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E-mail: ted.hsuanyun.chen@gmail.com**Keywords:** climate change adaptation, climate migration, inequality, disaster resilience, network analysisSupplementary material for this article is available [online](#)

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**Abstract**

Residential relocation following environmental disasters is an increasingly necessary climate change adaptation measure. However, relocation is among the costliest individual-level adaptation measures, meaning that it may be cost prohibitive for disadvantaged groups. As climate change continues to worsen, it is important to better understand how existing socioeconomic inequalities affect climate migration and how they may be offset. In this study we use network regression models to look at how internal migration patterns in the United States vary by disaster-related property damage, household income, and local-level disaster resilience. Our results show that post-disaster migration patterns vary considerably by the income level of sending and receiving counties, which suggests that income-based inequality impacts both individuals' access to relocation and the ability of disaster-afflicted areas to rebuild. We further find evidence that income-based inequality in post-disaster outmigration is attenuated in areas with higher disaster resilience, not due to increased relocation out of poorer areas but instead because there is decreased relocation from richer ones. This finding suggests that, as climate adaptation measures, relocation and resilience-building are substitutes, with the implication that resilience incentivizes *in situ* adaptation, which can be a long term drain on individual wellbeing and climate adaptation resources.

1. Introduction

Climate change-induced extreme weather events are increasing in frequency and severity. From droughts and wildfires in the west and southwest to hurricanes and floods along the eastern seaboard and the Gulf Coast, damages and bodily harm caused by disasters and extreme weather are rising to record levels in the U.S. Climate models predict these trends will continue (e.g. Trenberth *et al* 2015, Kossin 2018, Wing *et al* 2018). Coastal flooding and sea-level rise alone could lead to massive amounts of displacement and destroyed property (Hauer *et al* 2016). In addition to the overwhelming financial costs, exposure to disasters severely impact human welfare (Mills *et al* 2007, Shultz and Galea 2017).

In the face of worsening climate change, transformational adaptations such as the relocation of vulnerable systems rather than incremental improvements are increasingly necessary (Kates *et al* 2012). While these adaptations usually require overcoming difficulties associated with collective action, some have the benefit of being individually autonomous, meaning that their effectiveness to individuals does not hinge on coordinated behavior (Leary 1999). One such measure is residential relocation, whereby individuals or households move to different locations either to preempt or in response to the impact of climate change on their personal or economic welfare (Adams and Adger 2013). Prior work shows, for example, that internal migration patterns in the U.S. vary by climate-related crop yields (Feng *et al* 2012)

and exposure to disasters (Eyer *et al* 2018, Boustan *et al* 2020).

Despite the ostensible appeal of migration as a response to high concentrations of people living in increasingly inhospitable areas (Hauer *et al* 2016) and to the fact that post-disaster reconstruction is often inefficient (Moore 2017) and can be taxing on individual wellbeing (Koslov *et al* 2021), there are questions about the conditions under which migration is a viable adaptation measure to climate change, and how policies can be designed to facilitate these conditions.

First, because it relies primarily on individual-level means, climate migration is subject to existing socioeconomic inequalities (Warner and Afifi 2014). Most broadly applicable is the fact that, as one of the costliest individual-level climate adaptation measures, migration is an option limited to those with financial slack (McLeman and Hunter 2010). Disasters and extreme weather exacerbate these constraints as they can greatly devalue property. Government buy-out programs are often not enough to offset relocation costs (Kick *et al* 2011) and in many parts of the U.S., home insurance policies are set up in a way that the payout for relocation is lower than the payout for rebuilding (Insurance Information Institute 2021, United Policyholders 2021). Consequently, following disasters, poorer individuals often become trapped in afflicted areas because they lack the resources to relocate (Black *et al* 2013, Angelucci 2015, Boustan *et al* 2020).

Given the expectation that inequalities in climate migration are exacerbated by exposure to disasters, we ask whether they can be attenuated through disaster resilience, broadly defined as formal and informal institutions that improve an area's ability to withstand and rebound from disasters (Federal Emergency Management Agency 2021). Because we are interested in the relationship between disaster-induced inequalities and resilience, we focus on aspects of disaster resilience that are related to management and governance efforts aimed at coping with and adjusting to climate events. This approach directly links our work to the global environmental change literature, which conceptualizes resilience as how well a social system mitigates and adapts to changes brought by disasters (Burby *et al* 2000, Birkmann 2006, Janssen *et al* 2006, Cutter *et al* 2008). Under this framework, human agency is deemed to be pivotal in improving the disaster resilience of social systems.

