Environmental Change and Migration The Impact of Hurricane Sandy on the East Coast Migration System

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Abstract

Climate change is likely to trigger processes which will have an impact on population distribution. One of these processes is the increase in the number of extremely intense tropical cyclones. Several studies analysed Hurricanes Katrina and Rita, finding that while these two Hurricanes triggered massive evacuation, the population of the affected area rebounded mostly thanks to inflows from nearby unaffected counties. This work investigates the effects of Hurricane Sandy on the migration system of the East-Coast counties it affected. It uses data from the Internal Revenue Service annual county-level migration flows to test a set of hypotheses formulated by looking at previous studies, comparing the migration system of the pre-disaster period (2010-2011) to the one of the post-disaster period (2012-2013). I find that both the initial outflow and the subsequent recovery inflow are significantly smaller than they had been after Katrina. More precisely, when comparing affected and nearby counties, it appears that the former saw a decrease in inflows after Sandy compared to the latter. Based on these findings, I argue that Katrina and Sandy belong to two different categories of natural disaster when looking at their impact on migration. Katrina represents a *disruptive* type, with temporary depopulation followed by sustained recovery, while Sandy was *manageable*, with minor changes in migration trends, possibly leading to a decrease in net migration. Since these two types of disaster require different policy interventions, the present work, after having described Sandy's and Katrina's differential impact, tries to sketch possible policy responses.

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1 Introduction

The impact of climate change on population distribution and migration has increasingly attracted interest from both researchers and policymakers. The literature has identified three main components of environmental change that could lead to migration: alteration of precipitation patterns, extreme weather events, and sea level rise (Tacoli, 2009; McLeman and Hunter, 2010). Alarmingly, we are likely to witness a worsening in all three aspects. Indeed, in its Fifth Assessment Report (AR5), the Intergovernmental Panel on Climate Change (IPCC) asserts that global mean sea level will continue to rise; it is very likely that heat waves will occur more often and last longer; and that extreme precipitation events will become more intense and frequent in many regions (IPCC, 2014).

Moreover, albeit the globally averaged frequency of tropical cyclones is projected to decrease through the 21st century, the number of exceptionally intense cyclones is predicted to increase (Knutson et al., 2010). It thus seems that there are reasons to worry about an eruption of the environmental migration issue. Indeed, the IPCC (2014) explicitly speaks of a projected increase in the people displacement. If we want to be ready to face this phenomenon, we need to improve our knowledge of the relationship between migration and the environment.

The concept of *environmental refugee* was first brought to the policymakers' attention by El-Hinnawi et al. (1985). With the definition came the first estimate of 30 million displaced people worldwide. This figure was followed by Jacobson (1988)'s 10 million and by Myers (1993)'s frequently cited 25 million, forecasted to become 200 million by 2050. Many authors have criticised these estimates, often in strong terms, both for theoretical and methodological reasons (Black, 2001; Bates, 2002; Gemenne, 2011). In short, they contend that these numbers, rather than representing environmental refugees, are counting the people at risk of displacement through environmental change. However, the nature of the link between environmental change and migration, while still unclear, is unquestionably not deterministic. In other words, only a fraction of the population exposed to climate change chooses to migrate as an adaptation strategy.

In the wake of these criticisms, a new stream of the literature has developed trying both to construct a more robust theory and to collect more empirical evidence. For example, Black et al. (2013) built a framework where five drivers mediate the impact of environmental change on migration, then interact with personal characteristics, obstacles, and facilitators to determine the migration outcome. At the same time, the number of empirical studies has steadily increased, and so has the coverage for both regions and triggering events (Findley, 1994; Ezra, 2001; Henry et al., 2003; Arenstam Gibbons and Nicholls, 2006; McLeman, 2006; Massey et al., 2010).

Of particular interest for the present work, is the literature on the link between hurricanes in the US and migration. To my knowledge, four hurricanes have been the object of in-depth studies so far: Andrew (1992), Katrina (2005), Rita (2005), and Ike (2008) (see McLeman and Smit (2006) for Andrew and Peacock et al. (2014) for Andrew and Ike). Among these, Katrina and

Rita, usually studied together as they affected the same area and occurred within one month of each other, are the hurricanes about which we know the most (see for example Elliott and Pais (2006), Frey and Singer (2006), Groen and Polivka (2010) and Curtis et al. (2015)). However, not all studies agree on the impact of these extreme weather events on population distribution. Moreover, because of the particular region they hit and their exceptional material destructiveness, the conclusions reached by case studies may not hold external validity. In particular, the substantial impact which Katrina and Rita have had on the migration system of the affected counties, might not be found in other cases.

The present study aims to investigate this point by studying Hurricane Sandy. Hurricane Sandy made landfall in Brigantine, New Jersey, on October 29, 2012. Although it affected 24 states, New Jersey and New York were most strongly impacted. Storm surge flooded the New York City streets, tunnels and subway lines, and cut power in and around the City. In New Jersey, more than 346,000 homes were damaged or destroyed, and more than two million people lost power. Sandy was responsible for more than 200 deaths and caused damages amounting to some $70.2 billion, making it, at that time, the second-costliest hurricane after Katrina (Diakakis et al., 2015; FEMA, 2018; NOAA, 2017b). Although it was surpassed by Harvey and Maria in 2017, migration data for 2017 are not yet available, Sandy thus seems the natural candidate for comparison with Katrina. Moreover, the region hit by Sandy, i.e. the coastal counties on the Northern East Coast, has very different economic, social, historical, demographic, and political characteristics compared to Louisiana, Mississippi, and Alabama, the three states most affected by Katrina and Rita. If the analysis of Sandy's impact on the affected region's migration system led to results similar to the ones found for Katrina, we could be more confident about their external validity. Otherwise, we might conclude that Hurricanes' impact on migration depends in part on the characteristics of the affected region and the event itself. In this second case, more extensive analyses would be needed to improve our understanding, involving, for example, the study of other hurricanes: an attempt in this direction is the work of Fussell et al. (2017).

In the present study, I find that, compared to Katrina, the effects of Sandy on the migration system were significantly smaller. In particular, it seems that no recovery migration occurred. Moreover, while outflows to distant counties decreased after Katrina, following Sandy, it is precisely this group that witnessed the highest percentage gain. Finally, whereas disaster-affected counties experienced heightened infra-mobility after Katrina, this effect was only temporary after Sandy. Based on these differences, I hypothesise that Katrina and Sandy belong to different types of natural disasters, Katrina was a *disruptive* disaster while Sandy was a *manageable* one.

To allow other researchers to extend the present study, I decided to use only data which can be freely accessed. Furthermore, to increase comparability, I followed the methodology used by Curtis et al. (2015), to date one of the most comprehensive studies of Katrina's impact on migration, and have a set of replication files available on GitHub[1]. To improve on their work, I devoted a more

[1]These files are available in the following repository: `https://github.com/eugeniopaglino/Hurricanes_and_`

in-depth analysis to how the spatial distribution of flows changed after Sandy. Finally, while Curtis et al. (2015) focus only on the recovery period, I have also included the immediate aftermath.

The article proceeds as follows. The second section presents the theoretical background and reviews the relevant literature. I then describe the data and methods. The fifth section examines the results. The sixth section discusses the findings and offers a theoretical framework to explain the observed differences and their consequences for policymaking. In the final section, I explore the limitations and the contributions of the present study, I argue for its relevance, and I try to place it in a broader perspective.

2 The Environment-Migration Link

2.1 Insights from the Environmental Migration Literature

The beauty but also the complexity of this field is its location at the intersection of multiple disciplines: environmental sciences, demography, economics, geography, and sociology. Its multidisciplinary nature necessarily creates several complex challenges (Gemenne, 2011; Tacoli, 2009; McLeman and Hunter, 2010).

These challenges come from at least three sources. First, climate projections are subject to uncertainty at various levels, and this issue becomes more severe the smaller the area chosen. Second, we still lack an established theory that links environmental change to migration. Third, though recent years have seen progress, with promising new strategies coming from digital demography (Zagheni and Weber, 2012; Zagheni et al., 2014, 2017), complete good-quality data on migration flows is still very rare. This is especially true for movements within national borders or for migration in low-income countries.

All these challenges notwithstanding, the literature on environmental migration has grown substantially in the last decades, giving us both empirical regularities and theoretical foundations for the environment-migration link. I will now try to review these regularities, providing references to the existing empirical literature and building on previous reviews; in particular on Adamo (2010) and Findlay (2011). These regularities are useful for gaining a better understanding of the dynamics behind environmental migration, and we will refer to them when discussing the results. Two general points are worth mentioning before starting: first, climate change is just one factor that influences the decision to migrate - there are also economic, demographic, political, and social drivers (Lee, 1966; Black et al., 2011a); second, migration is only one amongst many adaptation strategies to climate change (Ezra, 2001).

A first recurrent pattern is that most potential migrants, i.e. individuals who could benefit by moving from their current residence to a new one, tend not to migrate even if the expected gains are substantial. This idea is already present in Lee (1966). Such inertia or "immobility

Migration

paradox" may be a consequence of several mechanisms. First, as pointed out by Lee (1966), individuals living in an area may be emotionally attached to that place and thus less objective in their judgment. Second, obstacles and costs of migration may loom large in the minds of those who are thinking about moving. Third, individuals might develop a *sense of place* or *place attachment*, especially if they have been living in a given area for a long time (Gieryn, 2000; Falk et al., 2006).

A second regularity is that if migration occurs, individuals are, *ceteris paribus*, more likely to move over short distances rather than longer ones. Two comments are in order here. First, *ceteris paribus* means here that two destinations should be comparable under all the relevant dimensions, including migration costs, social networks, and culture. Second, this principle does not necessarily imply that internal movements will be more frequent than international migration: see for example Henry et al. (2004). Borders may divide areas which have very similar characteristics and, sometimes, histories. Examples are India and Bangladesh (Black et al., 2011b) or Burkina Faso and Côte d'Ivoire. In these cases, international migration may be substantial. More generally, colonial ties, commercial relationships, or strong histories of exchange may considerably reduce the perceived distance between two countries, thus apparently, but not substantially, invalidating this principle. For what concerns climate change, however, the existing evidence suggests that both natural disasters and long-term processes such as shifts in rainfall patterns or land quality degradation are not likely to increase long-distance migration (Findley, 1994; Henry et al., 2004; Black et al., 2011b).

A third common aspect is the selectivity of migration whose nature and degree seem to depend on the type of movement. For distant and long-term moves, human capital, either in the form of education or in the form of work experience, increases the likelihood of migration, while for local and short-term moves it plays no or only a minor role (Henry et al., 2004; Massey et al., 2010). Gender is often significant with males moving more than females, although the gap tends to close in time of hardship. Race or ethnicity is also relevant. For example, individuals of the Mossi and the Hill Tibeto-Burmese ethnicities have a higher migration rate compared to other ethnic groups in, respectively, Burkina Faso and Nepal (Henry et al., 2004; Massey et al., 2010). Economic factors, such as home or land ownership, wealth, and availability of financial resources, are also important migration determinants. Those who move are on average poorer than the population at origin, but they are rarely among the poorest. Here, two opposite forces are at work. On the one hand there are substantial costs associated with migration, and only individuals with sufficient resources will be able to sustain them. At the same time, however, the wealthiest strata of a population will usually suffer less than others, even in times of hardship, see, for example, McLeman (2006).

Another frequent finding is that social networks are crucial determinants in terms of destination choice and they may sustain a migration network even after the initial triggering factors have disappeared. Such a process might result from two mechanisms (Massey et al., 1993). First, a potential migrant who can rely upon many social ties faces progressively lower migration costs.

