Gone with the Flood: Natural Disasters, Selective Migration, and Media Sentiment

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Abstract

This paper investigates the impact of floods on inter-county migration, using the 2006-2019 Integrated Public Use Microdata Series of the American Community Survey. Exploiting variations in flood timing as a quasi-natural experiment, we use a difference-in-differences method to show that floods cause 2.7% and 1.9% increases in outflow and inflow migration, respectively. They trigger younger, better-educated, and employed residents out of, and attract older, less-educated, and unemployed ones into affected counties. Such patterns can be amplified by media sentiment on flood risks. The selective migration induces decreases in housing prices and increases in housing rent, respectively, suggesting a structural change in the housing markets of flood-prone regions. A back-of-envelope calculation shows net annual losses of \$9.3 million and \$1.98 million due to flood-induced selective migration, conditional on education and age profiles, respectively. Our results shed light on how information provision interacts with migration incentives in wake of natural disasters.

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With global climate change, concerns over flood risk have been escalated in the past decade (Dangendorf et al., 2023). Recent studies suggest that flood risk is expected to grow by 26.4% by 2050, causing an estimated annual loss of $32.1 billion in the U.S. (Wing et al., 2022). Coastal areas in the U.S. could see flooding occurrences no less frequently than annually within the turn of this century (Marsooli et al., 2019), with the likelihood of an event capable of producing catastrophic flood doubled (Huang and Swain, 2022). Higher flood risks induced by climate change are especially troubling because flood-prone areas have historically been hotspots for settlements and urban development (Rentschler et al., 2023; Devitt et al., 2023): in the U.S. alone, nearly 42% of the population are living in coastal areas (Fleming et al., 2018). As sea levels continue rising, this puts an increasing number of neighbourhoods at risk of floods and inundation. By the end of this century, 2.5 million properties in the U.S. will be at risk of chronic flooding (Dahl et al., 2018).

Human settlement patterns alter in response to the escalating flood risks (Rigaud et al., 2018), which have a profound influence on local economic development beyond direct damages caused by floods. In fact, more than 650 million people worldwide have been displaced by floods in the past three decades (Kocornik-Mina et al., 2020). In the U.S., larger net migration outflows have been observed in states with higher flood risks in the past two decades. Figure 1a plots the net migration statistics at the state level in the U.S. between 2006 and 2019, while Figure 1b visualizes geographic flood risk. States with higher flood risk in the western and northeastern regions of the U.S. show net outward migration, while lower-risk states see a net inflow in general.

[Insert Figure 1 Here]

Although the impact of floods on human settlements has become increasingly salient, existing research on migration trends has focused on net migration (Bohra-Mishra et al., 2014; Hornbeck and Naidu, 2014; Chen et al., 2017). Mixed findings have been documented, with strong net outflow migration observed in response to some natural disasters (Hornbeck and Naidu, 2014; Chen et al., 2017) but little net outflow migration in other cases (Bohra-Mishra et al., 2014). One plausible reason for the puzzling minimal net outflow migration is that the post-disaster recovery plans introduced by local governments may, paradoxically, attract inward migration to these regions. Also, expected flood risks can lower local housing prices (Bernstein et al., 2019), attracting inward migrants who are more sensitive to housing affordability. Furthermore, some sociodemographic features, such as partisanship (Bernstein et al., 2022), are associated with heterogeneous beliefs in flood risks, resulting in selective residential sorting into flood-prone areas. Therefore, while the threats to human life and economic activities are expected to drive some outward migration from the flooded areas, some inward migration will also be concurrently attracted to these regions. Several recent studies explore the characteristics of *either* inflow *or* outflow migrants after such events and identify differences in migrant profiles (Bakkensen and Ma, 2020; Drabo and Mbaye, 2015; Sheldon and Zhan, 2022). Despite these insights, there remains a gap in understanding net migration by systematically examining outflow and inflow migration conditional on socio-demographics and based in the same affected region, and documenting the potential consequences of selective migration.

We hypothesize that floods will induce selective migration in the affected counties through the mechanism of an income effect. Specifically, higher-income residents are more likely to move out the flooded counties than lower-income residents, because the mobility of the latter is more financially constrained. This hypothesis is supported by the theory in Beine and Parsons (2015), which proposes a utility maximization function to highlight the importance of migration cost in the choice of relocation after climate change. Empirically, Cattaneo and Peri (2016) find that in low-income countries, liquidity constraints explain the low probability of relocation from areas experiencing extreme temperatures. Sheldon and Zhan (2022) document that although hurricanes and floods increase households' propensity to migrate out of their county, low-income households are less likely to move due to budget constraints. Drabo and Mbaye (2015) finds that higher-skilled and higher-educated (thus higher predicted lifetime income) residents are more likely to move out of areas after natural disasters.

Meanwhile, we expect that lower-profile migrants are more likely to move into flooded areas, as lower housing prices in the flooded areas reduce their relocation and living costs. In addition, they may be attracted by potential employment opportunities in affected areas under governments' recovery assistance. Several prior studies support this hypothesis. For example, Smith et al. (2006) document that low-income households surprisingly respond to storms by moving into the low-rent areas that experienced heavy damage. Bakkensen and Ma (2020) find that low-income and minority residents are more likely to sort into high flood risk areas, probably because they are attracted by amenities in the high-risk areas.

Since income in a specific year is subject to transitory shocks, while age, education, and employment status are better predictors for migrants' lifetime income, we separate the migration flows by their age, education, and employment status. In summary, our conceptual framework hypothesizes that due to the income effect, better-educated, employed, and younger residents are more likely to move out of flooded areas, replaced by less-educated, unemployed, and older inflow migrants.

To the best of our knowledge, this study is among the first to delve beyond the surface of net migration, systematically investigating the selective patterns, examining population replacement due to natural disasters, and quantifying the sizes of post-flood inflow and outflow migration across different socioeconomic groups. Such a partition is important because each of these statistics impacts the flooded regions differently. Migrant outflows bleed out human capital and local investment from affected areas, undermining economic development. On the other hand, inflows bring about their own set of problems; demand-pull inflation and sorting effects influence housing prices in receiving counties (Daepp et al., 2023). Assuming the socioeconomic profiles of both migrant groups are similar, immigrants that replace emigrants should mitigate their effects and vice versa. However, if this assumption is breached, the extent of each effect can vary. For instance, if the emigrating residents are more educated than the immigrating ones, the net loss in human capital will adversely affect local economic growth. Also, having older immigrants than emigrants will substantially impact the local fiscal planning for healthcare. Thus, it is crucial that we open this black box of migration and uncover any heterogeneous trends within the different demographics in order to understand both the short- and long-term consequences of flood shocks.

Moreover, the disclosure of climate risk by the media helps to increase awareness among the affected populations and reduce environmental inequality. A rich body of economics literature has documented how the provision of information influences households' decision-making. It is important to understand whether the selective migration patterns will be amplified with improved information transparency on climate risk. Richler (2019) demonstrates that information provision can prompt more risk-aware decisions, nudging consumers towards purchasing flood insurance. Other studies document evidence of information provision causing a price discount for houses in flood-prone zones (Lee, 2022; Niu et al., 2023; Hino and Burke, 2021; Gourevitch et al., 2023). These studies suggest that the supply of climate risk information helps residents better assess their flood risk, prompting movement out of dangerous counties. We hypothesize that due to the income effect, the outflow of residents with lower profiles is less sensitive to climate risk information because their mobility is more financially restricted. At the same time, such information nudges can also work in reverse on inflow migration: although news articles reporting floods increase the awareness of risks residents may face, these articles also frequently report governmental aid programs introduced as a response to floods (Jia et al., 2022), which would prompt inflow migration into affected counties (Kocornik-Mina et al., 2020; Deng et al., 2023). We hypothesize that low-profiles residents outside the flooded counties are more likely attracted by such good news.

Thus, this study investigates two questions. First, we analyze whether floods trigger selective outflow and inflow migration among different socioeconomic groups due to the income effect. Second, we investigate the role of media sentiment in the context of flood-induced selective migration. To answer these questions, we obtain an account of all flood events in the U.S. between 2006 and 2019 from the National Center for Environmental Information and investigate their impact on both immigration and emigration patterns. Our migration data is retrieved from the Integrated Public Use Microdata Series (IPUMS), which reports the anonymized responses from the individuals surveyed in the annual American Community Survey (ACS). Our news dataset is collected from the online database Factiva. Combining the three datasets, we employ a stacked Difference-in-

Differences (DID) strategy to estimate the impact of floods on outflow and inflow migration, and more importantly, on the selective migration, conditional on sociodemographic profiles.

Our results reveal that flood shocks cause both inflow and outflow migration to increase by 1.9% and 2.7%, respectively. More importantly, selective migration patterns are observed across distinct socioeconomic groups: flood events lead to inflows of lower-potential individuals (older, less educated, unemployed) into affected counties, while simultaneously prompting outflows of higher-potential individuals (younger, more educated, employed). We also find evidence that media sentiment of flood risks influences selective migration patterns. Positive news sentiment (e.g., government's post-disaster relief programs) is associated with a decrease in outflows of higher-potential individuals and an increase in inflows of lower-potential individuals into flooded counties. These selective migration patterns induced by floods have salient economic consequences. Taking the local housing market as an example, they result in decreases in housing prices and increases in housing rent over 3 years post-flood, suggesting a structural change in the housing markets of flood-prone regions. Using aggregate income as a proxy for the economic output, our conservative back-of-envelope calculations show that flood-induced selective migration by education and age leads to net annual losses of $9.3 million and $1.98 million, respectively, in the flooded counties.

Our study makes the following contributions: Firstly, we build on the literature documenting disaster-triggered migration by studying how flood events affect the inflow and outflow migration patterns in the U.S. Prior studies have mainly focused on net migration outflows, as the affected regions becoming less attractive residential locations (Bohra-Mishra et al., 2014; Chen et al., 2017; Hornbeck and Naidu, 2014). Nevertheless, a number of heterogeneities may be veiled behind the net migration patterns, depending on the socio-demographics of people who migrate. Different from past studies, we investigate the impacts of flood events on inflow and outflow migration separately. We theorize that in addition to increasing outflow emigrants from flooded regions, disaster relief programs could stimulate economic activities in the affected areas and thus incentivize immigration into these regions (Heger and Neumayer, 2019). We provide empirical evidence that both outflow and inflow migration increase after floods.

Further, we study the selective patterns of flood-induced migration across socioeconomic groups, related to the income effect. Several recent studies suggest that people from different socioeconomic groups make distinct residential location choices as responding to natural disasters (Bakkensen and Ma, 2020; Drabo and Mbaye, 2015; Sheldon and Zhan, 2022). We are among the first to systematically quantify the impact and compare the size of flood-induced outflow and inflow migration across different sub-population groups. We echo literature on the environmental injustice across different socioeconomic groups. Wing et al. (2022) document that flood damage in the U.S. is borne disproportionately by the poor. Lindersson et al. (2023) report an association between income inequality and flood mortality. Our findings on selective migration patterns complement these studies and provide new insights into the channels behind this disparity.

Finally, we add to the active literature studying the impact of information nudges on residential choices (Hino and Burke, 2021; Lee, 2022). Our findings demonstrate how the selective migration patterns across socioeconomic groups can be further amplified by information sentiment, in wake of natural disasters.

Results

Event Study

We estimate the impact of flood events on triggering migration using an event-study strategy from Equation (1) in **Methods**; that is, we investigate the year-by-year changes in migration in flooded counties ("treatment group") relative to the corresponding changes in surrounding non-flooded counties ("control group") over the same period.[1] Figure 2 plots event study results on the differences between the annual migration flows in the treatment and control groups in the $[-3, +3]$ year window around flood event, estimated from two methods—two-way fixed effects (TWFE) and CSDID (details in **Methods**).

[1]To ensure that all sampled flood events have at least one eligible control county that satisfies this requirement, we define the twelve nearest counties without flood events to the treatment counties as the surrounding control counties. We also vary the number of control counties as an alternative control group in our robustness check. Details are presented in the **Methods** Section.

[Insert Figure 2 Here]

Notably, the validity of the DID strategy hinges on the assumption of parallel pre-trends, which state that in the absence of treatment (a flood event), both treatment (flooded counties) and control groups (surrounding non-flooded counties) would have seen migration trends growing at identical rates. Figure 2 reveals that, with either estimation method, the differences between the treatment and control groups for both outflow and inflow migration are not statistically significantly different from zero in the pre-treatment period. Thus, the assumption of parallel pre-trends is likely held in our analysis.

With either method, we consistently observe positive growth in both outward and inward migration in the flooded counties post-treatment, relative to the migration numbers in surrounding non-flooded counties. The by-year increases in outward migration are also slightly larger than the increases in inward migration, but the differences are not statistically significant, implying a small increase in net outflow migration numbers after flood shocks.

Average Treatment Effect

We further quantify the average treatment effects using Equation (2) in **Methods**, and the results are reported in Panel A of Table 1. The coefficient of $Treat \times Post$ is interpreted as the average post-flood change in migration in flooded counties, compared to the scenario if there were no floods. Dependent variables in Columns (1) to (2) are the logarithmic forms of migration outflows and inflows, respectively. We find that three years after flood events, the outflow and inflow migration in flooded counties increase by 2.7% (Column (1)) and 1.9% (Column (2)), respectively. The two estimates are statistically significant at the 1% level. Combining these estimates with the average number of outflow and inflow migrants reported in Appendix Table A1, the estimated annual growth in outflow and inflow migrant numbers per county equals 459 and 317, respectively, after adjusting for the 1% sampling rate in the ACS. Consistent with previous studies (e.g., Bohra-Mishra et al., 2014), it translates to an increase in net outflow migration from flooded counties with a smaller magnitude. The patterns are consistent when the actual numbers of outflow and inflow migration, rather than their logarithmic forms, are used as dependent variables (Columns (3)–(4)). Meanwhile, placebo tests using randomized event years, as reported in Appendix Figure A1, support that the identified impacts on outflow and inflow migration are indeed due to the floods. In summary, these results reveal that flood events cause the number of migrants both out of and into flooded counties to increase.

[Insert Table 1 Here]

We report a battery of robustness check results in Appendix Tables A3 and A4 by including additional controls of post-disaster subsidy, housing price, firm entry and exit, using a winsorized sample, clustering standard errors at various levels, using different specifications of control counties, applying an alternative CSDID method (Callaway and Sant'Anna, 2021), or using median personal income as an alternative measure of income. Estimates in all robustness checks remain stable and statistically significant, with reasonable variations. Our results also survive the synthetic control approach, as reported in Table A5 and Figure A2 in the Appendix. Details of these robustness checks are elaborated in **Methods**.

In Panel B of Table 1, we further investigate the heterogeneous effects in counties with high and low historical flood frequencies accumulated up to 3 years before the flood event, relative to the median level of all U.S. counties (details in **Methods**). We find that the increase in outflow migration is larger in high-frequency than that in low-frequency areas after floods occur. In contrast, the increase in inflow migration is stronger if floods occur in low-frequency areas, compared to high-frequency areas.

