NBER WORKING PAPER SERIES

TAKEN BY STORM: HURRICANES, MIGRANT NETWORKS, AND U.S. IMMIGRATION

Parag Mahajan
Dean Yang

Working Paper 23756
http://www.nber.org/papers/w23756

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2017

We sincerely thank J. Clint Carter of the Michigan Research Data Center (MRDC) for his invaluable help and support. We appreciate feedback from seminar participants at LSE, Notre Dame, UC San Diego, U. Michigan, and U. Philippines (Diliman). Jared Stolove and Colin Case provided excellent research assistance. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Taken by Storm: Hurricanes, Migrant Networks, and U.S. Immigration
Parag Mahajan and Dean Yang
NBER Working Paper No. 23756
August 2017
JEL No. F22,O15,Q54

ABSTRACT

How readily do potential migrants respond to increased returns to migration? Even if origin areas become less attractive vis-à-vis migration destinations, fixed costs can prevent increased migration. We examine migration responses to hurricanes, which reduce the attractiveness of origin locations. Restricted-access U.S. Census data allows precise migration measures and analysis of more migrant-origin countries. Hurricanes increase U.S. immigration, with the effect increasing in the size of prior migrant stocks. Large migrant networks reduce fixed costs by facilitating legal immigration from hurricane-affected source countries. Hurricane-induced immigration can be fully accounted for by new legal permanent residents ("green card" holders).

Parag Mahajan
Department of Economics and
Gerald R. Ford School of Public Policy
735 S. State Street
Ann Arbor, MI 48109
paragma@umich.edu

Dean Yang
University of Michigan
Department of Economics and
Gerald R. Ford School of Public Policy
735 S. State Street, Room 3316
Ann Arbor, MI 48109
and NBER
deanyang@umich.edu

1 Introduction

Moving from one's country of origin is among the most consequential decisions a person can make. Substantial numbers of people migrate internationally: estimates of migration over the five-year periods between 1990-95 and 2006-10 range from 34 to 41 million international migrants, or roughly 0.6% of world population (Abel and Sander, 2014). Substantially larger numbers—more than 600 million adults—express a desire to move permanently to another country (Pelham and Torres, 2008). Labor migration to the developed world leads to large income gains for migrants,[1] which benefit not only the migrants themselves but also those remaining behind in origin countries. Remittances sent by migrants to their home countries amounted to $432 billion in 2015, far exceeding official development assistance (World Bank Group 2016). There is substantial evidence that international out-migration, and the remittances that subsequently flow back to origin areas, generate benefits at the household level in developing countries.[2] Additionally, aggregate gains in global economic output from freer international labor mobility are estimated to be very large.[3]

For all these reasons, it is important to understand the economics of international migration decisions. The seminal work of Sjaastad (1962) remains a basic and useful framework for such analysis. Individuals choose whether to stay at lower-wage home locations or to bear a fixed cost and migrate to a higher-wage destination. This parsimonious model makes a fundamental prediction: an increase in the return to migration should lead to greater increase in migration when the fixed cost of migration is lower. In this paper, our goal is to provide a convincing empirical test of this prediction.

We exploit exogenous variation in the returns to migration, as well as substantial cross-sectional variation in a key determinant of the fixed cost of migration. Our

[1] McKenzie et al. (2010), Clemens et al. (2016).

[2] Studies include Edwards and Ureta (2003), Yang and Martinez (2006), Yang (2006), Woodruff and Zenteno (2007), Yang (2008b), Adams Jr and Cuecuecha (2010), Adams and Cuecuecha (2010), Gibson et al. (2014), Ambler et al. (2015), Theoharides (2016), and Clemens and Tiongson (2017).

[3] See Moses and Letnes (2004), Moses and Letnes (2005), Iregui (2005), Klein and Ventura (2007), Walmsley and Winters (2005), and van der Mensbrugghe and Roland-Holst (2009) for estimates. Clemens (2011) provides a review.

outcome of interest is annual U.S. immigration rates from 1980 through 2004 for each observable origin location, as constructed from restricted-access Census data. Variation over time in the return to migration from specific origin areas is generated by hurricanes, which exogenously lower the attractiveness of remaining in one's origin area.[4] Our measure of the fixed cost of migration is the size of migrant networks in the U.S., as measured by the stock of previous migrants. Larger migrant stocks can lower the fixed costs of migration in a number of ways. Most directly, prior migrants create a less costly, legal route to immigration for their compatriots through family reunification immigration policies (Jasso and Rosenzweig, 1989). They can also play a role in closing information gaps in the labor and housing markets for incoming migrants.[5] We thus examine whether increases in the returns to migration driven by origin-country hurricanes have larger impacts on migration from countries that have larger pre-existing migrant networks in the U.S.

We find that hurricanes cause immediate increases in U.S. immigration on average. This effect is magnified among origin countries with larger pre-existing stocks of U.S. immigrants, consistent with our hypothesis. Our estimates indicate that the effect of hurricanes on migration is positive for countries with a migrant stock in the U.S. (as share of 1980 population) of at least 0.86%—roughly the 70th percentile across countries.[6] For a country at the 90th percentile of the prior migrant stock (5.6% of origin population), a one-standard-deviation increase in our measure of hurricane affectedness causes an inflow amounting to 0.029% of the origin population.

A key question is whether the migrant stock should be interpreted primarily as a proxy for migration-related fixed costs, or whether it stands in for some other omitted variable that is responsible for heterogeneity in the migration response to

[4] Yang (2008a), Noy (2009), Strobl (2011), Coffman and Noy (2012), Hsiang and Jina (2014), Imberman et al. (2012), Franklin and Labonne (2017), and Caruso and Miller (2015) among others. Rasmussen (2004) and Auffret (2003) find that the negative effects of natural disasters may be larger in developing countries.

[5] Key references include Massey (1988), Massey et al. (1994), Hatton and Williamson (1994), Carrington et al. (1996), Orrenius (1999), Munshi (2003), Amuedo-Dorantes and Mundra (2007), Epstein (2008), Dolfin and Genicot (2010), Beaman (2012), and Docquier et al. (2014).

[6] In the regression where the effect of hurricanes is allowed to vary with respect to the size of a country's prior U.S. migrant stock, the main effect of hurricanes is negative (although not statistically significantly different from zero).

hurricanes. We take two approaches to address this question. First, we seek evidence for mechanisms behind the heterogeneous effect. It appears that a key role played by migrant stocks is formally sponsoring relatives for legal, permanent immigration. If we replace our dependent variable of interest with legal immigration counts from the U.S. Department of Homeland Security (DHS), our coefficient estimates are strikingly similar. The full magnitude of the observed hurricane-induced immigration (from estimates using U.S. Census data) can be explained by legal, permanent immigration (from estimates using U.S. administrative data on immigration). Furthermore, this legal, permanent immigration is driven primarily by different forms of family sponsorship. These findings are strongly suggestive that migrant stocks reduce the fixed cost of migration by providing access to legal immigration channels.

Our second approach to addressing omitted-variable concerns is to gauge the stability of our key parameter, the coefficient on the hurricane-migrant stock interaction term, to the inclusion of additional control variables for other origin country characteristics, such as per capita GDP, distance from the U.S., and land area.[7] We show that the coefficient on our interaction term of interest is highly robust to inclusion of interaction terms with these other country characteristics. We therefore argue that hurricanes have heterogeneous effects across countries due to migrant stocks themselves, and not some other origin-country characteristic that may be correlated with migrant stocks.

