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The Uneven Economic and Demographic Impact of Hurricanes

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Abstract:
The effects of environmental change on human migration have become increasingly significant, frequent, and costly, particularly in the face of climate change and recent major natural disasters. Existing research has shown that environmental shocks affect migration, which in turn shapes wealth inequality in communities. In this study, we use FEMA disaster declaration data combined with IRS tax returns data to estimate whether and to what extent migration occurs disproportionately among particular social groups. IRS data will provide information on the number of returns classified into six income classes, which approximates the number of households, as well as the level and distribution of total adjusted gross income, wages, and salaries at the ZIP code level. Methodologically, we employ a staggered difference-in-differences design to compare trends in affected regions to other at-risk areas to assess the impact of a wide range of hurricane events that occurred between 2004 and 2021. In doing so, we allow the post-hurricane period to vary by intervention cohort, thereby analyzing (1) long-term effects, by running analyses to the last year for which data are available, and (2) whether their responses vary by different return times of hurricanes. Here, we expect the effects to differ between the short and long term, which will also depend on whether the areas are prone to sporadic, unexpected or recurrent hurricanes. The paper aims to further assess the role that federal disaster programs played in the ability for households and communities to adapt to following disasters. We will plot the event study estimates to show that the dynamic effects of the hurricane events gradually or abruptly grow during the various phases of post-periods, and whether they flatten afterward, as is expected if subsequent recovery effects have an impact. The findings will point towards developing equitable and effective resilience and adaptation strategies for reducing the adverse effects of economic and demographic losses caused by natural disasters.

1. Introduction

Since 1990, natural hazards, including earthquakes, tsunamis, storms, floods, typhoons, and volcanic eruptions, have grown worldwide, killing over 1.6 million people and costing an estimated USD 260–310 billion each year (Ward et al., 2020). Hurricanes are among the deadliest disasters (with 20,000 fatalities between 2000-2019), causing widespread destruction and loss of life (UNDRR, 2020). Their sheer intensity can devastate houses, infrastructure, and the growing populations in coastal cities, leaving survivors coping with loss, trauma, and uncertainty for years. The data connected to the increase in severe hazard phenomena clearly indicates the amplification of the risk of communities being displaced.

Between 2008 and 2018, it was observed that disasters resulted in the internal migration of approximately 24 million individuals on average (IDMC, 2019) which is expected to intensify as climate change accelerates. This figure surpasses the number of newly displaced individuals due to conflict and violence, exceeding it by more than threefold. The immediate aftermath of a hurricane often leads to significant population displacement (McGranahan et al., 2007). For example, hurricane Katrina alone, which impacted an area of 90,000 square miles along the Gulf of Mexico Coast, caused the displacement of 400,000 people (Logan et al., 2016). Hurricane Maria in 2017 displaced thousands of residents in Puerto Rico, many of whom migrated to the mainland U.S. (Rodriguez-Díaz, 2018). Therefore, in addition to their effects on mortality rates, hurricanes can also result in significant relocation from the afflicted area.

The literature on how hazards and disasters impact people is highly uneven and diverse based on demographic groups and impacts (Logan et al., 2016; Raker, 2020). Migrants who willingly or forced to leave their homes due to natural hazards or disasters often face uncertainties related to employment, social integration, and long-term settlement, while communities that receive them may lack adequate resources and infrastructure to support the increased population (Ionesco et al., 2016). The ability to take protective measures before a hazard, respond during the hazard, and recover after the hazard varies in different groups. For example, according to McGranahan et al. (2007), affluent settlements and groups had better capacity to respond to flooding during Hurricane Katrina and New Orleans. That means people who will have more resources will be indifferent and experience little to no change in their location. On the other hand, disadvantaged or marginalized groups might relocate from the vulnerable areas. However, again, McGranahan et al. (2007) also emphasized that the other way is also possible. Low-income people are forced to stay in vulnerable locations, while advantaged people move to less vulnerable areas depending on their economic condition (Logan et al., 2016). These distinct findings indicate a critical need for additional research. Research on disasters has predominantly focused on single events or isolated case studies. The existing research on disaster-induced relocation often neglects long-term demographic changes (Black et al., 2013; Curtis et al., 2015). Nevertheless, there is a rising call among scholars for comparative studies that account for differences across space and time (Elliott & Pais, 2010; Fussell, 2015).

The relocation policies across the globe are still not well developed to define and address the unique needs of disaster-induced migrants, who are neither strictly “economic migrants” nor “refugees” under existing international frameworks (McAdam, 2012). However, still, urban and regional planners and policymakers employ various strategies to address natural hazards. Some examples of such strategies include formulating land-use plans that impose limitations on development in areas prone to high-risk events, enacting regulations for future development and retrofitting, suggesting the implementation of hazard mitigation infrastructure, and formulating plans for post-disaster recovery (Burby et al., 2000). Scientific evidence highlights the growing threat to coastal and other high-risk communities due to warming in ocean temperature and more intense and frequent natural hazards (Kulp & Strauss, 2019). With the increased risk, the cost of mitigation will also increase; for example, protecting the state of Florida alone will cost $76 billion by 2040 (Woetzel et al., 2020). So, the Sendai Framework for Disaster Risk Reduction (DRR) prioritizes proactive disaster risk management, including implementing policies to relocate human populations away from disaster-prone areas (Hanna et al., 2019). However, relocation after a hazard is also a form of risk reduction. To fill in the policy gap, policymakers need to understand the patterns of migration caused by disasters. Specifically, understanding who relocates can help predict the economic impact on both the origin and receiving communities. This information helps policymakers design strategies that mitigate shocks and build resilience in both areas. This will aid in the planning and design of relocation projects by predicting future movement, ensuring the efficient use of resources for the benefit of both the origin and host areas.

Relocation significantly influences demographic composition, economic development, and social cohesion within regions and across borders. So, there is a crucial necessity for sustained research to understand the long-term impacts of natural hazards on the affected, both spatially and demographically. To analyze the impact of disasters on demographic change, this study will assess the demographic change after the second most prominent type of natural hazard—tropical storms—in the U.S. states from 2004 to 2022. The main objective of the study is to understand how different income groups are affected and relocate after experiencing tropical storms/hurricanes. This study stands out from the research design by utilizing spatial and statistical event analysis over such a long period to study demographic change. The study utilizes an event-study that will advance the literature to estimate the causal relationship at one of the smallest geographical level possible—zip code—while also considering the broader trends at the county level.

The structure of this article is as follows: first, a background on what we know from the literature so far on this topic will be summarized. Second, we describe our research design, the data, and the and the methodology that was adapted to study the tropical storms/hurricanes from 2004 to 2021 linking with the information on migration in those areas. Finally, in the result and discussion section, we discuss our findings.

2. Literature Review: Mapping the Literature on Trends of Relocation and Shift in Demographics

Different disasters such as floods, hurricanes, rising sea levels and many more can significantly affect the social and economic condition of affected communities, that might influence decisions about whether to evacuate, return, or permanently relocate from the affected areas. Disaster-induced relocation can significantly impact communities from different aspects, such as social, economic, and mental health (Boustan et al., 2020; Deryugina et al., 2018; Li & Feng, 2021; Milojevic et al., 2012). Different studies conducted on relocation in the Carteret Islands of Papua New Guinea, Vietnam’s Mekong Delta and after Aceh highlighted that, relocation after disasters often disrupt traditional livelihoods and economics due to insufficient support for integration into new environments (Arnall, 2014; Dun, 2011; Edwards, 2013; Zahriah et al., 2020). Insufficient support disrupts livelihoods by limiting access to resources and employment opportunities, lack of tailored resettlement policies, financial aid, and community consultation. The studies also showed that prolonged displacements can affect or sometimes weaken public services, social ties and support systems for communities or individuals and result into increased levels of psychological distress, including post-traumatic stress disorder (PTSD), anxiety, and depression (e.g.: Milojevic et al., 2012, Zahlawi et al., 2019). All these factors influence both immediate and temporary responses and long-term decisions regarding rebuilding and relocating (Binder et al., 2015), making it a key factor in understanding the broader social impact of hurricanes on individual and community shifts.