Networks provide information about how to reach the destination country (legally or illegally). They may arrange transportation and help with the necessary documents. They offer assistance during the search for a job, and lower the psychological costs of leaving one's community and culture. Second, networks reduce uncertainty regarding the outcome of migration. Potential migrants face risks from multiple sources. They may not know how quick they will find a job, how to reach their destination (especially when it involves illegality), where to eat and shop; where to live in the new country; and how to move around. Having a relative, a neighbour, or a friend who has already migrated means reliable advice on all these matters and possibly a reference for potential employers (Massey and España, 1987). As a consequence, two destinations which are equally attractive on paper may witness very different migration flows based on the presence or absence of a network. Once a network is in place, the flows will tend to increase over time unless a shock changes some fundamental characteristics of the established migration system (Lee, 1966).

Connected to this notion of social networks as facilitators of migration is the idea that communities may sometimes play a determinant role in collective migration decisions. An illustrative example is the role played by the New Orleans Vietnamese American Community in the Versailles neighbourhood after Katrina (Airriess et al., 2008). On the one hand, this neighbourhood was the result of migration from two Catholic dioceses in the former North Vietnam in the 1970s, thus the product of a very particular migration network. On the other hand, after Katrina struck Versailles neighbourhood, the assistance obtained through the Vietnamese community in New Orleans as well as at the national level was crucial in rebuilding and repopulating and these processes moved faster than in many other similarly affected areas in New Orleans.

To investigate different regularities demands distinct data and methodological requirements. While selectivity and, in some aspects, network effects can be studied only with adequate micro-data, the immobility paradox, the preference for short-distance movements, and, adopting a broader notion, the role played by networks can be examined even with aggregate data. The next section discusses my choices in this respect and the analytical framework I adopted.

2.2 The Environment-Migration Link: A Migration System Perspective

The four regularities I have presented exist at the macro level, where the decisions of many individuals come together to form discernible patterns. One way to capture this dimension is to study migrations in terms of a migration system perspective. We might think of a migration system as a structure emerging from a myriad of individual migration networks (i.e., the set of relationships that tie a migrant to other individuals), giving stability to flows from or to a specific area. In its simplest characterisation, a migration system has three elements:

1. a spatial unit of analysis (e.g., municipalities, counties, or states),
2. ties between these units (i.e., the presence of movements of individuals between pairs of units), and

3. flows across these ties.

In this work, I choose counties as the smallest spatial units, but I also discuss the results' sensitivity to different choices. I analyse variations in both ties and flows and try to understand if they modified the structure of the existing migration system.

The migration system perspective can be traced back, in the literature, at least to the work of Mabogunje (1970). There it was used to explain rural-urban migration in African countries, but, as Curtis et al. (2015) have shown, it is suitable to analyse other migration flows. While a micro-level study might uncover differences in responses to the Hurricane at the individual level, opting for a macro-analysis allows an investigation of the aggregate impact. Three reasons lie behind my choice of a macro analysis. First, there is a data constraint. While researchers who studied Katrina had, at their disposal, a set of *ad hoc* questions in the 2006 Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), no comparable microdata exists for Sandy. This puts a limit on the possibility of conducting individual-level analyses. The main issue, here, is that we have no reliable way to distinguish Sandy evacuees from other migrants. Second, while micro-level determinants of adaptation to natural disasters have received quite extensive coverage, macro-level effects on the migration system have been partly neglected. Third, understanding natural disasters' impacts on individuals is relevant for policymakers to design better recovery strategies in the aftermath and to improve infrastructural, institutional, and social resilience to future events. However, the importance of considering impacts at a more aggregate level is undeniable. For example, a policymaker able to predict where disaster-migrants will relocate will also be able to organise necessary assistance. At the same time, macro-level research helps improving population forecasts for areas with high environmental risk, allowing better planning of future interventions.

Given the limited number of articles which have taken a similar perspective when analysing the impact of natural disasters on migration, it is difficult to formulate precise hypotheses regarding the results of the present study. A similar approach, that inspired mine, is found in the articles written by Elizabeth Fussell, Katherine J. Curtis, and Jack DeWaard on Katrina (Fussell et al., 2014; Curtis et al., 2015; DeWaard et al., 2016). They found that, after Katrina, inflows to the disaster-affected counties intensified and became more spatially concentrated, involving mostly nearby counties, especially urban ones. At the same time, they also observed an intensification of migration flows within disaster-affected counties. Finally, they observed strong recovery migration, with inflows coming predominantly from nearby counties. Part of these findings is consistent with the empirical regularities I discussed before. For example, the increase in inflows from the unaffected areas of the Gulf of Mexico is consistent both with the idea that migrants prefer not to travel long distances and with the importance of existing networks. Also, the fact that migration is usually temporary implies that a majority of evacuees from disaster-affected counties would eventually return, as suggested by the results. However, what we could not have anticipated by looking at the regularities I illustrated is the magnitude of both post-disaster outmigration and recovery migration. These features, I think, may not hold when analysing a different event. Finally, while Curtis et al. (2015) report significant alterations in the migration system after Katrina, I believe that their results depend partially on the unit of analysis they chose. Although I do not have precise expectations regarding the consequences of this choice, I will explore how the results change when considering the disaster-affected counties as a single area instead of analysing each one separately. Based on these considerations, I offer three hypotheses:

- **H1**. outflows are likely to increase immediately before and after Sandy, as people flee the area at risk, and to stabilise afterwards, when they have returned;
- **H2**. inflows should follow a similar pattern in the aftermath and may then:
  - **H2a**. either decline as return migration terminates and immigration from other areas decreases due to the diminished attractiveness of the affected region;
  - **H2b**. or stabilise at a higher level compared to the pre-disaster period as a consequence of a successful recovery (as observed after Katrina);
- **H3**. overall changes in flows are likely to be smaller (in relative size) than those witnessed after Katrina.

After having described the data and the methodology I used, I will discuss whether the results support or do not support these hypotheses and of the policy implications of my findings.

3 Data

I will perform the analysis at the county level, covering all the continental United States. Following the methodology used by Fussell et al. (2014) and Curtis et al. (2015), I divided the counties of the continental United States into three groups: *disaster-affected*, *nearby*, and *distant*. I included in the disaster-affected group all counties which the Federal Emergency Management Agency (FEMA) designated for individual assistance[2]. These counties should be the ones that suffered most severely from Hurricane Sandy. The second group (nearby) includes all counties that meet four criteria:

1. they are coastal counties as classified by the National Oceanic and Atmospheric Administration (NOAA, 2017a);
2. they are to be found in Connecticut, Maryland, New Jersey, New York, Rhode Island, Delaware, Massachusetts, Pennsylvania, or Virginia;
3. they do not belong to the disaster-affected group;

[2]To identify these counties I have used the disaster declarations available on the FEMA website for the affected states: FEMA (2012a,b,c,d,e)

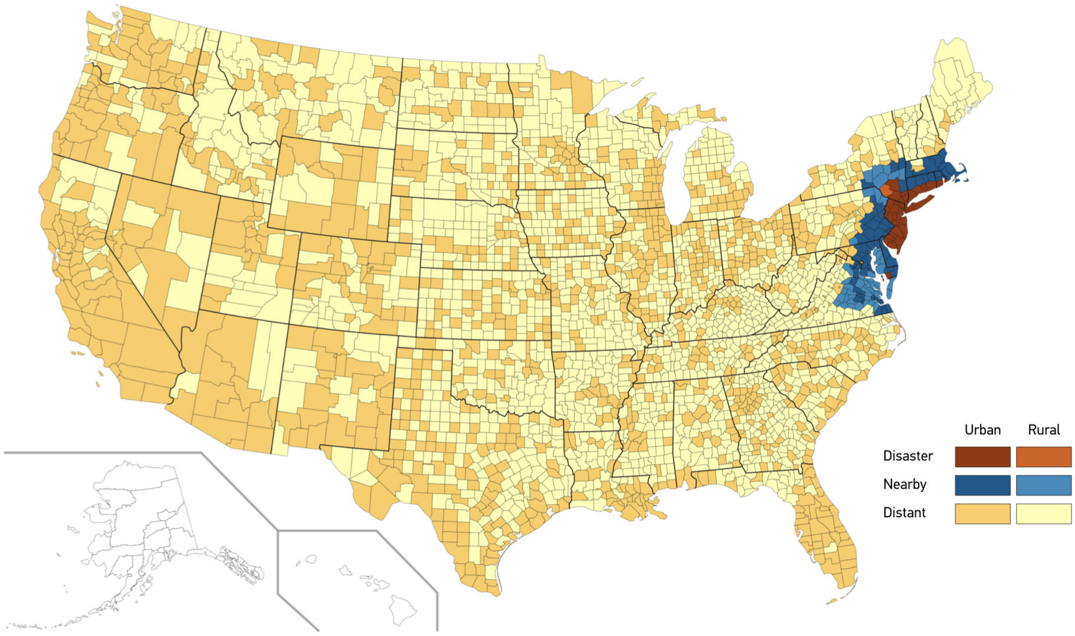

Fig. 1: Classification of the counties according to the FEMA designations and their geographical location

4. they are not bordering the Great Lakes.

To these counties, I have added all the counties not already included which are no more than one county away from the affected ones. Counties in this group should be broadly comparable to the ones in the disaster-affected group and, according to the second regularity, are also likely to be the preferred destinations of temporary relocation given their geographical proximity. Finally, distant counties are all other counties in the continental United States. I have further classified each county as rural if the percentage of its population living in rural areas was equal to or above 50%; otherwisea county was classified as urban. Percentages were taken from the 2010 census (Census Bureau, 2018). Table 1 summarises the classification.

	All	Disaster-Affected	Nearby	Distant
Urban	1,247	40	84	1,123
Rural	1,865	1	48	1,816
Total	3,112	41	132	2,939

Table 1: Summary of classification of continental counties

In Figure 1, I have represented the counties belonging to the various groups. In red disaster counties, in blue nearby counties, and in yellow distant counties. I have used a darker shade for urban counties and a lighter one for rural counties.

To understand whether the results would be similar under a different classification of counties, I have defined alternative groups, this time based on the FEMA Modeling Task Force (FEMA-MOTF)

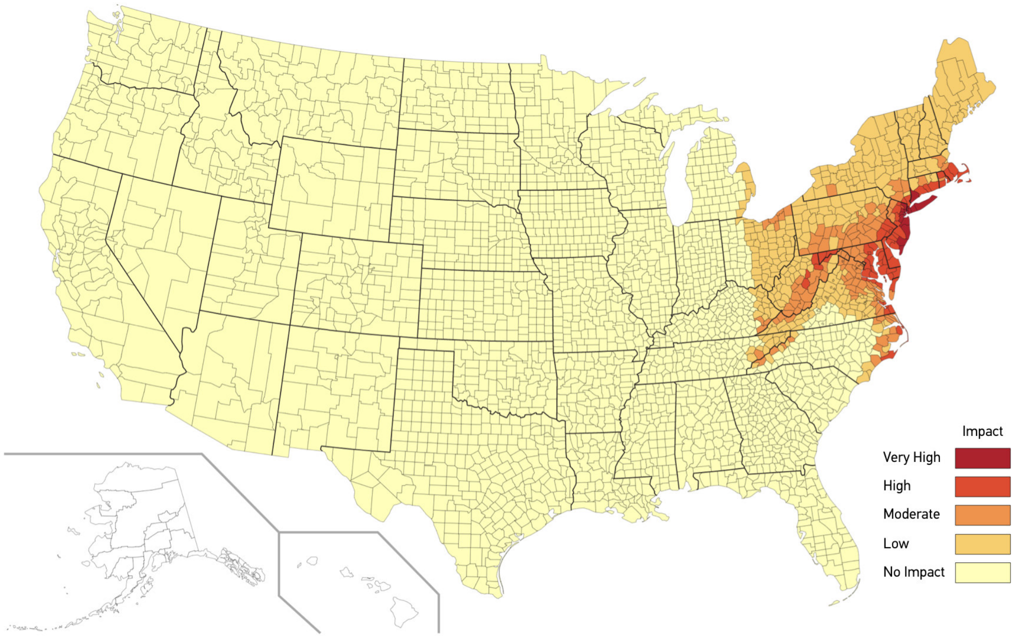

Fig. 2: Classification of the counties according to the FEMA-MOFT impact rank and their geographical location

report on Hurricane Sandy (FEMA-MOTF, 2014a)[3]. Compared to FEMA disaster declarations, the FEMA-MOFT report delivers more detailed information regarding Sandy's impact at the county level, ranging from the amount of rainfall to the number of structures that has suffered significant damage. The report also provides a final impact rank with four levels, which I have used to define the groups. The impact levels are: *low*, *moderate*, *high*, and *very high*. After having compared the maps in Figures 1 and 2, which depict the geographical location of the counties belonging to the different groups, I decided to consider counties with *high* and *very high* impact as disaster-affected, those with *low* and *moderate* impact as nearby, and those with no impact as distant. The maps also reveal that while counties designated for individual assistance by FEMA form a cluster in the coastal area of four states (Somerset County, Maryland is an exception), the FEMA-MOFT impact classification is more spatially heterogeneous and covers a wider area.

