Disaster-induced Migration Across U.S. States: The role of income heterogeneity

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Abstract: Climate change is increasing the frequency and intensity of natural disasters in coastal areas, yet more people are living in coastal areas. These trends are unfolding against a backdrop of rising income and wealth inequality in the United States. Disasters have direct effects on inequality when low-income households face higher risk exposure. Effects can also be indirect when disasters trigger migration that affects the resulting community composition. Although the distributional impacts of climate change are widely acknowledged, few empirical studies examine disaster-induced migration as a potential mechanism driving inequality. We analyze the effects of disasters on migration and show theoretically the potential for an inverted-U shape: low-income households are unable to move to other locations because of financial constraints, high-income households can adapt in place with mitigation investments such as elevating housing structures, and middle-income households are therefore most likely to migrate. We empirically quantify the extent to which migration response is heterongeous across income strata. Using a household-level dataset covering coastal counties in the Atlantic and Gulf coasts of the U.S., we find an inverted-U relationship between household economic resources (income and wealth) and the effect of natural disasters on out-migration decisions. The results are consistent with our theory that households with different economic resources use different adaptation strategies in response to natural disasters, suggesting long-run demographic change in natural disaster prone regions. Specifically, as middle-income households continue to migrate out because of an increase in future natural disaster events, we expect to see a higher concentration of low-income and very high-income households in the Atlantic and Gulf coast regions and further exacerbated income inequality. Our findings add to the literature on the distributional effect of climate-induced migration and indicate the equitable "migration as adaptation" outcome cannot be achieved in the current political-economic setting.

JEL Codes: Q54, Q56, R23

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1. Introduction

Economic inequality has risen since the 1970s in the United States (Piketty & Saez, 2014). Across the United States, the east coast region has witnessed a much higher economic inequality increase compared to the national average (Moller et al., 2009; Peters, 2013), with New York and Florida being ones of the top unequal states in the United States in 2015 (Sommelller & Price, 2018). Past research identifies that socioeconomic reasons such as economic development and demographic change (Moller et al., 2009) and the amenity anchoring effect (Lee & Lin, 2018; Smith & Whitmore, 2020; Ye & Becker, 2016) as the primary reasons for the spatially heterogenous trends in inequality. We examine the indirect effects from natural disasters such as flooding and hurricanes that can also exacerbate economic inequality in the east coast regions.

Natural disasters have caused substantial damage to the Atlantic and Gulf coasts of the U.S. in recent decades, and climate change damages are expected to worsen in the future (Oppenheimer et al., 2014). These concerns have stimulated many strands of research to better understand the impacts of natural disasters on affected communities. Two seemingly contradictory demographic trends have been observed. On the one hand, regions experiencing severe natural disasters tend to have higher poverty rates (Boustan et al., 2020; Schultz & Elliott, 2013). These regions, however, also tend to have higher socially advantaged groups such as wealthy and white households (Elliott & Pais, 2010; Howell & Elliott, 2019), even after controlling for amenity-based sorting into regions with high disaster risk (Raker, 2020). However, since the literature relies largely on macro-level statistics, estimates of the impact of natural disasters are a combination of the direct effect of natural disasters on the affected population and the indirect effect through migration, which changes the population composition in the affected regions. For example, the increasing socially advantaged group after a natural disaster might result from in-migration from high-income households, out-migration of low-income households, or direct effects of natural disasters on the affected population. These mechanisms provide widely different implications for policymakers.

In this paper, we estimate the indirect effects of natural disasters through migration behavior across different household income levels. Combining a rich household-level dataset with the occurrence of natural hazards, we use a rare event logit model to estimate the effect of natural disasters on the probability of out-migration for the affected population. We find that natural disasters fail to drive out low-income households potentially because of financial constraints. High-income households, which are less likely to be limited by financial constraints, are more likely to migrate after natural disasters. With more economic resources, the migration probability of the top-1-percentile-income households is not affected by the occurrence of natural disasters. This results could reflect top-1 percent household investments in natural hazards mitigation like housing elevation, or these households may pay a higher risk premium for properties located in low-risk regions. However, for the majority of the specifications, the effect of natural disasters on top-1-percentile-income households is not statistically significantly different from the effect of that on middle-income households, indicating such result might be due to the limited observations on top-1-percentile-income households and associated high estimate errors. In general, we still find a clear heterogeneous effect of natural disasters on out-migration probability, suggesting that migration of middle-income households after natural disasters is one of the factors driving changes in regional demographic trends and may contribute to the increasing economic inequality.

We find suggestive evidence that an inverted-U shape in migration response might be partially driven by disaster assistance. Repetitive loss properties, properties that are flooded and received the benefit from the National Flood Insurance Program (NFIP) multiple times, are considered one of the primary reasons for people to rebuild properties in natural disaster prone regions (Horn, 2018; Kousky & Michel-Kerjan, 2017). Despite NFIP, multiple federal assistance programs are disproportionately concentrated in counties with more economic and political resources (Dodlova & Zudenkova, 2021; Mach et al., 2019). Such high levels of federal assistance can create incentives for local households to mitigate in place rather than migrate. Using a non-parametric method, we predict expected federal assistance based on natural disaster damage and assign counties that receive higher than expected assistance as high assistance counties. Similarly, we assign counties with lower than expected assistance as low assistance counties. We find that natural disasters increase the probability of out-migration for top-1-percentile-income households if they reside in low-assistance area, while natural disasters do not have a statistically significant effect for top-1-percentile-income households if they reside in high assistance area. Such results suggest that federal assistance and rent seeking behaviors might be one reason for high-income households to stay in coastal regions with high natural disaster risk.

Our work contributes to several strands of literature. First, our work provides an alternative explanation for the macroeconomic effect of natural disasters. Previous empirical analyses often estimate the combined direct effect and indirect effect of natural disasters on local economies, which does not explain the microlevel mechanism of the natural disaster effect (Boustan et al., 2020; Smith et al., 2006). The rich household-level dataset enables us to estimate the heterogeneous effect of natural disasters on out-migration probability across income strata, which is one of the explanations for the simultaneous increases in low-income groups and high-income groups in coastal regions.

Second, our work is related to a large empirical literature testing the effect of climate change on migration. Social scientists have long argued over whether climate-induced migration is an impact of climate risk or migration as an climate adaptation strategy. Despite clear evidence of temperature and precipitation effects in the agriculture-based developing countries (Choquette-Levy et al., 2021; Hoffmann et al., 2020; Mueller et al., 2014), the evidence of natural disaster effects is mixed for both developing countries and developed countries. Previous researchers have found that natural disasters have positive (Boustan et al., 2020; Coniglio & Pesce, 2015; Hornbeck, 2012), no (Beine & Parsons, 2015; Bohra-Mishra et al., 2014), or mixed impacts (Boustan et al., 2012; Fussell et al., 2017) on international and internal migration. Our results suggest that the aggregate natural disaster effect depends on the local income distribution. As a result, although natural disasters might have aggregate impact on local migration that cancel out, the distributional impacts of natural disasters cannot be ignored.

Third, our work contributes to policy debates about the distribution of natural disaster relief. The public has criticized the repetitive loss properties and the potentially regressive nature of NFIP after NFIP fell into debt. While Bin et al. (2012) do not find evidence that the redistribution effect of NFIP is regressive, recent studies suggest that the Federal Disaster Loan Program and FEMA IHP grants disproportionately favor rich households (Begley et al., 2018; Billings et al., 2022). Disaster relief responses after Hurricane Katrina had a progressive impact since most of the subsidized population are low-income and minority groups (Bleemer & van der Klaauw, 2019; Muñoz & Tate, 2016). Our results indicate that anticipation of assistance might change the migration behaviors and thus change the demographic distribution. However, since all households are more likely to stay in natural disaster prone regions with the expectation of future assistance, we cannot determine the sign of the ex-ante distributional effect.

Finally, our results suggest that climate-induced migration also exists in developed country settings. Specifically, natural disasters, which are likely to increase in both intensity and frequency over time, may urge middle-income populations to migrate out of natural disaster prone regions. We also find suggestive evidence of potential poverty traps due to the immobility of low-income populations in the Atalantic and Gulf coast regions of the United States, which indicates that equitable managed retreat outcomes will not be achieved by the current state of disaster assistance policies. Thus, more policy instruments need to be designed to better cope with the increasing natural disaster risk and the associated adaptation and migration needs on the coast (Keeler et al., 2022; Mach et al., 2019; Siders et al., 2019).

In Section 2, we develop a theoretical model that gives rise to an inverted-U shape relationship between income and disaster-induced migration. We then describe the micro-data and methods that we use in Section 3. We summarize results, including robustness checks and the models that account for disaster assistance in Section 4. Section 5 concludes with a discussion of next steps and policy implications.

2. Theory

Our theoretical model builds on early work by Ehrlich & Becker (1972). Following their terminology, we assume that mitigation in place is a self-protection strategy, which means mitigation affects the probability of experiencing damage from a natural disaster if natural disasters occur nearby but does not affect the actual revealed damage if natural disasters do affect the household. We can write the expected utility of household choosing to invest in mitigation in place as

$$EU^I = \big(1 - p(p_0, I, Y)\big)U(Y - I) + p(p_0, I, Y)U(Y - D - I)$$

where Y is the household income, D is the natural disaster damage, p_0 is the natural disaster probability without mitigation, $p(p_0, I, Y)$ is the natural disaster probability for household who has income Y and invests I in mitigation infrastructure, and $U(\cdot)$ is a standard concave utility function.