Residential sorting models have been used in different studies to understand the disaster-induced population shifts, in terms of population form different demographics and economic classes. For example, Sheldon and Zhan (2022) employed multinomial and conditional logit models to examine hurricane and flood effects on migration patterns within the U.S., finding disasters increased short-distance migration rates by 1.6 percentage points and long-distance migration by 0.7 percentage points, mostly after severe disasters. Strobl (2011) used a fixed-effects model to assess hurricane impacts on county-level population growth and observed that, although hurricanes initially prompted outflows but economic growth, and financial support mechanisms (measured county-level per capita economic growth rates and per capita wealth using data from the Bureau of Economic Analysis (BEA)'s Local Area Personal Income Estimates) helped attract residents back over time, mitigating long-term declines. Boustan et al. (2020) employed county-level regression analysis on census data to examine the migration after hurricanes, finding that severe hurricanes led to increased out-migration by 1.5 percentage points while the housing cost decreases. Yet, this trend was often offset in mild disaster cases as returning residents stabilized population levels over the decade. However, it is important to consider the pre-existing trends of the affected area as Cross (2014) found that communities experiencing declining populations before disasters were more likely to experience large post-disaster population loss.

The decision-making and neighborhood patterns of relocation are often differentially influenced by race, income and financial resources. Bakkensen and Ma (2020) use a boundary discontinuity design to show that low-income and minority households are more likely to move into high-risk flood zones while higher-income groups tend to avoid these areas. This sorting behavior results in a disproportionately high concentration of low-income and minority households in flood zones, particularly in locations where housing costs are reduced by subsidies in the U.S. National Flood Insurance Program (NFIP). Smith et al. (2006) also observed that middle-income households were most likely to leave damaged neighborhoods, while lower-income residents often moved into these areas, attracted by lower housing costs. Sheldon and Zhan (2022) in their study also find that after hurricanes and floods, high-income households in the U.S. are more likely to relocate to safer, low-risk areas, whereas lower-income populations remain in high-risk zones due to financial limitations. However, Smith et al. (2006) in their study found that, higher-income households tended to stay, able to leverage insurance and personal resources for protection. Using geospatial modeling and U.S. Census data, Park & Franklin (2023) and combining survey data with FEMA flood maps and employed logistic regression models. Lieberman-Cribbin et al. (2021) find that that low-income, non-White, Black and Hispanic populations, and older populations are more frequently exposed to flood risks post-hurricane. Using Geographic Information Systems (GIS) to analyze census tract data from billion-dollar hurricanes (Hurricane Bob, Hurricane Andrew, and Hurricane Opal), Pais & Elliott (2008) found that the relocation pattern affects the region's demography also based on ethnicity and race. On average, black populations increased by 16%, while foreign-born and Hispanic populations increased by 27% and 39%, respectively. Curtis et al. (2015), also analyzing post-Hurricane Katrina migration, found that Black and lower-income populations faced greater obstacles to relocating due to limited financial means, which often forced them to remain in high-risk areas. As we can see, there are divergence in outcomes. This can be resulted from two factors- one the sense of safety and two availability of opportunity. The scope and opportunity created by reconstruction may have drawn population for labor market shaping different demographic responses to the similar disaster.

Different studies inside and outside the USA have used diverse methodologies and datasets to study disaster-induced migration. Many studies employed panel data and fixed effects regression models to examine the impacts of disasters on migration and economy. Boustan et al. (2020) used a century-long panel dataset with fixed-effects and decadal analysis to understand migration rates, housing prices, and income in response to federally declared disasters in the USA. The study found that severe disasters increase out-migration, lower housing prices, and are consistent with falling local productivity and labor demand. Strobl (2011) employs a hurricane destruction index (HDI), which incorporates localized wind speed and exposure data to measure hurricane intensity at the county level into a fixed-effects modeling at the coastal counties in the USA. He found that, hurricanes reduce county-level economic growth, with about 28% of the effect due to richer individuals migrating out. Fixed-effects models were also used to study disaster-induced migration in international studies. For example, Drabo and Mbaye (2015) employ a fixed-effects model on a panel of 67 developing countries (creating dummy variables for countries that experienced or did not experience disasters) to find out the effect of disasters on migration. Integrating economic indicators such as GDP and employment, the level of education, they assess the structural factors that exacerbate migration. Their findings indicate that disasters do have positive effect on migration, especially “brain drain” migration often occurs post-disaster, as skilled individuals with greater economic mobility are more likely to relocate internationally. Similarly, Spencer and Urquhart (2018) used a country fixed-effects model and a hurricane destruction index to measure the impact of hurricanes on migration from 30 Central American and Caribbean countries to the United States between 1989 and 2005 and found that hurricanes increased migration by 6% on average, with greater impacts observed for more damaging storms.

Another more frequently used method in disaster-induced migration is Difference-in-Difference (DID). Shakya et al. (2022) examined the impact of the 2015 earthquake in Nepal on international labor migration using a difference-in-differences approach. The study found that, international labor migration decreased in districts affected by the earthquake especially among males. The authors defined the “treatment” based on the severity of the earthquake’s impact, classified using the National Reconstruction Authority (NRA). The study designated 14 districts as "severely affected" based on the NRA’s classification. The remaining 61 districts of Nepal that were not classified as severely affected by the NRA were used as the comparison group in the study. Another study by Deryugina (2017) used DID to analyze the impact of hurricanes on fiscal and demographic patterns with a focus on government aid. The study found that, hurricanes lead to increased non-disaster government transfers, exceeding direct disaster aid and counties are generally resilient in terms of earnings and employment but may experience demographic shifts. The area used to compare to hurricane-affected regions consisted of counties that did not experience hurricanes during the study period but geographically similar. These counties were matched based on characteristics like population size, income levels, employment rates, and government transfer amounts. Similarly, Arias and Blair (2023) analyze the effects of

Hurricane Ian on climate migration attitudes and policy support in heavily impacted counties across Florida, Louisiana, Texas, and North Carolina using the DID approach. By comparing counties affected by Hurricane Ian to matched counties that were less affected, their analysis shows that disaster exposure leads to a temporary increase in support for climate migration policies and a heightened sense of urgency regarding climate adaptation.

Few other studies looked at how migration patterns and economic outcomes following a disaster can be studies spatially. Pais and Elliott (2008) apply Geographic Information Systems (GIS) to analyze post-hurricane recovery and demographic changes in coastal counties, focusing on how socio-economic disparities shape recovery outcomes. Bakkensen and Ma (2020) use a boundary discontinuity design to examine residential sorting across flood zones in hurricane-affected areas in South Florida. They found that, low-income and minority residents are more likely to move into high-risk flood zones. Park and Franklin (2023), for example, adopt a demographic change model that combines spatial data with U.S. Census records to trace racial and economic composition shifts along the Gulf and Atlantic coasts from 1970 to 2018 finding racial, ethnic, and age disparities exist in exposure to hurricane damage (i.e.: white and Hispanic populations are more exposed to storm surge damage, while minority populations are more vulnerable to wind damage).