Selective Migration

Since floods cause increases in both immigration and emigration, we proceed to investigate the demographics of these immigrant and emigrant populations. To unveil the selective migration patterns, we separate the outflow and inflow of migrants across three dimensions: (1) education, (2) employment, and (3) age. We compare high education (at least college degree holders) versus low education (up to high school diploma), employed versus non-employed (in the original location of residence in one year before the flood events), young (15-40 years old) versus old (40-60 years old).[2]

Figure 3 presents the different migration responses to the flood events between the higher-potential and lower-potential individuals, estimated from Equation (2), and the complete regression results are reported in Appendix Table A6. For each subgroup of migrant population, the point estimates represent the corresponding percent changes in migrant numbers in the flooded counties over the [-3, +3] year window around the year of the flood, relative to surrounding non-flooded counties over the same period. Figure 3a illustrates the selective patterns in emigration: higher-potential individuals in flood-prone counties—more educated, employed, or younger residents—are more likely to move out. After a flood event, the number of outflow migrants in these groups increases by 4.4%, 3.0% and 3.2%, respectively. Although there are flood-induced outflow of less educated, unemployed, and old individuals as well, the magnitudes are much smaller and/or with no statistical significance.

[Insert Figure 3 Here]

In contrast, the patterns are entirely different in the immigration flows to affected counties (Figure 3b). After a flood shock, the number of immigrants who are less educated, unemployed, or older increases by 2.7%, 3.7%, and 4.1%, respectively. However, we do not find statistically significant increases in immigration among the converse socioeconomic groups. These findings imply that, unlike the patterns in outflow migrants, lower-potential individuals are more likely to move into flood-prone counties in spite of recent floods. We find robust patterns when we include additional control variables of government subsidy, housing price, and firm entry/exit (Appendix Table A7), or use the synthetic control method to construct the control group (Appendix Figure A3).

These empirical results demonstrate distinct patterns of selective migration decisions being

[2]We chose 15 years old as the lower bound since the International Labor Organization (ILO) sets the general minimum age for admission to employment at 15 years old.

made across different demographics. Upon a flood event, we see a clear trend of higher-potential individuals moving out of affected counties, while these events attract lower-potential individuals into affected counties. Such patterns emerge as flood shocks cause current residents of affected counties to re-evaluate the risk of their current location, prompting them to emigrate. As higher-potential individuals are more able to relocate due to the income effect (Florida, 2019), we see higher levels of emigrants within these demographics. Conversely, lower-potential people are attracted to flooded regions as they see new opportunities that may arise from these events; as floods shock the local economy, the devaluation of residential property in the area makes these areas more affordable (Borenstein, 2023).

We complete our analyses on selective migration patterns by testing how the net outflow migration patterns vary by different population groups. In addition, we present a back-of-envelope calculation on the overall population changes in outflow, inflow, and net outflow migration, combining our estimates and the demographic information from the IPUMS ACS data. As reported in Appendix Table A8, we find the number of net outflow migration is positive for more educated, employed, and young people and negative for less educated, unemployed, and old people, consistent with selective migration patterns in our main results.

Strengthening Effect of Media Sentiment

Finally, we investigate whether media sentiment influences our observed post-disaster selective migration patterns. Since a rich expanse of literature has documented how information provision alters the climate risk evaluation (Lee, 2022; Niu et al., 2023; Hino and Burke, 2021; Richler, 2019), we hypothesize that different socioeconomic groups will respond to identical flood-related information on news media differently, leading to a strengthening effect on selective migration post floods. This is of great importance in today's landscape, where information on flood risk is becoming increasingly accessible on news media and its influence on general society is massive.

The media sentiment is measured using a machine learning method that extracts the news sentiment from a comprehensive database of newspaper articles published in either physical or digital formats in the U.S. over the study period from 2006 to 2019 (details in **Methods**). During this period under examination, newspapers played the leading source for information distribution. Even in the present day, the pre-eminent choice for the majority of U.S. residents in obtaining news continues to be news websites and publishers, although increasingly more through digital devices.[3] We justify that our newspaper data is capable in capturing the intensity of information dissemination via digital pathways by comparing the weekly number of news articles in our data with the Google search index for the keyword "flood" in the U.S. (Appendix Figure A4), where we see a clear co-movement, especially at the peak time.

In order to establish a causal inference of news sentiment on migration, we interact this variable with our initial DID setting to conduct a triple-difference analysis. To rule out potential confounders that may bias our analysis, several additional controls are included in this regression, including flood-related subsidies, housing price, firm entries and exists at the county level, because these variables are also likely to impact migration patterns. Specifically, subsidies entice potential immigrants/existing residents as it provides monetary incentive to stay within these counties. Also, the housing market may fluctuate post-disaster, and cheaper housing prices may motivate immigration into the county. Furthermore, firm entries result in job creation, thus promoting movement into these regions, and vice versa for firm exits. Last, the flood event fixed effects are included in the regression models to capture the severity of and damage caused by individual floods, which can correlate with the news sentiment.

Table 2 reports the estimated impacts of news sentiment on inflow and outflow migration after floods. The coefficient of interest here is $Treat \times Post \times Score$, which represents the impact of news sentiment on the percent changes in migrant numbers in the flooded counties. We see that "good news" (e.g., post-disaster recovery plan) triggers a decrease in emigration out of flooded counties for the high-educated and employed individuals: the numbers of emigrants in these demographics are lowered respectively by 2.8% and 1.6% with a one-standard-deviation increase in news sentiment. These patterns are mirrored for the young, which also see a 1.8% decrease in

[3]See: https://www.pewresearch.org/journalism/fact-sheet/news-platform-fact-sheet/.

emigration. All three estimates are statistically significant at the 1% level. Conversely, we see an inverse trend for inflow migration, where positive news sentiment attracts low-educated and unemployed individuals into the flooded counties. We see a one-standard-deviation increase in news sentiment is associated with a 1.6%, 2.4%, and 1.6% increase in low-educated, unemployed and old immigrants, respectively, with statistical significance at conventional levels.[4] Our results remain robust if using 1-year lagged variables of government subsidy, housing price, and firm entry/exit as control variables, or if we exclude these control variables in the regressions, as reported in Appendix Tables A10 and A11, respectively.

[Insert Table 2 Here]

Notably, the difference of coefficients $Treat \times Post$ between high- and low-profile groups in Table 2 captures the income effect on selective migration when the standardized sentiment score is at the average level (i.e., zero). For example, using education as a proxy for lifetime income, we find that when the media sentiment is at the average level, the flood-induced outflow of high- and low-educated migrants increase by 3.6% and 1.3%, respectively (coefficients of $Treat \times Post$ in Columns (2) and (3) of Panel A). The difference between the two estimates is statistically significant at the 1% level, implying the existence of a strong income effect when the media sentiment score is at the mean. If the media sentiment score increases by 1 standard deviation, the net effects (sum of the coefficients of $Treat \times Post \times Sentiment$ and $Treat \times Post$) on the high- and low-educated outflow migrants reduce to 0.8% and 0.1%, respectively, and the difference between the two estimates is not statistically significant. This indicates that positive media sentiment (e.g., "good news" on post-disaster recovery plans) can largely offset the selective outflow migration conditional on education. In reverse, negative news sentiment aggravates the selective outflow

[4]One example of "good" news comes from an article published by USA Today in September 2017, which reported that *"The House passed a $7.9 billion aid package Wednesday for victims of Hurricane Harvey, and the Senate is expected to attach a debt-limit extension to that bill...McConnell said that he would be supportive of the plan and intended to offer it as an amendment to the flood relief bill that passed the House on Wednesday"*. An example of "bad" news is an article published by The New York Times in September 2006, which reported: *"The early estimates suggested insured property damage around $5 billion or less from Hurricane Rita, not including the effects of flooding and the impact on offshore oil rigs, which are excluded in most of the calculations. The storm struck less heavily populated areas, with less force than Hurricane Katrina, mostly bypassing Galveston, Tex., and Houston, where damage up to $30 billion had been feared"*.

migration conditional on education. For inflow migration, the selective patterns conditional on education is offset by negative and aggravated by positive media sentiment. Similar patterns are observed when we use different classifications of migrants according to employment status or age. In summary, these results indicate that media sentiment significantly influences the selective migration patterns induced by the income effect.

Discussion

So far we have provided the first set of empirical evidence detailing the effects of floods on selective migration across different sociodemographic groups within the U.S. from 2006 to 2019. Higher potential individuals are more likely to leave flooded areas, while lower potential individuals are unexpectedly attracted to move into the flooded areas, plausibly due to better housing affordability and post-disaster recovery subsidies from governments. Such patterns give rise to a replacement effect in the local population. Moreover, we find that the selective migration patterns are further amplified by the media sentiment because higher- and lower-potential individuals are likely to respond to bad and good news about flood events differently. This trend is potentially a cause for concern in affected counties, as it has both short-term and long-term implications for the local economy. In the short term, local markets may see demand shocks as recent emigrants/immigrants may have different priorities and thus make different decisions. In the long term, the growth of the local economy may be hindered as more-abled workers migrate out.

Shorter-term Effect We first use the local housing market dynamics up to 3 years after floods as an indicator of the local economic consequences of selective migration in the short term (Baerlocher et al., 2023). The housing market reflects the immediate decisions made by migrants in treatment and surrounding control counties after a flood event, as moving into a new region requires them to find new housing arrangements. Using monthly housing price index and rent data from Zillow, we adopt the same DID empirical design to investigate the impacts of flood events on housing price and rent. Since the housing rent data from Zillow is available from 2015 onward, we use the monthly observations of housing price and rent from 2015 to 2019 for the analysis,[5] and the results are reported in Table 3. A flood event results in a decrease in monthly housing price growth rates in flooded counties by 0.053 percentage points, equivalent to a 1.9% decrease in housing prices over the 3-year period. However, the monthly housing rent growth rates in the flooded counties increase by 0.074 percentage points post-flood, translating to a 2.7% increase in housing rent over the 3-year period. These figures are significant at the 95% confidence interval.

[Insert Table 3 Here]

These patterns observed in the housing market are plausibly due to selective migration that arises from flood shocks. As higher-potential residents move out and lower-potential residents move in, the resulting population sees a shift in priorities: lower-potential immigrants with less wealth seek to rent housing, while the higher-potential emigrants seek to sell their recently deserted properties. This causes an increase in the supply of property sold, while an increase in the demand for rental properties. This coordination issue among the new emigrants and immigrants likely causes housing prices to fall and rental prices to increase. These fluctuations in the housing market demonstrate the striking short-term economic consequences of selective migration in affected counties.

Longer-term Effect These structural changes in the housing markets have further implications in the long term. As flood-prone counties cater to increasing renters, it gives rise to a moral hazard whereby homeowners are unwilling to renovate their homes in order to maintain low renting fees. This is especially concerning as many residential buildings in the U.S. are not built to handle climate change, and would leave the rental population more vulnerable to the elements (Sisson, 2023). This may exacerbate the already present environmental injustice borne across the rich and poor (Wing et al., 2022; Lindersson et al., 2023).

Apart from housing markets, flood-induced selective migration also has salient impacts on the local labor markets. As flood events trigger movements of higher-educated individuals out of

[5]The housing price data is available in our entire study period from 2006 to 2019, and the results are consistent using the full sample of housing price.

and lower-educated ones into flood-prone counties, the resulting brain drain also has adverse effects on local economic growth. We use the aggregate changes in individual income as a proxy for GDP and conduct a back-of-envelope estimation of the long-term impacts (Appendix Tables A13). Our regression results in Figure 3 reveal that flood events result in an increase in high-educated outflow migrants by 4.4% and low-educated outflow migrants by 1.7%, for a typical county with at least 65,000 residents. After adjustment for the 1% sampling rate in the ACS, these translate to 274 high-educated and 181 low-educated emigrants per year. Further multiplying these numbers by the average income of the high- and low-education groups, we estimate a total annual loss of $14.2 million from high-educated emigrants and $2.9 million from low-educated emigrants for a typical flood-affected county.

In contrast, we estimate a total annual gain of $3.2 million for high-educated immigrants and $4.5 million for low-educated immigrants per county after the flood events. Therefore, the total annual net loss due to selective migration by education levels is estimated to be around $9.3 million per county. In a worse scenario (i.e., consider the upper bound of 95% CI for the changes in outflow migration and the lower bound of 95% CI for the changes in inflow migration), the net annual loss can be as large as $25.9 million.

Similarly, we estimate the net loss due to flood-induced selective migration by age (Appendix Table A14). A higher outflow of young people and an increased inflow of old people result in a net annual loss of over $1.98 million, after factoring the 1% sampling rate in the ACS. This reduction in output has far-reaching consequences on economic growth as well, thus demonstrating another dimension of damage that these selective migration patterns can cause over a longer term.[6]

Due to global warming and climate change, the number of flood-prone areas is expected to rise over the next century. Migration out of zones at risk is one efficient, if not the best, solution to such threats (Fagan, 2008). Our results shed light on how natural disasters influence selective migration conditional on socioeconomic profiles. The back-of-envelope calculation indicates a net annual loss of $1.98 million or $9.3 million for a typical county with more than 65,000 residents,

[6]We skip the back-of-envelope analysis for selective migration by employment status, because of lack of income information for unemployed migrants.

conditional on age or education profiles. It thus calls for government interventions, such as fiscal policies, in the affected areas to retain the higher-profile individuals. On the other hand, as the vulnerable population (i.e., lower-educated, unemployed, and older) are more inclined to move into the affected regions post floods, welfare policies are needed to protect those population segments from environmental injustice.

As info-communication technology continues to develop, information relevant to floods and other natural disasters will become increasingly available to the public. Our findings show that the media sentiment can significantly influence the impact of floods on selective migration. In other words, how the news outlets portray the flood events can have various impacts on different sub-population groups. Considering the potential impacts of inaccuracy or biased information, we thus advocate for policies that improve transparency and coverage of floods and other natural disasters in news media.

This study has caveats. First, it is possible that the flood-induced outflow or inflow migration is temporary.[7] Unfortunately, the ACS is not a panel survey and does not trace the movement of the same individuals over multiple years (i.e., we only know where the survey respondents lived one year ago); we thus cannot examine whether migrants' relocations are permanent or temporary with current data limitation. Second, the annual ACS data are publicly available only for counties with at least 65,000 residents. Migration patterns for smaller counties, though generally facing lower flood risks, remain unclear. Future studies are warranted when public data become available that track annual individual migration over multiple years, particularly for counties with population less than 65,000 residents. Third, we extract *time-series* media sentiment from news articles, while recent studies point out that social media can also affect responses to flood risks (Cheng, 2024; Hu, 2022). Although *time-series* flood sentiment indices from social media are not publicly available, we provide suggestive evidence that social media connectedness can influence flood-induced migration at the county level (Appendix Table A15), using the *cross-sectional* Facebook data from Hu (2022). Future research on social media sentiment regarding floods in a time series

[7]Outflow migrants who move out of flooded areas may return at later time because of family ties or business purposes, and inflow migrants may leave after taking advantage of the benefits of relief programs.

would be valuable.

Methods

Data

Migration We retrieve individual-level migration data in 2006-2019 from the Integrated Public Use Microdata Series (IPUMS), which reports the anonymized responses from the individuals surveyed in the annual American Community Survey (ACS). The ACS is an ongoing nationally representative survey conducted over a 12-month period among U.S. counties, with the annual data available for counties with at least 65,000 residents. Using data from the U.S. Census Bureau, we tabulate that the population in counties covered by the annual ACS are around 84.2% of the total U.S. population during our study period.[8] Combining our data with the county-level flood risk scores from the Federal Emergency Management Agency (FEMA), we confirm that our data covers a majority of the counties that are prone to high flood risks.[9]

The ACS collects individuals' information on economic characteristics (employment status, occupation, income, etc.), housing characteristics (facility, tenure, house structure, etc.), demographic characteristics (age, sex, race, etc.) and social characteristics (educational attainment, marital status, migration, previous and current residence). Since the original ACS data from the U.S. Census Bureau rotates the tabulations on certain sociodemographic features over different periods, we use the IPUMS ACS data instead, which effectively addresses this issue by harmonizing sociodemographic variables across different years.[10]

[8] At the beginning of our sample period (i.e., in 2006), the total population in counties covered by the annual ACS survey were 248 million, equal to 83.1% of the total population in the U.S. at that time (298 million). Similarly, in the ending year (2019) of our study period, the annual ACS covered 2.81 million, or 85.2% of the total 330 million population in the U.S. The average coverage rate across all years in our study period equals 84.2%. The data bias from the exclusion of small counties with less than 65,000 people in the IPUMS ACS data, if any, is considered immaterial to impact the robustness of our findings.