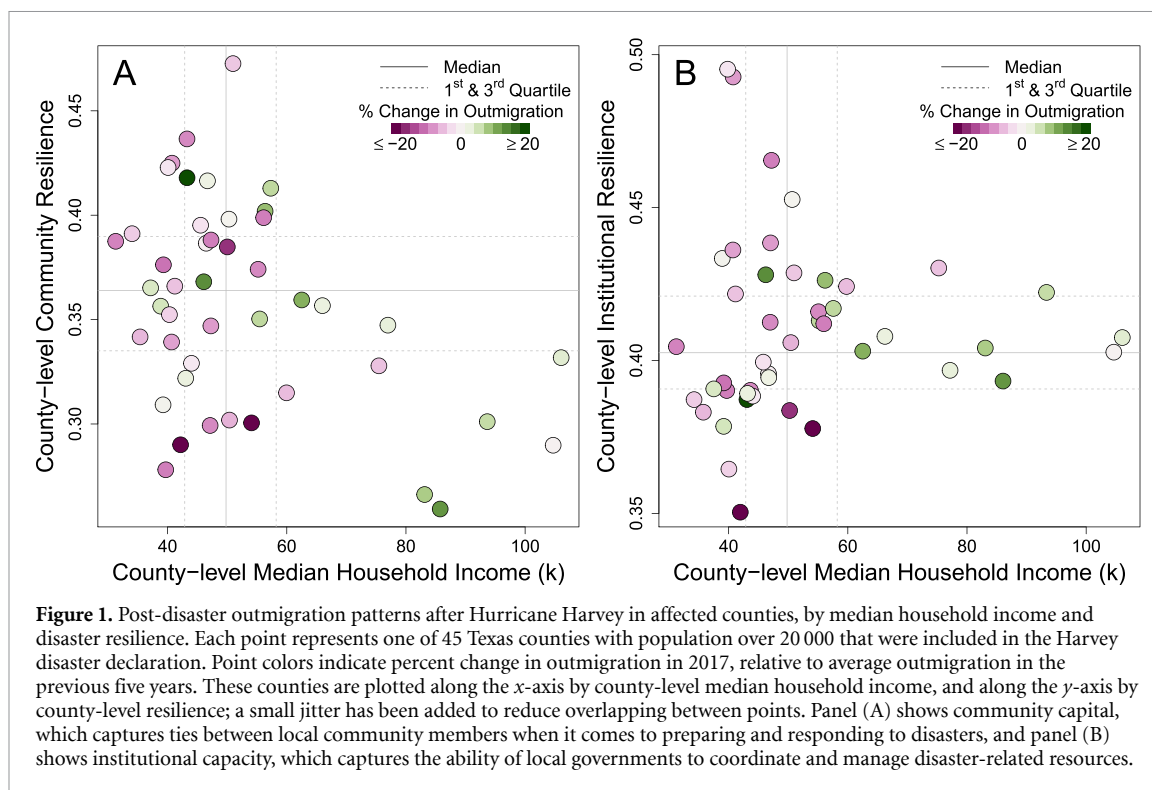
Disaster resilience has a dualistic relationship with climate migration (Binder *et al* 2015). By definition, measures that improve resilience reduce the impact of disasters and speed up recovery, which should on the one hand lower barriers to relocation for individuals who want to do so. At the same time, they also reduce the incentives for relocating because in terms of adapting to climate change, relocation and resilience-building can be considered as short-

to medium-term substitutes for each other. Given existing investments in resilience, *in situ* incremental adaptations become more attractive (Binder *et al* 2015). Further, there is evidence that strong social capital, often understood as a form of resilience, can lower individuals' risk perceptions (Wolf *et al* 2010) or even lead to post-disaster mooring effects (Aldrich 2012).

With these considerations in mind, we examine how internal migration patterns in the U.S. vary by disaster-related property damages and household income. We analyze these patterns at the county-dyad level over a ten year period from 2009 to 2018 using migration flow data. Because we view relocation as a measure of climate change adaptation, we pay additional attention to questions about how to maintain fairness, specifically whether expected inequalities in climate migration can be offset by different types of local-level disaster resilience.

To help build our theory and illustrate our research questions, we conducted an initial exploratory data analysis, shown in figure 1, of outmigration patterns from Texas counties that were affected by Hurricane Harvey. For this descriptive analysis, which shows the relationship between county-level outmigration, income, and resilience, we used the same data as our statistical models, which we describe later in our paper. As the figures show, it is clear that there is income-based inequality in post-Harvey relocation. Richer counties overwhelmingly experience outmigration after Harvey (shown with green), which fits well with our understanding that relocation is costly. Further, there is evidence of a resilience effect that mitigates income-based disparities in outmigration. This finding holds across two different measures of resilience, community capital and institutional capability. Among counties with low resilience, most poor ones experienced a decrease in outmigration after Hurricane Harvey (shown with pink), while most rich ones saw increased outmigration. On the other hand, among counties with higher resilience, the difference in outmigration patterns between those that are richer and those that are poorer becomes less apparent. Above the median level of resilience, the relationship between income and outmigration is weak.

In this exploratory data analysis, there is already evidence of patterns that speak to our research questions. In the remainder of this paper, we present findings from network regression models over a ten year period. We show that there is considerable heterogeneity in how households from different economic backgrounds respond to environmental disasters using relocation. Those from richer neighborhoods leave disaster-damaged areas while poorer households lack the capacity to migrate away from worsening conditions despite being exposed to environmental risks. We then show evidence that



these income-based inequalities in climate migration are attenuated in areas that have higher disaster resilience, both in terms of community capital and institutional capacity. Our findings speak to studies that look at how individuals respond to the risk of climate change through decisions to migrate (e.g. Piguet *et al* 2011, Adams and Adger 2013), and those that examine how the impacts of disasters and individuals' ability to respond to them vary by existing socioeconomic inequalities (e.g. Masozera *et al* 2007, Black *et al* 2013, McCaughey *et al* 2018).

A further benefit of our migration flow data is that it lets us study the entire migration calculus when individuals are faced with environmental hazards, from when they leave to where they go, thereby providing additional insights into how people consider climate factors when choosing where to live. We find evidence that richer areas can still attract immigration even after being afflicted by disasters while poorer areas do not. Additionally, higher disaster resilience in an area does not appear to be a draw for attracting immigration. Beyond engaging with prior evidence suggesting people do not or cannot account for the climate-related features of where they move to (e.g. Bell *et al* 2021, Hino and Burke 2021), which reduces the efficacy of climate migration as a climate adaptation measure, our findings contribute to the growing body of literature that emphasizes post-disaster relocation as a driver of societal restructuring with economic and social implications (e.g. Molloy *et al* 2011, Feng *et al* 2012, Hopkins 2012, Boustan *et al* 2020).

