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 is the increase in the number of the most 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 as a sustained counterstream developed. 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 after-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 the *disruptive* type, with temporary depopulation followed by sustained recovery, while Sandy the *manageable* one, 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 and Katrina differential impact, tries to sketch possible policy responses.

1 Introduction

The impact of climate change on population distribution and migration is a theme increasingly attracting interest from both researchers and policymakers. The literature has identified three main consequences 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. In its Fifth Assessment Report (AR5), the Intergovernmental Panel on Climate Change (IPCC) asserts that:

> surface temperature is projected to rise over the 21st century under all assessed emission scenarios. 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. The ocean will continue to warm and acidify, and global mean sea level to rise [IPCC, 2014].

Moreover, albeit the globally averaged frequency of tropical cyclones is projected to decrease over the 21st century, the number of the most intense ones is predicted to increase [Knutson et al., 2010]p. 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 displacement of people. 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. Subsequently, Jacobson [1988] brought the figure down to 10 million. However, the most frequently cited number is Myers [1993]'s 25 million, forecasted to become 200 million by 2050.

Many authors have expressed severe criticism on these estimates both for theoretical and methodological reasons [Bates, 2002, Gemenne, 2011b]. In short, they contend that these numbers, rather than representing environmental refugees, are counting the people at risk of displacement because of 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.

On the wake of these criticisms, a new stream of the literature has developed trying on the one hand to construct a more robust theory and on the other 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 looking both at 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 in the present work, is the literature on Hurricanes in the US and migration. To my knowledge, four Hurricanes have been the object of study so far: Andrew (1992), Katrina (2005), Rita (2005), and Ike (2008) (see McLeman and Smit [2006] 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 ones 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, because of the particular region they hit, the conclusions reached by case studies on these two Hurricanes 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 precisely to investigate this point by studying Hurricane Sandy. Before being surpassed by Harvey and Maria in 2017, Sandy was the second costliest US tropical cyclone after Katrina [NOAA, 2017b]. Given that migration data for 2017 are not yet available, Sandy seems the natural candidate for comparison with Katrina. Moreover, the region hit by Sandy, i.e., the coastal counties on the 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 could conclude that Hurricanes' impact on migration depends on the affected region's characteristics. In this second case, more extensive analyses would be needed to improve our understanding, involving, for example, the study of other hurricanes.

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. At the same time, while outflows to distant counties decreased after Katrina, following Sandy, it is precisely this group that witnessed the highest percentage gain. Finally, whereas disaster-counties experienced a heightened within mobility after Katrina, this effect was only temporary after Sandy. I hypothesise that Katrina and Sandy belong to different types of natural disasters, Katrina to the *disruptive* one while Sandy to the *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 decided to follow the methodology used by Curtis et al. [2015], to date one of the most comprehensive studies of Katrina's impact on migration, and to make a set of replication files available on GitHub. To improve on their work, I devoted a more 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've included in my study the immediate aftermath also.

The article proceeds as follows. The first section presents the theoretical background and reviews the relevant literature. Then I describe the data and methods. The fifth section examines the results. The sixth section discusses the findings and tries to develop a theoretical framework to explain the differences and their consequences on policymaking. In the final one, I examine 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 Challenges in the Environmental Migration Literature

The beauty and also the complexity of this field is its location at the intersection of multiple disciplines: environmental sciences, demography, economics, geography, sociology. Precisely this multidisciplinary nature places this field in front of different complex challenges [Gemenne, 2011b, Tacoli, 2009, McLeman and Hunter, 2010].

First, whether derived from Global Climate Models (GCMs) or finer-scale Regional Climate Models (RCMs), climate projections are subject to uncertainty at various levels, from estimating greenhouse gas and aerosol emissions to translating these into radiative forcing. For this reason, projections usually use model ensembles[1], which, however, do not solve the problem completely [Goodess, 2013]. Moreover, different scenarios in GCMs might dramatically change the outcomes in terms of migration (for example, by moving the increase in mean global temperature from $2°$to $4°$, Gemenne [2011a]). Finally, although GCMs and RCMs are now quite good at replicating the global evolution of temperature and precipitation extremes, they are not so accurate when it comes to forecasting the frequency and magnitude of extreme weather events at the regional level [Knutson et al., 2010].

Second, even if we had access to reliable models for climate change, we would still lack an established theory that links it to migration. Popular, although widely criticised, estimates for the number of environmental refugees such as El-Hinnawi et al. [1985], Myers [1993], Myers [1997], Myers [2002], or Christian Aid [2007] are usually derived in a deterministic manner by assuming that all individuals at risk will be forced to leave [Gemenne, 2011b]. Much debate surrounds this very definition.

[1]There are two general approaches to model ensembles: the first is to combine different models (*multi-model approach*); the second is to try different specifications for the model parameters (*perturbed physics ensemble approach*)

In one of the first contributions to this literature, El-Hinnawi et al. [1985] defined *environmental refugees* as:

> those people who have been forced to leave their traditional habitat, temporarily or permanently, because of a marked environmental disruption (natural and/or triggered by people) that jeopardized their existence and/or seriously affected the quality of their life. By environmental disruption in this definition is meant any physical, chemical, and/or biological changes in the ecosystem (or resource base) that render it, temporarily or permanently, unsuitable to support human life.

To make this definition more concrete, El-Hinnawi et al. [1985] describes three main types of *environmental refugees*:

1. those temporarily dislocated due to disasters, whether natural or anthropogenic;
2. those permanently displaced due to drastic environmental changes, such as the construction of dams; and
3. those who migrate based on the gradual deterioration of environmental conditions.

Although widely criticised, I believe that this definition is not problematic, per se. The issue is that subsequent works have progressively extended it to include individuals who move for reasons only indirectly related to climate change(for example, Myers [1993, 1997]). Furthermore, as first pointed out by Hugo [1996], the emphasis on the *forced* character of the movement creates a sharp division in what in reality is a continuum of agency in migration. For these reasons, Bates [2002] has proposed a different classification, based on three main categories and six sub-categories, which acknowledges the varying degree of agency on the side of the potential migrant and, at the same time, tries to restrict the definition to cases where environmental change plays a crucial role (see Table 1).

A clear definition is crucial both for defining the population of interest and, more specifically, for quantifying the number of people displaced by environmental change. However, estimates and accounts of environmental migration suffer also from another issue: the inability to determine what portion of individuals is at risk (what Mabogunje [1970] defines as *potential migrants*) and, among these, how many do eventually migrate. This inability stems, in turn, from the lack of a theory that links environmental risk to migration.

Several authors have tried to provide such a theoretical framework [Hugo, 1996, Bates, 2002, Black et al., 2011a][2]. Hunter [2005], in her review of the literature, points out that many classic migration frameworks incorporate ecological factors (for example Petersen [1958], Wolpert [1966], Lee [1966], Mabogunje [1970]). These factors have instead received less emphasis in neo-classical models, where they are implicit in the cost-benefit calculations agents are assumed to perform [Todaro, 1969, Harris and Todaro, 1970]. In a more recent contribution, Black et al. [2011a] provide a basic framework that incorporates environmental changes in a broad set of drivers derived from previous theoretical works. Paralleling this effort from a more practical point of view, several reviews summarising the research in this domain have appeared [Tacoli, 2009, Adamo, 2010, McLeman and Hunter, 2010], giving us a set of probabilistic regularities which strengthen our understanding of this phenomenon.

Third, although recent years have seen progress, with promising new strategies coming from digital demography [Zagheni and Weber, 2012, Zagheni et al., 2014,

[2]For a more concise overview see also Black et al. [2011b]

	Disaster		**Expropriation**		**Deterioration**	
	An unintended, catastrophic event triggers human migration		The willful destruction of environment renders it unfit for human habitation		An incremental deterioration of the environment compels migration as constraints to human survival increase	
Sub-Category	Natural	Technological	Development	Ecocide	Pollution	Depletion
Origin	Natural	Anthropogenic	Anthropogenic	Anthropogenic	Anthropogenic	Anthropogenic
Control over Migration	Forced	Forced	Voluntary	Voluntary	Forced	Forced
Type of Onset	Sudden	Sudden	Sudden	Sudden	Slow	Slow

Table 1: Classification of environmental refugees adapted from Bates [2002]

2017], complete good-quality data on migration flows is still very rare, especially when they involve movements across national borders or they take place in low-income countries. An effort to improve the reliability and coverage of data on migration will be necessary to increase our knowledge and ground our estimates on a firm basis.

Finally, as pointed out by many [McLeman and Hunter, 2010, Hunter, 2005, Tacoli, 2009], one crucial albeit often overlooked factor is the effect of public policies. Policies are not exogenous in this context. On the one hand, they shape the interaction between climate change and society. On the other hand, they represent a reaction to such a relationship, and they can mitigate or worsen its consequences [Ezra, 2001, Pais and Elliott, 2008, McLeman, 2011]. For this reason, forecasts of the number of environmental refugees derived under a *ceteris paribus* assumption on public policies may be misleading.

All these challenges notwithstanding, the literature on environmental migration has grown substantially in the last decades. In particular, natural disasters have attracted increasing interest, in part because researchers perceive them as perfect natural experiments [Elliott and Pais, 2006, Groen and Polivka, 2008, 2010, Fussell et al., 2014]. Indeed, because they are sudden-onset events and because their impact at the local level is partly random, the effects of natural disasters can be straightforwardly identified. On the contrary, if we want to study a gradual change in environmental conditions in a specific area (as in Findley [1994], for Mali; Massey et al. [2010], for Nepal; Henry et al. [2003] for Burkina Faso; Penning-Rowsell et al. [2013], for Bangladesh; or Adamo and Crews-Meyer [2006], for Argentina), it becomes difficult to distinguish between individuals who relocate because of it from those who do so for other reasons.