I have identified two periods: before Sandy (2010-2011) and after Sandy (2012-2013). However, in order to be able to replicate Curtis et al. (2015), I assembled migration data for the longer 1998-2015 period. These data come from the Internal Revenue Service (IRS) Statistics of Income Division (SOI) County-to-County Migration Data files (IRS, 2018). The files report inflows and outflows for each pair of U.S. counties, both as households and as individuals. Indeed, this is one of the principal source for studies of migrations patterns and trends in the United States (Molloy et al., 2011; Fussell et al., 2014; Curtis et al., 2015; Johnson et al., 2017).

Assembling the data from the IRS-SOI proved a complex operation because the format in which the county-to-county migration files are available changed over time. Two single outflows and in-

[3]The excel dataset I have used can be found here: `https://data.femadata.com/MOTF/Hurricane_Sandy/HurricaneSandyImpactAnalysis_FINAL.zip` (FEMA-MOTF, 2014b)

flows files in `.csv` format were available for 2008-2015. For 2004, 2006, and 2007 similar datasets were accessible, this time with `.dat` extension. For all the remaining years (1998-2003, and 2005), I could obtain only separated inflow and outflow excel files for each state. Although I have exercised the utmost caution, there may have been occasional mistakes given the different formats. As a further check, I have compared the dataset I obtained with the similar one constructed by Hauer and Byars (2019)[4], finding no major differences.

Alternative sources for migration data such as the American Community Survey (ACS) or the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), because of their limited geographical coverage, are less satisfactory for this analysis. A possible limitation of using IRS data is that, by including only taxpayers, it likely underrepresents individuals in the lowest income. However, Molloy et al. (2011) report that, according to the CPS, 87% of household heads filled tax returns in the period 1992-2009. The CPS data also reveals that tax filers are relatively more likely to migrate than nonfilers. We might thus expect that estimates obtained using IRS data overestimate real migration rates compared to CPS and the ACS data. However, when looking at trends, the three sources should give a similar picture.

For the period I have taken into consideration, using IRS data presents additional challenges. Beginning with 2011-2012, referring mostly to migration in 2011, SOI has introduced several enhancements to improve overall data quality, as well as to provide a new series of information (Pierce, 2015). These enhancements meant an increase in the total coverage rate by 4.7%. From a practical point of view, this implies that researchers should use caution when comparing statistics before and after 2011-2012. Moreover, when looking at both interstate and intercounty migration rates, there appears to be an anomaly with the IRS estimates from the 2014-2015 file. As pointed out by Stone (2016), the very sharp decline in both intercounty and interstate migration rates observed in the 2014-2015 file likely represents a discontinuity in the IRS-SOI data. The fact that no similar decrease is visible either in ACS or in CPS data supports this conclusion.

We get a more precise idea about these issues by looking at Figure 3, which presents intercounty and interstate migration rates from different sources. We see that while ACS and IRS estimates are similar, the ones from the CPS are significantly lower. The similarity between ACS and IRS estimates is surprising, as noted by Molloy et al. (2011), since the underlying methodologies are quite different. Starting from 2011, we see an increase in IRS estimates, which move away from ACS estimates. However, we also notice that the CPS estimates presents a similar pattern, although less pronounced. Given that the CPS underwent no change in methodology in the same period, part of the increase observable from 2011 onwards in IRS estimates might be real. On the contrary, the dramatic decrease in 2014 is unique to IRS estimates. A final caveat. When comparing estimates from ACS, IRS, and CPS in any given year, while the ACS refers to migration occurred in that year,

[4]Their work, which covers the 1990-2010 period, is available here: `https://github.com/mathewhauer/IRS-migration-data`. Because the structure of the dataset I produced is different from the one of Hauer and Byars (2019)'s, I could not compare each value across the two, I thus ran random checks to assess consistency.

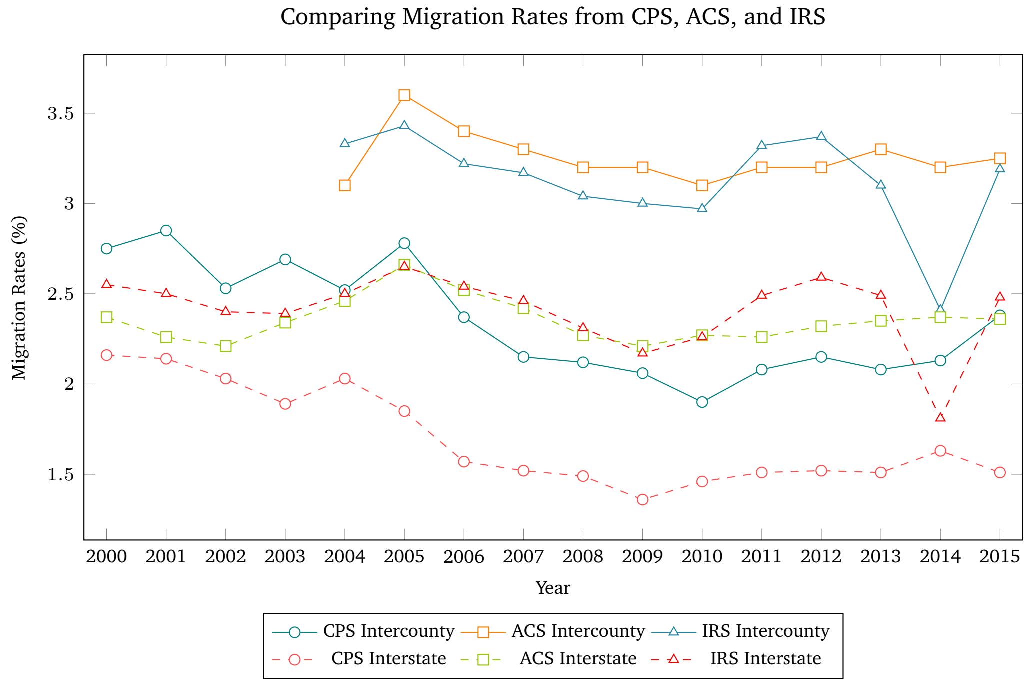

Fig. 3

Note: The data I used to construct the graph come from Stone (2016)'s article

the IRS and the CPS report mostly movements from the year before.

To address these two issues, I have taken two countermeasures. Following the procedure employed by Johnson et al. (2017), I have reduced all flows for the years after 2011 (included) by 4.7%. This should compensate for the increase in coverage rate at the aggregate level. Although the improvement in coverage might not be homogeneous across counties, I have no straightforward way to perform a more precise adjustment. However, given that the new procedure became effective with the 2011-2012 file, this gives us at least one year before Sandy with data comparable to the ones after, thus reducing the severity of this issue. I also examine how the results change if I include only 2011 in the pre-disaster period. This test should give me a measure, albeit an imprecise measure, of how much the change in methodology is responsible for the differences between the two periods. The second countermeasure is to limit the sample to 2013, thus avoiding the use of subsequent data files which may not be reliable. I could have employed more elaborate procedures to improve comparability, but I believe that what I have done is enough to guarantee that my results are not a consequence of discontinuities in the data. I will discuss robustness checks regarding these choices in the results section.

4 Methodology

The analysis consists of three parts. The first and the last follow the methodology adopted by Curtis et al. (2015), to guarantee the comparability of the results, while the second one extends their analysis by looking, in more detail, at how the spatial distribution of flows changed after the Sandy.

The first, more descriptive, part compares flows and ties across different groups of counties for two periods: before and after Sandy in my case, before Katrina and during Katrina recovery in Curtis et al. (2015). I define as a *tie* the presence of a flow of any size between two counties. I say that a *tie* exists between two counties i and j in a given period if a positive flow of any size was present for at least one year. This definition may be problematic when comparing longer intervals of time with shorter ones. The reason for this is simple. As we add more years to a period the number of *ties* can only increase. However, alternative definitions, for example, assigning a *tie* if a positive flow exists in each year, pose similar problems. To neutralise the impact of this issue, I decided to include the same number of years in both periods.

First, I built an inflow and an outflow matrix for each year in the period 2010-2013. For a generic year, the outflows matrix (the inflow matrix is similar and can be obtained by transposing the outflow matrix) looks like this:

$$O_t = \begin{bmatrix} o_{11t} & o_{12t} & o_{13t} & \cdots & o_{1nt} \\ o_{21t} & o_{22t} & o_{23t} & \cdots & o_{2nt} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ o_{n1t} & o_{n2t} & o_{n3t} & \cdots & o_{nnt} \end{bmatrix} \tag{1}$$

Here n is the total number of counties, o_{ijt} is the number of households moving from county i to county j in year t. By dividing each term of line i for the total population of county i in year t, we obtain county-to-county outmigration rates. Second, I built an in-ties and an out-ties matrix for each year. Starting from the inflow and outflow matrices, I replaced each positive element with a 1. Then, I focused on ties which were unique to one of the two periods. Such ties are interesting because they reflect changes in the migration system. Identifying them was straightforward. I subtracted the out-ties matrix for the post-disaster period to the one for the pre-disaster period. In the resulting matrix, the 1s identify out-ties unique to the pre-disaster period and the -1s those unique to the post-disaster period. I repeated the procedure for in-ties.

Finally, I was able to compute the number of unique in- and out-ties from disaster-affected counties to the other eight groups and to compare this number across the pre-disaster and the post-disaster periods[5]. If a system is perfectly stable, there should be no unique ties. If it is expanding, we should see more unique ties in the post-disaster period than in the pre-disaster one. Finally, if it is contracting, they should be more before than after the disaster. The comparison thus gives us a precise idea regarding the evolution of the migration system. We can also test for

[5]In doing this, I did not consider the ties which link the disaster-affected counties to themselves, as they do not represent migration flows.

changes more rigorously by using a difference in proportion test, comparing the number of ties observed with the theoretical maximum. Notice that between two groups of counties the number of ties can be at most equal to the number of counties in the first group multiplied by the number of counties in the second group (minus one if the groups are the same).

To analyse flows, I constructed two matrices with the averages for the pre- and the post-disaster periods respectively, first for outflows then for inflows. I then computed the inflows and outflows from disaster-affected counties to the other eight groups and compared it across the pre- and the post-disaster periods.

In the second part, I will examine the evolution of flows and ties across the two periods by looking at three pairs of maps. The first two compare inflows and outflows from disaster-affected counties before and after Sandy. The last one represents the changes in inflows and outflows, showing which counties experienced the highest gains or losses in terms of migration flows. I will focus on the spatial dimension of flows, paying attention to how the results compare to those obtained by looking at the tie tables. The key difference is that, while the tie tables consider each affected county separately, in the maps they will be aggregated into a single disaster-affected area. As discussed when formulating the hypotheses, this change of perspective may lead to different conclusions regarding the alteration of the migration system's spatial dimension.

