Distributions of flood risk: the implications of alternative measures of flood risk

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Abstract

Flooding imposes considerable property risk, and flood maps and flood insurance help prospective and existing property owners assess the potential risk. The US Federal Emergency Management Agency (FEMA) works with local and state officials to produce flood maps. Using these flood maps and demographic attributes, prior research has demonstrated correlations between the percent of a tract identified as disadvantaged and the percent of the tract covered by flood zones. Until recently, FEMA flood maps were the primary assessment tool for flood risk, but First Street Foundation (FSF) has developed its own flood risk tools. This paper compares these alternative flood risk measures as a percent of Census tracts in the southeastern US states and assesses models of the risk measures with demographic, housing, policy and control variables. The main results are first that the FEMA and FSF maps often reveal diverging levels of risk per tract. Second, the demographics correlating with tract-level risk differ markedly for the two risk measures. Third, the results vary considerably by state with more divergence in some states than others, and who is at risk of flooding across the states varies between the FEMA and FSF measures.

This is the author's manuscript of the article published in final edited form as:

Noonan, D., Richardson, L., & Sun, P. (2022). Distributions of Flood Risk: The Implications of Alternative Measures of Flood Risk. Water Economics and Policy, 08(03), 2240001. https://doi.org/10.1142/S2382624X2240001X

1 Introduction

Each year, flooding causes massive economic losses in the United States. In 2017, such losses reached approximately $300 billion (NOAA National Centers for Environmental Information 2021). With 250,000 rivers and streams and 3.5 million miles of shoreline, the U.S. experiences considerable risk of coastal and riverine flooding. Hurricanes and super storms regularly hit Gulf coast and Atlantic coast states, and 31 hurricanes caused at least a billion dollars each in inflation-adjusted damages in the US and its territories in the 30-year period from 1989 to 2018 (NOAA 2018, Congressional Research Service 2019). The Federal Emergency Management Agency (FEMA) estimates about 13 million Americans live in a floodplain with a one-percent chance of flooding annually, and a recent study with more complete coverage and a finer resolution model estimates nearly 41 million people are at risk (Wing et al. 2018). Furthermore, accelerated global warming and sea-level rise are expected to make rainfall heavier, hurricanes more severe, and flood disasters more frequent, which will very likely lead to unprecedented economic losses (Kahn 2014, Sant'Anna 2018, Wing et al. 2018). Better understanding the distribution of exposures to flood risk is thus vital to informing policies supporting mitigation of and recovery from flood disasters, especially for vulnerable populations.

To document flood risk and provide information to current property owners, developers, and prospective property owners, FEMA works with state and local officials to identify flood zones and develop Flood Insurance Rate Maps, known as FIRMs. Starting with a patchwork of state and local efforts to control development in flood plains, Congress passed the 1968 National Flood Insurance Act (and several subsequent amendments), which helped fund community efforts to identify flood zones or Special Flood Hazard Areas (SFHAs). By 1975, about half of all 21,000 communities nationwide had developed FIRMs, and by 1977 about 15,000 communities had done so (FEMA 2002). In 1990, FEMA implemented the Community Rating System (CRS), which is a program designed to give communities an incentive to implement hazard mitigation projects and policies in exchange for lower flood insurance rates for property owners in the community.

Despite improvements to the methodology of assessing hazards and various incentives to communities to incorporate hazard mitigation, FEMA flood risk maps face significant challenges. One shortcoming is that the FEMA maps do not cover all land area. Another shortcoming is that the FEMA maps may not reflect true flood risk because they do not incorporate updated data and models in a timely fashion. Further, the FEMA maps are politically influenced in ways that may mask the actual flood risk to properties (Hino and Burke, 2020). Despite these shortcomings, many studies (discussed further in the next section) have used FIRMs to characterize the percent of land in a county, zip code or census tract as being at risk of a 100-year flood (and we refer to this as the *SFHA risk* measure).

With the improvement of GIS data and computational resources, groups such as the First Street Foundation (FSF) have recently developed methods to identify the risk specific to each property. Therefore, one could develop a risk measure for a county, zip code, or census tract analogous to the *SFHA risk* measure. Whereas the *SFHA risk* measure is the percent of land in the tract subject to a 100-year flood zone risk, a similar risk measure using the FSF data reflects the percent of built properties in a census tract at a similar risk of a 100-year flood (and we refer to this as the *FSF risk* measure).

The *FSF risk* measure faces several questions as well in that it is relatively new data that have not been rigorously assessed, the determination of risk for a property is not as public as the FEMA process, there is no regular avenue for property owners or local public officials to challenge the results, and it does not have the procedural support of multiple actors across multiple layers of government shaping the decisions. On the other hand, the information is freely available to the public so it may already be shaping real estate decisions, and scholars have begun to use this data (e.g., Bradt et al. 2021, Rhubart and Sun 2021).

While the *FSF risk* measure could be similar to the *SFHA risk* measure for a tract, it is likely to be very different depending on how property owners and prospective buyers have reacted to the information revealed in FIRMs that were first developed over 50 years ago in many communities and at least 40 years ago in most communities. If no one is willing to accept flood risk and the SFHA maps accurately reflect risk, then no new properties would exist in the flood zones so the *FSF risk* measure would approach zero (depending on the number of grandfathered properties built before the maps were developed). Alternatively, if people are willing to accept some flood risk but flood insurance rates do not reflect the true cost (Burby 2001, Ben-Shahar and Logue 2016), then housing developers will build in the flood zones (Kousky and Michel-Kerjan 2015), and the *FSF risk* measure could be high. Moreover, due to the limitations listed above, the SFHA maps may not reflect the true risk to properties, and the *FSF risk* measure may be higher due to properties at risk of flooding but not in the land area designated as a flood zone in the FIRMs. The divergence in flood risk measures can help explain mixed results in the literature, especially for studies with spatially aggregate flood risk.

The dispersion of flood risk has several important equity implications, and the risk measures shed light on these equity concerns (Thaler et al. 2018). Inequities in the burdens associated with flood risk, insurance prices, and associated welfare effects arise from the complex interplay of income inequalities, racism, public policies, existing infrastructure, and sorting on personal preferences related to the various amenities available in a community. Studies suggest race and income are correlated with flood risk (Bakkensen and Ma 2020). Alternative risk measures may yield different characterizations of distributional equity in flood risk exposure.

Our primary goals in this paper are to first assess and compare the *SFHA risk* measure with the *FSF risk* measure for each tract with a digital FIRM in the Gulf and Atlantic Coast states from Texas to North Carolina. This region, on average, experiences the most hurricanes, endures the most flood damage, and files the most flood insurance claims. Second, we estimate models for each risk measure with several potential social equity indicators at the census tract level, including logged median household income, poverty rate, percent Black, percent Hispanic, percent 65 and older, and the percent of adults without a college degree. The results suggest that the type of risk measure matters greatly, as signs change and significance varies for some social equity measures across models. Further, the results suggest strong state heterogeneity as the signs and significance for many coefficients vary across states. Also, the introduction of controls for weather, population density, coastal status, housing characteristics, and whether a community participates in the CRS program have an impact on results of the models. Before assessing the results, we review the literature on flood risk and environmental inequities, and then turn to a discussion of the data and methods.

2 Background

Our analysis builds on prior literature to demonstrate how alternative flood risk measures and regional heterogeneity can influence assessments of inequitable risk. We first review research on flood risk management and uneven exposure to flood risks and policy impacts, especially for vulnerable populations. We then discuss flood risk information provision and its disproportionate impacts. Finally, we discuss alternative flood risk information and its possible distributional implications.

2.1 Flood Risk Management

Flood risk management and flood disaster recovery mechanisms operate in a complex system of individual and collective decisions involving real estate markets, a national flood insurance program, and local government planning, infrastructure, and regulation. More detailed reviews of the economics of the National Flood Insurance Program (NFIP), flood risk (Kousky and Michel-Kerjan 2017, Michel-Kerjan 2010, Georgic and Klaiber 2020), and the US housing market (Kousky et al. 2020) highlight several main lessons relevant here. Variation defines the system, whether it is variation across states and regions or variation in local flood risk. Flood risk and insurance claims extend well beyond 100-year floodplain boundaries, though attention to flood management outside SFHAs may be lacking. Alongside high variation is limited information, with outdated flood maps, private information, and challenges with low-probability events.

Economists have often focused on pricing in the form of insurance premia (e.g., Georgic and Klaiber 2020, Atreya et al. 2015), discounts for exposure to flood risk (e.g., Beltrán et al. 2018, Atreya and Czajkowski 2019), or how prices reflect new information (Hino and Burke 2020, Yi and Choi 2020). Policy analyses in flooding contexts have also shown the economic impacts of regulation (e.g., Frimpong et al. 2020, Wing et al. 2020, Highfield and Brody 2017) and mitigation subsidies (Davlasheridze and Miao 2019, Kousky et al. 2018, Davlasheridze et al. 2017). The central role of the NFIP naturally attracts considerable research attention, showing how it affects incentives and information (e.g., Wing et al. 2020, Kousky et al. 2018). Yet pricing, regulation, and insurance all have enormous distributional effects in the context of flood management. Current exposure and vulnerability to flood risk is unevenly distributed across different societal groups in the US, and policy reforms potentially have major distributional consequences. These distributional effects suggest why reforms have been lagging or suboptimal (Kahn and Smith 2017, Atreya and Czajkowski 2019).

2.2 Flood risk information and Disproportionate Impacts

Better understanding the distributional consequences of flood management mechanisms such as pricing, regulation, and insurance requires further appreciation of the crucial roles played by flood risk information. Risk information itself is often tied to public policy. Much risk information commonly available is itself a result of public agencies such as FEMA or regional floodplain managers. The flood insurance rate map (FIRM) issued at the county level represents some "official" flood risk information that affects flood insurance requirements and premiums as well as indirectly becoming capitalized into property values (e.g., Kousky et al. 2020, Hino and Burke 2020, Atreya et al. 2013). Floodplain managers, planners, and regulators can also take flood risk information into account in shaping a community's exposure to flood risk and its disaster recovery mechanisms. FIRMs that delineate which regions are in flood-prone areas, such as 100-year floodplains or SFHAs, can attract attention with special rules for property development, infrastructure or mitigation investments, post-disaster responses, and more. Flood events and the damage caused also provide new information for decision-makers. This can influence where recovery resources are directed (Finch et al. 2010), local communities' ability to recover (Jerch et al. 2020), and migration and future location decisions (Boustan et al. 2020).

The crucial role of information in pricing, regulatory, and insurance mechanisms implies important distributional implications of new information. New information about flood events can also affect flood insurance take-up rates even among those not directly affected by the flood event (Gallagher 2014). In addition, after a major flood event provides new information to residents about parcels' risks, market adjustments can result in substantial shifts in property values and rents that disproportionately affect certain groups of residents (Yi and Choi 2020). Owners of properties suffering above-expected damages can see their property damage compounded by losses from a larger flood risk discount to property values, and renters in areas suffering below-expected damages can see their rents increase alongside rising property values.