2.2 Empirical Regularities

In this subsection, I am going to review some fundamental regularities regarding environmental migrations. For each one, I will try to provide references to empirical articles. I will start with six principles proposed by Findlay [2011], which are not specific to environmental migrants but apply to this subcategory as well. Then I will review more specific findings from the literature on natural disasters.

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 paradox" may be a consequence of several mechanisms. First, as pointed out by Lee [1966], individuals living in an area may be emotionally attached and thus less objective in their judgement. 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]. A *sense of place* is the attribution of meaning to a built-form or natural spot while, as described by Gieryn [2000], "place attachments result from accumulated biographical experiences: we associate places with the fulfilling, terrifying, traumatic, triumphant, secret events that happened to us personally there". As Falk et al. [2006] argues, *sense of place* might be a crucial factor holding individuals in a given area only if its ties with a physical place are strong. Otherwise, transplantation may successfully occur by placing "an emphasis on *what* people do, de-emphasising somewhat *where* they do it".

Principles two and three jointly say that if migration occurs, individuals are, ceteris paribus, more likely to move over short distances rather than longer ones. Two comments are in order. First, ceteris paribus here means that two destinations should be comparable under all the five dimensions in our model, including the cost of migration, the presence of social networks, and culture. Second, this principle does not necessarily imply that internal movements will be more frequent than international ones (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., 2011c] or Burkina Faso and Côte d'Ivoire. In these cases, international migration may be substantial. For instance, Henry et al. [2004] report that, for males in Burkina Faso, 63.4 % of first migrations are international. More in general, 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., 2011c].

Migration is selective. However, the nature and the degree of selectivity 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 minor role [Henry et al., 2004, Massey et al., 2010]. Gender is often significant with males moving more than females, although in time of hardship the gap tends to close. Race or ethnicity is also relevant. For example, individuals of the Mossi and the Hill Tibeto-Burmese ethnicities have a higher migration rate in Burkina Faso and Nepal respectively [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 determinants of migration. Those who move are on average poorer than the population at the origin, but they are rarely among the poorest. As we argued before, there are substantial costs associated with migration and only individuals with sufficient resources will be able to sustain them. At the same time, the wealthiest strata of a population will usually suffer less than others, even in times of hardship. In the words of an Oklahoman migrant to California in the 1930s "Dust Bowl" migrations interviewed by McLeman [2006]:

> If you had your land [in Oklahoma] paid for, you probably made it [through the droughts][3]

Migration for them is thus not seen as a mean to achieve income security but as a way to further improve their social status. This dichotomy is somehow similar to Petersen [1958]'s distinction between "conservative" and "innovating" migration, albeit with a different connotation.

Principles five and six claim that social networks and "cultural distance" are crucial determinants in the destination choice and 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), may arrange transportation, help with the necessary documents, offer assistance during the job search period, and also lower the psychological costs of leaving one's community and culture. Second, networks reduce uncertainty regarding the outcome of migration. Potential migrants face risk from multiple sources. They may not know how quick they will find a job, how to reach their destination (especially when it involves illegal trespassing), where to eat and shop, where to live once arrived, and how to move around, thus lacking many essential elements in their cost-benefit calculations (in the neo-classical perspective). Having a relative, a neighbour, or a friend who has already

[3] The parentheses are from the original quote in McLeman [2006].

migrated means having reliable advice on all these matters and maybe reference to potential employers [Massey and España, 1987]. As a consequence, two destinations which under perfect information will be equally attractive may witness very different migration flows based on the presence or absence of a network, and 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 abandonment of Holland Island, Maryland by its residents. As Arenstam Gibbons and Nicholls [2006] describe, final abandonment was not a direct consequence of the gradual decrease in the amount of upland area but was due to the deterioration of the resident community which, after having lost a sizeable portion of its members, became unable to sustain itself. Another example that shows both roles played by social networks, facilitate migration and bond individuals together, is the case of the New Orleans Vietnamese American Community in the Versailles neighbourhood [Airriess et al., 2008]. On the one hand, this neighbourhood was the result of migration from two Catholic dioceses in former North Vietnam in the 1970s. 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 faster than many other similarly affected areas in New Orleans.

These six general principles can be augmented, in the case of environmental migrants, by looking at the findings of several studies in the natural disaster literature. A good starting point is Quarantelli [1982]. He distinguishes four *phases* of post-disaster sheltering: *emergency sheltering*, *temporary sheltering*, *temporary housing*, and *permanent housing*. These phases usually follow a chronological order from an individual point of view but not necessarily from a population perspective. Quarantelli [1982] presents four sets of "particular observations", one for each phase, that describe some regularities in post-disaster relocations.

First, movements observed during the emergency sheltering phase are not representative of what will happen once the peak of the crisis is over. As a consequence of the immediate danger, people will accept conditions they would not tolerate under normal circumstances. Moreover, shelters may appear in a particular location simply because a critical mass of people congregates there and then attracts others. Most people are likely to leave the affected areas before or just after a natural disaster and this fleeing is usually homogeneous in the population exception made for the most disadvantaged groups [Fussell, 2015].

Second, even when temporary shelters are available, individuals do not like to use them and mostly prefer to stay with friends or relatives. Even those who seek temporary shelter do so for the shortest possible period. In some instances, communities develop internal networks of assistance whereby less affected household offer help to most affected ones. It appears that such a phenomenon is more likely when a sizeable portion of households did not suffer extensive damage. An advantage of such neighbourhood organisations is that they tend to be more efficient than any bureaucracy in providing information, assistance and resources [Olshansky et al., 2012]. Examples of a prominent role played by these nongovernmental organisations are the aftermath of Hurricane Katrina in New Orleans and the recovery after the 1995 earthquake in Kobe [Airriess et al., 2008, Olshansky et al., 2012, Samuels, 2013].

Third, the acceptability of temporary housing measures (e. g. mobile homes and rental assistance) varies across social classes. Most disadvantaged households are more willing to accept mobile homes, while families with higher socioeconomic status favour rental assistance. Individuals prefer to stay as close as possible to their previous residences. However, only residents who did not suffer high damage can return to their homes soon after the emergency. Even in this group, homeowners fare much better. Their advantage stems from several factors: 1) compared to homeowners, renters have less control over the decision to rebuild; 2) rental housing tends to be of lower quality, older, and less able to withstand natural hazard; and 3) public and private assistance in the aftermath is often disproportionately targeted at property owners enabling them to recover faster [Peacock et al., 2014].

Fourth, once the recovery phase has ended, the social and demographic composition of the affected neighbourhoods is unlikely to be similar to the pre-disaster one for a long time. There is evidence that homeowners possess a substantial advantage over renters in terms of reconstruction time [Peacock et al., 2014]. Since homeowners tend to have higher incomes, be more educated, have more stable occupations and belong to advantaged ethnic, racial, or social groups, the reconstruction phase will witness a decrease in poverty rates, an increase in education levels, and a more uniform population in terms of ethnic, racial, and social-class composition [Elliott and Pais, 2006, Fussell, 2015]. Olshansky et al. [2012] argue that this deepening of preexisting inequalities is the consequence of *time compression*, that is, a an abnormal increase in the rate of capital replacement, demand for decisions, information flows, financing, and institutional formation. Because some institutions and social groups (such as homeowners and neighbourhood organisations) are better equipped to face such compression, these are likely to benefit in such a phase. However, this situation and its consequences are usually temporary. The majority of individuals belonging to all social groups finally return to their previous residences or resettle nearby and new immigrants in search of economic and employment opportunities arrive [Fussell, 2015].

Thanks to extensive studies carried out after Hurricane Katrina, we now have a better understanding of the processes underlying this compositional change. From the review of Fussell [2015], three main mechanisms seem to have been at play after Katrina. The first neighbourhoods reopened were also the least damaged, those where property values were higher, where the more socially advantaged residents lived, and where homeownership rates were highest. At the same time, homeowners with private insurance received payments more quickly and were thus able to better plan reconstruction or relocation. In contrast, the distribution of public assistance was much slower, and the compensations were on average lower. Finally, post-disaster rebuilding aimed at "building back better" was frequently shaped by the interests of what Pais and Elliott [2008] call the "recovery machine", "a coalition of business elites united with local political officials in pursuit of ongoing economic and demographic growth". These redevelopment projects reduced the supply of public housing and increased rents thus driving the more disadvantaged groups away from their previous residence to less expensive areas, often further away from New Orleans.

To conclude, I should also mention that not all the literature agrees on these general findings. For example, for the case of Hurricane Katrina, Frey and Singer [2006] reported that the compositional change was specific to New Orleans and the affected counties along the Mississippi coast. In contrast, most of the other affected counties witnessed no or very moderate change. Furthermore, while New Orleans' population became "more white, less poor, and more transitory", the three counties of Hancock, Harrison, and Jackson in Mississippi "lost a sizeable proportion of their white residents and homeowners". Likewise, while the area affected by Katrina had recovered its pre-disaster population by 2007 [Curtis et al., 2015], the recovery is yet incomplete in Orleans parish [Fussell, 2015]. Analogously, comparing the consequences of Hurricanes Andrew and Ike, Peacock et al. [2014] found that race and ethnicity were a significant predictor of recovery in the case of Andrew but not for Ike. More precisely, while after Andrew Hispanics and non-Hispanic Blacks suffered higher losses and slow recovery, positive effects were instead detected for Hurricane Ike. These findings point toward a possible heterogeneity of natural disasters' compositional effects, challenging the idea that the general principles I outlined before can describe the consequences of such events in a variety of environments.

2.3 Modelling the Environment-Migration Link

The nexus connecting environmental change and migration is a complex one. Individuals affected by natural disasters or gradual deterioration do not necessarily move as assumed by Meyers [Myers, 1993, 2005]. Usually, environmental change is just one factor that influences the decision to migrate together with economic, demographic, political, and social drivers [Lee, 1966]. Furthermore, migration is only one amongst many adaptation strategies [Ezra, 2001]. Finally, even under high economic and environmental distress, only some subgroups in a given population eventually move.