3. Hypotheses Postulation

The studies that were conducted before had mixed findings. But one thing is certain that, relocation generated by natural hazards and disasters have profound consequences that eventually reshape economic and demographic structures. However, most of the studies were conducted on specific events or regions and did not take into account the host community. While for the relocated population face challenges that we previously mentioned like disrupted livelihoods, weaker social networks and adapting to new environments, the host communities deal with increased demand for infrastructure, public services and economic resources that might lead to social tension. The previous literature review also highlights the economic struggles of relocated populations, particularly those with fewer resources. Based on the unclear findings, and lack of studies it is clear that additional study needs to be conducted utilizing more advanced empirical methodologies and models for better understanding of disaster-induced relocation for informed policy constructions and interventions. Hence, in our research we will focus on two questions- i) How do disasters affect population relocation? and ii) How do the relocation pattern vary across different income groups and destinations?

Hypothesis 1: Areas affected by disasters will experience higher relocation rates compared to areas that did not experience disasters.

Areas that experience disasters, such as hurricanes, earthquakes, or floods, often face significant challenges that can influence residents to relocate. The term "relocation rates" refers to the percentage of residents who relocate from their homes after a disaster, either to a safer or a less safe place. This hypothesis explores the social and demographic impacts of disasters that can help to make informed policy and resource allocation decisions. Understanding this dynamic is crucial for developing effective disaster response and urban planning strategies.

It is expected that the disaster-affected areas will experience more relocation due to the shock (Myers et al., 2008; Ramsdell & Rishel, 2007). The disaster affected areas face damaged infrastructure, loss of homes, and disruption of essential services, leading to relocate for better living conditions. On the other hand, areas that were not affected by disasters typically maintain their stability, reducing the necessity for residents to move.

Hypothesis 2: Relocation patterns will vary depending on income levels and low-income households are more likely to relocate.

Income level will influence the relocation rate significantly, meaning people with higher incomes will have more capacity to recover and thus low-income people will relocate. Low-income households often face greater challenges in recovering from disasters due to limited financial resources and lack of insurance. While, higher-income households typically have more resources to recover and rebuild, reducing the necessity to relocate. Understanding how income levels affect relocation can help tailor assistance programs to those most in need. Tan et al. (2022) conducted research on hurricane Katrina survivors with three waves of survey data over 12–15 years found that access to high-opportunity areas post-disaster is a strong determinant of economic recovery, particularly for low-income groups. So, it is crucial that relocation policies support the communities in relocating to places with less vulnerability and more opportunities with better infrastructure for long-term prospects.

4. Data

The analysis relies on two primary datasets. First, we draw on administrative tax records data in Florida for the years 2004 to 2021, sourced from the Internal Revenue Service's "SOI Tax Stats - Individual Income Tax Statistics - ZIP Code Data (SOI)" and "SOI Tax Stats - U.S. Population State and County Migration Data." The ZIP code dataset consists of 16,128 observations, which is a unit-year panel covering 896 ZIP code areas over an 18-year period. The county data includes 67 counties over an 18-year period, resulting in a total of 1,206 observations. Both datasets report the total number of returns, individuals, and adjusted gross income at the ZIP code and county levels. The ZIP code dataset provides detailed breakdowns of returns, individuals, and adjusted gross income by different income groups. The county-level data includes migration inflows and outflows, further divided into county-to-county and state-to-state migrations, distinguishing between patterns within the same state and those across different states.

Second, we use hurricane track data from the National Oceanic and Atmospheric Administration (NOAA), which includes records of hurricanes dating back to 1851, with information on longitude, latitude, and wind speed. For this study, the dataset was filtered to include only Florida and the study period from 2004 to 2021. Using the spatial join tool in ArcGIS Pro, we identify treated ZIP codes as those intersected by hurricane paths plotted onto the ZIP code shapefile. Among the intersected units, we identify the year-unit pairs to determine the treated units. If units were affected multiple times by the same hurricane or storm within the same year, or by different hurricanes or storms, they are counted as a single pair, as they share the same year and unit.

The resulting spatial join identifies 102 ZIP code-year pairs affected by storms, 31 ZIP code-year pairs affected by hurricanes, 96 county-year pairs affected by storms, and 25 county-year pairs affected by hurricanes. For the sake of simplicity, we define the treatment as the initial year intersected with the hurricane path within the sample period. Although this definition poses several empirical challenges, we begin with it for preliminary purposes and later expand the analysis to test its robustness under different definitions. This results in 78 ZIP codes affected by storms and 28 by hurricanes out of 896 ZIP codes, and 40 counties affected by storms and 21 by hurricanes out of 67 counties, all staggeredly treated over different years. Please see Table 1 for detailed information.

The study utilizes a geographical information system (GIS) to identify zip codes directly affected by hurricanes. However, when treatment is narrowly defined as ZIP codes intersected by the hurricane path, it risks underestimating the broader range of affected areas. This narrow definition also complicates the process of identifying and defining the comparison group, as it becomes difficult to accurately differentiate between treated areas and those that are comparable but remain untreated. This also has different implications for smaller versus larger units of analysis. Smaller units, like ZIP codes, enable precise identification of affected areas but may fail to capture the broader regional impact. Conversely, larger units, like counties, may dilute the observed effects, as the localized variations can be masked within the defined boundaries. In this draft, we focus on identifying patterns by defining the treatment group at the ZIP code level, where later-treated and early-treated areas serve as comparison groups for each other. At the county level, the comparison group consists of all other counties not intersected by the hurricane path. We plan to further refine our analysis by identifying plausibly untreated yet comparable areas. We will examine the spatial extent of each hurricane, creating a buffer zone defined by the average radius of the outermost closed isobar (ROCI). Zip codes falling outside this radius are considered geographically close and similar to the treated areas but not directly affected by the hurricane. Additionally, we will select only those zip codes within the same hurricane risk zones to improve comparability between treated and untreated areas. This approach allows us to treat the hurricane impact as plausibly random among zip codes that share similar risk profiles.

We merge zip code level data with IRS tax return data. As no existing datasets are tracking disaster-induced relocation, IRS Tax Return data has been used by previous studies to track migration or disaster-induced relocation (Curtis et al., 2015; Fussell et al., 2014). The data is derived from individual income tax returns (Forms 1040) filed with the Internal Revenue Service (IRS) over the 12-month period from January 1 to December 31 each year. This data set includes the 5-digit ZIP code, size of adjusted gross income, number of returns, number of individuals, and adjusted gross income. This provides information on the demographics, information on individual and community wealth, which are classified by the number of returns classified into income classes which approximates. Since the range of income brackets changes over time, we normalized them into five income brackets. These are coded as follows: lowest income group for incomes below $25,000; lower-middle income group for incomes between $25,000 and $50,000; middle income group for incomes between $50,000 and $75,000; upper-middle income group for incomes between $75,000 and $100,000; and highest income group for incomes of $100,000 and above.

The data on FEMA assistance will be collected from OpenFEMA datasets. As the relocation data is at zip-code level and FEMA assistance data is at the county level, the estimates for public assistance will be the average differences from groups of zip codes from different counties. As zip-codes are smaller geographic units that nest within counties, I will group multiple zip codes together that fall within the same county.

5. Method

We employ an event-study design to estimate the temporal effects of hurricanes on demographic outcomes. An event study is a quasi-experimental design similar to the Difference-in-Differences (DID) model, particularly useful for evaluating treatment effects over pre- and post-hurricane periods. The approach allows researchers to inspect the parallel trend assumption, ensuring that the treated and control areas exhibit similar trends before the hurricane. It also enables researchers to capture temporal effects, showing how the impact of a hurricane evolves over time, rather than relying on a single-coefficient average treatment effect. An event-study specification takes the following form:

$$lnV_{it} = \tau_t + \mu_i + \sum_{r=-4}^{5} \alpha_r U_{r,it} + \theta C_{it} + \varepsilon_{it} \tag{2}$$

where τ denotes year-fixed effects, and μ indicates area-fixed effects. $U_{r,it}$ represents a set of binary variables, indicating the number of years relative to the baseline year, which we chose as the year before the hurricane hit. The event window spans 4 years before to 5 years after the baseline year. As we normalize the event window around each hurricane spans over a 20-year sample period, we observe up to fifteen years before and eighteen years after the hurricanes. For simplicity, "4" denotes four or more years before the baseline year, while "5" represents five or more years after the baseline year. The parameters of interest, α_r, correspond to each indicator variable in $U_{r,it}$, capturing the temporal effects of hurricanes by comparing the differences in outcomes between affected and unaffected zipcodes over time. Indicator variables are coded as zero for areas not intersected by hurricane paths.