The differential or disproportionate effects of flood disasters for disadvantaged or socially vulnerable groups has been studied before (e.g., Chakraborty et al. 2021, Finch et al. 2010, Bin et al. 2017). But even before the flood event occurs, the differential exposure to flood risk of socially vulnerable groups points to distributional inequities 'upstream' of the subsequent disaster recovery needs. For instance, removing NFIP subsidies can have rather uneven impacts (Georgic and Klaiber 2020, Kahn and Smith 2017, Michel-Kerjan 2010). Bin et al. (2017) observe regressive attributes of the NFIP's insurance premiums and net premiums. Allaire (2020) also finds subsidized flood insurance to disproportionately benefit wealthy households. Income, race, expectations of future disaster relief, and other factors can affect flood insurance take-up rates and thus point to additional ways that disaster recovery mechanisms can have important distributional consequences (Allaire 2020, Atreya et al. 2015, Landry et al. 2021).

The uneven distribution of flood risks in the US does not map neatly onto a simple correlation between social vulnerability and flood risk exposure. Discrimination, short-term housing affordability, historical factors, and other mechanisms can lead to more flood risk exposure among disadvantaged groups. But the positive amenity values that often accompany flood risk (e.g., beachfronts and scenic views) can reverse this relationship, and help explain beachfront vacation homes and luxurious properties in flood-prone areas. Hurricane damage, largely in the form of flooding, rises with income internationally (Mendelsohn et al. 2012). Sea-level rise in the US also correlates with income and other demographics (Keys and Mulder 2020). Kahn and Smith (2017) observe mixed results when correlating income and flood risk especially between states. Kinzer et al. (2021) find mixed evidence for income and flood risk in general in the US, noting how the Mississippi Valley region exhibits a different sort of correlation between income and flood risk than in coastal Gulf State counties. Qiang's (2019) study of disparate exposure to flood risk also finds mixed results, with significant differences for some measures (e.g., age, employment) but not others (e.g., income, education). Recently, Tate et al. (2021) find ethnic minorities are overrepresented in high flood-risk areas while Rhubart and Sun (2021) find the opposite for ethnic minorities. Among other differences, these studies' use of different measures of flood risk suggests important differences in behavioral responses to different sorts of flood risk. Yet prior studies have not assessed these distributional inequities in flood risk by comparing different flood-risk measures, especially comparing the older and 'official' risk measures from SFHAs with newer publicly available alternatives.

2.3 Alternative flood risk information and Distributional Impacts

Flood risk information and related policies can affect the distribution of flood risks and damages. Except for studies of updating risk information based on a recent flood disaster event, most prior research relies on SFHA designations from FIRMs as the measure for flood risk. This reflects the information typically thought to be available to decision-makers. But it also acknowledges that this flood risk information is deeply flawed (Michel-Kerjan and Kunreuther 2011, Kousky et al. 2020, Wing et al. 2020). SFHA designations can be outdated and politically influenced (Hino and Burke 2020) and provide only binary measures of risk, leaving those outside a boundary to feel complacent (Wing et al. 2020). Yet improved and new sources of flood risk information are becoming available to floodplain managers and individual property owners. New information about, for example, sea-level rise can be seen to have significant economic implications even if not captured by SFHAs (Keys and Mulder 2020). New information about flood risks thus can have important distributional implications for current exposures and for future disaster recovery needs.

Flood risk information is crucial for policymakers to target mitigation and relief efforts to more vulnerable populations. New flood risk information can yield a new distribution of flood risk exposure even prior to any behavioral response to the new information. Just as alternative risk measures can yield different characterizations of distributional equity in flood risk exposure, they can also affect the distributional implications of flood disaster policies. For example, a policy that better aligns the risk information in FIRMs with reality has distributional implications in that it benefits vulnerable populations but not as much as others (Bakkensen and Ma 2020). Thus, comparing the distributions of risk exposure based on SFHAs to distributions based on a alternate risk measure gives insight into where those relative gains would occur. Similarly, policies targeting mitigation aid at flood-prone regions with vulnerable populations might miss the mark depending on the flood risk measure used. Comparing the distributional inequities across alternative risk measures can thus inform if and where the targeted aid might miss its mark. Better understanding the overlap between flood risk and social vulnerability is vital because social vulnerability affects a community's ability to recover from flood disaster damage (Jerch et al. 2020, Kousky et al. 2020).

Many studies of flood risk, especially at an aggregate level like tract or community, use measures of flood risk derived from FIRMs. Typically, this measure involves a share of developable land in a 100-year floodplain (or SFHA). Examples of recent studies using SFHA-based measures of flood risk abound, and studies of distributional equity include Bakkensen and Ma 2020, Keys and Mulder 2020, Kinzer et al. 2021, Noonan and Sadiq 2018, Qiang 2019, and Yi and Choi 2020. While others use measures from historic events (e.g., flood water depth estimates, insurance claims data), and a few construct their own flood risk measures (e.g., Tate et al. 2021), most scholars make use of existing flood risk measures more likely to be publicly available. As new flood risk measures become available, such as First Street Foundation's "Flood Factor," we expect more and newer measures to become more common in analyses involving flood risk (e.g., Rhubart and Sun 2021).

3 Data and Methodology

Our analysis seeks to examine the distributional equity related to SFHA and FSF risk measures and assess models of these risk measures by testing a variety of variables associated with distributional equity of flood risk. In this section, we first describe our data sources, assess summary statistics for our measures, and describe our methods.

3.1 Data Sources

This analysis primarily leverages three data sources. The first data source is 2010 US Census data, including various sociodemographic attributes and household characteristics. The 2010 Census data are important for two reasons. First, tracts change with each Census, and the 2010 data are most closely connected with the creation of those tracts. The 2010 data were available to public officials as they created the 2014 flood zone maps. Second, and relatedly, using the older, 2010 Census data helps to address the concern that flood risk maps and new risk information can affect who lives nearby and which socioeconomic groups are exposed to flood risk. We rely on Census data that predate the flood risk measures to mitigate the endogeneity that might arise when using more recent demographic data, such as the American Community Survey estimates.

The social equity measures are operationalized with tract-level data for logged median household income, the percent of a tract in poverty, percent Black, percent Hispanic,[1] percent aged 65 and over, and percent with no college degree. Further, Census data on population density and whether the tract is coastal or in a rural, unincorporated area are used as control variables. Our models with the full set of controls also include Census data on the housing stock in a tract, enabling us to control for the value of housing, share of housing that are rental properties, and the share of housing units built prior to 1970. These housing variables might affect local floodplain management, as property values, potentially less-invested renters, and grandfathering of older homes might affect flood risk exposure (Fischel 2005, Noonan et al. 2020). Table 1 lists all relevant variable names, definitions, and sources for our study.

The second data source is the National Flood Hazard Layer dataset.[2] It contains the 100-year floodplain maps (SFHA) for all the states in our study. We connect the SFHAs with 2010 census tract boundary maps to construct each tract's SFHA risk measure. Precisely, we obtain the overlapped areas between the SFHA and the tract boundary layers, aggregating them to the tract level and then divide the corresponding value by the overall tract area to derive the percent of SFHA for each tract. Additionally, note that because some areas do not have digital FIRMs, there will be a fraction of tracts without available SFHA share.[3]

[1] In this analysis, we call our variable "percent Hispanic," while the 2010 Census question asks "Is this person Hispanic, Latino or of Spanish Origin?" https://www.census.gov/prod/cen2010/briefs/c2010br-02.pdf
[2] We downloaded it from https://www.floodmaps.fema.gov in October, 2014.
[3] It is likely that areas without a digital FIRM are different than the tracts with an SFHA. Most of the counties without a digital FIRM tend to be rural, and they are likely to have fewer administrative resources. In a table available from the authors, we assess the summary statistics for the 1,830 tracts with no SFHA digital flood maps (thus not included in our

Table 1: Variable descriptions and data sources

VARIABLE NAME	DEFINITION	DATA SOURCE
Dependent Variables		
SFHA Risk	Percentage of each tract's area that overlaps an SFHA that represents at least a 1% annual chance of flooding (ranges from 0 to 100)	FEMA (DFIRMs downloaded October 2014)
FSF Risk	Percentage of each tract's risky properties (0 to 100)	First Street Foundation
Risk Difference	SFHA risk – FSF risk for each tract	
Equity Variables		
Log Median Income	log of tract median household income (dollars)	US Census (2010)
Poverty Rate	Percentage of total persons below the poverty level in a tract	US Census (2010)
Percent Black	Percentage of Black residents in a tract	US Census (2010)
Percent Hispanic	Percentage of Hispanic residents in a tract	US Census (2010)
Percent 65+	Percentage of tract residents aged 65 and over	US Census (2010)
Percent No College	Percentage of tract residents without a college degree among those 25+ years old	US Census (2010)
Control Variables		
January Sunlight	County-level mean hours of sunlight in January, 1941-70	USDA Natural Amenities Scale (1999)
July Temperature	County-level mean temperature for July, 1941-70	USDA Natural Amenities Scale (1999)
July Humidity	County-level mean relative humidity July, 1941-70	USDA Natural Amenities Scale (1999)
Percent Water	Percent of area covered in water in a county	US Census (2010)
Population Density	Total tract population divided by total land area	US Census (2010)
Unincorporated	Whether a tract is in a census designated place	US Census (2010)
Coastal County	Whether a tract is in a coastal county	US Census (2010)
CRS	Whether a tract is in the FEMA Community Rating System	FEMA (2013)
Percent Renters	Percent of tract housing units that are renter occupied	US Census (2010)
Log Housing Value	log of median value of owner-occupied housing units in a tract	US Census (2010)
Percent Old Buildings	Percentage of housing units built before 1970 among those housing units in a tract	US Census (2010)

The third data source is the parcel-level flood risk data from the First Street Foundation Flood Factor program (FSF). Although the SFHA maps are often used for the assessment of flood risk in the literature, several issues limit the value of the measures, such as the maps' incomplete

analysis), and those 15,241 tracts with an SFHA (and in our analysis). We find that the excluded tracts had a slightly higher mean percent of properties at FSF risk, and they are slightly poorer, more Hispanic, less educated, and older, but have a lower percent Black. They are slightly more likely to be in a coastal county and to be in a county with more water as a share of surface area.

coverage, dated information, and political intervention. Therefore, the SFHA risk measure may be unable to reflect the true flood risk for a building. Alternatively, the FSF flood risk data offer three advantages over the SFHA maps. First, FSF data can provide the parcel-level flood risk assessment, which allows for assessment of parcel-specific attributes (such as physical structure and elevation). In contrast, all buildings within the SFHA are typically treated as having the same flood risk, regardless of their other attributes. Second, SFHA maps do not take into account potential pluvial surface water flooding or other future risks, but FSF leverages the modeling of Fathom-US developed by Wing et al. (2017) to generate a comprehensive flood risk model. This model takes advantage of information on terrain, hydrography, hydrology, climate change, and four types of flooding (tidal, pluvial, fluvial, and surge). Finally, FSF has wider coverage. In comparison with incomplete area coverage in the SFHA maps, especially those remote rural areas, FSF data cover all geographic areas across the continental United States.