Our work has a number of features that distinguish it from past research. Most importantly, to our knowledge this paper is among the first to rigorously test, using plausibly exogenous variation in migration returns, a fundamental prediction of standard models: that the migration response to changes in migration returns will be larger when fixed migration costs are lower. Most previous work has examined the relationship between migration and either the costs of migration, on the one hand, or the returns to migration, on the other, but not the interaction between the two. Aside from the importance of confirming the theoretical prediction, this question has substantial policy relevance. Shocks to the returns to migration are

[7]Because our coefficient of interest is on an interaction term with hurricanes, these predetermined control variables must also be included as interaction terms in the same way.

pervasive, and of particular interest are shocks to economic and social conditions in migrant source countries due to causes such as war, political changes, or natural disasters. Policy-makers in destination countries would benefit from a better understanding of the determinants of migrant inflows that may result from such shocks. A closely related paper is Clemens (2017), who finds that previous migration plays a key facilitating role in determining the migratory response of Central Americans to violence in their home municipalities.

A second distinguishing feature of our work is that it focuses on immigration to the U.S., the world's largest migration destination. Migration to the U.S. accounted for 18.5% of global international migration flows from 1990-2010 (Abel and Sander, 2014). Conducting our analysis in the context of such an important and large migration destination reduces concern about external validity of the findings. Furthermore, because our unit of analysis is annual flows from all other locations worldwide, we can exploit considerable cross-sectional and temporal variation across countries in hurricane-induced shocks to migration returns, as well as cross-sectional variation in fixed costs across origin locations.

Finally, this study makes advances related to data. To our knowledge, this is the first empirical analysis of U.S. immigration that uses restricted-access U.S. Census data to construct country-by-year inflow estimates. With access to full 1-in-6 long-form responses to the U.S. Census, our measures of prior migration stocks and annual migration flows are more precise than any previous survey-based estimates used to examine the causal determinants of U.S. immigration from particular source countries. Importantly, we are also able to include many more origin countries in our sample than are visible in the public-access U.S. Census data, since the public data suppresses country identifiers with small respondent counts. This allows us to analyze migration flows from a larger sample of countries, and provides additional identifying variation because many small countries (e.g., island nations) are also hurricane-prone. We supplement these data with administrative records on U.S. legal immigration from the DHS. Finally, we construct hurricane-affectedness measures from satellite-based meteorological data, which are less prone to measurement error than more commonly-used disaster damage data that are assembled from reports of aid institutions, governments, or news agencies (Yang, 2008a).

Our work is generally related to the body of research on migration responses to the returns to migration, and particularly related to work emphasizing causal identification by focusing on the impact of exogenous shocks.[8] A number of studies have found that increases in the returns to migration, driven by shocks in either sending or receiving areas, do increase net outmigration. In some studies the identifying variation comes from shocks in the source locations,[9] while in others the variation in returns is generated by shocks in destination locations.[10] Other studies have found the opposite—that increases in the returns to migration driven by negative shocks in home areas lead to *less* outmigration (Halliday, 2006; Yang and Choi, 2007; Yang, 2008c). The latter set of findings may reflect the importance of migration fixed costs in combination with liquidity or credit constraints.[11] Bazzi (2017) finds that positive income shocks in origin areas in Indonesia lead to less migration in wealthier areas and more in poorer ones, which he ascribes to the role of liquidity constraints when there is a fixed cost of migration.

In examining the responsiveness of migration to negative shocks in source countries, our work is related to the large body of work on how households in developing countries cope with risk.[12] In particular, there is evidence that migration and remittances serve a risk-coping role, either ex ante (prior to shocks),[13] or ex post (after shocks occur).[14] Our findings suggest that migration is an international risk-coping

[8]There is also a body of work that examines the empirical correlation between migration and home-country wealth or income. Key examples include Hatton and Williamson (1998), Abramitzky et al. (2012), and Mayda (2010). The literature on the "mobility transition," a well-documented inverted-U-shaped cross-sectional relationship between country income and outmigration, is reviewed by Clemens (2014).

[9]For example, Munshi (2003), Baez et al. (2017), Cai et al. (2015), Gröger and Zylberberg (2016), Bohra-Mishra et al. (2014), Hanson and Spilimbergo (1999), Abarcar (2017), Kleemans and Magruder (forth.), Hatton and Williamson (1993), Marchiori et al. (2012), Hornbeck (2012), Missirian and Schlenker (2017), Hanson and McIntosh (2012), and Clemens (2017).

[10]For example, Yang (2006), McKenzie et al. (2014), Wozniak (2010), and Bertoli et al. (2016).

[11]Consistent with liquidity constraints inhibiting migration, Ardington et al. (2009), Bryan et al. (2014), and Angelucci (2015) find that cash transfers increase migration (but see Stecklov et al., 2005 for a contrary result on the context of the Mexican Progresa program).

[12]For example Morduch (1993), Udry (1994), Townsend (1994), Foster and Rosenzweig (2001), and Ligon et al. (2002), among many others.

[13]Stark and Levhari (1982), Rosenzweig and Stark (1989), Lucas and Stark (1985), Stark (1991).

[14]Jayachandran (2006), Blumenstock et al. (2016), Yang and Choi (2007), Yang (2008a), Jack and Suri (2013), De Weerdt and Hirvonen (2016), Morten (2016), and Clemens (2017).

mechanism, but that this benefit is concentrated in origin areas with large enough prior migrant stocks to reduce fixed costs of migration.

This paper is organized as follows. In Section 2, we outline a simple theoretical framework that provides predictions and guides interpretation of results. Section 3 provides a brief overview of U.S. immigration policy during our study period. Section 4 describes the data used in the empirical analyses, and Section 5 reports empirical results. Section 6 concludes.

2 Theory

We follow in the tradition of Sjaastad (1962) by modeling migrants as agents who compare the present discounted value of net income streams in destination areas and origin areas. A substantial subsequent literature has built on this starting point with the primary aim of examining migrant selectivity.[15] A subset of the literature explicitly takes account of migration fixed costs.[16] McKenzie and Rapoport (2010) adapt the notation of Chiquiar and Hanson (2005) to consider migration fixed costs that decline in the size of the migrant network at destination, and we follow their formulation. The literature tends to focus on implications of the theory for migrant selectivity (the extent to which the migration decision depends on relative returns to skill across migrant origin and destination). Instead, we focus on a key prediction of this model that has been under-emphasized: that the migration response to changes in the returns to migration will depend on the size of migration fixed costs. Because it is not our focus, we suppress consideration of migrant selectivity.

[15] Key previous works include Borjas (1987) seminal adaptation of the Roy (1951) model, as well as Greenwood (1985), Taylor (1987), Borjas (1991), Stark (1991), Chiswick (1999), Beine et al. (2001), Feliciano (2005), Chiquiar and Hanson (2005), Orrenius and Zavodny (2005), Clark et al. (2007), Ibarraran and Lubotsky (2007), Beine et al. (2008), Dolfin and Genicot (2010), McKenzie and Rapoport (2010), Akee (2010), Abramitzky et al. (2012), Ortega and Peri (2013), Bertoli et al. (2013), and Bertoli et al. (2016).

