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Analysis

What drives households to buy flood insurance? New evidence from Georgia

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ABSTRACT

Benefiting from access to detailed data on the federally run National Flood Insurance Program for the entire state of Georgia, USA, we analyze residential flood insurance purchasing behavior in that state over more than three decades (1978–2010). The demand for flood insurance on an extensive margin, based on take-up rates, is found to be relatively price inelastic. Aligned with the behavioral economics literature, recent flood events temporarily increase purchases, but this effect fades after 3 years. We also find that the proportion of developed area in floodplains has a significant positive impact on insurance take-up rates. Contrary to what is often assumed, we do not find evidence that insurance purchase and mitigation efforts are substitutes. Educated individuals, individuals over the age of 45, and African-Americans are, all else equal, more likely to purchase flood insurance.

1. Introduction

Insurance is one of the most widely recognized risk transfer tools for ex ante management of weather disasters such as floods. In the United States, after private insurers decided to leave the flood insurance market post the Great Mississippi Flood of 1927 and after several decades of reliance on government disaster relief, the federal government established the National Flood Insurance Program (NFIP) in 1968 (Dacy and Kunreuther, 1969; Michel-Kerjan, 2010). This national program offers flood insurance coverage to residents and small businesses in communities that adopt minimum floodplain management policies. The Federal Emergency Management Agency (FEMA), which maps flood risks, manages the program and sets flood insurance premiums. As of January 2015, there were over 5.4 million flood insurance policies-in-force in the United States managed through this federal program.

While the program has been in place for over forty-five years, academic research on its operation and the demand for flood insurance through the NFIP is fairly recent.[1] Browne and Hoyt (2000) provide the first non-survey based empirical analysis of homeowners' demand for flood insurance using actual flood insurance purchase data through a state-level analysis across the nation. Their work suggests that the flood insurance purchase decision is affected by both price and income, and that the decisions are highly dependent on prior year disaster losses. Kriesel and Landry (2004) use household-level data from coastal zones in the United States to examine participation in the NFIP for nine southeastern counties. They find participation responsiveness to price to be inelastic. Expanding upon this analysis, Landry and Jahan-Parvar (2011) confirm a price-inelastic demand for flood insurance and find that higher income households are more likely to purchase flood insurance, a finding that suggests that flood insurance is viewed as a normal good. Complementing recent efforts of FEMA to evaluate the NFIP's goals and performance, Dixon et al. (2006) identified factors contributing to the purchase of flood insurance using parcel-level data for 100 NFIP communities across the United States. They show that, as expected, the price of flood insurance has a negative (although not particularly strong) impact on demand, and that a higher proportion of homes in Special Flood Hazard Areas (SFHAs)[2] and subject to coastal flooding leads to higher demand for insurance. Three studies more recently have looked at specific states or cities: Zahran et al. (2009) show that household flood insurance purchases in Florida correlate strongly with local government mitigation activities. Additionally, they show that NFIP policy take-up rates correlate positively with prior flood experience, local hazard proximity conditions such as land area in the

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[1] An exception is the seminal work of Kunreuther et al. (1978) who employed field surveys and laboratory experiments to determine the factors influencing the voluntary purchase of insurance by homeowners against floods and earthquakes. They found that higher income increased the chances of having an insurance policy; those with at least a high school education and older people were more likely to buy flood insurance than their less educated and younger counterparts.

[2] SFHAs (alternatively, 100-year floodplains) are areas with a 1% annual chance of getting flooded.

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floodplain, and the education attainment levels of individuals in a locality. Michel-Kerjan and Kousky (2010) find similarly that the majority of policies in Florida are located within FEMA-designated SFHAs. Kousky (2010) examines the demand for flood insurance in St. Louis, Missouri and finds the take-up rates to increase with more land in high-risk floodplains and to decline with levee protection along major rivers. Building upon these earlier studies, we examine the demand for flood insurance using data on flood insurance policies-in-force in counties of another coastal state, Georgia, which has nearly $24 billion flood insurance coverage in force as of 2014. We expand on previous analyses in a number of important ways.

First, we explore a greater array of covariates in our analysis. In addition to controlling for economic variables (income, price) and risk related variables (recent floods, risk reduction efforts, percentage of development within floodplains) as in earlier studies, we also control for demographic variables such as education and age, and also race.

Earlier, survey-based studies have found that the purchase of disaster insurance increases with the level of education and with age (Kunreuther et al., 1978; Baumann and Sims, 1978). We will empirically test whether this is the case using a regression analysis over a longer period of time (1978–2010) and whether it applies specifically to flood insurance.

To the best of our knowledge, race has never been tested as an explanatory variable affecting flood insurance demand. This is surprising since it has been shown that minority groups often differ in terms of world view, socioeconomic status (which we control for here), family organization and structure, political efficacy and trust in social and political institutions compared to the majority group (see Perry and Mushkatel, 2008, for instance).

Vaughan and Nordenstam (1991) review evidence on differences in environmental risk perceptions across ethnicities, and put forth three hypotheses to explain them: differences in prior experiences with or exposure to various hazards, dissimilar general beliefs about risk and uncertainty, and differences on various qualitative dimensions that influence non-expert assessments of risk. A review of the literature by Fothergill et al. (1999) synthesizes findings on how various racial and ethnic groups perceive natural hazard risk, respond to warnings, are differently affected and recover from hazards. The review shows that there is indeed much variation across race and ethnic groups in the ways they perceive and deal with the risk of natural hazards. That different ethnic groups perceive the risk of a disaster differently has been shown in contexts other than floods. For instance, Turner et al. (1980) found that African-Americans in southern California were much more fatalistic about earthquakes and felt that there was not much one could do to protect against those. Similarly, Palm (1996) found that white men were consistently the least concerned group about the risk to their homes.

Owing to these variations in risk perception, we might thus expect to find variations between racial groups in the decision to purchase flood insurance. If confirmed, this can have important implications for improving the way in which information about flood risk and flood insurance are communicated to these different groups. Georgia presents an excellent case study to do so since the state has a fairly high percentage of minorities compared to the national average (31% African-American versus 13% nationally). Georgia indeed ranks third in the U.S. by the proportion of the state population that is African American, after Mississippi (37%) and Louisiana (32%) (U.S. Census Bureau, 2010).

