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Environmental migration as short- or long-term differences from a trend: A case study of Hurricanes Katrina and Rita effects on out-migration in the Gulf of Mexico

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Abstract

An environmental event that damages housing and the built environment may result in either a short- or long-term out-migration response, depending on residents' recovery decisions and hazard tolerance. If residents move only in the immediate disaster aftermath, then out-migration will be elevated only in the short-term. However, if disasters increase residents' concerns about future risk, heighten vulnerability, or harm the local economy, then out-migration may be elevated for years after an event. The substantive aim of this research brief is to evaluate hypotheses about short- and long-term out-migration responses to the highly destructive 2005 hurricane season in the Gulf of Mexico. The methodological aim is to demonstrate a difference-in-differences (DID) approach analysing time series data from Gulf Coast counties to compare short- and long-differences in out-migration probabilities in the treatment and control counties. We find a large short-term out-migration response and a smaller sustained increase for the disaster-affected coastal counties.

INTRODUCTION

Alarmist media warns of massive population displacements in the coming decades due to climate change (Lustgarten, 2020). Social scientists bring critical perspective to the discussion by using rigorous data and methods to study disasters as analogues for anticipated climate change effects on human behaviour. However, the current environmental migration literature is characterized by a diversity of data and methods that make it difficult to generalize about disaster effects on migration (Borderon et al., 2019; Fussell, Gray, & Hunter, 2014; Hoffman et al., 2020). This research brief has two aims. The methodological aim is to demonstrate how DID models can be used with geographically comprehensive time series data on disasters and human migration using difference-in-differences (DID) regression models to identify and measure short- and long-term changes in migration trends (Burke & Emerick, 2016; Hsiang, 2016). Our substantive aim is to test novel hypotheses about a highly destructive disaster event's effect on short- and long-term out-migration.

Climate change will have both short- and long-term impacts on human settlements and their residents. For example, and most relevant to our study, the warming of oceans increases the energy in tropical cyclones, making them more destructive when they make landfall and damage the built and natural environment and displace residents from their housing and livelihoods. In addition to tropical cyclones, rapid-onset shocks include tornados, precipitation-related flooding, mudslides, and wildfires, among others.[1] Rapid-onset events may increase out-migration and in-migration over the subsequent years, as residents relocate temporarily or permanently and new in-migrants settle in the disaster-affected location (Fussell, Curtis, & DeWaard, 2014; McLeman & Smit, 2006). Research on disaster-related migration focuses mainly on the immediate post-disaster period when out-migration dominates (Fussell et al., 2010; Groen & Polivka, 2010), although new sources of administrative data from social media, mobile phones, and credit histories make it possible to follow migration over longer periods (Acosta et al., 2020; DeWaard et al., 2020; Lu et al., 2016; Martín et al., 2020; Santos-Lozada et al., 2020). However, most places affected by disasters recover their population size over a longer period through recovery migration (Curtis et al., 2014). As highly destructive rapid-onset events become more frequent and overwhelm the capacity of communities to adapt, recovery migration may diminish as residents who perceive growing environmental risk decide to out-migrate and potential in-migrants elect to go elsewhere. In order to understand when and where climate-related changes in migration behaviour occur, we seek to increase our analytical toolkit to test hypotheses about the short- and long-term migration responses to disasters.

In this research brief, we measure the effect of Hurricanes Katrina and Rita– which struck the Gulf of Mexico coast on August 29, 2005 and September 24, 2005, respectively– to evaluate short- and long-DID models and the effect of varying temporal measures of out-migration in the pre- and post-disaster period. Hurricane Katrina remains one of the most destructive and costliest hurricane disasters in U.S. history (Blake et al., 2011; National Oceanic and Atmospheric Administration, N.D.-a, N.D.-b). The 2005 hurricane season damaged 21per cent of housing units in the five Gulf Coast states.[2] In the parishes hardest hit by Katrina and Rita the majority of housing units were damaged (United States Department of Housing and Urban Development, 2006).[3] Flooding and housing damage displaced over a million residents in the following year (Groen & Polivka, 2010). In New Orleans, the largest affected city, the bureaucratic complexity of recovery funding slowed the interlocked process of housing and population recovery (Colten et al., 2008; Comfort et al., 2010; Fussell, 2015; Kates et al., 2006). While all parishes experience increased in-migration for at least 1 year post-disaster, rural counties experienced minimal and short-term population recovery while metropolitan counties experienced sustained in-migration (Curtis et al., 2020). Here, we turn the focus to out-migration from the disaster-affected counties and, after demonstrating the crisis-driven out-migration response in the short-term, we ask whether this pattern is sustained over a longer period. We postulate that a sustained out-migration after disaster is driven by a combination of disaster-related housing and job losses as well as residents' and potential in-migrants' increased perception of environmental risk (Adeola & Picou, 2017; Dolfman et al., 2007; Groen et al., 2020). This is the first time we have focused on the long-term out-migration after Hurricanes Katrina and Rita.

TEMPORAL AND SPATIAL ELEMENTS OF ENVIRONMENTAL MIGRATION

The effect of environmental changes on migration is often inferred from the timing of a rapid onset environmental event and changes in the patterns of subsequent migration. For example, studies of hurricanes (DeWaard et al., 2020;

Fussell, Curtis, & DeWaard, 2014; Martín et al., 2020) or tsunamis (Gray et al., 2014) and their effects on out-migration infer a causal relationship based on the close timing of the event and a subsequent increase in the magnitude of out-migration. The shared hypothesis in these studies is that a disaster event will increase out-migration from the affected area in the period after the event. However, a study design that relies only on post-event observations in the disaster-affected area does not rule out spurious causes of increased out-migration. An improved design to demonstrate a causal effect includes pre- and post-disaster observations, preferably over multiple time units, and a comparable unexposed group that allows for estimates of the magnitude and duration of the disaster effect on out-migration (Alexander et al., 2019; Curtis et al., 2014; Raker, 2020).