[16] Key works in the literature that explicitly consider the fixed cost of migration to be a central aspect of the migration decision include Borjas (1987), Carrington et al. (1996), Chiquiar and Hanson (2005), Ibarraran and Lubotsky (2007), Gathmann (2008), McKenzie and Rapoport (2010), Grogger and Hanson (2011), Bertoli et al. (2013), Belot and Hatton (2012), Bertoli and Rapoport (2015), Kennan and Walker (2011), and Kosec et al. (2015). Empirical studies on the association between pre-existing migrant stocks and subsequent migration flows include Winters et al. (2001), Clark et al. (2007), Pedersen et al. (2008), Zavodny (1997), Hanson and McIntosh (2012), McKenzie and Rapoport (2010), Collins (1997), Collins and Wanamaker (2015), and Orrenius and Zavodny (2005).

2.1 Basic setup

Consider an individual in their "home" (non-U.S.) country deciding whether or not to migrate to the "foreign" country (the U.S.). Let w_h be the present value of the flow of the individual's future income in the home country, and w_f be the corresponding value for the foreign country. To simplify matters, we consider a one-time decision to migrate permanently to the foreign country.

Migration involves a fixed cost C, which we presume is a function of the migrant's network n. Previous work on migration networks suggests that the fixed cost of migration is lower when an individual has a larger migrant network, meaning $C' < 0$ (Massey et al., 1994; Carrington et al., 1996; Kanbur and Rapoport, 2005; Bauer et al., 2005). This could be true for a number of reasons. As emphasized in previous research, networks could help reduce search and information costs (e.g., related to legal and illegal modes of entry, employment, housing, etc.), provide social support during adjustment (a reduction in psychic costs), and sponsor relatives for legal immigration (allowing migrants to avoid costlier illegal entry routes and costly wait times imposed by quotas).[17]

Express migration costs in "time-equivalent" units (as a fraction of the present value of income flows in the foreign country):

$$\pi(n) = \frac{C(n)}{w_f}.$$

Assuming π is small, individuals migrate if:

$$\ln\left(w_f\right) - \pi(n) > \ln(w_h).$$

Because migration costs $C(n)$ decrease with migrant network size, so do time-equivalent migration costs $\pi(n)$. Express the natural log of time-equivalent migration costs as $\ln(\pi) = \mu - \gamma n$, where $\gamma > 0$.

Now, the condition for migration can be written as:

[17] These points have been emphasized by Massey (1988), Orrenius (1999), Orrenius and Zavodny (2005), Comola and Mendola (2015), and Dolfin and Genicot (2010). Networks could also provide financial assistance with paying fixed migration costs, which would be important in contexts where potential migrants are liquidity or credit constrained.

$$\ln\left(w_f\right) - e^{\mu-\gamma n} > \ln\left(w_h\right). \tag{1}$$

In this set-up, we can represent the individual's choice graphically. In Figure 1, the size of the migrant network n is on the horizontal axis, while the vertical axis is monetary value in logs. The right hand side of inequality (1) is the solid line at $\ln\left(w_h^0\right)$, which is horizontal because home-country income does not depend on network size. The left hand side of inequality (1) is represented by the solid upward-sloping curve: because migration costs decline in n, the net present value of the income stream in the foreign country rises in n. Individuals who choose to migrate are those with network size above the threshold $\underline{n}^0$, whose migration fixed costs are low enough to make migration worthwhile.

Now consider the impact of a negative shock to home economic conditions, so that the present value of the home income stream declines from w_h^0 to w_h^1. (In the empirics, we will interpret hurricanes as having this effect.) This is represented by a downward shift of the horizontal line representing the value of not migrating to the horizontal dashed line at $\ln\left(w_h^1\right)$.

2.2 Negative home shock does not affect migration costs

If the negative home-country shock has no effect on migration costs, the analysis is straightforward. This leads a new set of individuals to choose to migrate, since now the threshold network size for migration has fallen from $\underline{n}^0$ to $\underline{n}^1$ in Figure 1.

Within the population of those who had not migrated prior to the negative shock to the home economy, those migrating will be those with differentially higher network size (in the range from $\underline{n}^1$ to $\underline{n}^0$). Those with lower network size (below $\underline{n}^1$) will continue to remain in the home country.

2.3 Negative home shock affects migration costs

Predictions on the hurricane effect become ambiguous if the negative shock to the home economy does affect migration costs. It is most plausible that negative home-country shocks would raise migration costs. Loss of assets due to hurricanes could make it more difficult for credit-constrained households to pay the fixed migration costs. Negative shocks at home could make it more difficult to obtain credit to pay for the fixed costs of migration (Yang, 2008c), or could raise the opportunity cost of departure (Halliday, 2006). Negative aggregate shocks could also have general equilibrium effects that make it more difficult to pay the fixed costs of migration, such as reductions in asset prices (Rosenzweig and Wolpin, 1993) or wages (Jayachandran, 2006). In addition, increased demand for legal migration assistance as well as illegal migration services (migration smugglers or coyotes) could raise equilibrium prices for those services.

Imagine simply that the negative shock, a hurricane, raises the natural log of time-equivalent migration costs by H, so that $\ln(\pi) = \mu - \gamma n + H$. We can rewrite this as $\pi = e^{\mu-\gamma n+H}$, so the condition determining migration becomes:

$$\ln\left(w_f\right) - e^{\mu-\gamma n+H} > \ln\left(w_h\right) \tag{2}$$

It now becomes possible for a negative shock to either increase or decrease migration. These possibilities are also represented in Figure 1. A negative shock now also leads the curved line (the left hand side of inequality 2) to shift downward. If the increase in the log of time-equivalent migration costs is low (say H_{lo}), the downward shift is small, illustrated by the shift to the dashed curve labeled $\ln\left(w_f\right) - e^{\mu-\gamma n+H_{lo}}$. The net effect is still for migration to increase: the threshold network size for migration falls from $\underline{n}^0$ to $\underline{n}^2$.

On the other hand, if the shift is large enough (such as to the dotted curve in Figure 1, representing a larger increase in the log of time-equivalent migration costs H_{hi}), then, migration can actually decline—the threshold for migration actually rises from $\underline{n}^0$ to $\underline{n}^3$.

In sum, then, the theoretical predictions are ambiguous: negative shocks to economic conditions in the home country could increase migration by increasing the return to migration. It is also possible for negative home-country shocks to *reduce* migration, if such shocks themselves increase the fixed costs of migration, or reducing ability to pay migration fixed costs. Crucially, however, regardless of whether negative income shocks induce or impede migration, the interaction effect between these shocks and network size is unambiguously positive.[18] We thus seek to both

[18] To see this, define $\mathscr{L} \equiv \ln(w_f) - e^{\mu-\gamma n+H} - \ln(w_h)$, which is how far away a given individual

resolve a theoretical ambiguity and test a clear prediction using empirical tests, to which we turn in Section 5.

3 Immigration Policy During the Sample Frame

Before moving to our analysis, we summarize U.S. immigration policy from 1980 through 2004. The workings of U.S. immigration policy help us highlight features of immigrant stock networks that help facilitate immigration.