Black et al. [2011a] have proposed a framework that tries to combine all these aspects, arguing that it has the advantage of forcing researchers to specify how different drivers mediate the environmental change and lead to a migration outcome. Moreover, Black et al. [2011a] incorporate individual characteristics, obstacles, and facilitators into a unitary framework. Here the drivers constitute an intertwined network of push and pull factors on which personal and household characteristics, facilitators, and obstacles to migration all act as moderators (an idea that can be traced back to Lee [1966]).

This general model might seem too complicated, especially if we compare it with neo-classical migration models, where the only central determinant of migration is the expected income differential [Todaro, 1969, Harris and Todaro, 1970]. However, neo-classical models are not very good at replicating real migration flows. For example, Massey and España [1987] found that outmigration from Mexico to the US in the 1970s was not strongly related to fluctuations in real wages, unemployment, and inflation. On the other hand, neo-classical models, but also classic migration theories such as Lee [1966], correctly highlighted that perceived costs and benefits of migration are more relevant than real ones, a point not emphasised by Black et al. [2011a]. In this respect, Mortreux and Barnett [2009] have shown that subjective moderators (e.g. beliefs, level of information, values, and personal experiences) can be crucial in shaping individual migration decisions (see also Ezra [2001]).

Another possible weakness of Black et al. [2011a]'s framework is that it does not mention the reflexive connection between the environment and human societies. However, such a relationship is critical because, for example, changes in economic activity, urbanisation, agricultural practices may trigger environmental change as well as being affected by it [Fraser et al., 2003]. Finally, specific to the environment-migration link, there is evidence that environmental change modifies the migration system rather than altering flows within it [Findley, 1994, Fussell et al., 2014, Curtis et al., 2015]. This regularity should be part of any environment-migration model. Nevertheless, because it belongs to the macro rather than to the micro level, it is difficult to explain it in terms of individual decisions.

Overall, I believe that we can improve Black et al. [2011a]'s model by addressing its two main weaknesses: the lack of subjective moderators and the unidirectionality of the connection between the environment and human society. The result is presented in Figure 1.

A fist aspect to highlight is the double-headed arrow connecting environmental change to the five drivers derived from Black et al. [2011a]. To these I have added four moderators: information, beliefs, values, and personal experiences. The moderators jointly act as a filter that transforms real inputs into opinions. The idea that psychological factor can affect migration decision is not new and can be traced back at least to Lee [1966]. To quote from his *A Theory of Migration*: "The decision to migrate, therefore, is never completely rational, and for some persons the rational component is much less than the irrational". For example, individuals who have previously experienced a disaster might react differently to the risk of a new one. Beliefs can play a similar role, as shown in a quote from an old Polynesian women contained in Mortreux and Barnett [2009]:

> When I was little, there was a big hurricane, you know, hurricane Bebe in 1972. And it came in, the rain was like stones it hurt. And I thought this is it, this is the end of the world ... and at the time we went to find a safer place in another building and my grandfather and grandmother, they were still alive at the time, they said, you go, leave, find another place that is safe. You are young run, find protection. And if God says today is the day, then we stay here and go down with it. You know, that is the way with older people. And we left and stayed in a concrete house that was filled with water and we just sat and waited. After, we went back and our place was just the roof. But the roof was good you know, and my grandparents were sitting under it waiting, fine.

After having been filtered by the moderators, the original stimuli interact with facilitators and obstacles on the one hand and personal or household characteristics on the other. These are very important in shaping the final decision. For example, women are usually less likely to move (although their migration rate may increase substantially in periods of acute environmental stress) while individuals with more human capital are more likely to do so [Findley, 1994, McLeman and Smit, 2006]. Some evidence suggests that migration tends to become less selective in the presence of natural disasters or environmental crises such as droughts [Henry et al., 2003]. In terms of facilitators or obstacles, policies can be crucial as was the case during the 1970s and 1980s droughts in Ethiopia, when the government established a resettlement programme to reduce environmental pressure on the northern regions [Ezra, 2001]. This point should also remind us that migrants might not be fully autonomous in their decisions.

As a final point, it is worth noting that in principle this framework could be applied to other adaptation decisions, such as the adoption of family planning or the postponement of marriage. Indeed, from Ezra [2001]'s detailed analysis of Ethiopia, we can see that similar mechanisms seem to be at play.

2.4 A Migration System Perspective

The present work fits into Figure 1's framework by studying in detail the role played by the migration system in determining the macro response to natural disasters such as Sandy. The migration system as a whole belongs to the social drivers, and it spans the entire society. It emerges from a myriad of individual migration networks (i.e., the set of relationships that tie a migrant to other individuals such as relatives and friends) and it gives a stable structure 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.

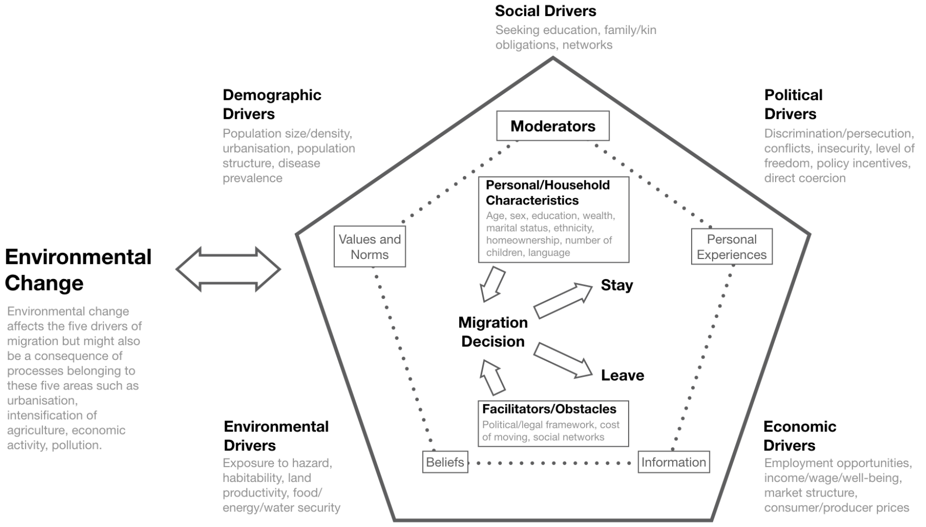

Figure 1: Linking environmental change to migration.

In this work, I choose counties as the smallest spatial units, but I also try to discuss the results' sensitivity to different choices. I analyse variations in both ties and flows and try to understand whether the existing migration system acts as a channel for the effects of natural disasters or if they tend to disrupt it.

The migration system perspective can be traced back 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 could uncover differences in responses to the Hurricane at the individual level, opting for a macro-analysis allows investigating the aggregate impact. Three reasons lie behind this choice. First, a data constraint, while researchers who studied Katrina had at their disposal a set of questions in the 2006 Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), no comparable microdata exists for Sandy, which poses a limit on the possibility of conducting individual-level analyses. The main issue, in this respect, 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 an extensive coverage, the macro-level effects on the migration system have been partly neglected. Third, albeit 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, 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 the necessary assistance where needed.

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. The most similar articles, that also inspired mine, are those written by Elizabeth Fussell, Katherine J. Curtis, and Jack DeWaard on Katrina [Fussell, 2015, Curtis et al., 2015, DeWaard et al., 2016]. They found that after Katrina inflows to the disaster-affected counties became more spatially concentrated, involving mostly nearby counties, especially urban ones, and intensified. At the same time, they also observed an intensification of migration flows within disaster-affected counties. Finally, they observed a strong recovery migration. Part of these findings is consistent with the empirical regularities I discussed before. For example, the increase in inflows from the unaffected area of the Gulf of Mexico is coherent with the idea that migrants prefer not to travel long distances. 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 principles I illustrated is the magnitude of both the post-disaster outmigration and the recovery migration. This features, I think, may not hold when analysing a different event.

Based on these considerations, I can make four hypotheses:

- **H1**. outflows are likely to increase immediately before and after Sandy and to stabilise afterwards;
- **H2**. inflows should follow a similar pattern in the aftermath and may then decline as the return migration terminates and immigration from other areas decreases due to diminished attractiveness of the affected region;
- **H3**. overall changes in flows are likely to be smaller (in relative size) than those witnessed after Katrina;
- **H4**. although I expect to observe spatial concentration/expansion when looking at each disaster-affected county separately, when considering them as a single macro-area, both processes should be less significant.

After having described the data and the methodology I used, I will discuss whether the results support or reject these hypotheses and what my findings imply in terms of policies.

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 in the continental United States into three groups: *disaster-affected* counties, *nearby* counties, and *distant* counties.