We assume that mitigation in place and migration are mutually exclusive strategies. As an alternative to mitigation, households could invest in migration with a cost m to migrate to another location with a natural disaster probability p_1, which also serves as a self-protection strategy. Hence, the expected utility of household after migration is

$$EU^m = (1 - p_1)U(Y - m) + p_1 U(Y - D - m)$$

We assume that $p(p_0, 0, Y) = p_0$, $p_I < 0$, $p_{II} > 0$, and $p_{IY} < 0$. Intuitively, for any income level, a household that does not invest in mitigation in place will face the same natural disaster probability p_0. The probability of damages from a natural disaster is decreasing with investment I, and the marginal effect of investment is decreasing. Furthermore, higher income households can find more efficient ways to mitigate and reduce the probability of experiencing damage from natural disasters.

Maximizing expected utility for the case of mitigation in place yields the first order condition

$$-(1-p)U'(Y-I) - pU'(Y-D-I) + p_I(U(Y-D-I) - U(Y-I)) = 0$$

and the second order condition

$$A = (1-p)U''(Y-I) + pU''(Y-D-I) + 2p_I\big(U'(Y-I) - U'(Y-D-I)\big)$$
$$+ p_{II}\big(U(Y-D-I) - U(Y-I)\big) < 0.$$ [1]

Proposition 1. There exist $\bar{Y}$ such that for all $Y \geq \bar{Y}$, $EU^I(I^*) \geq EU^m$[2].

For given Y, there is a unique $\tilde{I}(Y)$ such that $p(p_0, \tilde{I}(Y), \mathrm{Y}) = p_1$.

Since $p_Y < 0$ for all $c > 0$[3], we have $\frac{d\,\tilde{I}}{d\,Y} < 0$. Therefore, with higher income level, a household can invest fewer resources in mitigation in place to get the same natural disaster protection as migration. For sufficiently large $Y \geq \bar{Y}$ such that $\tilde{I}(\bar{Y}) \leq m$, households will not migrate in response to natural disaster risk. Therefore, in-place mitigation is the optimal choice for a high-income household.

Proposition 2. There exist $(p_0, p_1, \widehat{m}, \hat{Y})$, such that $EU^m > EU$. For the same $(p_0, p_1, \widehat{m})$, there exist $\underline{Y}$ such that for all $Y < \underline{Y}$, $EU^m < EU$.

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[1] Note that $p_{II} > 0$ and a concave utility function are not sufficient conditions for SOC to hold. An internal solution might not exist for our setting. To simplify the argument, we assume that second derivative $EU^I_{II} < 0$ for all suitable I.
[2] I^* refers to the optimal I to maximize EU^I.
[3] Since $p(p_0, 0, Y) = p_0$, $p_I < 0$, and $p_{IY} < 0$, we have $p_Y < 0$ for all $c > 0$.

Holding p_0, p_1, and m constant, we can define the expected utility gain from migration as

$$\Delta EU(Y) = EU^M - EU = (1-p_1)U(Y-m) + p_1 U(Y-D-m) - p_0 U(Y) - p_0 U(Y-D)$$

Suppose that there exists a minimal consumption c that households need to obtain. Let $U'(c) = +\infty$. We can find $\lim_{Y\to D+c} \Delta EU(Y) < 0$ and $\lim_{Y\to +\infty} \Delta EU(Y) > 0$ for any (p_1, p_0, m) pair. Since $\Delta EU(Y)$ is a continuous function, there exist $\hat{Y} = \min\{Y^*\}$ such that $\Delta EU(p_1, p_0, m, Y^*) = 0$.

As a result, we can find $\widehat{m} \in (0, m)$ so that $\Delta EU\left(p_0, p_1, \widehat{m}, \hat{Y}\right) > 0$. Moreover, for this updated $(p_0, p_1, \widehat{m})$ pair, we can again find $\underline{Y} = \min\{Y^*\}$ such that $\Delta EU(p_1, p_0, \widehat{m}, Y^*) = 0$. Note that since ΔEU is a continuous function, $EU^m < EU$ for all $Y < \underline{Y}$. Intuitively, this suggests that if households only choose between migration or not, low-income households will not migrate because of their budget constraints. The remaining question is whether $EU^m > EU^I(I^*)$ for middle income households.

Proposition 3. For some income $Y \in (\hat{Y}, \tilde{Y})$, a household's optimal solution is migration if $\frac{\partial EU}{\partial I}|_{I=0} < 0$.

Since $EU_{II}^I < 0$[4], if $\frac{\partial EU}{\partial I}|_{I=0} < 0$, the optimal investment level is $I^* = 0$ for EU^I. Moreover, since $EU^m > EU$ for $(p_0, p_1, \widehat{m}, \hat{Y})$ pair, there exist $\tilde{Y} > \hat{Y}$, such that since $EU^m > EU$ for all $Y \in$

[4] Note that $p_{II} > 0$ and concave utility function is not sufficient for $EU_{II}^I < 0$. We need to assume $EU_{II}^I < 0$ for proposition 3 to hold.

$(\hat{Y}, \tilde{Y})$. Thus, if mitigation in place is not efficient for middle-income households, the optimal strategy for middle-income households to decrease natural disaster risk is migration.

In all, we show that there exists an inverted-U shape relationship between household income and migration responses to natural disasters. Specifically, low-income households will not migrate and invest in mitigation in place because of budget constraints, while high-income households with more efficient in-place mitigation measures are more likely to invest in defensive infrastructure. As a result, middle-income households have the strongest incentives to migrate in response to natural disasters. The boundary between middle and high income is implicitly defined in the theoretical model such that there is not clear guidance on where the migration response reverses sign. In the empirical work below, we examine the relationship using four categories, separating out high income from top-1 percent income.

3. Data and method

3.1 Migration and Income data

We obtain a household-level migration sample based on the Data Axle historic residential database from 2010 to 2011[5]. Data Axle compiles longitude household-level information—including household age, race, presence of children, income, ownership status, and address—from real estate data, voter registration lists, public records, and more than 20 types of secondary

[5] We focus primarily on people working in coastal regions and drop college-age and retirement-age households (head of household age below 24 and above 65).

sources. Data Axle uses proprietary algorithms to estimate some some covariates from multiple data sources such as income. Address data, which primarily interest us, are mainly derived from deed transfers, tax assessors, and landline phone connections. After the collection of address data, the addresses are verified by a credit card billing statement within 2 years. If the mail has not been collected within the recent 90 days, Data Axle will note the housing unit as vacant. Thus, if a household migrated in 2009, we are unlikely to identify the household as a migrator in 2010 to 2011 period since the household that migrated in 2009 is unlikely to collect mail in the original address in 2010. As a result, the household will be identified as vacant in 2010 and thus dropped from our sample. Furthermore, the migration data are strongly correlated with Internal Revenue Service (IRS) and American Community Survey (ACS) data (See Appendix A1), which further validates the Data Axle dataset as a valid dataset to study household-level migration behaviors.

Another variable we are mainly interested in, estimated income, is derived from a combination of wage, home equity, and invested assets to represent all forms of earnings each household could obtain. By matching the name and the address of Data Axle consumer dataset with another large national survey of consumers from MRI-Simmons, the Data Axle dataset predicts the income of other households based on individual, household, and lifestyle characteristics. The U.S. is divided into different regions and subpopulations to ensure the goodness to fit. Moreover, the predicted income is further validated by the county-level income distributions from census data and zip-code-level income level IRS data. Income distributions fit well with most of the publicly available aggregate income data (Figure A4-A6). We also run several external validity tests by comparing other characteristics between the Data Axle sample and 2010 census data (Appendix A).

A key focus of income prediction in Data Axle dataset is to accurately detect the highest-income households. The top-1-percentile-income households in the Data Axle dataset are typical married couples, living in single-family houses in large metropolitan areas, and more likely to work in professional, legal, or managerial occupations. Moreover, they also have a higher likelihood of being golfers, which largely align with actual top-1-percentile-income population behaviors and gives us more confidence to use top-1-percentile-income households as one of the income categories.

3.2 Natural disaster and federal assistance data

The natural disaster data are retrieved from the National Oceanic and Administration (NOAA) storm event database. As the name suggests, floods and hurricanes are overrepresented in the NOAA storm event dataset (Gall et al., 2009). Specifically, NOAA is required to give every flood event a monetary damage amount even if the amount is an estimate. As a result, any natural disaster indicators based on damage are overrepresented with flood data. Since we are interested in the impact of all natural disasters on household migration, we rely on the fatality count as our indicator. As shown in Table 1, NOAA fatalities data provides a comprehensive representation of various natural disaster types, which helps us to estimate general natural disaster effects in coastal regions.

Figure 1 shows the distribution of annual average natural disaster fatalities, property damage, and total damage between 2007 and 2010 in all east coast counties in the U.S. Counties with darker shades experience higher damage or fatalities from natural disasters. As the map illustrates, the natural disaster events concentrate in New York, New Jersey, North Carolina, Florida, and Texas. Moreover, there is a suggestive spatial correlation between natural disaster fatalities and natural disaster damage, suggesting that fatality counts can serve as a reliable indicator of natural disaster damage.

Federal Emergency Management Agency (FEMA) assistance can be divided into three large categories: public assistance (PA), individual assistance (IA), and Hazard Mitigation Assistance (HMA). Among them, PA and IA are applicable only when the area receives the presidential declaration of an emergency or major disaster and the fund can be used for PA and IA respectively. PA generally covers funding for emergency work such as debris removal and emergency protective measures (including emergency sheltering) or permanent work such as the reconstruction of public facilities and buildings. IA generally covers individual housing and other individual expenditure. Since HMA mostly focuses on ex-ante hazard mitigation such as land acquisition and property retrofits, we only consider PA and IA as disaster relief.

