Controls Registry (ICR). For each house, we count the number of industrial sites listed on Florida's ICR within 3 km of the property, in the year of property sale. For additional details on the types of sites included, see Appendix.

[8] While our sample period begins in 2000, we use neighborhood characteristics from the 1990 Census instead of contemporaneous Census data to alleviate the endogeneity concern of neighborhood characteristics.

[9] Matching between sales and mortgage data is imperfect: we only recover information for 47 percent of our data. However, the resulting sample is representative compared to Census data. For details, see Appendix.

[10] The six counties include Miami-Dade, Broward, St. Lucie, Martin, Indian River, and Okeechobee. We lose Palm Beach County because no digitized flood map was available at the time of our analysis.

[11] This is consistent with the observed distribution of homes in the area. Using GIS data on all properties in Miami-Dade County, the authors estimate that 0.27 percent of properties are in the V zone compared with 0.23 percent observed in the V zone across our sample.

covered by the CRS program (see Appendix Table B.1).[12] We calculate an annual insurance coverage in our sample of $159,664 on average, with a median of $154,982 (see Appendix Table B.2). The full premium calculated prior to any discounts is, on average, $2,113 per year, with a median of $808. The pre-FIRM discounts then provide an average discount of almost $1,000 relative to the full premium. Houses in our sample receive CRS discount rates of between 0 and 25 percent, with an average of 12.0 percent. Incorporating CRS discounts brings the average fully subsidized insurance premium to $984 (with a median of $714 per year). Large investments in flood mitigation, such as flood-proofing and elevating structures, can certainly distort the researcher's measurement of the flood risk that is borne by the household, but the CRS discounts that we observe in our study area are low enough that they are unlikely to alter the underlying flood risk in practice.[13] We calculate the total discount as the difference between the calculated insurance premium before and after the CRS and pre-FIRM discounts. The average total discount in place is $1,129, which represents about a 50 percent discount off the non-discounted nominal insurance premium.

3.2. Empirical evidence

Before describing our model, we provide stylized evidence that sorting takes place according to observable household characteristics. We also present results from a hedonic model to situate our data and results within the dominant model approach of the existing literature. These two types of evidence strongly suggest the use of a model that allows for sorting decisions with respect to flood risk exposure and other correlated amenities to depend on individual characteristics, and support the notion that NFIP reforms may have some potentially important distributional consequences.

To assess sorting across flood zones in our data, Fig. 2 plots buyer characteristics against distance to the nearest X-A flood boundary (delineated by a vertical dashed line) for A and X zone houses within 5 km of this boundary. Using sales-level data for all properties in either the X or A flood zone, we regress a homebuyer attribute (e.g., an indicator for buyer race or income) on 1) a set of dummy variables based on a property's distance to the nearest flood boundary in 100-m increments, and 2) interactions between a dummy variable for whether the property is located in the A zone and the previous set of distance-to-boundary indicators.[14] The coefficients on the distance-to-boundary indicators represent the dependent variable average of properties located in the X zone that belong to particular distance-to-nearest flood boundary bins, and are plotted to the left of the dashed line in Fig. 2; the coefficients on the distance-flood zone interaction terms, representing the same average for properties in the A zone, are plotted to the right of the dashed line in Fig. 2. All averages are normalized to the 100-m distance on the X side of the boundary. Our underlying assumption is that, while flood risk may change continuously across the boundary, the flood risk information that is salient and internalized to homebuyers is the NFIP's official designations, which change discretely at the boundary. This is the information given to buyers in the buying process and also represents the overwhelmingly dominant source of information on flood risk during our data period.

Fig. 2(a) and (b) show that higher risk A zone areas are less white, and are primarily Hispanic. The share of Black buyers in Fig. 2(c) are mostly similar across X and A zones, although there is some evidence of fewer Black buyers in the area immediately across the X-A zone boundary. Fig. 2(d) plots the logarithm of income. As one crosses into the A zone, residents have higher income, though at about 3 km from the boundary, incomes begin to fall.[15] From a revealed preference perspective, this would suggest that Hispanics and higher income households are more likely to sort towards flood risk. However, given flood risks' spatial correlation with water amenities, this could also be driven by heterogeneous preferences for coastal amenities. Nevertheless, it is apparent from these figures that there are systematic differences in the distribution of race and income across flood zones.

[12] Appendix Table B.1 also presents several house characteristics by each of the discount schemes. The average prices of properties affected by the pre-FIRM and grandfathering discount schemes are lower, likely reflecting differences in the age, house structure (e.g., number of bathrooms), and neighborhood characteristics (number of environmental nuisances). The individuals who buy the homes under these discount schemes are also more likely to be Black or Hispanic and have lower income compared to those who bought post-FIRM or grandfathered properties.

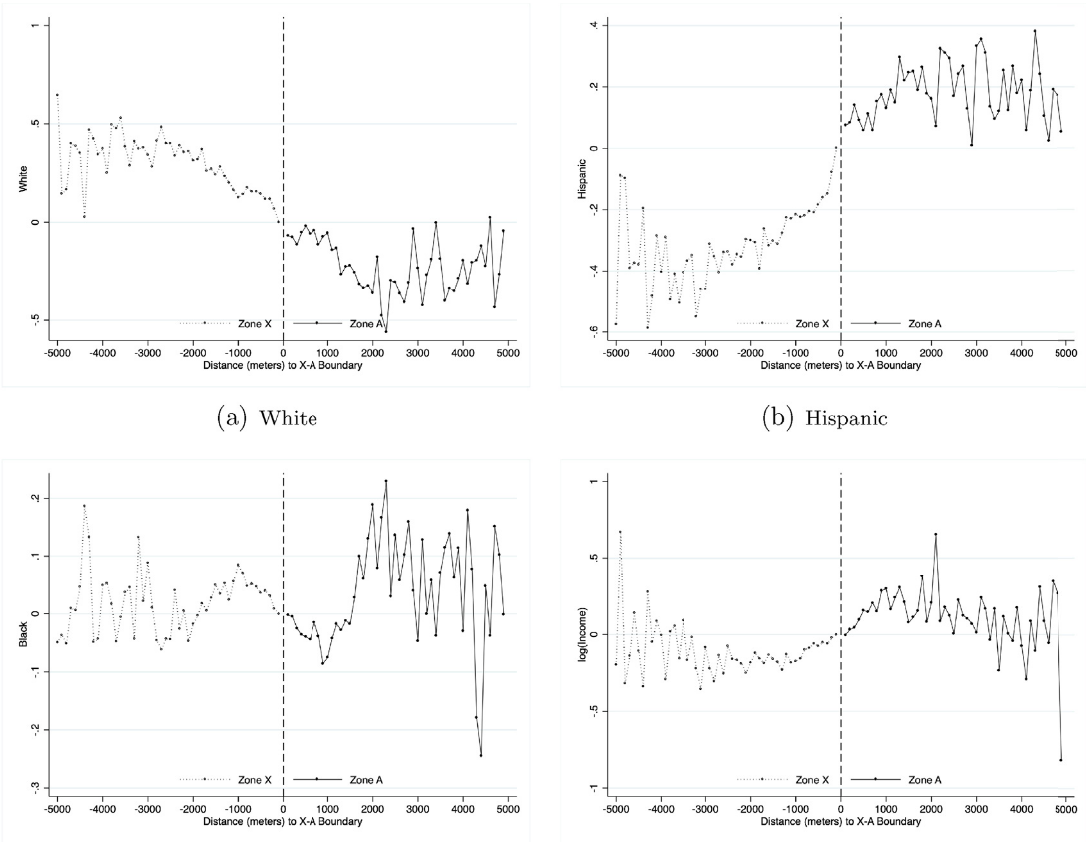
[13] The activities that communities can undertake to earn credit towards receiving a discount range from public information provision to flood mitigation measures (CRS credit class ratings range from 1 to 10, with 1 being the best and earning the most credit). The amount by which undertaken activities actually decrease household-level flood risk is potentially low. For example, across the United States, 93 percent of communities receive credits for outreach projects (credit type 330) whereas only 13 percent receive credits for flood protection activities (credit type 530) (FEMA, 2017). In addition, while a causal analysis of the impact of CRS on flood losses is an interesting area of future research, Michel-Kerjan and Kousky (2010) use a sample of CRS communities in Florida and find no difference in flood losses between CRS communities of classes 6 through 10 (with credit score ranging from 0 to 2499) while class 5 communities have, on average, 7 percent fewer losses than class 10 communities. This is suggestive evidence that the impact of the CRS on flood damages may be low.

[14] Specifically, for a sale observation i, the regression equation is

$$Y_i = \alpha + \sum_{d=1}^{50} \beta_d dist_i^{[100(d-1),100d]} + \sum_{d=1}^{50} \gamma_d \left(dist_i^{[100(d-1),100d]} \times zone_i^A \right) + \epsilon_i$$

where Y_i is an attribute of house i, $dist_i^{[100(d-1),100d]}$ is a dummy variable equal to 1 if a house i is between $100(d-1)$ and $100\,d$ m away from the nearest flood boundary, and $zone_i^A$ is a dummy variable equal to 1 if house i is located in zone A. We omit the 100-m distance bin so that all coefficients are interpreted relative to the dependent variable average in the 0–100 m distance bin on the X (or, in Fig. 2, left) side of the flood boundary.