6. Preliminary Findings

Results on Total Returns, Individuals, and Income

We begin by analyzing total measures of returns, individuals, and income to identify general patterns before and after hurricanes. At both the ZIP code and county levels, we observe decreases in total returns, individuals, and adjusted gross income following tropical and storms and hurricanes. Notably, at the ZIP code level, decreases in returns and individuals continue in the long term even after tropical storms.

When comparing the magnitude of these decreases across different samples, hurricanes generally result in larger decreases in total measures. However, while ZIP codes tend to show larger decreases compared to counties, these decreases are not always statistically significant. For instance, at the ZIP code level, hurricanes lead to a 7-12% decrease, but these changes are not statistically significant and also suggest the presence of pre-trends. In contrast, tropical storms lead to a statistically significant decline of 2-6% in ZIP code-level returns and individuals. Similarly, at the county level, hurricanes cause a significant 5% decline, whereas tropical storms result in a 1-3% decrease, which is not statistically significant enough to suggest large effects. Although no definitive conclusions can be drawn at this stage, the overall trend across different samples and comparisons suggests a decrease in the number of returns and individuals, while the impact on adjusted gross income appears to be less significant or more short-term. These results are presented in Tables 5 and 6.

Results on Relative Returns, Individuals, and Income by Income Group

We next estimate the dynamic effects of hurricanes on key outcomes, specifically focusing on the number of tax returns filed, the number of individuals, and the adjusted gross income by the five AGI classes, using ratio measures. Figures 1–3 display the results. In most of our regression results, we observe no discernible trends in the years leading up to the hurricane. This suggests that the impact of the hurricane can plausibly be considered unexpected.

First, regarding the number of returns ratio (Figure 1), we find that in zip codes affected by hurricanes, the number of returns in the lowest-income bracket decreases immediately and continues to decline over the following years. This decline is statistically significant through the third year after the hurricane, with the largest impact observed in that year——a 2 percentage point decrease in the ratio of returns. In contrast, we observe an increase in the ratio of returns for the highest income group, rising by 1 and 1.4 percentage points in the first and second years following the hurricane, respectively. However, these immediate increases are not statistically significant beyond the second year, although they remain positive. As for other AGI classes, we do not find any statistically significant effect of hurricanes on the number of tax returns in the years following the event.

In Figure 2, we observe similar patterns in the number of individuals, but the patterns are more significant. Overall, there is a decrease in the ratio of individuals within the two lowest income classes, the lowest and lower middle income groups, though these declines in the ratio do not persist in the long run. Similarly, the ratio of individuals in the middle and highest income groups increases, but the increases in ratio are only observed in the short term. Specifically, individuals in the lowest income class experienced an immediate decline of 1 percentage point after the hurricane, with the decrease reaching its peak at 2 percentage points in year 3. Similarly, the ratio of individuals in the lower middle income class saw an initial decline of about 1 to 2 percentage points following the hurricane. This decline persists until year 4 but becomes statistically insignificant in the long run. Interestingly, hurricanes lead to significant increases in the number of individuals in the middle income class. These increases are not immediately evident but gradually peak at 2 percentage points in year 3, becoming statistically significant before declining thereafter. No distinct patterns were observed in the upper middle income class, while the highest income group experienced a short-term increase of about 1 percentage point during the first two years. These results align with our expectations, as hurricanes often lead to the relocation of individuals. Some of these dynamics might not be fully captured when grouping households by tax returns.

In addition to demographic results, we also estimate the hurricane on adjusted gross income. The results are shown in Figure 3. We observed a clear downward trend in the AGI ratio for the lower-middle income group, the second income group, until year 4. The ratio significantly declines from year 1 to year 4. The magnitude of these effects ranges from 1.6 to 2 percentage points. Given that the average AGI ratio for this group is 0.19, these decreases represent a significant reduction in their contribution to total ZIP code-level income. A similar pattern was found in the lowest income group, with marginally significant effects observed until year 4 after the hurricane. In contrast, the highest income group experienced a significant increase in their share of AGI, rising by 3 to 5 percentage points. No significant changes were observed in the AGI ratios for the middle and upper-middle income groups in the post-hurricane period. These findings suggest that, in the aftermath of the hurricane, income distribution shifts, with higher-income groups contributing a larger share of total income, while the share from the two lowest-income groups declines. This shift may indicate a growing disparity in income distribution post-disaster, where wealthier groups capture a greater portion of total income, while lower-income groups see a reduced proportion of their contribution to the overall adjusted gross income.

Results on Relative Returns, Individuals, and Income by Inflow and Outflow Group

We analyze four different groups: (1) same-state outflow, (2) different-state outflow, (3) same-state inflow, and (4) different-state inflow. First, we examine how the ratio of tax returns varies across these groups. We find significant short-term increases in the ratio of returns for outflows migrating within the same state (county-to-county), with a peak in the third year, statistically significant at the 0.02 level. Similar patterns are not observed in outflows to different states. Regarding inflows, we observe a significant increase in the ratio of returns from same-state inflows in year 4. In contrast, inflows from different states, while not statistically significant, exhibit a declining trend rather than an increasing one in the post-hurricane period.

The ratio of individuals follows a similar pattern. We found significant increases in same-state outflows in years 2 and 3, while inflows from the same state show increases in years 3 and 4. However, the patterns for different-state groups show an opposite trend, though none of the results are statistically significant. These findings suggest that demographic replacement is occurring primarily at the county-to-county level rather than through interstate migration.

Income ratios for inflows and outflows across same-state and different-state groups also reveal interesting patterns. Significant inflows are found in the same-state group, leading to a long-term increase of 0.7 percentage points in income inflows.

Overall, these results indicate that post-hurricane migration patterns and income shifts occur more within the same state than across different states, which underscores the localized nature of demographic and economic changes.

Table 1: counts of hurricane-path intersected zip codes and counties by tropical storm and hurricane frequency

	Tropical storm			Hurricane		
Group	Freq.	Percent	Average interval	Freq.	Percent	Average interval
	(1)	(2)	(3)	(4)	(5)	(6)
Zip Code-Level:						
Intersected once	58	0.74	-	25	0.89	-
Intersected twice	16	0.21	7.56	3	0.11	13.33
Intersected 3 times	4	0.05	5.13			
Total	78	1	7.08	28	1	13.33
County-Level:						
Intersected once	8	0.20	-	17	0.81	-
Intersected twice	14	0.35	7.36	4	0.19	13.25
Intersected 3 times	13	0.33	5.15			
Intersected 4 times	4	0.10	4			
Intersected 5 times	1	0.03	4			
Total	40	1	5.94	21	1	13.25

Notes: The table reports the count of zip codes and counties categorized based on the number of tropical storms and hurricanes they experienced during the estimation sample period from 2004 to 2021. Columns (3) and (6), showing the average interval, indicate the average number of years between tropical storms and hurricanes for each group. The total number of frequencies is the sum of the number of treatments, each multiplied by its frequency count. There were 102 ZIP code-year pairs affected by storms, 31 ZIP code-year pairs affected by hurricanes, 96 county-year pairs affected by storms, and 25 county-year pairs affected by hurricanes. These correspond to the total number of intersections for each group, calculated by summing the number of zip codes or counties in each group multiplied by the number of times they were intersected by storms or hurricanes.