To determine whether counties receive higher than normal assistance levels conditional on natural disaster intensity, we run a nonparametric model predicting FEMA assistance by the natural disaster damage within the same period[6]. Specifically, as shown in Figure 2, we first predict the average assistance level conditional on the natural disaster damage in each counties. Then, we identify counties that receive higher than average federal assistance as high assistance regions and vice versa. Since the IA data is available from 2003 and the natural disaster used in this dataset begins in 2006, there is a limited temporal variation for us to estimate the average IA across years for each county. Thus, we use PA and natural disaster damage from 1999 to 2005 to determine which counties are more likely to receive higher than normal assistance levels, which

[6] The damage is adjusted to 2010 dollar by the consumer price index.

is likely known by east coast residents in 2010. As shown in Figure 3, the grey regions indicate regions that received higher than average assistance levels. We find that the assigned regions largely align with assigned regions if we use 1999 to 2021 PA data or 1999 to 2021 PA and IA data.

3.3 Empirical Strategy

We define household migration as a move to a different state because short-distance moves may not decrease household natural disaster risk and may not involve a change in the labor market. A move within the same county or to an adjacent county is arguably not mirgration at all because people can remain within the same labor market. Moreover, beause winter storms, coastal flooding, and hurricanes tend to affect a wide range of counties often in a geographically correlated way, migration to a county further away within the same state might not change natural disaster exposure. Implicitly, our model assumes that moves to reduce disaster risk within the same state are not considered migration, which is a limitation of our analysis. As a result, we conduct robustness checks using a less restrictive definition of migration. We further restrict our sample to the households where the head of the household is working age individuals (from 25 to 60). Therefore, our result should be interpreted as whether households will migrate and change their jobs after natural disasters.

Since the migration probability is small for the US Atlantic and Gulf coast populations[7], a logit model might underestimate the migration probability even for the large sample size that we collect. Thus, we apply therare event logit correction to correct for the bias (King & Zeng 2001).

[7] 6% of the population migrates across state and 12% of the population migrates across county in our sample.

To assess the heterogeneous effect of natural disasters by different income levels, we construct income bins representing low-, middle-, high-, and top-1-percentile-income level[8] and predict across state migration probability from 2010 to 2011 $\mathrm{P_i}$ using the rare event logit model. To decrease the computation demand while maintain the full sample for high- and top-1-percentile-income housholeds, our migration sample include 40% of households in low- and middle-income levels and have all of households in high- and top-1-percentile-income.

$$Ln\left(\frac{\mathrm{P_i}}{1-\mathrm{P_i}}\right) = \sum_{p}(\beta_p Income_{pi} + \gamma_p Income_{pi} Disaster_c) + \delta_1 HC_i + \delta_2 LC_{ct} + e_i + g_s + \xi_{iscb} \quad (1)$$

To further estimate the heterogenous effect of natural disasters by income level and by expected assistance level, we use

$$Ln\left(\frac{P_i}{1-P_i}\right) = \sum_{p}\left(\beta_p Income_{pi} + \gamma_b Income_{pi} Disaster_c Assistance_c\right) + Assistance_c$$
$$+\delta_1 HC_i + \delta_2 LC_{ct} + e_i + g_s + \xi_{iscb} \quad (2)$$

where *i*, *s*, *c*, *t*, *p* index household, state, county, tract, and percentile bin respectively.

$Disaster_c$ is the county level fatality rate, $Income_{pi}$ are the dummy variables indicating whether household i belongs to a specific percentile group p, HC_i is the household characteristics, and LC_{cb} is the county, or block-level local characteristics, which include labor market characteristics, housing market characteristics, and natural amenity levels, r_i is an indicator for

[8] We define low-, middle-, high-, and top-1-percentile income groups as households with bottom 0-50 percentiles ($0-97,000), 50-90 percentiles ($97,000-176,000), 90-99 percentile ($176,000-455,000), and 99-100 percentiles (above $455,000) income in the collected sample.

race, g_s is the state fixed effect[9] and ξ_{iscb} is the error term with an extreme value distribution. Since renters and owners might migrate in systematically different ways, we estimate our base specification for owner and renter samples separately. The identification assumption is that the natural disaster intensity over a long time period is an exogenous shock unrelated to local adaptation measures. Specifically, the natural disasters impose similar risk on all populations within the affected regions. As a result, if we control for the population density by converting fatality counts into fatality rates, the natural disasters intensity indicator is spatially random. Since the cross-state migration rate is low and we need to account for small sample bias, we use state-level fixed effect as a proxy for local natural disaster intensity. Our main specification that focus on owners has 5,094,229 total observations and 23,237 observed migration events, and we cluster the standard errors at county level.

4. Results

4.1 Income depended natural disaster effect

We find that natural disasters have a negative but statistically insignificant effect on the out-migration probability for owners from the bottom 0-90 and 99-100 income percentile distribution and a positive and statistically significant effect on owners from 90-99 income percentile distribution (Figure 4). Furthermore, we find a statistically significant difference in the marginal effect for low-income homeowners and middle-income homeowners at the 5% statistical significance level and between high-income homeowners and the top-1-percentile homeowners at the 10% statistical significance level. The results are consistent with our hypothesis that low-

[9] Area includes (i) the Atlantic coastal region and (ii) the Gulf Coast coastal region, which has different coastal hazard patterns.

income households with limited economic resources might not migrate out after natural disasters because of financial constraints. With an increase in income, middle- and high-income households, who have greater economic resources, might view migration as the optimal adaptation strategy in natural disaster prone regions and migrate out. However, households at top-1-percentile-income distribution with greater access to resources may invest in high-cost high-return in-place adaptation strategies to decrease the natural disaster effect and not respond to the natural disaster by migrating out. Households with the ability to adapt in place might place a higher value on the economic opportunities and coastal amenities provided and continue to stay in the natural disaster prone regions.

For renters, we observe a similar trend at a bottom of the income distribution. Specifically, while low-income renters do not respond to natural disasters, natural disasters increase the out-migration probability of middle-income renters. Since high-income renters are limited in our sample and the coefficient is highly volatile, we interpret the drop in natural disaster effect for high-income renters as a sign of seasonal renters or abnormal behaviors. However, none of the estimated marginal effects is economically significant. Even for a county with all high-income owners, one standard deviation change in natural disaster fatality rate will increase 0.16 standard deviation across state migration rate. Similarly, for a county full of middle-income renters, one standard deviation change in natural disaster fatality rate will increase 0.48 standard deviation across state migration rate, indicating that natural disasters are not the main drivers of migration. Thus, the indirect effect of disaster-inducted migration contributes a limited amount to rising inequality in coastal regions.

4.2 Robustness

We examine the robustness of our results by running a set of similar specifications. Specifically, we change the definition of migration from across-state to across-county or across-zip code migration (Figure B1), change the natural disaster fatality collection period from 4-year to 3-year or 5-year (Figure B2), change the natural disaster indicators from natural disaster fatality rate to natural disaster damage of major natural disaster event[10] (Figure B3), change the working-age head of household definition around 25-60 (Figure B4), try differentincome range cutoffs (Figure B5), and switch predicted income estimate to predicted wealth indicators (Figure B6). While we lose statistical significance in the marginal effect for middle-income households, the heterogeneous nature of the effect of natural disasters and the trend in migration response across income groups remains similar. Overall, the robustness checks confirm that the baseline estimates provide a qualitatively robust result with lots of quantitative differences on the high-income end of the distribution. For all specifications, we cannot reject the hypothesis that the marginal effect of natural disasters on top-1-percentile-income households is statistically different from that on high-income households because of the large variations for the top-1-percentile-income estimate, indicating top-1-percentile-income households might migrate because of natural disasters in some specific scenarios. However, we can reject the hypothesis that the effect of natural disasters on low-income households is the same as the effect of natural disasters on high-income households. Thus, we are confident that there is an increase in natural disasters effect on migration from low-income households to high-income households. However, we do not know whether the effect of natural disasters becomes flat, increases, or decreases between high-income and top-1-percentile-income households.

[10] Number of natural disaster cause more than 3 fatality count.

We note that the power of this analysis is limited by the rare occurance and limited variation in natural hazards across counties or zipcodes. Though we have a large migration sample with 5,094,229 owners and 1,369,511 renters, natural disasters are often not the prominent reason for households to migrate, which makes it challenging to discern statistically significant effects of natural disasters on migration.

4.3 Heterogeneous natural disaster effect conditional on assistance level

Government assistance is also likely to change household behaviors after natural disasters. If low-income households get assistance from the government, they are more likely to adapt to future natural disasters, whether by migration or by rebuilding houses with more mitigation infrastructure. For middle-income households, if they get the assistance, they may use the loan to move to safer places nearby (Mach et al., 2019), migrate to other regions, or rebuild bouses with more mitigation infrastructure. For high-income households, there is extensive discussion about whether the subsidies provided by the government are the main reason that they can remain in natural disaster prone regions (Billings et al., 2022; Muñoz & Tate, 2016).

Results shown in Figure 5 provides suggestive evidence for the last point. Specifically, in low assistance regions, natural disasters have a statistically significant positive effect on the out-migration rate for both high- and top-1-percentile-income households. However, in high assistance regions, natural disasters have a statistically insignificant negative effect on out-migration. While their 95 confidence intervals overlap with each other, most of the coefficients lie outside of the 95 confidence intervals of their counterpart, suggesting a difference in the natural disaster effect on top-1-percentile-income households. Such results provide suggestive evidence that unequal distribution and potential regressive distribution of natural disaster relief is one of the reasons for the top-1-percentile-income households to stay in coastal regions. Moreover, it also indicates that the seemingly large confidence interval of the aggregate natural disaster effect on out-migration probability of the top-1-percentile-income households might be due to heterogeneous responses in different regions.

5. Discussion

Research on human mobility and coastal hazards focuses largely on the short-term effects and immediate movements associated with evacuation and dislocation (Deryugina et al., 2018; Groen & Polivka, 2008). However, such short-term evacuation response might not indicate the long-term response (Hauer et al., 2020). Studying long-term migration into and out of regions exposed to changing climate risk is important for understanding the likely adaptation responses of coastal communities. While it is challenging to causally indentify hazard-induced short-term dislocation from climate-induced long-term drivers of migration, our work takes a first step in understanding the marginal effect of natural disaster events on across-state migration away from the bundle of local amenities in the disaster affected region.