The outline of today's U.S. immigration policy regime has its origins in the 1965 Amendments to the Immigration and Nationality Act. This legislation abolished preferential treatment for Europeans and created a system in which a majority of visas were allocated to relatives of U.S. citizens of residents. It was also the first law to distinguish between immediate relatives (spouses, children under age 21, and parents) of U.S. citizens, who became exempt from quotas, and other types of immigrants who fell into one of seven new preference tiers subject to numerical limitations (Kandel, 2016). Further, by 1979, all country-specific quotas were abandoned in favor of an overall quota. In 1981, the overall quota stood at 270,000 for all those subject to the cap (Clark et al., 2007). Among the capped tiers, first preference goes to unmarried adult sons and daughters of U.S. citizens, second preference goes to spouses and children of green card holders (LPRs), third preference goes to married sons and daughters of U.S. citizens, and fourth preference goes to siblings of U.S. citizens. Thus, while green card holders can sponsor a limited set of relatives from home, they are substantially constrained in this ability relative to naturalized immigrants.

The major change to policy that occurred during our sample period was the Immigration Act of 1990, which increased allowable total immigration to 675,000 and increased the limit of family-based immigrants subject to quotas from 290,000 to 480,000 (Kandel, 2016). Technically, immediate relatives of U.S. citizens came under this 480,000 cap for the first time, but in practice, the cap is "permeable" and inflows of such migrants remain uncapped to the present day. The remaining

---

is from reaching the cutoff that causes her to migrate. We then have $\frac{d^2\mathscr{L}}{dHdn} = \gamma e^{\mu-\gamma n+H} > 0$ where we have assumed $\frac{d^2\ln(w_h)}{dHdn} = 0$. Evidence for this assumption is shown in Section C of the Appendix. Thus, an individual below the cutoff is pushed further towards it when a hurricane hits if they have a larger pre-existing network.

195,000 allotments are slotted for employment visas (140,000) and a new category of "diversity" visas (55,000) allocated to countries that did not send many migrants to the U.S. between 1965 and 1990 (Clark et al., 2007).

An additional change that occurred during our sample period was the 1986 Immigration Reform and Control Act (IRCA), which granted legal status to millions of undocumented workers. While this legislation had many consequences, it mainly affects our results through its disproportionate legalization of migrants from certain countries, perhaps creating a positive shock in the *effective* stock of network capital in the United States for these countries. This is especially true given how important legal status and citizenship are to being able to serve as a beach head for compatriots under the current regime. A more minor point is that the legal permanent resident (LPR) status granted to these previously undocumented workers clearly did not result from new entries into the United States. We will thus subtract these "inflows" from our overall measure of LPR admissions in the DHS data.

4 Data

4.1 Sample Definition

Our sample consists of foreign territories listed in Table A1 of the Online Appendix. Given how often many of these areas are hit by hurricanes and because of the level of detail our data affords us, we treat many non-sovereign territories as separate countries (e.g., Guadeloupe or Martinique).[19] We drop countries that are U.S. territories because of their preferential treatment in immigration policy. We also drop countries from the former Soviet Union and the European land mass.[20] North Korea and Eritrea are excluded because of a lack of reliable migration information for the entire sample period. Additionally, some countries that contain inconsistent migration information due to border redefinition are combined to retain consistency throughout the sample period. These include the Netherlands Antilles minus

[19] From this point forward, use of the word "country" includes these non-sovereign territories.

[20] The splitting of the Soviet Union does not enable us to have reliable migration information for these countries throughout the sample period. Europe is rarely hit by hurricanes, and because it contains mostly developed countries is not likely to provide a useful migration counterfactual.

Aruba,[21] Sudan,[22] and Guadeloupe.[23] Finally, we also drop any country without an immigrant stock estimate from the 1980 Census. This left us with a balanced panel of 159 countries.

4.2 Hurricane Index

Hurricanes are storms that originate over tropical oceans with wind speeds above 33 knots.[24] These severe storms create damages through storm surges, strong winds, and flooding, and their radius of impact can be anywhere from 60 to 900 miles. Thus, depending on the severity of the storm, there is a wide scope for hurricanes to inflict extensive damage, particularly when infrastructure is weak and production is agriculture-oriented. Hurricanes occur in six basins: Atlantic, East Pacific, West Pacific, South Pacific, South Indian, and North Indian. Yang (2008a) provides a more detailed definition of hurricanes and their architecture.

We construct a hurricane index representing the average hurricane exposure of residents in a given country-year following Yang (2008a). This index uses data from meteorological records, rather than impact estimates compiled from news reports, governments, or other similar sources due to concerns about measurement error and potential misreporting of hurricane damages (motivated, for example, by a desire to attract greater international disaster assistance). The meteorological data on hurricanes consists of "best tracks" compiled by Unisys from the National Oceanic and Atmospheric Administration's Tropical Prediction Center (for the Atlantic and East Pacific hurricane basins) and the Joint Typhoon Warning Center (for the West Pacific, South Pacific, South Indian, and North Indian hurricane basins).[25] The best tracks contain information on the hurricane's maximum wind speed and the geographic coordinates of its center (or "eye") at six-hour intervals. Figure 2 displays all hurricane best tracks from 1980 through 2004.

The best track data naturally take hurricanes as the unit of analysis, and so

[21] Curacao, Bonaire, Saba, St. Eustatius, and Sint Maarten. The Netherlands Antilles was not dissolved until 2010.

[22] South Sudan and Sudan. South Sudan broke off from Sudan in 2011

[23] Guadeloupe and St. Barthelemy. St. Barthelemy broke off from Guadeloupe in 2003.

[24] Hurricanes are also known in different regions as typhoons and cyclones. For simplicity, in this paper hurricanes, typhoons, and cyclones will all be referred to as hurricanes.

[25] http://weather.unisys.com/hurricane/. From this point forward hurricanes, typhoons, and cyclones will all be referred to as hurricanes.

in their raw form give no indication of countries affected. Section A of the Online Appendix describes in detail how we turn this best track data into a country-by-year index. Other papers have utilized similar hurricane indices to study their impacts on various outcomes on land masses (Strobl, 2011; Strobl and Walsh, 2009; Ouattara and Strobl, 2014; Hsiang and Jina, 2014; Hsiang, 2010). All use a model based on best tracks to simulate the wind speed faced by geographical areas a certain distance away from the best track line.[26]

The resulting index can be described as "intensity-weighted hurricane events per capita," in which intensity is a nonlinear function of hurricane-force wind speed. The key features of this index are that it measures the average "affectedness" by hurricanes for residents of a country in a given year. It rises in the number of hurricanes affecting a country, the share of the population affected, and in the intensity (wind speed) of the hurricanes to which people were exposed. In Table 1 we provide basic summary statistics of the hurricane index. Out of 3,895 country-year observations, 641 have non-zero values of the index. The standard deviation of the non-zero values is 0.0520.

4.3 Immigrants in the United States: Stocks and Inflows

4.3.1 U.S. Census Bureau

The primary source for our immigration data is confidential data provided by the U.S. Census Bureau, who granted us access to the full set of responses from the 1980 and 2000 Long Form Censuses along with the 2005 through 2015 American Community Survey (ACS) 1-year files. The 1980 and 2000 Census Long Form provide 1 in 6 counts of all persons living in the United States along with demographic information. The ACS 1-year files provide a one percent sample of all persons living in the United States in a given year. Online Appendix Section B describes how we utilize these data sources to construct two key variables: sending-country-by-year estimates of migration inflow rates (m_{jt}) and sending country estimates of 1980 U.S. immigrant stocks ($s_{j,1980}$).