2. Methods

To study how post-disaster relocation in the U.S. varies by income levels and disaster resilience, we compiled a network data set that comprises (1) the internal migration flow between counties in the U.S. and (2) county-level characteristics such as disaster exposure and median household income. Our data exists annually for the decade from 2009 to 2018. Using this data set, we fit annual gravity models of internal migration, which allow us to study how county-level characteristics relate to both outmigration and immigration. A gravity model, which incorporates sender and receiver factors into consideration when fitting a probable distribution between two locations, is a common approach in studies that use dyadic migration flow data (e.g. Reuveny and Moore 2009, Backhaus *et al* 2015, Poot *et al* 2016, Eyer *et al* 2018, Liu *et al* 2019). Our main focus is on the interaction effects between exposure to environmental disasters, household income, and local disaster resilience, which we show using hypothesis tests on the model coefficients and marginal effect plots.

2.1. Data and measures

We combined meteorological, administrative, and academic sources to create our annual network data set from 2009 to 2018. For computational reasons, we excluded counties with population levels below 20 000 from our data set. Additionally, to account for any different migration behaviors due to long distances to and from the contiguous U.S., we also

Table 1. Summary of variables and model terms.

County-level measure	Source	Included model terms		
		Sender	Receiver	Distance ^a
Disaster-induced Property Damage	SHELDUS	•	•	
Median Household Income	ACS	•	•	•
Community Capital Resilience	BRIC	•	•	
Institutional Capability Resilience	BRIC	•	•	
Population	ACS	•	•	•
Median Age	ACS	•	•	•
Percent Bachelors or higher	ACS	•	•	•
Percent Unemployed	ACS	•	•	•
Percent White Population	ACS	•	•	•
Percent Native-born Population	ACS	•	•	•
GOP Vote Share	MIT Election Lab	•	•	•
Percent Manufacturing Employee	NAICS			•
Disaster-induced Bodily Harm	SHELDUS	•	•	
Geographical Location	—			•
State	—			•

^a Distance terms are calculated by taking the absolute difference between sender and receiver for the given county-level measure, with the exception of *Geographical Location* which is the Euclidean distance between sender and receiver centroids and *State* which is a binary variable for whether the sender and receiver are in the same state.

excluded all Alaskan and Hawaiian counties (and equivalent administrative units). These subsetting steps reduced the number of counties to 1834 from 3143, but retain over 90% of all internal migration in the U.S.

Table 1 provides an overview of our data set, including key variables, their source, and how they were included in our models. We outline detailed information on key variables below. In the supplementary information (available online at stacks.iop.org/ERL/17/034043/mmedia), we present descriptive statistics of these key variables (S1) and details about confounding factors (S2).

2.1.1. Migration flows

Our outcome variable is county-to-county annual migration flow, which we log-transformed after adding a value of 1 before fitting our models to account for observed dyads with extremely high migration levels. We obtained this data from the U.S. Internal Revenue Service (IRS), which estimates county-to-county migration using changes in taxpayers' filing addresses. A taxpayer or taxpaying household is considered to have moved in a given year if their return address differs from the next year's address. In other words, migration in year t represents change in residence between years t and $t + 1$. The data set provides both the number of individuals and households that moved. We focus on household migration because climate events affect households as a whole rather than at the individual level.

How the IRS estimates migration presents two considerations for the migration statistics. First, it misses relocation-and-returns that occur between tax filings in two consecutive years, as the address for the temporary residence never gets recorded. Second,

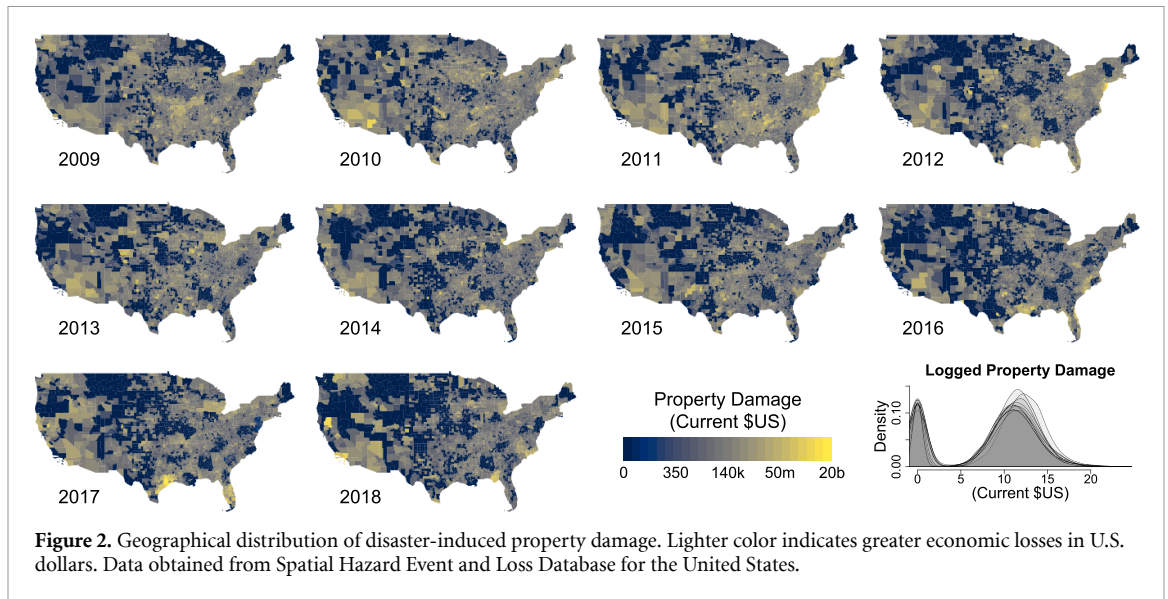
for longer term moves, households that move before they file their taxes in a given year will be counted as having moved in the previous year, which means the annual migration statistics do not map perfectly onto other statistics that are based on calendar years. To address this second point, we show in the supplementary information (S3) that our results are robust to disaster exposure statistics temporally rebound to account for the majority of these mismatches.