By examining heterogeneity in the impact of natural disasters across income strata, our work highlights inequalities in the exposure to climate risk and in the ability to adapt through investments in risk mitigation in place and through migration. Our analysis consistently shows that low-income households with limited resources are at a higher risk of being in a poverty trap because of the inability to move to a location with lower climate risk and limited federal assistance to help mitigate damages. This result underscores the need for climate adaptation policies and targeted subsidies or buyoutr programs for low income households. Our current analysis focuses on income heterogeneity but future work could examine the role of wealth in more detail and other aspects of inequality, such as inequality across race, to better understand the heterogeneity in the distribution of risk and adaptive capacity.

An inverted U-shaped relationship between income and migration following natural disasters suggests that economic inequality in hazard prone communities will increase over time. Climate-induced migration patterns also have implications for population redistributions and changes in demographic composition of communities with respect to income, age, racial distributions, housing tenure (renters v. homeowners). As climate change intensifies, the magnitude of the impact of natural disasters will likely exacerbate existing inequities through changes in demographic composition. Our work tells a cautionary tale highlighting the need for climate adaptation policies that explicitly consider the enivironmental justice implications of outcomes over time.

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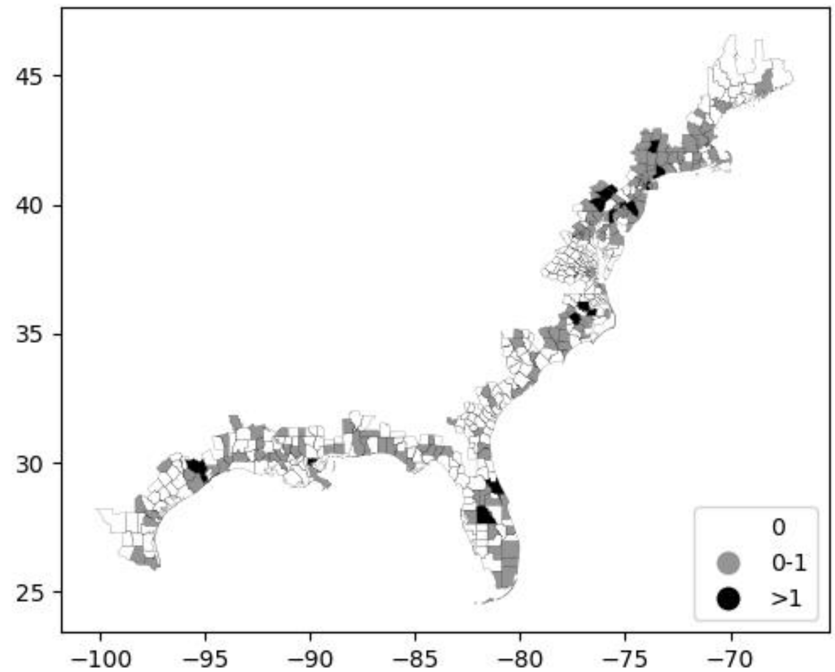
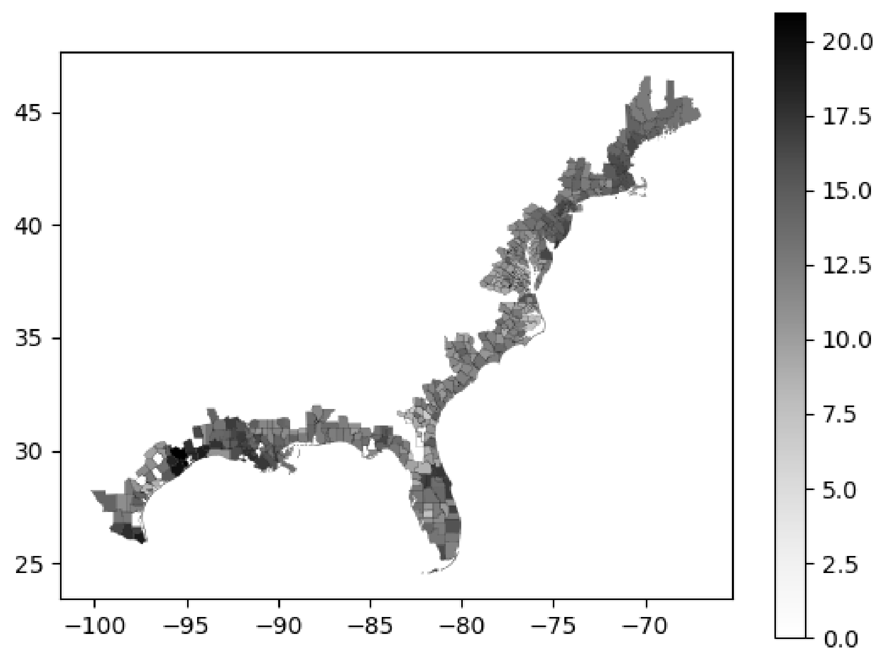
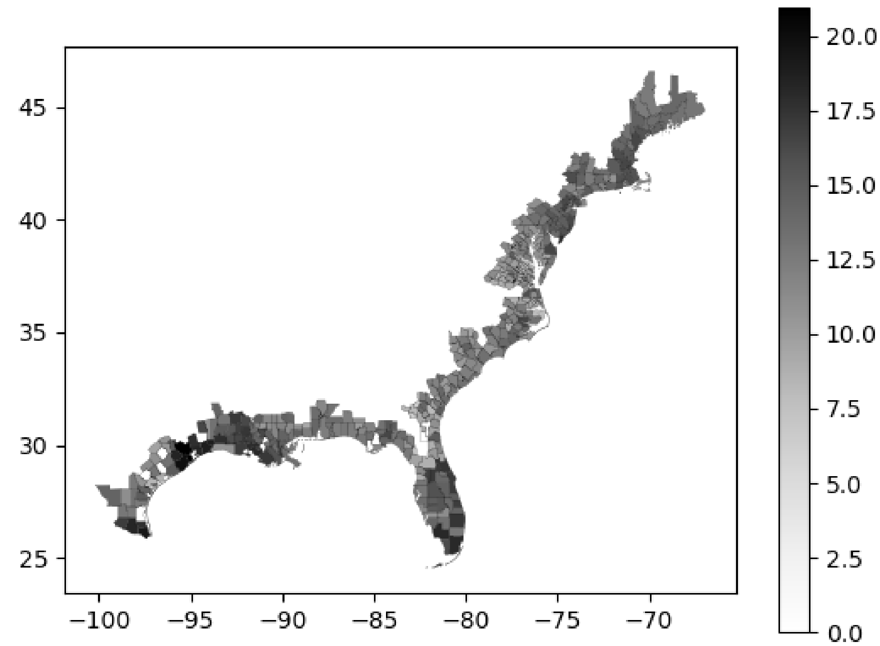


A. Average annual fatalities from natural disasters



B. Natural log of average annual property damage from disasters



C. Natural log of average annual total damage from disasters
Figure 1. The distribution of natural disasters in east coast regions from 2007 to 2010