Table 2: tropical storm and hurricane descriptive statistics

	Tropical storm			Hurricane		
The number of zip codes intersected by the path	Freq.	Percent	Average wind speed	Freq.	Percent	Average wind speed
	(1)	(2)	(3)	(4)	(5)	(6)
Zip Code-Level:						
1-3	21	0.68	38.86	6	0.60	93.06
4-6	6	0.19	39.40	3	0.30	92.62
7-9	3	0.97	39.39	1	0.10	89.29
Over 10	1	0.32	47.14			
Total	31	1	40.90	10	1	93.11
County-Level:						
1-3	31	0.97	39.37	10	1	92.75
4-6						
7-9						
Over 10	1	0.03	47.39			
Total	32	1	40.78	10	1	92.75

Notes: The table summarizes the prevalence and strength of 37 tropical storms and hurricanes occur from 2004 to 2021, categorizing them by the number of zip codes intersected by each path. Four storms at the zip code level and five storms at the county level developed into hurricanes, depending on the storm path captured at smaller or larger units of analysis. As a result, they are included in both samples.

Table 3. Summary Statistics of ZIP Code Data (2004-2021)

Variable	Obs	Mean	Std. Dev.	Min	Max
Total number of returns	16,128	10,080	7,331	200	45,920
Total number of individuals	16,128	18,689	13,544	350	89,890
Total adjusted gross income (in thousands)	16,128	60,172	235,851	8	5,797,019
Ratio of returns for:					
lowest income group	16,128	0.42	0.11	0.09	0.84
lower-middle income group	16,128	0.25	0.04	0.00	0.51
middle income group	16,128	0.13	0.03	0.00	0.32
upper-middle income group	16,128	0.07	0.03	0.00	0.18
highest income group	16,128	0.13	0.10	0.00	0.77
Ratio of individuals for:					
lowest income group	16,128	0.34	0.12	0.00	0.77
lower-middle income group	16,128	0.25	0.05	0.00	0.56
middle income group	16,128	0.14	0.03	0.00	0.36
upper-middle income group	16,128	0.09	0.03	0.00	0.20
highest income group	16,128	0.18	0.13	0.00	0.85
Ratio of adjusted gross income for:					
lowest income group	16,128	0.12	0.08	–0.08	0.56
lower-middle income group	16,128	0.19	0.09	0.00	0.52
middle income group	16,128	0.15	0.05	0.00	0.72
upper-middle income group	16,128	0.12	0.04	0.00	0.48
highest income group	16,128	0.43	0.22	0.00	1.02

Table 4. Summary Statistics of State and County Migration Data (2004-2021)

Variable	Obs	Mean	Std. Dev.	Min	Max
Total number of returns	1,206	102,949	168,779	1,332	1,078,824
Total number of individuals	1,206	207,314	334,431	3,107	2,053,818
Total adjusted gross income (in thousands)	1,206	6,618	11,546	47	83,155
Ratio of returns for:					
same state outflow	1,206	0.05	0.02	0.02	0.16
different state outflow	1,206	0.03	0.01	0.00	0.09
same state inflow	1,206	0.06	0.02	0.02	0.21
different state inflow	1,206	0.04	0.02	0.00	0.13
Ratio of individuals for:					
same state outflow	1,206	0.05	0.02	0.02	0.15
different state outflow	1,206	0.03	0.01	0.00	0.10
same state inflow	1,206	0.05	0.02	0.01	0.22
different state inflow	1,206	0.04	0.02	0.00	0.12
Ratio of adjusted gross income for:					
same state outflow	1,206	0.04	0.02	0.00	0.52
different state outflow	1,206	0.02	0.01	0.00	0.13
same state inflow	1,206	0.04	0.02	–0.01	0.39
different state inflow	1,206	0.05	0.03	0.00	0.25

Table 5. Total results (Zip Code-Level)

	Tropical Storm			Hurricane		
	Returns	Individuals	AGI	Returns	Individuals	AGI
	(1)	(2)	(3)	(4)	(5)	(6)
$T_{\leq -4}$	0.006	0.011	−0.007	0.156*	0.191*	0.252**
	(0.021)	(0.024)	(0.028)	(0.082)	(0.098)	(0.116)
T_{-3}	0.005	0.000	0.010	0.150*	0.186*	0.203*
	(0.014)	(0.015)	(0.020)	(0.084)	(0.101)	(0.111)
T_{-2}	0.017	0.015	0.014	0.123	0.150	0.188*
	(0.013)	(0.013)	(0.018)	(0.075)	(0.094)	(0.104)
T_{-1}	0.004	0.005	−0.004	0.106	0.122	0.168*
	(0.009)	(0.009)	(0.014)	(0.067)	(0.075)	(0.089)
T_1	−0.028**	−0.028**	−0.041**	−0.100	−0.099	−0.006
	(0.013)	(0.012)	(0.018)	(0.076)	(0.078)	(0.083)
T_2	−0.031**	−0.032**	−0.029*	−0.124	−0.125	−0.033
	(0.015)	(0.015)	(0.017)	(0.092)	(0.090)	(0.086)
T_3	−0.038**	−0.041**	−0.025	−0.107	−0.108	0.000
	(0.019)	(0.020)	(0.022)	(0.084)	(0.079)	(0.080)
T_4	−0.035	−0.037*	−0.028	−0.086	−0.089	−0.010
	(0.022)	(0.022)	(0.021)	(0.076)	(0.072)	(0.081)
$T_{\geq 5}$	−0.059*	−0.059*	−0.051	−0.067	−0.074	−0.005
	(0.031)	(0.033)	(0.033)	(0.061)	(0.058)	(0.074)
Treatment	78×18 years	78×18 years	78×18 years	28×18 years	28×18 years	28×18 years
Control	X	X	X	X	X	X
Obs.	1,404	1,404	1,404	504	504	504

Table 6. Total results (County-Level)

	Tropical Storm			Hurricane		
	Returns	Individuals	AGI	Returns	Individuals	AGI
	(1)	(2)	(3)	(4)	(5)	(6)
$T_{\leq -4}$	−0.021	−0.022	0.002	0.026	0.022	0.042
	(0.031)	(0.033)	(0.042)	(0.026)	(0.028)	(0.076)
T_{-3}	−0.024	−0.025	−0.022	0.028	0.022	0.053
	(0.022)	(0.023)	(0.030)	(0.016)	(0.017)	(0.034)
T_{-2}	−0.019	−0.021	−0.013	0.022	0.016	0.023
	(0.015)	(0.016)	(0.021)	(0.014)	(0.015)	(0.038)
T_{-1}	−0.010	−0.012	−0.002	0.016	0.011	0.026
	(0.009)	(0.009)	(0.013)	(0.014)	(0.015)	(0.031)
T_{1}	−0.006	−0.008	−0.009	−0.033*	−0.035**	−0.011
	(0.011)	(0.012)	(0.016)	(0.017)	(0.018)	(0.026)
T_{2}	−0.013	−0.013	−0.023	−0.042**	−0.042**	−0.023
	(0.013)	(0.014)	(0.020)	(0.018)	(0.019)	(0.030)
T_{3}	−0.016	−0.017	−0.032	−0.047**	−0.046**	−0.021
	(0.016)	(0.017)	(0.023)	(0.018)	(0.019)	(0.030)
T_{4}	−0.020	−0.021	−0.034	−0.044**	−0.043**	−0.010
	(0.018)	(0.019)	(0.027)	(0.018)	(0.020)	(0.033)
$T_{\geq 5}$	−0.036	−0.035	−0.048	−0.015	−0.015	0.035
	(0.029)	(0.030)	(0.042)	(0.029)	(0.031)	(0.048)
Treatment	40×18 years	40×18 years	40×18 years	21×18 years	21×18 years	21×18 years
Control	27×18 years	27×18 years	27×18 years	46×18 years	46×18 years	46×18 years
Obs.	1,206	1,206	1,206	1,206	1,206	1,206