[15] We note that for all of these figures, estimates become noisy as one moves farther away from the boundary (the vertical dashed line) on the A zone side. This is because A zone represents inland flooding; as such, increasing the distance from this boundary could either mean being closer to the V zone or to a different, lower risk area.



(a) White (b) Hispanic

(c) Black (d) log(Income)

Note. Each figure plots the coefficients from a regression of some attribute against distance-to-flood boundary dummy variables at 100-meter increments from the X zone (on the left) to the A zone (on the right). All points are normalized to the 100-meter distance on the X side of the boundary.

Fig. 2. Buyer characteristics by distance to flood boundary.

Disentangling sorting over flood risk from its correlated amenity value would be important to recover unbiased preference parameter estimates. Our boundary fixed effects model, combined with neighborhood demographic controls, is aimed at accomplishing this. Table 2 assesses mean differences between A and X zone characteristics using low flood risk properties where the area opposite its flood boundary is of high flood risk, and vice versa.

We provide mean differences for the full sample and various distance-to-boundary samples (i.e. 5, 3, 1, 0.5, or 0.3 km), along with corresponding t-statistics that the mean difference is equal to 0. While we generally reject that mean differences are equal to 0, the unconditional differences decrease as we narrow the window of consideration around the flood boundary.[16] We thus restrict our sample to properties where the nearest flood boundary is at most 1 km away in our boundary discontinuity design, limiting our comparison to houses near the same but opposite sides of a boundary through the use of boundary fixed effects. The boundary discontinuity design alone would be insufficient to deal with differences across flood boundaries due to sorting based on preferences for endogenous neighborhood differences.[17] Thus, we also control for endogenous neighborhood attributes (e.g. race and income), which we include from the 1990 Census at the tract level, in addition to allowing for heterogeneous preferences across homebuyers.

To further assess our sample restriction, we demonstrate that different distance-to-boundary sample limitations within 1 km do not materially affect the results of a hedonic model with boundary fixed effects. Table 3 presents hedonic regressions of the

[16] We also find graphical support for this in Appendix Figure B.1 that uses distance-to-boundary figures (similar to Fig. 2) with various spatial characteristics as the dependent variable.

[17] This is noted by Bayer et al. (2007) in the context of sorting over school districts.

Table 2
Differences in Mean Attributes by Zone (A vs. X).

Distance from Boundary	Full Sample		5 km		3 km		1 km		0.5 km		0.3 km	
	Mean Δ	T-stat.	Mean Δ	T-stat.	Mean Δ	T-stat.	Mean Δ	T-stat.	Mean Δ	T-stat.	Mean Δ	T-stat.
Price	20,450.21	1.89	20,199.20	1.51	19,752.20	1.46	10,097.14	0.81	2,951.64	0.25	−5,281.57	−0.57
Single Family	−0.18	−8.31	−0.18	−6.92	−0.18	−6.88	−0.16	−6.41	−0.13	−5.84	−0.11	−4.50
Condominium	0.18	8.51	0.18	7.15	0.18	7.08	0.16	6.57	0.13	6.00	0.11	4.53
Age	−0.35	−0.30	−0.44	−0.20	−0.23	−0.10	−0.48	−0.30	0.16	0.13	0.63	0.60
Pre-FIRM	0.11	3.75	0.11	1.97	0.12	2.19	0.10	2.61	0.12	3.65	0.13	4.50
ICR within 3 km	−0.14	−2.07	−0.15	−1.68	−0.14	−1.61	−0.14	−1.65	−0.14	−1.94	−0.17	−2.59
School Quality	−4.11	−3.29	−4.09	−1.19	−4.57	−1.37	−3.60	−1.66	−3.12	−1.90	−3.20	−2.25
Dist. to Park	−3.81	−4.54	−3.72	−3.33	−3.60	−3.27	−2.96	−3.11	−2.65	−3.03	−2.17	−2.82
Dist. to River	34.72	8.01	34.09	3.79	33.57	3.80	26.40	4.23	23.73	4.77	22.27	5.00
Share Hispanic ('90)	0.06	3.09	0.06	1.97	0.06	2.26	0.05	2.45	0.05	2.85	0.06	3.24
Share Black ('90)	−0.02	−1.89	−0.02	−1.62	−0.01	−1.47	−0.01	−1.42	0.00	−0.47	0.01	1.13
Per Capita Income ('90)	821.17	0.92	771.04	0.95	524.47	0.63	278.21	0.32	−109.98	−0.12	−399.15	−0.45

Note: The table assess differences in mean attributes between A and X flood zones (i.e. A-X) for the full sample (columns 1 and 2) and sub-samples of houses at various distances from the nearest boundary (columns 3–10). T-statistics test the null hypothesis that the difference in mean attributes for a specified sample is 0. All t-tests are clustered at the boundary ID level.

Table 3
Hedonic regressions.

Dep. Var.:Annual Rent	*Panel A. Progression of Controls*			
		Add Flood Controls		Boundary (<1 km)
	(1)	(2)	(3)	(4)
SFHA	−2,203***(80.15)	−1,642***(91.70)	−1,120***(85.84)	−658.6***(100.1)
Elevation		−477.8***(33.89)	−168.0***(31.81)	−263.8***(47.82)
Relative BFE		460.6***(16.47)	904.5***(16.30)	1,081***(22.21)
Distance to Coast:				
<0.1 km			14,392***(268.4)	11,022***(400.5)
<0.5 km			11,854***(177.5)	7,948***(295.2)
<1 km			9,908***(192.9)	6,663***(263.0)
<2 km			6,000***(148.5)	5,022***(199.5)
<3 km			3,521***(141.9)	2,539***(177.7)
<4 km			2,269***(152.6)	808.2***(196.2)
<5 km			2,161***(150.6)	255.3 (186.3)
Observations	48,174	48,174	48,174	31,601
	Panel B. Alternative Specifications			
	Other Boundary Distance Buffers			Ignore Price Supports
Sample Restriction:	<800 m	<500 m	<300 m	None
SFHA	−657.6***(103.5)	−542.7***(113.9)	−681.6***(126.0)	−18.84 (83.21)
Observations	29,044	23,194	17,594	48,174

Note. All regressions include county and year fixed effects. The (omitted) base group for flood zone is zone X. A set of controls that are consistent with the sorting model are included but not shown, including house characteristics (single, condo, age, Pre-FIRM) and neighborhood characteristics (ICR's within 3 km, school quality, distance to the nearest park and river, 1990 Census share Hispanic, share Black, and median income.). Column (4) of Panel A limits the sample to houses within 1 km of a flood boundary and includes boundary fixed effects. Panel B re-estimates the boundary fixed effects specifications with different buffer distances (columns 1–3), and re-estimates the specification in column (3) of panel A but ignores price supports (column 4).

annual rental price on house, flood, and other spatial attributes. The annual insurance premium subsidy is subtracted from annual rental prices to adjust for flood-insurance discounts. Each column represents a separate regression. Our coefficients of interest are Special Flood Hazard Area (SFHA) indicator variables, denoted "SFHA", that designate high flood risk (zones A or V) status, where the omitted group is composed of X zone houses exposed to lower flood risk. All regressions include controls on house characteristics (house type indicators, number of bathroom, bedrooms, square foot, age, and pre-FIRM status), neighborhood characteristics (local environmental quality, school quality, distance to the nearest park and river), year fixed effects, and county fixed effects.

In panel A, sales prices are approximately $2,203 lower for properties in the SFHA zone relative to those in the X zone (column (1)). Upon progressively adding controls for surface elevation, base flood elevation, and distance-to-coast bins,[18] houses in SFHA zones sell for $1,120 lower than comparable houses in the X zone. Notably, there is a very steep price gradient with respect to distance to the coast in column (3).[19] We next restrict our sample to houses within 1 km of a flood boundary and re-estimate the model to include boundary fixed effects, following Black (1999), in column (4). Our MWTP estimate for SFHA zone houses becomes -$659, or 5.8 percent of average housing prices in our sample (assuming a 5 percent discount rate in perpetuity), which is comparable to previous work.[20] In panel B, we estimate the boundary fixed effects model with various distance-buffer sample restrictions. These estimates are economically similar and are not statistically different than the model using a 1-km buffer; we therefore use the 1-km sample restriction in estimating the sorting model.[21] Our main estimation sample using the boundary discontinuity design consists of 32,027 sales across 784 tracts, where the average price is $225,434.[22]

Last, we can also use the hedonic model to assess the importance of accounting for premium subsidies. The last column of Table 3 re-estimates the model in column (3) without boundary fixed effects, but uses annual rents that ignore the price supports that we calculate for each house. The SFHA zone coefficient is -$19. These differences point to the variation in discounts between zones and the extent to which ignoring price supports will matter for hedonic and sorting estimates.

[18] The omitted category is houses farther than 5 km from the coast.

[19] While most properties within 0.1 km of the coast are also in the SFHA (see Appendix Table B.3), approximately 9 percent of houses within 0.1 km of the coast are not in an SFHA, which allows us to separately identify the effects of locating near the coast from that being in the SFHA.