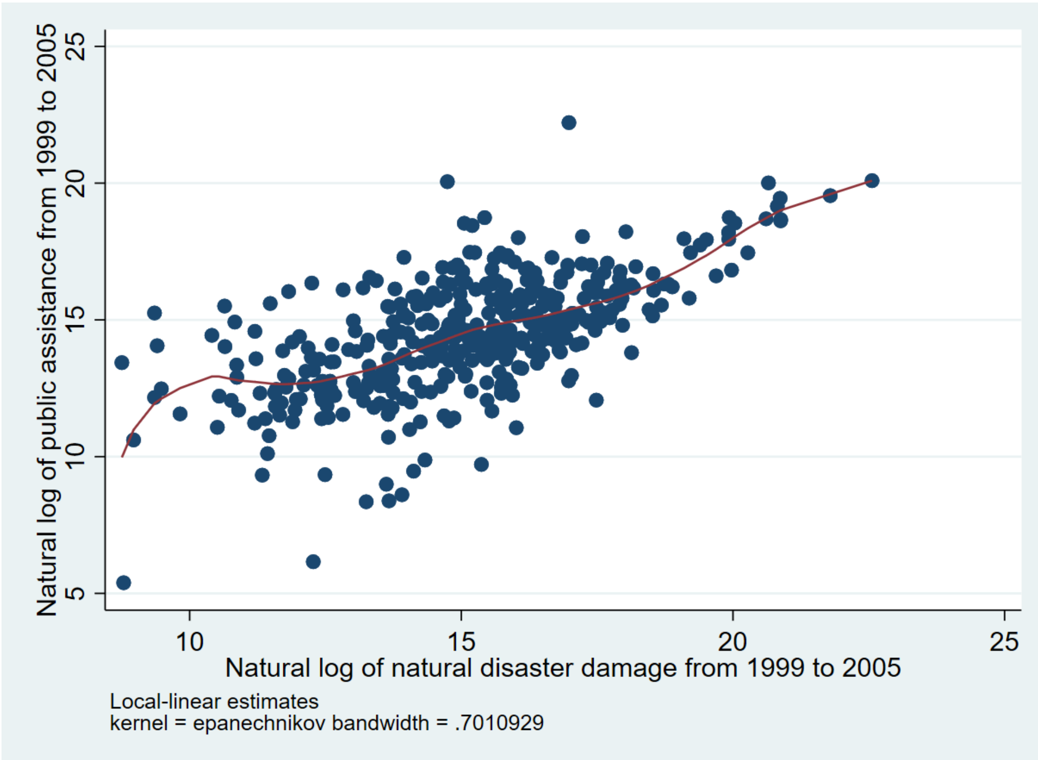
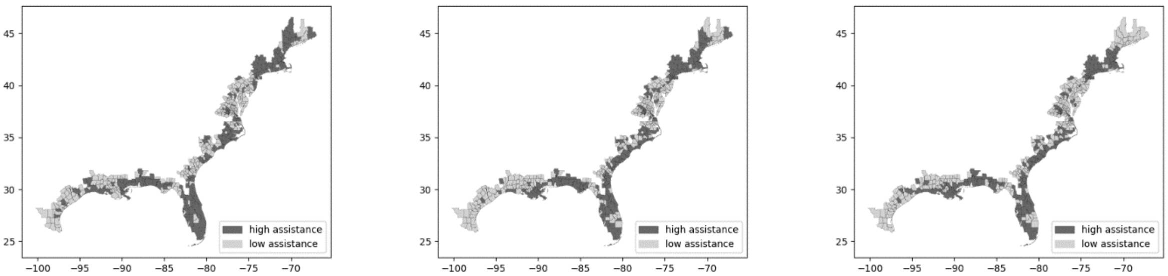
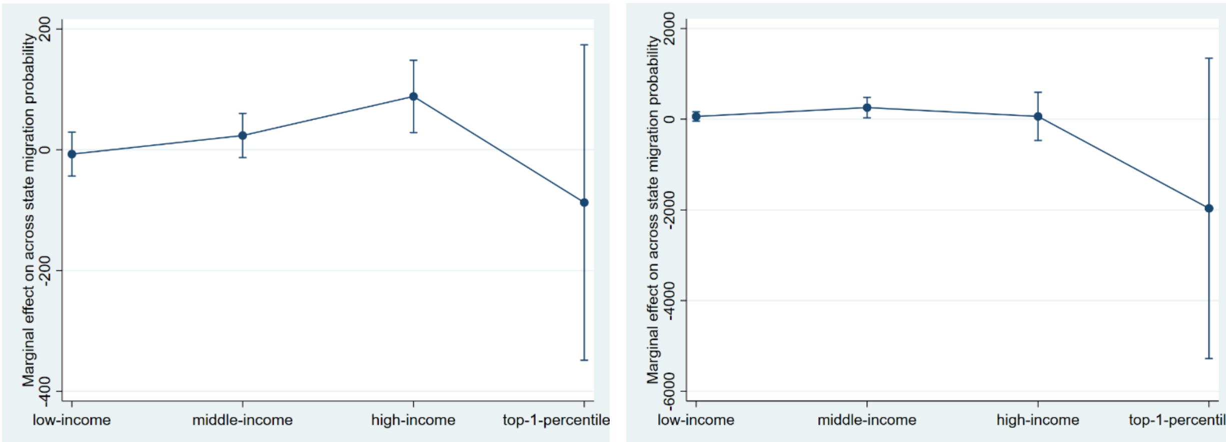


Figure 2. Nonparametric relationship between the FEMA assistance and damage



PA from 1999 to 2005 PA from 1999 to 2020 PA and IA from 1999 to 2020

Figure 3. Counties which Receive higher than Average Federal Assistance Conditional on Damage Level



Owners Renters

Figure 4. Marginal effect of natural disasters on migration probability

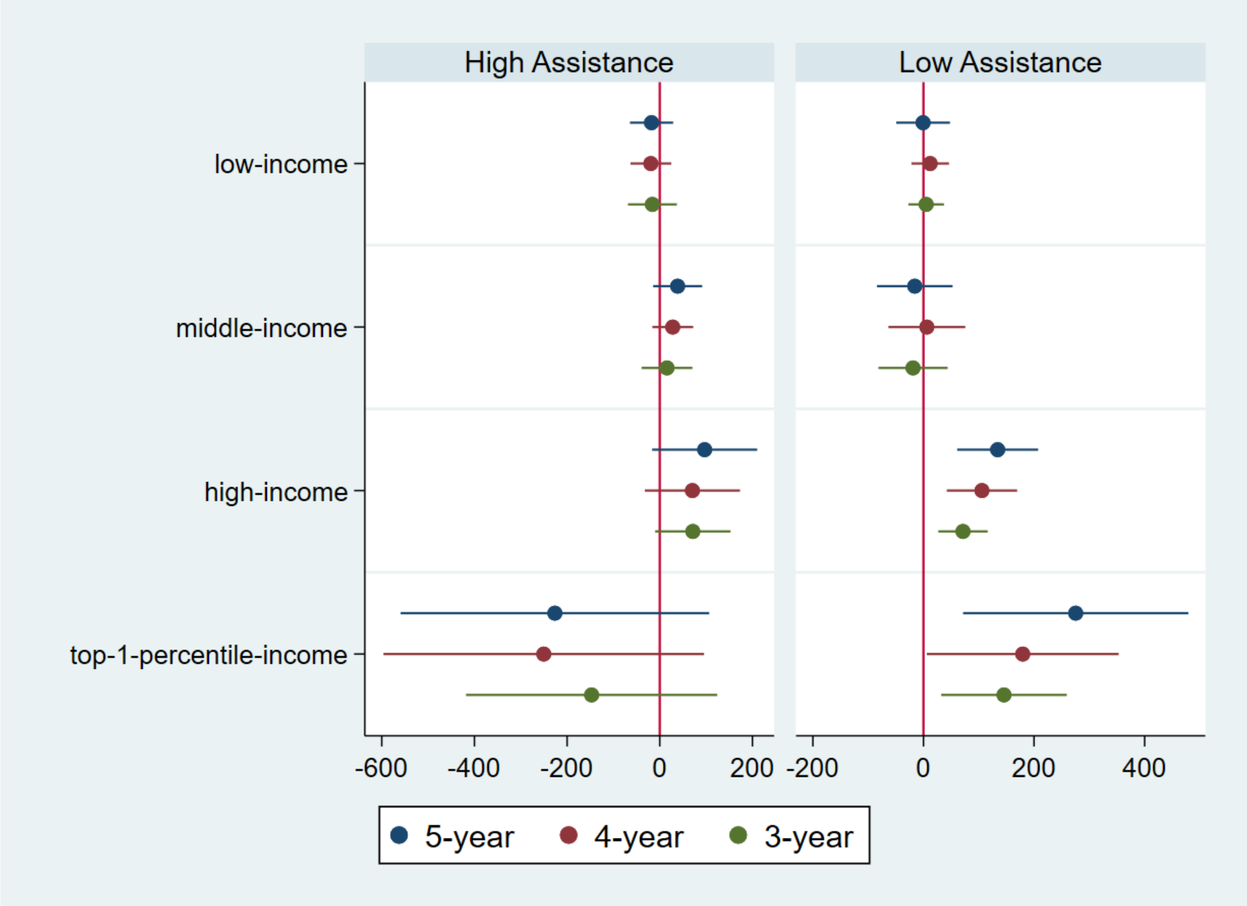


Figure 5. Heterogeneous effect of natural disaster across different assistance levels

Natural disaster type	Fatalities	Percentage of fatalities
Winter Weather	169	35.96%
Hurricane	56	11.91%
Flooding	54	11.49%
Heat	51	10.85%
Wind	44	9.36%
Tornado	32	6.81%
Others	64	13.62%

Table 1. Distribution of natural disaster fatalities by types from 2007 to 2010

	Variable	Obs	Weight	Mean	Std. Dev.	Min	Max	Definition	Source
Household level data	head_hh_age	5398861	10715658	46.36185	8.423423	27	57	head of household age	infoUSA
	find_div_1000	5398861	10715658	0.002324	0.048155	0	1	predicted income divided by 1000	infoUSA
	estmtd_~1000	5398861	10715658	272.3606	272.0468	0	9999	Estimated property value	infoUSA
	child	5398861	10715658	0.002324	0.048155	0	1	whether the household hold has a child during the migration time	infoUSA
	owner	5398861	10715658	1	0	1	1	whether the household is owner	infoUSA
	MIstate	5398861	10715658	0.004414	0.066291	0	1	whether houshold migrate across state	infoUSA
	MIcounty	5398861	10715658	0.008837	0.09359	0	1	whether houshold migrate across county	infoUSA
Natural disaster data	fr_5	5382077	10676614	1.21E-06	2.44E-06	0	7.56E-05	Average fatality rates between 2006-2010	NOAA storm event database
	fr_4	5385777	10685409	1.20E-06	2.60E-06	0	9.45E-05	Average fatality rates between 2007-2010	NOAA storm event database
	fr_3	5386804	10687879	1.24E-06	2.98E-06	0	0.000126	Average fatality rates between 2008-2010	NOAA storm event database
Demographic	age_24	5398753	10715496	0.319642	0.064901	0	0.986931	percentage of individual whose age is lower than 24	census
	age_60	5398753	10715496	0.138125	0.068667	0	1	percentage of individual whose age is higher than60	census
	white	5398753	10715496	0.749597	0.224704	0	1	percentage of individual who is white	census
	hispanic	5398753	10715496	0.132604	0.182189	0	1	percentage of individual who is hispanic	census
other socioeconomics	density	5397954	10713617	4516.379	9851.927	0	215427.6	population divided by number of housing	census