Snow (1855) famously employed the DID design to show that contaminated water caused London's cholera epidemic in 1854. Snow found higher mortality rates among the residents of neighbourhoods using water supplied from a cholera-infected area of the Thames River compared to those residents living in adjacent neighbourhoods whose water supply came from an uninfected upstream water intake. As all other conditions in the two adjacent neighbourhoods were the same, this design provided clear evidence that water was the cause of the cholera outbreak. The inclusion of the comparison group allowed Snow to rule out miasma, or bad air, which was the favoured explanation for cholera transmission. Identification of water as the likely vector provided a clue to ultimate cause of cholera. This type of design with a treatment and control group is preferable to a simple before-and-after design because it more convincingly identifies the treatment as the cause of the change. Since Snow's study, the DID design has been employed in many health and social science disciplines to evaluate the population effects of environmental and economic shocks and policy changes (Angrist & Pischke, 2009; Burke & Emerick, 2016; Hsiang, 2016; Imbens & Wooldridge, 2009; Perraillon et al., 2019; Wing et al., 2018).

The basic DID design involves a pre- and post-event period for all exposed and unexposed geographic units.[4] The untreated comparison group pattern serves as a counterfactual to the treated group pattern, allowing us to attribute any differences to the event, assuming that all units are otherwise the same on average (Gangl, 2010; Rubin, 2005). How the periods are defined depends on the temporal units in the dataset and whether the research analyst aggregates multiple time units. A short-DID model compares the outcome measure in two adjacent or closely timed periods, such as the period immediately before and after an event. A long-DID model compares the outcome measure in two more widely spaced time periods, such as a period one or two decades before an event and the period immediately after the event. We demonstrate how defining time periods in different ways in the DID models allows us to test distinct hypotheses about the effects of disaster exposure on short- and long-term out-migration behaviour.

Our first analysis compares each pair of adjacent years throughout the entire period of observation to evaluate the hypothesis that an extreme event, in this case the disaster in the Gulf of Mexico that followed Hurricanes Katrina and Rita, increased out-migration from treated counties in the year after the event and that an increase of this magnitude is not evident in any other year under observation. Our second analysis benefits from the long time-series data to move beyond the short-term effect of the disaster on out-migration and tests the hypothesis that there is an upward shift in the level of out-migration in the post-disaster period. We eliminate observations in the first post-disaster year and incrementally increase the number of years included in the pre- and post-event period in a short-DID model to assess how sensitive any shift in out-migration probability is to the number of years included in the model. Finally, in our third analysis we compare results of the short-DID model with those of the long-DID model to test the hypothesis that the upward shift in the level of out-migration in the post-disaster period holds relative to earlier time periods. In other words, we assess whether the post-disaster out-migration pattern is a departure from the long-term trend.

The DID design is particularly compelling in disaster and environmental studies for a number of reasons (Hsiang, 2016). First, a necessary assumption is that the event is exogenous, that is, assignment to treatment and control is not correlated with the outcome. In our case, the probability that a place experiences a highly destructive hurricane should be unrelated to the probability of out-migration. This assumption has face validity but can be made robust through the careful selection of observations and inclusion of controls in the DID model. Second, the temporal order of events is easily established to show which observations occurred before and after the disaster event. Third, a simple design comparing pre- and post-event observations for the exposed and unexposed groups produces unbiased estimates and efficient standard errors, even for small samples (Bertrand et al., 2004; Donald & Lang, 2007). Finally, DID is a feasible approach to studying disasters since randomized controlled trials are not possible given the unpredictable occurrence of a disaster.

An emerging possibility for studying the effect of disasters on population outcomes with DID designs comes from new opportunities to create multiregional migration time series datasets. This type of dataset measures migration transitions, that is, migration trips rather than migrants. These transitions are aggregated into directional flows between region i and region j occurring during interval t to $t+1$ (Rogers et al., 2010). For example, the United States Internal Revenue Service Migration Data (Gross, 1999), the source of the data used in this analysis, measures out-migration from county i to county j for all US counties in the interval between tax-filing years t and $t+1$. This type of multiregional dataset imposes geographic and temporal boundaries on the data, a necessity for analytic purposes as well as privacy protection. We expect that multiregional migration transition datasets constructed from administrative datasets and georeferenced digital trace data with more flexible spatial and temporal units will become more widely available in the future (DeWaard et al., 2020; Fiorio et al., 2021). With data and methods in hand, social scientists will be well positioned to expand our understanding of links between environment and migration.

DATA

We measure migration flows with the Internal Revenue Service (IRS) Statistics of Income Division (SOI) County-to-County Migration Data files. The data include all U.S. federal income taxpayers, thereby underrepresenting the very poor and older populations, who are less likely to file income tax returns or be included as dependents on others' tax returns, as well as the small percentage of tax returns filed after late September of the filing year (Gross, 1999). The few variables available in the public use dataset on income are derived from income tax forms but do not include household social or demographic measures. The data include information about a tax-filing household that migrated from one county to another between tax filing years. If tax filings for a single taxpayer in subsequent years indicate a change of address and movement from one county to another, the taxpayer is designated an out-migrant from the county of residence in the first tax filing year and an in-migrant to the county of residence in the second tax filing year. The date of migration is not precisely determined in this method. Instead, a migration is determined to have occurred sometime between the date of filing in 2005 and the date of filing in 2006.