[26] Strobl (2011) uses population weights when measuring the effect of hurricanes on economic activity, while Hsiang and Jina (2014) do not.

4.3.2 Department of Homeland Security (DHS)

Our second source of migration inflow data comes from the Department of Homeland Security (DHS). In addition to producing the annual *Yearbook of Immigration Statistics* (1996-2015), the DHS houses the records of the former Immigration and Naturalization Service (INS), who produced similar publications for past years titled the *Statistical Yearbook of the Immigration and Naturalization Service* (prior to 1996). Starting in 1982, these annual publications contain counts of legal permanent residence (LPR) statuses granted by country of last residence, which we use to construct an alternate measure of migration inflows. They also contain information on non-immigrant entries into the U.S. by country of birth and class of admission starting in 1983, which we use to construct a new panel that measures potentially temporary migration.[27] Data through 1996 are available only as hard-copy portable documents. We thus double-entered and cross-checked each relevant table to ensure accuracy in these outcome variables.[28]

The DHS data provides some important advantages over our confidential Census data beyond their use as a robustness check. First, the counts were all taken officially during the year of a given immigrant's receipt of LPR status or non-immigrant entry and thus do not suffer from attrition due to death or return migration. Second, in the case of LPR entries, country of last residence provides a more direct indicator of hurricane-induced migration than country of birth. Third, the DHS data allows us to separate classes of LPR admission, such as uncapped family reunification, capped family sponsorship, and refugees. This allows us to examine whether eligibility for immigration due to family-reunification policies is a mechanism through which our effects operate.

Finally, the non-immigrant entry panel allows us to understand two additional facets of hurricane-induced migration into the United States. First, it helps us assess whether there is a component of such migration that is potentially temporary. Second, it helps us elucidate the phenomenon of conditional entry followed by either a

[27] According to the DHS Office of Immigration Statistics, non-immigrant data is not available in 1997 due to concerns about data quality in that year.

[28] The hard copies are available at in the U.S. Citizenship and Immigration Services Historical Library's General Collection.

switch of status or an overstay on a temporary visa, a process through which much legal and illegal permanent migration occurs.

There are, however, also drawbacks to the DHS data that highlight its complementarity with our estimates from the confidential Census Bureau data. First, the DHS LPR measures do not distinguish between new inflows and changes in status from temporary to permanent residence. Second and relatedly, backlogs and backlog reduction efforts create uncertainty around how reliably the DHS estimates can be used to measure changes in actual entries—as compared to switches in status from temporary to permanent—over time. Third, the DHS data cannot shed light on undocumented entries, while these may be captured by the Census and ACS surveys (which purposely do not inquire about legal status.)[29] Fourth, while it contains information about class of admission, the DHS does not allow us to examine many other important demographic characteristics of migrants, such as age. Finally, neither the Census nor the DHS data can correct for migrants who still live abroad but whom obtain a green card (LPR status) to engage in repeated circular migration (Redstone and Massey, 2004).

5 Analysis

5.1 Specification

In order to test the theoretical implications described in Section 2, we exploit the exogeneity of our objective hurricane index and conduct reduced form analyses that test its impact on migration inflows to the U.S. For this purpose, we rely primarily on two specifications:

$$y_{jt} = \beta_0 + \beta_1 H_{jt} + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \tag{3}$$

$$y_{jt} = \gamma_0 + \gamma_1 H_{jt} + \gamma_2 (H_{jt} \times s_{j,1980}) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \tag{4}$$

where y_{jt} is an outcome and t runs from 1980 through 2004. Our primary results are for $y_{jt} = m_{jt}$ where m_{jt} is the number of immigrants from country j to the U.S. in year t as a proportion of country j's population in 1980. Analogously, $s_{j,1980}$ is the stock of immigrants from country j already in the U.S. in 1980 as a proportion of

[29] Individuals who are captured in the DHS non-immigrant data may enter legally and then later overstay their visas, becoming undocumented.

country j's population in 1980. Including stocks as a proportion of 1980 population also allows us to interpret $s_{j,1980}$ as a rough measure of likelihood a given migrant knows someone in the U.S.

The inclusion of year fixed-effects (δ_t) accounts for time-varying changes in the overall ability of foreigners to migrate to the United States. Common issues such as changing demand in the U.S. economy and back-logs in the immigration system that are not country-specific are important components of δ_t. Country-fixed effects, η_j control for fixed factors that affect how likely denizens of country j are to migrate to the U.S., such as distance. They also absorb the main effect of $s_{j,1980}$. We also allow for differential country-specific linear time trends with the inclusion of $\phi_j t$, which account for long-run linear trends in migration from country j to the U.S. Standard errors are clustered at the country level (Bertrand et al., 2004).

Our main hypothesis is that $\gamma_2 > 0$ when $y_{jt} = m_{jt}$. Exogenous natural disasters such as hurricanes will serve as an impetus for migration when there is a sufficient stock in the U.S. to facilitate the process. The coefficients β_1 and γ_1 are theoretically ambiguous. In the presence of credit constraints, an asset or income shock created by a hurricane could prevent migration by reducing the ability of sending country denizens from paying the fixed costs necessary to leave. On the other hand, the income shock could exacerbate the income gap for unconstrained sending country denizens, pushing those at the margin to engage in migration. We do, however, expect that $\gamma_1 < \beta_1$, given that β_1 absorbs the effect for high-stock countries.

5.2 Results

In Online Appendix Section C, we first establish that our hurricane index captures events that create economically relevant losses in potential sending countries. In the context of our theoretical framework from Section 2, we interpret these losses as an increase in the return to migration to the U.S. by decreasing w_h in the form of asset losses, personal harm, and longer-run declines in economic growth. We focus here on our primary results, with m_{jt}—immigrant inflows from country j in year t as a proportion of country j's 1980 population—as the outcome of interest. As described in Section B of the Online Appendix, m_{jt} is created using access to confidential data from the U.S. Census Bureau. These data allow us to create accurate counts of immigrant inflows to the U.S., even for small countries that often go overlooked in such studies. Additional results demonstrating that our results are not due to outlier countries, either on the migration or hurricane dimension, are available upon request.

5.2.1 *Primary Results on Migration*

Table 2 presents the results of estimating Equations (3) and (4) with m_{jt} as the outcome. Column 1 of Panel A demonstrates that, on the whole, hurricanes induce positive levels of migration across our sample of 159 countries ($\beta_1 > 0$). Column 2 illustrates that this effect operates largely through the stock channel: $\gamma_2 > 0$, suggesting that the ability of sending-country denizens to use migration as an ex-post response to hurricanes relies heavily on the presence an established network within the United States. This indicates a potentially crucial role for family reunification and other forms of sponsorship from within the U.S. in response to natural disasters abroad, motivating further investigation along these margins below.[30]

We further split m_{jt} into separate age bins to investigate the characteristics of these hurricane-induced migrants. Table 3 shows that the youngest migrants—aged 0 to 12—as well as prime-aged migrants—aged 18 to 44 account for the majority of the effect seen in Table 2. Qualitatively, this aligns with the notion that working-aged adults and their children are most likely to respond to the combined impetus of an income shock and the pre-existence of a migration network.