[9] The county-level flood risk score from the FEMA is scaled to a range between 0 and 100, and has a mean of 50. The counties covered by our annual ACS data have an average flood risk score of 76, while the small counties not reported in the annual ACS data only have an average flood risk score of 45.

[10] See the details of harmonized variables in the IPUMS ACS data: https://usa.ipums.org/usa-action/variables/group.

Although the IPUMS ACS is not a panel dataset that tracks the same individuals over years, we can measure the cross-county migration flows at the aggregate county-year level. Specifically, the migration section in the IPUMS dataset includes information on whether the survey respondents had changed residence since the previous year. Respondents who live in the "*same house*" as in the previous year are categorized as non-movers, while those who lived in a "*different house*" are categorized as movers. Further, the IPUMS ACS data track the county that the respondent currently lives in and the county that the respondent lived in the previous year, respectively. Based on this information, we can identify the survey respondents who have moved to a different county since the previous year. Finally, the number of inward immigrants to a receiving county is measured as the sum of cross-county movers who now live in that county. The number of outward emigrants for a county is measured as the sum of cross-county movers who lived in that county one year ago.

In the heterogeneity analysis, we further measure the migration flows by subgroups of different socio-demographic status. The ACS survey provides information on respondent's age, education level, and employment status in the previous year. Thus, we can calculate the total number of outflow (or inflow) migrants in each socio-demographic subgroup at the county-year level. Appendix Table A1 reports the summary statistics for our migration data.

Notably, past literature has documented that when conducting analysis of minority sociodemographic subgroups in small geographic areas (i.e., at the *census tract* or *block* level), the measurement errors in the ACS could be large due to inadequate sample sizes (MacDonald, 2006; Napierala and Denton, 2017; Spielman et al., 2014). Recent literature endeavours to overcome this data limitation by conducting the analysis at the county level, which results in larger sample sizes of survey respondents and helps to reduce the measurement errors (Currie and Schwandt, 2016; Sheldon and Zhan, 2022). Thus, we follow this strand of literature to conduct our analysis at the county level. As the annual ACS covers counties with at least 65,000 residents, the concern for small sample sizes at the county level is further alleviated.

Flood Data We rely on the data from the National Center for Environmental Information to identify counties with a history of flooding across the United States. The dataset includes the location (states, counties and zones) of 48 different types of natural disaster events and detailed information on the events, which includes the start time, end time, number of injured victims, damages to property and cause of disaster, from January 1950 to October 2022. We obtain information from 2,218 flood events between 2006-2019 in 360 counties.

Media Sentiment To obtain our database of flood-related news articles, we accessed the online database Factiva, which is a world-leading business intelligence platform that covers over 33,000 global sources.[11] It covers news content encompassing both digital and print formats, which is consistent with the trends nowadays that more Americans get news with digital pathways. Compared with other data sources like social media, we consider news articles, which are from institutional sources, may capture more accurate information on flood severity and post-disaster recovery assistance, and they are less likely subject to the bias from radical social media users according to the spiral of silence theory (Vilone and Polizzi, 2024).

We obtained all news articles from the 5 most subscribed national newspapers (Wall Street Journal, New York Times, USA Today, Washington Post, and Los Angeles Times) that included keywords of "flood damage", "flood recovery", "flood relief", "flood subsidy(ies)", "disaster funds" & "flood". We cleaned our article dataset, expanding contractions and removing stopwords and special characters from each text. We then proceeded to run a sentiment analysis through the cleaned articles to obtain sentiment scores for each article, using the natural language processing package TextBlob.[12] Following this, we standardized the scores of each article, transforming them such that the mean and variance of sentiment scores are 0 and 1 respectively. We constructed the "state" dimension by identifying articles that mention any U.S. state(s) and extracting the state name. In order to capture the strongest shocks from the news articles each year of the state, our measure of media awareness is the minimum sentiment score (i.e., the strongest negative sentiment) of articles at the year-state level. We then winsorize the top and bottom 1% outliers of the sentiment score in our regression analysis.

[11] See: https://www.dowjones.com/professional/factiva/
[12] See: https://textblob.readthedocs.io/en/dev/.

Housing Price The housing price data we use in this study is obtained from Zillow, a real estate data vendor that estimates home values in approximately 8,000 neighborhoods in metropolitan areas across the United States. Specifically, we use the Zillow Home Value Index (ZHVI) for all property types at the county level, which is a smoothed, seasonally adjusted measure of the typical home value (i.e., homes in the 35th to 65th percentile range) in a given region, including newly constructed homes and/or homes that have not traded on the open market.

The housing rent data is also obtained from Zillow. Specifically, we use the Zillow Observed Rent Index (ZORI), a smoothed measure of the observed monthly market rent of typical homes (listed rents that fall into the 40th to 60th percentile range for all homes and apartments) in a given region. The ZORI has been adjusted using a repeat-rent method, which is weighted to the rental housing stock, so it is representative across the entire market, not just those homes currently listed for-rent. Both the housing price and rent data were collected at the county and month level. We match our flood event data with the Zillow housing price data between 2006 and 2019, while the rent data is available between 2015 and 2019 only.

Other Control Variables We include the following macroeconomic control variables at the county-year level: GDP, population size, unemployment rate, and per capita income, which are obtained from the U.S. Bureau of Economic Analysis (BEA). Specifically, the per capita income is calculated by dividing the total personal income of a county by its population in a specific year, while the total personal income includes the income from wages, proprietors' income, dividends, interest, rents, and government benefits. We then remove the top and bottom 1% outliers of these variables in our regression analysis. The public firm entry and exit data are obtained from the Augmented 10-X Header Database, which collects the headquarter addresses from the annual financial reports of all public firms listed in the three stock exchanges in the U.S. The information on government subsidies provided for post-flood economic recoveries is collected from the OpenFEMA Dataset, an administrative data provided by the U.S. Department of Homeland Security. The number of new housing units is collected from the U.S. Building Permits Survey.

Strategy

Event Study Analysis We conduct an event study analysis to check the trends between treatment and control groups prior to treatment. To have a clean identification, we require that a treated county, which has flood events in year *t*, does not experience floods in any other years in the [*t*-3, *t* +3] year window. In other words, our sample does not include counties that experience cumulative floods in the previous and subsequent 3 years. Nevertheless, it is possible that a treated county in our sample experiences multiple floods in a specific year *t*, and we consider these multiple floods in the same county and year as one treatment event. To construct the control group, we keep only the surrounding counties that do not have floods in the [-3, +3] year window as the control counties. With these restrictions on the treatment and control groups, we alleviate the concern that flood events can be geographically autocorrelated within a certain period.

We identify the control group from surrounding counties, regardless of the geographic shapes of the boundaries; the control counties are not necessarily to be adjacent. Specifically, we first sort counties based on their distances to the treatment county. For adjacent counties, we consider the distance to be zero, and for non-adjacent counties, we use the distances between centroids. Then, we identify the counties with the nearest *n* surrounding ones that do not experience floods in the [-3, +3] year as the control group. To ensure that all sampled flood events have at least one eligible control county that satisfies this requirement, our main sample ends up using surrounding counties that are within the twelve nearest counties as the control group (n = 12). Then, we merge the annual migration numbers in the treatment and control counties of each flood event around the [-3, +3] year window as the regression sample.

The event study model is specified as Equation (1) below:

$$\begin{aligned} Y_{i,t} = {} & \alpha_1 Treat_{i,j,t} + \sum_{p=2,3} \beta_p Pre^p_{i,j,t} + \sum_{q=1}^{3} \beta_q Post^q_{i,j,t} + \sum_{p=2,3} \delta_p Treat_{i,j,t} \times Pre^p_{i,j,t} \\ & + \sum_{q=1}^{3} \delta_q Treat_{i,j,t} \times Post^q_{i,j,t} + X'_{i,t}\lambda_X + \omega_i + \theta_t + \mu_{s,t} + \rho_j + \epsilon_{i,j,t}. \end{aligned} \tag{1}$$

Specifically, $Y_{i,t}$ is the outcome variable of interest for county i in year t, such as the total number of outflow migrants (in logarithmic form). $Treat_{i,j,t}$ is a dummy variable equal to 1 for county-year observations in the treatment group of flood event j. It equals 0 for the matched county-year observations in the control group. We use a set of dummy variables denoting each year in the [-3, -2] years window before the treatment ($\sum_{p=2,3} Pre^{p}_{i,j,t}$) and the [+1, +3] years window after the treatment ($\sum_{q=1}^{3} Post^{q}_{i,j,t}$). Using 1 year before treatment time t as the base group, we estimate the differences between the migration flows in the treatment and control groups in each year in the $[t-3, t+3]$ window, represented by the coefficients of the interaction terms (δ_p and δ_q). If the assumption of parallel pre-trends holds, we should expect that differences between the migration flows in the treatment and control group are not statistically different from zero in the pre-treatment period (δ_p), while the difference turns positive post-treatment (δ_q).

$X_{i,t}$ is a set of macroeconomic control variables at the county-year level, including GDP (in logarithmic form), unemployment rate, population size (in logarithmic form) and average income per capita (in logarithmic form). ω_i denotes the county fixed effects, which capture the time-invariant unobserved features of the county, such as its size or length of boundary. θ_t represents the year fixed effects, which capture the impacts of time-variant confounding events at the national level, such as the global financial crisis. It is also possible that counties in the treatment and control groups are from different states. Our empirical model accounts for this difference by controlling for the granular state times year fixed effects: $\mu_{s,t}$ represents the state times year fixed effects for state s that county i belongs to, which captures the time-variating confounding factors at the state level, such as state government subsidies. We also include the flood event fixed effects (ρ_j), which control for the potential unobserved variations in treatment sizes (i.e., the severity of either one single flood or multiple floods in the same year). $\epsilon_{i,j,t}$ is the error term. We cluster the standard errors at the flood event level.

Notably, the flood events shocked the treated counties in a staggered fashion. Recent literature has highlighted potential bias in traditional staggered DID estimates, with several alternative methods being proposed to address the issue (Baker et al., 2022; Sun and Abraham, 2021; Marcus and Sant'Anna, 2021).[13] Our baseline model and the event study model are close to one of these alternative methods—the stacked DID design with two-way fixed effects (TWFE), which creates event-specific data sets that are then stacked together (Cengiz et al., 2019). The difference here is that a standard stacked DID design requires the control group to be never treated, while we relax this requirement due to the lack of counties that are never flooded; instead, we select surrounding counties that have no floods in the [-3, +3] window as the control group. Stacked DID pools together the average treatment effect (ATT) on the treated estimates from good pairs, thus mitigating bias introduced by a standard staggered DID estimation. Additionally, it applies Ordinary Least Squares (OLS) to determine weights for combining treatment effects across cohorts, ensuring the efficiency of estimates (Baker et al., 2022). The corresponding event-study result is presented in Figure 2a.

To further alleviate the concern for the staggered treatment issue, we also implement an alternative method—the Callaway and Sant'Anna DID strategy (CSDID)—as a robustness check (Callaway and Sant'Anna, 2021). This method estimates all possible good comparisons for the estimation and then aggregates them by putting more weight on larger and more precise estimators. The corresponding event-study result is presented in Figure 2b. Moreover, we conduct Honest DID to assess the sensitivity to violations of parallel trends in a CSDID model (Rambachan and Roth, 2023).

In summary, we identify the surrounding counties as control group, assuming if there were no flood events, surrounding counties would experience similar migration trends after controlling for other covariates, such as macroeconomic factors at the county-year level, county fixed effects, year fixed effects, and state times year fixed effects. This assumption is verified by the flat pre-tends plotted in Figure 2.

Average Treatment Effect We estimate the average treatment effect by employing a DID

[13]The bias mainly originates from the variations in treatment timing and heterogeneous treatment effects. The parameter in the standard DID estimates the average difference by comparing the same unit across time, as well as by comparing different units with and without treatment at the same point in time. If the treatment effects are heterogeneous and the timing of the treatment varies across units, comparing later treated units with earlier treated units (control units) can be problematic (bad comparison). As control observations were already treated, the standard DID model would assign negative weights to these units.

strategy, using the same sample in the event study analysis. Intuitively, this empirical design seeks to estimate the causal impact of flood events on migration by comparing the migration trends in control and treatment groups before and after treatment. As explained in the event study analysis, the treatment group consists of counties where flood events occurred, and the control group consists of surrounding counties to treatment counties.

The baseline DID regression model is specified as follows:

$$Y_{i,t} = \beta_1 Treat_{i,j,t} + \beta_2 Post_{i,j,t} + \beta_3 Treat_{i,j,t} \times Post_{i,j,t} + X'_{i,t}\lambda_X + \omega_i + \theta_t + \mu_{s,t} + \rho_j + \epsilon_{i,j,t}. \tag{2}$$

For the county-year observations in both the treatment and control groups of flood event j, the dummy variable $Post_{i,j,t}$ equals 1 if year t is after the occurrence of flood j. Otherwise, it equals zero. Therefore, the coefficient of the interaction term $Treat_{i,j,t} \times Post_{i,j,t}$ represents the average impact of floods on migration flow in the affected counties. Other variables have the same definitions as in Equation (1). Standard errors are clustered at the flood event level.

To verify our results, we conduct a placebo test, following Bakkensen et al. (2019). Specifically, for each flood event in a county, we randomly assign the event year and consider these assigned county-year observations as the placebo treatment group. Then, we adopt the same methodology in our main analysis to construct the regression sample, selecting neighbouring counties without the placebo flood events within a [-3, +3] year window as the control group. Last, we estimate the coefficient of $Treat \times Post$ with this placebo regression sample. We repeat this process 1,000 times and plot the distribution of the estimates, as well as their p-values, in Appendix Figure A1. For both inflow and outflow migration, the mean of the placebo coefficients is close to zero, as indicated by the vertical dashed line. Also, most p -values (as shown in the Y-axis) are larger than 5% (i.e., above the horizontal dashed line), indicating that most of the placebo DID estimates are not statistically significant. These results imply that when we randomly select the flood starting year, the placebo events do not show any effects on migration outcomes. In other words, the identified impacts on outflow and inflow migration are indeed due to the flood events.

We reinforce our causal inference by conducting a battery of robustness checks. In Columns

(1) of Panels A and B in Appendix Table A3, we include additional controls for post-disaster recovery subsidies, housing prices, and public firm entry/exit in the outflow and inflow regressions, respectively. To check whether our results are driven by extreme cases in our sample, Column (2) uses a winsorized sample, removing the observations with the top 1% of the outflow or inflow migration. Column (3) clusters standard errors at the county level. To assess the sensitivity of our results to control groups, we use the 20 nearest counties without flood events to the treatment counties as the alternative control group in Column (4).