The third part, more analytical and focused on recovery migration, consists first in estimating a modified gravity model and then in applying a differences-in-differences approach to identify the effect of Sandy on immigration to disaster-affected (the treatment group) and nearby counties (the control group). The modified gravity model regresses the logarithm of the flow from county j to county i in period t on the logarithm of the population in county i in period t, the logarithm of the population in county j in period t, a dummy variable for the post-disaster period, and a dummy for each pair i,j.

$$\ln y_{ijt} = \alpha_{ij} + \beta_1 \ln p_{it} + \beta_2 \ln p_{jt} + \lambda t_t + \varepsilon_{ijt} \tag{2}$$

The differences-in-differences model adds an interaction term, $(t_t \times k_k)$, for disaster-affected counties in the post-disaster period.

$$\ln y_{ijt} = \alpha_{ij} + \beta_1 \ln p_{it} + \beta_2 \ln p_{jt} + \lambda t_t + \delta(t_t \times k_k) + \varepsilon_{ijt} \tag{3}$$

The presence of a dummy for each sending-receiving county pair ensures that we are controlling for all characteristics of that pair which are fixed over time: for example, the distance between the two counties. For this reason, the group dummy k_k in Equation 3 can be included only in the interaction with the period dummy t_t.

For each part, I will compare the results for Sandy with the ones obtained for Katrina by previous authors or, when not available, by additional analyses. This exercise will reveal which findings hold in both cases and can thus be generalised to similar situations and which findings are instead, specific to one of the two hurricanes.

5 Results

Before analysing Sandy, I have tried to replicate Curtis et al. (2015)'s results for Katrina. The only finding that I was unable to reproduce is the decline in the percentage increase in inflows to the disaster-affected counties after Katrina when considering groups of counties farther away from the affected area (see Table 3 in Curtis et al. (2015)). This replication exercise is relevant for two reasons. First, by checking that the methodology I am using can replicate their results, I can convincingly argue that substantial differences between results obtained on Sandy and the ones obtained on Katrina are not due to methodological differences. Second, having demonstrated that the underlying data is very similar, and by making them available online, I allow other researchers to more easily conduct further analyses on this or other events.

I can now present the results I obtained by applying the described methodology to the analysis of Hurricane Sandy's effects on the migration system. I start by investigating Sandy's impact on the number of unique ties. In Table 2, we observe results that are quite different from the ones obtained by Fussell et al. (2014) and Curtis et al. (2015). The number of unique out-ties increased substantially after Sandy with larger increments for nearby and distant counties. This pattern suggests that the outmigration system expanded rather than contracting. In-ties follow the opposite trend with an overall decrease as a consequence of a substantial increase for disaster-affected counties, stability for nearby counties, and a marked reduction for distant ones. This evolution hints at a contraction in the immigration system. Globally, it seems that Sandy pushed some individuals to abandon the most affected areas even going far away to do so. At the same time, individuals from nearby and distant counties lost their interest in moving to disaster-affected counties.

Number of Unique Ties Between Disaster-Affected Counties and:	Out-Ties			In-Ties		
	Before	After	% Change	Before	After	% Change
All	254	378	48,82**	257	197	-23,35**
Disaster	29	33	13,79	29	33	13,79
Nearby	76	88	15,79	52	38	-26,92
Distant	149	257	72,48**	176	126	-28,41**
All (Urban)	246	370	50,41**	250	192	-23,2**
Disaster (Urban)	28	33	17,86	28	33	17,86
Nearby (Urban)	71	84	18,31	50	35	-30
Distant (Urban)	147	253	72,11**	172	124	-27,91**

Table 2: Comparing Ties between the pre- and the post-disaster periods using adjusted data for the years after 2011 (included).

Notes: Percentage changes in the number of ties are estimated by two-sample difference in proportion test. * $p < .05$, ** $p < .01$, *** $p < 0.001$

Looking at flows in Table 3, we see a similar picture. Outflows increased, more toward distant counties, and less toward disaster-affected and nearby ones. Inflows too, witnessed an overall increase, driven by the increment from disaster-affected counties while inflows from the other groups decreased. This evidence supports the conclusion that there was no sustained recovery migration after Sandy but rather a post-disaster outmigration. Indeed, for both the pre-disaster and the post-disaster periods, the total net flow is negative, and the population loss due to migration becomes more intense after Sandy. This development shows that disaster-affected counties were probably not attracting many new migrants before Sandy and became even less able to do so after the hurricane.

Using unadjusted data (see Tables 9 and 10 in the Appendix) does not change the results qualitatively. The most notable difference is that the decrease in the number of in-ties loses significance for distant counties, making non-significant also the overall change. Results are similar also adopting the alternative classification of counties based on the FEMA-MOTF (2014a) report using adjusted data (see Table 11 and Table 12 in the Appendix). I further investigated what happens to the flow table when I include only 2011 in the pre-disaster period[6]. This check should give us an idea about the possible effect of the methodological change that occurred in that year. I find that while the changes in outflows become smaller and those in inflows become greater (in absolute terms), the patterns are unchanged with distant counties still having the most relevant variations. In any case, as I mentioned in the data section, I do not see this strategy, that is keeping only 2011 in the pre-disaster period, as necessarily being more robust.

I have also analysed the two years in the post-disaster period separately to distinguish the outcomes in the immediate aftermath from those in the post-emergency period. In this additional analysis, I have considered only flows. Examining Tables 4 and 5, which compare average flows in 2010-2011 to those in 2012 and 2013, we see that the increase in outflows was stronger in the immediate aftermath while it subsequently declined. On the contrary, while inflows from all groups increased in 2012, there was an overall decline in 2013, more pronounced for nearby and distant counties. On the whole, the results in Tables 3, 4, and 5 give partial support for Hypothesis 1 and strong support for Hypothesis 2a over 2b. Indeed, outflows increased immediately after Sandy, as stated in Hypothesis 1, but then they did not go back to their pre-disaster level, especially when looking at distant counties as a destination. This latter finding suggests that Sandy intensified preexisting outflows by making the affected area relatively less appealing. Looking at inflows, we find an increase shortly after Sandy and then a decline below the pre-disaster level, as stated in Hypothesis 2a. As with outflows, this trend suggests that, after Sandy, the affected area became less capable of attracting new immigrants, worsening its net migration balance.

To get an idea about how these trends compare to what happened after Katrina, we can look at Figure 4, which portraits the evolution of inflows and outflows for Katrina-affected counties over the 1999-2013 period. I have drawn an identical graph for Sandy in Figure 5. Three aspects are

[6]I considered only flows because, as I discussed in the methodology section, comparisons of the number of ties may not be meaningful when the two periods do not include the same number of years

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	463,659,	486,037,	4.83%	429,818	433,609	0.88%
Disaster Affected	319,320	328,916	3.01%	319,329	328,916	3.00%
Nearby	55,377	55,895	0.94%	46,058	44,442	-3.51%
Distant	88,962	101,226	13.79%	64,431	60,251	-6.49%
All (Urban)	461,254	483,459	4.81%	428,159	432,000	0.90%
Disaster Affected (Urban)	318,421	328,014	3.01%	318,553	328,172	3.02%
Nearby (Urban)	54,000	54,400	0.74%	45,302	43,667	-3.61%
Distant (Urban)	88,833	101,045	13.75%	64,304	60,161	-6.44%

Table 3: Comparing households flows between the pre- and the post-disaster periods using adjusted data for the years after 2011 (included)

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	463659	496863	7.16%	429818	449502	4.58%
Disaster Affected	319320	337459	5.68%	319329	337459	5.68%
Nearby	55377	56719	2.42%	46058	46177	0.26%
Distant	88962	102685	15.43%	64431	65866	2.23%
All (Urban)	461254	494148	7.13%	428159	447840	4.60%
Disaster Affected (Urban)	318421	336470	5.67%	318553	336730	5.71%
Nearby (Urban)	54000	55193	2.21%	45302	45364	0.14%
Distant (Urban)	88833	102485	15.37%	64304	65746	2.24%

Table 4: Comparing households flows between the pre-disaster period and 2012 using adjusted data for the years after 2011 (included)

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	463659	475105	2.47%	429818	417663	-2.83%
Disaster Affected	319320	320352	0.32%	319329	320352	0.32%
Nearby	55377	55077	-0.54%	46058	42683	-7.33%
Distant	88962	99676	12.04%	64431	54628	-15.21%
All (Urban)	461254	472658	2.47%	428159	416116	-2.81%
Disaster Affected (Urban)	318421	319534	0.35%	318553	319591	0.33%
Nearby (Urban)	54000	53609	-0.72%	45302	41955	-7.39%
Distant (Urban)	88833	99515	12.02%	64304	54570	-15.14%

Table 5: Comparing households flows between the pre-disaster period and 2013 using adjusted data for the years after 2011 (included)

worth noting. First, the change in flows after Katrina was much higher than the one after Sandy, both in inflows and in outflows, lending support to Hypothesis 3. Second, the direction of the change, instead, was the same, with both outflows and inflows increasing in the immediate aftermath, the former more than the latter. Third, while, after Katrina, inflows immediately surpassed outflows, leading to positive net migration, this did not happen after Sandy. On this third point, notice that it does not necessarily imply that the entire area affected by Katrina experienced population growth after the hurricane. Indeed, while the total population of the region had already reached its pre-disaster level in 2007 (Figure 4), if we look at Orleans parish, recovery appears to have been still incomplete in 2013 (see Figure 9 in the Appendix). From a preliminary analysis, the situation seems more homogeneous across Sandy-affected counties. However, the available time-series is too short for an investigation of the long-term dynamics. To conclude, I want to point out that the differences in the magnitude of changes and the sign of net migration are probably connected. In other terms, the rise in inflows after Katrina was partly a consequence of the enormous number of evacuees who left the affected area in the first place.

Outflows and Inflows in Katrina Disaster-Affected Counties

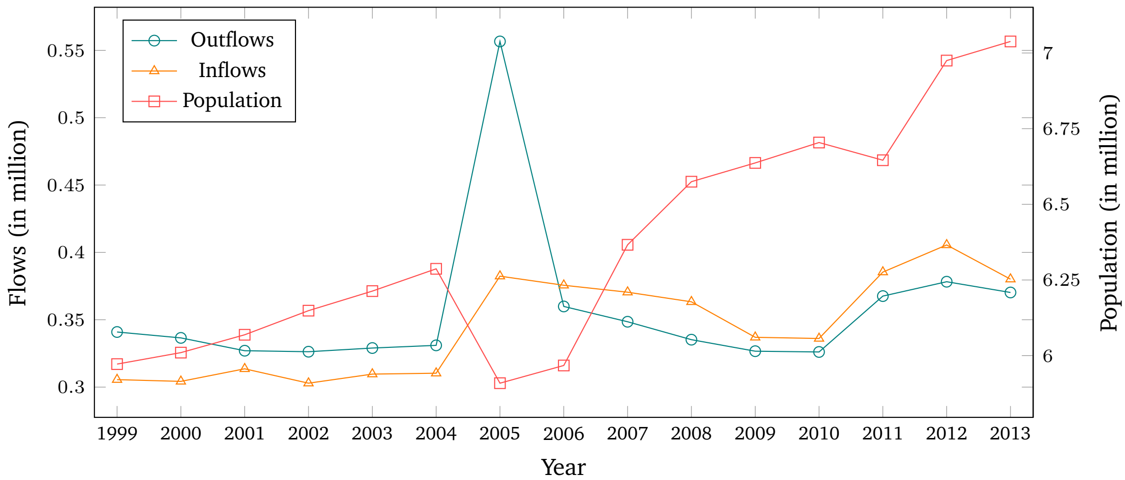

Fig. 4

Notes: Here the numbers refer to individuals and are computed by using the Internal Revenue Service County-to-County migration files.