Operationally, I included in the disaster-affected group all counties which the Federal Emergency Management Agency (FEMA) designated for individual assistance[4]. These counties should be the ones that suffered the most severe impact from Hurricane Sandy. The second group 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 belong to Connecticut, Maryland, New Jersey, New York, Rhode Island, Delaware, Massachusetts, Pennsylvania, or Virginia;
3. they do not belong to the disaster-affected group;
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 principles 2 and 3 in Findlay [2011], are also likely to be the preferred destinations of temporary relocation given their geographical proximity. Finally, distant counties are all the remaining ones in the continental United States. Overall, 41 belong to the

[4]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]

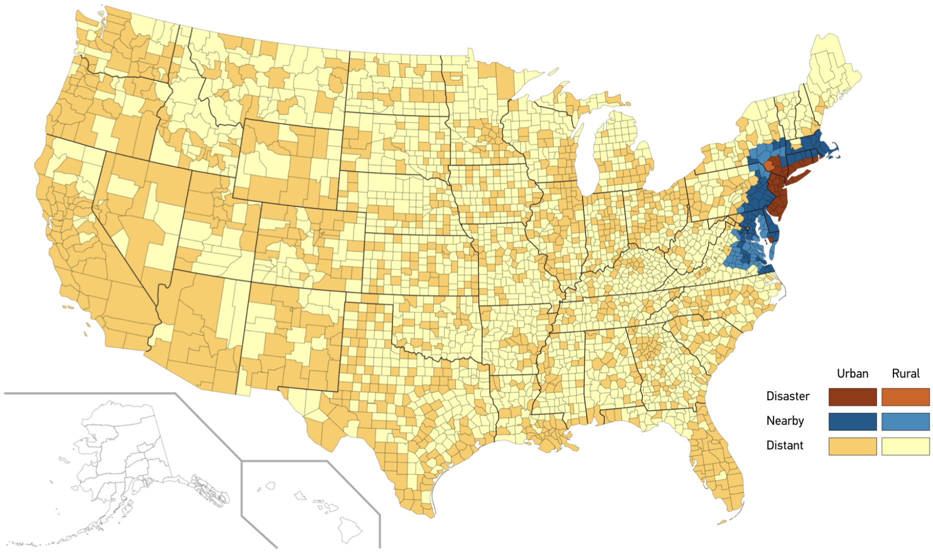

Figure 2: Classification of the counties according to the FEMA designations and their geographical location

first group, 132 to the second, and the remaining 2939 to the third. I have further classified each county as rural if the percentage of its population living in rural areas was equal or above 50% and urban otherwise, based on the 2010 census [Census Bureau, 2018]. Table 2 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 2: Summary of classification of continental counties

In Figure 2, I have represented the counties belonging to the various groups. In red the disaster counties, in blue the nearby counties, and in yellow the distant counties. I've used a darker shade for urban counties and a lighter one for rural counties.

To understand whether the results would be similar under different classifications of counties, I have defined alternative groups, this time based on the FEMA Modeling Task Force (FEMA-MOTF) report on Hurricane Sandy [FEMA-MOTF, 2014a][5]. 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 with 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 2 and 3, which depict the geographical location of the counties belonging to the different groups, I decided that I would 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 (exception made for Somerset County, Maryland), the FEMA-MOFT impact classification

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

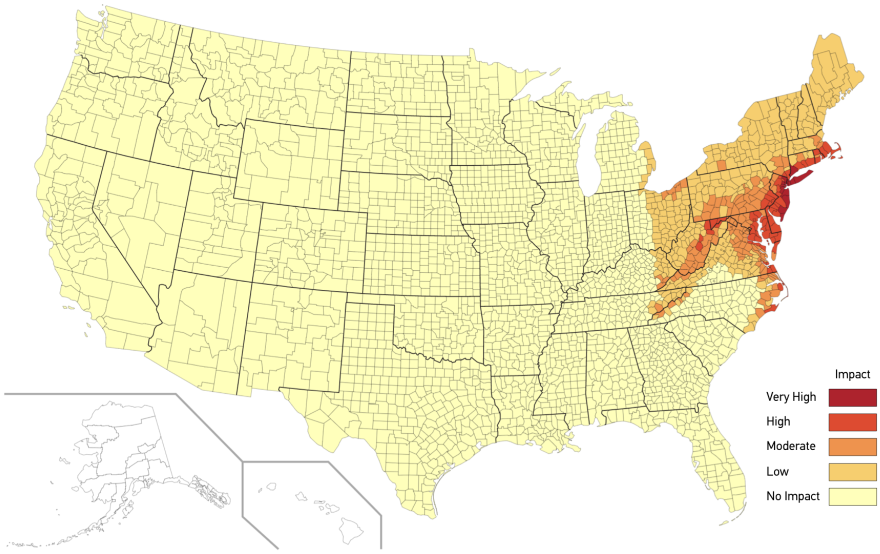

Figure 3: Classification of the counties according to the FEMA-MOFT impact rank and their geographical location

is more spatially heterogeneous and covers a wider area.

I have identified two periods: before Sandy (2010-2011) and after Sandy (2012-2013). The migration data comes from the Internal Revenue Service (IRS) Statistics of Income Division (SOI) County-to-County Migration Data files [IRS, 2018]. This files report inflows and outflows for each pair of U.S. counties, both as households and as individuals. Many articles in the migration literature use this source for the United States as it includes all U.S. federal income taxpayers [Molloy et al., 2011, Fussell et al., 2014, Curtis et al., 2015, Johnson et al., 2017].

Assembling the data from the IRS-SOI has been a complex operation because the format in which the county-to-county migration files are available changed over time. Two single outflows and inflows files in `.csv` format were available for the period 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 inflows and outflows excel files for each state. Although I've exercised the utmost caution, manipulating all these files might have led to occasional mistakes. As a further check, I've compared the dataset I obtained with the similar one constructed by Mathew Hauer[6], finding no 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 the IRS data is that, by including only taxpayers, it likely underrepresents individuals in the lowest deciles of the income distribution. However, Molloy et al. [2011] report that, according to the CPS, 87% of household heads filled the 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 with the IRS data overestimate real migration rates compared to the CPS and the ACS. However, when looking at trends, the three sources should give a similar picture.

[6] His work, which covers the 1990-2010 period, is available here: `https://github.com/mathewhauer/IRS-migration-data`

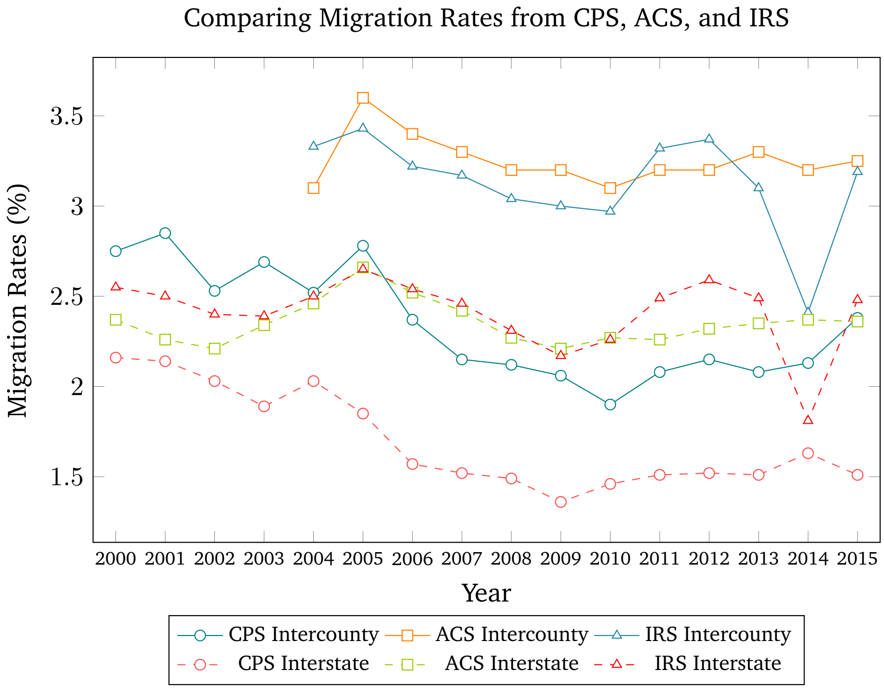

Figure 4

Note: The data I used to construct the graph comes from Stone [2016]'s article

For the period I have taken into consideration, using the IRS data presents additional challenges. Beginning with data for 2011-2012, referring to migration occurred mostly in 2011, SOI has introduced several enhancements to improve the overall quality of the data, 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 in the 2014-2015 file. As pointed out by Stone [2016], the very sharp decline in both intercounty and interstate migration rates observed in 2014 (that is, in the 2014-2015 file) is likely a discontinuity in the IRS-SOI data. The fact that no similar decrease is visible nor in the ACS neither in the CPS supports this conclusion.

We can get a more precise idea about these issues by looking at Figure 4, which presents intercounty and interstate migration rates from different sources. We see that while the ACS and the IRS estimates are similar, the CPS ones are significantly lower. The similarity between ACS and IRS is surprising, as noted by Molloy et al. [2011], since the underlying methodologies are quite different. Starting from 2011, we can see the increase in the IRS estimates, which move away from the ACS ones. However, we shall also notice that the CPS 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 the IRS estimates might be real. On the contrary, the dramatic decrease in 2014 is unique to the IRS estimate. A final caveat when comparing estimated from ACS and IRS is that, for any given year, while the ACS refers to migration occurred in that year, the IRS reports mostly movements happened in the year before.

To address these two potential 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 straigthforward way to perform a more precise adjustment. However, given that the new procedure became effective beginning 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 will also examine how results change if I include only 2011 in the pre-disaster period. This test should give me a measure, albeit incomplete, 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 to use subsequent data files which may not be reliable. I could have used more elaborate procedures to improve comparability, but I believe that what I have done is enough to guarantee that the results I found are not the consequences 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 exploring more in detail how the spatial distribution of flows changed after the hurricane.

The first part, more descriptive, compares flows and ties across different groups of counties in the 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. Given a period, I say that a *tie* exists between two counties i and j 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 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) looks as follows:

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

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 can obtain outmigration rates. Second, I built an in-ties and out-ties matrix for each year. Starting from the inflows and outflows matrices, I replaced each positive element with a 1. Then, I focused on ties which were unique to one of the two periods (present in one but not in the other). These are interesting because they reflect changes in the migration system. Identifying them was straightforward. I subtracted the out-ties matrix for the after-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 after-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 it across the pre-disaster and the after-disaster periods. If a system is perfectly stable, there should be no unique ties. If it is expanding, we should see more unique ties in the after-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 changes more rigorously by using a difference in proportion test, that is, by 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 after-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 after-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, looking at which counties experienced the highest gains or losses in 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. This part also allows me to change the unit of analysis from the affected counties taken individually to the entire area.