Figure 1. Results for Number of Tax Returns by Income Group

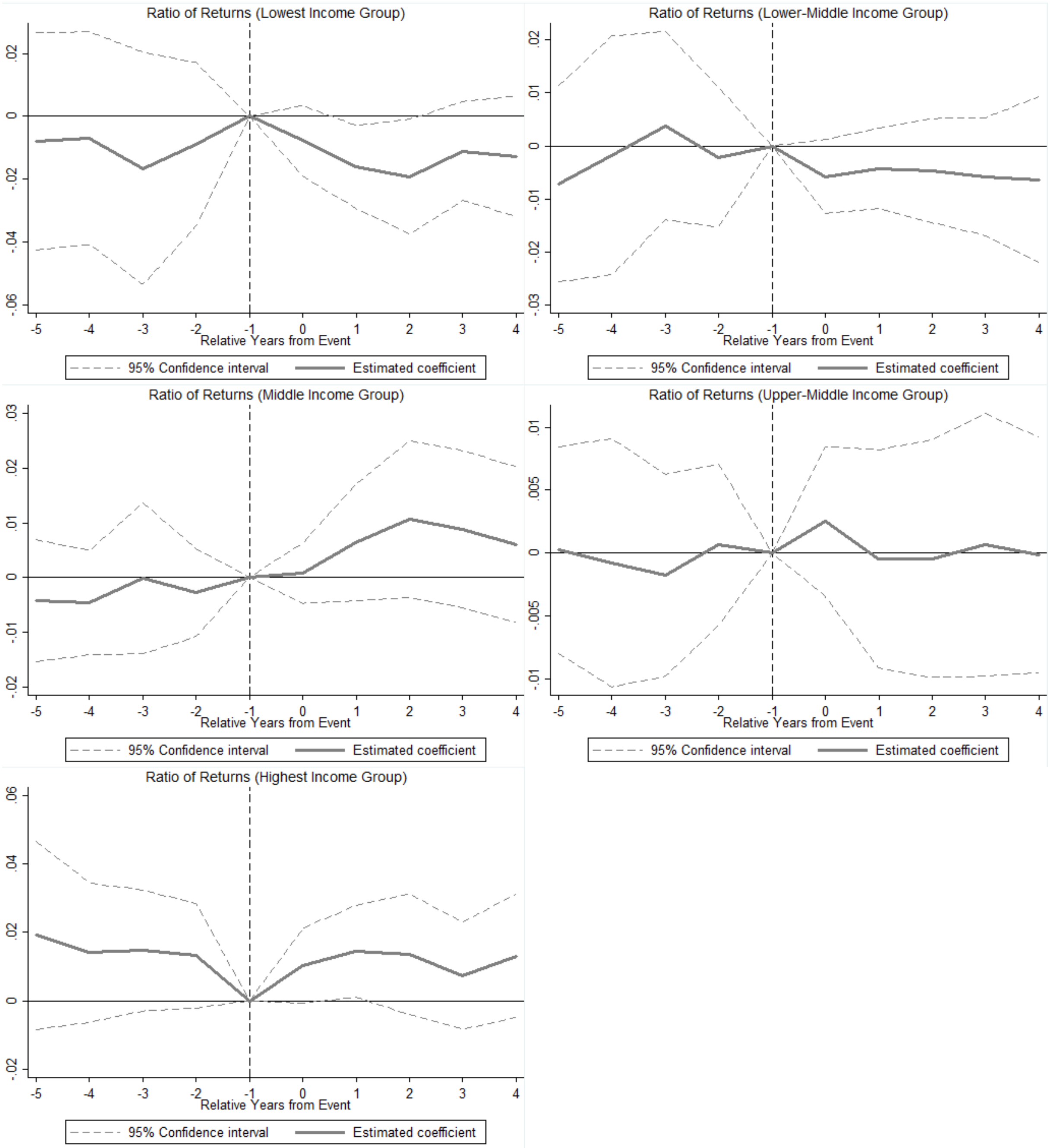


Figure 2. Results for Number of Individuals by Income Group

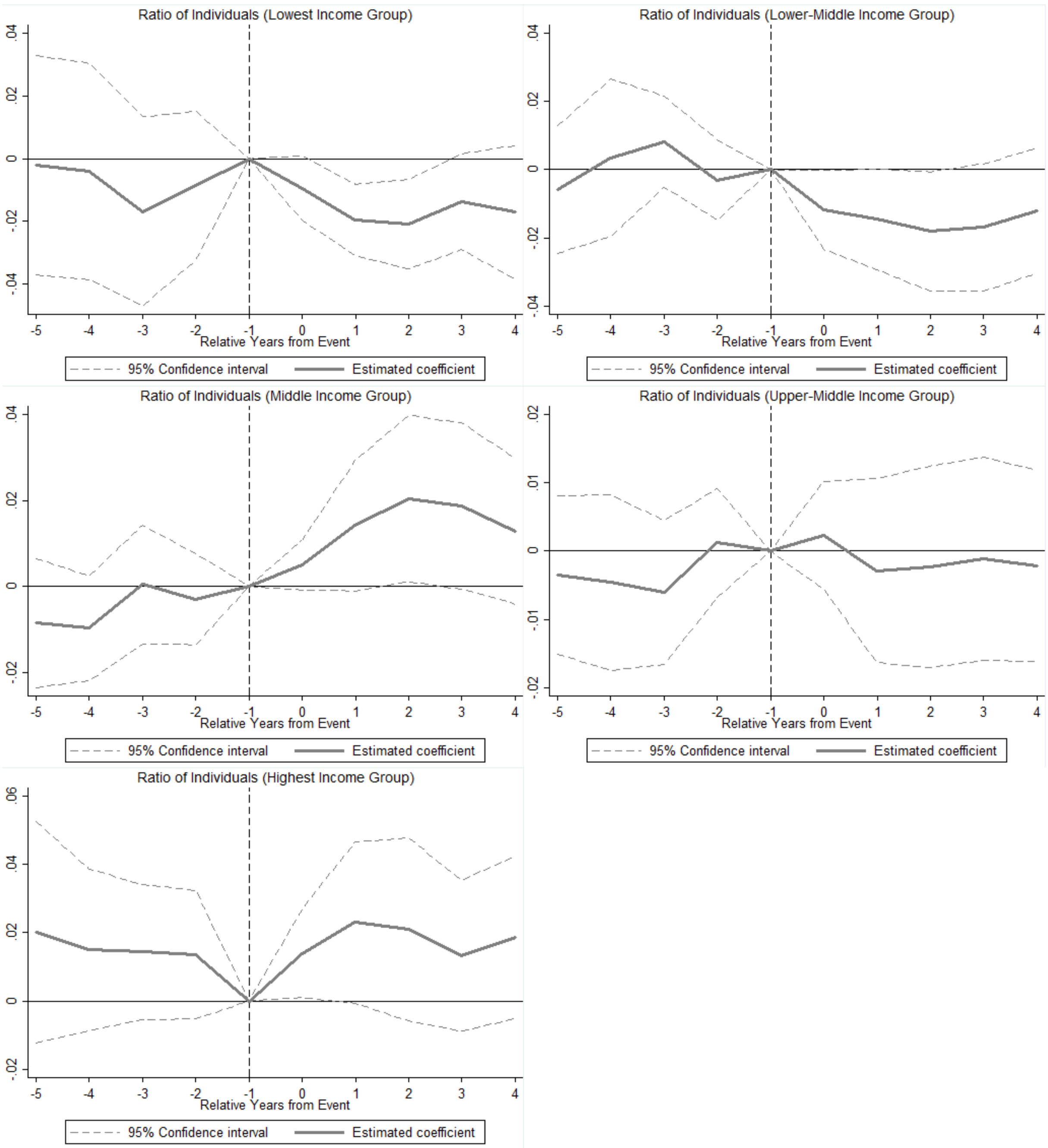


Figure 3. Results for Size of Adjusted Gross Income by Income Group