5.1 A Second Look at Ties

One issue with the concept of ties, as I have defined it, is that an increase in the number of ties does not necessarily mean that the migration system is expanding geographically. If we look, for example, at the flows between disaster-affected counties and all other counties, a new connection may either involve counties previously outside the system or counties which were already inside but that did not have a tie with that specific county. In the first case, the number of ties increases but the number of counties in the system remains the same. Only in the second instance can we

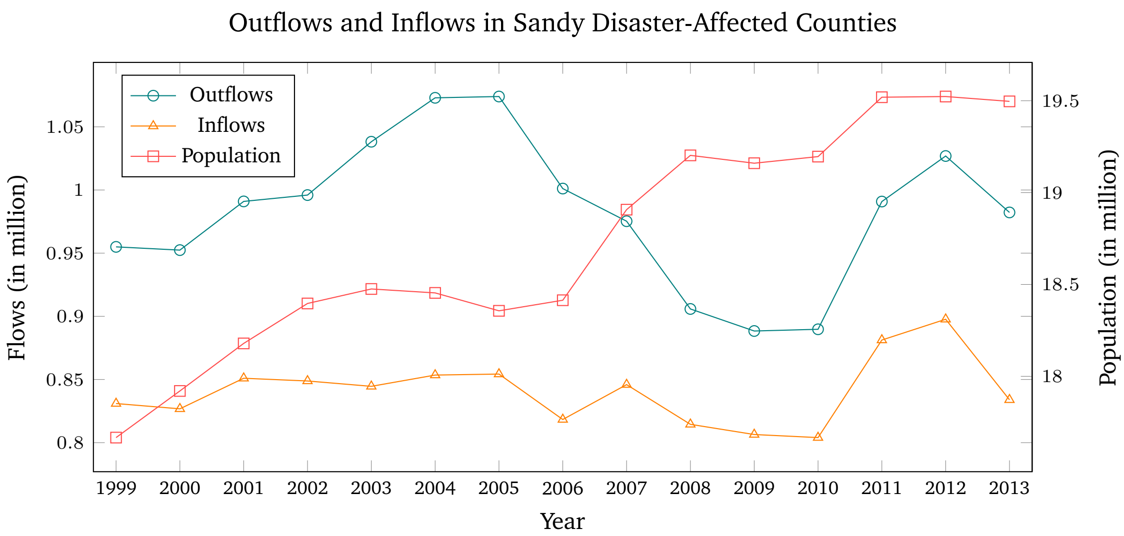

Fig. 5

Notes: Here the numbers refer to individuals and are computed by using the Internal Revenue Service County-to-County migration files.

say that the network expands. For this reason, the conclusions we reach by looking at the numbers in Table 2, may not reflect the intuitive notion of expansion/contraction. To analyse this second dimension, I have constructed three pairs of maps which allow for an immediate understanding of how the spatial distribution of migratory flows changed after Sandy.

In Figure 6, we see the evolution of outflows from disaster-affected counties across the two periods. I have coloured each US county according to the average flow it received from disaster-affected counties before and after Sandy with darker shades indicating bigger flows. We see that a large share of migrants tended to resettle in nearby counties. However, some distant destinations also appear to be popular. Among the latter, there is the San Francisco and Los Angeles areas in California as well as coastal counties in Florida. If we compare the two periods, we notice two aspects. First, as we already knew from Table 3, outflows have increased. We can see this by noting how many counties became darker, especially distant ones. Second, the spatial distribution of the outmigration system did not change significantly. There are some new entries, like Williamson County in Tennessee, and some losses, like Champaign County in Illinois, but the bulk of counties remain the same. This second finding gives us three valuable insights. While the number of outties increased after Sandy, the migration system did not expand spatially. Most of the additional outmigrants chose destinations to which other disaster-affected counties were already connected. If we consider the disaster-affected counties as a single geographical region, the effects of Hurricane Sandy on out-ties would appear negligible. The choice of the unit of analysis is thus very influential on the conclusions one reaches.

In Figure 7, we see an analogous picture for inflows. Here the system did, indeed, become more spatially concentrated around the disaster-affected counties. Moreover, that area became slightly

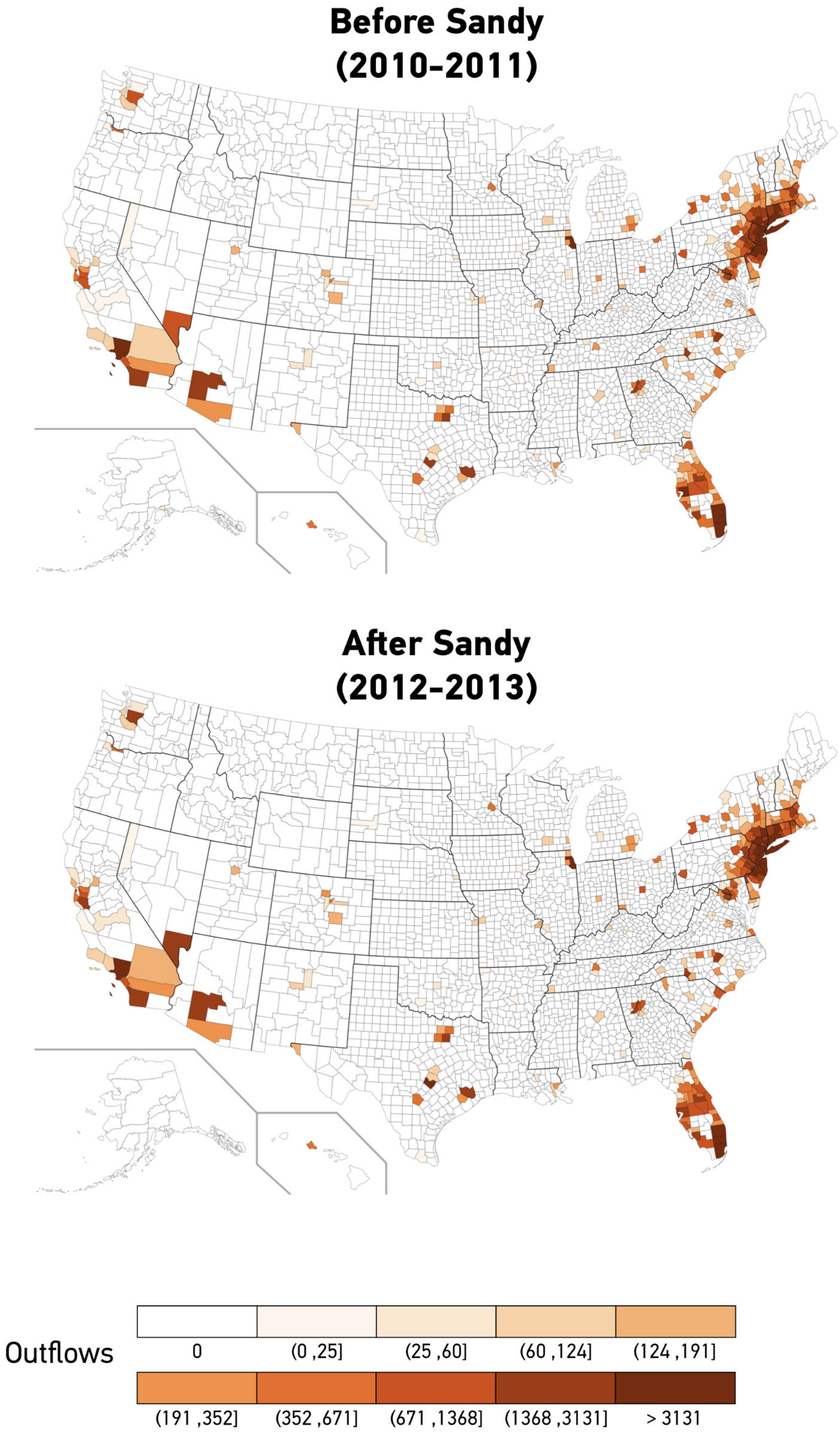

Fig. 6: Comparing Outflows from Disaster-Affected Counties Before and After Sandy

Notes: each shade of red (excluding the white) represents approximately a decile of the outflows distribution pooling together the two periods and keeping only strictly positive flows. To be more precise, each one contains 11.11% of the observations, except for the white one. Flows are computed for households as in the flow tables.

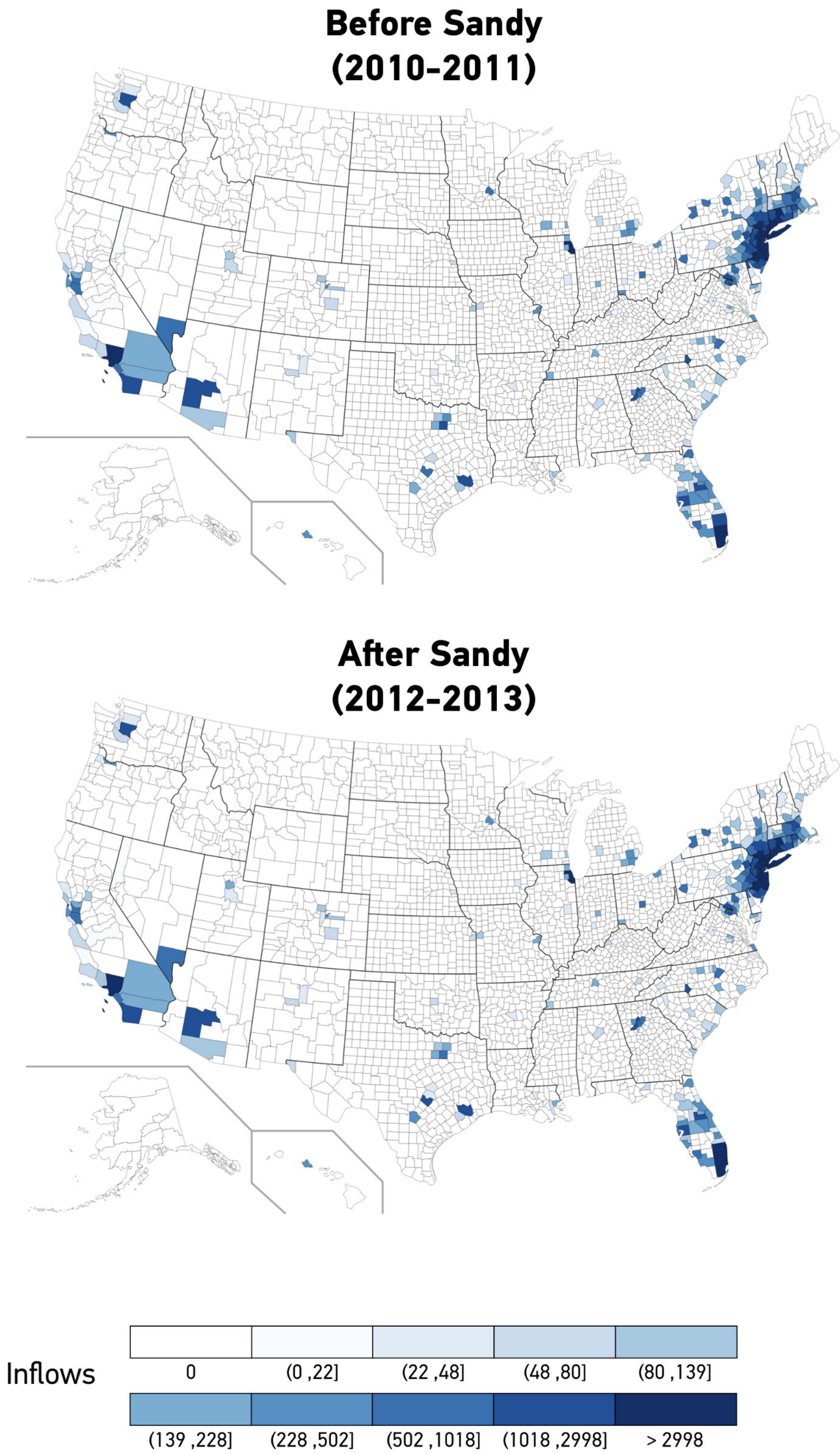

Fig. 7: Comparing Inflows to Disaster-Affected Counties Before and After Sandy

Notes: each shade of blue (excluding the white) represents approximately a decile of the inflow distribution pooling together the two periods and keeping only strictly positive flows. To be more precise, each one contains 11.11% of the observations, except for the white one. Flows are computed for households as in the flow tables.