We are interested in migrations that occurred after August 29, 2005, which were likely to have been precipitated by Hurricanes Katrina and Rita. We find these migrations in the file that identifies migrants by comparing addresses for tax years 2005 and 2006. Since the disaster occurred in between tax filing dates – April 15, 2005 and April 15, 2006 – we expect there were more migrants among those who filed taxes in 2006 than for tax year 2005. Table 1 shows that prior to 2006, county-level out-migration probabilities were about 0.071, or 7.1% of all tax-filing residents and their dependents, for all coastal counties. In 2006, the out-migration probability rose to 8.7% in all coastal counties and to 10.3% in disaster-affected counties. Out-migration probabilities were close to their pre-disaster levels in years 2007 through 2011. One concern with this data is that in 2006 and 2007, tax-filings by residents of the disaster-affected area were lower than usual because the federal government allowed late filings for those living in these counties and late filings were not included in the dataset (Johnson et al., 2008). Therefore, since disaster-affected residents were less likely to file, our estimates of out-migration are downwardly biased and tests of significance are conservative.

Considering the limited options for migration data, researchers agree that the IRS migration data are the best publicly available source for tracking changes in internal migration in the United States at small spatial scales, specifically counties (Engels & Healy, 1981; Isserman et al., 1982; Molloy et al., 2011). The Current Population Survey (CPS) indicates that in each year between 1992 and 2009, approximately 87% of household heads filed tax returns, making the IRS data reliable for identifying population-level trends (Molloy et al., 2011). Non-tax-filing households who have

TABLE 1 Out-migration probabilities, by type of county and period.

Type of county	Pre-disaster period 1990–2005	Disaster year 2005–2006	Post-disaster period 2006–2011	Counties	County-years
All coastal counties, all years	0.071	0.087	0.074	160	3360
Not FEMA designated	0.075	0.077	0.073	97	2037
FEMA designated	0.065	0.103	0.075	63	1323
Metropolitan counties	0.071	0.101	0.079	92	1618
Metropolitan adjacent rural counties	0.073	0.072	0.068	90	1399
Non-adjacent rural counties	0.066	0.060	0.058	25	343

Note: Out-migration probabilities are calculated by comparing tax-return addresses in pairs of years. Each probability is reported for a year-pair, such as 2005–2006. The counties in the rural–urban continuum categories do not sum to 160 because some counties changed statuses during the observation period. The number of county-years sums to 3360 because all years are represented.

no reportable source of income, such as retirees and those receiving only government benefits or other unearned income, are less likely to migrate in general, hence the results may overestimate migration probabilities. However, this bias affects all geographies and all years and therefore will not affect estimates of the differences in out-migration probabilities between counties. The IRS data allow us to estimate annual inter-county migration flows pre-dating and following the 2005 hurricane season in the style of a natural experiment. We use data from tax-filing years 1991 through 2011. We exclude later years because methodological changes in the way the IRS processes the data created a discontinuity in the series starting in 2011 that makes later migration counts non-comparable to the years under analysis (DeWaard et al., 2022; Hauer & Byars, 2019).

We define our geographic area of interest as the 162 coastal counties and parishes[5] in the five Gulf of Mexico states of Texas, Louisiana, Mississippi, Alabama, and Florida[6] (Table 1; Wilson & Fischetti, 2010). A coastal county has at least 15% of its land within the nation's coastal watershed or a coastal cataloguing unit (National Oceanic and Atmospheric Administration, N.D.-a, N.D.-b). We selected these coastal counties because they are all exposed to the Atlantic hurricane season which lasts from June 1 to November 30 and therefore vulnerable to the damaging winds and precipitation that occur when a hurricane makes landfall. Similar hurricane potential supports the exogeneity assumption that exposure to the treatment does not depend on the outcome, in this case, out-migration rates. We also use the US Department of Agriculture Rural–Urban Continuum (RUC) codes to control for differences between the treatment and comparison group in the distribution of metropolitan, metropolitan adjacent, and metropolitan non-adjacent counties.[7]

The treatment in this quasi-experimental design is exposure to the two category five hurricanes that made land-fall on the U.S. Gulf Coast in 2005 and resulted in federal disaster declarations: Hurricane Katrina (August 29, 2005) and Hurricane Rita (September 24, 2005). The two hurricanes occurred within a month of each other and affected many of the same counties making it difficult to distinguish their effects. We categorize counties as treated or untreated according to whether they received a disaster declaration for either Hurricane Katrina or Rita from the Federal Emergency Management Agency (FEMA) and were eligible for the Individual Assistance Program (IAP), an indicator that the disaster was so destructive that many households were affected (Figure 1). The FEMA IAP provides disaster survivors with the full range of authorized programs and services including emergency housing and food assistance, unemployment assistance, temporary housing, repair, replacement, and permanent housing construction. Of the 160 Gulf of Mexico coastal counties included in the analysis, 63 received FEMA IAP disaster declarations. We refer to these as disaster-affected counties. The comparison counties are the remaining 97 coastal counties.

The unit of analysis is the county-year. Each county has 21 years of data covering tax-filing years 1991 to 2011. Table 1 shows the number of counties and county-years for each of the variables used in the DID regression, as well