5.2.2 *Citizenship Status of Stock*

To begin exploring how these networks operate, we examine how the citizenship status of the 1980 stock affects the response to hurricanes. Differences in the ability of citizens versus non-citizens in promoting immigration allow us to roughly distinguish between different types of migrant network benefits. While both citizens and non-citizens can provide informational, financial, or psychic benefits, prior migrants who are citizens have the greatest ability to sponsor relatives for legal immigration (legally enshrined in the 1965 Amendments to the Immigration and Nationality Act.) For example, in 2004, 42.9 percent of the 946,142 legal immi-

[30] See Section E in the Online Appendix for placebo tests which demonstrate that future hurricane index values are not correlated with current migration flows.

grants admitted to the U.S. were able to bypass numerical quotas because they were immediate relatives of U.S. citizens. Another 12 percent were subject to numerical limitations, but also gained entry due to family sponsorship by a U.S. citizen (Department of Homeland Security 2006).[31] Thus, in the specification

$$m_{jt} = \pi_0 + \pi_1 H_{jt} + \pi_2 (H_{jt} \times s^{\text{citizen}}_{j,1980}) + \pi_3 (H_{jt} \times s^{\text{non-cit}}_{j,1980}) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \quad (5)$$

we expect $\pi_2 > \pi_3$. Table 4 shows evidence for this differential effect: only the the interaction term on the U.S.-citizen portion of the migrant stock has a positive and statistically significant coefficient. This motivates a deeper look into how different classes of legal entrants respond to natural disasters.

5.2.3 DHS Results

For this purpose, we turn to data from the Department of Homeland Security's annual *Yearbook of Immigration Statistics*, and the former Immigration and Naturalization Service's annual *Statistical Yearbook of the Immigration and Naturalization Service*, which allow us to separately examine entries of legal permanent residents (LPR) and legal non-immigrants—those who are only granted temporary visas. This generates two new outcome variables, m^{DHS}_{jt} where $DHS = \{LPR, \text{non-imm}\}$. Our specification remains the largely the same, with one exception. The DHS data does not allow us to distinguish between new entries and changes of status. Well-known back-logs in the immigration processing system can therefore create lag between shocks in sending countries and the enumeration of a migrants who gain LPR status if they enter as temporary residents first. In 2013, for example, 54 percent of family-based immigrants adjusted status from temporary to LPR compared to 46 percent who actually represented new entries (Kandel, 2016). We therefore increase the lag order in our specification by taking a simple average of H_{jt} and $H_{j,t-1}$, which we denote $H_{j,t,t-1}$. Our modified specifications become:

$$m^{DHS}_{jt} = \beta_0 + \beta_1 H_{j,t,t-1} + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \quad (6)$$

$$m^{DHS}_{jt} = \gamma_0 + \gamma_1 H_{j,t,t-1} + \gamma_2 (H_{j,t,t-1} \times s_{j,1980}) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \quad (7)$$

[31] Note that these "admissions" include new arrivals and changes of status.

The results from these models are presented in Table 5, where the first two columns present the results using our restricted-access estimates of migration inflows for comparison.[32]

There is a robust, positive effect of the stock interaction term on legal migration: γ_2 is estimated to be positive for both immigrant and non-immigrant entries. Temporary, non-immigrant entries also experience a large increase in response to the combined effect of existing stocks and hurricane shocks. In fact, in the year during and after a hurricane strike, respondent non-immigrant entries represent a much larger inflow than legal permanent residents. However, given that they are only admitted temporarily, only a small fraction of these non-immigrant entrants may end up staying in the United States long enough to be enumerated in the 2000 Census or one of the ACS surveys we use to calculate the original m_{jt} variable.

In the row titled "Prop. of Census Inflows," we calculate the proportion of inflows implied by the second column, produced by restricted-access migration counts m_{jt}, that can be explained by inflows reflected in the fourth and sixth columns, produced by data from the DHS (m_{jt}^{DHS}). This is done by obtaining predicted values from Equation (7), then multiplying by 1980 country population and summing over these fitted values to produce aggregate inflow estimates implied for each outcome. We then divide these aggregate inflow estimates by the result of the same calculation from the second column. This exercise reveals that entries at the time of hurricane incidence in sending countries are substantially larger than those that are enumerated by later surveys like the 2000 Census and 2005 through 2015 ACS. Given that a majority of temporary entrants do not stay in the U.S., for example, we find that non-immigrant entries are more than 50 times greater than those implied by our restricted-access results. We also find that LPR entries, that should be more permanent, acount for more than twice the number of entries picked up by our restricted-access measures. Even accounting for death, remigration, and statistical noise, this implies that the effects found in Table 2 and the second column of Table 5 can be fully explained by a legal immigration response.

The detail of the DHS data allows us to further probe some of the mechanisms

[32] The set of countries has been restricted to be the same across all estimated specifications. We lose three countries to lack of data availability from the DHS.

implied by our results thus far. In particular, the citizenship results from Table 4, the large response of legal, permanent inflows from Table 5, and the realities of the U.S. immigration system described in Section 3 suggest that family sponsorship may play a crucial role in allowing immigration to serve as an ex-post response to natural disaster shocks in sending countries. Table 6 suggests that this is the case. More than a third of the network interaction effect detected for LPRs in Table 5 can be traced to parents, spouses, or children of U.S. citizens—classes of immigrants who are not subject to numerical limitations ($m_{jt}^{LPR,\text{immed}}$). We further find that among immigrants who are subject to numerical limitations, the network effect is especially salient for family-sponsored entrants ($m_{jt}^{LPR,\text{fam}}$).[33] Meanwhile, categories of entry that should not be affected by hurricanes in sending countries, such as refugees, employer-sponsored immigrants, or diversity lottery winners do not show the same heterogeneity with respect to migrant stocks.

5.3 Robustness and Mechanisms

The findings presented in Section 5 are consistent with immigrant stocks reducing the fixed cost of migration, allowing for a greater migratory response to hurricanes from source countries. There is, however, a concern of interpretation: the migrant stock could simply be correlated with omitted variables that are responsible for this observed heterogeneity. To gauge the robustness of our network-driven interpretation of the results to omitted variable concerns, we estimate regressions with the following specification

$$m_{jt} = \rho_0 + \rho_1 H_{jt} + \rho_2 (H_{jt} \times s_{j,1980}) + \rho_3 (H_{jt} \times c_j) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \qquad (8)$$

This estimating equation is a modifies of our main specification, (4), by adding an additional set of interaction terms with time-invariant control variables c_j.[34]

[33] Note that this data is only available starting in 1992.

[34] We also include interaction terms with $c_j^{missing}$, dummy variables that account for some of these variables being unavailable for certain countries. When a variable is missing for a certain country, $c_j^{missing} = 1$ (and is 0 otherwise). When $c_j^{missing} = 1$, we replace the missing value of c_j with 0. The coefficient on the interaction term with $c_j^{missing}$ then represents heterogeneity in the responsiveness to hurricanes among all countries for which that variable is missing. Note the vector of main effects are not included in the regression because they are absorbed by the country fixed effects.