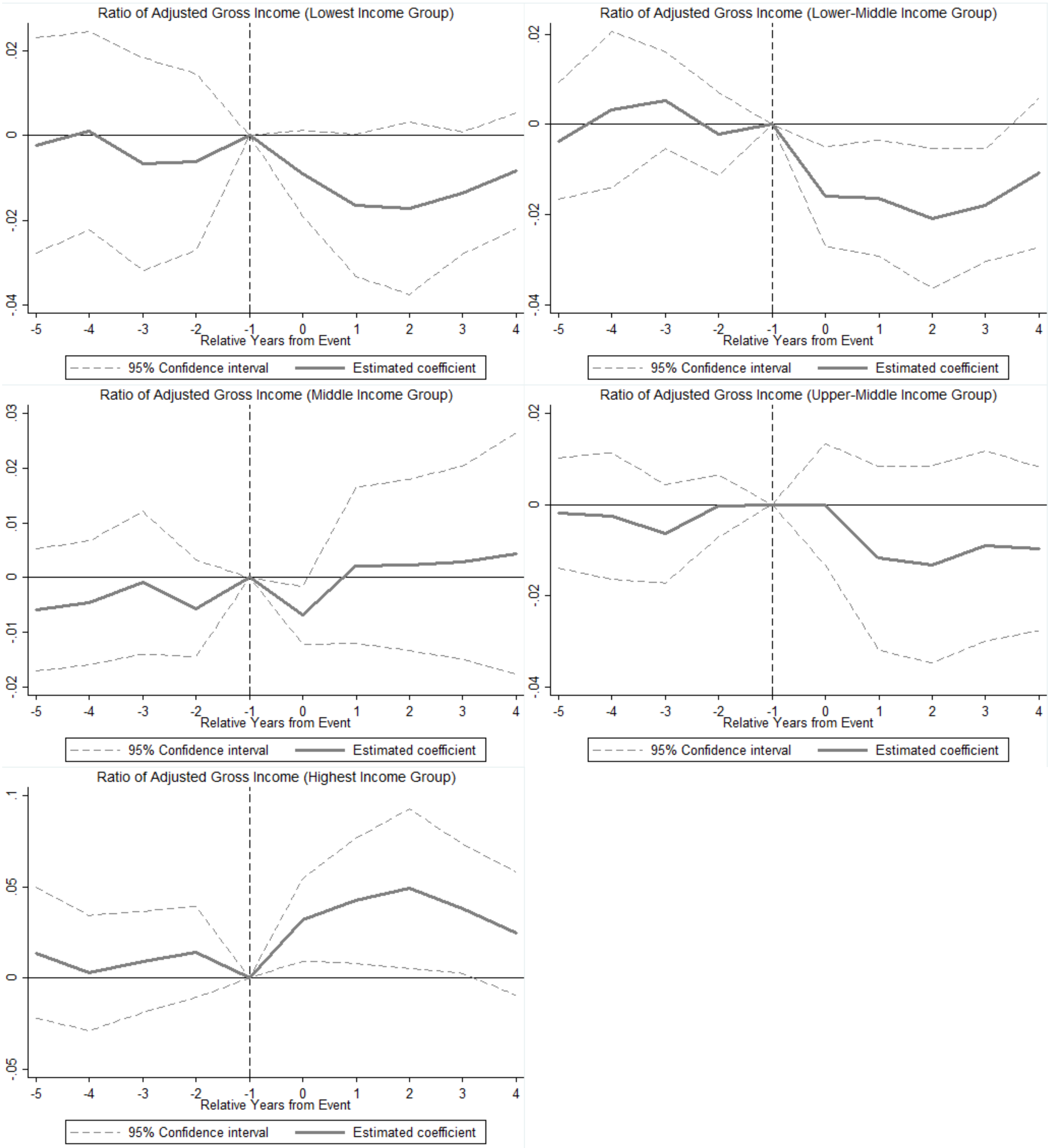


Figure 4. Results for Number of Tax Returns by Inflow and Outflow Group

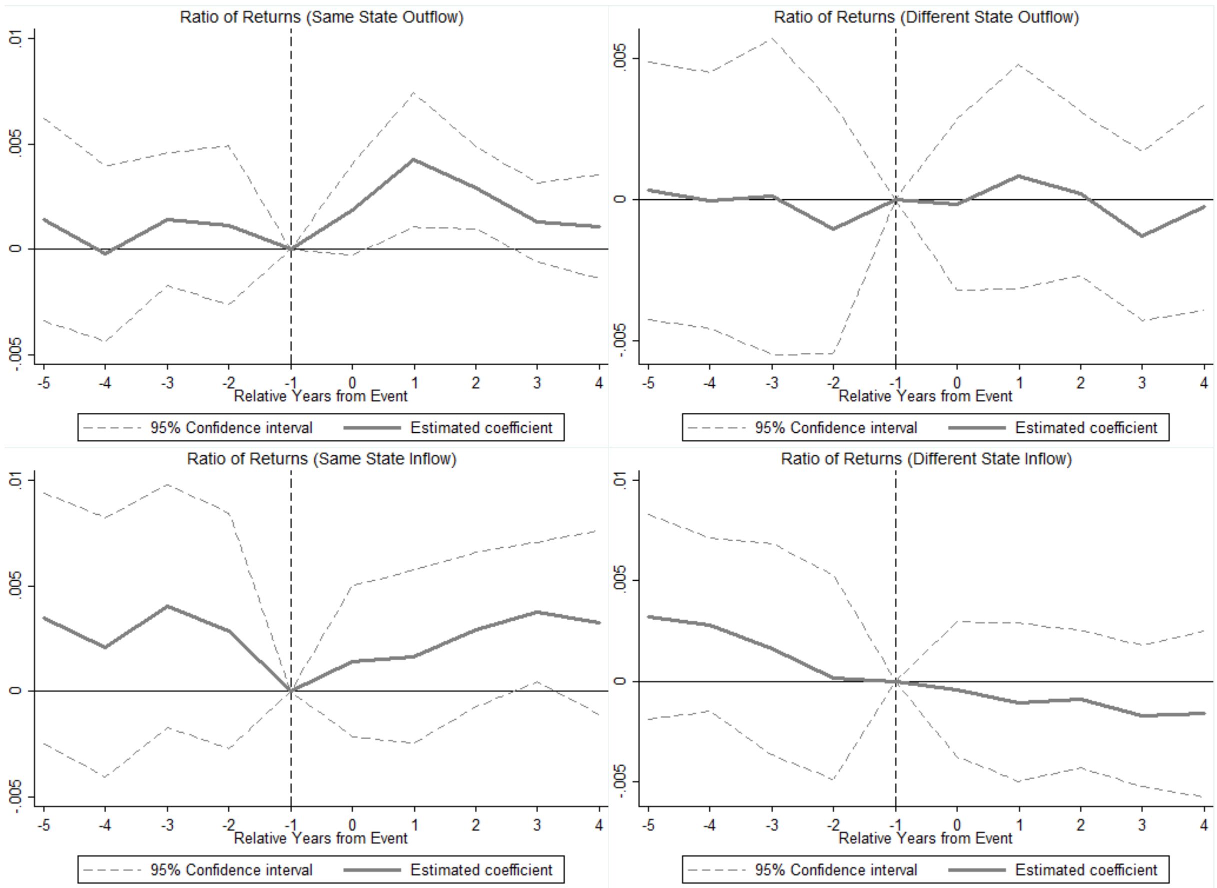


Figure 5. Results for Number of Individuals by Inflow and Outflow Group