The third part, more analytical, consists first in estimating a modified gravity model and then in applying a difference-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 after-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 difference-in-differences model adds an interaction term, $(t_t \times k_k)$, for disaster-affected counties in the after-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 in this study. This exercise will reveal which findings hold in both cases and can thus be generalised to similar situations and which instead are specific to one of the two Hurricanes.

5 Results

5.1 Replication of Curtis et al. [2015]

Before illustrating the results I have obtained looking at Sandy, I would like to briefly present the ones I have reached trying to replicate the article by Curtis et al. [2015]. This exercise might seem superfluous, but I believe that it is of primary importance for three reasons. First, by showing 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 also the underlying data is very similar, and by making available online the code I have used to produce it from the original IRS-SOI files, I'll allow other researchers to more easily conduct further analyses on these or other events. Finally, this section will be useful to recap past findings, making it easier to compare them with the ones in this article.

I will focus on Tables 1 and 2 in Curtis et al. [2015], comparing them with the ones I have obtained. From Tables 3, 4, 5 and 6, we can see that the replication was successful. For the ties tables (3 and 4), the differences are small both for the actual numbers and for the changes over time. Moreover, differences which are significant in Curtis et al. [2015] table are so also in the replicated one. Only two coefficients which are significant at the 95% level in the replicated table are not so in the original one. However, by looking at the *z-stats*, we see that the differences are small. In any case, the discrepancies disappear if we look at the 99% significance level.

What this tables tells us is that out-ties decreased significantly after Katrina and that the decrease was more marked for distant counties as we would expect if the migration system was contracting. Looking at in-ties, we see that the immigration system expanded between disaster-affected and nearby counties while it contracted within the former.

Looking at the flows tables (5 and 6), we see that the differences are negligible and that the picture delivered is essentially the same. While outflows exceeded inflows in the pre-disaster period, the opposite occurred in the recovery phase, a sign of recovery-migration. More in detail, immigration from nearby counties increased the most in relative terms, followed by distant ones, and by disaster-affected counties.

A possible limitation of Curtis et al. [2015] is that the outcomes for ties are very sensitive to changes in the years included in the two periods. In particular, the marked decrease in the number of out-ties seems to be a consequence of the definition adopted by the authors. Indeed, by removing the first year then the first two from the pre-disaster period, all changes first decline in absolute value and then turn positive. Variations in the number of in-ties follow the same pattern with all changes increasing in magnitude and becoming positive. However, results for flows are more robust and do not show dramatic variations when the years included change.

Moving to the modified gravity model and the difference-in-differences model, I obtained qualitatively similar results with one exception concerning the size of the coefficient on the period dummy in the gravity models for inflows to disaster-affect counties, while Curtis et al. [2015] find that it decreases with distance from the disaster area, I observe no significant variation. In any case, the most relevant coefficient for the analysis, i.e. the treatment effect δ in Equation 3, is always positive and significant, implying that recovery migration to disaster-affected counties took place.

Number of Unique Ties Between Disaster-Affected Counties and:	Out-Ties				In-Ties			
	Before	After	% Change	z-stat	Before	After	% Change	z-stat
All	612	258	-57.84**	12.03	457	442	-3.28	0.50
Disaster Affected	46	30	-34.78	1.86	46	30	-34.78	1.86
Nearby	97	55	-43.30**	3.44	72	96	33.33	-1.87
Distant	469	173	-63.11**	11.70	339	316	-6.78	0.90
All (Urban)	550	224	-59.27**	11.77	395	402	1.77	-0.25
Disaster Affected (Urban)	45	29	-35.56	1.89	45	29	-35.56	1.89
Nearby (Urban)	77	41	-46.75**	3.36	55	78	41.82*	-2.02
Distant (Urban)	427	153	-64.17**	11.42	295	295	0.00	0.00

Table 3: Table 1 in Curtis et al. [2015]

Number of Unique Ties Between Disaster-Affected Counties and:	Out-Ties				In-Ties			
	Before	After	% Change	z-stat	Before	After	% Change	z-stat
All	611	258	-57.77**	12.00	457	444	-2.84	0.43
Disaster Affected	46	30	-34.78	1.86	46	30	-34.78	1.86
Nearby	96	55	-42.71**	3.37	72	98	36.11*	-2.01
Distant	469	173	-63.11**	11.70	339	316	-6.78	0.90
All (Urban)	533	209	-60.79**	11.94	384	379	-1.30	0.18
Disaster Affected (Urban)	43	29	-32.56	1.68	44	27	-38.64*	2.05
Nearby (Urban)	72	37	-48.61**	3.39	50	73	46.00*	-2.10
Distant (Urban)	418	143	-65.79**	11.65	290	279	-3,79	0.46

Table 4: Replication of Table 1 in Curtis et al. [2015]

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	131,411	137,424	4.58%	121,310	144,854	19.41%
Disaster Affected	49,959	54,030	8.15%	49,959	54,030	8.15%
Nearby	28,711	31,338	9.15%	23,727	30,863	30.08%
Distant	52,742	52,056	-1.30%	47,624	59,960	25.90%
All (Urban)	126,576	132,684	4.83%	116,920	140,062	19.79%
Disaster Affected (Urban)	49,595	53,634	8.14%	49,595	53,634	8.14%
Nearby (Urban)	26,018	28,587	9.87%	21,079	27,969	32.69%
Distant (Urban)	50,896	50,400	-0.97%	46,247	58,459	26.41%

Table 5: Table 2 in Curtis et al. [2015]

Total Flow Size Between Disaster-Affected Counties and:	Out-Flows			In-Flows		
	Before	After	% Change	Before	After	% Change
All	131,337	137,401	4.62%	121,259	144,847	19.45%
Disaster Affected	49,967	54,026	8.12%	49,969	54,030	8.13%
Nearby	28,570	31,337	9.68%	23,595	30,868	30.82%
Distant	52,800	52,038	-1.44%	47,695	59,949	25.69%
All (Urban)	122,859	128,775	4.82%	114,080	136,567	19.71%
Disaster Affected (Urban)	49,630	53,624	8.05%	49,624	53,606	8.02%
Nearby (Urban)	23,889	26,363	10.36%	19,421	26,004	33.90%
Distant (Urban)	49,340	48,788	-1.12%	45,035	56,957	26.47%

Table 6: Replication of Table 2 in Curtis et al. [2015]

5.2 What about Sandy?

5.2.1 Flows and Ties

I now turn to 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 7, we observe results 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 toward a contraction in the immigration system. Globally, it seems that Sandy pushed some individuals to abandon the most affected areas not necessarily in favour of nearby regions. 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 7: Comparing Ties between the pre- and the post-disaster periods using adjusted data for the years after 2011 (included).

Looking at flows in Table 8, 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 after-disaster periods, the total net flow is negative, and the population loss due to migration becomes more intense after Sandy. This development shows that probably disaster-affected counties were not attracting many new migrants before Sandy and became even less able to do so after the Hurricane.

Using unadjusted data (see Tables 14 and 15 in the Appendix) does not change the results qualitatively. The most notable difference is that the decrease in the number of in-ties looses 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 Tables 16 and 17 in the Appendix). I've further investigated what happens to the flows table when I include only 2011 in the pre-disaster period[7]. This check should give us an idea about the possible effect of the methodology 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

[7] I've 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 8: Comparing 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 9: Comparing 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 10: Comparing Flows between the pre-disaster period and 2013 using adjusted data for the years after 2011 (included)

most relevant variations. In any case, as I mentioned in the data section, I don't see this strategy, that is keeping only 2011 in the pre-disaster period, as necessarily 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 after-emergency period. In this additional analysis, I've considered only flows. Examining Tables 9 and 10, which compare average flows in 2010-2011 to those in 2012 and 2013, respectively, we see that the increase in outflows was stronger in the immediate aftermath while it declined afterwards. On the contrary, while inflows increased in 2012 for all origins, they witnessed an overall decline in 2013, more pronounced for nearby and distant counties. On the whole, the results in Tables 8, 9, and 10 give partial support for Hypothesis 1 and strong support for Hypothesis 2. 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 2. As with outflows, this trend suggests that, after Sandy, the affected area become 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 5, which portraits the evolution of inflows and outflows for Katrina disaster-affected counties over the 1999-2013 period. I've drawn an identical graph for Sandy in Figure 6[8]. Three aspects are worth noticing. 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 change's direction, 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 5), if we look at Orleans parish, the recovery appears to be yet incomplete in 2013 (see Figure 12 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, that is, 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.

5.2.2 A Second Look at Ties

One issue with the concept of tie 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 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 we can say that the network expands. For this reason, the conclusions we may reach by looking at the numbers in Table 7, while correct may not reflect the intuitive notion of expansion/contraction. To analyse this second dimension, I have constructed three pairs of maps which allow

[8]For completeness, I've drawn similar graphs in terms of rates, they can be found in Figure 10 and 11 in the Appendix.