Finally, an important characteristic of this data set is that dyads with fewer than a certain number of moves are not reported by the IRS. For households, this threshold is 10 from 2009 to 2012 and 20 from 2013 to 2018. Following prior studies from the US internal migration literature that use this data (Curtis *et al* 2015, Eyer *et al* 2018, Liu *et al* 2019), we set these censored observations at 0. In the supplementary information (S4), we show that our results are robust to the universal application of the higher censoring threshold implemented in 2013, and to alternative specifications for the censored observations.

Despite these shortcomings, the IRS migration data remains one of the best available sources for tracking internal migration changes in the U.S. (Molloy *et al* 2011, Curtis *et al* 2015), and has been used in numerous studies of U.S. internal migration (e.g. Curtis *et al* 2015, Eyer *et al* 2018, Liu *et al* 2019).

2.1.2. Property damage from extreme weather events

We use disaster-induced property damages to capture the severity and impact of disasters on individuals living in a county, as economic losses is a widely-observed outcome after environmental disasters. We obtained damage estimates from the Spatial Hazard Event and Loss Database for the United States (SHELDUS; CEMHS 2020). This database, which is widely



used in disaster and hazards research (e.g. Borden and Cutter 2008, Cortés and Strahan 2017, Doktycz and Abkowitz 2019), was constructed based on data from the National Weather Service and contains estimates of economic losses and the number of bodily harms at the county level. Estimates of property damage, specifically, combine multiple sources including insurance companies, emergency managers, the U.S. Geological Survey, the U.S. Army Corps of Engineers, power utility companies, and newspaper articles (CEMHS 2020). SHELDUS records property damage in actual U.S. dollars, resulting in a right-skewed distribution. To account for this, we used the log-transformed property damage in our models.

Figure 2 shows the distribution of property damages across the U.S. While there are persistent patterns in the regions that experience the most damages—coastal areas prone to flooding and other hurricane damages, wildfire and drought areas in the west and southwest—there is considerable year-to-year variation that improves our model inferences.

2.1.3. Income

To measure economic capacity, we use county-level median household income from the American Community Survey (ACS) 5-year estimates, which includes income and benefits in U.S. dollars adjusted by inflation. Similar to property damage, we log-transformed our income data before including it in our models.

2.1.4. Community and institutional resilience

Given our interest in understanding climate-induced inequalities, in this study we focus on aspects of disaster resilience that are related to management and governance efforts aimed at coping with and adjusting to climate events. To capture these resilience dimensions, we use measures from the Baseline

Resilience Indicators for Communities index (BRIC; Cutter *et al* 2014, Cutter and Derakhshan 2020), which is based on the theoretical framework of the ‘disaster resilience of place’ model (Cutter *et al* 2008). A large component of this model focuses on interactions among socioecological systems that yield different levels of resilience in communities. Drawing on this concept of interconnected systems in disaster resilience, the BRIC index comprises six subindices, social, economic, community, institutional, infrastructure, and environmental. The BRIC index has been a standard measure in the disaster resilience literature and was recently included as a component of the Federal Emergency Management Agency’s National Risk Index, which is a composite score for a community’s overall risk to natural hazards (Zuzak *et al* 2020).

To capture resilience in the governance of response and recovery, we use the community capital and institutional capacity indices, which for us reflect different sides of disaster resilience governance. Specifically, they respectively represent the informal and formal sides of local-level measures that facilitate coping with disaster-related disruptions (Cutter *et al* 2014). Among many factors contributing to local resilience, previous studies have emphasized the importance of these informal social capital and formal governance structures in particular (Tierney 2012). First, denser social networks and tighter bonds within the community are mechanisms that allow afflicted areas, even those with lower wealth, to overcome severe disaster-related damages (Aldrich 2012). Close social connections among community residents facilitate post-disaster recovery and reconstruction because they make the necessary coordination smoother (Cox and Perry 2011, Aldrich and Meyer 2015). Similarly, the capacity of formal institutions, obtained through preparedness training and disaster

experience, affords effective collaboration among relevant actors in the face of disasters, which is required for quick response and mobilization of resources (Chen *et al* 2013). In this sense, institutional capacity is crucial to disaster resilience because it is directly tied the ability of communities to reduce socioeconomic vulnerability (Papathoma-Köhle *et al* 2021).

Both resilience measures are index variables in the [0,1] range with 1 indicating a higher level of resilience. The community capital measure, which captures the connectivity among local citizens and their ability to assist neighbors in emergency situations, is based on variables related to volunteerism, religious affiliation, attachment to place, political engagement, citizen disaster training, and civic organizations. The institutional capacity measure, which captures aspects related to local government coordination in managing and assigning resources during a disaster, is based on variables regarding mitigation spending, flood insurance coverage, governance performance regimes, jurisdictional fragmentation, disaster aid experience, local disaster training, population stability, nuclear accident planning, and crop insurance coverage. In the supplementary information (S5), we list all variables that constitute our resilience measures. We also present the marginal and joint distributions of these variables (S1) that show the two measures are not strongly correlated with each other, but internally consistent across time.

Since the indices are only available for two time points, 2010 and 2015, we used the one that is more temporally-proximate to each given year in our data set. Specifically, the resilience measures for 2010 are used for 2009–2012, and the 2015 measures are used for 2013–2018. In the supplementary information (S6), we show that our results are robust to models using resilience values linearly interpolated and extrapolated from the 2010 and 2015 data.