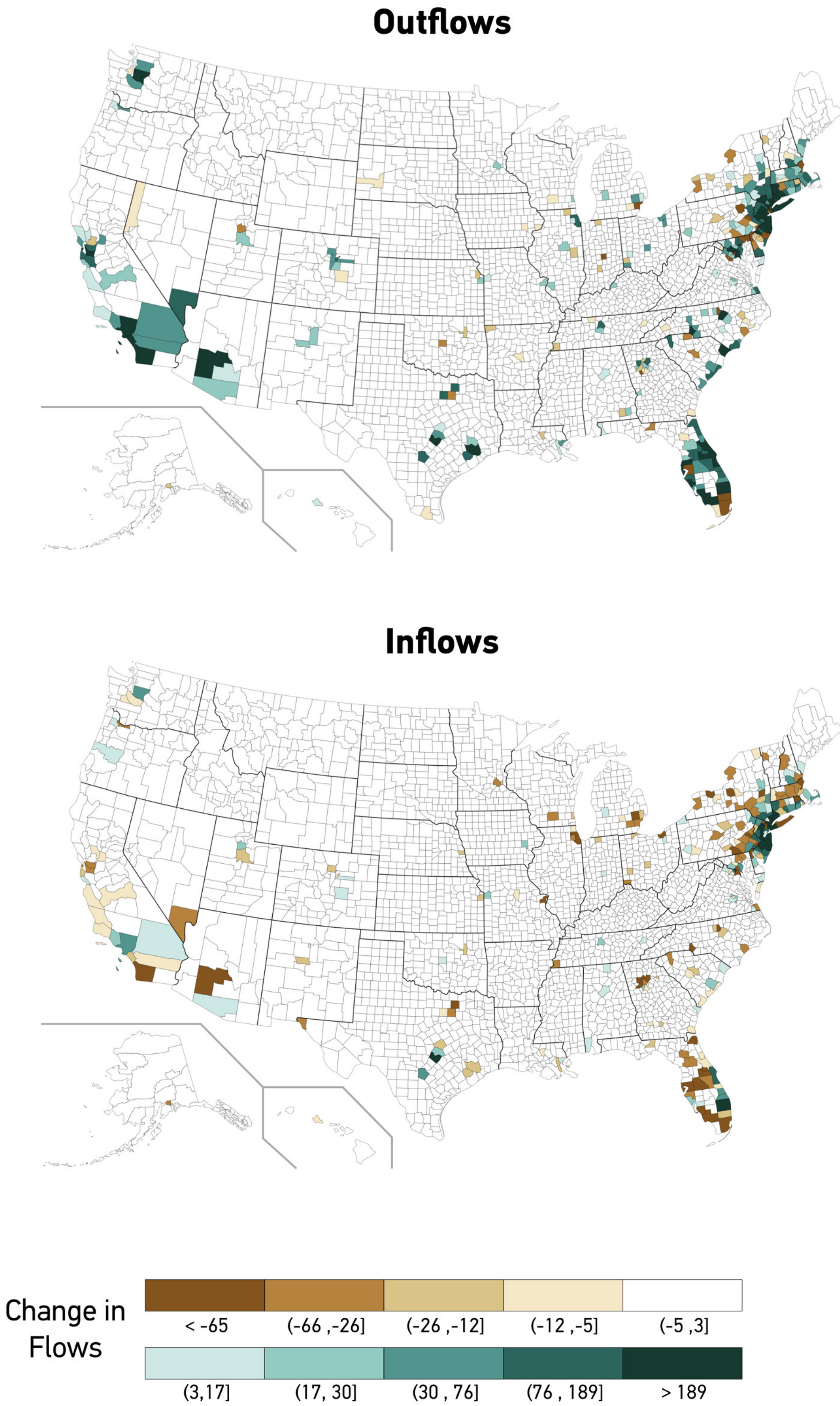

Fig. 8: Who Gained and Who Lost Migration Flows from/to Disaster-Affected Counties

Notes: each different shade/color (excluding the white) represents a decile of distribution of changes in flows considering only non-zero values. Flows are computed for households as in the flow tables.

darker, signalling an increase in outflows to disaster-affected counties. At the same time, most distant counties become lighter, a sign that inflows from these to disaster-affected counties have decreased. A second aspect to notice is that in both periods, the immigration and the outmigration systems are very similar to one another. This similarity suggests that migration networks play a significant role in the choice of destinations. For this reason, new counties will seldom join the system, and this seems to hold true also in the face of an external shock such as Sandy. We find, as well, support for Lee (1966)'s idea that for each stream, a counterstream develops. To summarise, while at the county-level Sandy seems to have altered the migration systems, when we move to the regional level, the system appears rather stable while the change involves flows within it.

Finally, in Figure 8, we see which counties lost and which gained outflows (top) and inflows (bottom). As we saw in Table 3, the number of outmigrants increased more than that of immigrants. Indeed, many more green counties (representing an increase in flows) are visible on the top map than in the bottom one. An interesting fact is that, in many cases, those counties that gained more immigrants from the disaster-affected area are also those that saw the largest decrease in outmigration to that area (e.g., San Diego County in California). We also see increased mobility within disaster-affected counties. Overall, when looking at changes in flows, we observe that outflows tended to expand outward to distant counties while inflows showed the opposite tendency.

To compare these findings for the two hurricanes, I have drawn two analogous maps constructed with Katrina data (see Figure 10 and Figure 11 the Appendix). They show a decrease in out-ties, more apparent in distant counties, which thus supports the idea of a spatial contraction of the outmigration system. There are no similar changes in the spatial distribution of inflows, but there is a glaring increase testified by the much darker colours visible in the bottom map. Overall, I would say that the results are in line with what we would have expected looking at the analysis for Sandy. While changes in ties at the county level suggest considerable variations in the geographical distribution of flows, once we move the study to the disaster-affected area as a single region, this effect becomes less clear.

The findings in this subsection suggest that migration networks do not consist exclusively of close relationships among individuals (relatives, friends, or acquaintances). They could also include indirect connections. For example, a migration network may unite migrants from New York to San Francisco and *vice-versa* even if the individuals who participate in it do not know each other personally. It suffices that potential migrants at origin know that they can find a community with cultural characteristics similar to theirs at destination. These indirect ties might not be as powerful as personal ones, but they could nevertheless play a role in shaping the spatial distribution of flows. In other words, we could have both a *narrow* (stronger) and a *broad* (weaker) network. From this perspective, what we would have interpreted as a new connection outside the *narrow* network, is perhaps just an increase in flows within the *broad* one.

5.2 Did Recovery Migration Occur?

To conclude the results section, I will examine the outcomes of the gravity model and the differences-in-differences model. Table 6 presents the results of the gravity model. Here, we are mostly interested in the coefficients on the time variable, which tell us how inflows to disaster-affected and nearby counties varied after Sandy. For disaster-affected counties, the results confirm the findings in Table 3. Inflows from disaster-affected and nearby counties were stable but declined significantly from distant ones. The picture for nearby counties, as receivers, is very different. In this case, inflows from all origins increased, with the magnitude of the increase decreasing with the distance. In both cases, there are no substantial differences between urban and rural counties. These results would suggest that disaster-affected counties suffered a relative decline in inflows compared to nearby-counties. However, to get a more precise idea of this, we need to turn to the differences-in-differences model in Table 7. It turns out that our intuition was correct, the treatment effect is negative and significant, for all sending regions.

This evidence supports the conclusion that Sandy caused a decline in immigration to disaster-affected counties. Such an outcome is contrary to the one observed by Curtis et al. (2015) in their analysis of Katrina and suggests that no recovery migration developed after Sandy. Nevertheless, I should discuss one argument against making a direct comparison: while Curtis et al. (2015) analysed the recovery period after Katrina (2007-2009), I considered the post-disaster period after Sandy (2012-2013). Maybe this explains the observed difference. However, looking at Figure 4, it seems that, for inflows, the post-Katrina trend observed in 2007-2009 is just the continuation of that in the immediate 2005-2006 aftermath, suggesting that the Sandy-Katrina differences do not depend on the period considered. Indeed, I reran the differences-in-differences analysis on the Katrina dataset, using 2005-2007 as the post-disaster period, and the treatment effect remains positive and significant, except when the sending region is the disaster-affected one. While a more careful investigation would be needed to make this conclusion more robust, I do not think that the sustained recovery migration observed after Katrina versus its absence after Sandy is solely the result of a methodological difference.

6 Discussion: *Disruptive* and *Manageable* Natural Disasters

The present study showed that the outmigration system of the areas affected by Sandy became denser (more connections) and expanded, especially toward distant counties. However, when considering the disaster-affected counties as a single macro region, the expansion appears to be less relevant, suggesting that the increase in out-ties involved mostly counties which had already a connection to the affected area. The immigration system followed a reverse pattern and became more spatially concentrated except within disaster-affected counties. Even in this case, the contraction appears less evident when moving to the macro level. Looking at flows, while outflows

	Sending Region							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Inflow From the Origin to the Destination County)	All Counties	Disaster-Affected Counties	Nearby Counties	Distant Counties	All Counties, Urban	Disaster-Affected Counties, Urban	Nearby Counties, Urban	Distant Counties, Urban
Receiving Region								
Disaster-Affected Counties (Treatment Group)								
Ln(Population at the Origin)	1.627***	1.673***	1.091**	1.920***	1.669***	1.706***	1.225***	1.931***
	(0.153)	(0.183)	(0.342)	(0.212)	(0.154)	(0.183)	(0.349)	(0.214)
Ln(Population at the Destination)	0.269*	1.120***	0.716**	-0.346	0.210	1.069***	0.577*	-0.369
	(0.132)	(0.187)	(0.254)	(0.198)	(0.134)	(0.186)	(0.258)	(0.202)
After Sandy	-0.00832	0.00465	0.00790	-0.0302***	-0.00855	0.00502	0.00632	-0.0293***
	(0.00464)	(0.00710)	(0.00967)	(0.00739)	(0.00469)	(0.00713)	(0.00985)	(0.00743)
Nearby Counties (Control Group)								
Ln(Population at the Origin)	0.945***	0.595*	1.010***	1.224***	0.992***	0.604*	1.007***	1.279***
	(0.0925)	(0.237)	(0.175)	(0.122)	(0.0942)	(0.237)	(0.185)	(0.122)
Ln(Population at the Destination)	0.557***	1.530***	1.219***	-0.319	0.475***	1.522***	1.104***	-0.360*
	(0.113)	(0.313)	(0.172)	(0.165)	(0.117)	(0.313)	(0.184)	(0.169)
After Sandy	0.0289***	0.0491***	0.0304***	0.0178**	0.0293***	0.0492***	0.0350***	0.0155**
	(0.00354)	(0.00908)	(0.00537)	(0.00543)	(0.00371)	(0.00911)	(0.00572)	(0.00561)

Table 6: Gravity model regression of changes over time (after Sandy) in inflows to disaster-affected and nearby counties.