Another potential concern in our results is that nearby counties to a flooded county are also likely to experience floods. Although we have alleviated this concern in our main analysis by only including surrounding counties that do not experience floods in the [-3, +3] year window as the control group, residents in the control counties may still perceive a higher risk of floods after their neighbouring counties are flooded and thus change their residential locations. To further alleviate this potential issue of spatial spillovers, we conduct a robustness check that removes control counties that are adjacent or very close (i.e., within 50 km) to the treated counties. We report the corresponding results in Column (5) of of Panels A and B in Appendix Table A3.

In addition, to alleviate the concern for potential model specification issues with the staggered DID method (Baker et al., 2022; Sun and Abraham, 2021; Marcus and Sant'Anna, 2021), we use the CSDID method by Callaway and Sant'Anna (2021) to calculate the average treatment effect. Columns (6) of Panels A and B in Table A3 report the corresponding results. For all these additional tests, we find the results remain robust in both the magnitudes and the statistical significance.

Moreover, we use median personal income, rather than per capita income, as the control variable to exclude potential impact from extreme values and check the robustness of our results. The information on median personal income is collected from the BEA. The corresponding results are reported in Appendix Table A4. Our estimates remain consistent.

Last, we conduct a robustness check using the synthetic control approach. Specifically, we construct a synthetic control county for each of the flooded county, following the method in

Arkhangelsky et al. (2021). For each treatment event in year t in our sample, we identify all other counties that do not have floods in the [-3, +3] year window and use them to form a synthetic control. The matching is based on outcome variables (e.g., outflow or inflow migration) in the pre-treatment period and the macroeconomic control variables (unemployment rate, population, income per capita, and GDP). We pool all treated counties, together with their one-to-one matched synthetic control counties, as the regression sample and estimate the treatment effect following our stacked DID model. We include the county fixed effect, considering each synthetic control as a separate county. The state-year fixed effects are omitted in this model, since a synthetic control may constitute counties from different states. Other fixed effects (i.e., year and flood event) and macroeconomic control variables are the same as in our baseline models. Table A5 and Figure A2 in the Appendix present the average treatment effect and the event-study result using the synthetic control approach, respectively. These estimates are similar to the ones in the baseline analyses, showing the robustness of our results.

Details of our heterogeneous analysis across counties with high and low flood frequencies are as follows: Since our baseline DID model requires that a treated county, which has flood events in year t, do not experience floods in any other years in the [t-3, t+3] year window, we exploit the ex-ante flood frequency before t-3. Specifically, we calculate the cumulative flood frequency in the county before year t-3 and compare it with the corresponding flood frequencies in other counties. If the cumulative flood frequency of the county is higher than the median of all counties, we define it as a high-frequency area. Otherwise, it is a county with low flood frequency. Then, we estimate the average treatment effects using subsamples of floods in high-frequency and low-frequency areas, respectively. We report the corresponding estimation results in Panel B of Table 1.

Selective Migration Our heterogeneous analysis across the different demographics also uses Equation (2), imposing the relevant restrictions on the outcome variable $Y_{i,t}$. For example, in the analysis of outward migration of young residents, we use the number of young migrants, rather than the total number of migrants, as the outcome variable. The control variables and fixed effects remain the same as in Equation (2). The corresponding results are visualized in Figure 3 and are fully reported in Appendix Table A6.

We conduct several robustness checks for the selective migration patterns. First, confounding factors like post-disaster government assistance, housing price, and firm entry/exit may impact the selective migration patterns. For example, less educated or low-income residents may have fewer job opportunities somewhere else, and they may rely on public assistance and affordable housing, especially after severe flood events. To disentangle the confounding factors, we conduct a robustness check by replicating the analyses on selective migration but with additional control variables on post-disaster government assistance, housing price, and firm entry/exit. The results are reported in Appendix Table A7, and the estimates are consistent with our main results.

In addition, we check the robustness of the selective migration patterns using the synthetic control approach. The construction of the synthetic samples is the same as in our analysis of the average treatment effect in **Methods**. The results are presented in Appendix Figure A3. We find the same patterns as in our main results: The more educated, employed, or younger residents move out of the flooded counties, while their counterparts (i.e., the less educated, unemployed, and older residents) are attracted into the flooded counties. In summary, our findings remain robust using the synthetic control approach.

To test how the net outflow migration patterns vary by different population groups, we first replicate the analyses using the difference between outflow and inflow migration (in logarithmic form) as the dependent variable. The corresponding results are presented in Panel A of Appendix Table A8. Further, we present a calculation of the overall population changes in outflow, inflow, and net outflow migration, combining our estimates and the demographic information from the general population. As reported in Panel B, we estimate the changes in migrant numbers in each sociodemographic group using the point estimate of percentage change retrieved from Appendix Table A6 times the average migration number in that sub-population group obtained from our IPUMS ACS regression sample (Appendix Table A1). The change in the net outflow migrant number equals the change in the outflow migrant number minus the change in the inflow migrant number in the group. The patterns are consistent with our main results: high-potential people move out of and low-potential people enter the flooded areas.

Media Sentiment To study the effect of media awareness on migration choice, we ran a triple-difference identification strategy using the following model:

$$\begin{aligned} Y_{i,t+1} = {} & \beta_1 Treat_{i,j,t} + \beta_2 Post_{i,j,t} + \beta_3 Treat_{i,j,t} \times Post_{i,j,t} + \beta_4 Score_{i,t} + \beta_5 Score_{i,t} \times Treat_{i,j,t} \\ & + \beta_6 Score_{i,t} \times Post_{i,j,t} + \beta_7 Score_{i,t} \times Treat_{i,j,t} \times Post_{i,j,t} + X'_{i,t}\lambda_X + \omega_i + \theta_t + \mu_{s,t} + \rho_j + \epsilon_{i,j,t}. \end{aligned} \tag{3}$$

This model is similar to the baseline Equation (2), but with key differences in the additional full interactions between the news sentiment ($Score_{i,t}$) and the dummy variables $Treat_{i,j,t}$ and $Post_{i,j,t}$. Thus, the coefficient of the triple interaction term (β_7) is the variable of our interest, which represents the differential treatment effect on the outcome variable in the post-treatment period resulting from the sentiment in news reports. Other control variables and fixed effects remain unchanged as in Equation (2). In particular, with the control of flood event fixed effects that captures the treatment intensity (i.e., severity) of each specific flood event, our specification identifies the variations in migration flow driven by additional information nudges beyond the severity of an individual environmental disaster.

To verify that our newspaper data is capable in capturing the information dissemination via digital pathways like search engines, we correlate our newspaper data with the Google search index for the keyword “flood” in the U.S.[14] We find that the weekly number of news articles in our data has a clear co-movement and positive correlation with the Google search index of floods in the U.S. during our sample period, especially at the peak time (Appendix Figure A4). It further lends support for using our news article data in capturing the information channel.

We also conduct a robustness check for the impact of media sentiment on selective migration. In our main result, we include additional controls, such as housing prices, flood-related subsidies at the county-year level, and the annual number of public firms entering and leaving each county, to shut off possible alternative channels. Nevertheless, these control variables, such as housing prices

[14]See: https://trends.google.com/trends/

in the current period, can be endogenous, as they could be reversely influenced by the number of migrants. To address this issue, we alternatively use the 1-year lagged housing price, as well as post-disaster subsidies and firm entry/exit, in the regressions. Reverse causality between housing prices and migration flows can be well mitigated under this method. We report the corresponding results in Appendix Table A10. Note that the sample size under this practice is smaller than the one used in the baseline analysis, due to missing values in some lagged variables. Our estimates remain robust, in both economic magnitude and statistical significance.

In addition, we caution that the coefficients of channels should be considered as rough estimates, as the channels could be potentially correlated. As a robustness check, we remove these additional controls in the regression and report the results in Appendix Table A11. Again, our results survive the robustness check.

Social Media Finally, as an additional test, we use the *cross-sectional* measurements of connectedness between U.S. counties on Facebook from Hu (2022) to investigate the impacts of social media on flood-induced migration. Specifically, the social connectedness between two counties represents the relative probability that users from these two counties are friends on Facebook. We consider that county j is highly connected with county i if the social connectedness score between i and j is higher than the median of all pairwise scores between the U.S. counties. Otherwise, j is considered as a low-connectedness county with i. For a given county i, we classify its outflow outflow migration into two categories: moving *to* high- vs. low-connectedness counties. The same classification applies to the inflow migration, as *from* the high- vs. low-connectedness counties. We hypothesize that due to the information dissemination on social media, cross-county migration after floods is more likely to happen between counties that are highly connected on social media.

To test this hypothesis, we replicate our heterogeneity analysis across sub-population groups with Equation (2), using the outflow (or inflow) migration from high- and low-connectedness counties as the outcome variables separately. We report the corresponding results in Appendix Table A15. Aligned with our hypothesis, we find that the increases in both outflow and inflow migration after floods are larger between highly connected counties on social media, compared to counties with low connectedness.

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Table 1: Impact of Floods on Migration

Panel A. Baseline Results

	(1) log(Outflow)	(2) log(Inflow)	(3) Outflow	(4) Inflow
Treat × Post	0.027***	0.019***	7.766***	3.552***
	(0.005)	(0.007)	(1.106)	(1.281)
Macroeconomic Controls	Yes	Yes	Yes	Yes
Flood Event Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405
R-squared	0.98	0.97	0.99	0.98
Mean Dependent Variable	4.83	4.80	169.85	167.09

Panel B. Heterogeneity by Cumulative Flood Frequency

	(1) High frequency log(Outflow)	(2) Low frequency log(Outflow)	(3) High frequency log(Inflow)	(4) Low frequency log(Inflow)
Treat × Post	0.031**	0.005	0.013	0.038**
	(0.007)	(0.011)	(0.008)	(0.015)
Macroeconomic Controls	Yes	Yes	Yes	Yes
Flood Event Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,806	6,599	9,806	6,599
R-squared	0.98	0.98	0.98	0.97
Mean Dependent Variable	4.89	4.74	4.86	4.70

Notes: Panel A reports the overall impact of floods on outflow and inflow migration. Panel B reports the heterogeneous effects of floods on counties with high or low cumulative flood frequency till 3 years before the flood event, relative to the median level in all U.S. counties. Unreported macroeconomic control variables include unemployment rate, population, income per capita and GDP at the county-year level. Full results with all coefficients are reported in Appendix Table A2. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Impact of Media Sentiment on Selective Migration

Panel A. Outflow Migration

	(1) Total log(Outflow)	(2) High Education log(Outflow)	(3) Low Education log(Outflow)	(4) Employed log(Outflow)	(5) Unemployed log(Outflow)	(6) Young log(Outflow)	(7) Old log(Outflow)
Treat × Post × Score	-0.016***	-0.028***	-0.012**	-0.016***	-0.009	-0.018***	-0.013
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Treat × Post	0.022***	0.036***	0.013*	0.025***	-0.000	0.027***	0.012
	(0.006)	(0.009)	(0.007)	(0.006)	(0.011)	(0.006)	(0.010)
Subsidy	0.009	0.001	0.008	0.009	0.016	0.010	0.016
	(0.008)	(0.011)	(0.010)	(0.008)	(0.014)	(0.010)	(0.013)
log(Housing Price)	0.027	0.061	-0.010	0.102***	-0.197***	0.034	-0.031
	(0.030)	(0.045)	(0.035)	(0.031)	(0.053)	(0.032)	(0.053)
Firm Entry	0.016***	0.013**	0.017***	0.010***	0.025***	0.017***	0.023***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)	(0.006)
Firm Exit	0.010**	-0.011*	0.018***	-0.006	0.045***	0.007	0.018***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)	(0.007)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.98	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.83	3.72	4.38	4.54	3.40	4.53	3.47

Panel B. Inflow Migration

	(1) Total log(Inflow)	(2) High Education log(Inflow)	(3) Low Education log(Inflow)	(4) Employed log(Inflow)	(5) Unemployed log(Inflow)	(6) Young log(Inflow)	(7) Old log(Inflow)
Treat × Post × Score	0.010*	-0.000	0.016**	0.004	0.024***	0.010*	0.016*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)	(0.009)
Treat × Post	0.020***	0.009	0.030***	0.011	0.042***	0.011	0.042***
	(0.007)	(0.010)	(0.009)	(0.008)	(0.012)	(0.008)	(0.012)
Subsidy	0.002	0.011	-0.009	-0.000	-0.015	-0.008	0.038***
	(0.008)	(0.011)	(0.008)	(0.008)	(0.012)	(0.008)	(0.013)
log(Housing Price)	-0.216***	-0.071	-0.365***	-0.154***	-0.367***	-0.152***	-0.341***
	(0.036)	(0.050)	(0.041)	(0.038)	(0.059)	(0.040)	(0.055)
Firm Entry	0.009**	0.017***	0.007	0.006	0.032***	0.015***	-0.008
	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)	(0.005)	(0.007)
Firm Exit	0.002	0.002	0.001	0.007*	0.002	-0.004	0.013*
	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)	(0.005)	(0.007)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.97	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.80	3.68	4.34	4.51	3.34	4.48	3.42

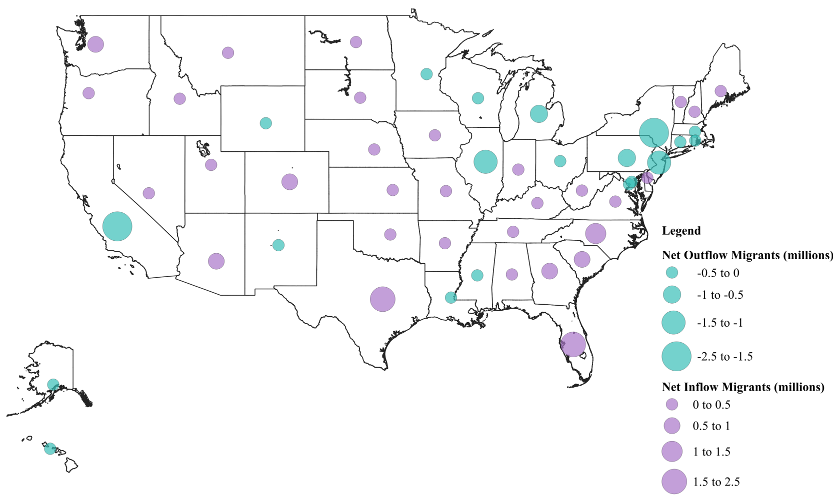
Notes: Unreported macroeconomic control variables include unemployment rate, population, income per capita and GDP at the county-year level. Full results with all coefficients are reported in Appendix Table A9. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Impact of Floods on Housing Market

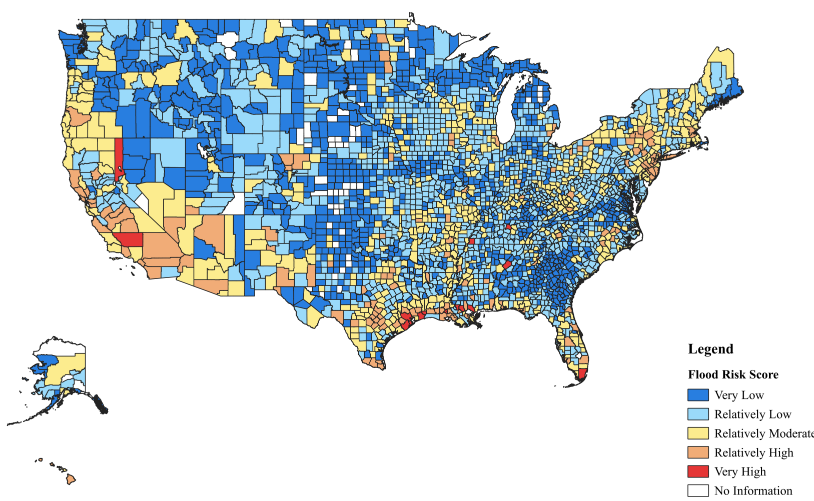
	(1) Monthly Price Growth (%)	(2) Monthly Rent Growth (%)
Treat × Post	-0.053***	0.074***
	(0.015)	(0.019)
Macroeconomic Controls	Yes	Yes
Flood Event Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Year-month Fixed Effects	Yes	Yes
State-year Fixed Effects	Yes	Yes
Observations	49,845	20,208
R-squared	0.36	0.26
Mean Dependent Variable	0.48	0.32