Control variables c_j include a range of potential omitted variables. For example, $s_{j,1980}$ may proxy for sending country incomes (log real 1980 GDP per capita). Countries with higher incomes may be expected to both have higher $s_{j,1980}$ and more responsiveness to hurricanes if income makes credit constraints less binding for paying migration fixed costs. Financial development, measured by domestic credit as a proportion of GDP, may play a similar role. Migrant stocks may also proxy for distance to the U.S., with closer countries having both a higher $s_{j,1980}$ and lower migration fixed costs. We may expect that immigrant communities that are more concentrated geographically (say in migrant enclaves) may be better able to facilitate new immigration, perhaps due to closer social network connections. We thus include a measure of within-U.S. geographic concentration of immigrant stocks in 1980, $HHI_{j,1980}$. Larger countries, either in population or area, may naturally offer more opportunities for internal migration, thus creating lower $s_{j,1980}$'s and lower responsiveness to hurricanes. Similarly, countries that have more alternate international migration destinations, such as those connected to popular destinations in Europe, may feature lower stocks and lower responsiveness, so we utilize a measure of 1990 immigrant stocks in non-U.S. destinations as a control variable.

Online Appendix Section D details the construction of each of these variables. Here, we focus on Table 7, which displays the results of estimating Equation (8) with each individual control variable as well as with the complete set. The estimated coefficient $\hat{\rho}_2$ remains remarkably stable, and statistically significant, in each regression. There appears to be a robust effect of the stock of immigrants itself, as opposed to the many factors it may additionally proxy for.

6 Conclusion

We examine how international migration responds to changes in the returns to migration, and how this response depends on the costs or barriers that migrants face in moving. We examine this question in the context of a quarter-century of migration to the U.S., the world's largest migration destination, from virtually all other origin locations worldwide. In our analysis, we exploit the occurrence of hurricanes, which exogenously increase the returns to migration by making origin areas less attractive, and ask whether the migration response to hurricanes depends on the size of prior migrant stocks from the same country. Our migration outcomes are unusually precise, measured either from from restricted-access, full-count responses to the U.S. Census or actual legal immigration counts from U.S. government administrative data. We find that, on average, countries more affected by hurricanes see more migration to the U.S. as a result. This migration response is indeed larger (as a share of origin-country population) among countries with larger stocks of prior U.S. migrants. This effect can be fully explained by observed increases in legal, permanent immigration. A key role played by previous migrant networks appears to be sponsoring relatives for legal immigration.

This study is among the first testing a basic prediction of models of migration that derive from Sjaastad (1962): that migration will increase more in response to an increase in the return to migration when the costs of or barriers to migration are lower. They are also of substantial policy interest. Immigration has long been one of the most contentious issues in the public realm, and the policy debate should be informed by a better understanding of how and when shocks in migrant-origin countries will actually lead to increased migration.

Our findings are also relevant for understanding the economic impacts of natural disasters and the ways in which affected populations cope in their aftermath. Disasters cause extensive human losses and economic damages worldwide. Hurricanes are among the most damaging, accounting for roughly 40 percent of deaths and 38 percent of monetary damages caused by all natural disasters from 1995 through 2015 (CRED Centre for Research on the Epidemiology of Disasters). With climate change, hurricanes are expected to become more intense (Emanuel, 2005). Our results highlight a previously under-emphasized role of immigration policy: it affects the ability of disaster victims to cope with negative shocks by migrating. The ability of disaster victims worldwide to seek safe haven in the U.S. is highly determined by U.S. family reunification immigration policies and the presence in the U.S. of compatriot communities who can take advantage of those policies.

References

Abarcar, Paolo, "The Return Motivations of Legal Permanent Migrants: Evidence from Exchange Rate Shocks and Immigrants in Australia," 2017.

Abel, Guy J and Nikola Sander, "Quantifying global international migration flows," *Science*, 2014, *343* (6178), 1520–1522.

Abramitzky, Ran, Leah Platt Boustan, and Katherine Eriksson, "Europe's tired, poor, huddled masses: Self-selection and economic outcomes in the age of mass migration," *The American Economic Review*, 2012, *102* (5), 1832–1856.

Adams, Richard H and Alfredo Cuecuecha, "Remittances, household expenditure and investment in Guatemala," *World Development*, 2010, *38* (11), 1626–1641.

Akee, Randall, "Who leaves? Deciphering immigrant self-selection from a developing country," *Economic Development and Cultural Change*, 2010, *58* (2), 323–344.

Ambler, K., D. Aycinena, and D. Yang, "Channeling Remittances to Education: A Field Experiment among Migrants from El Salvador," *Amer. Econ. J.: App. Econ.*, 2015, *7* (2), 207–232.

Amuedo-Dorantes, Catalina and Kusum Mundra, "Social networks and their impact on the earnings of Mexican migrants," *Demography*, 2007, *44* (4), 849–863.

Angelucci, Manuela, "Migration and financial constraints: Evidence from Mexico," *Review of Economics and Statistics*, 2015, *97* (1), 224–228.

Ardington, Cally, Anne Case, and Victoria Hosegood, "Labor supply responses to large social transfers: Longitudinal evidence from South Africa," *American Economic Journal: Applied Economics*, 2009, *1* (1), 22–48.

Auffret, Philippe, *High Consumption Volatility: The Impact of Natural Disasters?*, The World Bank, 2003.

Avakov, Alexander V., *Two Thousand Years of Economic Statistics, Years 1–2012*, Algora Publishing, 2015.

Baez, Javier, German Caruso, Valerie Mueller, and Chiyu Niu, "Droughts augment youth migration in Northern Latin America and the Caribbean," *Climatic Change*, 2017, *140* (3), 423–435.

Bauer, Thomas, Barbara Dietz, Klaus F Zimmermann, and Eric Zwintz, "German migration: Development, assimilation, and labour market effects," *European Migration: What Do We Know?*, 2005, pp. 197–261.

Bazzi, Samuel, "Wealth Heterogeneity and the Income Elasticity of Migration," *American Economic Journal: Applied Economics*, 2017.

Beaman, Lori A, "Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the US," *The Review of Economic Studies*, 2012, *79* (1), 128–161.

Beine, Michel, Frédéric Docquier, and Hillel Rapoport, "Brain drain and economic growth: theory and evidence," *Journal of Development Economics*, 2001, *64* (1), 275–289.

_ , Frederic Docquier, and Hillel Rapoport, "Brain drain and human capital formation in developing countries: winners and losers," *The Economic Journal*, 2008, *118* (528), 631–652.

Belot, Michèle VK and Timothy J Hatton, "Immigrant Selection in the OECD," *The Scandinavian Journal of Economics*, 2012, *114* (4), 1105–1128.

Bertoli, Simone and Hillel Rapoport, "Heaven's Swing Door: Endogenous Skills, Migration Networks, and the Effectiveness of Quality-Selective Immigration Policies," *The Scandinavian Journal of Economics*, 2015, *117* (2), 565–591.

_ , Jesús Fernández-Huertas Moraga, and Francesc Ortega, "Crossing the border: Self-selection, earnings and individual migration decisions," *Journal of Development Economics*, 2013, *101*, 75–91.

_ , Jesús Fernández-Huertas Moraga, and Sekou Keita, "The Elasticity of the Migrant Labour Supply: Evidence from Temporary Filipino Migrants," *The Journal of Development Studies*, 2016, pp. 1–13.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How Much Should We Trust Difference-in-Difference Estimates?," *Quarterly Journal of Economics*, 2004, *119* (1).

Blumenstock, Joshua E., Nathan Eagle, and Marcel Fafchamps, "Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters," *Journal of Development Economics*, 2016, *120*, 157 – 181.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M Hsiang, "Nonlinear permanent migration response to climatic variations but minimal response to disasters," *Proceedings of the National Academy of Sciences*, 2014, *111* (27), 9780–9785.