2.2. Estimation and testing

We combined the data described above to fit annual network regression models where the outcomes are annual directed networks with logged migration flow edges and county- and dyad-level covariates as predictors. Our focus is on the predictors discussed above and their interactions, but this network framework allows us to control for the host of confounders summarized in table 1. In these network models, coefficient estimates on predictors are obtained using ordinary least squares (OLS), while testing for statistical significance is based on nonparametric permutation methods because using conventional standard errors from OLS estimation with our interdependent county-dyad observations will lead to over-rejection of the null hypotheses (Krackhardt 1988). Specifically, network data, such as the migration patterns we are working with, tend to be characterized by interdependence between observations that violates the conditional independence assumption for

OLS, which results in biased estimates of uncertainty (Dekker *et al* 2007, Cranmer *et al* 2017).

To account for interdependence between dyadic observations in our network data, we use the multiple regression quadratic assignment procedure (MRQAP). The MRQAP is a nonparametric hypothesis testing approach based on the comparison of the observed test statistic (e.g. coefficient of a predictor) against a null distribution that breaks the association between the outcome and the predictor while preserving the interdependence between observations (Krackhardt 1988). Because the null distribution produced by the MRQAP retains all the same network structures as the observed data, it serves as a valid comparison to the test statistic. This means that an extreme value of the test statistic compared to the null distribution can be attributed to an actual association between the outcome and the predictor (i.e. lets us reject the null hypothesis of no association).

We constructed our MRQAP null distributions using residual-based permutation methods, which have been shown in simulation studies to perform better compared to other MRQAP permutation approaches, as they are more robust to multicollinearity in the predictors and skewness in the data (Dekker *et al* 2007)⁴. Residual-based permutation methods have additionally been shown to work well for testing interaction effects (Buzkova 2016), which is the focus of our study.

Similar to prior studies that use network approaches to study migration patterns (e.g. Abel *et al* 2019, Liu *et al* 2019, Schon and Johnson 2021), we fit separate annual models instead of coercing all coefficients to be the same. This immensely reduces computational requirements at little cost to inferential validity⁵; as our results show, we have enough power to detect hypothesized effects, and the estimated coefficients are consistent across annual models.

We fit a set of three models for each year in our data set. The base model, for which dyad ij has logged migration from sender county i to receiver county j , is

⁴ Depending on the test, we used either the double semi-partialing permutation method (Dekker *et al* 2007) or the Freedman-Lane semi-partialing permutation method (Freedman and Lane 1983). In all cases, we build the null distribution using 100 permutations. Details of the MRQAP approach and the different permutation methods used in this study are presented in the supplementary information (S7).

⁵ We conduct OLS estimation and MRQAP testing using the `sna` (Butts 2020) package in R (R Core Team 2021). The bottleneck in our computational pipeline is the memory requirement, as the space complexity scales linearly with the number of dyadic observations. With each year having approximately 3.4 million dyadic observations, a model with all ten years pooled would have approximately 34 million observations. In concrete terms, consider that conducting one hypothesis test for our 2009 main model already requires more than 14 GB of memory in addition to loaded data, which is approximately 1.5 GB.

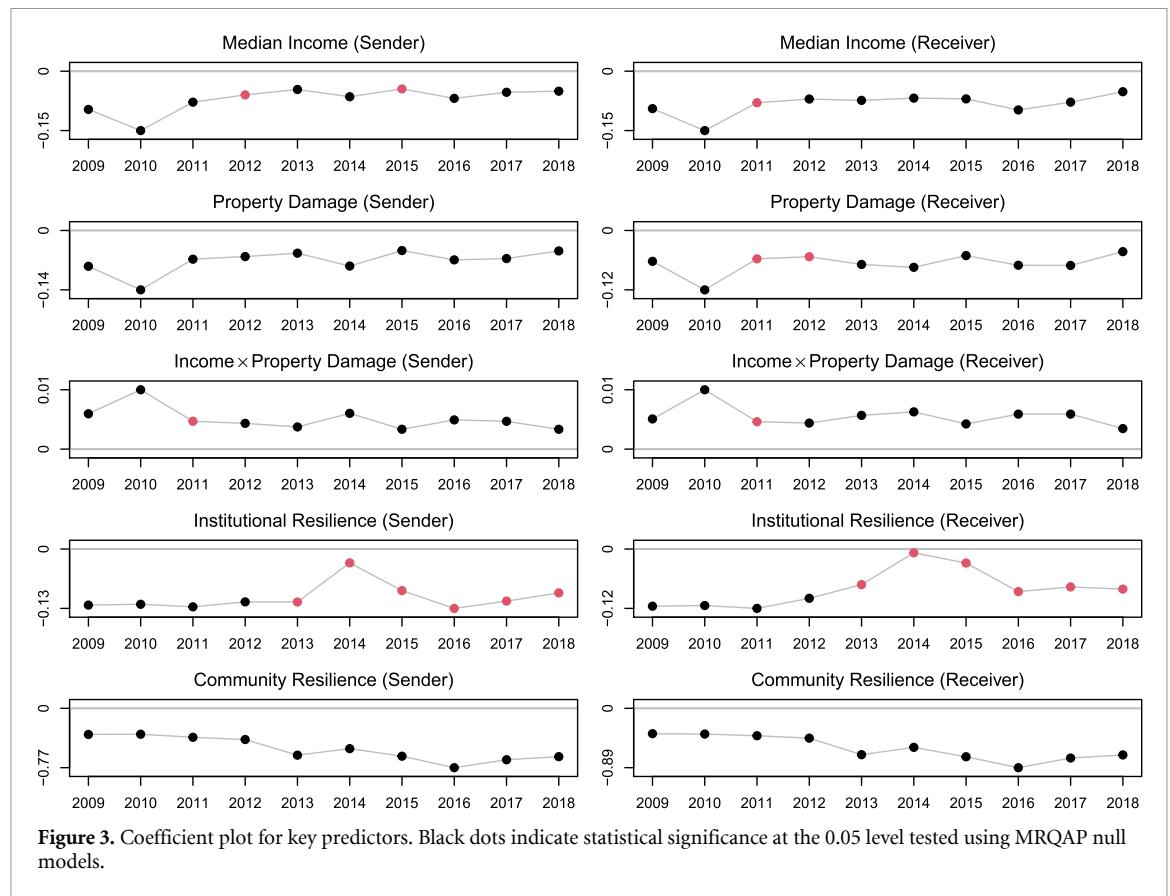


Figure 3. Coefficient plot for key predictors. Black dots indicate statistical significance at the 0.05 level tested using MRQAP null models.