		5398	1071	0.03	0.02				
	vacancy	732	5445	7233	8138	0	0.7	percentage of housing which is vacant	census
	seasonal_	5398	1071	0.02	0.07		0.91	percentage of housing which is seasonal	
	vacancy	732	5445	744	1271	0	1015	vacant	census
		5398	1071	1046	254.	521.			
	hud	861	5658	.28	4834	5	1677	2-bedroom housing price	HUD
	manufact	5220	1041	0.05	0.03		0.33	percentage of workers working in	
	uring	910	5098	5256	4593	0	1401	manufacturing industry	BEA
	agricultur	5220	1041	0.01	0.01		0.32	percentage of workers working in	
	al	910	5098	0799	9125	0	5584	agricultural/fishing/forestry industry	BEA
		5220	1041	0.53	0.09	0.06	0.72	percentage of workers working in	
	service	910	5098	4196	2639	2748	2372	service industry	BEA
labor		5220	1041	4563	1371	1942	1219	mean household income over the past	
market	income	910	5098	2.87	5.54	1.33	30	12 months	ACS
	unemploy	5398	1071	8.77	1.88				
	ment	861	5658	0805	8299	4.3	20.4	percentage of unemployment individual	ACS
				-	-				
		5220	1041	0.01	0.04	0.31	0.31	the occupation growth rate over past 5	
	jgr	910	5098	23	722	1656	5324	years	BEA
natural		5398	1071	0.72	0.44				
amenity	shoreline	861	5658	7074	5463	0	1	whether county has a shoreline	NOAA
		5289	1047	9105	2299	5997	1536	average daily winter sunlight (KJ/m^2)	
	win_sun	075	9389	.044	.66	.301	4.67	(1979-2011)	NLDAS
	win_temp	5289	1047	33.4	12.9	6.32	61.4	average minimum daily sumer	
	erature	075	9389	0004	0846	1	54	temperature (oF) (1979-2011)	NLDAS
	sum_tem	5289	1047	1282	969.	39.9	3776	average maximum daily sumer	
	perature	075	9389	.191	1808	5504	.594	temperature (oF) (1979-2011)	NLDAS
	sum_hum	5289	1047	84.9	4.73	67.2	97.8	average summer daily precipitation	
	idity	075	9389	6911	6258	14	99	(mm) (1979-2011)	NLDAS

Table 2. Summary statistics for owner sample

Appendix A. External validation for Data Axle dataset

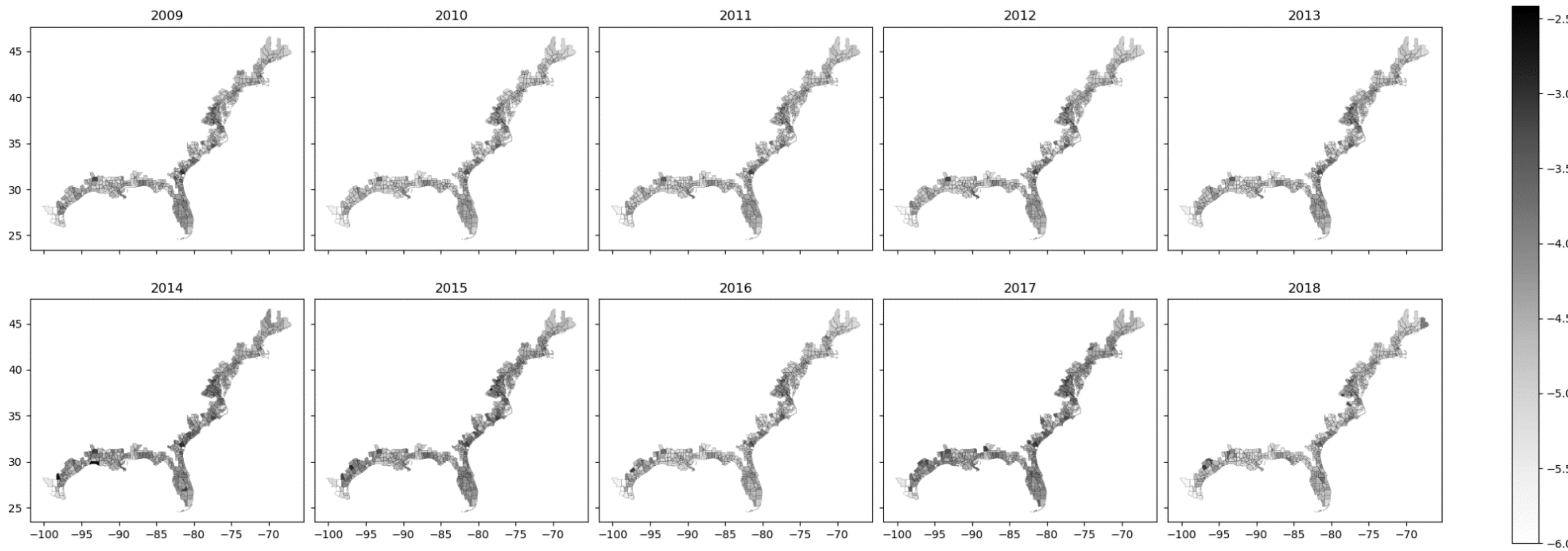


Figure A1. Natural log of Outmigration rate for each east coast county in Data Axle dataset

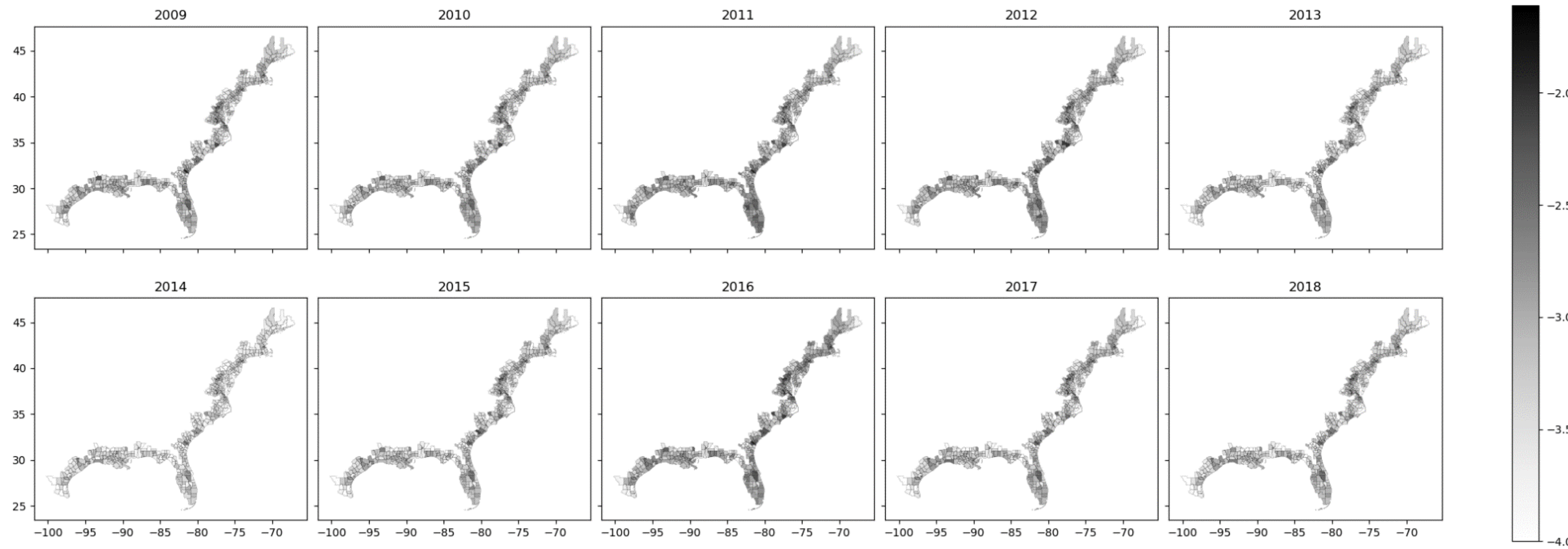


Figure A2. Natural log of outmigration rate for each east coast county in IRS dataset

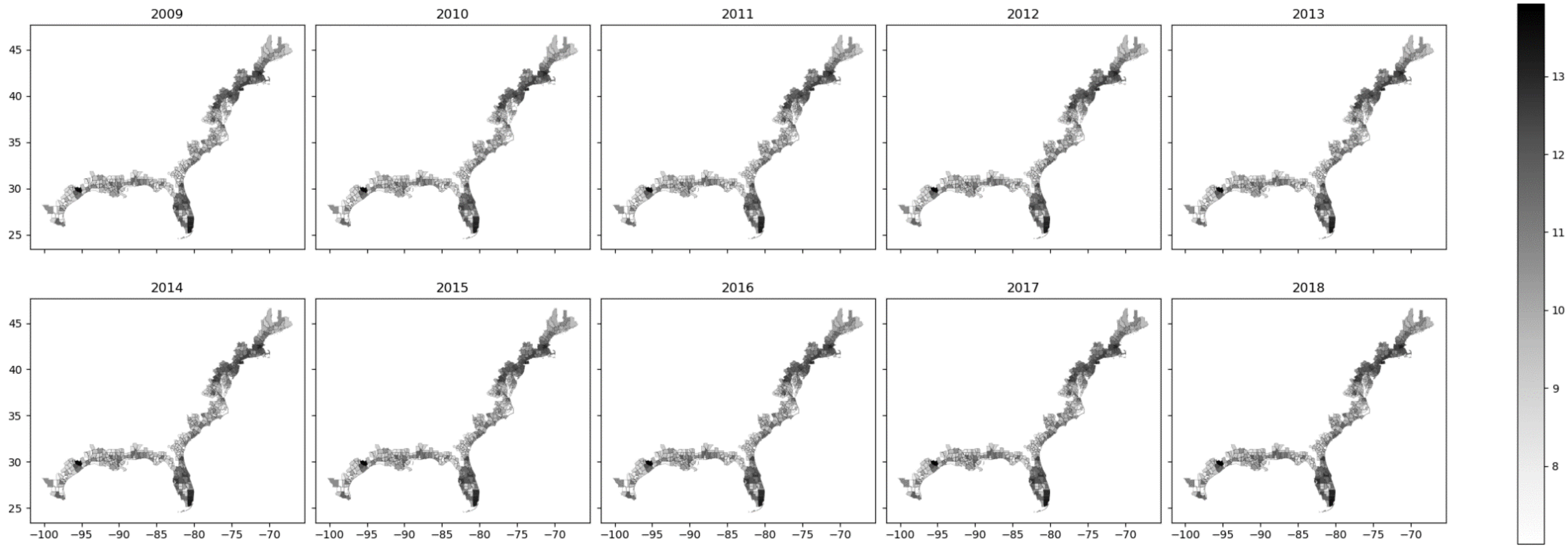


Figure A3. Natural log of number of observations in each coastal county in the Data Axle dataset