[20] For example, Harrison et al. (2001), Bin et al. (2008), and Zhang (2016) find that houses in flood prone areas sell for a price discount ranging between 5 and 11 percent.

[21] It is difficult to completely decouple flood risk from its correlated amenity value. As such, the various spatial controls included may also capture flood-related risks such as storm surge, which may result in biasing the estimated MWTP to avoid flood risk towards zero. We assess this potential by re-estimating the main boundary fixed effect hedonic specification without various spatial controls in Appendix Table B.4. While the coastal distance bins and BFE may be capturing flood-related risks, the hedonic regressions suggest that 1) the resulting bias toward zero as a result of including the coastal distance bins may not be very large, and 2) inclusion of BFE, on net, does more to control the positive amenities associated with flood risk.

[22] Summary statistics for the boundary fixed effects sample are presented in Appendix Table B.5.

4. Model

We estimate household willingness to pay to avoid flood risk using a residential sorting framework that we adapt to incorporate preferences to avoid flood risk.[23] In what follows, we describe the household's choice set, their preferences, and their optimization problem.

Choice Set Beginning with the sample of houses in the Miami-Dade CSA that are near flood boundaries, a household chooses to live in one of several types of housing in these neighborhoods. In particular, it makes a discrete, residential location decision based on the attributes of each location it is facing and the costs of living there. A specific choice of housing is constructed as a combination of the following geographic and house characteristics: census tract, flood category (X, A, V), house structure,[24] building type, base flood elevation (BFE) if available, pre-FIRM status, and one of eight distance-to-coast bins ranging from less than 100 m to more than 5 km.[25] We incorporate pre-FIRM status, house and building type, and BFE into the residential choice because they determine the specific NFIP rate used to compute insurance premiums.[26] In addition, we include coastal distance bins in order to better control for the unobserved impact of water-related amenities later on. Because not all house types are available in each year, the number of available choices (J_t) will vary from year to year as well. Our categorization of choice results in approximately 2,150 alternatives to choose from in each year from 2009 to 2012.[27] For the remainder of the paper, we refer to each of these choices as a "residence."

Our data and choice framework imply several assumptions that we must make about how households make decisions with respect to residential location. First, our sample in South Florida and our boundary sample restriction places a limitation on the extent of the market. Previous work using sorting models have considered similarly sized markets.[28] Data from the Census for our study area and time frame also suggest that the extent of the market considered here is appropriate.[29] Moreover, re-estimating our sorting model without the boundary sample restriction recovers a higher flood risk willingness to pay that is comparable to the hedonic estimate without boundary fixed effects (likely driven by correlated unobservables), but does not alter our conclusions about the distributional implications of our sorting results.[30] Second, we assume that households choose where to live conditional on moving in a given year (the year of sale). In other words, we do not model the decision of whether and when to move, but just where to move conditional on moving. Third, all households are assumed to face the same choice-set in the CSA. Differences in consideration sets can impact preference estimates (Kuminoff, 2009). In addition, recent work has also shown that subtle forms of housing discrimination, e.g., the number of houses or sample of neighborhoods shown by a realtor, can drive wedges in choice sets that are correlated with race and ethnicity (Christensen and Timmins, 2018). However, the U.S. Department of Housing found that on most discrimination measures, Hispanic homebuyers in Miami faced similar levels of discrimination as the overall incidence of random discrimination (irrespective of race) in the Miami sample (Turner et al., 2002).[31] While we do not argue that housing discrimination is not an issue in this context, we believe our results are still relevant given that there has been little work to assess whether sorting based on socioeconomic status with respect to flood risk even exists, whether it be driven by discrimination, preferences, or other factors such as, e.g., differential beliefs (Bakkensen and Barrage, 2017) or access to information (Hausman and Stolper, 2019). We note that the underlying sorting mechanisms are an important area of future research. In addition, to the extent that systemic discrimination or other channels would not be undone by flood insurance program reforms, the parameters recovered from our model could still be used to estimate our policy counterfactuals.

Household Preferences A household's preference for a residence j at time t depends on the characteristics of the residence. Many of these characteristics are observed by the econometrician and include structural and geographic characteristics such as the distance to various (dis)amenities (e.g. the coast, highways). There are also aspects of residences that factor into a household's decision that are not observed by the econometrician. Let X_{jt} denote attributes of a residence that are observed and ξ_{jt} describe those that are not. A subset of observable attributes $X_{1jt} \in X_{jt}$ include housing structure-related variables. In practice, these are indicators for single family houses, condominiums, pre-FIRM status (also a proxy for age), and distance-to-coast bins, where the omitted category is for residences located more than 5 km away from the coast. A second set of attributes $X_{2jt} \in X_{jt}$ includes indicators for whether a residence is located in a Special Flood Hazard Area (SFHA) (i.e. A or a V zone), whether BFE

[23] Recent examples of work using residential sorting models that are most relevant to our paper include Bayer et al. (2007), Klaiber and Phaneuf (2010), Tra (2010), and Ma (2019).

[24] The housing structure types are assigned based on the NFIP rate structures, which are '1 to 4', '2 to 4', single, mobile, and residential. The overlap in categories (e.g. '1 to 4' versus single family) is due to different housing categorizations being used for different flood zones. For example, pre-FIRM houses in zone 'AE' are categorized by mobile, single, '2 to 4', and other; on the other hand, the categories that are used if the houses are post-FIRM are '1 to 4', mobile, and other.

[25] One kilometer distance bins are used for houses located between 1 and 5 km of the coast. Within 1 km, we additional categorize houses to be within 100 m, 100–500 m, and 500–1000 m. Houses located more than 5 km away from the coast are considered to be in one category.

[26] For details, see Appendix.

[27] The number of choices, J_t, for $t = 2009, \ldots, 2012$ is respectively 2,408, 2,180, 2,137, and 1,893.

[28] Tra (2010) examines locational choices in the Los Angeles metropolitan area, Sieg et al. (2004) focus on five counties in southern California, Bayer et al. (2007) and Bayer et al. (2016) examine moving within the San Francisco Bay Area (consisting of six counties), and Klaiber and Phaneuf (2010) model housing decisions in the Minnesota Twin Cities area.

[29] Table B.6 in the appendix shows aggregate statistics from the Census for all movers from our study area between 2009 and 2013. It reveals that 69.8 percent of all moves within our study area were within-county moves, and 76.8 percent of all moves were within the CSA.

[30] These results are available from the authors upon request.

[31] See, for example, Exhibit A4-4 in the supplemental materials from Turner et al. (2002).

is assigned,[32] surface elevation, the distance to the nearest river and park, local environmental quality, and school quality. We also allow households to have preferences over neighborhood sociodemographics by including tract-level per capita income, share of population that is Black and share that is Hispanic. As contemporaneous demographics are likely to be endogenous, we include these characteristics as determined in 1990 instead of using 2010 Census characteristics.[33] For attributes that are not constant within a choice (e.g. school quality), an average is taken among each observed house in that choice. In order to assign neighborhood choices with the nearest flood zone boundary, we assign the boundary identifier of the choice to be that of the house closest to any boundary of all houses in that choice set. Among the set of characteristics in X_{2jt}, we separately denote the indicator for belonging to a high risk floodplain, our attribute of interest, as $SFHA_j$, which proxies for flood risk.

For flood risk and X_{2jt}, we allow households to have heterogeneous tastes based on its race/ethnicity and income quintile, denoted by $Z^i = (1, z_1^i, \ldots, z_K^i)$. These observable characteristics include indicators for Black and Hispanic (with the omitted group being white or Asian) and for four of the five income quintiles (where the omitted group is the lowest income quintile).[34] To additionally capture heterogeneous tastes for positive water-based amenity value, we include an indicator for a residence being within 100 m of the coast in X_{2jt}. Lastly, we allow for tastes to vary based on an idiosyncratic component that is household- and residence- specific, ϵ_{jt}^i.

Given the attributes of residences, households trade off between enjoying the services provided by the residences with the flow cost of living in that location, P_{jt}, which enters linearly into household utility.[35] Since we do not observe the prices of houses that individuals do not choose, we calculate all rental prices for residential choices by taking the average house price of houses that sold in that location and then annuitize the average price with a 5 percent discount rate (in perpetuity).[36] We then account for insurance premium subsidies here by subtracting the discount in annual insurance premium from the annual rent. A household i receives the following indirect utility from choosing to move to residence j at time t:

$$V_{jt}^i = \alpha_{x1} X_{1jt} - \alpha_p P_{jt} + \xi_{jt} + \alpha_r^i SFHA_j + \alpha_{x2}^i X_{2jt} + \epsilon_{jt}^i \tag{1}$$

where

$$\alpha_\ell^i = \alpha_{0,\ell} + \sum_{k=1}^{K} \alpha_{k,\ell} z_k^i \; for \; \ell = \{r, x2\} \tag{2}$$

In anticipation of the need to deal with unobserved factors that are correlated with flood risk and price (elaborated in the next section), we re-write the indirect utility, V_{jt}^i, so that it can be separated into choice- and individual- specific components:

$$V_{jt}^i = \delta_{jt} + \left(\sum_{k=1}^{K} \alpha_{k,r} z_k^i \right) SFHA_j + \left(\sum_{k=1}^{K} \alpha_{k,x2} z_k^i \right) X_{2jt} + \epsilon_{jt}^i \tag{3}$$

where

$$\delta_{jt} = \alpha_{0,r} SFHA_j + \alpha_{x1} X_{1jt} + \alpha_{0,x2} X_{2jt} - \alpha_P P_{jt} + \xi_{jt} \tag{4}$$