As noted, the FSF faces several challenges, including that it has not been thoroughly assessed by independent third parties, it does not allow for input from property owners or local officials, and it has not had years of scrutiny by experts at different levels of government. Further, FSF measures do not directly link to formal regulation or rules for insurance. Despite its strengths and weaknesses, FSF is publicly available for any property owner, prospective buyer, or public official to use. It is on real estate websites, such as Realtor.com, so it is likely to be shaping recent real estate and development decisions.

We can observe each parcel's probability of being flooded in the FSF data over the next 30 years. It reports three flood depth thresholds, including > 0 cm, > 15 cm, and > 30 cm, with separate predictions for 2020, 2025, 2030, 2035, 2045 and 2050. Our research is focused on using the 2050 parcel-level flood risk data with a threshold > 15 cm for indicating whether a parcel confronts flood risk in the future. Specifically, if a property's cumulative probability of being inundated above 15 cm in the following three decades (after 2020) exceeds 0.3, then it will be considered as a risky property in our study. The 0.3 likelihood provides a relative comparison to the official definition for the 100-year floodplain over a 30-year span of FSF flood risk measure.[4] Because FSF data also include the tract information in which a particular property is located, we can calculate the percentage of properties facing flood risk at the tract level based on our risky parcel

[4] Over 30 years, we would expect at least 1 flood in a floodplain 26% of the time, which we round up for comparison to the FSF measure.

definition. Hence, we will use the tract-level percent of risky parcels as the FSF risk measure in our analysis and conduct the comparison with the SFHA risk measure of the percent of land at risk as indicated by a flood map.[5]

After cleaning and transforming the datasets, we merge them together via a tract FIPS code and employ the merged dataset to conduct our empirical analyses. As mentioned above, because there are some tracts lacking SFHA information, our focus is constrained to those tracts with both SFHA and FSF risk measures. Furthermore, our study focuses on the Gulf Coast and Atlantic Coast states of Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Texas. The states sustain the most hurricane damage, experience the most flood damage, and account for over half of all flood insurance policies (Kousky et al. 2020). Over a third of all flood insurance policies are in Florida, 12% are in Texas, and almost 9% of all policies are in Louisiana.

3.2 Summary Statistics

To understand the nature of the data used in the analyses, Table 2 shows the summary statistics for all the dependent and independent variables. The analysis is limited to the 15,241 tracts that have an SFHA digital flood map and FSF estimates for the properties in the tract.

The mean for *SFHA risk* is 19.4, and this can be interpreted as 19 percent of the land in the average tract is in a SFHA flood zone. One can see that the range is from dry tracts with zero percent of the land in a flood zone to tracts that are entirely covered by a flood map (such as a swamp or river delta). Similarly, the mean *FSF risk* is 13.1, and this is interpreted as 13 percent of the properties in an average tract are at risk of a 30-year flood according to FSF. The *Risk Difference* measure is the difference between the *SFHA risk* and the *FSF risk* measures, and one can see that the average tract has a value of 6.4 so a greater share of the land is in a flood zone within the tract than the percent of properties at risk in the tract.

[5] There are two caveats. One is that FSF data include both residential and non-residential properties but there is no variable available to distinguish them. As a result, our tract-level *FSF risk* measure can only reflect the average flood risk exposed to all types of built properties. The other caveat is that a parcel could have multiple housing units, which could lead to a deviation from the overall number of housing units observed in the Census data. For more information on the FSF methodology see https://assets.firststreet.org/uploads/2020/06/first_street_foundation first_national_flood_risk_assessment.pdf

Table 2: Summary Statistics for all variables in analysis

	Count	Minimum	Maximum	Mean	Std dev
SFHA risk	15241	0.00	100.00	19.41	22.88
FSF risk	15241	0.00	100.00	13.07	20.40
Risk Difference	15241	-100.00	99.63	6.35	20.14
log median income	15241	8.52	12.61	10.90	0.46
Poverty rate	15241	0.00	96.30	16.66	12.08
Percent Black	15241	0.00	99.51	22.48	24.56
Percent Hispanic	15241	0.00	99.36	17.55	22.16
Percent 65+	15241	0.00	89.37	13.65	8.17
Percent no college	15241	0.00	100.00	75.13	17.60
January Sunlight	15241	121.00	249.00	171.93	26.33
July Temperature	15241	68.20	87.90	81.29	2.58
July Humidity	15241	29.00	80.00	64.82	12.71
Percent water	15241	0.00	75.00	7.52	11.40
Population density	15241	0.00	29.81	0.92	1.27
Unincorporated	15241	0.00	1.00	0.07	0.26
Coastal County	15241	0.00	1.00	0.28	0.45
CRS	15241	0.00	1.00	0.35	0.48
Percent renters	15241	0.00	100.00	34.04	20.35
log housing value	15241	9.21	13.82	11.83	0.58
Percent old buildings	15241	0.00	100.00	30.21	24.37

Some tracts exhibit considerable divergence between the risk measures. At the two extremes, the *SFHA risk* measure could be 100 percent of a tract's land area (such as a swamp) with very few properties at risk so an *FSF risk* measure approaching zero, and at the other extreme there could be tracts with very limited flood zone land areas designated in the FIRMs but all properties in the tract are at risk as assessed by FSF so the *FSF risk* measure could approach 100 percent. Among the independent variables, two notable values are that about a quarter of the tracts are in coastal counties and about a third are in the CRS.

In the following subsection, we develop a framework used to analyze how socioeconomic attributes correlate with the two flood risk measures. We include income, poverty rate, ethnic minority status, percent over age 65, and those with no college education.

3.3 Methodology

Our study mainly exploits the following regression model to explore how various tract-level covariates correlate with each of the flood risk measures:

$$Y_j = X_j^{1}\alpha + Z^{1}{}_{j}\beta + D_s + \varepsilon_j \quad (1)$$

Here, Y_j denotes the flood risk at tract j. Specifically, we use three different types of risk measures: the *SFHA risk* measure, the *FSF risk* measure, and the *Risk Difference* between the two risk measures. X_j represent social equity variables, including the logged median household income, poverty rate, percent Black, percent Hispanic, percent aged 65+, and percent no college. Z_j are control variables, including temperature, sun light, humidity, percent of land covered by water in a county, population density, unincorporated area, coastal county, a measure of whether a community participates in the Community Rating System (CRS), share of houses occupied by renters (percent renters), median value of owner-occupied housing units (housing value), and the share of properties built before 1970 (percent old buildings). Controls for climate and coastal location help account for natural conditions that can increase flood risk. Warmer, wetter locales may face more potential for flooding, just as areas with more water features may have greater flood risk. We also control for flood management capacity and development density, which can affect exposure to flood risks in a tract, through population density, whether the tract is in an incorporated place, and whether its community is in the CRS. D_s stands for the state fixed effects. ε_j is the error term.

Under the above model specification, our first model was a spatial regression with state-level fixed effects and tests for state-level heterogeneity. We conducted a Chow test to assess whether model parameters are stable across states. The null hypothesis of the Chow test is that all states have identical coefficients for the independent variables, and the significant results suggest that the coefficients are not the same across states so separate models are warranted. We find strong evidence to suggest that pooling all states would mask some statistically significant state-level variation. This is consistent with Kahn and Smith (2017) who find important between-state variation in the patterns of income and flood risks. It also allows for us to identify large state-level differences in relationships that suggest an important role for state-level policy in shaping flood risk distributions.

Given the inherently spatial component of the data, spatial dependence in the data is an important concern for the models. We tested the models with the Moran's I statistic for residuals as well as Lagrange Multiplier (LM) and likelihood ratio tests.[6] The LM tests (Anselin et al. 1996) reveal that a spatial lag model is the most appropriate, so we use a spatial lag in each of our models (i.e., a spatial lag for *SFHA risk*, a spatial lag for *FSF risk*, or a spatial lag for the *Risk Difference* measure consistent with the dependent variable in each model).[7] The spatial lag coefficient (or ρ) is significant across the models. The results for some variables in the OLS model change when estimating the spatial lag models, but the overall pattern is similar.

Before turning to the spatial lag models for the risk measures, we first explore the differences in the *SFHA risk* and *FSF risk* measures.

3.4 Differences in Risk Measures

As mentioned earlier, one of the goals of this analysis is to assess whether and how the *SFHA risk* and *FSF risk* measures are different across the sample of states. If the existence of flood maps deters development of properties inside the flood zones and both SFHAs and FSF measure similar risk, we would expect more land to be at risk of flood (SFHA) than properties at risk (FSF). Alternatively, if a flood zone designation does not deter people moving into properties at risk and/or FIRMs do not account for all potential flood risk, then we may see more properties at risk as a percent of a tract (FSF) than land at risk (SFHA).

For illustration purposes, consider Figure 1, which displays maps in the southeast region of Harris County, Texas (which includes Houston and Pasadena). Figure 1a is a map of the region with some markers for reference as well as a boxed area that is the focus of maps 1b and 1c (which show

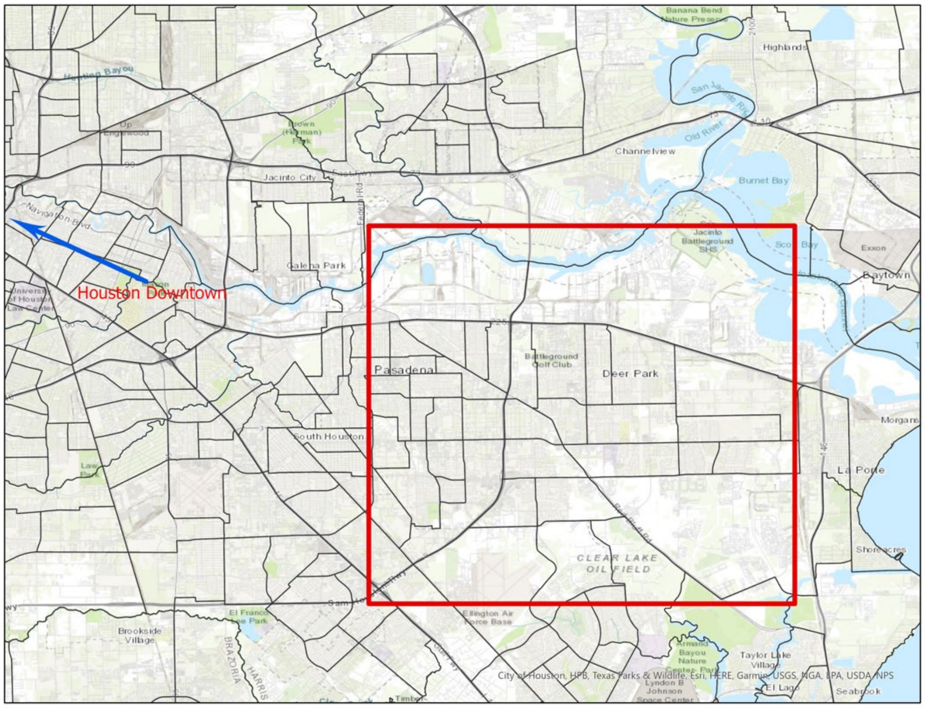
[6] We also conducted several other diagnostic tests. Concerns about the normality of the residuals lead to several normality tests and graphs of the residuals relative to a normal curve. We have too many models to share the graphs or tests, but the OLS residuals are roughly normal. In some cases, the residuals are peaked a bit more in the central region of the normal curve (leptokurtic), and there is no unusual skewness. We also tested for multicollinearity in the overall model and the individual state models, and no VIFs exceeded 10, a standard marker of severe multicollinearity.
[7] The spatial lag models estimated here modify equation (1) to become: $Y_j = \rho WY' + X_j'\alpha + Z_j'\beta + D_s + \varepsilon_j$. Here ρ represents the spatial lag parameter, while W is the spatial weights matrix (a first-order contiguity matrix in our case). This model accounts for the possibility of 'contagion' among tracts as one tract's outcome measure might affect its neighbors' outcomes.