Second, our empirical strategy controls for the percentage of population in a "non-participating" county,[3] and also for the proportion of owner-occupied homes and renter-occupied homes in a county. It is indeed important to control for the "non-participating" community's population as they are ineligible to purchase flood insurance. Consequently, having more "non-participating" communities in a county diminishes the insurance take-up rates. That said, we find that only 32 communities exited the program over the period we studied and mostly in later years. These communities had only 14 policies-in-force when in the NFIP so we do not expect this variable to have a significant effect, but still consider it.

Third, our analysis benefits from a much longer time period and a larger sample size compared to earlier studies which used only a few years of data and a few counties to examine the demand for flood insurance (for example, Kriesel and Landry, 2004 and Landry and Jahan-Parvar, 2011 used 1998–1999 survey data for nine coastal counties). Here we use extensive panel data from 153 counties in Georgia for a period of 33 years (1978–2010).

We find evidence of price-inelastic demand for flood insurance and a positive income effect. We also find that recent flood damages have a positive impact on the adoption of flood insurance, consistent with previous literature (Baumann and Sims, 1978; Kunreuther et al., 1978; Kriesel and Landry, 2004; Carbone et al, 2006; Petrolia et al, 2013). Consistent with the availability heuristic (Tversky and Kahneman, 1973), wherein people rely on immediate examples of a hazard that come to mind while estimating their probabilities, we find that this impact fades over time; the significance vanishes after 3 years.

We also find that publicly funded mitigation assistance (dollars spent by the government on flood mitigation per capita) has a positive but insignificant effect on the decision to purchase flood insurance. This is contrary to insurance theory that assumes insurance and mitigation to be substitutes (e.g., Ehrlich and Becker, 1972; Mossin, 1968).

Regarding the demographic variables, we confirm that the demand for flood insurance increases with education level and age and find that the demand increases with the proportion of African-Americans in the county. The new finding on race is important for the reasons we discussed before. As one intuitively expects, the proportion of developed area in the floodplain is found to be positively related to the number of policies purchased in a county, whereas having a larger percentage of population in non-participating communities in a county is negatively related to the number of policies purchased.

The article is organized as follows. Section 2 provides a brief overview of the operation of the NFIP as it relates to our study. Section 3 discusses our hypotheses based on the literature and the data. Section 4 introduces our methodological approach. Section 5 discusses the results and Section 6 concludes.

2. The National Flood Insurance Program

The National Flood Insurance Act of 1968 created the NFIP as a voluntary partnership between the federal government, communities and private insurers. The NFIP develops flood maps, establishes the deductible/limit menu, and sets premiums, including subsidized premiums for certain existing properties (see Michel-Kerjan, 2010 for a review). Over 90 private insurers collaborate with the program to sell flood insurance policies through their networks and provide claim adjustments. They receive an allowance for doing so on behalf of the federal government but do not bear any risk. While there is a small private market for flood insurance, it represents only 5% of what is sold through the NFIP (Dixon et al., 2006).

A significant problem with the NFIP lies in its implementation. Effective flood damage prevention depends a great deal on the ability and willingness of community planners and property owners to adapt to the program. Due to low take-up rates even at subsidized premiums, Congress passed the Flood Disaster Protection Act of 1973, establishing mandatory purchase requirement for homeowners residing in the SFHA with a mortgage from federally-backed lenders. However, in a survey conducted a decade after the NFIP was instituted, it was found

[3] "Non-participating" communities are those that are no longer in NFIP due to either getting suspended from the program or that have withdrawn from the program.

that only 12% or fewer responding individuals of a community participating in the NFIP were aware of the building codes or land use regulations to mitigate flood damage; and only 1% were aware of the insurance mechanism to manage flood risk (Kunreuther et al., 1978). The mandatory purchase requirement was thus strengthened by the National Flood Insurance Reform Act of 1994. In the same year, the Flood Mitigation Assistance Program (FMA) was created with the goal of reducing insurance claims under the NFIP by providing funds for projects to reduce the risk of flood damage to buildings that are insured by the NFIP. Additionally, the Community Rating System (CRS) program was implemented in 1990 to provide incentives to communities to go beyond the NFIP minimal requirements to reduce flood risks. Efforts by the community are scored by FEMA and allow residents of active CRS communities to benefit from a reduction in their flood insurance premium (the higher the score the higher the insurance discount).

While more people are insured today against flooding than were 25 years ago, the low take-up rate for flood insurance remains a vexing issue. A *New York Times* analysis published a few days after Hurricane Katrina in 2005 revealed that "in the Louisiana parishes affected by the hurricane, the percentage of homeowners with flood insurance ranged from 58% in St. Bernard's to 7% in Tangipahoa. Six out of 10 residents in Orleans Parish had no flood insurance (Bayot, 2005)". More recently, it was found that "only 20% of New York City households in the area inundated by Hurricane Sandy had flood insurance at the time of the disaster, despite Sandy occurring a year after Hurricane Irene in the same area (NYC, 2013)".

Although flood hazard and flood insurance information is publicly available, Chivers and Flores (2002) find evidence that most households living in flood zones of Colorado were not mindful of the existing flood risk classification nor were aware of the flood insurance rates and requirements when submitting their offer to purchase a property. Flood hazard disclosure requirements may prove effective in increasing flood risk awareness. Troy and Romm (2004) and Pope (2008) find that state disclosure laws (in California and North Carolina) brought down the prices of properties in the floodplain by approximately 4% in both cases, suggesting that before the state disclosure laws, a significant fraction of buyers were unaware of flood risks.[4] Kriesel and Landry (2004) find that, although compliance is not full, the flood insurance requirements of FDIC-backed mortgage lenders increase the probability that homeowners in the flood zone hold such insurance, suggesting that the additional sale and disclosure requirement for mortgage lenders impact both knowledge and requirements to purchase flood insurance.