$$\begin{aligned}
 Migration_{ij} = & \beta_1 PropDamage_i + \beta_2 HouseholdInc_i \\
 & + \beta_3 PropDamage_i \times HouseholdInc_i \\
 & + \beta_4 PropDamage_j + \beta_5 HouseholdInc_j \\
 & + \beta_6 PropDamage_j \times HouseholdInc_j \\
 & + \beta_7 CommResil_i + \beta_8 CommResil_j \\
 & + \beta_9 InstResil_i + \beta_{10} InstResil_j \\
 & + \mathbf{X}'_{ij} \mathbf{B} + \beta_0 + \epsilon_{ij}
 \end{aligned} \tag{1}$$

where \mathbf{X}_{ij} indicates a set of covariates at sender, receiver, and dyad-levels, including population, median age, percent of bachelor degree or higher, percent of unemployed population, percent of white population, percent of Native-born population, GOP vote share, percent of manufacturing employee, geographic distance between county centers, and whether the origin and destination counties are in the same state. These model terms are summarized in table 1.

From each of these base models, we examined the effect of ten predictors measuring disaster exposure, household income, resilience, and their interactions on in- and outmigration (i.e. $\beta_1, \beta_2, \dots, \beta_{10}$). In two extensions to the base model, we allowed the interactive effect of property damage and household income on outmigration to vary by, respectively, community capital resilience and institutional capacity resilience in the sending county.

In addition to directly testing coefficients, we present the main focus of our study, the interactive

effects of property damage and household income, using marginal effect plots that show how the effect of exposure to disasters vary by county-level median household income. In a second set of results, we further disaggregate these marginal effects by county-level disaster resilience. For clarity of presentation, we computed these effects as the percent change in migration flow when county-level property damage increases from none to the median observed value in the given year. We tested the statistical significance of these marginal effects using the MRQAP.

3. Results and discussion

Figure 3 reports the yearly coefficient estimates for our predictors of interest from our base model (i.e. equation (1))⁶. While there are some variations across years, most of the reported terms have relatively stable estimates.

3.1. Income-based inequality in post-disaster migration

The positive coefficient estimates for the interaction term between median household income and disaster-induced property damage combined with the negative coefficients estimates on both base terms

⁶ Results for all model terms in tabular form are presented in the supplementary information (S8).

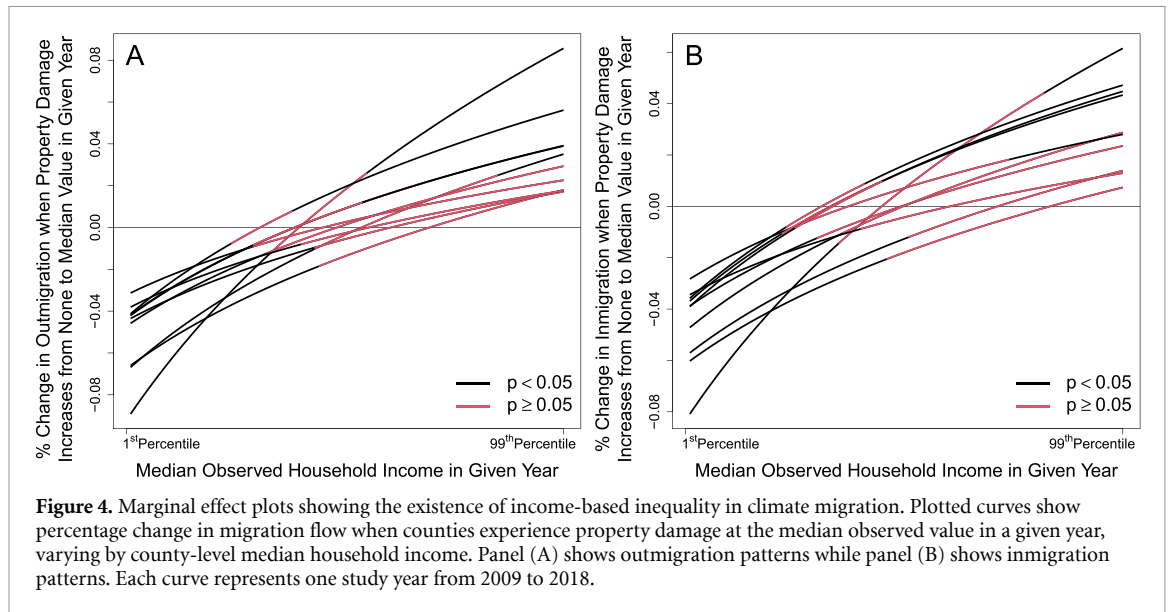


Figure 4. Marginal effect plots showing the existence of income-based inequality in climate migration. Plotted curves show percentage change in migration flow when counties experience property damage at the median observed value in a given year, varying by county-level median household income. Panel (A) shows outmigration patterns while panel (B) shows immigration patterns. Each curve represents one study year from 2009 to 2018.

indicate that internal migration in the U.S. is responsive to environmental disasters, but the response pattern differs by the economic status of those affected. Specifically, while individuals living in richer areas are generally less likely to move (i.e. negative coefficient estimate on the household income outmigration term)—which comports with findings from the broader migration literature (Molloy *et al* 2011, Clemens 2014)—they are more likely to respond to disaster-induced property damage by relocating from afflicted areas. Conversely, individuals from poorer areas tend to move more frequently, but become more immobile after being exposed to disaster-related property damages.