Census tract lines). One can see that this area is east of downtown Houston (that would be to the left beyond the map), and west of the San Jacinto Bay (to the right on the map) that leads out to the Gulf of Mexico.

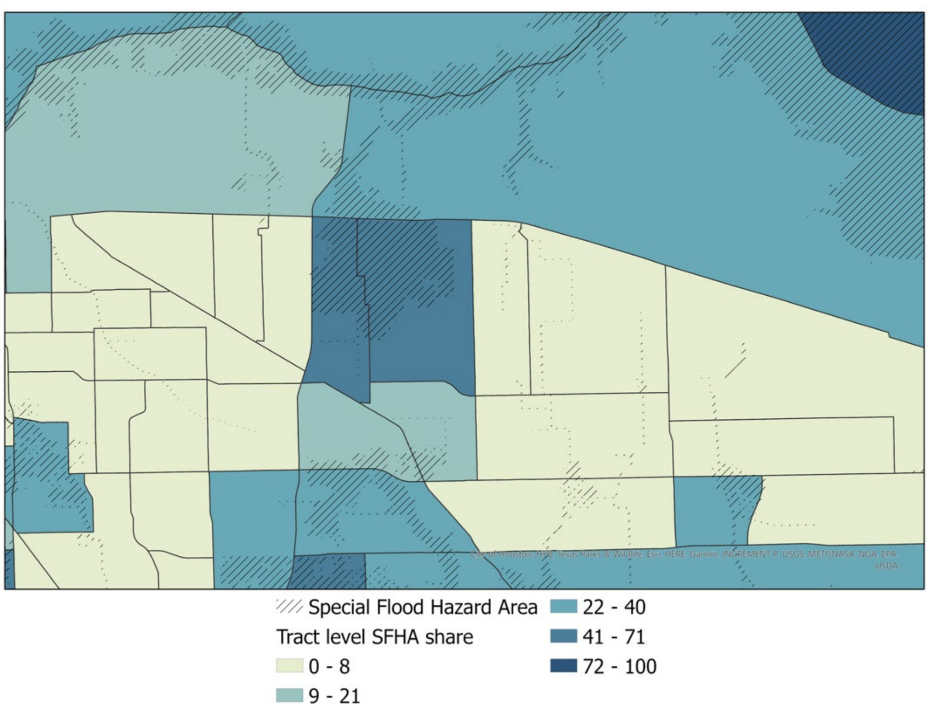
Map 1b includes thatched areas showing the flood zones, as defined by FEMA, and shading of the tracts reflects the *SFHA risk* measure as a percent of land covered by a flood zone. One can see more risk in the northern portion of the map as well as the central area of the map. For reference, the thatched area and tract line between the two large tracts at the top center is the Buffalo Bayou, a major waterway that runs from downtown Houston (beyond the upper left corner) over to where it empties into the bay (beyond the right corner). Focusing on the two dark blue boxes in the center of the map, the left tract is in Pasadena, Texas (which also covers many of the tracts on the central left portion of the map and some in the lower central portion of the map), and the right dark blue tract is Deer Park (which also contains tracts above, to the right, and below that tract). There are several bayous in this region, and they can be seen in the thatching and reflected in the blue shading of the tracts.

Alternatively, the map in Figure 1c shows the *FSF risk* measure with shading in the tracts. The upper-right (northeast) section has the greatest percent of properties at risk and the other tracts in the upper section are somewhat risky. This map also shows built properties that are not at risk of a 100-year flood probability in gray and built properties deemed by FSF to be at risk in red. Notably, several tracts in the upper area and the lower-right area of figures 1b and 1c reveal risk by either measure, but some tracts look very different on the two maps. Whereas the *SFHA risk* measure shows moderately high risk for a central corridor of tracts, those tracts have very low levels of *FSF risk*. In other words, properties in those tracts have avoided the riskiest flood zones that are prevalent in those tracts. Alternatively, there are several tracts in a triangle in the left center of the map that have very low *SFHA risk* (with no noticeable thatching for a flood zone in those tracts and no shading of the tract in 1b), and yet those tracts have light to medium shading for *FSF risk* with several clusters of red dots indicating built properties at risk of a 100-year flood. This sort of deviation between the two measures is seen throughout the data. For example, the correlation between the two risk measures is 0.52 for the 548 tracts in Harris County, Texas, and the correlation for all the tracts in our sample is 0.57.

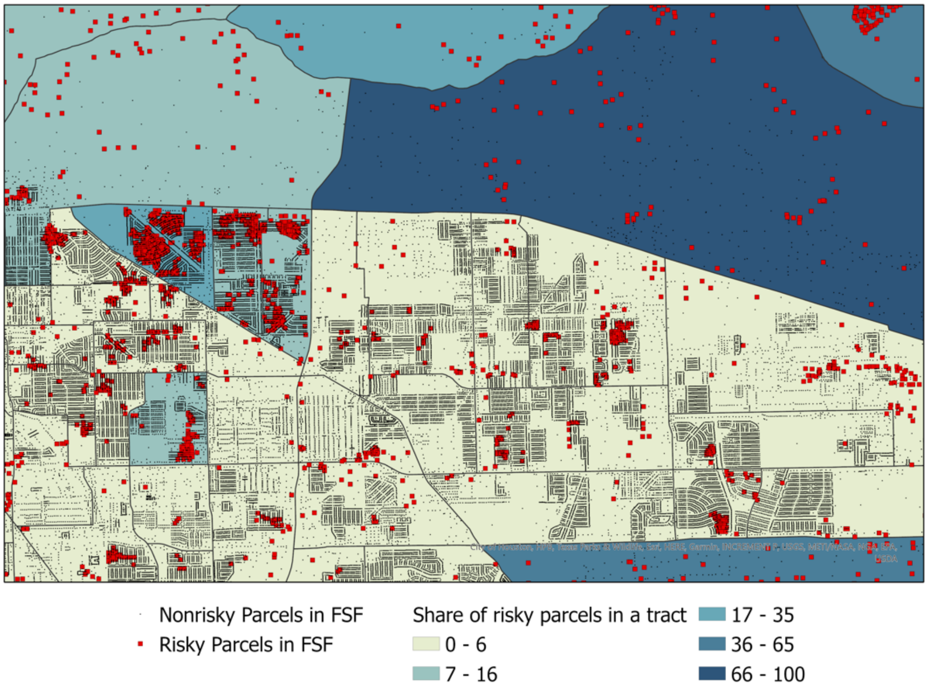
Figure 1: A comparison of risk measures for tracts in southeastern Harris County, Texas



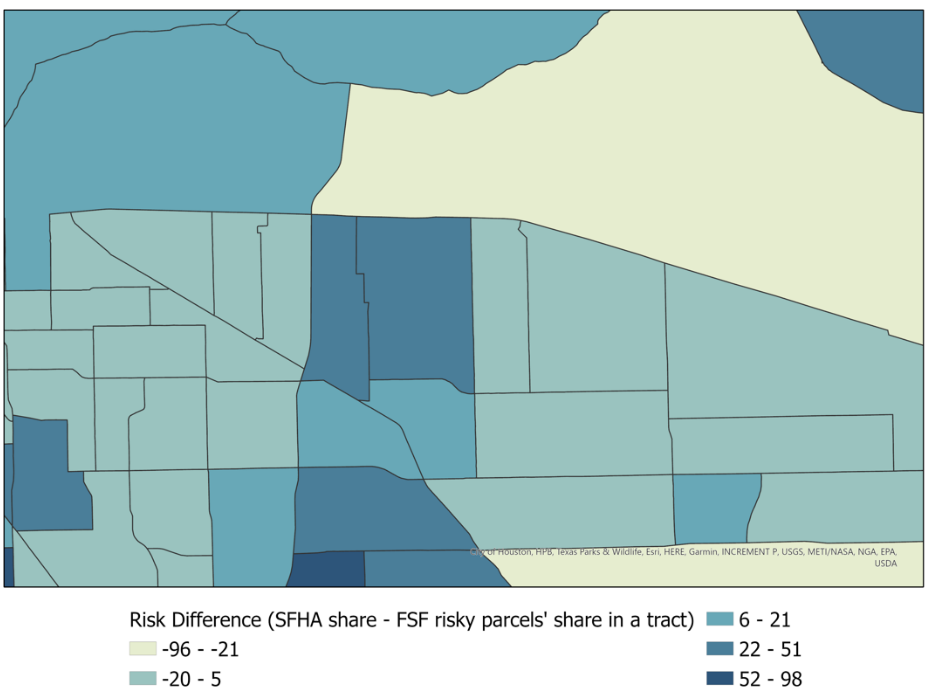
1a) An inset map of Harris County that contains parts of Houston and Pasadena



1b) A map of Census tracts indicating flood zones and *SFHA risk* measure



1c) A map indicating *FSF risk* by Census tracts with markers for risky properties



1d) A map of Census tracts with the *Risk Difference* measure

To assess the flood-risk measures more fully at the tract level, we provide summary statistics in Table 3 (*SFHA risk*) and Table 4 (*FSF risk*) for each state. The two tables imply that all the Gulf and Atlantic coast states in the sample have substantial variation at the tract level in terms of both *SFHA risk* and *FSF risk* measures. The average tracts in Florida, Louisiana, and Mississippi have the highest *SFHA risk*, and Georgia, North Carolina and South Carolina have the lowest. The pattern is similar for *FSF risk*, but the mean values are lower so the percent of properties at risk in a tract is generally lower than the percent of land at risk across the states. The maximum level of *FSF risk* for South Carolina in Table 4, 50.3%, is much lower than the other states' maximums of 100%. This may be due to numerous coastal tracts in South Carolina that did not have digitized SFHA maps as of 2014, the date for which we downloaded FIRMs, and this led to those tracts being dropped from the sample of tracts.