In addition to problems with low flood insurance penetration under the NFIP, Hurricane Katrina in 2005 and Hurricane Sandy in 2012 demonstrated that the premiums collected by this federal program were insufficient for the program to provide claim payments by itself when large disasters strike, without borrowing money from the U.S. Treasury, as the program was designed to do. The volume of claims after Hurricane Katrina was so high (more than the cumulative claim payments by the program since its inception) that, combined with Hurricanes Rita and Wilma, and then Hurricane Ike in 2008, it put the NFIP in debt for $18 billion (Michel-Kerjan, 2010). Hurricane Sandy in 2012 increased the debt even more. As of July 2013, the NFIP's debt was approximately $24 billion in total. The NFIP's debt and the current premium structure have raised concerns regarding its long-term financial solvency. Some advocacy groups have argued that the program disproportionately benefits wealthy households with expensive waterfront properties, but with a few exceptions (e.g., Bin et al., 2011), there has not been much research to determine who benefits from and who bears the cost of the NFIP.[5]

In 2012, the U.S. Congress passed the (Biggert–Waters) Flood Insurance Reform Act (BW-12) with a key provision to increase the existing discounted flood insurance premiums to full-risk levels, aimed to make the program more financially sound. However, BW-12 was revised in March 2014 curbing the planned insurance rate increase with the passage of the Homeowner Flood Insurance Affordability Act (HFIAA-14), in response to constituent concerns over affordability of the proposed premium increases. The program is up for renewal again in 2017 and could benefit from a more solid understanding of who is purchasing flood insurance and thus will be affected by changes in the program.

3. Data and Hypotheses

3.1. Hypotheses

To establish the hypotheses of our empirical analysis we rely on findings from previous literature as well as theories underpinning the demand for insurance. Previous studies have noted that spending on insurance is viewed by homeowners as a poor investment (Baumann and Sims, 1978; Kunreuther et al., 1978). Other research, both theoretical and empirical, suggests a positive relationship between income and insurance purchases, and a negative relationship between price and insurance purchases (Kunreuther et al., 1978; Browne and Hoyt, 2000). We thus hypothesize that an increase in income will positively affect the decision to purchase flood insurance, while an increase in the price of the premium will affect it negatively.

Subjective perception of risks – influenced by events such as recent flooding – also affects the decision to buy flood insurance. Household surveys in the Netherlands and Germany have established such relationships between individual flood risk perceptions and willingness to pay for flood insurance (Botzen and van den Bergh, 2012; Seifert et al., 2013). In the United States, Petrolia et al. (2013) found that the likelihood of holding flood insurance increased with previous flood event experience. Browne and Hoyt (2000), Dixon et al. (2006), and Lindell and Hwang (2008) all find that flood experience serves as an immediate reminder of exposure to flood risk, resulting in higher demand for flood insurance which is mostly attributed to the availability heuristic (Tversky and Kahneman, 1973). On the other hand, the "gambler's fallacy" may lead some people to believe that the odds of another flood occurring in the area in subsequent years have declined after a recent flood (Kunreuther and Michel-Kerjan, in press). Croson and Sundali (2005) find evidence of the gambler's fallacy in their laboratory research in casinos. In the context of natural disasters, a recent review article by Pidot (2013) shows that individuals recently struck by hurricanes think that the hurricane was a once in a lifetime event, not to happen again. Based on the opposing predictions of the availability heuristic and the gambler's fallacy, we are agnostic about the sign of the relationship between past flood damage and demand for flood insurance.

Mitigation (actions taken to lower exposure) reduces the expected loss from flooding and, therefore, could reduce the perceived need for flood insurance. Burby (2006) provides evidence that the federal government's actions, such as building levees, make residents feel safer, supporting the common assumption that mitigation may serve as substitute for flood insurance. We expect to find a negative relationship between government investment in mitigation and the demand for

[4] Troy and Romm found the price discount to be more marked in neighborhoods with larger Hispanic population shares, suggesting that this group was particularly uninformed about flood risks.

[5] Various proposals for reforming the NFIP have been suggested, including issuing long-term insurance contracts tied to the property instead of one-year renewable policies tied to the individual homeowner (Kunreuther and Michel-Kerjan, 2010) to reduce the number of residents canceling their policies after just 2 or 3 years as has been shown to be the case (Michel-Kerjan et al., 2012), using federal funds to compensate existing landowners, and targeting properties deemed high-risk or environmentally sensitive to purchase flood insurance (Barnhizer, 2003).

Table 1
Drivers of flood insurance purchasing decision.

Variables	Hypothesized sign	Results
Income	+	+
Price	−	−
Recent flood event	?	+
Mitigation	?	+ (insignificant)
Race	?	+ (for African-American) & − (insignificant for Whites)
Education (high school & up)	+	+
Age	+	+ (for 45 & up)
Home occupancy (owner)	?	− (insignificant)
Home occupancy (renter)	?	+ (insignificant)
Percent of floodplain in developed area of a county	+	+
Proportion of population in “non-participating” communities in NFIP	−	− (insignificant)

flood insurance, as found by Browne and Hoyt (2000). However, Zahran et al. (2009) show that local government mitigation efforts, such as activities under CRS which translate to flood premium discounts, lead to more people buying flood insurance. Botzen et al. (2009) find that homeowners are willing to make investments in mitigation in exchange for premium discounts. In the U.S., community participation in the NFIP is required in order to purchase flood insurance. Therefore it is important to control for the proportion of population in a county that does not participate in the NFIP, which we hypothesize will be negatively related to the demand for flood insurance.

There is also evidence that the same people who behave in a less risky manner are more likely to purchase insurance because they are prudent people generally speaking (Finkelstein and McGarry, 2006). In addition, one might expect that mitigation expenditures are highest in SFHAs where the potential benefits and need for mitigation are the largest. For that reason, our regressions control for objective exposure to flood risk with a variable capturing the proportion of floodplain in developed areas of a county. We hypothesize that households in the floodplain demand more flood insurance due to perceived risk of flood and, therefore, this variable should have a positive impact on the demand for flood insurance.[6]

As indicated above, we are not aware of prior research that has tested whether racial differences impact the adoption of flood insurance. In regard to tolerance of risk, Sung and Hanna (1996) find that whites are more likely to be willing to take risks and that blacks tend to be less risk tolerant. Survey research by Palm (1998) suggests that non-white households exhibit a greater fear of disaster although it is unclear if that fear translates into the purchase of flood insurance or any other mitigation activities. Thus, the racial difference in the adoption of flood insurance is ambiguous and needs to be tested empirically.

As mentioned in the introduction section, the adoption of disaster insurance is found to be positively related to the level of education and age. Therefore, we hypothesize that a higher level of education and age will have a positive impact on the demand for flood insurance. Similarly, the findings of Riley and Chow (1992), that risk aversion rises at the age of 65, are consistent with the demand for flood insurance increasing with age.