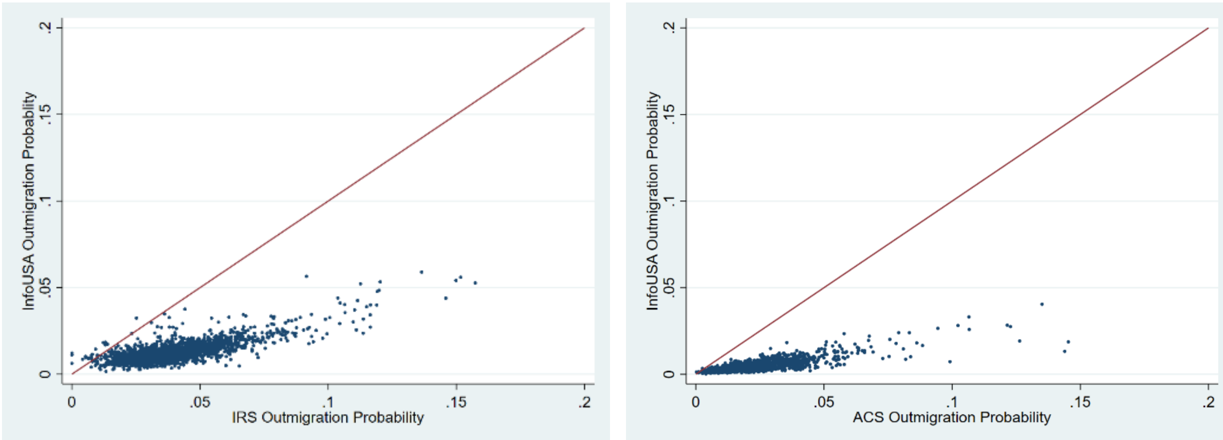
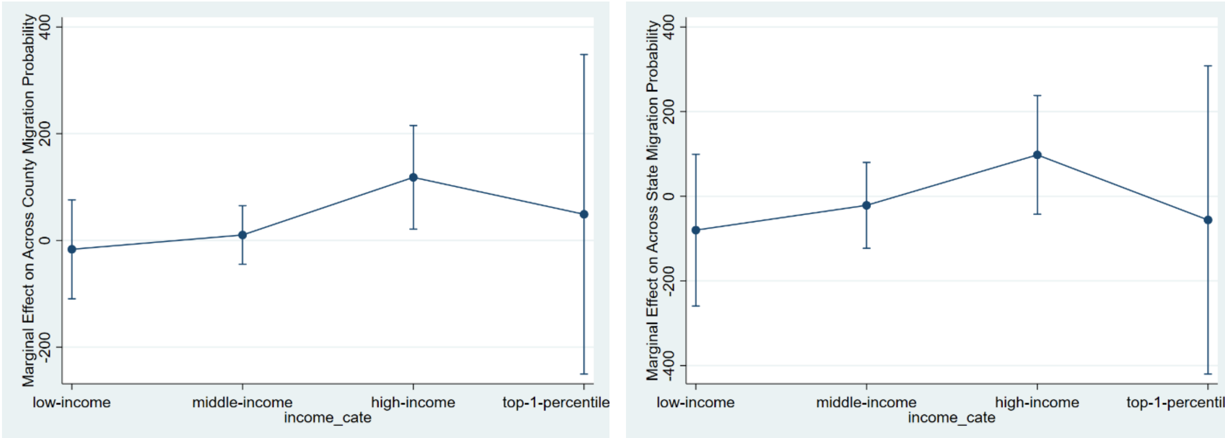


Figure A4. Scatterplot between IRS, ACS and Data Axle data

Figure A1 and Figure A2 show the out-migration probability calculated by Data Axle dataset and IRS dataset, which identifies migrators based on change of the address in the tax return. While the scope of the migration rate is different, we can see similar spatial trends in both figures. In Figure A4, we can more clearly view the high correlation ship between Data Axle out-migration probability and IRS out-migration probability (correlation coefficient=0.7074, p-value<0.0001) and ACS out-migration probability (correlation coefficient=0.8209, p-value<0.0001). Moreover, as shown in Figure A1 and A3, places with higher out-migration rates tend to be places with higher Data Axle observations. As a result, the high out-migration rate in those regions is unlikely to result from the fluctuation of Data Axle migration rate. However, while Data Axle migration rate is linearly correlated with IRS and ACS migration rate, Data Axle data does provide a much smaller out-migration rate compared to other data sources. Thus, our results might be an underestimate of true natural disaster effect on migration, which might be one reason why the effect of natural disasters on migration probability is relatively small.

Appendix B. Robustness test for inverted-U shape relationship



Across county migration Across zipcode migration

Figure B1. Robustness test for alternative migration definition

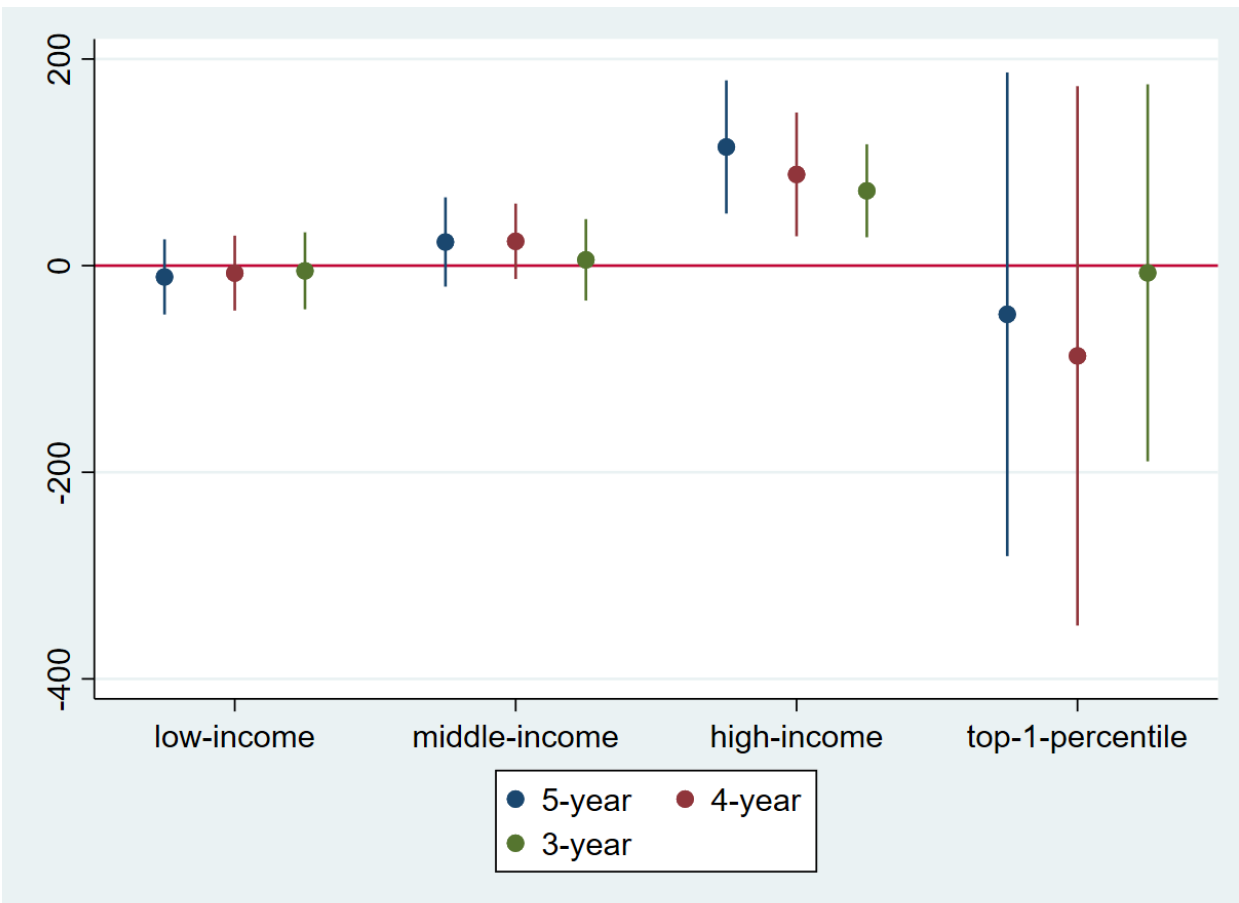
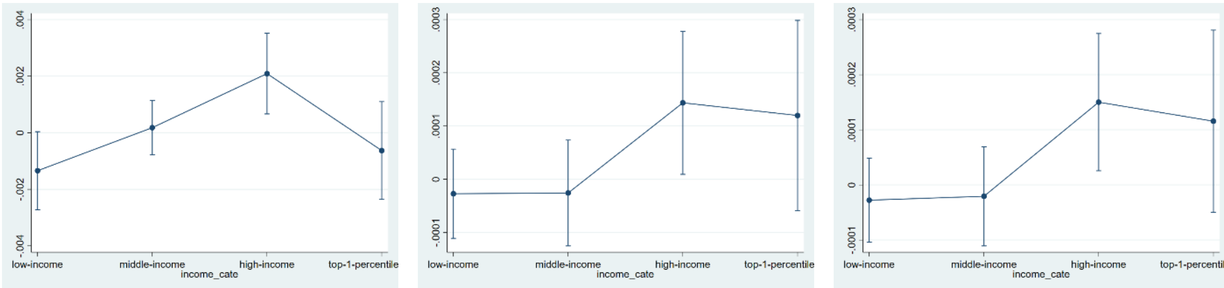
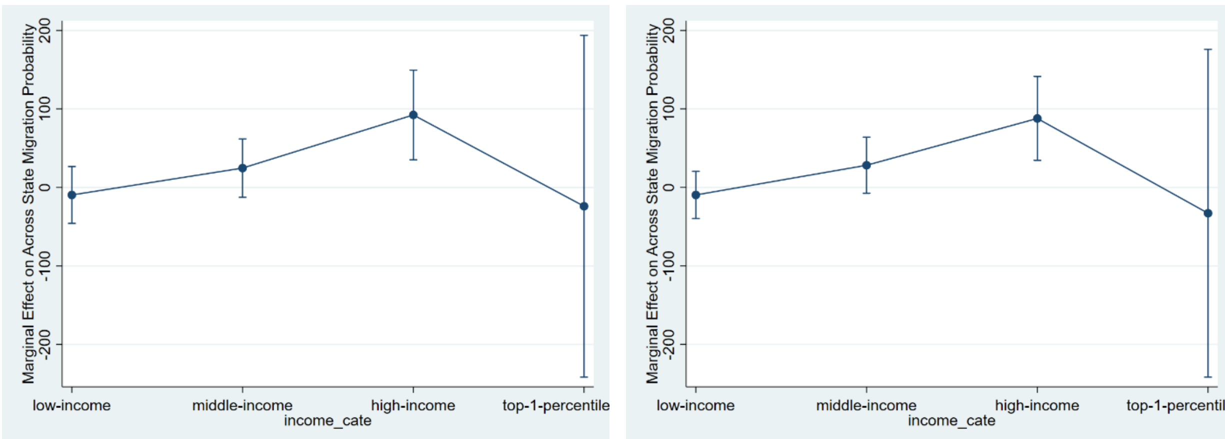