The choice-specific component, δ_{jt}, represents the mean utility of the base (or omitted) group, which consists of whites and Asians in the lowest income quintile. The parameter $\alpha_{k,r}$, the coefficient on the interaction between the individual's type and the neighborhood's floodplain, represents the additional utility from living in $SFHA_j$ that a household of type k receives *relative to* the base group. The parameter $\alpha_{k,x2}$ is similarly interpreted with respect to the set of attributes in X_{2jt}. These heterogeneous preference parameters, or the coefficients on individual-specific components of utility ($\alpha_{k,r}$, $\alpha_{k,x2}$), are distinguished from the base group parameters on the choice-specific components of utility ($\alpha_{0,r}, \alpha_{x1}, \alpha_{0,x2}, \alpha_P$) because they will be estimated in stages.[37]

Conditional on moving at time t, household i chooses to live in residence $d_t^i = j$ if it yields the highest utility among all other alternatives:

$$d_t^i = j \text{ if } V_{jt}^i \geq V_{j't}^i \;\; \forall \; j' \neq j \tag{5}$$

[32] Recall that 91 percent of our sample does not have a base flood elevation assigned by the NFIP, and so we include an indicator for BFE assignment in the utility function even though we use the actual level of base flood elevation in computing the insurance premium, when applicable.

[33] We include neighborhood demographic characteristics mainly to serve as controls. As these lagged demographics may still be endogenous, we refrain from interpreting the coefficients on these characteristics.

[34] In robustness checks, we allow race-income specific preferences as well.

[35] This setup assumes that household budget constraints enter linearly into the utility, ruling out income effects. Income limitations on the choice of residence are more likely to appear through differential choice sets than in choice probabilities.

[36] The user cost of housing used is similar to that estimated for Miami from Himmelberg et al. (2005).

[37] For the subset of neighborhood characteristics (rental price and attributes X_{1jt}) where we have assumed homogeneous preferences, the coefficients on these variables apply to all groups.

Further assuming that household idiosyncratic tastes for choices are distributed i.i.d. Type I Extreme Value, the expected probability that a household chooses residence j has the following closed form expression (McFadden, 1978):

$$Pr^i_{jt} \equiv Pr\left(V^i_{jt} \geq V^i_{j't}\ \ \forall\ j' \neq j \mid X, P, Z\right) = \frac{e^{V^i_{jt}}}{\sum_{j'} e^{V^i_{j't}}} \tag{6}$$

With $N_t\ \in\ N$ residents moving at time t, the predicted share of each residence that is chosen can be calculated by averaging over the probability that individuals choose each location in that period:

$$s_{jt} = \frac{1}{N_t} \sum_{i}^{N_t} Pr\left(V^i_{jt} \geq V^i_{j't}\ \ \forall\ j' \neq j \mid X, P, Z\right)\ \ \forall j,\ t \tag{7}$$

5. Estimation

Estimation of the problem will proceed in two stages. Stage 1 recovers individual-specific preference parameters and mean utilities using Maximum Likelihood Estimation. Stage 2 follows with a regression that decomposes the mean utility estimates from stage 1 to recover the remaining base group parameters. We refer to this regression as a "mean utility decomposition." It is in this stage that we include boundary fixed effects and employ an instrumental variables strategy to deal with the endogeneity of price. Standard errors are bootstrapped using 500 draws of the sample with replacement.[38] We detail each step below.

Stage 1 In the first stage, we build the following log-likelihood function based on predicted choice probabilities that are consistent with our locational choice model:

$$\ell\ell(d, X, P, Z) = \sum_{t}^{T} \sum_{i}^{N_t} \sum_{j}^{J_t} 1(d^i_t = j) \cdot log\ Pr^i_{jt} \tag{8}$$

The indicator, $1(d^i_t = j)$, is equal to 1 if a household i actually chooses to live in neighborhood j. We maximize the log-likelihood to estimate the parameters in the household's utility. Recall that location-specific attributes (such as flood risk) has been characterized by a set of J mean utilities, δ_{jt}. In this stage, we recover these mean utilities first, instead of the coefficients on the various attributes $(\alpha_{0,r}, \alpha_{0,x1}, \alpha_{x2}, \alpha_p)$ that contribute to these mean utilities. This procedure then returns the set of mean utility parameters, δ_{jt}'s, and household-specific taste parameters, $(\alpha_{k,r}, \alpha_{k,x2})$, that best explain the actual choices made in the data according to our model. Practically, we normalize the mean utility of one choice in each period to be 0 and then solve for the mean utilities of the remaining choices using a Berry (1994) contraction mapping routine. The contraction mapping routine to recover the δ_{jt}'s is nested in an outer loop of the likelihood estimation procedure that varies the household-specific taste parameters, $(\alpha_{k,r}, \alpha_{k,x2})$.

A benefit of estimating mean utility parameters first instead of the choice-specific parameters directly is that we postpone dealing with endogeneity concerns associated with the choice- and period- specific unobservable, ξ_{jt}, until the second stage, where mean utility is linear in parameters.[39] Furthermore, using a contraction mapping yields computational savings, which is important given the large number of choice alternatives in our setting.

Stage 2 With the first stage estimates in hand, the second stage regresses the estimates of residence mean utilities on neighborhood attributes to recover the preferences for these attributes:

$$\hat{\delta}_{jt} = \alpha_{0,r} SFHA_j + \alpha_{x1} X_{1jt} + \alpha_{0,x2} X_{2jt} - \alpha_P P_{jt} + \xi_c + \xi_t + \xi_{jt} \tag{9}$$

The coefficients on attributes for which households have heterogeneous preferences $(\alpha_{0,r}, \alpha_{0,x2})$ represent the preferences of the base group, while those on the remaining attributes (α_{x1}, α_P) represent the average preferences of all households. Here, we additionally introduce county (ξ_c) fixed effects to control for unobserved differences between counties, and year (ξ_t) fixed effects to adjust for macroeconomic price trends.

Equation (9) can be estimated by OLS; however, we are concerned with two important endogeneity issues. First, cost of living in a neighborhood, P_{jt}, will likely be correlated with unobserved neighborhood quality, ξ_{jt}. In this respect, we follow the approach taken in Bayer and Timmins (2007) by constructing instruments based on the exogenous attributes of distant communities that affect the price of neighborhood j. The logic behind this instrument is based on the equilibrium sorting model: the cost of living in a community j depends, in part, on the availability of residences in distant communities that may be considered substitutes. The exclusion restriction is satisfied with this instrument because while the attributes of farther-away communities can affect price in equilibrium, the attributes of these distant communities should not directly enter into the utility of living in residence j. We use the share of urban, open land in nearby communities as an instrument, which is a measure of undeveloped

[38] This is to account for estimation error for the second stage estimates, which performs estimation using first stage estimates.

[39] Berry (1994) shows that we can recover the set of mean utilities in this way by inverting choice shares; in other words, there is a unique vector of δ_{jt}'s that sets the predicted shares of choice alternatives equal to the observed shares.

land.[40]

To implement this instrument, let $\widehat{\ }$'s indicate first-stage estimates. Using a guess of the price coefficient, $\alpha_P^{(0)}$, we adjust the estimated mean utility for a location with the cost of living there by moving price to the left side of the equality in (9), $\widehat{\delta}_{jt} + \alpha_P^{(0)} P_{jt}$. Next, we estimate the following modified version of equation (9) with the adjusted mean utilities as the dependent variables and additionally include the share of undeveloped land within a 1-, 3-, and 5- kilometer radius, denoted by $\widetilde{U}_j$,

$$\widehat{\delta}_{jt} + \alpha_p^{(0)} p_j = \alpha_{0,r} SFHA_j + \alpha_{x1} X_{1jt} + \alpha_{0,x2} X_{2jt} + \alpha_{\widetilde{U}} \widetilde{U}_j + \xi_c + \xi_t + \widetilde{\xi}_{jt} \tag{10}$$

Since we have allowed characteristics of neighboring residences (within 5 km of choice j) to directly affect mean utility, the error $\widetilde{\xi}_{jt}$ now captures attributes of distant neighborhoods (i.e. farther than 5 km) that affect cost of living in j. With the estimates from the modified mean utility regression (10), which we denote with *'s, we can formulate a modified version of the mean utility, where $\widetilde{\xi}_j$ are set to 0,

$$\widetilde{\delta}_{jt} = \alpha_{0,r}^* SFHA_j - \alpha_p^{(0)} p_j + \alpha_{x1}^* X_{1jt} + \alpha_{0,x2}^* X_{2jt} + \alpha_{\widetilde{U}}^* \widetilde{U}_j + \xi_c + \xi_t \tag{11}$$

We then solve for the vector of prices, p_j^{IV}, that sets predicted shares based on $\widetilde{\delta}_{jt}$ equal to actual shares σ_{jt}:

$$\sigma_{jt} = \frac{e^{\widetilde{\delta}_j + \left(\sum_{k=1}^K \alpha_{k,r} z_k^i\right) SFHA_j + \left(\sum_{k=1}^K \alpha_{k,x2} z_k^i\right) X_{2jt}}}{\sum_{j'} e^{\widetilde{\delta}_{j'} + \left(\sum_{k=1}^K \alpha_{k,r} z_k^i\right) SFHA_{j'} + \left(\sum_{k=1}^K \alpha_{k,x2} z_k^i\right) X_{2j't}}} \tag{12}$$

The difference in predicted and actual shares is driven by variation in developed land that is more than 5 km away (i.e. $\widetilde{\xi}_j$), which we do not expect to directly influence the utility of living in a given location. Thus, the prices, $p_{j,t}^{IV}$, that clear the market will also reflect this variation. In practice, the instrumental variables estimates may be sensitive to the initial guess for the price coefficient. We repeat this procedure with updated guesses of the price coefficient until the final price coefficient estimate is stable.