Table 3: The summary statistics of *SFHA risk* (% of tract land in a flood zone)

	min	max	mean	sd	p1	p5	p50	p95	p99
AL	0.00	92.83	12.97	13.68	0.00	0.14	8.96	37.65	76.21
FL	0.00	100.00	33.72	28.29	0.00	0.00	26.48	97.27	100.00
GA	0.00	97.84	11.60	13.63	0.00	0.00	7.94	35.46	78.85
LA	0.00	100.00	37.43	31.70	0.00	0.00	28.67	100.00	100.00
MS	0.00	100.00	24.09	20.57	0.00	3.34	17.39	69.49	98.69
NC	0.00	99.83	11.58	15.40	0.00	0.43	6.77	41.85	86.34
SC	0.00	100.00	11.94	17.76	0.00	0.00	6.58	47.33	100.00
TX	0.00	100.00	15.16	18.95	0.00	0.00	9.25	54.36	100.00
Total	0.00	100.00	19.41	22.88	0.00	0.00	10.71	74.06	100.00
N	15241								

Table 5 gives us a clear sense of how different the *SFHA risk* and *FSF risk* measures are for each state. The *Risk Difference* is measured as the *SFHA risk* net *FSF risk*, and a positive value means more land is at risk in a tract than the percent of properties at risk in the tract. Alabama and North Carolina have the lowest mean *Risk Difference* so the percent of land and the percent of properties at risk are generally similar. In contrast, Louisiana has the highest mean *Risk Difference* as well as the highest values among the 90th and 99th percentile tracts so in many of its tracts the percent of land at risk is much greater than the percent of properties at risk. States show considerable variation as eight states have a maximum of more than 90% and five states have a minimum less than -90%, and the standard deviations all exceed ten percent. The distinction between the *SFHA risk* and *FSF risk* measures are large at the tract level, and such a difference is common among the Gulf and Atlantic coast states.

Table 4: The summary statistics of the *FSF risk* (% of tract properties at risk)

	min	max	mean	sd	p1	p5	p50	p95	p99
AL	0.13	100.00	11.77	10.89	0.88	3.10	9.27	28.48	72.95
FL	0.00	100.00	25.26	32.28	0.09	0.86	10.05	99.95	100.00
GA	0.00	100.00	8.32	10.22	0.66	2.30	6.32	17.00	75.70
LA	0.00	100.00	19.72	23.71	0.12	1.56	11.43	87.58	100.00
MS	0.00	100.00	14.39	16.30	0.67	2.62	11.05	39.56	99.36
NC	0.00	100.00	9.67	12.41	1.61	2.73	5.92	28.18	80.18
SC	0.00	50.31	6.85	4.67	1.06	2.54	5.87	13.55	24.30
TX	0.00	100.00	7.37	12.23	0.00	0.26	4.45	22.87	79.82
Total	0.00	100.00	13.07	20.40	0.00	0.97	6.53	64.42	100.00
N	15241								

Table 5: The summary statistics of the *Risk Difference* between SFHA and FSF (Unit: %)

	min	max	mean	sd	p1	p5	p50	p95	p99
AL	-99.06	77.67	1.21	12.24	-22.93	-11.43	-0.41	20.88	50.34
FL	-100.00	99.63	8.45	28.07	-71.76	-41.61	7.51	55.77	79.64
GA	-90.18	85.55	3.28	11.25	-17.27	-8.88	1.49	22.82	48.89
LA	-100.00	94.71	17.71	36.61	-100.00	-39.61	11.87	85.92	93.66
MS	-56.16	92.90	9.70	18.10	-27.07	-9.24	5.45	47.33	69.64
NC	-44.96	71.67	1.91	11.45	-27.49	-14.45	0.64	21.31	45.08
SC	-26.08	96.58	5.09	16.72	-14.62	-7.69	1.06	39.56	91.36
TX	-93.67	98.44	7.79	16.95	-24.89	-8.08	3.75	39.93	80.17
Total	-100.00	99.63	6.35	20.14	-53.27	-16.61	2.57	43.87	77.67
N	15241								

The pattern of results for the *SFHA risk*, *FSF risk*, and the *Risk Difference* measures suggest different risk exposures across communities. Considering the different types and levels of risk, in the next section we estimate models for each of the types of risk at the aggregate level and then separately at the state level.

4 Models of Flood Risk

Our approach starts with an analysis using spatial regression models, and the results strongly support the use of state fixed effects in the models. Therefore, the models for all states (n=14,251) always include state fixed effects. When states are separately modeled, the results look very different. The Chow tests (F statistics reported for each model in Table 6) confirm the structural shift among states, so our preferred approach estimates state-specific models. We present the results for Texas and Florida in tables 7 and 8 as the largest states in the study. An online appendix provides the other states' results. Further, the diagnostics suggest the need for a spatial lag model so we include the spatial lag appropriate for each dependent variable in all models.

Overall, the results suggest a complicated relationship for equity attributes and various flood-risk measures, and the Chow tests in Table 6 suggest the need for state-specific analyses. Additionally, one can see very different coefficients for many of the variables in the Texas versus Florida models in Tables 7 and 8 respectively. To further understand the mechanisms behind the complex relationship, in the following sections, we analyze more comprehensive models by conducting state-specific studies and adding housing attributes, policy variables, and other control variables.

4.1 Pooled coastal state results

Table 6 presents five models, including the baseline equity models for *SFHA risk* and *FSF risk* using only the key demographic measures related to population vulnerability (i.e., income, race, ethnicity, age, and education). We expand on these restricted-form baseline models by adding several control variables in columns 2 (for the SFHA model) and 4 (for the FSF model). One can see evidence of disparate exposures to *SFHA risk*, where tracts with lower percent Black or fewer adults with no college education face lower flood risk using the *SFHA risk* measure, but this finding fades considerably in column 2 when the control variables are included. A similar comparison of the

FSF baseline and full models (in columns 3 and 4) shows more substantial shifts. The significant signs reverse for the percent Hispanic and the percent no college coefficients. Controlling for other geographic, housing, policy, and other controls can affect how uneven the exposure to flood risk appears. Estimates of inequitable risk, for either measure, are sensitive to model specification (Noonan 2006).

Overall, a few other tendencies emerge. It appears that logged median household income predicts flood risk poorly, but higher poverty rates tend to be found in riskier tracts. Tracts with older populations tend to have much greater risk. Areas with greater shares of Black residents do not tend to have higher flood risks in these models, though the evidence for Hispanics is more mixed. Unsurprisingly, there is strong evidence of spatial spillovers in these models, and the controls indicate that coastal and wetter tracts tend to have higher flood risks by either measure. Also as expected, the magnitude of the spatial lag (ρ) declines as more geographic control variables are included in the model and thus account for more of the spatial dependence in the data.

Our main focus in this analysis centers on the divergence or difference between these two flood risk measures. The rightmost column shows that the *Risk Difference* is significantly associated with several key socioeconomic indicators. This confirms the differences in coefficients between columns 2 and 4 and tests for their statistical significance. Note that a positive coefficient here, such as for poverty rate, indicates tracts having a higher *SFHA risk* value than a *FSF risk* value. Tracts with greater poverty rates, greater percent of Blacks, greater percent of Hispanics, and more college educated residents tend to have *SFHA risk* exceeding *FSF risk* estimates. Tracts with more minorities, more poverty, and more education are associated with tracts having more land in flood zones but relatively fewer properties at risk. This is a crucial distinction, because it demonstrates how using alterative measures of flood risk may capture very different results. *Risk Difference* in this case shows that tract-level aggregates based on land area in floodplains diverge from shares of properties at risk, and that divergence is systematically related to important socioeconomic indicators. Clearly, the measure of risk affects the assessment of equity effects.

Table 6: Spatial Regression Results for the Atlantic and Gulf states

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
log median income	0.82	-0.36	-0.77	-0.53	0.25
	(0.65)	(0.72)	(0.48)	(0.53)	(0.68)
Poverty rate	0.07***	0.10***	0.05***	0.06***	0.04**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Percent Black	-0.02**	-0.01	-0.02***	-0.02***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Percent Latino	0.03***	0.03***	0.02***	-0.01**	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Percent 65+	0.30***	0.29***	0.27***	0.27***	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Percent no college	-0.04***	-0.00	-0.07***	0.03***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
January Sunlight		0.05***		0.02**	0.02*
		(0.01)		(0.01)	(0.01)
July Temperature		0.42***		-0.07	0.40***
		(0.10)		(0.07)	(0.10)
July Humidity		0.16***		0.01	0.11***
		(0.03)		(0.02)	(0.03)
Percent water		0.23***		0.23***	-0.03*
		(0.02)		(0.01)	(0.02)
Population density		-0.13		0.87***	-0.96***
		(0.14)		(0.10)	(0.13)
Unincorporated		1.96***		0.35	1.58***
		(0.52)		(0.38)	(0.49)
Coastal county		1.42***		1.32***	-0.73
		(0.52)		(0.38)	(0.49)
CRS		-0.29		0.11	-0.45

		(0.31)		(0.23)	(0.30)
Percent renters		0.00		0.03***	-0.02**
		(0.01)		(0.01)	(0.01)
log housing value		2.42***		3.26***	-1.36***
		(0.45)		(0.33)	(0.43)
Percent old buildings		-0.03***		-0.00	-0.03***
		(0.01)		(0.00)	(0.01)
Constant	-7.18	-76.40***	12.00**	-35.48***	-24.58**
	(7.93)	(12.44)	(5.92)	(9.16)	(11.86)
ρ	0.80***	0.76***	0.94***	0.89***	0.82***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
State FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	15,241	15,241	15,241	15,241	15,241
State FE t_test (F value)	353.9***	202.7***	150.1***	98.6***	54.3***
Chow_test (F value)	10871.0***		31740.5***		11373.6***

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

Next, we shift our attention to the other variables in the *Risk Difference* model. Most of the climate controls are more closely associated with tracts with more land at risk than properties, but the opposite is true for watery regions and more densely populated tracts. Of more interest are variables related to housing stock and flood management policy. Notably, tracts in communities participating in the FEMA CRS program – which provides incentives for communities to undertake hazard mitigation efforts – do not appear to have significantly different risks based on either measure and do not exhibit systematically higher or lower *Risk Difference*. As the divergence between the two risk measures is consistent with tendencies to locate housing development near-but-outside of SFHAs or for FEMA to measure risk differently than FSF, the lack of significance for CRS points to an alignment between alternative risk measures in communities practicing more proactive flood management. The housing variables each show negative associations with *Risk Difference*. This suggests that past decisions on zoning and housing development are strongly associated with tracts that tend to have a greater percent of properties at risk relative to the percent of land area in flood zones. In this model, tracts with older construction, more expensive homes, and fewer rental properties tend to have more properties at risk of flooding than would be expected based on the share of land area in floodplains.

4.2 State results

Because state-level heterogeneity characterizes these data, we take the pooled results as initial estimates with considerable caution. Thus, we estimate separate regressions (analogous to each model in Table 6) for each state in the sample. Here, we display and discuss the results for Texas and Florida as the two biggest Gulf states. We briefly discuss the results for the other states, but we leave the tables for the other states in the appendix.