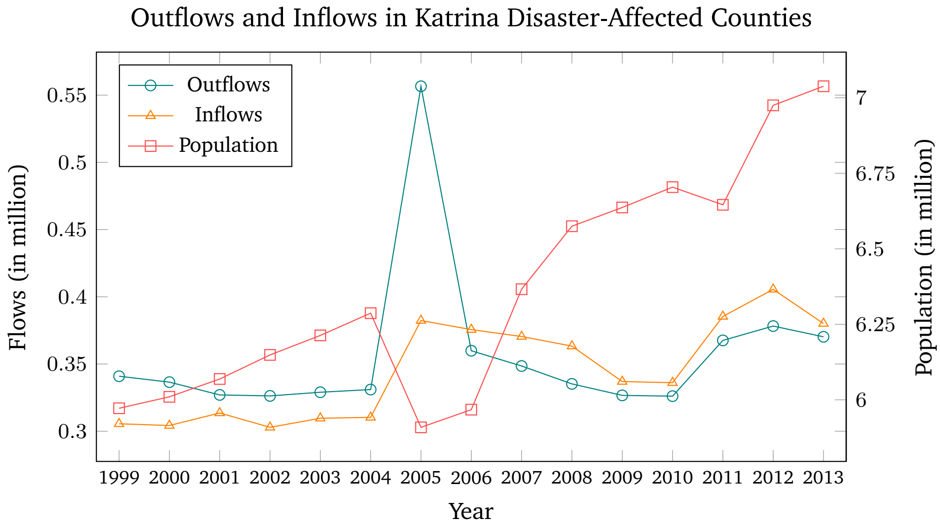

Figure 5

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

for an immediate understanding of how the spatial distribution of migratory flows changed after Sandy.

In Figure 7, we can 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 can 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, we can recognise the San Francisco and Los Angeles areas in California as well as coastal counties in Florida. If we compare the two periods, we can notice two aspects. First, as we already knew from Table 8, outflows have increased. We can see this by noticing that many counties became darker. Second, the spatial distribution of the outmigration system did not change significantly. There are some new entries, as 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 out-ties 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 may reach.

In Figure 8, we see an analogous picture for inflows. Here the system does indeed become more spatially concentrated around the disaster-affected counties. Moreover, that area becomes slightly darker, signaling an increase in outflows to disaster-affected counties. At the same time, most far 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 each other. 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 also in the face of an external shock such as Sandy. We also find support for Lee [1966]'s idea that for each stream, a counterstream develops. Jointly, Figures 7 and 8 support Hypothesis 4, that is, while the

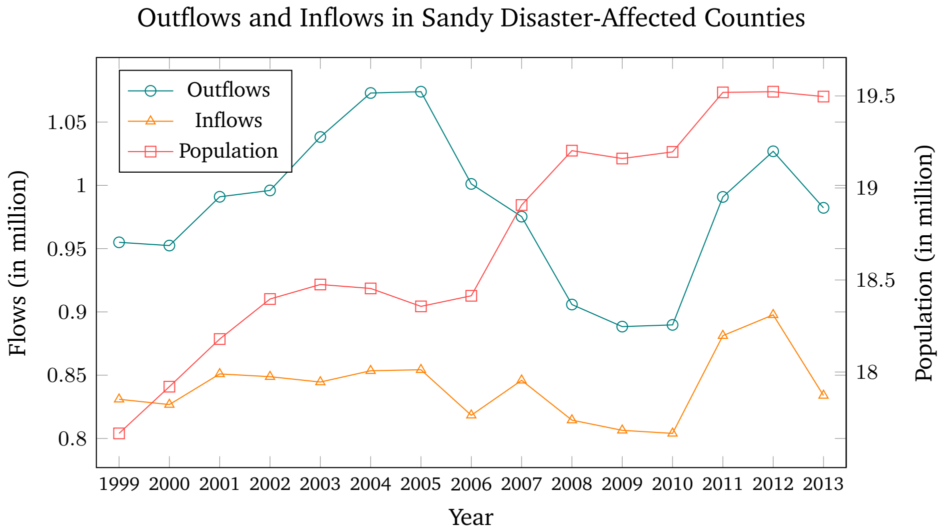

Figure 6

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

spatial distribution of the migration system for each disaster-affected county changed, such changes are almost invisible at the macro level.

Finally, in Figure 9, we see which counties lost and which gained outflows (top) and inflows (bottom). As we saw in Table 8, the number of outmigrants increased more than those of immigrants. Indeed, many more green counties (representing an increase in flows) are visible in the top map than in the bottom one. An interesting fact is that, in many cases, those counties that gained more immigrants are also those that lost more outmigrants (e.g., San Diego County in California). It appears, however, that disaster-affected counties while gaining immigrant also saw an increase in the number of outmigrants, a sign of increased mobility. Overall, when looking at changes in flows, we can observe that outflows tended to expand outward to distant counties while inflows showed the opposite tendency.

To compare these findings across the two hurricanes, I've included in the Appendix analogous maps constructed with Katrina data (Figures 13 and 14). 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) but could include even 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 the origin know that they can find a community with cultural characteristics similar to theirs at the destination. This indirect ties might not be as powerful as personal ones, but they could nevertheless play a role in shaping the spa-

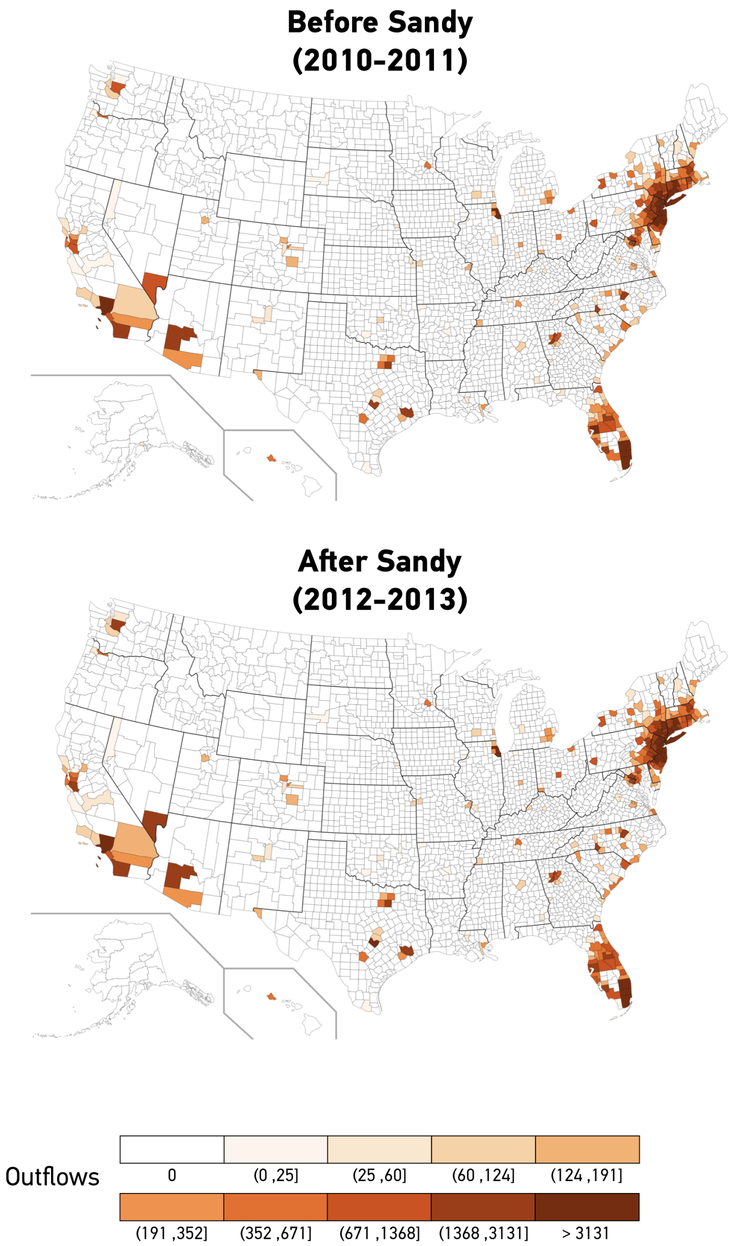

Figure 7: Comparing Outflows from Disaster-Affected Counties Before and After Sandy

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.

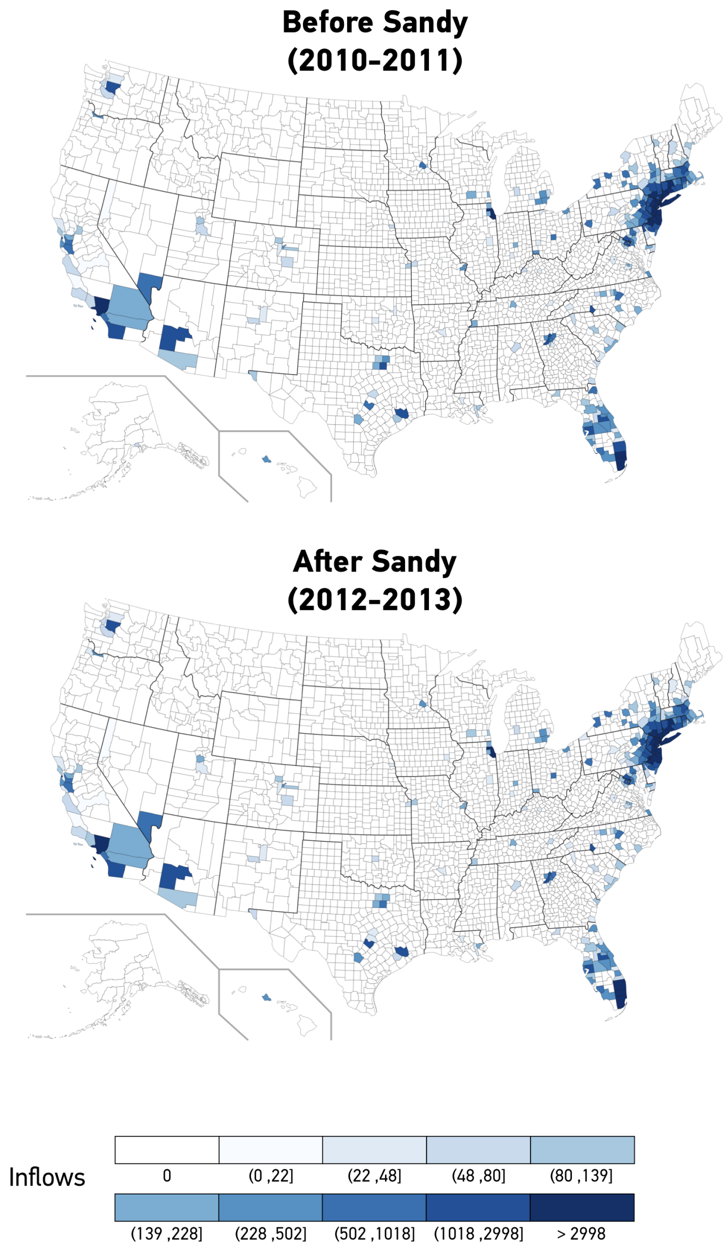

Figure 8: Comparing Inflows to Disaster-Affected Counties Before and After Sandy

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.