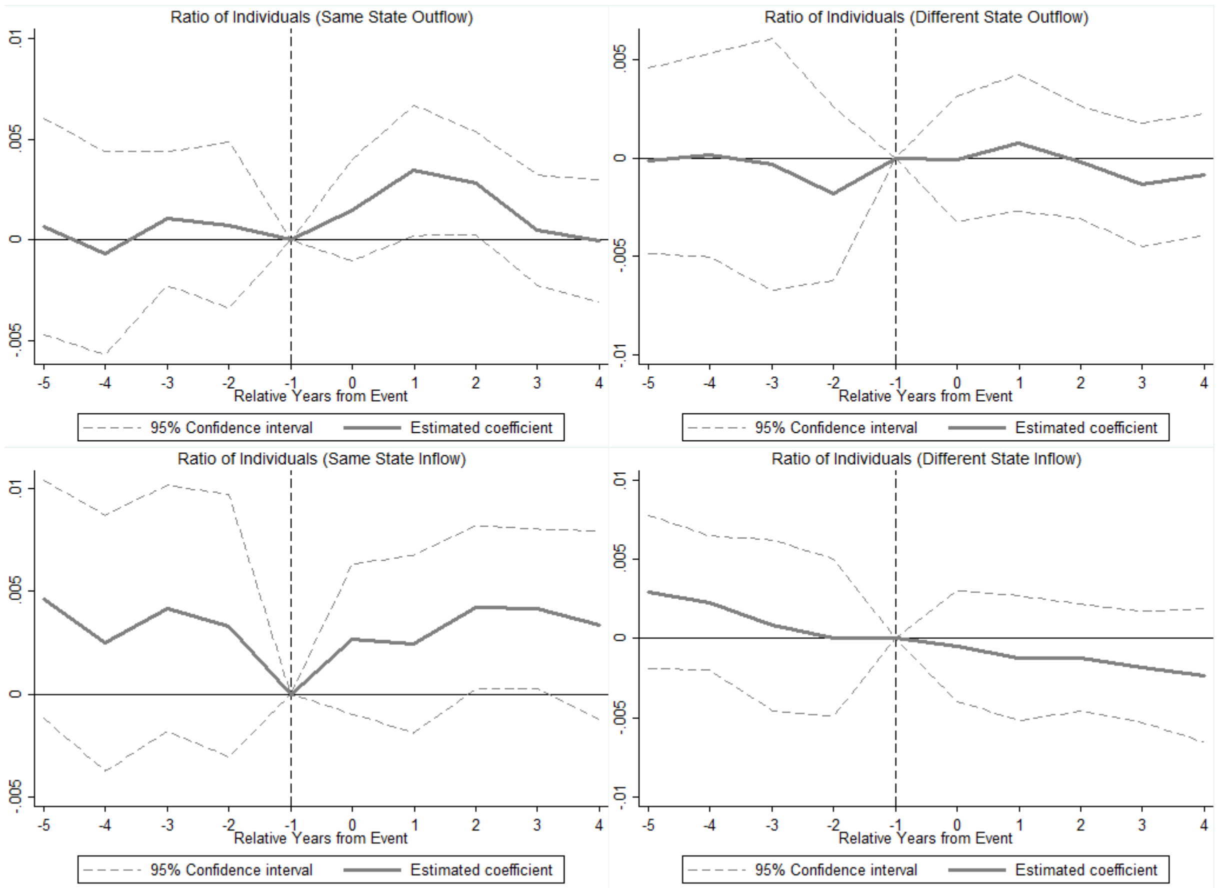
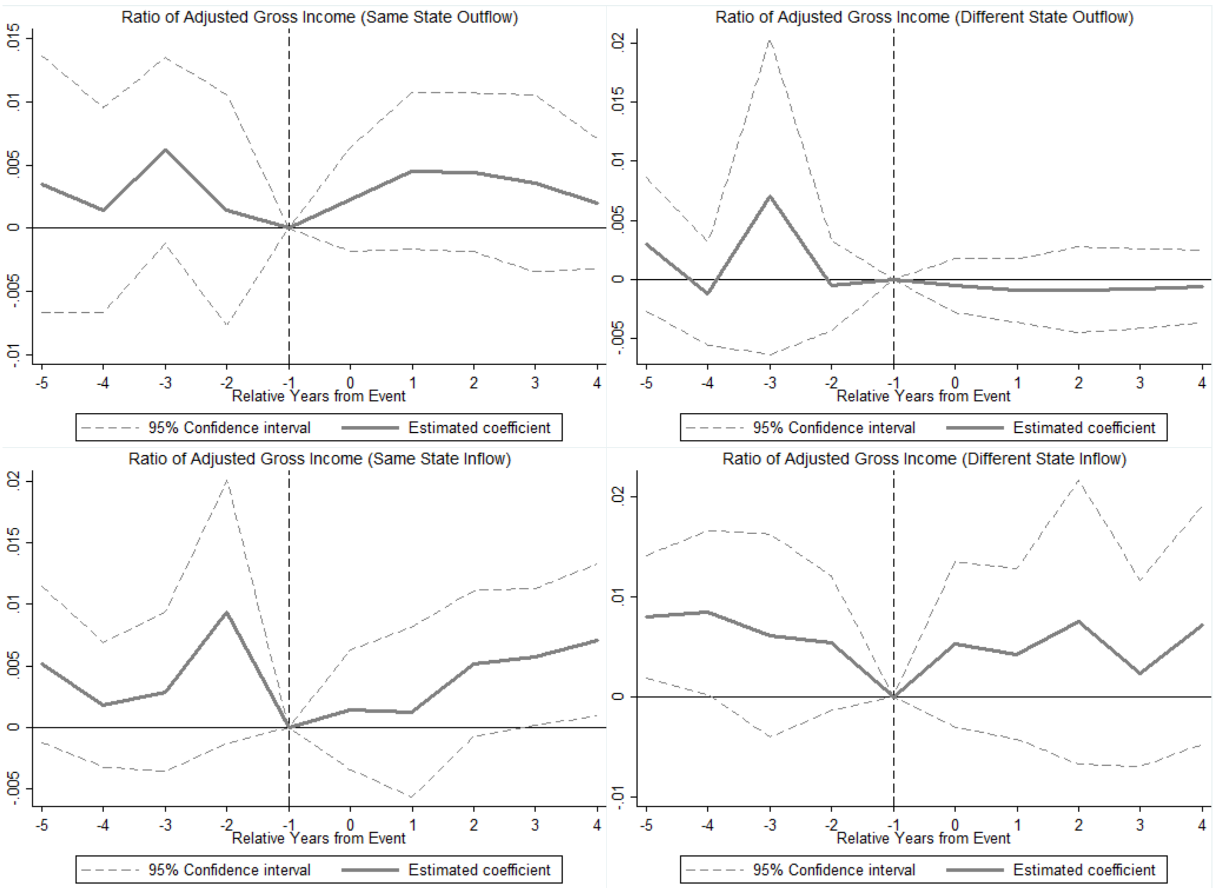


Figure 6. Results for Size of Adjusted Gross Income by Inflow and Outflow Group



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