The effect of the owner-occupied home status on the demand for insurance is unclear. On one hand it should be positive, as for most homeowners, the house is a primary asset in their portfolio (Flavin and Yamashita, 2002) and one would want to protect it. On the other hand, as we indicated above, many homeowners do not purchase flood insurance.

[6] Also, as noted earlier in the article, properties in the SFHA are affected by state disclosure requirements and mandatory purchase of flood insurance if they have FDIC-regulated mortgage lenders.

Table 2
NFIP policies-in-force, premium and coverage in Georgia from 1978 to 2010.

Year	Policies-in-force (PIF)	Premium collected (2010 $)	Coverage (2010 thousand $)
1978	10,502	861,713	343,034
1979	13,348	1,105,861	472,011
1980	14,570	1,250,727	578,935
1981	14,563	1,921,371	651,969
1982	15,036	2,771,714	711,642
1983	15,596	2,905,571	783,435
1984	16,774	3,391,955	938,647
1985	18,018	3,895,232	1,228,856
1986	19,706	4,651,514	1,498,005
1987	20,396	5,267,443	1,665,969
1988	21,271	5,595,801	1,839,428
1989	23,069	6,467,600	2,388,232
1990	32,741	9,128,278	3,170,013
1991	28,129	8,756,679	2,805,169
1992	29,383	9,744,305	2,963,670
1993	31,400	10,803,381	3,337,091
1994	39,337	13,974,896	4,205,946
1995	42,761	16,511,970	5,049,496
1996	46,445	19,206,888	5,938,711
1997	50,725	22,613,901	6,932,214
1998	54,655	25,853,306	7,813,618
1999	58,318	27,262,323	8,779,346
2000	61,600	28,446,564	9,768,575
2001	62,718	29,442,985	10,511,775
2002	63,730	30,852,160	11,221,265
2003	65,618	33,396,557	12,041,183
2004	68,106	35,963,182	13,520,381
2005	74,387	39,881,447	15,700,573
2006	81,607	45,786,366	18,320,810
2007	84,047	50,360,780	19,856,870
2008	85,632	54,860,728	20,894,858
2009	90,602	59,427,670	22,533,477
2010	91,131	63,256,224	23,047,444

Table 1 presents the variables that are expected to affect the flood insurance purchasing decision and their hypothesized signs.

3.2. Data

We collected our data from several sources. County-level data on NFIP policies-in-force from 1978 to 2010 were provided to us by FEMA.[7] This dataset includes the number of policies-in-force (PIF), flood insurance premium collected, and flood insurance coverage in-force for a given county and for a given year (Table 2). Over this period, the number of NFIP flood insurance policies-in-force increased almost 9-fold (from about 10,500 to over 91,000), while the population in the state less than doubled (from about 5.2 million in 1978 to 9.7 million in 2010). As of 2010, the last year covered by the study, there was nearly $24 billion of NFIP flood insurance coverage in place in Georgia, a level that has grown only by a few percentage points since. Additionally, also from FEMA, we obtained data on Flood Mitigation Assistance (FMA) provided to counties in Georgia.[8]

We obtained a GIS file with floodplain maps and land cover data for the state of Georgia from Georgia's GIS clearinghouse and overlaid FEMA floodplain maps onto the land cover layer to calculate the proportion of developed area of a county that falls in a floodplain. This ensures that the uninhabited floodplain areas of the county are excluded from the analysis.[9] Ideally, we would have performed the analysis using household-level data, but for privacy reasons, data at this level of disaggregation were not available from FEMA.

[7] We thank the Mitigation Directorate at FEMA, DHS for providing the data.

[8] NFIP-participating communities with approved hazard mitigation plans are eligible to apply for FMA grants. For more details see: http://www.gema.ga.gov/Mitigation/Pages/Flood-Mitigation-Assistance-%28FMA%29.aspx.

[9] We thank an anonymous referee for pointing this out. We used the 100-year floodplain since flood insurance is mandatory for the 100-year floodplain properties only and excluded 500-year properties from the floodplain variable.

Table 3
Variables and descriptive statistics for county-level analysis (1978–2010).

Variable	Description	Mean	Std. dev.	Min	Max
PIF/1000pop	Policies-in-force per 1000 population	4.95	19.25	0.01	240.28
Income	Per capita income (in thousands, 2010 constant dollars)	25.5	6.13	12.22	65.91
Price	Cost per $1000 of coverage (2010 price)	4.46	2.39	0.37	30.38
Recent_Flood	Flood damage per capita in prior year ($)	10.99	113.00	0	3986.23
Mitigation	Flood Mitigation Assistance per capita ($)	0.004	0.083	0	3.366
PercentFP	Percent of floodplain that intersect with urban area in a county	0.62	0.72	0.00006	4.38
NoNFIP	Percent of population in "non-participating" communities	1.08	3.28	0	31.36
Race					
African-American %	Percent of African-Americans	25.60	17.17	0	82.99
White %	Percent of whites	69.00	16.52	18.9	98.8
Education					
High school %	Percent of high school graduates	32.81	5.36	16.5	54
College %	Percent of college graduates	13.16	7.06	4.24	48.1
Occupancy					
Owner %	Percent of owner occupied households	58.92	12.71	0	87.54
Renter %	Percent of renter occupied households	41.08	12.71	12.45	100
Age					
Age 25 to 44	Percent of age group 25 to 44	32.20	6.39	16.9	66.96
Age 45 to 64	Percent of age group 45 to 64	21.12	4.36	1.32	34.7
Age 65 & up	Percent of age group 65 & up	11.08	3.54	0.43	29.2
Eco-regions					
Blue Ridge & Ridge Valley	1 if Blue Ridge or Ridge Valley Eco-region, Else 0	0.094	0.20	0	1
Piedmont	1 if Piedmont Eco-region, Else 0	0.425	0.49	0	1
SE plains	1 if South East Plains Eco-region, Else 0	0.374	0.48	0	1
Coastal	1 if Coastal Plain Eco-region, Else 0	0.104	0.30	0	1

Data on total flood damage per capita in previous years was collected from SHELDUS, a county-level hazard dataset derived from the National Climatic Data Centre.[10] The socio-demographic variables: *Age*, *Education*, *Income*, *Occupancy* and *Race* come from the Bureau of Economic Analysis and the U.S. Census Bureau. The variable *Income* is available annually; *Age*, *Education*, *Occupancy* and *Race* were interpolated decennial data from the U.S. Census Bureau to get yearly estimates.[11]

Table 3 reports the summary statistics of the variables included in the model. The average per capita income over the period 1978–2010 was almost $26,000 (2010 prices). The average number of policies-in-force per thousand population at the county level was 4.95.[12] The average cost was $4.46 per $1000 of flood insurance coverage (2010 prices). The mean flood damage per capita during the preceding flooding event was $11.[13] Federal mitigation spending was on average only $0.004 per capita for the State of Georgia over our study period. On average, 0.62% of the developed county areas fall in the floodplain with a maximum of 4.38% in Glynn County.