Notes: Fixed-effects for each sending-receiving county pair are included. Robust standard errors are presented in parentheses. The results exclude all cases where the sending and the receiving county are the same (i.e. non migrants).
* $p < .05$, ** $p < .01$, *** $p < 0.001$

	Sending Region							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Inflow From the Origin to the Destination County)	All Counties	Disaster-Affected Counties	Nearby Counties	Distant Counties	All Counties, Urban	Disaster-Affected Counties, Urban	Nearby Counties, Urban	Distant Counties, Urban
Ln(Population at the Origin)	1.183***	1.049***	1.062***	1.457***	1.232***	1.067***	1.094***	1.500***
	(0.0813)	(0.153)	(0.156)	(0.111)	(0.0826)	(0.154)	(0.163)	(0.111)
Ln(Population at the Destination)	0.457***	1.372***	1.027***	-0.280*	0.385***	1.342***	0.897***	-0.315*
	(0.0850)	(0.171)	(0.142)	(0.125)	(0.0873)	(0.172)	(0.149)	(0.128)
After Sandy	0.0248***	0.0409***	0.0335***	0.00963	0.0246***	0.0411***	0.0377***	0.00726
	(0.00340)	(0.00873)	(0.00523)	(0.00516)	(0.00357)	(0.00876)	(0.00558)	(0.00534)
Treatment Effect	-0.0262***	-0.0282**	-0.0329***	-0.0257**	-0.0259***	-0.0279**	-0.0371***	-0.0232**
	(0.00532)	(0.0108)	(0.00983)	(0.00826)	(0.00545)	(0.0108)	(0.0101)	(0.00839)

Table 7: differences-in-differences analysis of Sandy's impact on inflows to disaster-affected and nearby counties.

Notes: Fixed-effects for each sending-receiving county pair are included. Robust standard errors are presented in parentheses. The results exclude all cases where the sending and the receiving county are the same (i.e. non migrants).
* $p < .05$, ** $p < .01$, *** $p < 0.001$

increased, with the increase driven by distant counties, inflows decreased, especially inflows from nearby and distant counties. The differences-in-differences analysis, comparing changes in inflows to disaster-affected and nearby counties, confirms that no or very weak recovery migration took place in the former.

A point has emerged from the comparison between Sandy and Katrina: natural disasters, and hurricanes, in particular, are not all the same in terms of their impact on migration. While Katrina caused massive displacement and, partly as a consequence, recovery migration in the affected area, Sandy did not trigger either of the two processes. It appears that these two hurricanes belong to two distinct categories of natural disasters when it comes to their effects on migration. Katrina represents a *disruptive* natural disaster. There is almost complete evacuation and then, because of catastrophic damages and an intense, albeit unequal, reconstruction process, there comes long-term recovery migration whereby the returning evacuees mix with newcomers in search of opportunities (Pais and Elliott, 2008; Olshansky et al., 2012; Fussell, 2015). Sandy, on the contrary, represents the *manageable* type of natural disaster which does not cause either extended abandonment of the area at risk or broad reconstruction and, consequently, does not give rise to recovery migration, leading instead to a decrease in net migration. Table 8 tries to summarise this typology.

Note that, for a natural disaster to be of the disruptive type, it is not enough to have an extensive evacuation. There should also be impediments of some sort to a rapid return and a reconstruction phase where Pais and Elliott (2008)'s "recovery machine", "a coalition of business elites united with local political officials in pursuit of ongoing economic and demographic growth", generates new opportunities. If this second condition is not satisfied, we could in principle have a short-lived explosion in outmigration just before the event followed immediately after by a corresponding increase in inflows, with little impact on the migration system equilibrium. Similarly, while the extent of damage is undoubtedly relevant in determining which kind of natural disaster has taken place, it is not the only factor. The vulnerability of the area, for example, will be equally important, together with the prevention measures enacted by the institutions in charge and, as suggested by a recent study, long-term population trends at the time of the event (Fussell et al., 2017). Further studies, covering more events, are needed to shed light on which mechanisms are likely to lead to one type of disaster or the other.

One could ask why we should care about this typology. A possible answer, I believe, is that these two types of disaster require, for many reasons, different policy interventions. First, the individuals in need of assistance will be mostly in the nearby area after a disruptive event (as evacuees) and in the affected one following a manageable disaster. Second, while the relocation of former residents of the affected areas to regions less prone to natural hazards may be possible after a disruptive event (although politically difficult), it may be unfeasible after a manageable one (McLeman, 2011). Third, while, after a disruptive event, the reconstruction phase gives policymakers a chance to improve the resilience of the affected area, they will have many additional constraints after a manageable disaster. Acknowledging that not all natural catastrophes are equal is a first step toward designing better policies.

	Disruptive	Manageable
Before the Disaster	Complete evacuation of the area at risk.	Partial evacuation of the area at risk.
Immediate Aftermath	The extended damage prevents return migration for the groups that suffered the most. Racial minorities, low-income groups, and renters are likely to have the lower return rates.	Most of the evacuees return to their residence. Some individuals, however, leave the affected area on a long-term basis and, at the same time, inflows to the region decline.
Long-Term	Sustained recovery migration leads to a rebound in the population as a consequence of positive net migration. Inflows comprise both returning evacuees and new residents in search of opportunities offered by the reconstruction process.	The long-term effect on migration are small in magnitude but might lead to a worsening of net migration resulting both from a permanent increase in outflows and a decline in inflows.

Table 8: Distinguishing between *Disruptive* and *Manageable* Natural Disasters

Institutions, other than providing immediate assistance during the emergency phase, should also address two additional issues: the inequalities generated by the disaster; and the prevention of future occurrences. These two issues are not independent as the most affected individuals are also likely to suffer the most if a new disaster were to occur. After a disruptive event, tackling these issues will entail helping disadvantaged evacuees who do not have the resources or the possibility to return either by ensuring they do so or by assisting them in rebuilding new lives in the area where they have relocated. When planning such interventions, policymakers should consider that many evacuees may have left the affected area. The choice between these two alternatives (return or relocate) is not simple and depends on both the politicians' and the beneficiaries' will. However, climate change projections tell us that we should expect more catastrophic cyclones hitting coastal areas, therefore rebuilding in the same place may not be a forward-looking option. Indeed, to mitigate future risks, one can envision either a *hard* response, based on new protective infrastructures, or a *soft* one, which consists of relocating individuals and activities to less hazard-prone regions. After a manageable event, addressing inequality will require more local interventions in the affected region (such as public assistance to households). However, because these events are less likely to generate significant relocation, it may be more difficult to reorganise the human geography of the affected area in such a way as to reduce vulnerability. Nonetheless, policymakers should consider incentivising outmigration by providing both financial and non-financial assistance.

Overall, what this study and the previous literature agree on is that we should not expect a population redistribution process to occur automatically. After Katrina, sustained recovery migration allowed the population of the affected region to rebound and, even though this phenomenon did not take place after Sandy, there too the population did not decline. Policymakers cannot ignore people's desire to rebuild in the same place, but they should be clear about the risks entailed by such a decision and offer attractive alternatives.

7 Conclusion

Because of both climate change and socio-demographic processes on the other, we will likely experience more frequent extreme weather events with devastating impact on coastal areas in the coming years. With climate change, rising sea levels together with an increase in the frequency of the most catastrophic hurricanes will add more stress to areas which are already struggling to cope with the current situation (IPCC, 2014; Knutson et al., 2010). Thinking of socio-demographic facts, an increase in the population of coastal areas, especially cities, will heighten their sensitivity to such disasters and may also reduce their adaptive capacity (Donner and Rodríguez, 2008). As reported by NOAA (2013), while coastal counties represent less than 10% of the total area in the United States (excluding Alaska), they contain almost 40% of the total population. Furthermore, population density in coastal counties is more than four times the national average.

To increase our understanding of what demographic consequences these events might have, I have analysed the impact of Hurricane Sandy on the migration system of the affected counties. In particular, I wanted to compare Sandy with Katrina. This comparison is relevant because Sandy is to date the second costliest US hurricane for which sufficient migration data to conduct a complete analysis is available. Moreover, while many studies have investigated Katrina, we know much less about other events. Following Curtis et al. (2015), I have adopted a migration system perspective, devoting particular attention to recovery migration. Compared to previous studies, I have explored more in detail than previous studies how the impact changed in the immediate aftermath compared with the subsequent year and how the hurricane influenced the spatial distribution of flows.

This work contributes to the existing literature by adding a comprehensive investigation of an understudied event, adopting a methodology close to the one used by studies on Katrina to allow comparability. Furthermore, it develops a typology of natural disasters according to their impact on migration. This typology, distinguishing *disruptive* from *manageable* events, is intended as a tool for researchers and policymakers to formulate reasonable expectations on the effects of future disasters. Finally, making available both the data I used and a set of replication files on GitHub, I hope to encourage other researchers to extend my analysis by covering other events or aspects of Sandy's impact I have ignored.

Before summarising the results and analysing the policy implications of the present study, I want to discuss its limitations. First, as mentioned in the data section, the IRS-SOI data, by covering only taxpayers, likely underrepresents older and very poor individuals. Given that these two groups have, on average, a lower propensity to migrate, the IRS-SOI probably, then, overestimates mobility. In addition to this issue, which affects all studies using IRS-SOI data, the period of interest for the study of Sandy poses some additional problems caused by a change in methodology in 2011 and the drop in migration rates in 2014, which does not appear in any other source. The main consequence of these issues is that I had to limit the period of study to 2010-2013, renouncing to an analysis of long-term impacts. I also had to apply some adjustments to the data.

These limitations notwithstanding, I find that outflows from disaster-affected counties increased substantially after Sandy, especially to distant ones. The increase was stronger in 2012, but was also significant in 2013. On the contrary, inflows rose slightly in 2012 then declined significantly in 2013, more so from nearby and distant counties. In terms of spatial distribution, while outflows saw an expansion, inflows contracted. However, such distributional changes disappear if we consider disaster-affected counties as a single region. In that case, it does not appear that recovery migration took place. On the contrary, a differences-in-differences analysis comparing disaster-affected and nearby counties reveals that the former saw an additional decrease in inflows compared to the latter. This finding is not completely unexpected as the population recovery observed after Katrina was in part a function of the extraordinary magnitude of post-Katrina evacuation and reconstruction. Moreover, other studies which analysed the New Orleans area and other counties along the Mississippi coast found conflicting dynamics in these two regions. In particular, the magnitude of Katrina's effects appears to have been much higher in New Orleans than in other affected areas (Frey and Singer, 2006). The results summarised here appear to be robust to changes in the years included in the pre- and post-disaster periods and in the classification of counties.

The different impact Katrina and Sandy had on migration prompted me to develop a tentative typology where Katrina-type events, with significant effects on migration and sustained population recovery, are labelled as *disruptive*. Sandy-type events, with minor impact on the migration systems possibly leading to a decrease in net migration, are, on the other hand, classified as *manageable*.

What general conclusions should we draw from the present study? The impacts observed after Katrina may not be representative of what we should expect after other hurricanes. Outflows may not increase dramatically, and massive population displacements may not take place. At the same time, sustained population recovery may not occur in other circumstances. This scenario is relevant for policymakers as it implies that the vast majority of individuals at risk will not move even after having suffered severe consequences from a natural disaster. It would thus be preferable either to increase adaptive capacity and reduce sensitivity in the areas at risk by improving, for example, protective infrastructures or to actively promote relocation to less hazard-prone regions. Policymakers should also consider that it is usually the vulnerable groups that suffer the most after natural disasters. They are not only vulnerable, in general, they are also less able to adapt. This environmental inequality or injustice at the micro level acts on top of the macro level injustice intrinsic in climate change, which follows from the major countries responsible for it not being the ones it affects the most. Policymakers should address both these points when designing policies to mitigate environmental change.