Notes: Unreported macroeconomic control variables include unemployment rate, population, income per capita, GDP and total new housing units at the county-year level. Full results with all coefficients are reported in Appendix Table A12. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Correlation between Net Migration and Flood Risk in the US



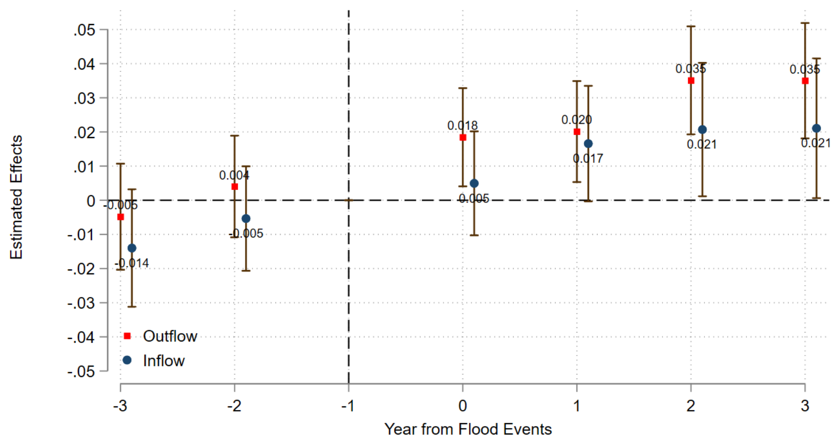
(a) Net Migration



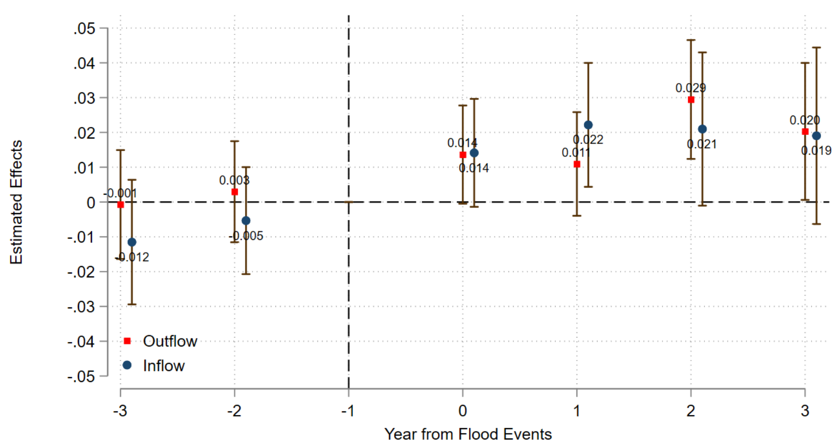
(b) Flood Risk Map

Notes: This figure shows (a) the net migration in the U.S. at the state level between 2006 and 2019 and (b) the average flood risk in the same period at the county level. Data on state-to-state migration flows is obtained from United States Census Bureau; National flood risk index is obtained from Federal Emergency Management Agency.

Figure 2: Event Study Results



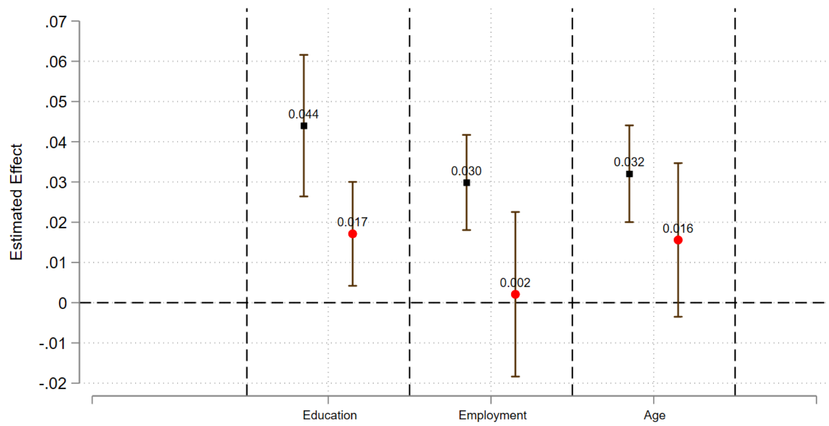
(a) TWFE



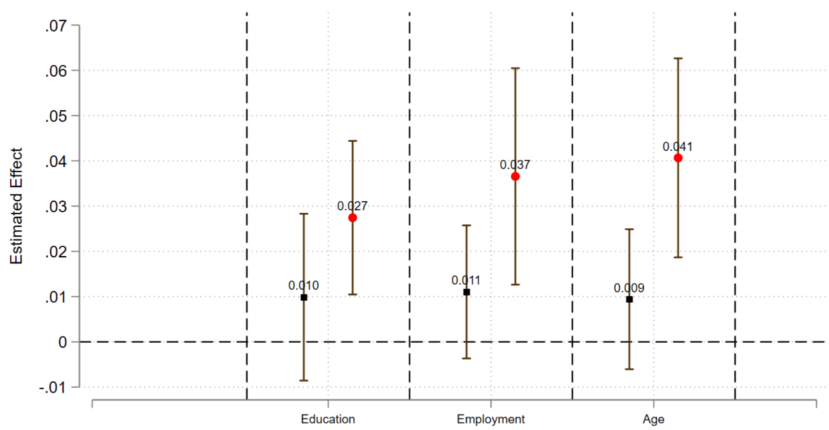
(b) CSDID

Notes: This figure plots the event-study results of the impacts of flood events on outward and inward migration, estimated using (a) the stacked TWFE method and (b) CSDID method. Error bars indicate 95% confidence intervals.

Figure 3: Selective Migration Patterns after Floods



(a) Outflow Migration



(b) Inflow Migration

Notes: The figure plots the flood-induced selective migration patterns in (a) outflow migration and (b) inflow migration. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Error bars indicate 95% confidence intervals.

Internet Appendix

Appendix A. Supplementary Tables

Table A1: Summary Statistics

Panel A: Number of Outflow Migrants

	Obs	Mean	SD
Total	16,405	169.85	160.71
– Higher-educated (in or above college degree)	16,405	62.16	67.30
– Lower-educated (below college degree)	16,405	106.58	99.55
– Employed	16,405	127.71	120.72
– Unemployed	16,405	42.14	44.51
– Young (< 40 years old)	16,405	126.18	119.07
– Old (≥ 40 years old)	16,405	43.67	43.33

Panel B: Number of Inflow Migrants

	Obs	Mean	SD
Total	16,405	167.09	158.15
– Higher-educated (in or above college degree)	16,405	62.25	71.72
– Lower-educated (below college degree)	16,405	103.68	95.45
– Employed	16,405	126.54	120.43
– Unemployed	16,405	40.55	45.51
– Young (< 40 years old)	16,405	124.62	118.87
– Old (≥ 40 years old)	16,405	42.47	43.57

Panel C: Other Control Variables

	Obs	Mean	SD
Sentiment score (standardized)	16,405	-0.21	1.10
Unemployment rate (percent)	16,405	6.38	3.05
Annual personal income (thousand USD)	16,405	44.08	13.10
Population (thousand)	16,405	438.58	461.75
Annual housing price (thousand USD)	16,405	214.66	135.60
County subsidy for flood (thousand USD)	16,405	209.18	1794.51
Number of firms moving in	16,405	0.54	1.58
Number of firms moving out	16,405	0.57	1.76

Panel D: Housing Market Variables

	Obs	Mean	SD
Monthly housing price (thousand USD)	49,845	205.89	122.47
Monthly rent (thousand USD)	20,208	1.29	0.41

Table A2: Impact of Floods on Migration: Full Table with All Variables

Panel A. Baseline Results

	(1) log(Outflow)	(2) log(Inflow)	(3) Outflow	(4) Inflow
Treat × Post	0.027***	0.019***	7.766***	3.552***
	(0.005)	(0.007)	(1.106)	(1.281)
Treat	-0.022**	0.015	-1.456	-1.494
	(0.011)	(0.015)	(1.803)	(2.416)
Post	-0.012**	-0.006	-2.654***	-0.820
	(0.005)	(0.005)	(0.666)	(0.757)
Unemployment Rate	0.015***	0.003	3.929***	-0.240
	(0.003)	(0.006)	(0.676)	(0.920)
log(Population)	0.646***	0.340**	118.272***	-53.285**
	(0.094)	(0.137)	(22.657)	(26.305)
log(Income per capita)	-0.055	0.100*	-1.221	42.812***
	(0.056)	(0.054)	(14.573)	(12.899)
log(GDP)	0.129***	0.048	-33.227***	-32.359***
	(0.032)	(0.047)	(8.926)	(9.308)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405
R-squared	0.98	0.97	0.99	0.98
Mean Dependent Variable	4.83	4.80	169.85	167.09

Panel B. Heterogeneity by Cumulative Flood Frequency

	(1) High frequency log(Outflow)	(2) Low frequency log(Outflow)	(3) High frequency log(Inflow)	(4) Low frequency log(Inflow)
Treat × Post	0.031**	0.005	0.013	0.038**
	(0.007)	(0.011)	(0.008)	(0.015)
Treat	-0.063***	0.002	0.025	-0.002
	(0.023)	(0.013)	(0.038)	(0.019)
Post	-0.011*	-0.008	-0.006	-0.005
	(0.006)	(0.009)	(0.006)	(0.009)
Unemployment Rate	0.019***	0.014***	0.022***	-0.031***
	(0.004)	(0.005)	(0.006)	(0.012)
log(Population)	0.517***	0.709***	-0.405*	1.056***
	(0.151)	(0.139)	(0.226)	(0.211)
log(Income per capita)	-0.155*	0.010	0.098	0.139*
	(0.087)	(0.078)	(0.089)	(0.081)
log(GDP)	0.158***	0.076*	0.134*	-0.095
	(0.057)	(0.041)	(0.071)	(0.066)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,806	6,599	9,806	6,599
R-squared	0.98	0.98	0.98	0.97
Mean Dependent Variable	4.89	4.74	4.86	4.70

Notes: This table presents the full list of coefficient estimates for all variables in Table 1. Panel A reports the overall impact of floods on outflow and inflow migration. Panel B reports the heterogeneous effects of floods on counties with high or low cumulative flood frequency till 3 years before the flood event, in relative to the median level in all U.S. counties. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Impact of Floods on Migration: Robustness Check Using Alternative Empirical Models

Panel A. Outflow Migration

	(1) log(Outflow)	(2) log(Outflow)	(3) log(Outflow)	(4) log(Outflow)	(5) log(Outflow)	(6) log(Outflow)
Treat × Post	0.027***	0.026***	0.027***	0.026***	0.031***	0.018***
	(0.005)	(0.005)	(0.009)	(0.005)	(0.006)	(0.006)
Treat	-0.021*	-0.022**	-0.022**	-0.012	-0.020	
	(0.011)	(0.011)	(0.011)	(0.008)	(0.016)	
Post	-0.012**	-0.012**	-0.012*	-0.011***	-0.011**	
	(0.005)	(0.005)	(0.007)	(0.003)	(0.005)	
Unemployment Rate	0.015***	0.014***	0.015*	0.012***	0.013***	
	(0.004)	(0.003)	(0.008)	(0.003)	(0.004)	
log(Population)	0.626***	0.663***	0.646***	0.699***	0.685***	
	(0.096)	(0.093)	(0.169)	(0.082)	(0.109)	
log(Income per capita)	-0.070	-0.056	-0.055	-0.026	-0.128*	
	(0.056)	(0.056)	(0.131)	(0.049)	(0.066)	
log(GDP)	0.128***	0.136***	0.129*	0.088***	0.131***	
	(0.032)	(0.032)	(0.071)	(0.027)	(0.038)	
Subsidy	0.010					
	(0.008)					
log(Housing Price)	0.030					
	(0.030)					
Firm Entry	0.016***					
	(0.004)					
Firm Exit	0.009**					
	(0.004)					
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	26,041	12,943	15,415
R-squared	0.98	0.98	0.98	0.97	0.98	-
Mean Dependent Variable	4.83	4.83	4.83	4.79	4.86	4.84

Panel B. Inflow Migration

	(1) log(Inflow)	(2) log(Inflow)	(3) log(Inflow)	(4) log(Inflow)	(5) log(Inflow)	(6) log(Inflow)
Treat × Post	0.019***	0.018**	0.019*	0.023***	0.018**	0.019**
	(0.007)	(0.007)	(0.011)	(0.006)	(0.008)	(0.008)
Treat	0.016	0.013	0.015	0.008	0.027	
	(0.015)	(0.015)	(0.016)	(0.012)	(0.024)	
Post	-0.006	-0.006	-0.006	-0.010***	-0.006	
	(0.005)	(0.005)	(0.007)	(0.004)	(0.006)	
Unemployment Rate	-0.004	0.003	0.003	0.005	0.000	
	(0.007)	(0.006)	(0.013)	(0.005)	(0.008)	
log(Population)	0.465***	0.369***	0.340	0.386***	0.198	
	(0.140)	(0.136)	(0.294)	(0.101)	(0.162)	
log(Income per capita)	0.127**	0.081	0.100	0.109**	0.145**	
	(0.056)	(0.053)	(0.102)	(0.047)	(0.070)	
log(GDP)	0.034	0.057	0.048	0.030	0.098*	
	(0.047)	(0.046)	(0.104)	(0.036)	(0.053)	
Subsidy	0.002					
	(0.008)					
log(Housing Price)	-0.212***					
	(0.036)					
Firm Entry	0.009**					
	(0.004)					
Firm Exit	-0.000					
	(0.004)					
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	26,041	12,943	15,415
R-squared	0.97	0.97	0.97	0.97	0.97	-
Mean Dependent Variable	4.80	4.79	4.80	4.75	4.84	4.81

Notes: This paper presents robustness checks for the impact of floods on migration. Column (1) includes additional control variables of annual housing prices, government subsidies for post-flood recovery, and numbers of public firm entries and exits. Column (2) presents results after removing outliers in outflow/inflow migration at the top 1%. In Column (3), standard errors are changed to be clustered at the county level. Column (4) uses the alternative control group, consisting of the 20 nearest counties to the treatment counties. In Column (5), we remove the control counties within 50km of treatment counties. Column (6) presents the estimates using the CSDID method. Standard errors are clustered at the flood event level, except for Column (3) which is at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Impact of Floods on Migration: Robustness Check Using Median Personal Income as Control Variable

	(1) log(Outflow)	(2) log(Inflow)	(3) Outflow	(4) Inflow
Treat × Post	0.027***	0.019***	7.777***	3.657***
	(0.005)	(0.007)	(1.103)	(1.288)
Treat	-0.012**	-0.006	-2.663***	-0.866
	(0.005)	(0.005)	(0.668)	(0.758)
Post	-0.021**	0.014	-1.376	-1.729
	(0.011)	(0.015)	(1.802)	(2.399)
Unemployment Rate	0.015***	0.002	3.773***	-0.595
	(0.003)	(0.006)	(0.677)	(0.933)
log(Population)	0.630***	0.331**	104.677***	-65.032**
	(0.094)	(0.139)	(23.487)	(27.208)
log(Median Personal Income)	-0.091	0.035	-48.685***	-13.224
	(0.062)	(0.080)	(15.795)	(15.616)
log(GDP)	0.146***	0.056	-18.823**	-20.553**
	(0.034)	(0.051)	(8.487)	(9.848)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405
R-squared	0.98	0.97	0.99	0.98
Mean Dependent Variable	4.83	4.80	169.85	167.09