Figure B2. Robustness check for alternative natural disaster indicator ranges

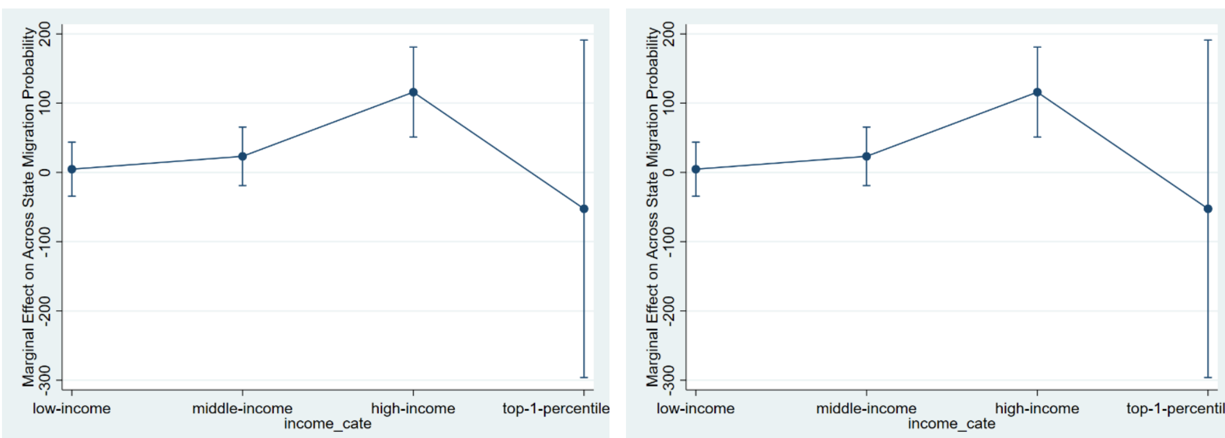


Major event Property damage Total damage

Figure B3 Robustness check for alternative natural disaster indicators



20-60 30-60



25-55 25-65

Figure B4 Robustness check for alternative working age people

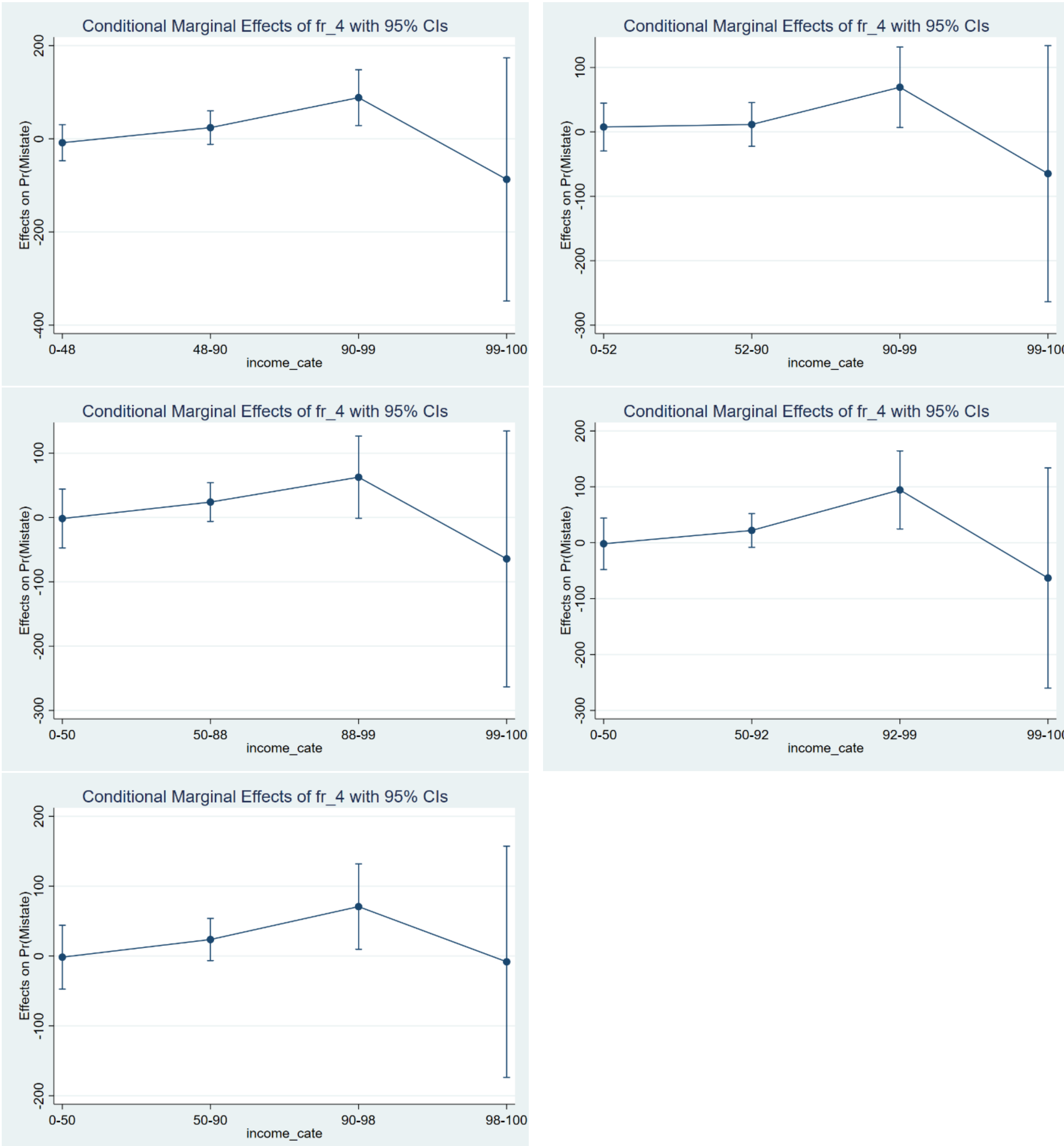
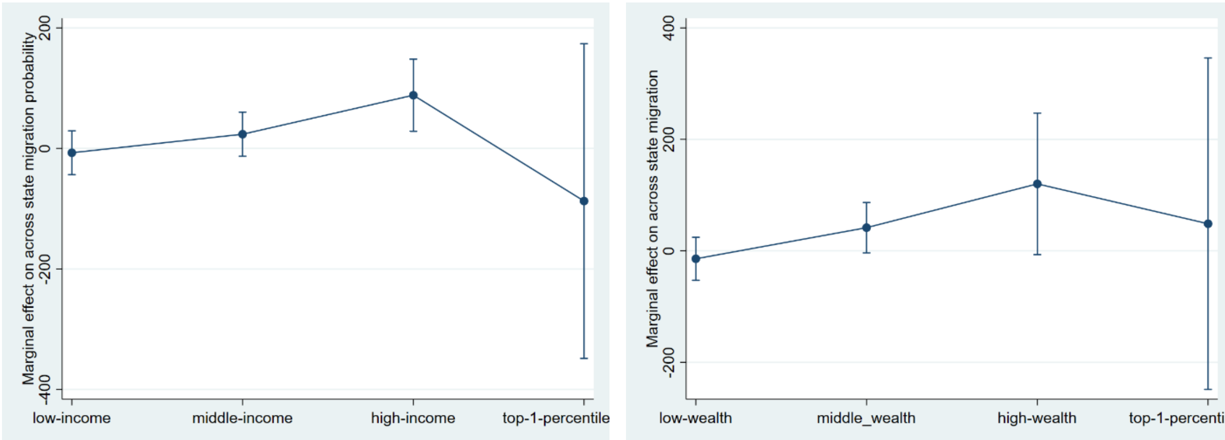


Figure B5 Robustness check for alternative income cutoffs



Income strata Wealth strata

Figure B6. Robustness check for wealth distribution