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8 Appendix

Number of Unique Ties Between Disaster-Affected Counties and:	Out-Ties			In-Ties		
	Before	After	% Change	Before	After	% Change
All	265	420	58,49**	258	241	-6,59
Disaster Affected	30	37	23,33	30	37	23,33
Nearby	71	94	32,39	50	56	12
Distant	164	289	76,22**	178	148	-16,85
All (Urban)	258	412	59,69**	252	234	-7,14
Disaster Affected (Urban)	29	37	27,59	29	37	27,59
Nearby (Urban)	68	90	32,35	48	51	6,25
Distant (Urban)	161	285	77,02**	175	146	-16,57

Table 9: Comparing Ties between the pre- and the post-disaster periods using unadjusted data for the years after 2011 (included)

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	474,131	506,697	6.87%	439,425	452,139	2.89%
Disaster Affected	325,889	341,816	4.89%	325,898	341,816	4.88%
Nearby	56,717	58,540	3.21%	47,163	46,670	-1.05%
Distant	91,525	106,341	16.19%	66,364	63,653	-4.09%
All (Urban)	471,649	503,973	6.85%	437,728	450,414	2.90%
Disaster Affected (Urban)	324,970	340,879	4.90%	325,106	341,044	4.90%
Nearby (Urban)	55,296	56,949	2.99%	46,387	45,820	-1.22%
Distant (Urban)	91,383	106,145	16.15%	66,235	63,550	-4.05%

Table 10: Comparing Flows between the pre- and the post-disaster periods using unadjusted data for the years after 2011 (included)

Number of Unique Ties Between Disaster-Affected Counties and:	Out-Ties			In-Ties		
	Before	After	% Change	Before	After	% Change
All	453	618	36.42%	451	409	-9.31%
Disaster Affected	84	117	39.29%	84	117	39.29%
Nearby	167	149	-10.78%	129	111	-13.95%
Distant	202	352	74.26%	238	181	-23.95%
All (Urban)	434	597	37.56%	428	391	-8.64%
Disaster Affected (Urban)	80	110	37.50%	76	113	48.68%
Nearby (Urban)	152	135	-11.18%	114	99	-13.16%
Distant (Urban)	202	352	74.26%	238	179	-24.79%

Table 11: Comparing Ties between the pre- and the post-disaster periods using the classification based on the FEMA-MOTF (2014b) report

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	669559	700913	4.68%	631523	644144	2.00%
Disaster Affected	452880	466666	3.04%	452862	466666	3.05%
Nearby	106741	109267	2.37%	99122	102245	3.15%
Distant	107750	122872	14.03%	77516	73149	-5.63%
All (Urban)	662638	693363	4.64%	625518	638089	2.01%
Disaster Affected (Urban)	449069	462588	3.01%	449072	462885	3.08%
Nearby (Urban)	103652	105837	2.11%	96918	100023	3.20%
Distant (Urban)	107729	122830	14.02%	77505	73097	-5.69%

Table 12: Comparing Flows between the pre- and the post-disaster periods using the classification based on the FEMA-MOTF (2014b) report

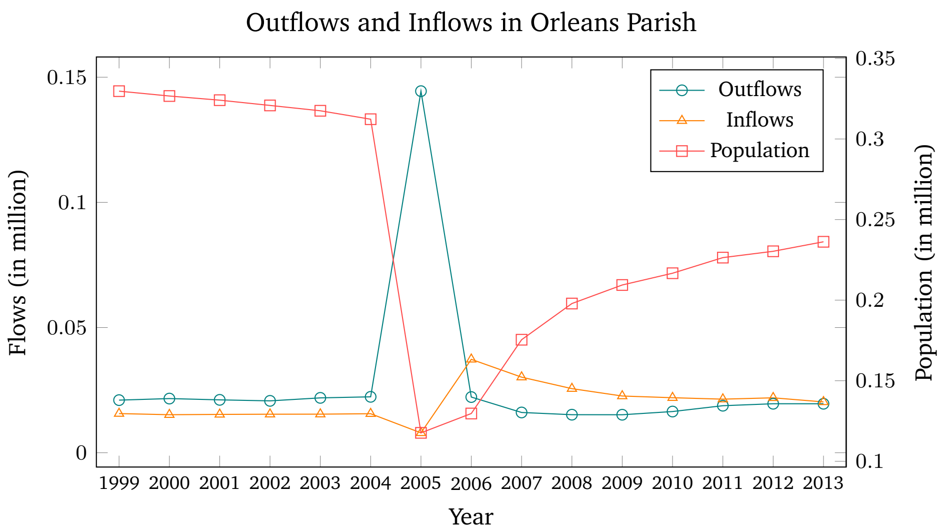

Fig. 9

Notes: Here the numbers refer to individuals and are computed by using the Internal Revenue Service County-to-County migration files.

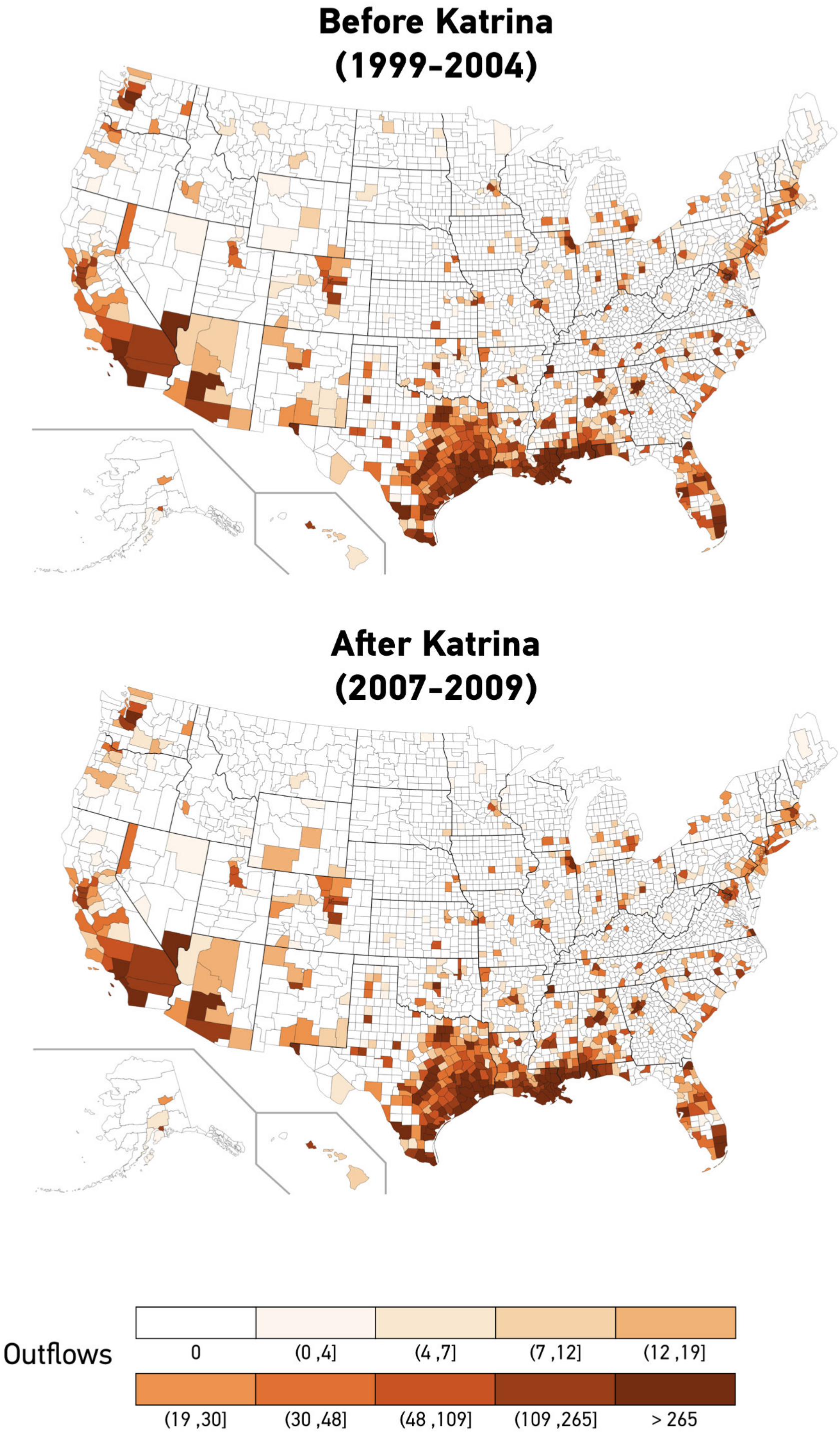

Fig. 10: Comparing Outflows Before and After Katrina

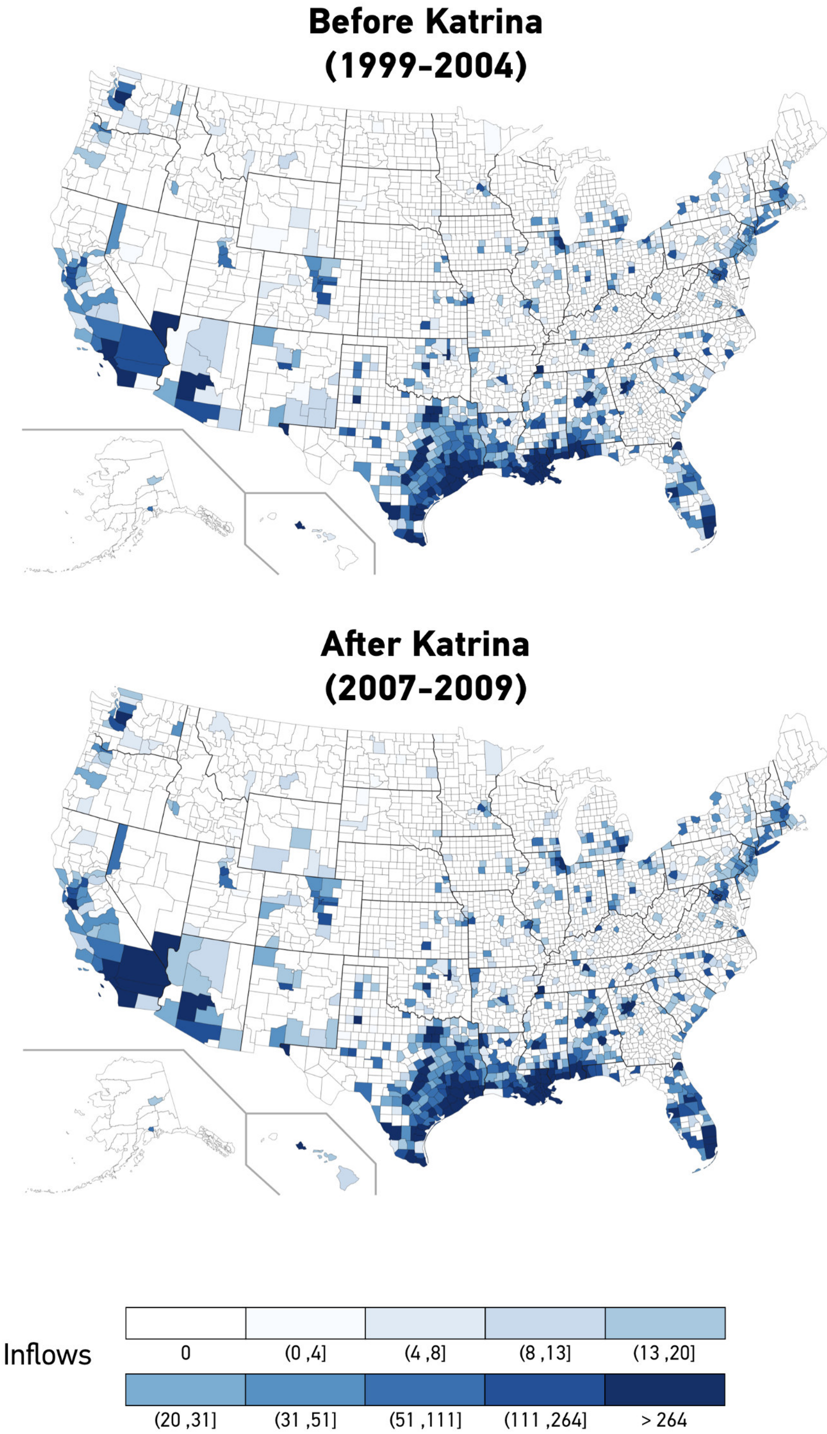

Fig. 11: Comparing Inflows Before and After Katrina