Table 4 reports the comparison of the summary statistics between coastal and inland counties. We find much higher market penetration in coastal counties. The cost per $1000 of flood insurance coverage is not statistically different between inland and coastal counties, indicating that the level of risk is, according to the FEMA risk mapping, not that different on average (even though the risk perception might be). The mean flood damage per capita per year is actually higher in inland counties ($11.86) than in coastal counties ($6.63). It is worth mentioning that all the significant flood events during our period, such as those in Albany (1994 and 1998) and Atlanta (2009), were in inland counties. The amount per capita spent on mitigation is much higher for the coastal counties, a 5-to-1 ratio, compared to spending in inland counties. Interestingly, we find no significant differences among the socio-economic variables between coastal and inland counties.

4. Methods

4.1. Econometric Model

Using the data described above, we analyze the demand for flood insurance across 153 counties[14] in Georgia for the period 1978–2010. We estimate the following demand equation:

$$\begin{aligned}\ln(PIF/1000\text{pop})_{\text{it}} &= \beta_0 + \alpha_i + \beta_1 \ln(\text{Income})_{\text{it}} + \beta_2 \ln(\text{price})_{\text{it}} \\ &+ \sum_{j=1}^{6} \varphi_j \ln(\text{recent\_flood})_{i(t-j)} + \beta_3 \ln(\text{Mitigation})_{\text{it}} + \beta_4 \text{PercentFP}_i + \beta_5 \text{NoNFIP}_{\text{it}} \\ &+ \sum_{j=1}^{2} \eta_j Race_{jit} + \sum_{j=1}^{2} \tau_j \text{Education}_{jit} + \sum_{j=1}^{2} \rho_j \text{Occupancy}_{jit} + \sum_{j=1}^{3} \xi_j Age_{jit} \\ &+ \sum_{j=1}^{4} \gamma_j \text{Ecoregions}_{ji} + \delta_t + \varepsilon_{\text{it}}.\end{aligned} \tag{1}$$

The dependent variable is the logarithm of the number of flood insurance policies-in-force (*PIF*) purchased per 1000 population in a county-year.[15] The income variable, ln(*Income*), is the log of per capita income in the county during the year. The variable ln(*Price*) is the log of the cost per $1000 of insurance coverage. We measured the cost per $1000 of flood insurance coverage (*Price*) by dividing the dollar value of the premium paid by residents for flood insurance in the county during the year by the dollar value of NFIP insurance coverage (in thousands) in the county during the year. Taking the natural logarithm of

[10] SHELDUS refers to Spatial Hazard Events and Losses Database for United States. Details on how the data is collected can be found at http://webra.cas.sc.edu/hvri/products/sheldusmetadata.aspx.

[11] We calibrated an exponential curve to the decennial data (1980, 1990, and 2000) for each county. Using a linear curve to estimate the data, however, did not change the results.

[12] There is a large difference in market penetration between coastal counties (21 policies-in-force per 1000 population) and inland counties (only 2 policies-in-force per 1000 population).

[13] This is aligned with the $9.8 figure in Browne and Hoyt (2000).

[14] Of the 159 counties in Georgia, data were missing for 6 counties: Clay, Lincoln, Marion, Schley, Treutlen and Webster.

[15] Following Zahran et al. (2009), we replaced the dependent variable with the number of policies-in-force per 100 households in a county and the results were robust.

Table 4
Variables and descriptive statistics: coastal counties and inland counties.

Variables	Coastal counties		Inland counties	
	Mean	Std. dev.	Mean	Std. dev.
PIF/1000pop	20.53	43.43	1.83	3.05
Income ($ thousands)	23.32	5.94	26.40	6.66
Price	4.16	2.14	4.52	2.43
Recent_Flood	6.63	57.56	11.86	121.07
Mitigation	0.01	0.14	0.002	0.07
African-American%	26.59	11.10	25.40	18.14
White %	69.62	11.91	68.87	17.29
High school %	34.88	5.56	32.39	5.22
College %	11.45	5.32	13.51	7.32
Owner %	60.31	12.64	58.63	12.71
Renter %	39.68	12.64	41.36	12.71
Age 25 to 44	32.08	5.40	32.23	6.58
Age 45 to 64	19.71	4.75	17.03	3.64
Age 65 & up	10.03	3.50	12.94	1.84
Floodplain %	1.38	1.34	0.53	0.54
No NFIP participation	0.20	0.67	1.18	3.44

both the income and the price allows us to interpret the results as income and price elasticities of the demand of flood insurance, respectively.

According to the availability heuristic, recent large flood events could heighten risk perceptions and this could influence the decision to purchase flood insurance. To control for the effect of recent flooding on individuals' demand for flood insurance we use the variable ln(*Recent_Flood*) that measures the dollar value of total flood damage per capita in the county during the preceding year. Atreya et al. (2013) and Bin and Landry (2013) find that large flood events result in a marked price drop for properties in floodplains but that this effect vanishes over time, as early as four years after the flood. To capture the potential decay in the effect of experiencing a flood, we included up to six lags for the ln(*Recent_Flood*) variable, that is, we include annual total flood damages per capita for the preceding six years. To measure the effect of federal assistance to mitigate flood damages on the decision to purchase flood insurance, we included per capita flood mitigation assistance by FEMA per county-year: ln(*Mitigation*). *PercentFP* denotes the percentage of developed county land within the 100-year floodplain. *NoNFIP* is the percentage of population in a county residing in communities that do not participate in the NFIP.