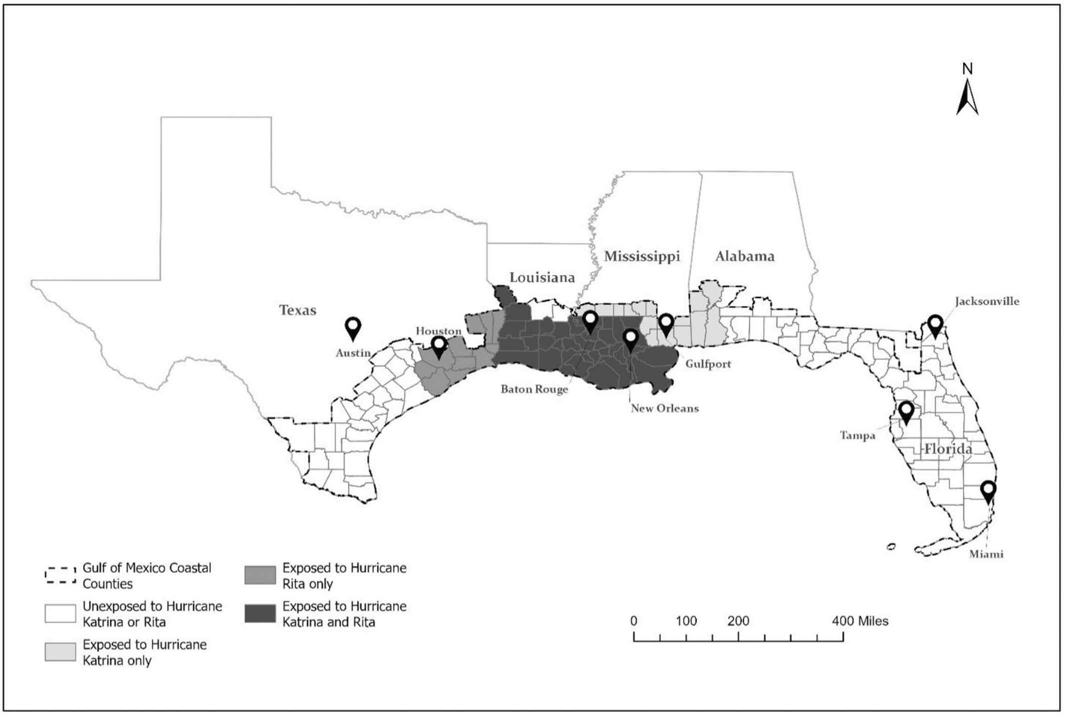

FIGURE 1 Treated and untreated counties in the Gulf of Mexico coastal region. *Note*: Counties exposed to hurricanes Katrina and Rita in 2005 are treated counties. All other counties are untreated.

as the out-migration probabilities for each category of the independent variables in the pre-disaster (1991–2005), the disaster (2006), and the post-disaster (2007–2011) periods. (Recall that the IRS dates refer to the year of tax-filing and covers all migrations that happened in the previous year. For example, the year 2006 refers to the period between April 15, 2006 and April 15, 2005, which would include the 2005 hurricane season.) The table shows that among all coastal counties, there are sufficient numbers of FEMA designated (63) and non-FEMA designated (97) counties to support the analysis. Most counties are metropolitan (92) or metropolitan adjacent rural (90) counties, with far fewer non-adjacent rural (25) counties. As expected, the average out-migration probabilities for FEMA designated counties are higher in 2006 than in the pre-disaster and post-disaster periods but there are only very small differences in out-migration probabilities over these periods in counties that were not FEMA designated.

METHODS

The core assumption of a DID design is that any unmeasured determinants of the outcome are time- and group-invariant. The implication is that the trend in out-migration probabilities should be similar within and between groups, ceteris paribus. To evaluate this assumption we graph annual migration probabilities by county, distinguishing between the treated and untreated counties (Figure 2). Visual inspection shows that, with the exception of the years between 2005 and 2006 in the treatment group, the lines are largely parallel with minimal variability.

The general form of the DID estimating equation is as follows:

$$Y_{gt} = \beta_0 + \beta_1 T_g + \beta_2 P_t + \beta_3 \left(T_g{}^* P_t\right) + \beta_{z4} X_{gt} + \varepsilon_{gt}$$

Here, Y_{gt} represents the out-migration probabilities for treated and untreated groups, indexed by g, and for each period, indexed by t. T_g indicates membership in the treatment (t = 1) or comparison group (t = 0), P_t represents the

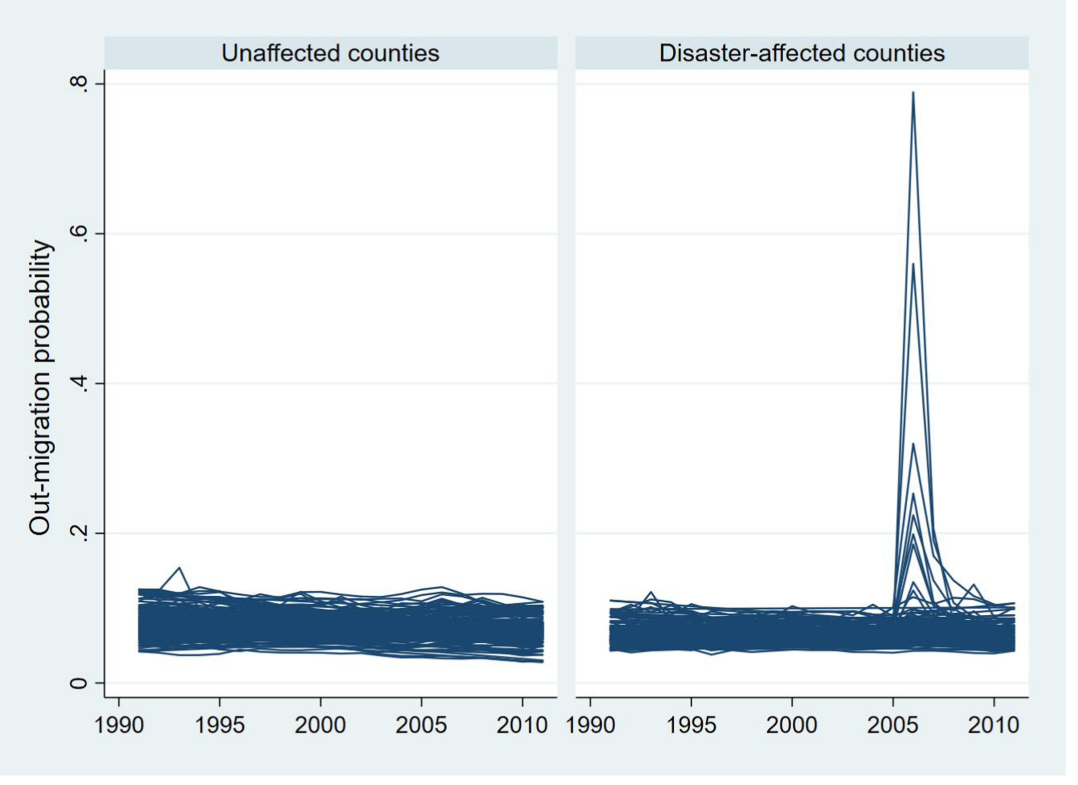

FIGURE 2 Out-migration probabilities by disaster-affected and non-disaster-affected counties.