Examining the results for Texas in Table 7, one can see in the baseline equity model for *SFHA risk* that all the demographic variables except for percent Black are significant. A simple model suggests a story of substantial inequities in flood risk exposure, but most of these coefficients are either insignificant in the unrestricted model with more control variables or insignificant in the model using *FSF risk*. This inconsistency across models in Texas reinforces the sensitivity to model specification as well as the divergence between the alternative risk measures. Consistent results include the insignificance of the income measure and how the roles of poverty rate and percent 65+ are fairly robust to inclusion of more controls. Tracts with more poverty and more seniors tend to have more flood risk, regardless of how its measured. No positive and significant coefficient is found for the race and ethnicity measures, regardless of the risk measure or inclusion of controls.

The *Risk Difference* results in Table 7 show how the full models tell a similar story for risk inequities between the two risk measures. Tracts with greater poverty rates and with a lower percent Black tend to have a higher percent of land at risk relative to the percent of properties at risk. The significant coefficient for percent Black underscores how analyses of inequitable risk exposures can yield different results by using different risk measures. While this can help explain some of the mixed results in the previous literature, it also may have more substantive meaning. Tracts with greater minority populations may have less land area at risk of flood but not fewer properties at risk. This result recommends a focus on exposure of people and property to risk while also raising questions about whether certain subpopulations tend to be better or worse at avoiding flood risk conditional on other regional factors. The other key demographic variables do not exhibit statistically significant associations with *Risk Difference* in Texas. How much these results depart from those in Table 6 underscores the importance of allowing for state-level heterogeneity.

Table 7: Spatial Regression Results for Texas

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
Log median income	0.63	-1.52	-0.57	-0.16	-1.25
	(1.16)	(1.26)	(0.67)	(0.74)	(1.24)
Poverty rate	0.10***	0.10***	0.04**	0.04*	0.06*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Percent Black	-0.04**	-0.06***	0.00	-0.01	-0.04**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Percent Latino	-0.06***	-0.01	-0.01*	0.00	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Percent 65+	0.16***	0.14***	0.08***	0.12***	0.02
	(0.04)	(0.05)	(0.03)	(0.03)	(0.05)
Percent no college	0.07***	-0.03	-0.01	-0.02	-0.01
	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
January Sunlight		0.09***		0.08***	-0.01
		(0.02)		(0.01)	(0.02)
July Temperature		0.61***		0.47***	0.05
		(0.23)		(0.14)	(0.23)
July Humidity		0.38***		0.28***	0.03
		(0.07)		(0.04)	(0.07)
Percent water		0.86***		0.56***	0.24***
		(0.05)		(0.03)	(0.04)
Population density		-2.31***		-0.15	-1.99***
		(0.26)		(0.15)	(0.25)
Unincorporated		0.31		0.69	-0.27
		(1.53)		(0.90)	(1.51)
Coastal county		-0.49		-1.56**	1.01
		(1.26)		(0.74)	(1.24)

CRS		0.02		-0.58*	0.58
		(0.54)		(0.32)	(0.53)
Percent renters		-0.01		0.02**	-0.03**
		(0.01)		(0.01)	(0.01)
log housing value		-1.92**		-0.74	-1.17
		(0.82)		(0.48)	(0.81)
Percent old buildings		-0.03***		-0.01*	-0.02*
		(0.01)		(0.01)	(0.01)
Constant	-7.24	-35.55	7.92	-53.99***	29.48
	(14.19)	(29.29)	(8.27)	(17.28)	(28.76)
ρ	0.75***	0.61***	0.86***	0.73***	0.66***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Number of Obs	4,338	4,338	4,338	4,338	4,338

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

Turning to Florida, the results in Table 8 show how the socioeconomic inequities in flood risk exposure differ based on risk measure and by state. Overall, we see a different pattern than what is observed in Texas. For Florida, percent Black is consistently and significantly negatively associated with flood risk. Tracts with greater shares of Black residents tend to have lower flood risk whether measured as a percent of land area in floodplains (*SFHA risk*) or a percent of properties at risk (*FSF risk*). Also, in Florida unlike Texas, flood risk appears lower in tracts with greater shares of the population lacking college education, at least until other control variables are included. Both Florida and Texas results tend to confirm an insignificant role for household income and positive associations for poverty rate and for percent 65+ and risk across all risk models. The results show tracts with more households in poverty or with more seniors being more likely to have a greater share of flood zones and a higher percent of properties at risk.

Table 8: Spatial Regression Results for Florida

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
log median income	1.97	0.98	-0.51	-1.40	2.53
	(1.70)	(1.93)	(1.56)	(1.75)	(1.86)
Poverty rate	0.13**	0.13**	0.14***	0.09*	0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Percent Black	-0.07***	-0.08***	-0.05***	-0.11***	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Percent Latino	0.08***	-0.03	0.01	-0.14***	0.11***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Percent 65+	0.33***	0.33***	0.31***	0.31***	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Percent no college	-0.18***	0.02	-0.23***	0.05	-0.04
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
January Sunlight		-0.05		0.02	-0.08**
		(0.04)		(0.03)	(0.03)
July Temperature		-0.15		-1.32*	0.65
		(0.87)		(0.79)	(0.84)
July Humidity		-0.66***		-0.57***	-0.03
		(0.15)		(0.14)	(0.15)
Percent water		0.12***		0.19***	-0.06**
		(0.03)		(0.03)	(0.03)
Population density		1.50***		1.67***	-0.16
		(0.24)		(0.22)	(0.23)
Unincorporated		5.42***		-0.17	5.48***
		(1.34)		(1.22)	(1.29)
Coastal county		-0.63		-0.43	-0.94
		(1.07)		(0.97)	(1.03)
CRS		-2.26***		-0.69	-1.56**

		(0.78)		(0.71)	(0.75)
Percent renters		0.08***		0.12***	-0.05*
		(0.03)		(0.02)	(0.02)
log housing value		8.05***		10.59***	-3.72***
		(1.07)		(0.97)	(1.03)
Percent old buildings		-0.06***		0.00	-0.06***
		(0.02)		(0.01)	(0.02)
Constant	-3.94	-35.97	22.38	25.34	-8.21
	(20.94)	(73.09)	(19.24)	(66.11)	(70.29)
ρ	0.77***	0.74***	0.93***	0.87***	0.84***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Number of Obs	3,555	3,555	3,555	3,555	3,555

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

Notably, the Florida estimates show a different, mixed pattern for the percent Hispanic. Tracts with a greater percent of Hispanics tend to have greater *SFHA risk*, although that effect fades with other geographic and housing controls. Conversely, Florida tracts with more Hispanics are associated with lower *FSF risk* when those controls are included. Results for the *Risk Difference* model reinforce this divergence in risk exposure patterns between the two flood risk measures. Florida tracts with greater shares of Hispanics tend to have significantly more land area overlapping 100-year floodplains than they have properties at risk of flooding. Similarly, tracts in Florida with a greater percent of Black residents also tend to show significantly greater exposure to risk defined by land area in floodplains than by properties at risk. In Texas by contrast, Table 7 shows that the divergence in risk measures is significantly associated with poverty rate (positive) and with percent Black (negative). The divergence between the two flood risk measures does not exhibit a significant association with the other socioeconomic variables in Florida. Finally, percent no college shows a rather mixed set of results.

The results also differ between the two states with respect to the other variables (housing, policy, geographic controls). The pattern of results for each of these variables contrasts sharply between Texas and Florida. For example, the climate-related variables all exhibit positive and significant relationships with flood risk, by either measure, in Texas. But they are only weakly associated with flood risk in Florida, except for the humidity measure, which has a negative and significant coefficient. Other geographic controls also show inconsistent results between the two states, except for Percent water, which is unsurprisingly positively associated with flood risk in all models. Notably, the policy-related CRS measure is only significantly associated with *FSF risk* in Texas and only significantly associated with *SFHA risk* in Florida. For the percent renters, Texas exhibits a positive association with *FSF risk* only, while Florida shows that tracts with more rental housing tend to have both more land area and more properties at risk. Conversely, for percent old buildings, Florida exhibits a negative association with *SFHA risk* only, while Texas shows tracts with more pre-FIRM housing tend to have less land area and fewer properties at risk. The most striking inconsistency between states for housing variables comes from housing value, where Texan tracts with greater average housing values tend to have lower flood risks and the reverse holds in Florida.

Of particular interest here are the *Risk Difference* results, which show whether the patterns of divergence between the alternative risk measures are different between the states. In Texas, the divergence tends to grow for tracts with more water, lower density, fewer rental properties, and fewer old houses. In Florida, the divergence tends to be greater for tracts with less water, less winter sunlight, in unincorporated areas, outside of the CRS, with fewer rental properties, with lower housing values, and fewer old houses. Clearly the patterns differ between the two states. Some of these results may be particularly telling. For example, if we expect that communities that have joined the CRS – conditional on their land areas in 100-year floodplains (*SFHA risk*) – to redirect development to lower-risk areas, then *Risk Difference* should be more negative in tracts in CRS communities. Yet Florida and not Texas shows this sort of association.

We also estimate models for the other states in the sample, separately. The online appendix contains the tables of results. The estimates confirm the idea of strong state heterogeneity. Similar to Texas and Florida, the results for the socioeconomic and policy variables are inconsistent across states and in comparisons across the risk measures within states. A few findings stand out. First, some states show a significant and negative association between tract income and flood risk. Higher incomes are associated with lower *SFHA risk* (Alabama), lower *FSF risk* (Georgia), or both (North Carolina). Yet other states still show no significant coefficient for logged median household income. Combined with poverty rate occasionally predicting greater flood risk, these results reinforce the heterogeneity across states in flood risk exposure to different socioeconomic groups. The mixed pattern for higher income and lower income residents in these coastal states are consistent with the nonlinear and mixed patterns found in other studies (Mendelsohn et al. 2012, Keys and Mulder 2020, Kahn and Smith 2017, Kinzer et al. 2021).

Second, evidence across states does not reveal a consistent pattern of inequitable exposure to flood risk for racial and ethnic minority populations. Tracts with a greater percent of Black residents have lower flood risks in Louisiana, but the evidence suggests this pattern is reversed and limited to just *FSF risk* in South Carolina and is even more mixed in North Carolina. Other states show no consistent association. Similarly, Hispanic populations appear to locate in tracts with greater flood risk in Georgia and Mississippi but not in other states.

Third, the most consistent result is greater exposure to flood risk for tracts with more seniors. The share of residents aged 65 or more is associated with greater flood risk in Alabama, Georgia, Mississippi, North Carolina, and South Carolina (*FSF risk* only). Louisiana alone fails to show the positive coefficient for Percent 65+. Fourth, socioeconomic indicators tend to not be associated with the divergence between the two risk measures (i.e., *Risk Difference*), and only inconsistently so when comparing among these states. In South Carolina, none of the demographic variables have significant coefficients for *Risk Difference*. In Mississippi and North Carolina (and Florida), tracts with greater shares of Black residents tend to have more exposure to flood risk for land area than for properties. *Risk Difference* is greater in tracts with more seniors only in Alabama, Georgia, and Louisiana. Yet this divergence follows with tract income differently for Georgia (positive) than for Alabama (negative).