The decision to buy flood insurance could also depend on whether the county is coastal or is located inland.[16] We control for regional variation in Georgia by including dummies for the five eco-regions in Georgia: Blue Ridge, Ridge and Valley, Piedmont, Southeast Plains; the control group being the coastal plains. This distinction separates the higher elevation Blue Ridge, Ridge and Valley, and Piedmont from the low-lying southeast plains and coastal plains.[17]

Unlike most previous papers, we include the socio-demographic characteristics of the households at the county level in our models. *Race* in Eq. (1) is measured with two variables — the percentage of the population who is African-American and the percentage of white population in a county. The *Education* variables include the percentage of high school graduates and the percentage of college graduates in a county. Three different age categories are included in the *Age* variable: 25 to 44, 45 to 64, and 65 and up. All these variables are entered as a percentage of total population in a county. We also include the percentage of houses in the county that are rented and the percentage of houses that are owner-occupied (*Occupancy*). The distinction between the owner-occupied and non-owner occupied properties is important since a substantial portion of the non-owner occupied properties are located in flood zones.

4.2. Estimation Methods

First, we estimated Eq. (1) using a fixed effects (FE) panel regression; δ_t are the year fixed effects that capture any common time trends across counties over the study period, while α_i denotes a county-specific intercept that controls for unobserved characteristics at the county level that are constant over time. We note, however, that the location in the floodplain variable (*Percent FP*) and the *Ecoregion* dummies do not vary over time and drop from the FE model. [18] Thus, we also estimated Eq. (1) using a random-effects (RE) model including these time-invariant variables. We conducted a Hausman test to determine the best model to use in our case. The test failed to reject the null that the coefficients estimated by the efficient RE estimator and the consistent FE estimator are the same ($\chi^2 = 19.25$, p-value $= 0.99$), and thus we opted for a RE model.

With over 30 years of data, serial autocorrelation is a concern in our model. We performed a Wooldridge test (Wooldridge, 2002; Drukker, 2003) and indeed found evidence of serial autocorrelation ($F = 130.40$, p-value < 0.001). Therefore, we corrected the RE model for serial autocorrelation.

5. Results

5.1. Market Penetration

We first estimate county-level market penetration rates, that is, the proportion of households in a county that have purchased flood insurance. As expected, penetration rates are highest in coastal counties where the proportion of land in the floodplain is higher.[19] Fig. 1 shows market penetration rates by county for 2010. We divided the total number of residential policies-in-force by the total number of household with data from the 2010 U.S. Census. The top five counties with the highest percentage of market penetration in 2010 were Glynn (44.86%), Bryan (40.28%), Chatham (27.42%), Camden (19.22%), and McIntosh (10.50%).

Not surprisingly, there is a strong correlation between the market penetration and the proportion of floodplain area within a county.[20] The coastal counties where the percentage of floodplain is the largest tend to have the highest penetration rates (Fig. 1 and Table 5), most likely because of the mandatory purchase requirement for properties in 100-year floodplains with a mortgage and because residents may be more aware of the risk they face. Our measure of market penetration, however, refers to the total number of properties in a county, and not specifically to those in the floodplain. Another factor that could potentially explain the market penetration rate is a recent flooding event in a county. Atreya et al. (2013) find that after a significant flood event ("the flood of the century") in 1994 in Dougherty County, GA, the take up rates increased dramatically. Dougherty is precisely the county with the largest market penetration among inland counties in Georgia (Fig. 1).

5.2. Regression Results

We report the results of the estimation of Eq. (1) in Table 6. The first column shows the estimates from the fixed effect (FE) model. We compare these results with those from a random effects (RE) model in the second column (2) while still dropping the time-invariant variables. In the third column (3) we estimate a RE model that includes important

[16] Dixon et al. (2006) found a significant regional variation and higher market penetration in coastal counties.

[17] The eco-regions are characterized by a large degree of homogeneity in geographical phenomena including geology, physiography, vegetation, climate, hydrology, and soils. A simpler distinction between inland and coastal counties by including a coastal dummy did not change the results.

[18] The floodplain maps were not updated in the 33 years covered in our sample. Georgia started a map modernization program in partnership with FEMA in 2009 to develop and update flood hazard maps for all its counties.

[19] Supporting Dixon et al. (2006), Kousky (2010) also finds a higher market penetration in census tracts with more land in the 100-year and 500-year floodplains in St. Louis County, Missouri.

[20] The correlation coefficient between the two is 0.70.