period which varies according to the hypothesis being tested, X_{gt} represents any county-year specific covariates, and ε_{gt} is an error term. The intercept term, β_0, estimates the effects of any time-invariant variables, while β_1 and β_2 estimate the group and period effects, respectively, and β_{z4} estimates the effect of any county-year covariates. The effect of the treatment on the treated, specifically the effect of the disaster, is captured by β_3, the coefficient for the interaction of the treatment groups and the period. The coefficient tests the hypothesis that the effect of the treatment on the change in out-migration of the treated population is statistically significantly different than that for the outcomes of the untreated population. In other words, the effect of disaster exposure increases out-migration probabilities in the exposed population but not in the unexposed population. As is often the case with interaction terms, the adjusted predictions, shown as figures, are more easily interpretable than the regression coefficients, and we rely on the figures to support our interpretation of the results.

In this analysis, we vary the units measured by P_t, the pre- and post-disaster periods. In the first model, we compare two adjacent years through the entire period of observation, using a dataset with two treatment groups in two periods, the most basic short differences DID approach. In the second model, we compare the pre- and post-disaster periods, omitting the years spanning the disaster, in order to assess change in the coefficients associated aggregating more years of observations. We omit the years spanning the disaster because the out-migration in that year is attributable to the direct effects of the disaster, while in the pre- and post-years out-migration is plausibly a choice behaviour. We increase the number of years included in each period from 1 to 5 years, a more nuanced short differences DID approach. We include an equal number of years in the pre- and post-period to balance the number of observations. In the third model, we compare two different five-year pre-disaster periods between 1991 and 2000 to the five-year post-disaster period, 2007–2011, a long differences DID approach. Each model corresponds to one of the hypotheses stated in the previous section.

RESULTS

Our first hypothesis is that disaster exposure increased out-migration from the affected counties in the year after the event and that the increase in out-migration is significantly greater than that observed in any previous or subsequent year. Out-migration in this year is assumed to be attributable to the destruction of the built and natural environment as caused by the hurricanes. The annual DID models in Table 2 allow us to evaluate this hypothesis. Each column reports the estimated coefficients for a DID model based on two adjacent years of data and includes controls for metropolitan status. The coefficient for disaster designated coastal counties indicates that before 2005 out-migration was slightly lower (β_1 = −0.01) than in other counties, on average, and statistically significant in all equations through 2003–2004. There is no difference in out-migration probabilities between the first and second pair of years for the comparison counties throughout the period of observation (β_2 = 0.00). The key term is the interaction between treatment and period. In the year pair 2005–2006 there is a change in the pattern, specifically, a large and statistically significant interaction term (β_3 = 0.04, $p < 0.001$), representing the positive effect of disaster exposure on out-migration probabilities. Specifically, disaster exposure increased out-migration probabilities from the treated counties by about four points compared to unexposed counties, making the estimated probability of out-migration for a treated county 10.7 compared to 7.1 in an untreated county (Figure 3).

There are several things to note about the DID results for the first post-disaster pair of years, 2006–2007. First, the constant term (α = 0.09, $p < 0.001$) is larger than in any other year, reflecting the heightened out-migration probabilities in unaffected Gulf of Mexico coastal counties after the hurricanes. Figure 3 shows this more clearly: while out-migration from treated counties was slightly lower in this period, out-migration from untreated counties was higher. These out-migrants from untreated counties may be the recent migrants who in-migrated from the disaster-affected counties in the previous year, as well as long-term residents who moved in response to employment and housing opportunities created by the disaster. Second, the main effect coefficient for disaster-affected counties (β_1 = 0.02, $p < 0.001$) is large and statistically significant. This indicates that in 2006, the reference year, adjusted out-migration probabilities were higher in disaster-affected counties than other counties. This is consistent with the 2005–2006 model results in which out-migration from the disaster-affected counties grew to very high levels. Third, the coefficient on the interaction term is similar in magnitude to the main effect coefficient for disaster-affected counties although it is negative and not statistically significant (β_3 = −0.02, $p < 0.10$), indicating that out-migration probabilities for these counties declined in 2007 to levels similar to those of non-designated counties and are not statistically significantly different from out-migration probabilities in the reference group, that is, the non-disaster-affected counties in 2006. This drop

TABLE 2 Annual DID models estimating out-migration probabilities for disaster-affected and other coastal counties, 1991–2011.

	1991–1992	1992–1993	1993–1994	1994–1995	1995–1996	1996–1997	1997–1998	1998–1999	1999–2000
Disaster-affected (β_1)	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**
Year two (β_2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Interaction (β_3)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Metropolitan (ref.)									
Metro adjacent rural	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Non-adjacent rural	0.00	0.00	−0.01	***−0.01***	−0.01	0.00	−0.01	***−0.01***	−0.01
Constant	**0.08**	**0.08**	**0.08**	**0.08**	**0.08**	**0.07**	**0.08**	**0.08**	**0.08**
	−0.01	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**	**−0.01**
Observations	320	320	320	320	320	320	320	320	320
R-squared	0.09	0.09	0.09	0.09	0.10	0.11	0.13	0.14	0.11

Note: Bold indicates $p < 0.001$; bold italics indicates $p < 0.01$.

in out-migration probabilities in disaster-affected counties is also evident in Figure 3. This post-disaster population churning in 2006–2007 is rarely considered in studies of disaster-related migration. It involves out-migration from unaffected counties that received large numbers of out-migrants from the disaster-affected counties in the year of the disaster, as well as lower out-migration from the depopulated disaster-affected counties.