Second, water-related amenities are likely to be correlated with flood risk, i.e., $E\left[\xi_{jt} SFHA_j\right] \neq 0$. Recall that we categorized residences using distance-to-coast bins and BFE. Inclusion of these distance bins as fixed effects avoids the comparison of houses with vastly different levels of coastal access. Conditional on distance to the coast, inclusion of average elevation also provides some control of the quality of coastal view. Finally, we include boundary fixed effects to compare residences just on either side of a flood zone boundary, which subsume our county-level fixed effects ξ_c. To the extent that these controls are imperfect, however, the unobserved amenity correlates should attenuate our flood risk parameter estimate.

6. Sorting over flood risk

Do individuals sort over flood risk? We first present our base group estimates from the mean utility decomposition and then follow with estimates of the sorting parameters.[41] The first two columns of Table 4 give our main estimates from the mean utility decomposition and standard errors. These estimates are a result of applying the Bayer and Timmins (2007) instrumental variables strategy for price, which exploits variation in the share of undeveloped land in nearby communities. Boundary fixed effects are included but not shown. For comparison, we present OLS estimates in the final two columns.[42]

First, the magnitude of the IV price coefficient (−1.739) is much larger than the OLS estimate (−0.005). The F-statistic from the first stage regression is 26.65, significantly larger than the rule of thumb of 10 suggested by Staiger and Stock (1997). The direction of the bias is consistent with cost-of-living being positively correlated with the quality of unobserved amenities. Our main coefficient of interest, *SFHA*, finds that living in a high risk floodplain decreases utility for those in the base group (we return to magnitudes shortly).[43] Focusing on the coefficients of other amenities in the decomposition, we also find that their signs are generally reasonable: households like school quality, single family homes, and newer houses (proxied by pre-FIRM status), and dislike environmental nuisances (although it is not statistically significant) and distance from the coast, parks, and

[40] This data is assessed from digitized files provided by the Florida Fish and Wildlife Conservation Commission and Florida Natural Areas Inventory. For details, see https://www.fnai.org/LandCover.cfm.

[41] We present the stage 2 estimates before stage 1 because the parameter estimates (recovered from stage 1) are interpreted *relative* to the base group estimates as discussed in section 4.

[42] Recall that households have heterogeneous preferences for a subset of the amenities, namely flood zone, surface elevation, BFE assignment, distance to the nearest river and park, 0.1 km coastal bin indicator, environmental quality, school quality, and neighborhood sociodemographics (tract-level per capita income, share Black, and share Hispanic). Estimates in Table 4 thus represent the utility of the base group of white and Asian households in the lowest income quintile. For all other attributes (price, single, condominium, pre-FIRM status and distance-to-coast bins greater than 0.1 km), the coefficients should be interpreted as the average effects on utility for all groups.

[43] Less than 1 percent of our sample lives in the V zone, which is representative of the spatial distribution of the population with respect to flood risk in this area. With so few observations in the V zone, we are unable to estimate heterogeneous preferences to live in the V zone separately by household type and therefore combine the V and A zones in estimation.

Table 4
Mean utility decomposition ($J = 8{,}618$).

	Price IV		OLS	
	est.	s.e.	est.	s.e.
Rent (α_p)	−1.739	0.302	−0.005	0.001
SFHA	−1.235	0.379	−0.085	0.039
BFE Assigned	−14.446	2.649	−0.294	0.076
Elevation	−0.275	0.159	0.144	0.014
Coast < 0.1 km	15.284	3.294	−1.842	0.159
Income	0.273	0.059	−0.062	0.002
Black	−14.035	2.177	−2.264	0.118
Hispanic	−15.611	2.856	−2.247	0.158
School Quality	11.318	5.514	−1.482	0.413
Dist. to River	−1.570	0.530	−0.131	0.039
ICR within 3 km	0.078	0.077	0.069	0.010
Dist. to Park	−0.415	0.081	0.002	0.005
Single	4.220	0.779	0.755	0.039
Condo	−11.800	2.299	0.644	0.047
Pre-FIRM	−8.149	1.404	0.148	0.019
Distance to Coast:				
<0.5 km	12.111	2.340	−0.535	0.054
<1 km	10.525	2.006	−0.567	0.049
<2 km	6.268	1.296	−0.578	0.039
<3 km	2.526	0.709	−0.546	0.036
<4 km	0.143	0.466	−0.536	0.039
<5 km	−1.170	0.416	−0.404	0.037

Note. The estimates from the mean utility decomposition are in "utils" and will be converted to a dollar value using the coefficient α_p on Rent (in 2010 \$1,000's) in Table 5. The specification includes county and year fixed effects, which are not shown. All distances are in kilometers, and elevation is in meters. Standard errors are bootstrapped using 500 sample draws with replacement.

rivers. We note that for many of these attributes, the coefficients from OLS estimation are counter-intuitive, highlighting the need for the IV.

Next, we present the sorting estimates for flood risk in Table 5. We use the price coefficient (α_p) to convert all estimates into a dollar measure for marginal willingness to pay (MWTP) rather than present estimates in utils.[44] Note that we include the MWTP estimates for the "Base Group" in Table 5, which are simply the mean utility estimates from the first stage converted into a dollar value.[45] We do this to aid the interpretation of the sorting parameter estimates. For example, a particular (non-base) group's MWTP to live in a floodplain is the sum of the base group's MWTP and its (heterogeneous) parameter estimate (converted to a dollar value). The main results are listed in the first two columns of Table 5. We list the average and standard deviations of income by group for reference in the last two columns. On average, the base group is willing to pay \$710 per year to *avoid* living in a high risk flood zone. Assuming a 5 percent discount rate, this represents 6.3 percent of average housing prices given an average price in the sample of \$225,434. Relative to this group, the MWTP to *avoid* flood risk is close to 87 percent as high for Hispanic owners, and about 68 percent as high for Black owners. The MWTP also increases with income, where those in the two highest income quintiles have willingnesses to pay that are approximately 9–28 percent higher compared to the base group. While all groups dislike flood risk, low income and minority groups are more likely to sort into floodplains. If protection from flood risk is a normal good, then it is intuitive that willingness to pay to avoid flood risk increases with income or wealth.[46] This may also explain the low MWTP estimates for minorities, who have an average income that is \$24 thousand (Hispanic) and \$57 thousand (Black) less than whites and Asians (who have an average income of \$111 thousand overall).[47]

We present flood risk estimates that ignore NFIP price supports in the second two columns. Ignoring premium discounts biases the MWTP estimate downward (consistent with our hedonic estimates), where the MWTP to avoid flood risk is actually positive. As such, the model that ignores these discounts attributes higher flood risk exposure than what is actually internalized for these individuals for the housing costs paid. In other words, the same amount of housing cost reduction looks to be compensating a much larger increase in exposure to flood risk than in reality. Again, these results motivate the importance of

[44] Raw utility estimates are presented in Table B.7 of the appendix. MWTP estimates for other spatial characteristics are presented in Appendix Table B.8.

[45] Specifically, the base group MWTP for flood risk is computed as $\frac{\alpha_{0,r}}{\alpha_p} \times 1000$ (since annual rent is in \$1000's of dollars).

[46] See also Appendix Table B.8 for sorting results over other spatial amenities and nuisances. In particular, we find a similar income gradient for elevation, BFE assignment, and proximity to the coast, which confirms our earlier intuition that these variables proxy for access to water-related amenities.

[47] In Table B.9 of the appendix, we additionally provide preference estimates by race-by-median-income groups. The base group of low-income, white or Asian residents is willing to pay \$755 per year to avoid living in a high risk flood zone, which is similar to the previous base group estimate. The same general patterns emerge as before: white and Asian households are more likely avoid flood risk relative to minorities, holding income constant. Conditional on race and ethnicity, flood risk avoidance generally increases with income.

Table 5
Sorting estimates for flood zone.