Notes: This paper presents robustness checks for the impact of floods on migration, using median personal income, rather than income per capita, as an alternation control variable. Standard errors are clustered at the flood event level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Impact of Floods on Migration: Robustness Check Using the Synthetic Control Approach

	(1) log(Outflow)	(2) log(Inflow)
Treat × Post	0.026***	0.021**
	(0.010)	(0.010)
Post	-0.019***	-0.013**
	(0.006)	(0.005)
Unemployment Rate	0.007**	-0.009***
	(0.003)	(0.003)
log(Population)	0.606***	0.051
	(0.141)	(0.156)
log(Income per capita)	-0.130**	0.287***
	(0.057)	(0.089)
log(GDP)	0.142***	0.227***
	(0.042)	(0.060)
Flood Event Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	12,824	12,824
R-squared	0.99	0.99
Mean Dependent Variable	5.51	5.53

Notes: This table reports the robustness check results on the impact of floods on migration, using the synthetic control approach. The coefficient of variable *Treat* is omitted due to fixed effects. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Impact of Floods on Selective Migration Patterns

Panel A. Outflow Migration

	(1) High Education log(Outflow)	(2) Low Education log(Outflow)	(3) Employed log(Outflow)	(4) Unemployed log(Outflow)	(5) Young log(Outflow)	(6) Old log(Outflow)
Treat × Post	0.044***	0.017***	0.030***	0.002	0.032***	0.016
	(0.009)	(0.007)	(0.006)	(0.010)	(0.006)	(0.010)
Treat	-0.029*	-0.019	-0.019	-0.025	-0.025**	-0.007
	(0.016)	(0.014)	(0.012)	(0.018)	(0.012)	(0.018)
Post	-0.020***	-0.006	-0.013**	-0.007	-0.014***	-0.007
	(0.007)	(0.006)	(0.005)	(0.009)	(0.005)	(0.008)
Unemployment Rate	0.012*	0.012***	0.010**	0.015***	0.014***	0.021***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
log(Population)	0.546***	0.642***	0.568***	1.121***	0.613***	0.856***
	(0.157)	(0.109)	(0.100)	(0.164)	(0.106)	(0.167)
log(Income per capita)	-0.276***	0.022	-0.113*	-0.038	-0.141**	0.240**
	(0.078)	(0.062)	(0.058)	(0.099)	(0.061)	(0.098)
log(GDP)	0.022	0.198***	0.149***	0.056	0.204***	0.009
	(0.052)	(0.037)	(0.037)	(0.059)	(0.036)	(0.055)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	3.72	4.38	4.54	3.40	4.53	3.47

Panel B. Inflow Migration

	(1) High Education log(Inflow)	(2) Low Education log(Inflow)	(3) Employed log(Inflow)	(4) Unemployed log(Inflow)	(5) Young log(Inflow)	(6) Old log(Inflow)
Treat × Post	0.010	0.027***	0.011	0.037***	0.009	0.041***
	(0.009)	(0.009)	(0.007)	(0.012)	(0.008)	(0.011)
Treat	-0.017	0.032	0.001	0.054**	0.019	-0.009
	(0.015)	(0.020)	(0.012)	(0.027)	(0.017)	(0.018)
Post	-0.003	-0.008	-0.004	-0.007	-0.002	-0.014*
	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Unemployment Rate	-0.006	-0.002	-0.005	0.017	0.001	0.004
	(0.006)	(0.007)	(0.004)	(0.011)	(0.007)	(0.007)
log(Population)	0.457***	0.169	0.422***	0.204	0.485***	-0.103
	(0.167)	(0.153)	(0.134)	(0.239)	(0.152)	(0.177)
log(Income per capita)	0.198**	0.086	0.115*	-0.077	0.180***	-0.188***
	(0.087)	(0.066)	(0.061)	(0.093)	(0.063)	(0.072)
log(GDP)	0.025	0.077	0.073	-0.028	-0.036	0.299***
	(0.064)	(0.052)	(0.046)	(0.080)	(0.055)	(0.060)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	3.68	4.34	4.51	3.34	4.48	3.42

Notes: High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Impact of Floods on Selective Migration Patterns: Robustness Check by Including Additional Control Variables

Panel A. Outflow Migration

	(1) High Education log(Outflow)	(2) Low Education log(Outflow)	(3) Employed log(Outflow)	(4) Unemployed log(Outflow)	(5) Young log(Outflow)	(6) Old log(Outflow)
Treat × Post	0.044***	0.017***	0.030***	0.002	0.032***	0.015
	(0.009)	(0.007)	(0.006)	(0.010)	(0.006)	(0.010)
Treat	-0.030*	-0.018	-0.020*	-0.023	-0.025**	-0.006
	(0.016)	(0.014)	(0.012)	(0.018)	(0.012)	(0.018)
Post	-0.020***	-0.006	-0.013**	-0.008	-0.014***	-0.007
	(0.007)	(0.006)	(0.005)	(0.009)	(0.005)	(0.008)
Unemployment Rate	0.002	0.009	0.009	0.018	0.011	0.017
	(0.011)	(0.010)	(0.008)	(0.014)	(0.010)	(0.013)
log(Population)	0.067	-0.006	0.108***	-0.197***	0.038	-0.028
	(0.046)	(0.035)	(0.031)	(0.053)	(0.032)	(0.053)
log(Income per capita)	0.010*	0.010**	0.003	0.017**	0.010**	0.012*
	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)	(0.006)
log(GDP)	-0.018***	0.016***	-0.013***	0.044***	-0.001	0.018***
	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)	(0.007)
Subsidy	0.015**	0.011***	0.013***	0.008	0.015***	0.019***
	(0.007)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
log(Housing Price)	0.506***	0.635***	0.510***	1.215***	0.587***	0.863***
	(0.158)	(0.111)	(0.099)	(0.171)	(0.109)	(0.170)
Firm Entry	-0.291***	0.017	-0.130**	-0.021	-0.152**	0.236**
	(0.077)	(0.062)	(0.057)	(0.097)	(0.060)	(0.099)
Firm Exit	0.027	0.193***	0.155***	0.033	0.203***	0.000
	(0.052)	(0.037)	(0.036)	(0.059)	(0.035)	(0.055)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	3.72	4.39	4.54	3.40	4.53	3.47

Panel B. Inflow Migration

	(1) High Education log(Inflow)	(2) Low Education log(Inflow)	(3) Employed log(Inflow)	(4) Unemployed log(Inflow)	(5) Young log(Inflow)	(6) Old log(Inflow)
Treat × Post	0.010	0.027***	0.011	0.037***	0.010	0.040***
	(0.009)	(0.009)	(0.008)	(0.012)	(0.008)	(0.011)
Treat	-0.016	0.033*	0.001	0.056**	0.020	-0.008
	(0.015)	(0.020)	(0.012)	(0.027)	(0.017)	(0.018)
Post	-0.003	-0.008	-0.004	-0.007	-0.002	-0.015*
	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Unemployment Rate	0.012	-0.009	0.000	-0.015	-0.007	0.039***
	(0.011)	(0.008)	(0.008)	(0.012)	(0.008)	(0.014)
log(Population)	-0.066	-0.360***	-0.149***	-0.367***	-0.149***	-0.334***
	(0.050)	(0.041)	(0.038)	(0.059)	(0.040)	(0.056)
log(Income per capita)	0.015**	0.006	0.004	0.020**	0.012**	-0.011*
	(0.006)	(0.005)	(0.005)	(0.008)	(0.005)	(0.007)
log(GDP)	-0.004	0.000	0.003	-0.001	-0.007	0.007
	(0.006)	(0.005)	(0.004)	(0.007)	(0.005)	(0.007)
Subsidy	-0.008	-0.013*	-0.010**	0.006	-0.003	-0.008
	(0.006)	(0.007)	(0.005)	(0.011)	(0.007)	(0.007)
log(Housing Price)	0.492***	0.378**	0.507***	0.405*	0.566***	0.118
	(0.169)	(0.155)	(0.138)	(0.241)	(0.155)	(0.181)
Firm Entry	0.200**	0.137**	0.135**	-0.033	0.196***	-0.130*
	(0.089)	(0.065)	(0.062)	(0.094)	(0.064)	(0.075)
Firm Exit	0.017	0.056	0.063	-0.050	-0.045	0.271***
	(0.064)	(0.051)	(0.045)	(0.080)	(0.054)	(0.060)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	3.68	4.34	4.51	3.34	4.49	3.42

Notes: This table presents the robustness check results for the impact of floods on selective migration patterns, using additional control variables such as government subsidy, housing price, and firm entry/exit. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Impact of Floods on Net Migration

Panel A. Impact of Floods on Net Outflow Migration by Sociodemographic Groups

	(1) High Education log(Outflow) –log(Inflow)	(2) Low Education log(Outflow) –log(Inflow)	(3) Employed log(Outflow) –log(Inflow)	(4) Unemployed log(Outflow) –log(Inflow)	(5) Young log(Outflow) –log(Inflow)	(6) Old log(Outflow) –log(Inflow)
Treat × Post	0.034***	-0.010	0.019*	-0.034**	0.023**	-0.025*
	(0.013)	(0.011)	(0.010)	(0.016)	(0.011)	(0.015)
Treat	-0.013	-0.051*	-0.020	-0.080**	-0.044*	0.002
	(0.025)	(0.029)	(0.018)	(0.036)	(0.025)	(0.024)
Post	-0.018*	0.002	-0.008	-0.000	-0.012	0.007
	(0.009)	(0.008)	(0.007)	(0.012)	(0.008)	(0.011)
Unemployment Rate	0.018**	0.013*	0.015***	-0.002	0.013*	0.017**
	(0.008)	(0.008)	(0.006)	(0.013)	(0.007)	(0.009)
log(Population)	0.089	0.473**	0.147	0.917***	0.128	0.959***
	(0.230)	(0.187)	(0.163)	(0.286)	(0.187)	(0.228)
log(Income per capita)	-0.474***	-0.064	-0.228***	0.039	-0.321***	0.429***
	(0.107)	(0.086)	(0.071)	(0.143)	(0.075)	(0.124)
log(GDP)	-0.003	0.121*	0.076	0.084	0.241***	-0.290***
	(0.079)	(0.063)	(0.053)	(0.090)	(0.062)	(0.077)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.58	0.79	0.64	0.62	0.67	0.52
Mean Dependent Variable	0.04	0.04	0.03	0.06	0.05	0.04

Panel B. Changes in Net Outflow Migrant Numbers by Sociodemographic Groups

	Outflow			Inflow			Net Outflow
	Annual Average	Change (%)	Change (Number)	Annual Average	Change (%)	Change (Number)	Change (Number)
High Education	6,216	4.40%	273.5	6,225	1.00%	62.3	211.3
Low Education	10,658	1.70%	181.2	10,368	2.70%	279.9	-98.8
Employed	12,771	3.00%	383.1	12,771	1.10%	140.5	242.6
Unemployed	4,214	0.20%	8.4	4,214	3.70%	155.9	-147.5
Young	12,618	3.20%	403.8	12,618	0.90%	113.6	290.2
Old	4,367	1.60%	69.9	4,367	4.10%	179	-109.2

Notes: Panel A of this table examines how the net migration patterns vary by different population groups after floods. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Panel B, the changes in outflow or inflow migrant numbers in each sociodemographic group equal the estimates of percentage change from Table A6 times the average migration number in that population group. The change in the net outflow migrant number equals the change in the outflow migrant number minus the change in the inflow migrant number in the group.

Table A9: Impact of Media Sentiment on Selective Migration: Full Table with All Variables

Panel A. Outflow Migration

	(1) Total log(Outflow)	(2) High Education log(Outflow)	(3) Low Education log(Outflow)	(4) Employed log(Outflow)	(5) Unemployed log(Outflow)	(6) Young log(Outflow)	(7) Old log(Outflow)
Treat × Post × Score	-0.016***	-0.028***	-0.012**	-0.016***	-0.009	-0.018***	-0.013
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Treat × Post	0.022***	0.036***	0.013*	0.025***	-0.000	0.027***	0.012
	(0.006)	(0.009)	(0.007)	(0.006)	(0.011)	(0.006)	(0.010)
Treat × Score	0.002	0.000	0.000	-0.010***	0.021***	0.002	0.004
	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
Post × Score	0.005**	0.011***	0.002	0.005*	0.001	0.005	0.008**
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Post	-0.010**	-0.017**	-0.005	-0.011**	-0.007	-0.013**	-0.005
	(0.005)	(0.007)	(0.006)	(0.005)	(0.009)	(0.005)	(0.008)
Treat	-0.019*	-0.026	-0.016	-0.017	-0.020	-0.022*	-0.004
	(0.011)	(0.016)	(0.014)	(0.011)	(0.018)	(0.012)	(0.018)
Subsidy	0.009	0.001	0.008	0.009	0.016	0.010	0.016
	(0.008)	(0.011)	(0.010)	(0.008)	(0.014)	(0.010)	(0.013)
log(Housing Price)	0.027	0.061	-0.010	0.102***	-0.197***	0.034	-0.031
	(0.030)	(0.045)	(0.035)	(0.031)	(0.053)	(0.032)	(0.053)
Firm Entry	0.016***	0.013**	0.017***	0.010***	0.025***	0.017***	0.023***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)	(0.006)
Firm Exit	0.010**	-0.011*	0.018***	-0.006	0.045***	0.007	0.018***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)	(0.007)
Unemployment Rate	0.015***	0.014**	0.011***	0.012***	0.008	0.015***	0.019***
	(0.004)	(0.007)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
log(Population)	0.621***	0.493***	0.640***	0.499***	1.237***	0.585***	0.867***
	(0.096)	(0.158)	(0.111)	(0.100)	(0.170)	(0.109)	(0.170)
log(Income per capita)	-0.068	-0.291***	0.015	-0.132**	-0.026	-0.155**	0.231**
	(0.056)	(0.077)	(0.062)	(0.057)	(0.098)	(0.060)	(0.099)
log(GDP)	0.126***	0.024	0.193***	0.151***	0.039	0.202***	0.001
	(0.032)	(0.052)	(0.037)	(0.036)	(0.059)	(0.035)	(0.056)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.98	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.83	3.72	4.38	4.54	3.40	4.53	3.47