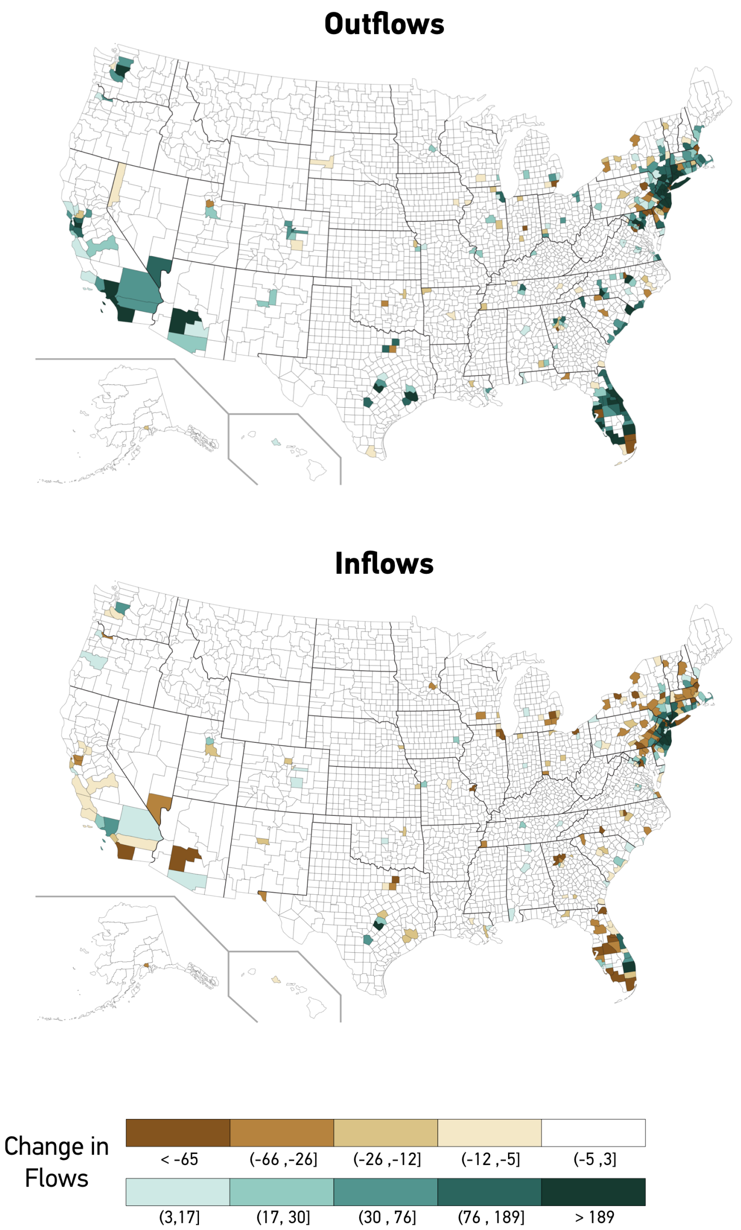

Figure 9: Who Gained and Who Lost Migration Flows from/to Disaster-Affected Counties

Notes: each different shade/color (excluding the white) represents a decile of distribution of changes in flows considering only non-zero values.

tial distribution of flows. In other words, we could have both a *narrow* (stronger) and a *broad* (weaker) network. Then, what we would have interpreted as a new connection outside the *narrow* network, may be just an increase in flows within the *broad* one.

5.2.3 Did Recovery Migration Occur?

To conclude the results section, I will examine the outcomes of the gravity model and the difference-in-differences model. Table 11 presents the results of the gravity model. Here, we are mostly interested in the coefficients on the time variable, which tells us how inflow to disaster-affected and nearby counties varied after Sandy. For disaster-affected counties, the results confirm the findings in Table 8. Inflows from disaster-affected and nearby counties were stable but declined significantly from distant ones. The picture for nearby counties, as the receiving region, 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 in this sense, we need to turn to the difference-in-differences model in Table 12. 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 opposite to the one observed by Curtis et al. [2015] in their analysis of Katrina and suggests that no recovery migration developed after the Sandy. However, 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 one after Sandy (2012-2013), maybe this explains the observed difference. However, looking at Figure 5, it seems that, for inflows, the post-Katrina trend observed in 2007-2009 is just the prosecution of that in the immediate aftermath 2005-2006, suggesting that the Sandy-Katrina differences do not depend on the period considered. Indeed, I reran the difference-in-differences analysis on the Katrina dataset, using 2005-2007 as the after-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 don't think that the sustained recovery migration observed after Katrina versus its absence after Sandy is solely the result of methodological differences.

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, when moving to the macro level, the contraction appears less evident. Looking at flows, while outflows increased, with the increase driven by distant counties, inflows decreased, especially from nearby and distant counties. The difference-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. In terms of the hypotheses I formulated in the background section, I found evidence to support all of them.

A point has emerged from the comparison between Sandy and Katrina: natural disasters, and hurricanes, in particular, are not all the same when looking at their im-

	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 11: 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 12: Difference-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).
* $p < .05$, ** $p < .01$, *** $p < 0.001$

pact 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 the *disruptive* type which causes almost complete evacuation and then, because of catastrophic damages and an intense, albeit unequal, reconstruction process, triggers a long-term recovery migration whereby the returning evacuees mix with newcomers in search of opportunities. Sandy, on the contrary, represents the *manageable* type which does not cause extended abandonment of the area at risk in the first place and, consequently, does not give rise to recovery migration, leading instead to a decrease in net migration. Table 13 tries to summarise this typology.

Notice 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" generates new opportunities. If this second condition is not satisfied, we could in principle have a short-lived boom in outmigration just before the event followed immediately after by a corresponding increase in inflows, with little impact on the migration system equilibrium. On the same line, while the extent of damage is undoubtedly relevant in determining to which type a natural disaster will belong, 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. Further studies, covering more events, are needed to shed light on which mechanisms are likely to lead to one type or the other.

One could ask why we should care about this typology. One 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 hard), 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.

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 can successfully return or by assisting them in rebuilding new lives in the area where they have relocated. The choice between these two alternatives is not simple and depends on both the politicians' and the beneficiaries' will. However, climate change forecasts tell us that we should expect more catastrophic cyclones hitting coastal areas, therefore building back in place may not be a forward-looking strategy. 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 requires compensating the market mechanisms which tend to favour homeowners and, in general, wealthier individuals. On the mitigation side, 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 to reduce vulnerability. However, policymakers should consider incentivising outmigra-

	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	A 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 13: Distinguishing between *Disruptive* and *Manageable* Natural Disasters

tion 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 made the population of the affected region 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 place, but they should be clear on the risk entailed by such a decision and offer attractive alternatives.

7 Conclusion

Because of climate change on the one hand 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. On the climate change side, rising sea level 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]. On the socio-demographic side, an increase in the population of coastal areas, especially cities, will heighten their sensitivity to such stress 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, the population density in coastal counties is more than 4 times the national average.

To increase the 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 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 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 preserve 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 will allow 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 implication 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 the very poor and older individuals. Given that these two groups have, on average, a lower propensity to migrate, the IRS-SOI probably 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 the 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, and 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. At 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 witnessed a contraction. However, such distributional changes disappear if we consider disaster-affected counties as a single region. It does not appear that recovery migration took place. To the contrary, a difference-in-differences analysis comparing disaster-affected and nearby counties reveals that the former saw a 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. 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 include in the pre- and after-disaster periods and in the classification of counties.

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

What general conclusions can 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, the incredible population recovery may not occur in other circumstances. This scenario is relevant also for policymakers as it implies that the vast majority of individuals at risk won't 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 more vulnerable groups that suffer the most after natural disasters because they are at the same time the most vulnerable and those that can less readily adapt. This environmental inequality or injustice at the micro level acts on top of the macro level one 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 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 14: 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 15: 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 16: 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 17: Comparing Flows between the pre- and the post-disaster periods using the classification based on the FEMA-MOTF [2014b] report