We illustrate the substantive effect of income in modifying the relationship between disaster exposure and outmigration flows using the marginal effect plot in panel (A) of figure 4. Here, the curves present, by year, how the percent change in county-level outmigration given median observed values of disaster-induced property damage varies by county-level income⁷. As the figure shows, in poor counties, an increase from no property damage to the median observed property damage of a given year is associated with a statistically significant decrease in outmigration of approximately 5%. This pattern holds across all years, indicating that there is a robust effect of property damages in decreasing outmigration when those afflicted lack resources to cope with damages. As the afflicted area becomes richer, the pattern is reversed. At a sufficiently high level of median household income, exposure to disaster-related property damage is associated with approximately 5% increase in outmigration, which is statistically significant in five of the ten annual models.

⁷ Data coverage for the variables that constitute the interaction terms is presented in the supplementary information (S1).

In sum, the results here indicate that households in richer areas are more likely to relocate after experiencing disasters when compared to otherwise normal times, while households from poorer areas become less likely to do so following disasters. These findings offer evidence corroborating our prior discussion on the existence of income-based inequality in post-disaster migration. Given their lack of resources, poorer households are likely to become trapped in disaster-afflicted areas. The implication of this is that where there access to adaptation measures is unequal, climate change is likely to exacerbate existing socioeconomic inequalities.

3.2. Disaster resilience is associated with lower income-based inequality

To see how local features that reduce the impact of disasters and improve recovery affect income-based inequality in post-disaster migration, we extended the base model by allowing the interaction effect between household income and property damage to further vary by two different types of disaster resilience. Our results, presented as marginal effects plots in figure 5, indicate that both community capital and institutional capacity are statistically significant predictors of whether income-based inequality in post-disaster migration exists in a county. In these marginal effects plots, the curves again present how the effect of property damage on county-level outmigration varies by county-level income. In both panels, there are two sets of curves, with the solid lines representing low resilience counties and the dotted lines representing high resilience counties.

As the solid lines in figure 5 show, in counties with low disaster resilience, income-based inequality in post-disaster migration follows a similar pattern as in the base model. In poorer counties, individuals are less likely to move out after exposure to disasters, whereas those from richer counties are instead

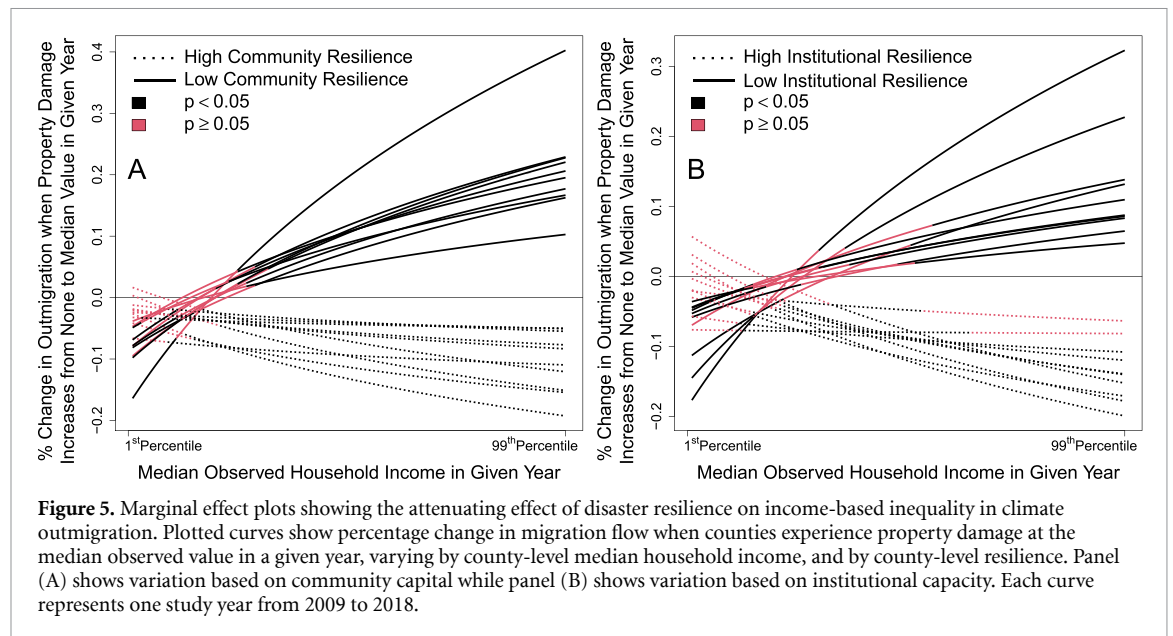


Figure 5. Marginal effect plots showing the attenuating effect of disaster resilience on income-based inequality in climate outmigration. Plotted curves show percentage change in migration flow when counties experience property damage at the median observed value in a given year, varying by county-level median household income, and by county-level resilience. Panel (A) shows variation based on community capital while panel (B) shows variation based on institutional capacity. Each curve represents one study year from 2009 to 2018.

more likely to leave. The strength of the relationship in both extended models is much stronger than in the base model, with the estimated percent change in most years ranging from -10% to 20% when going from the lower end of the income range to the higher end, whereas the same figures in the base model are estimated to be a much smaller -6% to 4% range. When looking at counties with high disaster resilience, however, we see that these outmigration patterns differ drastically. As the dotted lines in both plots show, individuals living in high resilience counties are generally less likely to move out following disasters. In both extended models, this finding holds for the range of observed income except in the poorest counties where disaster-related property damage has a statistically imperceptible effect on outmigration. The intervening effect of both types of disaster resilience on post-disaster migration discussed here holds across all years despite the mixed statistical significance on the coefficient estimates for institutional resilience shown in figure 3. This suggests that the role of resilience on outmigration is better understood as being conditional on disaster experience rather than as a factor in general relocation.