Panel B. Inflow Migration

	(1) Total log(Inflow)	(2) High Education log(Inflow)	(3) Low Education log(Inflow)	(4) Employed log(Inflow)	(5) Unemployed log(Inflow)	(6) Young log(Inflow)	(7) Old log(Inflow)
Treat × Post × Score	0.010*	-0.000	0.016**	0.004	0.024***	0.010*	0.016*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)	(0.009)
Treat × Post	0.020***	0.009	0.030***	0.011	0.042***	0.011	0.042***
	(0.007)	(0.010)	(0.009)	(0.008)	(0.012)	(0.008)	(0.012)
Treat × Score	-0.006**	-0.000	-0.010***	-0.006*	-0.006	-0.005	-0.011**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Post × Score	-0.023***	-0.014**	-0.028***	-0.022***	-0.018***	-0.019***	-0.039***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)	(0.006)
Post	-0.007	-0.002	-0.009	-0.005	-0.008	-0.003	-0.016*
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Treat	0.014	-0.016	0.030	0.000	0.052*	0.018	-0.011
	(0.015)	(0.016)	(0.020)	(0.013)	(0.027)	(0.018)	(0.018)
Subsidy	0.002	0.011	-0.009	-0.000	-0.015	-0.008	0.038***
	(0.008)	(0.011)	(0.008)	(0.008)	(0.012)	(0.008)	(0.013)
log(Housing Price)	-0.216***	-0.071	-0.365***	-0.154***	-0.367***	-0.152***	-0.341***
	(0.036)	(0.050)	(0.041)	(0.038)	(0.059)	(0.040)	(0.055)
Firm Entry	0.009**	0.017***	0.007	0.006	0.032***	0.015***	-0.008
	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)	(0.005)	(0.007)
Firm Exit	0.002	0.002	0.001	0.007*	0.002	-0.004	0.013*
	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)	(0.005)	(0.007)
Unemployment Rate	-0.005	-0.009	-0.014**	-0.011**	0.006	-0.004	-0.009
	(0.007)	(0.006)	(0.007)	(0.005)	(0.011)	(0.007)	(0.007)
log(Population)	0.468***	0.496***	0.385**	0.512***	0.415*	0.570***	0.120
	(0.140)	(0.169)	(0.155)	(0.138)	(0.241)	(0.154)	(0.181)
log(Income per capita)	0.129**	0.199**	0.138**	0.137**	-0.045	0.193***	-0.127*
	(0.055)	(0.089)	(0.065)	(0.062)	(0.094)	(0.064)	(0.075)
log(GDP)	0.031	0.016	0.053	0.059	-0.048	-0.046	0.263***
	(0.047)	(0.064)	(0.051)	(0.045)	(0.080)	(0.054)	(0.060)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.97	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.80	3.68	4.34	4.51	3.34	4.48	3.42

Notes: This table presents the full list of coefficient estimates for all variables in Table 2. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Impact of Media Sentiment on Selective Migration: Robustness Check by Using 1-Year Lagged Control Variables for Other Channels

Panel A. Outflow Migration

	(1) Total log(Outflow)	(2) High Education log(Outflow)	(3) Low Education log(Outflow)	(4) Employed log(Outflow)	(5) Unemployed log(Outflow)	(6) Young log(Outflow)	(7) Old log(Outflow)
Treat × Post × Score	-0.018***	-0.030***	-0.014**	-0.018***	-0.010	-0.020***	-0.011
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Treat × Post	0.019***	0.031***	0.010	0.020***	0.000	0.023***	0.010
	(0.006)	(0.009)	(0.007)	(0.006)	(0.011)	(0.007)	(0.010)
Treat × Score	0.003	0.002	0.001	-0.009**	0.022***	0.003	0.003
	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
Post × Score	0.007***	0.013***	0.004	0.006**	0.002	0.007**	0.007*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Post	-0.008*	-0.014**	-0.003	-0.008	-0.006	-0.010*	-0.004
	(0.005)	(0.007)	(0.006)	(0.005)	(0.009)	(0.005)	(0.008)
Treat	-0.021*	-0.029*	-0.018	-0.021*	-0.027	-0.024*	-0.010
	(0.011)	(0.016)	(0.015)	(0.012)	(0.018)	(0.012)	(0.019)
Subsidy$_{t-1}$	0.002	0.005	0.000	0.005	-0.031**	-0.003	0.011
	(0.007)	(0.010)	(0.008)	(0.007)	(0.015)	(0.008)	(0.015)
log(Housing Price)$_{t-1}$	0.146***	0.280***	0.091***	0.215***	-0.001	0.142***	0.182***
	(0.025)	(0.038)	(0.029)	(0.028)	(0.043)	(0.028)	(0.042)
Firm Entry$_{t-1}$	0.009**	-0.018***	0.020***	-0.004	0.040***	0.006	0.018***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)	(0.007)
Firm Exit$_{t-1}$	-0.005	-0.027***	0.011**	-0.006	-0.004	0.013***	-0.056***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.008)	(0.004)	(0.006)
Unemployment Rate	0.017***	0.020***	0.011***	0.013***	0.014**	0.015***	0.026***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
log(Population)	0.585***	0.415***	0.594***	0.486***	1.055***	0.554***	0.761***
	(0.096)	(0.156)	(0.112)	(0.100)	(0.170)	(0.109)	(0.165)
log(Income per capita)	-0.041	-0.277***	0.038	-0.096*	-0.029	-0.130**	0.258***
	(0.056)	(0.074)	(0.063)	(0.057)	(0.101)	(0.061)	(0.100)
log(GDP)	0.121***	0.027	0.191***	0.137***	0.060	0.191***	0.018
	(0.032)	(0.052)	(0.037)	(0.036)	(0.061)	(0.035)	(0.056)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,260	16,260	16,260	16,260	16,260	16,260	16,260
R-squared	0.98	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.84	3.73	4.39	4.55	3.41	4.54	3.47

Panel B. Inflow Migration

	(1) Total log(Inflow)	(2) High Education log(Inflow)	(3) Low Education log(Inflow)	(4) Employed log(Inflow)	(5) Unemployed log(Inflow)	(6) Young log(Inflow)	(7) Old log(Inflow)
Treat × Post × Score	0.011**	-0.000	0.018***	0.006	0.024***	0.012**	0.016*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)	(0.009)
Treat × Post	0.025***	0.011	0.036***	0.015**	0.045***	0.015*	0.050***
	(0.007)	(0.010)	(0.009)	(0.008)	(0.012)	(0.008)	(0.012)
Treat × Score	-0.023***	-0.015***	-0.029***	-0.023***	-0.018***	-0.020***	-0.040***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)	(0.006)
Post × Score	-0.007**	-0.000	-0.012***	-0.007**	-0.007	-0.006*	-0.011**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Post	-0.009*	-0.000	-0.013**	-0.008	-0.009	-0.005	-0.020**
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Treat	0.009	-0.020	0.026	0.000	0.041	0.015	-0.020
	(0.017)	(0.016)	(0.023)	(0.013)	(0.029)	(0.019)	(0.018)
Subsidy$_{t-1}$	-0.005	0.004	-0.013	-0.006	-0.010	-0.010	0.038***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)	(0.012)
log(Housing Price)$_{t-1}$	-0.119***	-0.076**	-0.192***	-0.078**	-0.187***	-0.064*	-0.408***
	(0.032)	(0.037)	(0.039)	(0.033)	(0.061)	(0.038)	(0.039)
Firm Entry$_{t-1}$	-0.004	-0.008	-0.004	0.002	-0.006	-0.007*	0.008
	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)	(0.007)
Firm Exit$_{t-1}$	-0.004	-0.007	-0.004	-0.006	0.007	-0.008	0.007
	(0.005)	(0.006)	(0.005)	(0.005)	(0.008)	(0.005)	(0.007)
Unemployment Rate	-0.001	-0.010*	-0.006	-0.009*	0.013	-0.001	-0.009
	(0.007)	(0.006)	(0.007)	(0.005)	(0.011)	(0.007)	(0.007)
log(Population)	0.408***	0.672***	0.221	0.506***	0.181	0.532***	0.077
	(0.140)	(0.169)	(0.155)	(0.139)	(0.242)	(0.156)	(0.181)
log(Income per capita)	0.107*	0.219**	0.088	0.136**	-0.111	0.190***	-0.198**
	(0.055)	(0.088)	(0.065)	(0.062)	(0.095)	(0.064)	(0.077)
log(GDP)	0.019	-0.011	0.052	0.049	-0.054	-0.056	0.245***
	(0.047)	(0.064)	(0.052)	(0.046)	(0.081)	(0.055)	(0.061)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,260	16,260	16,260	16,260	16,260	16,260	16,260
R-squared	0.97	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.8	3.69	4.34	4.52	3.34	4.49	3.43

Notes: This table presents the robustness check results for the impact of media sentiment on selective migration patterns, using 1-year lagged control variables for other channels. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Impact of Media Sentiment on Selective Migration: Robustness Check by Excluding Control Variables for Other Channels

Panel A. Outflow Migration

	(1) Total log(Outflow)	(2) High Education log(Outflow)	(3) Low Education log(Outflow)	(4) Employed log(Outflow)	(5) Unemployed log(Outflow)	(6) Young log(Outflow)	(7) Old log(Outflow)
Treat × Post × Score	-0.016***	-0.028***	-0.012**	-0.016***	-0.009	-0.018***	-0.013
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Treat × Post	0.022***	0.036***	0.013*	0.025***	0.001	0.027***	0.012
	(0.006)	(0.009)	(0.007)	(0.006)	(0.011)	(0.006)	(0.010)
Treat × Score	0.002	-0.000	0.001	-0.011***	0.023***	0.002	0.005
	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
Post × Score	0.006**	0.011***	0.002	0.005*	0.001	0.005	0.008**
	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Post	-0.010**	-0.017**	-0.005	-0.011**	-0.007	-0.013**	-0.005
	(0.005)	(0.007)	(0.006)	(0.005)	(0.009)	(0.005)	(0.008)
Treat	-0.019*	-0.025	-0.017	-0.017	-0.024	-0.022*	-0.005
	(0.011)	(0.016)	(0.014)	(0.011)	(0.018)	(0.012)	(0.018)
Unemployment Rate	0.015***	0.012*	0.012***	0.009**	0.016***	0.014***	0.020***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
log(Population)	0.639***	0.533***	0.637***	0.560***	1.121***	0.607***	0.850***
	(0.094)	(0.157)	(0.109)	(0.100)	(0.164)	(0.106)	(0.167)
log(Income per capita)	-0.053	-0.272***	0.024	-0.109*	-0.040	-0.138**	0.242**
	(0.056)	(0.078)	(0.062)	(0.058)	(0.099)	(0.061)	(0.098)
log(GDP)	0.127***	0.018	0.197***	0.145***	0.060	0.202***	0.008
	(0.032)	(0.052)	(0.037)	(0.037)	(0.059)	(0.036)	(0.055)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.98	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.83	3.72	4.38	4.54	3.40	4.53	3.47

Panel B. Inflow Migration

	(1) Total log(Inflow)	(2) High Education log(Inflow)	(3) Low Education log(Inflow)	(4) Employed log(Inflow)	(5) Unemployed log(Inflow)	(6) Young log(Inflow)	(7) Old log(Inflow)
Treat × Post × Score	0.010*	-0.000	0.017**	0.004	0.025***	0.011*	0.016*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)	(0.009)
Treat × Post	0.021***	0.009	0.031***	0.011	0.043***	0.012	0.043***
	(0.007)	(0.010)	(0.009)	(0.008)	(0.012)	(0.008)	(0.012)
Treat × Score	-0.022***	-0.014**	-0.028***	-0.021***	-0.018***	-0.019***	-0.038***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)	(0.006)
Post × Score	-0.006**	-0.000	-0.010***	-0.006**	-0.007	-0.005	-0.011**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Post	-0.007	-0.002	-0.009	-0.005	-0.008	-0.003	-0.016*
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.006)	(0.008)
Treat	0.013	-0.017	0.029	-0.001	0.050*	0.017	-0.013
	(0.016)	(0.016)	(0.021)	(0.013)	(0.028)	(0.018)	(0.018)
Unemployment Rate	-0.005	-0.009	-0.014**	-0.011**	0.006	-0.004	-0.009
	(0.007)	(0.006)	(0.007)	(0.005)	(0.011)	(0.007)	(0.007)
log(Population)	0.468***	0.496***	0.385**	0.512***	0.415*	0.570***	0.120
	(0.140)	(0.169)	(0.155)	(0.138)	(0.241)	(0.154)	(0.181)
log(Income per capita)	0.129**	0.199**	0.138**	0.137**	-0.045	0.193***	-0.127*
	(0.055)	(0.089)	(0.065)	(0.062)	(0.094)	(0.064)	(0.075)
log(GDP)	0.031	0.016	0.053	0.059	-0.048	-0.046	0.263***
	(0.047)	(0.064)	(0.051)	(0.045)	(0.080)	(0.054)	(0.060)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405	16,405	16,405	16,405
R-squared	0.97	0.96	0.96	0.97	0.93	0.97	0.93
Mean Dependent Variable	4.80	3.68	4.34	4.51	3.34	4.48	3.42

Notes: This table presents the robustness check results for the impact of media sentiment on selective migration patterns, excluding the control variables for other channels. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Impact of Floods on Housing Market: Full Table with All Variables

	(1) Monthly Price Growth (%)	(2) Monthly Rent Growth (%)
Treat × Post	-0.053***	0.074***
	(0.015)	(0.019)
Treat	-0.035	-0.183***
	(0.059)	(0.069)
Post	0.017	-0.012
	(0.016)	(0.021)
Unemployment Rate	-0.145***	0.041
	(0.033)	(0.075)
log(Population)	-0.712	-0.321
	(0.500)	(0.857)
log(Income per capita)	0.224	-1.058**
	(0.346)	(0.513)
log(GDP)	-0.128	-0.124
	(0.155)	(0.292)
log(New Housing Units)	-0.001	0.007
	(0.004)	(0.010)
Flood Event Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Year-month Fixed Effects	Yes	Yes
State-year Fixed Effects	Yes	Yes
Observations	49,845	20,208
R-squared	0.36	0.26
Mean Dependent Variable	0.48	0.32

Notes: This table presents the full list of coefficient estimates for all variables in Table 3. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Aggregate Changes in Income due to Selective Migration by Education

Panel A. Outflow Migration

	High Education			Low Education		
	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI
Change (%) in Migrants	2.64%	4.40%	6.16%	0.42%	1.70%	3.00%
× Average Migrant Population	6,216	6,216	6,216	10,658	10,658	10,658
Change (Number) in Migrants	164	274	383	45	181	320
× Average Income	51,806	51,806	51,806	15,962	15,962	15,962
Change in Aggregate Income	8,501,503	14,169,000	19,832,750	713,458	2,892,070	5,108,101

Panel B. Inflow Migration

	High Education			Low Education		
	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI
Change (%) in Migrants	-0.86%	1.00%	2.83%	1.05%	2.70%	4.44%
× Average Migrant Population	6,225	6,225	6,225	10,368	10,368	10,368
Change (Number) in Migrants	-53	62	176	109	280	460
× Average Income	51,332	51,332	51,332	16,154	16,154	16,154
Change in Aggregate Income	-2,739,790	3,195,430	9,047,500	1,753,823	4,521,970	7,437,860

Notes: This table presents a back-of-envelop estimation of aggregate changes in income due to flood-induced selective migration by education. High (low) education refers to migrants with degrees at or above (below) the college level. Panels A and B calculate the changes in aggregate income of outflow and inflow migration due to flood events, respectively. The average population of high-education and low-education migrants are equal to the corresponding mean values in Table A1, adjusted by the sampling rate of ACS (1%). The percentage changes in migrants are from Columns (1) and (2) in Table A6. The average income is obtained from the ACS dataset.