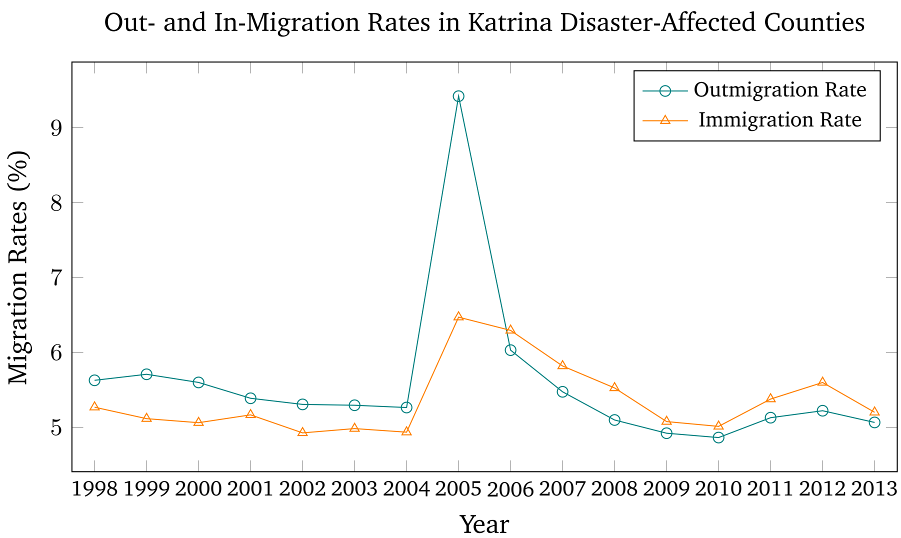

Figure 10

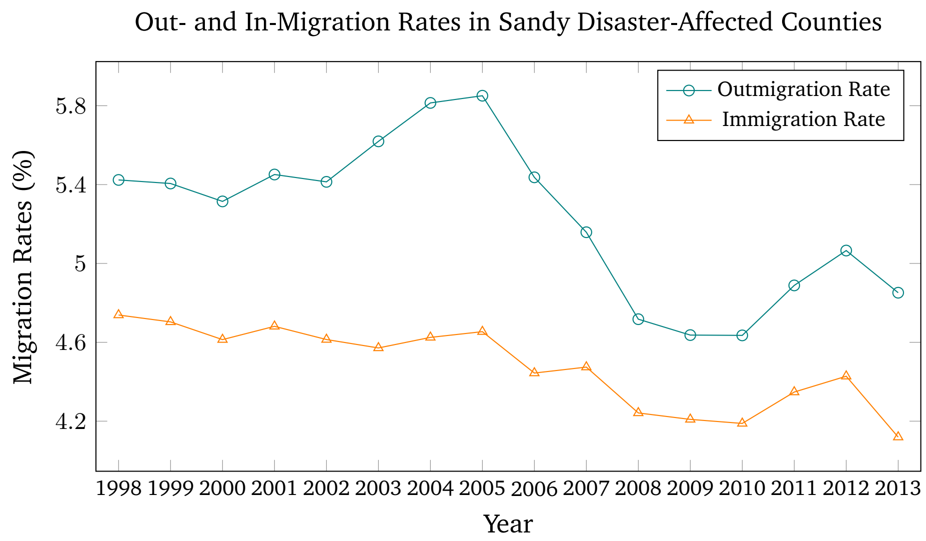

Figure 11

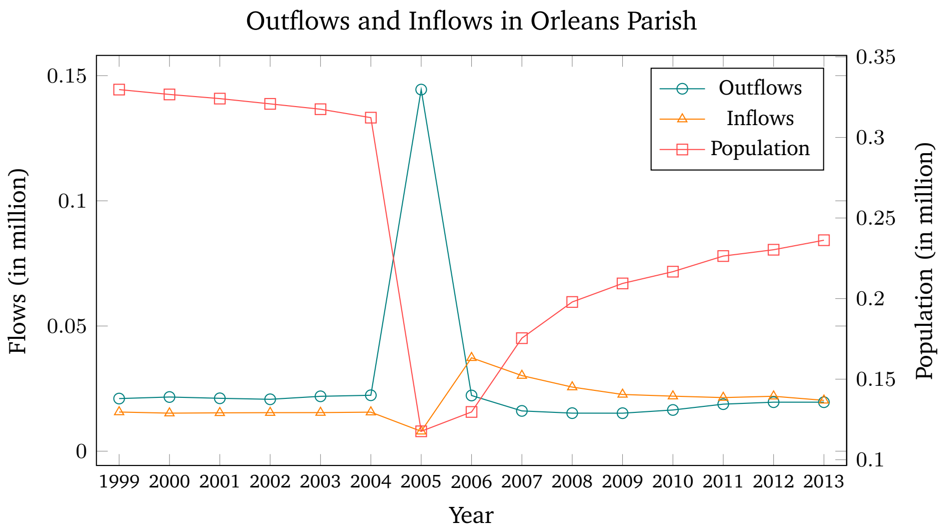

Figure 12

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

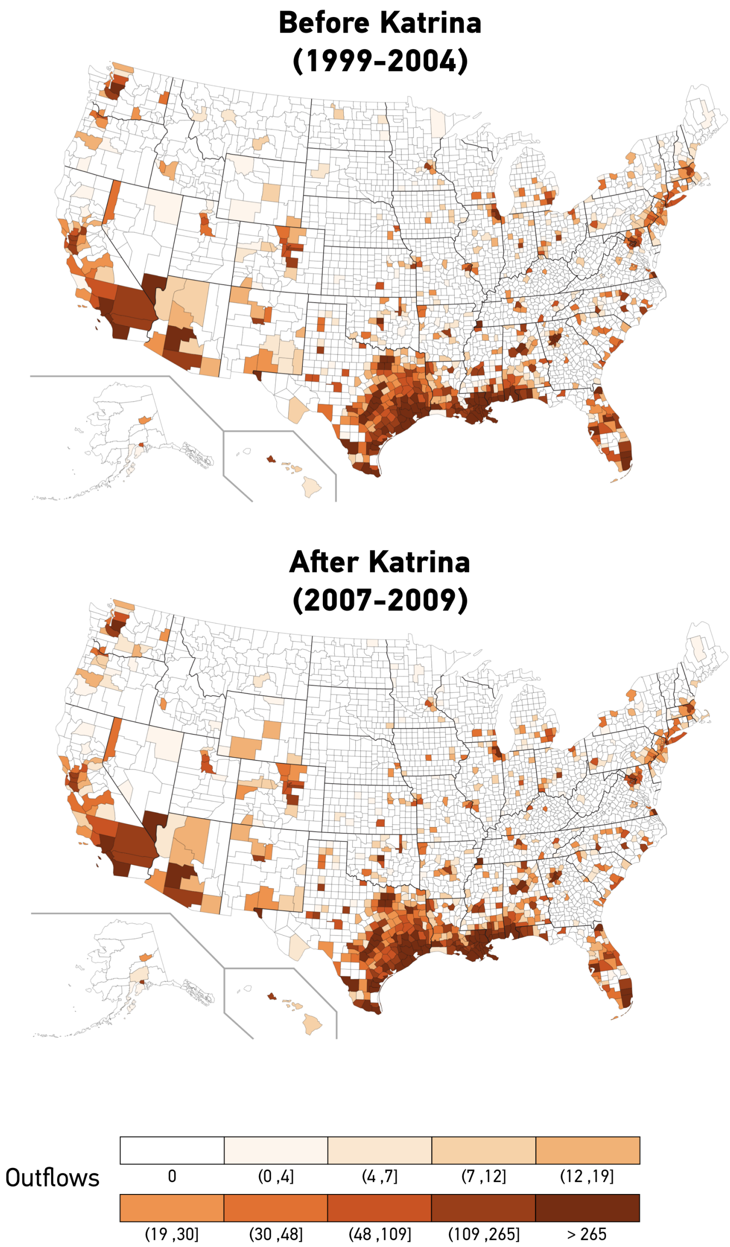

Figure 13: Comparing Outflows Before and After Katrina

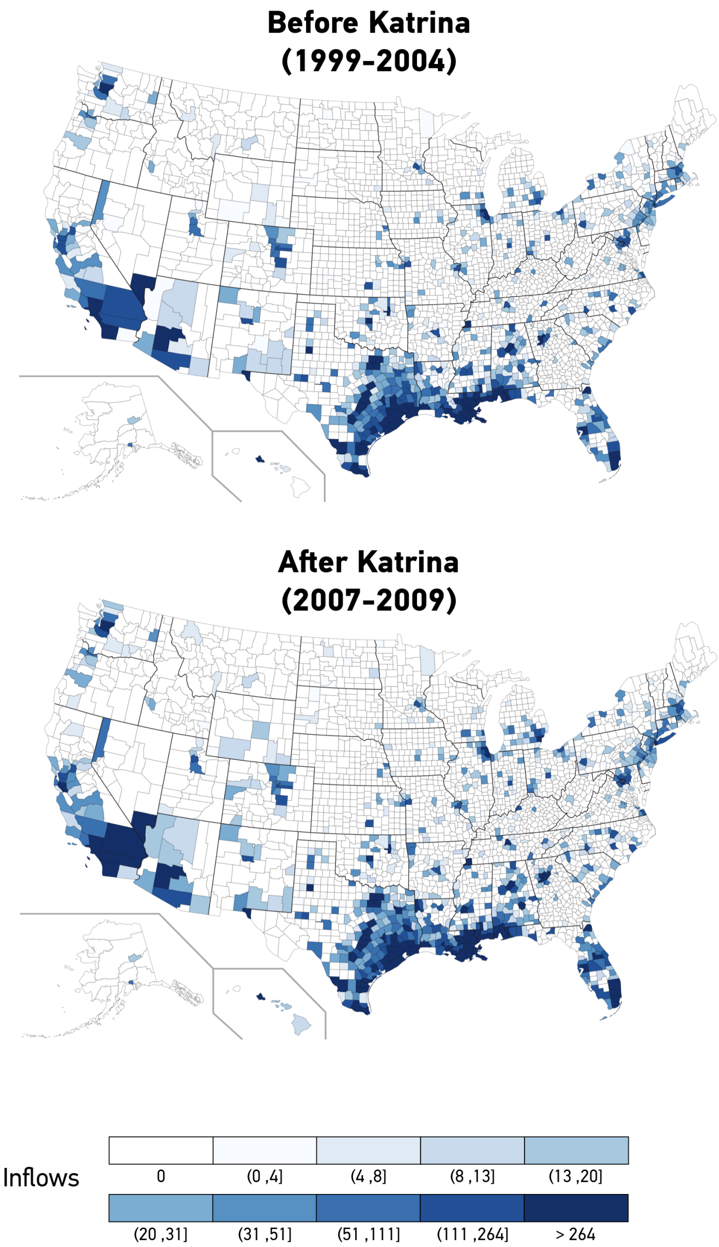

Figure 14: Comparing Inflows Before and After Katrina