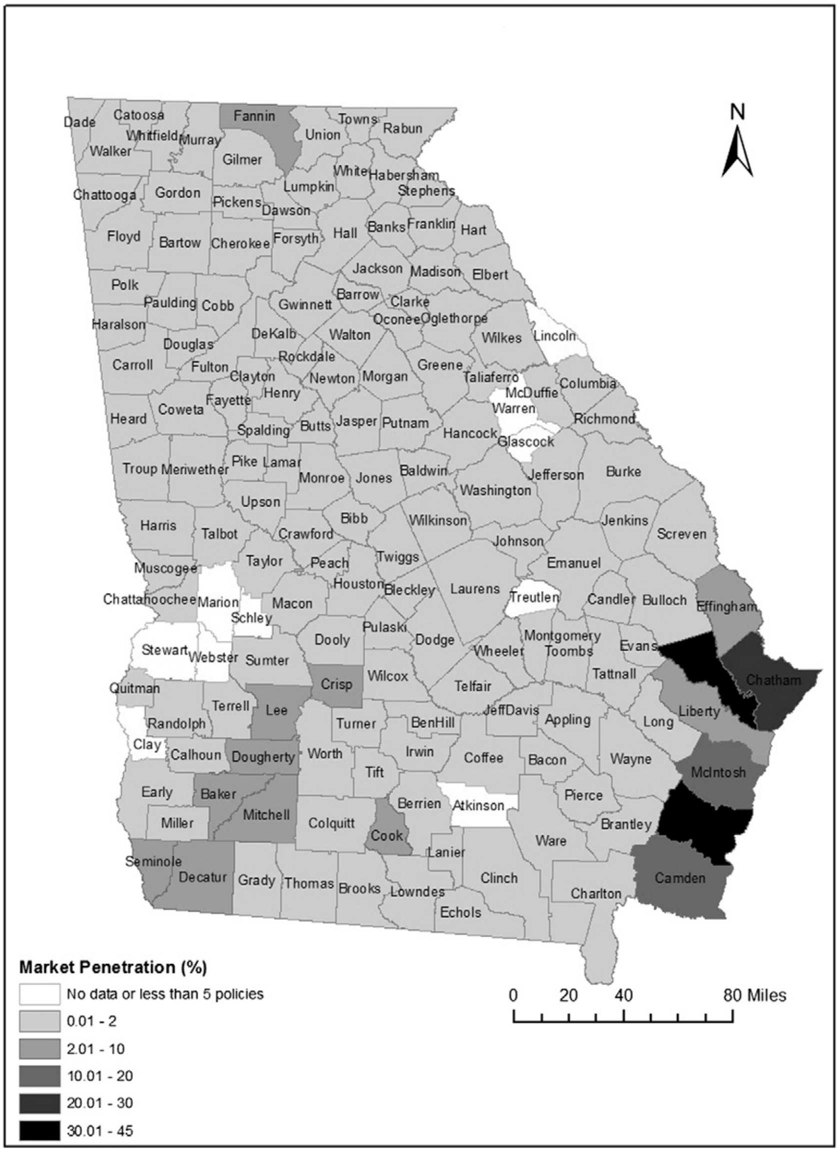

Fig. 1. Flood insurance market penetration in Georgia defined as the rate of policies-in-force divided by the number of housing units., 2010.
Source: Authors prepared map based on data provided by FEMA.

time-invariant variables that drop from the FE model: *Percent FP* and *Eco-region dummies*. In the fourth column (4) we estimate a RE model that is corrected for serial autocorrelation.

The empirical analysis supports hypothesis that income and price significantly influence the decision to buy flood insurance. The estimated income elasticity in the RE model (column 4) is 0.39 and statistically significant at a 5% level. The estimated coefficient for the price elasticity of insurance (where price is measured by the cost per \$1000 dollars of coverage) is negative and statistically significant at a 1% level across all models, with a point estimate ranging from −0.16 to −0.30. This is broadly consistent with previous studies at the state level (Browne and Hoyt, 2000) and individual level (Kriesel and Landry, 2004) that find an inelastic demand for flood insurance.

Table 5
Top 5 counties in Georgia for percent of floodplain area and flood insurance market penetration.

County	Floodplain (%)	County	Market penetration (%)
Glynn	72.24	Glynn	44.86
Chatham	72.22	Bryan	40.28
Camden	54.68	Chatham	27.42
Bryan	54.14	Camden	19.22
Ware	52.43	McIntosh	10.50

Note: As of 2010.

Our empirical findings also suggest that, consistent with the availability heuristic, flood damage in previous years has a significant positive impact on the decision to buy flood insurance. This effect is statistically significant for damages up to three years back, and then it vanishes (replacing per capita damage in previous years by the number of flood events in the county did not change the results).

We find a positive but insignificant relationship between flood mitigation assistance and flood insurance purchases at the county level, which is in contrast to the general assumption that mitigation and insurance are substitutes. This result could be due to the fact that the mitigation assistance funds used by Georgia are too small to have an economically meaningful impact on the demand for flood insurance.

We find a strong positive relationship between the proportion of developed area in a floodplain and the policies-in-force in a county, implying that people living in floodplains are in fact more likely to buy flood insurance. This result could be driven by the mandatory purchase requirement for the properties with a federally backed mortgage in the 100-year floodplain. Results show that a unit increase (measured in

Table 6
Regression results — dependent variable: ln(policies-in-force/1000 population).

Variables	(1) Fixed effects	(2) Random effects	(3) Random effects[a]	(4) Random effects[b]
ln(*Income*)	0.261	0.380*	0.408**	0.390**
	(0.203)	(0.200)	(0.199)	(0.191)
ln(*Price*)	−0.302***	−0.299***	−0.298***	−0.156***
	(0.040)	(0.040)	(0.039)	(0.030)
ln(*Recent_Flood*) ($t-1$)	0.015*	0.016**	0.016**	0.026***
	(0.007)	(0.007)	(0.007)	(0.004)
ln(*Recent_Flood*) ($t-2$)	0.018**	0.018**	0.018**	0.024***
	(0.007)	(0.007)	(0.007)	(0.005)
ln(*Recent_Flood*) ($t-3$)	0.016**	0.016**	0.017**	0.023***
	(0.007)	(0.008)	(0.008)	(0.006)
ln(*Recent_Flood*) ($t-4$)	0.003	0.004	0.005	0.008
	(0.008)	(0.008)	(0.008)	(0.006)
ln(*Recent_Flood*) ($t-5$)	0.007	0.008	0.008	0.009*
	(0.008)	(0.007)	(0.007)	(0.005)
ln(*Recent_Flood*) ($t-6$)	0.0004	0.001	0.001	0.005
	(0.007)	(0.007)	(0.007)	(0.004)
ln(*Mitigation*)	0.073	0.071	0.078	0.018
	(0.067)	(0.070)	(0.07)	(0.035)
PercentFP	–	–	1.016***	1.009***
			(0.140)	(0.152)
NoNFIP	0.080	−0.048	−0.023	−0.0327
	(0.058)	(0.0296)	(0.02)	(0.026)
African-American %	0.018***	0.014***	0.014***	0.0105**
	(0.003)	(0.003)	(0.003)	(0.004)
White %	−0.009**	−0.005	−0.004	−0.0002
	(0.004)	(0.003)	(0.003)	(0.002)
High school %	0.05***	0.049***	0.051***	0.0435***
	(0.006)	(0.006)	(0.006)	(0.010)
College %	0.031***	0.033***	0.034***	0.0445***
	(0.008)	(0.007)	(0.007)	(0.012)
Owner %	−0.0005	−0.005**	−0.003	−0.0005
	(0.002)	(0.002)	(0.002)	(0.003)
Renter %	0.001	0.005*	0.0015	−0.0015
	(0.003)	(0.003)	(0.003)	(0.004)
Age 25 to 44	0.022**	0.018*	0.015	0.0043
	(0.009)	(0.009)	(0.009)	(0.017)
Age 45 to 64	0.069***	0.057***	0.060***	0.0472**
	(0.015)	(0.013)	(0.013)	(0.021)
Age 65 & up	0.104***	0.076***	0.068***	0.0565**
	(0.018)	(0.016)	(0.015)	(0.0254)
Blue Ridge & Ridge Valley	–	–	−0.219	−0.362
			(0.447)	(0.470)
Piedmont	–	–	−1.726***	−1.669***
			(0.268)	(0.286)
SE plains	–	–	−1.047***	−0.932***
			(0.287)	(0.300)
Constant	−7.250***	−7.971***	−7.773***	−7.172***
	(2.090)	(2.049)	(2.028)	(2.068)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2887	2887	2887	2887
R-Squared	0.668	0.665	0.666	0.666