Table A14: Aggregate Changes in Income due to Selective Migration by Age

Panel A. Outflow Migration

	Young			Old		
	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI
Change (%) in Migrants	2.00%	3.20%	4.41%	-0.35%	1.60%	3.47%
× Average Migrant Population	12,618	12,618	12,618	4,367	4,367	4,367
Change (Number) in Migrants	252	404	556	-15	70	151
× Average Income	23,740	23,740	23,740	46,087	46,087	46,087
Change in Aggregate Income	5,991,026	9,585,642	13,210,213	-705,145	3,220,210	6,978,628

Panel B. Inflow Migration

	Young			Old		
	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI	Lower Bound 95% CI	Mean Point Estimate	Upper Bound 95% CI
Change (%) in Migrants	-0.61%	0.90%	2.49%	1.87%	4.10%	6.26%
× Average Migrant Population	12,462	12,462	12,462	4,247	4,247	4,247
Change (Number) in Migrants	-75	112	310	79	174	266
× Average Income	24,144	24,144	24,144	46,593	46,593	46,593
Change in Aggregate Income	-1,821,140	2,707,920	7,488,212	3,693,578	8,113,100	12,395,670

Notes: This table presents a back-of-envelop estimation of aggregate changes in income due to flood-induced selective migration by age. Panels A and B calculate the changes in aggregate income of outflow and inflow migration due to flood events, respectively. The average population of young and old migrants are equal to the corresponding mean values in Table A1, adjusted by the sampling rate of ACS (1%). The percentage changes in migrants are from Columns (5) and (6) in Table A6. The average income is obtained from the ACS dataset.

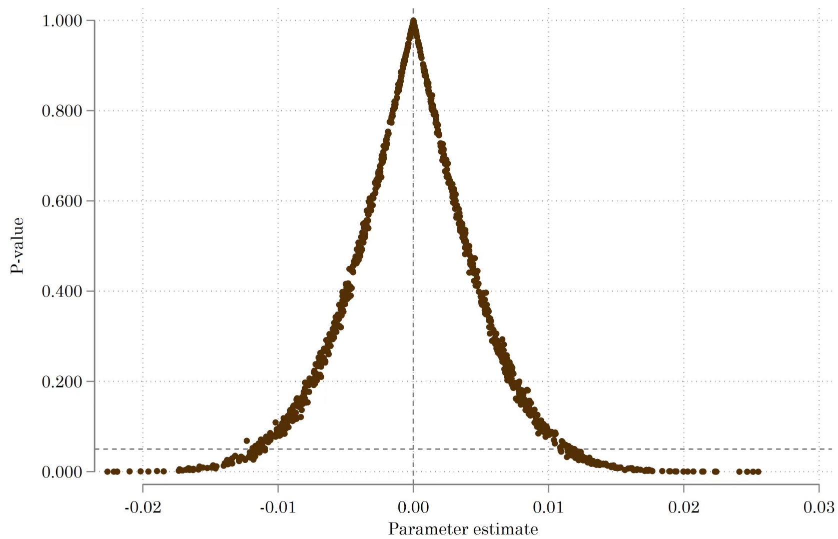
Table A15: Impact of Social Media Connectedness on Flood-induced Migration

	(1) High Connectedness log(Outflow)	(2) Low Connectedness log(Outflow)	(3) High Connectedness log(Inflow)	(4) Low Connectedness log(Inflow)
Treat × Post	0.022***	0.014	0.018**	0.004
	(0.007)	(0.009)	(0.009)	(0.010)
Treat	-0.008	-0.032**	0.003	0.030
	(0.014)	(0.015)	(0.017)	(0.020)
Post	-0.010*	-0.011	-0.001	-0.010
	(0.006)	(0.007)	(0.006)	(0.008)
Unemployment Rate	0.007*	0.017***	-0.001	0.002
	(0.004)	(0.005)	(0.008)	(0.007)
log(Population)	0.841***	0.615***	0.225	0.701***
	(0.117)	(0.148)	(0.157)	(0.191)
log(Income per capita)	-0.063	0.078	0.169***	0.053
	(0.058)	(0.107)	(0.064)	(0.076)
log(GDP)	0.070*	0.176***	0.027	0.039
	(0.038)	(0.058)	(0.051)	(0.070)
Flood Event Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
State-year Fixed Effects	Yes	Yes	Yes	Yes
Observations	16,405	16,405	16,405	16,405
R-squared	0.95	0.96	0.94	0.96
Mean Dependent Variable	4.24	3.90	4.13	3.92

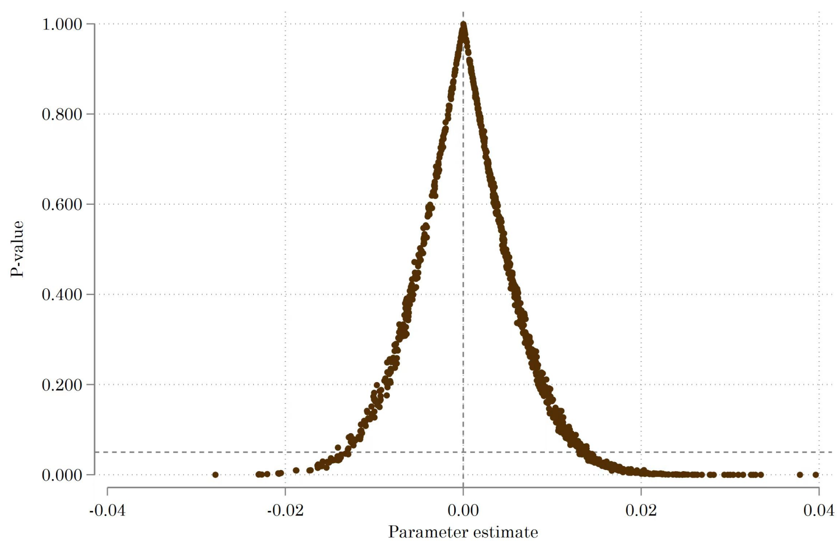
Notes: This table reports the heterogeneous impacts of floods on outflow and inflow migration between counties with high or low connectedness on social media (i.e., Facebook). High (low) connectedness refers to migration between a pair of origin and destination counties that has a social media connectedness score higher (lower) than the median of all pairwise scores between the U.S. counties. The pairwise social media connected scores between the U.S. counties are obtained from https://dataforgood.facebook.com/dfg/docs/methodology-social-connectedness-index. Standard errors are clustered at the flood event level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B. Supplementary Figures

Figure A1: Impact of Floods on Migration: Placebo Test Results



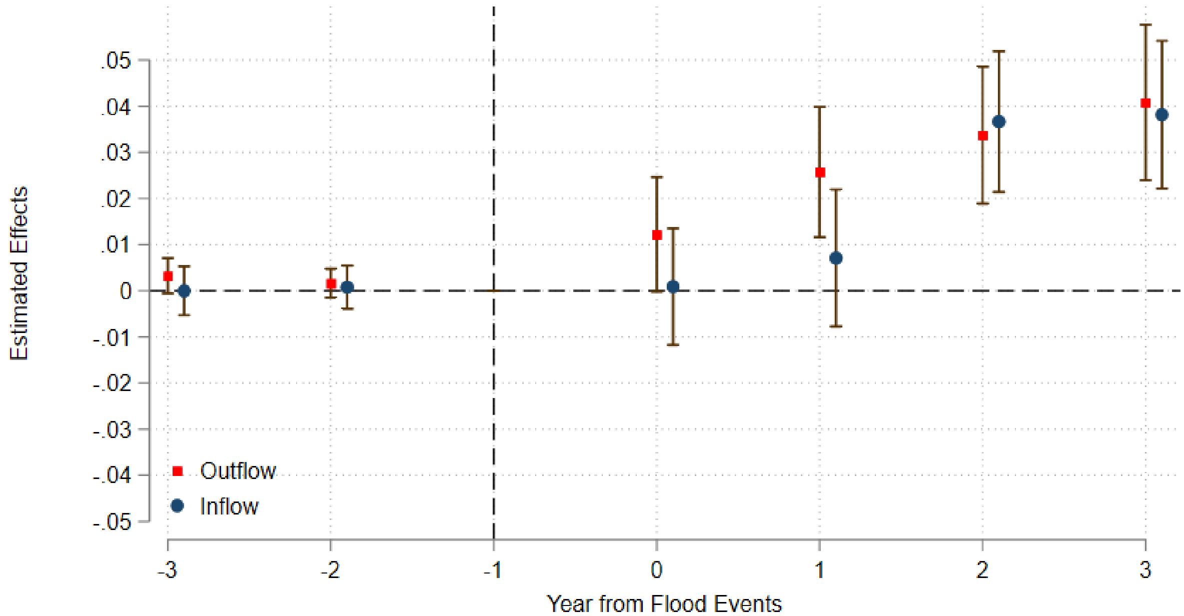
(a) Outflow Migration



(b) Inflow Migration

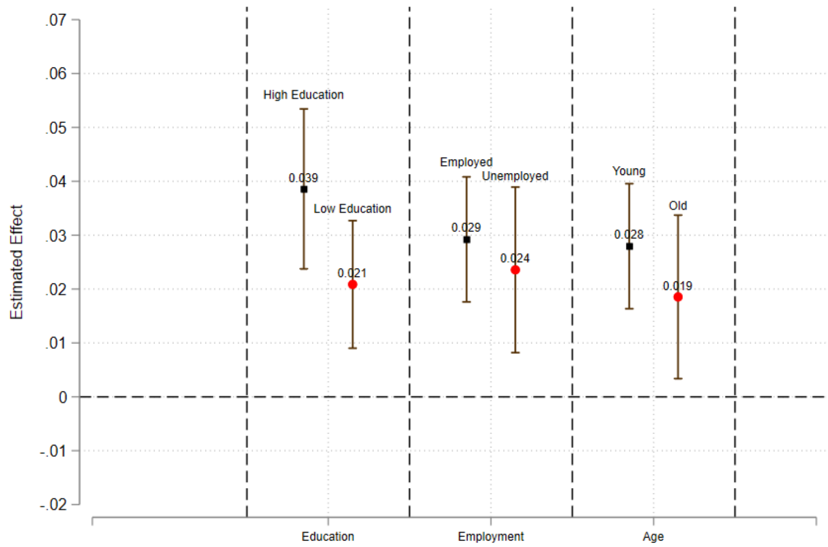
Notes: Panels A and B of this figure show the distribution of the placebo-test estimates for the impacts of floods on outflow and inflow migration, respectively. For each flood event in a county, we randomly assign an event year as a placebo treatment, and we repeat this process 1,000 times to get the distribution. The y-axis in the figures represents the p-values of the estimates, and the horizontal dashed line refers to the 5% significance level.

Figure A2: Event Study Results: Robustness Checks Using the Synthetic Control Approach

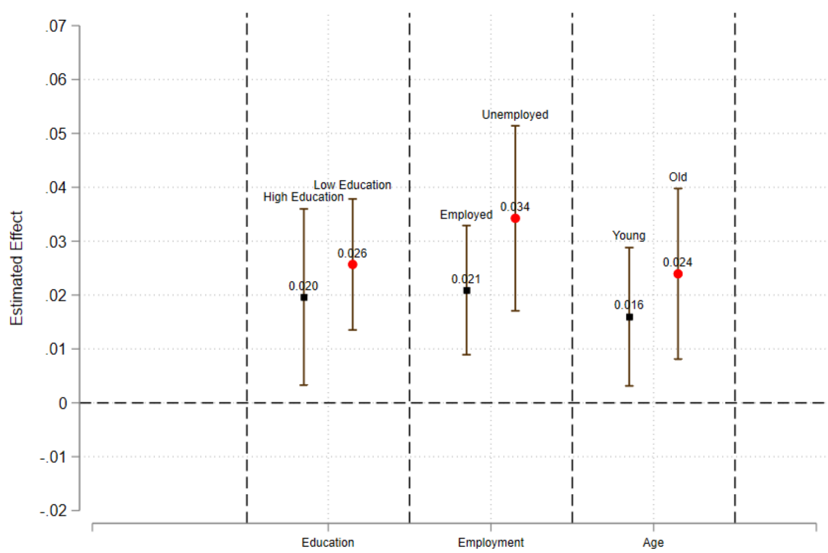


Notes: This figure plots the robustness check results for the event-study analysis of the impacts of flood events on outward and inward migration, using the synthetic control approach. Error bars indicate 95% confidence intervals.

Figure A3: Selective Migration Patterns after Floods: Robustness Checks Using the Synthetic Control Approach



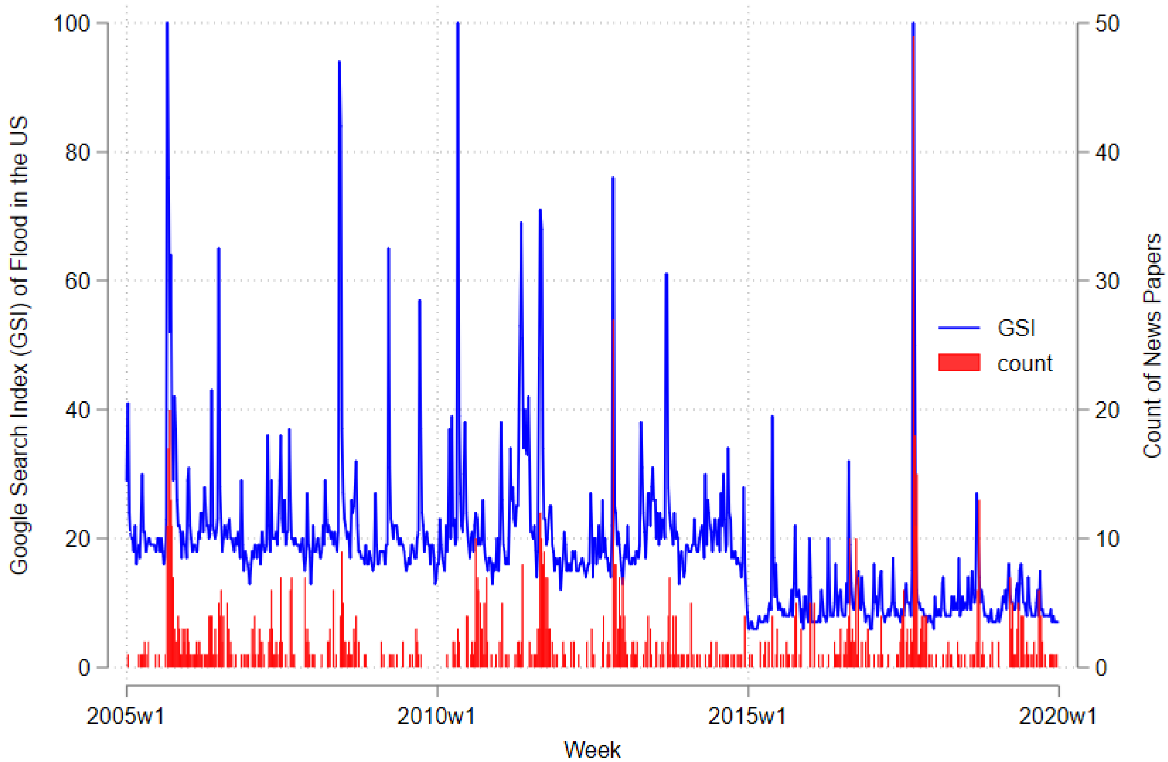
(a) Outflow Migration



(b) Inflow Migration

Notes: The figure plots the robustness check results for the flood-induced selective migration patterns in (a) outflow migration and (b) inflow migration, using the synthetic control approach. High (low) education refers to migrants with degrees at or above (below) the college level. Employed (unemployed) individuals are classified by their employment status in 1 year before the flood. Young (old) individuals are those under (in or above) the age of 40. Error bars indicate 95% confidence intervals.

Figure A4: Correlation between Google Search Index of Flood and Number of News Articles



Notes: This figure shows the correlation between the weekly Google search index (GSI) of the keyword "flood" in the U.S. and the number of flood-related news articles in the Factiva database between 2005 and 2019. The GSI is obtained from https://trends.google.com/trends/.