In the DID results for each year pair from 2007 to 2008 forward there are no statistically significant differences in out-migration probabilities between years or treatment groups and no significant interaction terms. This is a departure from the pre-disaster results in which disaster-affected counties, which had not yet experienced Hurricanes Katrina and Rita, show slightly lower out-migration probabilities than those that were not affected by the 2005 hurricanes. These results support our hypothesis that the 2005 hurricane season increased out-migration probabilities for disaster-designated counties compared to the previous year. They also show that there is no similar increase in any other year, ruling out the possibility that the effect of the disaster on out-migration is within normal variation.

Our second hypothesis posits that the disaster following Hurricanes Katrina and Rita increased out-migration probabilities for multiple years beyond the year in which the disaster took place. While the previous analysis of year pairs indicates that the largest increase in out-migration probabilities occurred between 2005 and 2006, here we evaluate the effect of the disaster on out-migration probabilities in the period following the disaster excluding the immediate pre-post disaster years. Using the short DID model we estimate the equation using groups of year-pairs before and after 2005–2006, excluding the year-pair 2005–2006 (Table 3). The first model (1) compares out-migration probabilities for year pairs 2004–2005 and 2006–2007 for disaster-affected counties using the out-migration probabilities of other coastal counties that did not receive a FEMA IAP designation as the counterfactual. The second through fifth models (2–5) increase the number of year-pairs in the pre- and post-period by an increment of one.

In the first model in Table 3, the statistically significant interaction term (β_3 = 0.013, $p < 0.01$) indicates that out-migration probabilities for disaster-designated counties were higher by 0.013 points in the post-disaster period relative to the non-designated counties in the pre-disaster period (α = 0.08). Figure 3 shows the estimated out-migration probabilities for each of the pre- and post-disaster periods and county groups. Specifically, between the pre- and post-disaster periods out-migration probabilities in disaster-affected counties increased from 6.4 to 7.7. The corresponding increase for non-affected counties was a trivial change from 7.4 to 7.5. In the second through fifth models, the same pattern is apparent. The interaction term is statistically significant and positive in all cases, indicating the significant effect of disaster exposure on out-migration probabilities regardless of the number of years-pairs included in the period, although the magnitude of the coefficient diminishes slightly when more years are included.

2000–2001	2001–2002	2002–2003	2003–2004	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	2010–2011
−0.01	**−0.01**	***−0.01***	**−0.01**	***−0.01***	−0.01	***0.02***	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	***0.04***	−0.02	−0.01	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	***−0.02***	***−0.02***	**−0.01**	**−0.01**	**−0.01**	***−0.01***
−0.01	−0.01	−0.01	***−0.01***	***−0.02***	−0.03	−0.03	***−0.02***	***−0.02***	***−0.01***	***−0.01***
0.08	**0.07**	**0.07**	**0.07**	**0.07**	**0.08**	**0.09**	**0.08**	**0.08**	**0.07**	**0.07**
−0.01	**−0.01**	***−0.01***	**−0.01**	***−0.01***	−0.01	***0.02***	0.00	0.00	0.00	0.00
320	320	320	320	320	320	320	320	320	320	320
0.10	0.10	0.10	0.09	0.11	0.08	0.07	0.08	0.08	0.08	0.08

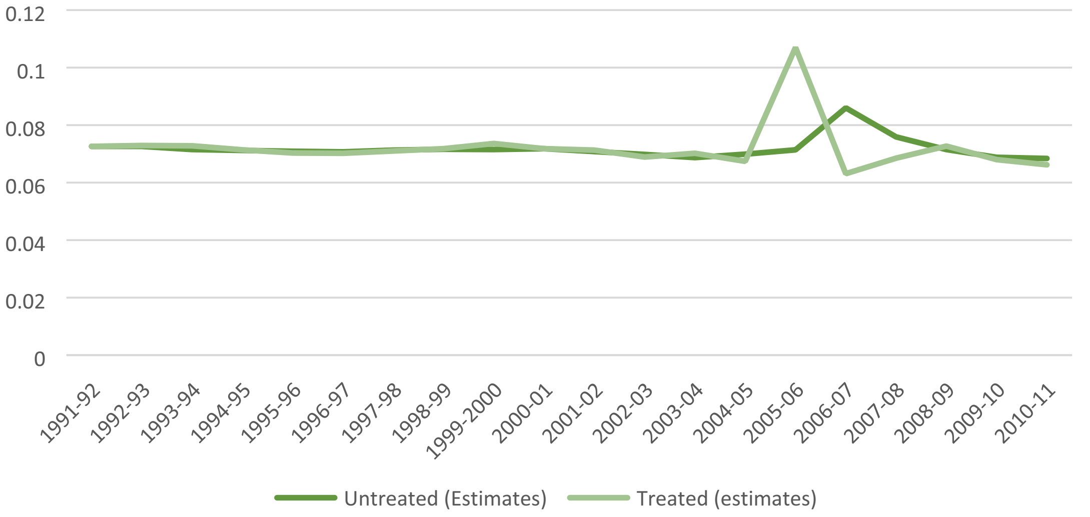

FIGURE 3 Adjusted out-migration probabilities for disaster-affected and unaffected coastal counties.

TABLE 3 Short and long differences in out-migration probabilities.