Our results here first provide systematic evidence suggesting that disaster resilience has an attenuating effect on income-based inequality in post-disaster migration. Further, this finding directly speaks to the dualistic nature of disaster resilience. Specifically, what is disaster resilience's net effect on outmigration given that alleviating the dangers of climate impacts will make it easier for individuals to relocate but also reduce their incentives to do so? Our results indicate that the latter effect is stronger, as higher resilience is associated with lower post-disaster outmigration among richer areas rather than higher post-disaster outmigration among poorer areas. The economically capable, who have the means to relocate—which they

do in low resilience areas—choose instead to stay. As we previously discussed, relocation and resilience building are substitute climate change adaptation measures, and given sufficient existing resilience, it appears that *in situ* incremental adaptations are generally more attractive.

3.3. Climate factors associated with immigration

In addition to studying outmigration patterns, our understanding of relocation as a climate change adaptation measure also benefits from considering how climate factors impact where people move to. Not only is this relevant to assessing how effective the net effect of relocation is (Eyer *et al* 2018), migration is generally important in itself because it drives social reorganization (Feng *et al* 2012, Liu *et al* 2019). Our county-to-county migration flow data allows us to look at these immigration patterns. We focus on two primary findings, which correspond to the factors we looked at for outmigration.

First, we again find richer and poorer areas faring differently after exposure to disasters. This is most readily evident from the marginal effect plot in panel (B) of figure 4, which shows how the percent change in county-level immigration given median observed values of property damage varies by county-level income.

As the figure shows, our model estimates poorer counties to experience decreased immigration after disasters exposure while richer counties are expected to see increased immigration given disaster-related property damages. These results echo prior work that finds environmental disasters to have a pull on immigration both in the U.S. (Eyer *et al* 2018) and abroad (Naik *et al* 2007). This phenomenon occurs for a host of reasons, including increased demand for labor to rebuild the afflicted areas or because individuals from disaster-afflicted regions will congregate

to economically-developed locales within the region. Together, these patterns imply that richer counties will end up with more resources to rebuild after environmental disasters while poorer counties will find it difficult to access proper resources to cope with damages (Masozera *et al* 2007, McCaughey *et al* 2018). Again, our results indicate that disasters may have a disproportionate impact on low-income households not only in terms of the accessibility of relocation as an adaptive measure, but also in how societal resources become distributed across areas.

Finally, we find that higher disaster resilience is not a draw for relocating individuals, which is apparent from the statistically insignificant or negative coefficient estimates on the two receiver resilience terms shown in figure 3. Our finding corroborates studies that show individuals do not favor areas with lower climate risk when relocating (Bell *et al* 2021, Hino and Burke 2021). These results imply that out-migration needs to be coupled with incentives for moving to resilient areas to be a viable climate adaptation measure, and also suggest it could be fruitful for future work to look deeper into what draws individuals to move to lower resilience areas.

4. Conclusion

In this study we considered post-disaster relocation as a climate change adaptation measure by looking at how internal migration patterns in the U.S. varied by disaster-related property damage, household income, and local-level disaster resilience. We show that existing economic inequalities can lead to unfairness in access to measures of climate change adaptation. While relocation is arguably an increasingly necessary climate adaptation measure (Kates *et al* 2012), it may only be viable for certain segments of the population, leaving those lacking the necessary resources to be relocated trapped in areas most vulnerable to the effects of climate change.

Additionally, income-based variation in post-disaster migration patterns could also exacerbate socioeconomic segregation, as we find evidence that disaster-afflicted areas differ considerably by wealth in their ability to attract immigration after being exposed to disasters. This implies that, comparatively speaking, richer counties will have greater access to resources for rebuilding from disasters. Our results here fit with and further contribute to a growing body of literature that emphasizes socioeconomic sorting as a major driver of vulnerability to climate change (e.g. Feng *et al* 2012, McCaughey *et al* 2018, Boustan *et al* 2020).

Finally, we find that income-based inequalities in post-disaster migration tend to be attenuated in areas with higher disaster resilience. Individuals living in these areas are generally less likely to relocate following disasters in all but the poorest of counties, where

there is no statistically significant difference. This speaks to how disaster resilience incentivizes *in situ* adaptation rather than transformational adaptation approaches such as relocation (Binder *et al* 2015).

Our findings have several policy implications for climate change adaptation. While residential relocation is an individually autonomous adaptation measure, it is subject to unfairness that aligns with existing socioeconomic inequalities. Efforts to improve local resilience appear to alleviate these inequalities and reduce climate-related socioeconomic segregation. At the same time, it is important that these measures do not introduce perverse incentives that keep individuals in vulnerable areas, which can additionally be taxing on individual wellbeing (Koslov *et al* 2021) and on climate governance resources in the longer term (Anderson *et al* 2019).

Speaking to this, future research might explore how policy incentives can reduce climate-related inequalities while promoting outmigration from vulnerable areas. One avenue worth exploring are policies that aim to reconcile the inconsistency between insurance payout for relocation and those for rebuilding, such as for example the recent push in California to enforce nondiscrimination for relocation in its insurance code (United Policyholders 2021). On this final point, it is critical to be cognizant that individuals generally do not favor moving to areas with higher resilience, meaning that whether through incentives or greater awareness, policies should aim to encourage relocation specifically to climate resilient areas.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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