Base Group	Include Discount		Ignore Discount		Income (in $1000's)	
	est.	s.e.	est.	s.e.	mean	s.d.
White/Asian, Quintile 1	−710.49	218.11	818.34	169.15	30.28	5.89
Relative to Base Group	est.	s.e.	est.	s.e.	mean	s.d.
Black	229.25	29.40	257.18	32.99	53.85	57.17
Hispanic	91.74	20.96	102.92	23.51	86.50	134.08
Quintile 2	−15.94	24.12	−17.89	27.06	45.69	4.30
Quintile 3	−31.00	24.60	−34.78	27.60	63.90	6.39
Quintile 4	−62.65	25.43	−70.29	28.53	94.74	12.59
Quintile 5	−198.03	27.12	−222.16	30.42	235.17	245.23

Note. Base group estimates (for white/Asian households in the first income quintile) are recovered from stage 2, and all standard errors are bootstrapped. The parameter estimates (by race/ethnicity and income group) are recovered from stage 1. All estimates have been converted to a (real 2010) dollar value using the estimated coefficient on rent and represent an annual (flow) MWTP per household. Estimates for non-base group categories should be added to the base group estimate to recover the preference for that group. The unconditional average income for the white/Asian group is $111 thousand. Average house price is $225,434.

accounting for related program discounts in sorting and hedonic analyses.

These results provide a basis for the concern that the correlation between environmental risk and vulnerable groups can be driven at least in part by sorting, and, in particular, the "coming to the nuisance" by more vulnerable groups and, at the same time, the systematic flight from the nuisance by less vulnerable groups (Depro et al., 2015; Banzhaf et al., 2019). While we posit that income is an important underlying driver of heterogeneity, it is unlikely to be the whole story. There could be various factors correlated with income that contribute to sorting, which we cannot disentangle, including differential tastes (Banzhaf and Walsh, 2008), beliefs (Bakkensen and Barrage, 2017), access to information (Hausman and Stolper, 2019) and learning (Ma, 2019), or housing discrimination (Christensen and Timmins, 2018), all of which can moderate adaptation and resiliency to natural disasters. Although we do not have the ability to separate these alternative mechanisms and note this as an important area of future research, such heterogeneity will likely leave low-income and minority groups relatively more exposed to high risk areas. Finally, this evidence of sorting reaffirms the established result that capitalization effects estimated from hedonic price models should be interpreted with care as they may combine preferences to avoid risk with changes in the implicit prices of flood risk (and other amenities) as people move heterogeneously into and out of neighborhoods (Kuminoff et al., 2010; Kuminoff and Pope, 2014).

7. Implications for policy reform

Public programs are paramount for disaster preparedness and recovery, yet continued calls for reform highlight concerns over their performance and fiscal costs (Michel-Kerjan, 2010; Deryugina, 2017). The National Flood Insurance Program (NFIP), in particular, has long faced scrutiny for the prevalence of discounted premiums and outdated flood maps (Michel-Kerjan, 2010; Michel-Kerjan and Kunreuther, 2011). Designated as a financially "high risk" program by the Government Accountability Office, historical payouts have exceeded premiums, with NFIP debt at $20.5 billion as of February 2018 and expected costs exceeding revenue by $1.4 billion annually (CBO, 2017; GAO, 2018). In addition, while flood risk maps are the primary source of flood risk information in the United States, almost two-thirds of the flood maps have not been updated in the past five years (Keller et al., 2017). Despite a recommendation from the Department of Homeland Security that the NFIP should improve its management of floodplain mapping, funding for flood map updates has been slow to follow and politically uncertain (OIG, 2017).

Moreover, previous NFIP reform attempts have been unsuccessful despite historical bipartisan support, due, in part, to concerns about insurance affordability if price supports end (DHS, 2018; Kousky, 2018). In July 2012, Congress passed, with bipartisan support, the Biggert-Waters Flood Insurance Reform Act that slowly phased out some key price discounts, including grandfathering and discounts for pre-FIRM properties. However, this legislation was tempered in the eventual 2014 Homeowner Flood Insurance Affordability Act, which slowed the removal of pre-FIRM discounts and re-instated grandfathering through Congressional mandate.[48] Even with efforts to improve fiscal soundness, the affordability of flood insurance remains a key policy goal of the NFIP (Kousky and Kunreuther, 2014). A small but growing area of literature assesses the potential distributional consequences of the current NFIP and affiliated programs (Bin et al., 2012, 2017; Kahn and Smith, 2017; Noonan and Sadiq, 2018).

7.1. Empirical approach

We use the structural parameters recovered from the sorting model to assess how potential reforms to insurance prices and flood-risk information under the National Flood Insurance Program may lead to differential changes in household welfare and

[48] Premium changes under the Biggert-Waters reform did not begin until 2013 and therefore do not affect our sample (FEMA, 2013a). For an assessment of the impact of the reforms on housing markets, see recent empirical work by, e.g., Gibson et al. (2017) and Indaco et al. (2018).

hazard exposure. First, we estimate the compensating variation across race and income groups for three simulated types of price changes, as well as the predicted reallocation of household types across flood-risk zones. The three price reforms include discontinuation of: (1) pre-FIRM insurance rates, a preferential rate structure at the property-level for housing stock built before the first flood insurance rate map (FIRM) was released in their community; (2) Community Rating System (CRS) discounts, a price reduction of up to 45 percent off flood insurance premium prices determined by flood activities at the community level; and (3) preferred rate grandfathering, a rule that allows properties with pre-existing flood insurance contracts to maintain preferential rates after new flood maps are released. We note that there are no current efforts to remove or alter the CRS program. Pre-FIRM rate structures are currently being phased out and grandfathering was eliminated in 2012 and then brought back by act of Congress in 2014. The specific reforms that we consider are therefore highly relevant to the present policy discussion.[49] Second, we utilize recent risk-map changes in Florida to assess the value of new risk-map information by comparing household welfare under up-to-date information (from new risk maps) versus welfare based on location choices made using previous risk maps. We then compare these benefits to the costs of map revisions.

We apply our sorting estimates to counterfactual exercises with the necessary assumption that the drivers of sorting and, importantly, heterogeneity remain fixed. The specific source and the time-invariance of heterogeneity are both important caveats in interpreting our predicted NFIP reform impacts. What drives heterogeneity is crucial for regulators to select the appropriate policy to counteract undesirable sorting outcomes.[50] The persistence of heterogeneity over time will also affect the distribution of welfare impacts. While our data do not allow us to identify the mechanism leading to sorting and the drivers may also change in the long-run, the results from the next set of empirical exercises demonstrate the scope for both overall and distributional impacts of reform, which is novel to this literature.[51] However, to the extent that the underlying sorting mechanisms are not immediately impacted by changes to the flood insurance program, our results would represent short- and medium-term policy impacts.

7.2. CRS and pre-FIRM price supports

We first examine a counterfactual scenario in which NFIP premiums are set to risk-based rates after the removal of pre-FIRM and CRS price supports. Specifically, we calculate the compensating variation associated with these price changes following McFadden (1999):

$$CV_{PE} = \frac{1}{-\alpha_p}(E \max_{j \in 1,\ldots,J}(V(p^1, SFHA, X, \epsilon)) - E\, max(V(p^0, SFHA, X, \epsilon))) \tag{13}$$

Table 6 presents the dollar value of impacts overall and by race and income groups upon removing all price supports other than grandfathering (top panel), pre-FIRM discounts only (middle panel), or CRS discounts (bottom panel). On average, removing both pre-FIRM and CRS discounts causes individuals to lose \$209 per year (shown in the first cell of the top panel).[52] The magnitude of losses increases with income. Not only do higher income households dislike flood risk, they are most likely to live in high risk areas due to their demand for coastal amenities. By race, the per household impacts on white and Asian households are generally lowest.

We view these impacts relative to income in Fig. 3, which plots the losses as a percentage of the average income in each race and income-bin cell. While the highest income quintile groups lose the most in levels, removal of all price supports presents the largest burden for the lowest income groups (conditional on race).[53] This suggests that a policy that removes these discounts would be regressive. Compared to the impacts on whites and Asians, Hispanics experience somewhat larger impacts as a share of income.

Table 7 presents the change in distribution of race and income across the low risk zone X, the high inland flood risk zone A, and the high coastal flood risk zone V after removing both the CRS and pre-FIRM discounts. We see two important trends. First, price reforms would lead to fewer people in harm's way, with a migration towards low risk areas and away from higher risk A zone areas of between 2 and 14 percent and from coastal zone V areas, which (currently) receive large discounts, by between 2 and 54 percent. However, we also note that the higher risk zones will tend to become increasingly minority and low income as we predict a stronger out-migration of white/Asian and high-income groups from these areas. Thus, our results highlight that policy change could have large distributional impacts with potentially long lasting implications for disaster vulnerability, recovery, and fiscal policy (Arrow et al., 1996; Robinson et al., 2016; Banzhaf et al., 2019).

[49] We acknowledge that the CRS counterfactual is the least politically relevant of the three policies, in part because of the multitude of flood preparedness measures that localities are incentivized to engage in through the CRS. We ultimately decided to present the impacts from removing the CRS as we still believe the CRS program to be an interesting point of comparison for the pre-FIRM and grandfathering programs, including as a benchmark for the current distributional impacts of the programs across race, ethnicity, and income groups, as well as the overall welfare impacts of the program, both before and after potential reforms.

[50] For example, should the policy lever be in an information campaign to adjust heterogeneous beliefs or to enforce realtor reporting of shown properties to prevent subtle forms of housing discrimination?

[51] Due to these limitations, we abstract from general equilibrium price and sorting changes in our counterfactual exercises, which would require additional strong assumptions on top of those already imposed.