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; a) includes time invariant variables; b) includes time invariant variables and is corrected for serial autocorrelation using the xtregar command in STATA.

percentage point increments) in the proportion of developed area in floodplains is associated with a 1.009 proportionate rise in the NFIP take up rates. For Georgia, this means that an increase in the developed area in floodplain by 1 percentage point (for example from 1% to 2%) increases the *count* of NFIP policies per 1000 population by 5, that is, by approximately 100%. Our estimate for the effect of *PercentFP* is larger than in most of the earlier studies, however, we note that our calculation of *PercentFP* is more precise in that we do not take into account the undeveloped area of a county that falls in the floodplain.

Race, education and age all have a significant impact on flood insurance purchases. We consistently find that the higher the proportion of African-American population in a county, the higher the flood insurance take-up rate. A unit increase in the proportion of African-American population (measured in percentage point increments) increases the NFIP policies per 1000 population by 1.05% (column (4) in Table 6). We do not find a significant relationship between the proportion of white population in a county and the flood insurance take-up rates. These two findings are certainly worth pursuing in future research.

Regarding education, the result suggest that for the average county, a 1 percentage point increase in the percentage of high school graduates is associated with a 4.35% increase in NFIP policies per 1000 population and the magnitude of the effect is the same for college graduates as well. We find that on average, there is a positive and significant effect associated with age and insurance take-up rates. For example, in column (4), a 1 percentage point increase in the age group 45 to 64 in the average county is associated with an approximately 4.7% increase in the policies-in-force per 1000 population. This increase is 5.6% for the age group 65 and up.

We do not find a significant relationship between the occupancy of a home on the insurance take-up rates except in column 2, where an increase in owner-occupied homes in a county is associated with decreased flood insurance policies-in-force while an increase in renter-occupied homes in a county is associated with increased flood insurance policies-in-force. This result may be attributable to tax benefits of owning rental properties, that is, landlords get to deduct insurance from income, which homeowners do not. It is also consistent with a moral-hazard argument whereby landlords insure their properties against generic hazards, including floods, as a precaution from careless tenants. This finding is not surprising in light of statistics by the Congressional Budget Office (CBO) (2007) that roughly one-quarter of the coastal properties with subsidized flood insurance are not primary residences and that 20% of the NFIP flood insurance contracts were for non-principal residences.

Lastly, we find that compared to coastal plains in Georgia, other eco-regions buy fewer flood insurance policies as suggested by negative and significant coefficients of the eco-region variables. The results are robust to including a dummy for coastal counties in a separate regression instead of controlling for different eco-regions in Georgia.

Of all the results, of particular interest to this paper is the effect that race has on the uptake of flood insurance policies. In order to check for the robustness of our results, we estimated a number of alternative regressions. First, we tested whether the effect of race that we see in our result was conditional upon income levels. To do this, we ran a separate model including the interaction of the race variable with income. Although statistically significant, the magnitude of the interaction term was extremely small to make any difference to the results. Similarly, we interacted the race variable with the price of insurance. This interaction was insignificant, suggesting that the effect of race was not mediated by the price of insurance. We then separated our sample into two periods: 1978–1994 and 1995–2010 to see if the effect of race has remained the same over these two time periods.[21] To our surprise, we find that there was no significant effect of race in the pre-1994 period; in contrast, in the post-1994 period the effect was much stronger (positive and significant at the 1% level for the African-American variable, and negative and significant at the 5% level for the white variable), suggesting that our results are driven by the most recent observations.[22]

6. Conclusions

The National Flood Insurance Program was established by the federal government in the United States in 1968 to provide affordable flood

[21] We chose 1994 as our cutoff date since the mandatory purchase requirement was strengthened after the 1994 Reform Act.

[22] The results are available upon request. Another variable that stood out in the pre- and post-1994 analyses is "recent flood event". We find that in the pre-1994 sample period, the effect of recent flooding was significant for up to 5 lags ($t-5$) while in the post 1994 sample period the effect was significant only for up to 2 lags ($t-2$). This points to a change in mindset that is much more oriented to short-term thinking in the second half of the sample period.

insurance to homeowners and to mitigate flood losses through community-enforced building and zoning ordinances. The NFIP has long struggled with the low take up of flood insurance coverage despite the enduring efforts to overcome this challenge. Our analysis of the factors that influence Georgia homeowners' decisions to purchase flood insurance should contribute to the emerging research literature aiming to better understand the drivers of flood insurance purchases. We also depict flood insurance market penetration in the state of Georgia.

Unsurprisingly, the flood insurance market penetration rate is higher in coastal counties than inland. More generally, our analysis at the county level for the period 1978–2010 suggests that, as we would expect, the counties with higher proportion of developed land within floodplains purchase more flood insurance policies. We also find the price elasticity of flood insurance to be fairly low (at −0.30, −0.15) suggesting that those exposed the most want and do purchase that coverage. At a time when issues of affordability are at the forefront of the NFIP's reform debate, the finding that an increase in the price of premiums does not highly impact the take-up of flood insurance can help policymakers make informed policy decisions.

Our findings suggest that other determinants of risk perception, such as having experienced recent flood events, have a significant positive effect on the number of policies-in-force, supporting the hypothesis of the availability heuristic. A recent flood event can be easily brought to mind and therefore heightens the perceived probability of a future flood, which leads to purchasing flood insurance. We found that this effect vanishes after 3 years, however; memory is short.

Demographic variables such as education and age are found to have a significant effect on the number of policies-in-force in a county. It is interesting to note that age groups above 45 are more likely to buy flood insurance which may be suggestive that these age groups are more risk averse than their younger counterparts and that therefore awareness campaigns regarding the role of insurance in reducing losses should target the younger population. We also tested the impact of race and found that areas with higher concentration of African-Americans had, all things being equal, a higher demand for flood insurance. It would be interesting to perform a similar analysis nationwide to see if race has the same effect as in Georgia. FEMA flood risk awareness campaigns have never segmented target audience by race or age. Our analysis suggests that it might be important to do so.

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