	Short differences					Long differences	
Post-disaster years	2007	2007–2008	2007–2009	2007–2010	2007–2011	2007–2011	2007–2011
Pre-disaster years	2005	2004–2005	2003–2005	2002–2005	2001–2005	1996–2000	1991–1995
	(1)	(2)	(3)	(4)	(5)	(7)	(6)
Disaster-affected counties (β_1)	***−0.010***	**−0.009**	**−0.009**	**−0.009**	**−0.009**	**−0.010**	**−0.010**
Post-disaster period (β_2)	0.001	0.002	0.001	−0.001	−0.002	**−0.004**	**−0.005**
Post-disaster*Disaster-affected (β_3)	***0.013***	***0.008***	***0.007***	**0.007**	**0.006**	**0.007**	**0.007**
Metro-adjacent rural counties	**−0.008**	**−0.007**	**−0.006**	**−0.005**	**−0.004**	**−0.003**	**−0.004**
Non-adjacent rural counties	***−0.019***	**−0.017**	**−0.013**	**−0.012**	**−0.011**	**−0.010**	**−0.009**
Constant	**0.078**	**0.077**	**0.076**	**0.076**	**0.076**	**0.078**	**0.079**
Observations	320	640	960	1280	1600	1600	1600
R-squared	0.110	0.097	0.083	0.069	0.066	0.069	0.064

Note: Bold indicates $p < 0.001$; bold italics indicates $p < 0.01$.

As expected, the difference in out-migration probabilities between pre- and post-disaster periods is negligible for the counties that did not receive disaster declarations. These findings confirm our hypothesis that out-migration probabilities from disaster-affected counties were elevated for as much as 5 years after the initial large out-migration between 2005 and 2006.[8] This provides some support for the notion that in the disaster-affected counties residents' experienced greater risk in the environment and were incorporating that into their migration decisions.

Finally, we hypothesize that the elevated post-disaster out-migration probabilities are a significant departure from a long-term trend. Using the long DID approach we assess whether the post-disaster out-migration probabilities are statistically significantly different from the out-migration probabilities of the disaster-affected and unaffected counties in the previous decade. Building from the comparison of the five-year post-disaster period to the period immediately before the disaster (model 5), we make comparisons with the same number of observations to two earlier five-year periods, the 1991–1995 period (model 6) and the 1996–2000 period (model 7). The estimated coefficients for the interaction term are positive and significant and nearly the same magnitude regardless of the pre-disaster reference period. Figure 4 shows that the sets of out-migration probabilities for each of the long DID

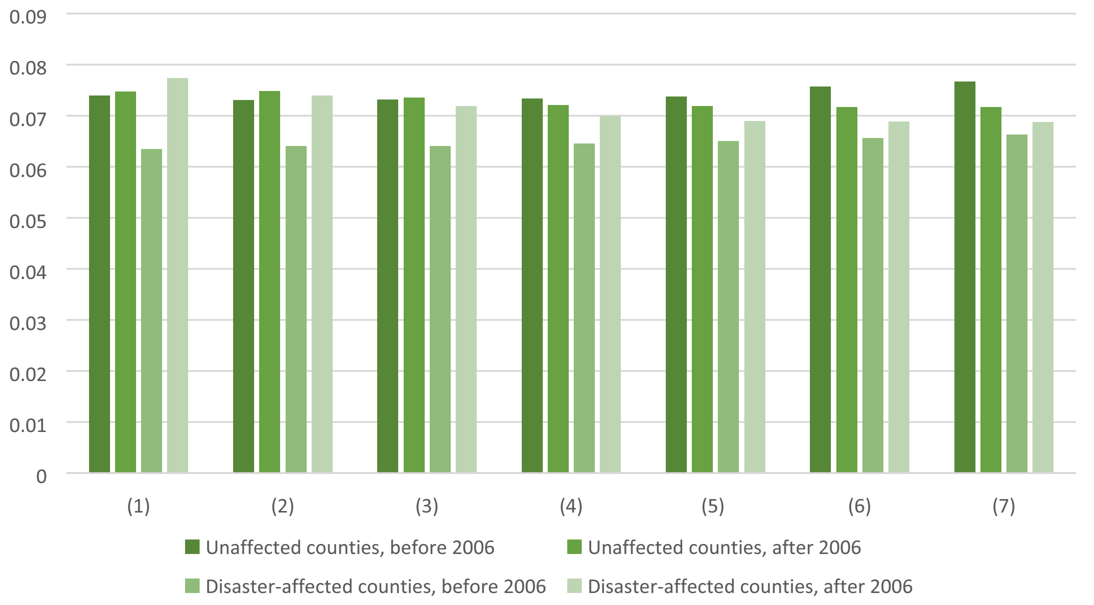

FIGURE 4 Adjusted out-migration probabilities for short DID (1–5) and long DID (6–7) models with varying numbers of years and periods in the reference group. *Note*: The first set of bars (1) compares adjusted out-migration probabilities in year-pairs 2004–2005 and 2006–2007; the second set (2) compares out-migration probabilities in 2003–2005 and 2006–2008; the third set (3) compares out-migration probabilities in 2002–2005 and 2006–2009; the fourth set (4) compares out-migration probabilities in 2001–2005 and 2006–2010; the fifth set (5) compares out-migration probabilities in 2000–2005 and 2006–2011; the sixth set (6) compares out-migration probabilities in 1990–1995 and 2006–2011; the seventh set (7) compares out-migration probabilities in 1995–2000 and 2006–2011.

models are nearly identical regardless of the reference period selected. These findings confirm our hypothesis that out-migration probabilities after the disaster are a departure from the long-term pattern of out-migration.

CONCLUSION

As climate change increases the strength and frequency of weather hazards it is predicted that people will migrate away from hazard prone places, not only in response to disaster events but in anticipation of future events. This expectation is widely held, but we are still developing data and methods to evaluate the timing and magnitude of these migration responses. The substantive aim of this research brief is to assess hypotheses about the well-known short-term out-migration response and the as yet unstudied long-term out-migration response to the highly destructive 2005 hurricane season in the Gulf of Mexico. The methodological aim of the research brief is to demonstrate the application of short- and long-difference-in-differences (DID) to county-level migration data for the US. The DID approach is ideal for the analysis of administrative records and other types of big data because it employs a quasi-experimental design including pre- and post-disaster observations for both the disaster-treated counties and nearby untreated counties to identify the effects of disasters on migration behaviour. Our contribution in this paper is to show how the DID approach combines with geographical time series data to test hypotheses about short-term and long-term out-migration responses. In doing so, we contribute to an emerging body of research focused on identifying data and methodologies that allow for attribution of migration to climate-related environmental changes (Borderon et al., 2019; Hoffman et al., 2020; Hsiang, 2016).