[52] Note that we currently assume that there are no costs to move as we do not observe homebuyers' previous locations, so these welfare impacts can be seen as a lower bound on the true welfare costs (i.e., the true cost of the policy reform may be more negative).

[53] Corresponding figures that separately remove subsidies are similar (presented in Appendix Figure B.2).

Table 6
Impact of removing price supports by race and income (2010 $USD).

All	Overall	Q1	Q2	Q3	Q4	Q5
Overall	−209.31	−174.07	−190.68	−193.73	−215.65	−272.44
White/Asian	−191.67	−135.33	−162.86	−170.45	−195.12	−251.36
Black	−184.18	−167.02	−185.65	−187.83	−209.29	−257.07
Hispanic	−234.19	−202.73	−214.60	−218.48	−244.70	−308.69
Pre-FIRM	Overall	Q1	Q2	Q3	Q4	Q5
Overall	−191.29	−157.01	−172.40	−176.45	−198.09	−252.56
White/Asian	−175.39	−122.50	−147.12	−155.23	−178.85	−232.15
Black	−166.58	−149.73	−167.63	−170.63	−191.66	−237.64
Hispanic	−214.23	−182.93	−194.21	−199.13	−225.38	−287.64
CRS	Overall	Q1	Q2	Q3	Q4	Q5
Overall	−96.04	−78.84	−85.69	−83.74	−97.46	−134.47
White/Asian	−89.88	−58.36	−74.37	−76.22	−90.56	−125.31
Black	−94.89	−85.77	−96.73	−94.76	−107.11	−138.60
Hispanic	−102.89	−89.60	−91.20	−88.85	−105.69	−149.60

Note. Table calculates the compensating variation required after removing all or one of the price supports under the NFIP by race and/or income quintile and represent an annual (flow) welfare change per household in real 2010 $USD.

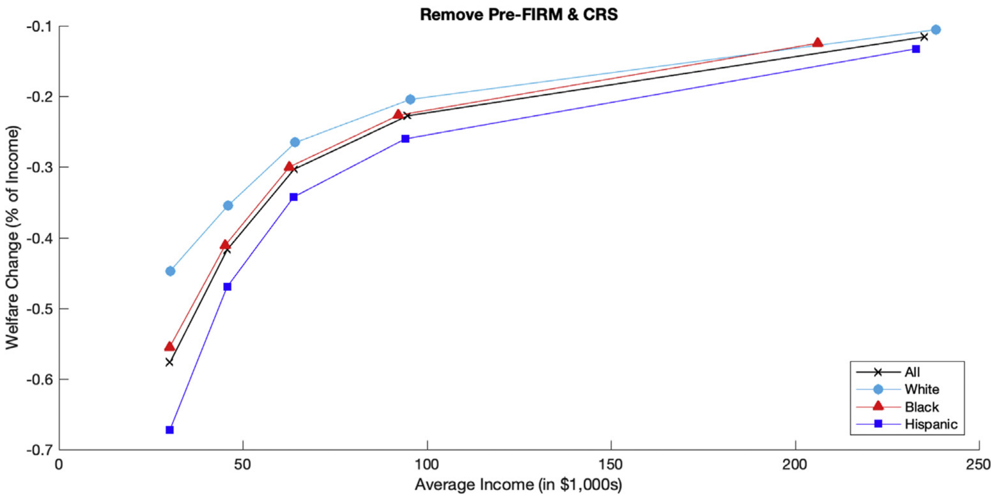


Fig. 3. Losses as a percentage income, remove NFIP price supports.

7.3. Grandfathering

An important feature of the NFIP program is grandfathering, which allows a household who would have faced a higher risk zone after a flood map update, the option to maintain its original flood insurance premium from a pre-existing policy. We can assess the losses from removing grandfathering from the following thought experiment: using a snapshot of updated flood maps as of 2016, we compare the change in household welfare from a map update with grandfathered rates to the change in welfare from the same map update except without grandfathered rates. In the case where a zone is mapped into a lower risk area, we retain the premium based on the lower risk level in the grandfathering scenario, assuming that households are given this option. We operationalize this by first mapping all houses according to flood insurance maps as of 2016. We then calculate the 2016 zone premiums according to current NFIP rates, CRS discounts, and community boundaries.

In general, most zone X houses remain as zone X after the map changes. However, there was a large share of zone A houses that would eventually be "downgraded" to zone X, and similarly, a small portion of V zone houses during our sample would become X or A zone houses.[54] We note that the direction of the change in flood zone can impact the size of losses from removing

[54] Appendix Table B.10 presents a transition matrix for current zones to future zones. A large share comes from Broward County (FIPS 12011). The V zone "downgrades" come primarily from Miami Dade county (FIPS 12086).

Table 7
Percent changes in race/income distribution by zone.

All	Zone X	Zone A	Zone V
White/Asian	11.55	−11.74	−54.36
Black	2.24	−2.32	−2.01
Hispanic	13.86	−14.27	−29.86
All	Zone X	Zone A	Zone V
Q1	4.70	−4.87	−4.03
Q2	4.89	−5.06	−4.90
Q3	4.84	−4.98	−10.11
Q4	5.52	−5.64	−19.45
Q5	7.71	−7.77	−47.75

Note. Table aggregates the changes in predicted shares after all NFIP price supports are removed.

Table 8
Values from map updates (2010 $USD).

Group	(1) Remove Grandfathering	(2) Value of Better Risk Information
Overall	−305.87	103.38
Zone X	−304.12	102.34
SFHA	−307.69	104.46
White/Asian	−241.13	144.09
Black	−238.29	59.75
Hispanic	−391.28	70.47
Q1	−225.37	78.72
Q2	−268.53	85.35
Q3	−315.03	92.98
Q4	−350.40	108.07
Q5	−370.16	151.83

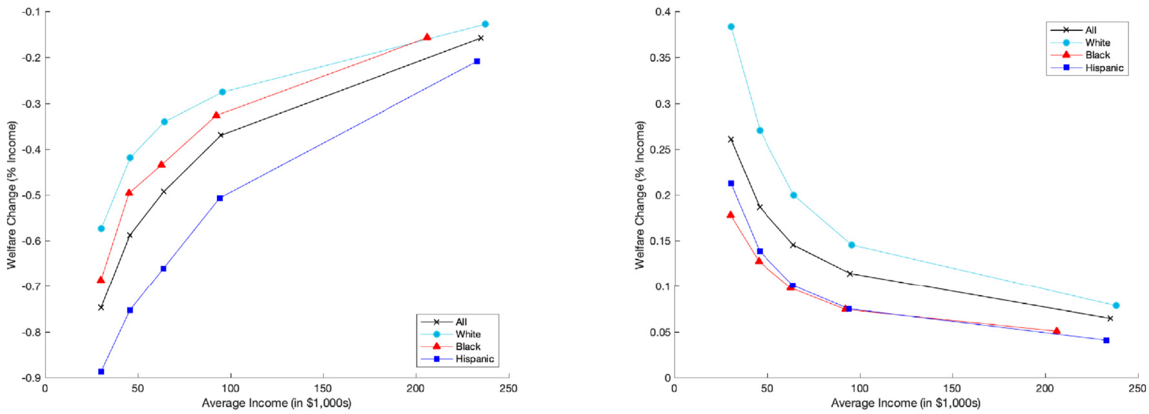
Note. Column 1 of this table provides the compensating variation required from removing the grandfathering option given the current flood map updates from the 2016 FIRMs and represent an annual (flow) welfare change per household in real 2010 $USD. Column 2 then calculates the value of this information.

grandfathering. In addition, since some areas within a residential choice (partially defined by the original flood zone) could have experienced an update whereas other areas (within the same choice) do not, we replace the flood zone dummy from our model with the share of houses that are A or V zones (according to the updated flood map) in our counterfactual analysis.

Column (1) of Table 8 presents the impacts of removing grandfathering. Within each group, we then stratify by race, income, and the current zone (actually chosen). Overall, we find that all groups lose without the grandfathering option, where the average loss is $305 per year. The average loss for white and Asian households ($241) is lower than that for Hispanic households ($391), and similar to that for Black households ($238). We again assess the regressivity of a policy that removes grandfathering in Fig. 4(a). We divide the average welfare loss of each race and income group by the group's average income. As before, we see that removing grandfathering causes disproportionate burden on the lowest income groups. For example, the annual losses represent almost 0.75 percent of income for the bottom income quintile compared to less than 0.2 percent for the top quintile. These losses also disproportionately impact Hispanic households. At the bottom quintile, the difference in income share between white/Asian and Hispanic households is about 0.3 percentage points.