For the policy-related variables, the results show more consistency. Across all the states except Georgia, tract flood risk is greater in tracts in the CRS. This relationship is significant only for *FSF risk* in Mississippi and South Carolina, which is somewhat surprising if we expect that joining the CRS is a response to greater risk and SFHAs rather than FSF risk would guide management decisions (Sadiq and Noonan 2015). Housing variables tend to not be significantly associated with flood risk, although tracts with more rental properties may have more flood risk in Georgia and Mississippi and less flood risk in South Carolina. Flood risk is also greater where housing values are greater in North Carolina and in Georgia *(FSF risk* only). While the pooled results in Table 6 indicate strong tendencies for the divergence in these risk measures to track along with housing variables, the state-by-state results do not show similar patterns. Though Georgia resembles Texas and Florida in this regard – where *Risk Difference* declines with higher renter rates, housing value, and shares of old homes – the other coastal states do not. Overall, the regression estimates for the states confirm the state heterogeneity found elsewhere, and the results recommend further work on state context and policy.

5 Discussion

Flood risk varies widely across geographic regions, just as concentrations of more socially vulnerable populations do. Yet understanding flood risk exposure for vulnerable populations depends crucially on how flood risk is measured. Some socioeconomic groups tend to have disproportionate exposure to one measure of flood risk but not another. The difference can be particularly important when some risks involve more readily available public information, flood insurance requirements, and additional flood management efforts, while other flood risk measures may provide better or supplemental information that is recently becoming more available. Tracts with greater divergence in risk measures may reflect behavioral responses to different incentives. Official floodplains may steer development to just outside flood zone boundaries, while (subsidized) flood insurance may provide substantial recovery benefits to those outside SFHAs yet still facing flood risk. Thus, the different measures of flood risk may drive usage of flood insurance and disaster recovery resources differently and reveal different distributions of flood damage across vulnerable populations conditional on those risks.

FEMA (2021) has recently announced a major update to the risk rating methodology it uses in the NFIP, known as "Risk Rating 2.0." This new methodology substantially updates how flood risk is calculated for properties and should lead to significant changes in insurance premiums for new policies and renewals effective on 1 October 2021 and 1 April 2022, respectively. Risk Rating 2.0 takes into account more information, better modeling, and improved actuarial practices to better calibrate rates to actual flood risk and rebuilding costs, thus reducing the reliance on (SFHA) flood zone designations for determining rates. As a result, going forward, we expect insurance premiums to reflect flood-risk measures that more closely align with the FSF flood risk measures than a simple categorical measure based on 100- or 500-year floodplain boundaries. In this way then, the maps and analysis presented here can be viewed as suggestively showing the distributional aspects of Risk Rating 2.0 closing the "gap" between the SFHA-based risk and the newer and more flexible measures of apart risk from SFHA boundaries. Under Risk Rating 2.0, we might expect the *Risk*

Difference to shrink toward zero as this risk information from FEMA converges toward the *FSF risk*. The results here, showing substantial differences in risk inequities observed for the two different risk indicators, suggest that the major shift in how FEMA rates flood risk implies a switch from one pattern of inequity to another. Using SFHA coverage to proxy for risk may be misleading in describing the inequities in risk exposure. For example, Florida tracts with more Hispanic residents may indeed tend to face lower flood risks than we would detect from 100-year floodplain designations alone.

The more behavioral aspects of the switch to Risk Rating 2.0, however, is likely to be much more complicated. Insofar as the FIRMs and SFHA floodplains are the primary source of public information about the spatial contours of flood risk, then adjusting insurance premiums may not affect economic behavior much. Further, because rules mandating the purchase of flood insurance remain based on SFHA boundaries, which are not changed under Risk Rating 2.0, the policy impact on behavior may not change much with Risk Rating 2.0. We expect the price signal sent to current property owners and developers to lead to some turnover and real estate markets to capitalize these new risk values, which could affect the demographic characteristics of those exposed to flood risk. Accordingly, we might see the results presented here as indicating where the biggest impacts might be felt. Where increased risk ratings lead to higher insurance premiums and property price impacts, our results could indicate the sorts of demographics associated with those locations. In those places, we might also see more relocation or turnover. Based on tables 7 and 8, for example, if tracts with more negative *Risk Difference* values will tend to have more properties receiving higher risk ratings under Risk Rating 2.0, then we might expect to see more turnover and possible demographic change in those areas (i.e., tracts with lower poverty rates and more Black residents in Texas and with fewer Black and Hispanic residents in Florida).

The complexity and mixed nature of these results describing flood risk distributions highlights the importance of the many causal mechanisms that generate the observed distributions (Banzhaf et al. 2019). Better understanding the drivers of the distributions of flood risk exposure and damages remains a priority. Most recent studies (e.g., Bradt et al. 2021, Kahn and Smith 2017, Bin et al. 2017) emphasize describing the disparities rather than explaining how they arise. One important exception, Bakkensen and Ma (2020), shows how sorting over flood risk matters greatly and how flood risk preferences appear correlated with race and income. They find that minority and low-income residents are more likely to move into flood-prone areas. Beyond income, Bakkensen and Ma argue that race and other factors appear to play an important role in sorting over flood risk, which itself is important for understanding and mitigating welfare effects associated with flood risks and policy changes.

Although these results underline important distributional concerns with flood risk and how sensitive the evidence is to alternative risk measures, limitations in the data and analysis suggest areas for future research. Our work shows how basing flood risk on shares of land area in SFHAs may capture risk for areas rather than properties or households. While FSF data attempts to remedy this, it does not align temporally with risk as measured by SFHAs. And neither risk measure perfectly aligns with the timing of the Census socioeconomic data. Regardless, as is common with studies of environmental inequities (Noonan 2008, Banzhaf et al. 2019), relying on aggregated data can miss important patterns and limit hypothesis testing at the individual level (e.g., parcels, households). While we expect use of aggregate and area measures of flood risk to continue and this study demonstrates important sensitivities, future research would do well to leverage more refined data when possible.

Further, our results show how generalizing even from one state to another is problematic. We would not expect that these results for Gulf and southern Atlantic states would apply to other US states. Those regions, where flood damage may be more frequent outside of SFHAs and may be more related to riverine flooding as opposed to coastal flooding, warrant their own study. Future research could also address key temporal dynamics around changing flood risk, regulation, and SFHAs. Examining when FIRMs are updated and how risks and development patterns change can help provide more causal evidence behind distributional inequities. Likewise, future research could benefit from examining elevation data. Explaining why we see certain groups more exposed to flood risk but not reside in flood plains can provide important guidance to policy reform. As suggested here, we expect that the role of private or additional flood risk can complement risk and regulatory information contained in SFHA boundaries. This can lead to different behavioral responses in terms of locations of housing development, sorting, and price adjustments. New information about flood risk can affect how we interpret the influence of those risk measures in future analyses.

6 Conclusion

Although an initial analysis points to large inequities in flood-risk exposure across vulnerable demographic groups, the baseline analysis masks important heterogeneities. First, the pattern of inequities varies markedly depending on which measure of risk is used. For instance, in the pooled models percent Hispanic positively associates with *SFHA risk* but negatively associates with *FSF risk*, perhaps consistent with strong sorting behavior around risk based on access to information (Bakkensen and Ma 2020). In state-specific unrestricted models for Texas and Florida, the negative association between the tract percent of Blacks becomes significant (Texas) or loses its significance (Florida) when we switch from the *FSF risk* measure to examining risk based on *SFHA risk*. Similar differences are revealed in many of the separate state estimates. Evidence of inequities clearly hinges on the risk measure used.

Second, the results point to considerable heterogeneity across states. The inequitable flood-risk exposure story changes dramatically from one state to the next. This complicates any simple narrative, because patterns of disproportionate exposure to flood risk for socially vulnerable populations in Texas do not resemble those in Florida, and so on. As more researchers begin to use these new flood risk measures, as a substitute or complement to SFHA-based measures, the analysis here demonstrates just how sensitive results can be.

Third, the state-level heterogeneity also points to an important role for state-level policies in affecting the distribution of flood risk. The significance of policy-related measures in the results also suggests that policy at the local level – such as participating in extra flood management via the CRS or affecting housing patterns – can also influence flood risk exposure.

Fourth, we are particularly interested in those areas where the two flood risk measures diverge, because they reflect different development patterns and highlight areas that may be most affected by dissemination of new information or insurance rate maps. If updating FIRMs or revising insurance premiums shifts risk information from FEMA to resemble the First Street Foundation risk assessments more closely, then the findings here point to those most affected by reducing the *Risk Difference*. FEMA 2021 notes, "lower-valued homes are paying more than their share of the risk," which is somewhat consistent with our results. Greater *Risk Difference*, where SFHA-based risk is much greater than FSF-based risk, is associated with low-valued homes overall (specifically, in Florida and Georgia). Bakkensen and Ma (2020) argue that improving flood map information will improve the welfare of residents. Although they estimate such improvements to be progressive with minorities valuing information improvements less, our findings indicate where the gap between *FSF risk* and *SFHA risk* is greatest and thus for whom map improvements may be greatest. Tracts with more negative *Risk Difference* values (e.g., those with a greater number of old properties in TX and tracts with more older citizens in FL) should stand to gain more from improved risk information from FSF. In addition, releasing better flood risk information may lead to considerable re-sorting. New FSF information where *Risk Difference* is not equal to zero might be expected to harm residents, who now see their housing values decline and possibly move to mitigate the harm.

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Appendix

Table A1: Spatial Regression Results for Alabama

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
log median income	-1.33	-4.16**	-0.34	-0.49	-3.58**
	(1.70)	(1.81)	(1.40)	(1.52)	(1.69)
Poverty rate	0.08*	0.11**	0.08**	0.09**	0.02
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Percent Black	-0.00	0.01	-0.01	-0.01	0.02
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Percent Latino	-0.08	0.03	-0.02	-0.00	0.02
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)
Percent 65+	0.19***	0.10	0.30***	0.30***	-0.20***
	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)
Percent no college	-0.03	-0.13***	-0.01	-0.04	-0.09**
	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
January Sunlight		0.07		-0.01	0.07
		(0.07)		(0.06)	(0.07)
July Temperature		1.24***		0.42	0.81*
		(0.45)		(0.38)	(0.42)
July Humidity		-0.72		-0.13	-0.57
		(0.58)		(0.49)	(0.54)
Percent water		0.31*		0.25	0.06
		(0.19)		(0.16)	(0.17)
Population density		-7.80***		-1.73**	-6.11***
		(0.93)		(0.77)	(0.86)
Unincorporated		-1.41		-1.15	-0.30
		(1.50)		(1.26)	(1.40)
Coastal county		-0.88		-0.64	-0.12
		(5.50)		(4.62)	(5.16)

CRS		4.05***		2.20***	1.85**
		(0.96)		(0.80)	(0.89)
Percent renters		0.02		0.01	0.01
		(0.03)		(0.02)	(0.03)
log housing value		0.55		-1.03	1.60
		(1.37)		(1.15)	(1.28)
Percent old buildings		-0.00		-0.02	0.02
		(0.02)		(0.02)	(0.02)
Constant	17.15	-10.46	3.56	-3.86	-7.27
	(20.89)	(46.54)	(17.16)	(39.10)	(43.61)
ρ	0.77***	0.70***	0.71***	0.67***	0.72***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Number of Obs	1,169	1,169	1,169	1,169	1,169