Substantively we find that Hurricanes Katrina and Rita increased both short- and long-term out-migration responses in the treated counties. While the disaster caused a large increase in out-migration between 2005 and 2006, the years that span the highly destructive 2005 hurricane season, it also elevated out-migration probabilities in the following years (2007–2011) relative to both the immediately preceding 5 year period (2001–2005) and earlier five-year periods (1991–1995 and 1996–2000). From this we conclude that the elevated out-migration probabilities in the post-disaster period are a departure from the long-term out-migration migration pattern. This suggests that the disaster altered the migration decisions of residents in affected counties. This provides suggestive evidence that as hurricanes become more destructive, residents may increasingly reduce their exposure to these hazards by moving out of coastal counties, especially those that are recovering from a disaster.

The study has several limitations. First, counties and parishes are a large geographic unit with fixed boundaries that do not map neatly onto a hazard impact footprint, a problem known as the modifiable areal unit problem (Fotheringham & Wong, 1991). Consequently, the effect of the disaster on out-migration is estimated imprecisely and we might have failed to detect a relationship when a relationship exists. Second, the temporal scale of the data is also somewhat indeterminate given variability in tax-filing dates. It would be preferable to measure the actual date of a residential move, but there is no systematic collection of such data for the entire US. Third, we measure disaster exposure as any county that FEMA designated as being disaster-affected and made eligible for the FEMA Individual Assistance Program. This broad and indirect measure of disaster exposure could be improved to more precisely measure the damages and losses that drive out-migration, such as the number of housing units damaged or destroyed, ground-level observations of damages, job losses, or other ways in which a disaster affects lives and livelihoods. Despite these limitations, which may have affected the precision of our estimates, we found statistically significant relationships that support our hypotheses about overall patterns of change.

The finding that the 2005 hurricane season increased both short-term and long-term out-migration probabilities among disaster-affected counties in the Gulf of Mexico coastal counties contributes to a larger body of research on environmental migration (Borderon et al., 2019; Hoffman et al., 2020; Hsiang, 2016). Methodologically, it demonstrates the use of short- and long-differences in disaster-related out-migration probabilities using a multiregional migration time series dataset. To date, few researchers have considered how migration responses change over time, most likely due to the lack of both data and methods. As big data opportunities make the creation of multiregional migration time series data possible, this approach will become more feasible. Substantively, the novel finding of this study is that after the disaster residents' out-migration probabilities remain elevated for several years. While the reasons for this enduring shift are not revealed by this study, more studies of post-disaster migration decision-making are warranted (Bardsley & Hugo, 2010; Gussmann & Hinkel, 2020; Rhodes & Besbris, 2022; Schwaller & BenDor, 2021; Yamamoto & Esteban, 2017). Furthermore, it suggests that federal and state government disaster recovery policies that incentivize residents to move out of harms' way may become more appealing in areas that have suffered repeated losses or are highly exposed to hazards (U.S. Government Accountability Office, 2020; Siders, 2019). Finally, while increased out-migration probabilities persist for multiple years, their magnitude is modest in the Gulf Coast counties affected by the 2005 hurricane season. State and federal government programs should consider these long-term migration patterns when developing disaster recovery and climate adaptation policies.

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PEER REVIEW

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DATA AVAILABILITY STATEMENT

The Statistics of Income (SOI) Migration Data for 1990-2011 used in this analysis are publicly available at the following website: https://www.irs.gov/statistics/soi-tax-stats-migration-data.

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ENDNOTES

[1] Rapid-onset events contrast with slow-onset environmental changes, such as drought, desertification, permafrost thaw, and glacial melting, which may require different research designs to observe environment-migration relationships.

[2] The Gulf Coast states include Alabama, Florida, Louisiana, Mississippi, and Texas.

[3] For example, 90 per cent of housing units in Cameron Parish (LA) were damaged; 90 per cent in Hancock County (MS); 81per cent in Plaquemines Parish (LA); 81per cent in St. Bernard Parish (LA); 71per cent in Orleans Parish (LA); and 71per cent in St. Tammany Parish (LA) (US Department of Housing and Urban Development 2006).

[4] We use the terms "affected", "exposed", and "treated" equivalently from here forward as treatment is the term used in experiments, although the treatment in this case occurs when a county is affected by or exposed to a disaster.

[5] In Louisiana a parish is equivalent to a county. For brevity, we refer to both as counties from here on.

[6] Two counties – Vernon Parish in Louisiana and Kenedy County in Texas – were not included in the analysis. Kenedy County was dropped because its time series data included county-years in which fewer than ten households migrated and, due to privacy concerns, the count is not reported. Vernon Parish has a small population, and out-migration probabilities were very high and variable, thereby violating the assumption that all geographic units had parallel out-migration trends prior to the exposure. Analyses that include these two counties were not substantively different from the reported results.

[7] Note that the number of counties in each of these categories is greater than the total number of counties because some counties changed their RUC status during the observation period and are therefore double counted. The number of county-years in each category sums to 3360, the total number of county-years in the analysis.

[8] Recall that each period includes migration that occurred within a set of one year intervals. When these one year intervals are aggregated, they are represented by the first and last years of each year-pair. For example, the period in model two includes out-migration probabilities from the 2006–2007 and the 2007–2008 year pairs in the post-disaster period.

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