7.4. Flood map updates

Improvement of flood maps is critical for optimal household decision-making, yet funding to FEMA's flood mapping program is politically uncertain. To quantify the benefits of flood map revisions, we use the updated flood insurance maps to learn about



(a) Remove Grandfathering   (b) Value of Information

Fig. 4. Welfare changes from map updates as a percentage of income.

the value of the information provided by these maps. We calculate the value of information following Leggett (2002) as

$$cv = \frac{1}{\alpha_P}\left[ln\left(\sum_{j,t} e^{V^1_{jt}}\right) - ln\left(\sum_{j,t} e^{V^0_{jt}}\right) - \sum_{j} \pi^0_{jt}\left(V^1_{jt} - V^0_{jt}\right)\right] \tag{14}$$

The term, V_{jt}, again represents the conditional value of choosing choice j at time t. The superscripts, 0 and 1, on V_{jt} respectively index before and after flood map release, and π^0_{jt} is the probability of selecting neighborhood j given the pre-updated (or old) flood maps. As before, α_P, refers to the marginal utility of income. The “log-sum” terms (or inclusive values) in equation (14) is the expected value from choosing optimally (less a Euler's constant, which is eventually differenced out); this is a result from taking the expectation of the maximum of the utility, i.e. $E\left[max_j\left\{e^{V_{jt}}\right\}\right]$, where the ϵ_{jt}'s have been integrated out based on their assumed extreme value distribution, similar to the measure of compensating variation used previously. The difference between the first two inclusive values in the brackets gives the change in welfare before and after the flood map update. The last term, derived by Leggett (2002), adjusts for any potential loss an individual might incur. It does so by giving more weight to alternatives that are only more attractive under the old information set, where the weight is the choice probability association with the old information set. Intuitively, cv is loss from making a sub-optimal decision that would have seemed optimal with the old map.

Column (2) of Table 8 presents the value of information as calculated based on equation (14). On average, there are positive gains from release of current flood map information, where the average value of the update is $103 per year. In terms of a dollar value, maps provide the least value to Black households ($60 compared to $144 and $70 for white/Asian and Hispanic households, respectively), and the highest value to high-income households ($152). However, plotting the benefits as a share of income as before in Fig. 4(b), we find that information provision is progressive. On average, the benefits are 0.25 percent of income for households in the bottom quintile compared to 0.1 percent for the top quintile. Not only do flood maps have positive value, it potentially has a progressive impact across those who use the information. These results once again highlight how policy change can have important distributional consequences in the presence of sorting based on socioeconomic status.[55]

8. Policy discussion

Are these impacts large? Table 9 presents a simple aggregation exercise with impacts scaled up to all households in the Miami-Dade, Port St. Lucie, Ft. Lauderdale Combined Statistical Area (CSA).[56] Recall that these distributional costs are not simply the sum of the increases in insurance premiums, but also account for the re-sorting that will occur in response to premium changes. We find that price reforms can have large distributional costs en masse. Removal of all three price supports would lead to a $353 million annual loss for affected homeowners in the CSA. The removal of pre-FIRM price supports alone, currently being phased out under the 2012 and 2014 reforms, costs approximately $131 million per year.

[55] Our results assume equal access to and understanding of this information. As flood maps are easily available online and flood risk must be disclosed in the buying process, we assume this to be true but note that the impacts of unequal access to or understanding of information across groups is an important area of future work.

[56] We also scale the cost estimates (down) by the fraction of flood insurance uptake across the region (29.1 percent). We do not scale the value of new flood map information down because the flood map information is freely and publicly available regardless of flood insurance status and therefore would benefit all residents.

Table 9
Aggregate impacts from policy reform.

Policy	Aggregate Impacts ($ millions)
Remove CRS and Pre-FIRM	-$143.5
Remove Pre-FIRM Only	-$131.1
Remove Grandfathering	-$209.7
Value of Map Revisions	$243.5

Note. Table presents aggregate impacts of policy reform for the Miami-Dade, Port St. Lucie, Ft. Lauderdale CSA. Note that these figures do not represent changes in overall social welfare as not all costs and benefits are included.

While we do not estimate a full benefit-cost analysis of removing NFIP price supports, there are several important societal benefits from bringing the program into fiscal balance based on how the program is financed.[57] One potentially large benefit is the resulting migration from higher- to lower- risk areas through the re-sorting process. From Table 7, we find a significant, albeit heterogeneous, shift from high risk flood zones, and especially the coastal V zone, to the low risk X zone. As historical damages from flood-related events have topped $1.18 billion since 2000 in our study area, fewer properties in harm's way would be expected to reduce future damages.[58] It also hints that migration could likely be an important (albeit costly) channel to mitigate climate risks.

The ability to re-sort also highlights the importance of accounting for behavioral responses to policy change in estimating costs and benefits. Household welfare costs from insurance price reforms are significantly lower relative to costs estimated assuming no behavioral (resorting) response. At the no-response extreme, people cannot re-sort in the face of a policy change and the upper bound of the welfare cost can be inferred from the calculated insurance premium change. In this case, the expected welfare loss experienced by households are, on average, only 18.5 percent of the price discounts removed. That is, the overall welfare loss of $209 from removing price discounts in our setting is 18.5 percent of the welfare loss under the assumption that people have prohibitive moving costs and cannot re-sort. It is important to note that, due to data limitations, our model does not allow for moving costs. Our estimated welfare costs thus implicitly assume costless moving and should be interpreted as lower bounds. Within various race, income, or race-by-income groups, this lower bound welfare cost for removing price discounts ranges between 12.7 and 34.2 percent of the upper bound cost that assumes no re-sorting.[59] In aggregate, if no resorting occurs and discounts are removed, the welfare cost across individuals in the Miami-Dade, Port St. Lucie, Ft. Lauderdale CSA would be an estimated $774 million per year, highlighting both the magnitude of the current price discounts and also the potential political difficulty in removing them.

Lastly, our results hint that the current policy potentially incentivizes individuals to undertake more risk and is suggestive evidence of a moral hazard response to the price supports currently in place. While policy reform may well be a desirable goal, policy change could have large distributional and efficiency impacts that should be considered in designing reform solutions (Zeckhauser, 1981; Arrow et al., 1996; Robinson et al., 2016; Banzhaf et al., 2019).

Turning to the value of new flood map information, we find that flood risk map updates are valuable sources of information and are appealing from both a distributional and efficiency perspective. Aggregate benefits of new maps to residents of South Florida are an estimated $244 million per year. While no public record of the costs to revise the maps across the CSA exists, we estimate the average cost to update maps since 2000 has been approximately $4.8 million per county, implying a one-year benefit-to-cost ratio of 7.3 from new maps.[60] Given that large coastal counties are more expensive to map, even if costs were triple this estimate, the benefit-cost ratio for a single year of map use would still exceed 2.4. Assuming the maps remain valid for five years and a 5 percent interest rate, the discounted present net benefits of these new map revisions is approximately $1.3 billion. More generally, the value of new flood maps is determined by many factors including the distribution of properties as well as the magnitude (and frequency) of map changes: all else equal, older or more outdated maps are more likely to have larger benefits from a revision since they would have greater inaccuracies relative to more recently developed maps. As flood risk remains a critical concern for Florida (Hallegatte et al., 2013), these results highlight the importance of high quality flood risk information for decision making.

[57] The NFIP funds its debt from three main sources: (1) cross-subsidization (i.e., higher rates) from other policies (CBO, 2017), (2) funds borrowed (plus affiliated interest payments – currently about $300 million per year) from the U.S. Treasury, and (3) (infrequent) NFIP debt cancellation through Congress. Thus, welfare benefits of fiscal soundness would depend on the allocation of savings to each group, and other factors including the marginal cost of public funds (Browning, 1976).

[58] Figure calculated by the authors from the NCEI's Storm Events Database.

[59] We present the pre-FIRM and CRS combined subsidies overall and by race, income, and race-by-income groups in Appendix Table B.11.

[60] According to the CBO (2017), the NFIP allocates approximately $200 million per year for flood map updates. Given the current effective map date for the more than 20,000 communities in the NFIP (available from FEMA's Community Status Book Report), we estimated the average annual cost per new county map from 2000 to 2018 to be $4.8 million. As there are seven counties within the CSA, we calculate 7.26 = $244 million/(4.8∗7). In our conversations with map developers at the NFIP, they note that map costs can range greatly across the size and complexity of counties, with larger coastal counties being more expensive.

9. Conclusion

This paper examines sorting over flood risk and the implications for policy reform. Using 2009 to 2012 housing sales data from Florida's Miami-Dade-Ft. Lauderdale-Port St. Lucie Combined Statistical Area, we build and estimate a residential sorting model with a boundary discontinuity design to recover sorting parameters based on individual socioeconomic status that account for flood insurance price discounts. We then use our estimates to assess the distributional impacts of removing NFIP price supports, as well as to calculate the value of flood map updates.

We find clear evidence of sorting, specifically that low income and minority groups are more likely to sort into high flood risk areas. We also highlight how the presence of sorting has important policy implications. In particular, we note the need to account for behavioral responses in estimating the consequences of policy change, as policy reform can potentially trigger unwanted consequences that can fall more heavily on traditionally disadvantaged communities. While reform may well be a desirable policy goal, distributional impacts can have long lasting implications for disaster vulnerability, recovery, and fiscal policy (Arrow et al., 1996; Robinson et al., 2016; Banzhaf et al., 2019). In addition, we show how behavioral responses can mitigate the costs of policy reform through the resorting process. Lastly, our results reaffirm the importance of high quality risk information for households to make decisions. In addition to providing new valuation estimates for flood risk, our results shed light on the distributional impacts of natural disaster policy reform and its potential role in shaping disproportionate flood risk exposure in the United States.

Appendix A. Supplementary Online Appendix

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2020.102362.

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