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

Table A2: Spatial Regression Results for Georgia

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
Log median income	0.01	0.25	-1.75**	-1.84**	2.23**
	(1.04)	(1.09)	(0.70)	(0.75)	(1.08)
Poverty rate	0.01	0.03	-0.02	-0.03*	0.07**
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Percent Black	-0.00	0.01	-0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Percent Latino	-0.01	0.05**	0.03*	0.04**	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Percent 65+	0.13***	0.11**	0.24***	0.24***	-0.16***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.05)
Percent no college	0.00	-0.05**	-0.05***	-0.03*	-0.02
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
January Sunlight		-0.09**		-0.08***	0.01
		(0.04)		(0.02)	(0.04)
July Temperature		0.71***		0.55***	-0.01
		(0.21)		(0.14)	(0.20)
July Humidity		0.23**		0.06	0.14
		(0.10)		(0.07)	(0.10)
Percent water		0.01		0.04	-0.06
		(0.08)		(0.05)	(0.07)
Population density		-2.82***		-1.01***	-1.49***
		(0.40)		(0.27)	(0.40)
Unincorporated		0.90		0.36	0.58
		(0.58)		(0.40)	(0.58)
Coastal county		18.42***		7.94***	7.66***
		(2.17)		(1.47)	(2.11)
CRS		-1.42**		-1.21***	0.18

		(0.63)		(0.44)	(0.63)
Percent renters		0.05***		0.04***	0.00
		(0.02)		(0.01)	(0.02)
log housing value		-0.24		2.03***	-2.36***
		(0.77)		(0.53)	(0.77)
Percent old buildings		-0.05***		-0.00	-0.04***
		(0.01)		(0.01)	(0.01)
Constant	1.12	-50.73**	21.79**	-37.93**	-2.80
	(12.72)	(22.17)	(8.62)	(15.22)	(22.03)
ρ	0.85***	0.62***	0.90***	0.81***	0.68***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Number of Obs	1,937	1,937	1,937	1,937	1,937

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

Table A3: Spatial Regression Results for Louisiana

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
Log median income	3.49	-0.70	1.39	-0.23	-1.40
	(5.77)	(6.17)	(3.36)	(3.61)	(6.41)
Poverty rate	0.20	0.11	0.00	0.04	0.07
	(0.16)	(0.16)	(0.09)	(0.09)	(0.17)
Percent Black	-0.15***	-0.12**	-0.07**	-0.07**	-0.04
	(0.05)	(0.06)	(0.03)	(0.03)	(0.06)
Percent Latino	-0.33	0.00	0.54**	0.30	-0.26
	(0.40)	(0.42)	(0.23)	(0.25)	(0.44)
Percent 65+	-0.50*	-0.58*	0.07	0.15	-0.63**
	(0.28)	(0.30)	(0.16)	(0.17)	(0.31)
Percent no college	0.20**	-0.11	0.15***	0.14*	-0.25*
	(0.10)	(0.14)	(0.06)	(0.08)	(0.14)
January Sunlight		1.00**		-0.39	1.54***
		(0.47)		(0.28)	(0.49)
July Temperature		-3.32		0.70	-4.48*
		(2.35)		(1.39)	(2.45)
July Humidity		2.24***		-0.38	2.70***
		(0.75)		(0.44)	(0.78)
Percent water		0.32*		0.16	0.05
		(0.18)		(0.11)	(0.19)
Population density		-15.11***		0.60	-13.92***
		(2.84)		(1.64)	(2.91)
Unincorporated		-0.96		1.20	-1.15
		(5.06)		(2.96)	(5.25)
Coastal county		-18.90***		11.82***	-26.30***
		(5.86)		(3.39)	(6.28)
CRS		6.95**		3.24**	2.79

		(2.75)		(1.61)	(2.83)
Percent renters		0.09		-0.04	0.13
		(0.11)		(0.06)	(0.11)
log housing value		-1.64		-1.92	1.80
		(4.98)		(2.91)	(5.17)
Percent old buildings		0.08		-0.04	0.13*
		(0.07)		(0.04)	(0.08)
Constant	-27.86	46.57	-22.32	40.74	3.10
	(70.44)	(216.33)	(40.95)	(126.71)	(224.78)
ρ	0.65***	0.55***	0.87***	0.71***	0.69***
	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)
Number of Obs	584	584	584	584	584

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

Table A4: Spatial Regression Results for Mississippi

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
Log median income	-0.02	-1.98	0.00	-1.04	-0.56
	(3.73)	(3.97)	(2.11)	(2.25)	(3.52)
Poverty rate	0.10	-0.02	0.08	0.08	-0.09
	(0.10)	(0.10)	(0.06)	(0.06)	(0.09)
Percent Black	0.06	0.07*	-0.02	-0.01	0.08**
	(0.04)	(0.04)	(0.02)	(0.02)	(0.03)
Percent Latino	1.06***	0.81***	0.64***	0.47***	0.32
	(0.21)	(0.23)	(0.12)	(0.13)	(0.20)
Percent 65+	0.52***	0.50**	0.42***	0.37***	0.14
	(0.18)	(0.21)	(0.10)	(0.12)	(0.18)
Percent no college	0.01	0.06	0.01	0.06	0.01
	(0.07)	(0.09)	(0.04)	(0.05)	(0.08)
January Sunlight		-0.14		0.02	-0.18
		(0.22)		(0.13)	(0.20)
July Temperature		4.51***		0.32	3.68***
		(1.17)		(0.65)	(1.05)
July Humidity		-0.26		0.00	-0.30
		(0.23)		(0.13)	(0.20)
Percent water		-0.36*		-0.56***	0.26
		(0.21)		(0.12)	(0.18)
Population density		-10.79***		-3.19**	-6.58***
		(2.24)		(1.27)	(1.96)
Unincorporated		-0.82		-0.36	-0.27
		(3.40)		(1.93)	(3.01)
Coastal county		18.94**		29.20***	-15.87**
		(7.46)		(4.46)	(6.66)
CRS		2.50		2.53**	-0.40

		(1.87)		(1.06)	(1.65)
Percent renters		0.20***		0.03	0.17***
		(0.06)		(0.03)	(0.05)
log housing value		3.15		2.67	0.80
		(3.16)		(1.79)	(2.79)
Percent old buildings		0.02		0.02	-0.00
		(0.05)		(0.03)	(0.04)
Constant	-4.32	-350.25***	-6.09	-56.69	-259.01**
	(45.49)	(117.53)	(25.71)	(65.81)	(104.32)
ρ	0.65***	0.54***	0.91***	0.72***	0.62***
	(0.04)	(0.05)	(0.02)	(0.04)	(0.05)
Number of Obs	642	642	642	642	642

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

Table A5: Spatial Regression Results for North Carolina

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
Log median income	-0.46	-3.16***	-2.43***	-2.85***	-0.34
	(1.16)	(1.19)	(0.87)	(0.90)	(1.02)
Poverty rate	0.05	0.06*	0.03	0.04	0.02
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Percent Black	0.01	0.04***	-0.02**	0.01	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Percent Latino	-0.06*	0.01	-0.04	0.00	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Percent 65+	0.30***	0.15***	0.28***	0.17***	-0.02
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
Percent no college	-0.05**	-0.01	-0.05***	-0.01	0.01
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
January Sunlight		-0.03		0.03	-0.06**
		(0.03)		(0.02)	(0.03)
July Temperature		0.77***		-0.46***	1.07***
		(0.13)		(0.10)	(0.12)
July Humidity		0.34***		0.14***	0.15**
		(0.07)		(0.05)	(0.06)
Percent water		0.31***		0.25***	0.04
		(0.03)		(0.03)	(0.03)
Population density		-4.84***		-1.34***	-3.14***
		(0.63)		(0.48)	(0.54)
Unincorporated		0.38		0.41	0.13
		(0.83)		(0.63)	(0.71)
Coastal county		1.16		3.42***	-2.65**
		(1.29)		(1.01)	(1.10)
CRS		2.05***		0.82*	1.13**

		(0.56)		(0.42)	(0.48)
Percent renters		0.02		-0.01	0.03*
		(0.02)		(0.01)	(0.02)
log housing value		6.99***		3.23***	3.59***
		(0.92)		(0.70)	(0.79)
Percent old buildings		0.01		0.02**	-0.01
		(0.01)		(0.01)	(0.01)
Constant	6.88	-127.46***	29.62***	12.89	-123.83***
	(14.15)	(20.98)	(10.62)	(15.74)	(18.38)
ρ	0.86***	0.60***	0.87***	0.65***	0.71***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Number of Obs	2,147	2,147	2,147	2,147	2,147

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

Table A6: Spatial Regression Results for South Carolina

	(1)	(2)	(3)	(4)	(5)
	SFHA risk	SFHA risk	FSF risk	FSF risk	Risk Difference
log median income	1.99	-1.88	0.07	-0.87	-1.00
	(2.56)	(2.48)	(0.77)	(0.78)	(2.49)
Poverty rate	0.02	-0.03	0.04**	0.05**	-0.06
	(0.07)	(0.07)	(0.02)	(0.02)	(0.07)
Percent Black	0.01	0.00	0.02***	0.02***	-0.02
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)
Percent Latino	-0.13	-0.17*	-0.04	-0.04	-0.13
	(0.10)	(0.10)	(0.03)	(0.03)	(0.10)
Percent 65+	0.08	0.06	0.14***	0.12***	-0.06
	(0.11)	(0.11)	(0.03)	(0.03)	(0.11)
Percent no college	-0.01	-0.06	-0.04***	-0.06***	-0.02
	(0.04)	(0.06)	(0.01)	(0.02)	(0.06)
January Sunlight		0.08		-0.02	0.09
		(0.08)		(0.02)	(0.08)
July Temperature		-0.43		-0.05	-0.24
		(0.68)		(0.21)	(0.68)
July Humidity		0.31		0.14**	0.20
		(0.23)		(0.07)	(0.23)
Percent water		-0.16		-0.01	-0.17
		(0.13)		(0.04)	(0.13)
Population density		-4.05***		-0.50	-3.95***
		(1.46)		(0.46)	(1.46)
Unincorporated		2.63**		0.47	2.26*
		(1.32)		(0.41)	(1.32)
Coastal county		35.43***		7.26***	28.08***
		(2.88)		(0.90)	(2.89)
CRS		-0.36		2.03***	-1.75

		(1.61)		(0.52)	(1.62)
Percent renters		0.01		-0.03**	0.04
		(0.04)		(0.01)	(0.04)
log housing value		3.24		0.02	2.96
		(2.05)		(0.64)	(2.05)
Percent old buildings		0.02		0.01	0.01
		(0.03)		(0.01)	(0.03)
Constant	-18.10	-9.68	3.63	13.23	-28.63
	(31.03)	(60.64)	(9.38)	(18.99)	(60.77)
ρ	0.78***	0.67***	0.38***	0.33***	0.68***
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)
Number of Obs	869	869	869	869	869

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