Borjas, George J, "Self-Selection and the Earnings of Immigrants," *The American Economic Review*, 1987, *77* (4), pp. 531–553.

_ , "Immigration and self-selection," in "Immigration, Trade, and the Labor Market," University of Chicago Press, 1991, pp. 29–76.

Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak, "Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh," *Econometrica*, 2014, *82* (5), 1671–1748.

Cai, Jing, Alain de Janvry, and Elisabeth Sadoulet, "Social Networks and the Decision to Insure," *American Economic Journal: Applied Economics*, April 2015, *7* (2), 81–108.

Carrington, William J, Enrica Detragiache, and Tara Vishwanath, "Migration with endogenous moving costs," *The American Economic Review*, 1996, pp. 909–930.

Caruso, Germán and Sebastian Miller, "Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 Ancash Earthquake," *Journal of Development Economics*, 2015, *117*, 134–150.

Chiquiar, Daniel and Gordon H Hanson, "International migration, self-selection, and the distribution of wages: Evidence from Mexico and the United States," *Journal of Political Economy*, 2005, *113* (2), 239–281.

Chiswick, Barry R, "Are immigrants favorably self-selected?," *The American Economic Review*, 1999, *89* (2), 181–185.

Clark, Ximena, Timothy J. Hatton, and Jeffrey G. Williamson, "Explaining U.S. Immigration, 1971-1998," *The Review of Economics and Statistics*, 2007, *89* (2), pp. 359–373.

Clemens, Michael A, "Economics and Emigration: Trillion-Dollar Bills on the Sidewalk?," *The Journal of Economic Perspectives*, 2011, *25* (3), pp. 83–106.

_ , "Does development reduce migration?," in "International Handbook on Migration and Economic Development" Chapters, Edward Elgar Publishing, 2014, chapter 6, pp. 152–185.

— , "Violence, Development, and Migration Waves: Evidence from Central American Child Migrant Apprehensions," Technical Report, Center for Global Development 2017. Working Paper 459.

— **and Erwin R Tiongson**, "Split Decisions: Household Finance When a Policy Discontinuity Allocates Overseas Work," *The Review of Economics and Statistics*, 2017, *99* (3), 531–543.

— **, Claudio E Montenegro, and Lant Pritchett**, "Bounding the price equivalent of migration barriers," 2016.

Coffman, Makena and Ilan Noy, "Hurricane Iniki: measuring the long-term economic impact of a natural disaster using synthetic control," *Environment and Development Economics*, 2012, *17* (02), 187–205.

Collins, William J., "When the Tide Turned: Immigration and the Delay of the Great Black Migration," *The Journal of Economic History*, 1997.

— **and Marianne H. Wanamaker**, "The Great Migration in Black and White: New Evidence on the Selection and Sorting of Southern Migrants," *The Journal of Economic History*, 2015.

Comola, Margherita and Mariapia Mendola, "Formation of Migrant Networks," *The Scandinavian Journal of Economics*, 2015.

CRED (Centre for Research on the Epidemiology of Disasters), "The Human Cost of Weather Related Disasters: 1995-2015," 2016.

Department of Homeland Security, "2004 Yearbook of Immigration Statistics," 2006.

Dilley, Maxx, Robert S. Chen, and Uwe Deichmann, *Natural Disaster Hotspots: A Global Risk Analysis*, With Jonathan Agwe et al. Disaster Risk Management Series, vol. 5. Washington, D.C.: World Bank, D 2005.

Docquier, Frédéric, Giovanni Peri, and Ilse Ruyssen, "The Cross-country Determinants of Potential and Actual Migration," *International Migration Review*, 2014, *48* (s1), S37–S99.

Dolfin, Sarah and Garance Genicot, "What do networks do? The role of networks on migration and coyote use," *Review of Development Economics*, 2010, *14* (2), 343–359.

Edwards, Alejandra Cox and Manuelita Ureta, “International migration, remittances, and schooling: evidence from El Salvador,” *Journal of Development Economics*, 2003, *72* (2), 429–461.

Emanuel, Kerry, “Increasing destructiveness of tropical cyclones over the past 30 years,” *Nature*, 2005.

Epstein, Gil S, “Herd and network effects in migration decision-making,” *Journal of Ethnic and Migration Studies*, 2008, *34* (4), 567–583.

Feenstra, Robert C., James R. Markusen, and Andrew K. Rose, “Using the gravity equation to differentiate among alternative theories of trade,” *Canadian Journal of Economics*, May 2001, *34* (2), 430–447.

Feliciano, Cynthia, “Educational selectivity in US immigration: How do immigrants compare to those left behind?,” *Demography*, 2005, *42* (1), 131–152.

Foster, A. and M. Rosenzweig, “Imperfect Commitment, Altruism, and the Family: Evidence from Transfer Behavior in Low-Income Rural Areas,” *Rev. Econ. Stat.*, 2001, *83* (3), 389–407.

Franklin, Simon and Julien Labonne, “Economic Shocks and Labour Market Flexibility,” 2017.

Gathmann, Christina, “Effects of enforcement on illegal markets: Evidence from migrant smuggling along the southwestern border,” *Journal of Public Economics*, 2008, *92* (10), 1926–1941.

Gibson, John, David McKenzie, and Halahingano Rohorua, “Development impacts of seasonal and temporary migration: A review of evidence from the Pacific and Southeast Asia,” *Asia & the Pacific Policy Studies*, 2014, *1* (1), 18–32.

Greenwood, Michael J, “Human migration: Theory, models, and empirical studies,” *Journal of Regional Science*, 1985, *25* (4), 521–544.

Gröger, André and Yanos Zylberberg, “Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon,” *American Economic Journal: Applied Economics*, 2016, *8* (2), 123–153.

Grogger, Jeffrey and Gordon H Hanson, “Income maximization and the selection and sorting of international migrants,” *Journal of Development Economics*, 2011, *95* (1), 42–57.

Halliday, Timothy, "Migration, risk, and liquidity constraints in El Salvador," *Economic Development and Cultural Change*, 2006, *54* (4), 893–925.

Hanson, Gordon H. and Antonio Spilimbergo, "Illegal Immigration, Border Enforcement, and Relative Wages: Evidence from Apprehensions at the U.S.-Mexico Border," *American Economic Review*, December 1999, *89* (5), 1337–1357.

Hanson, Gordon H and Craig McIntosh, "Birth rates and border crossings: Latin American migration to the US, Canada, Spain and the UK," *The Economic Journal*, 2012, *122* (561), 707–726.

Hatton, Timothy J and Jeffery G Williamson, "International migration and world development: a historical perspective," in "Economic aspects of international migration," Springer, 1994, pp. 3–56.

Hatton, Timothy J. and Jeffrey G. Williamson, "After the Famine: Emigration from Ireland, 1850-1913," *The Journal of Economic History*, 1993.

Hatton, Timothy J and Jeffrey G Williamson, *The age of mass migration: Causes and economic impact*, Oxford University Press on Demand, 1998.

Hornbeck, Richard, "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe," *American Economic Review*, June 2012, *102* (4), 1477–1507.

Hsiang, Solomon M., "Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America," *Proceedings of the National Academy of Sciences*, 2010, *107* (35).

_ **and Amir S. Jina**, "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones," *NBER Working Paper Series*, 2014, (20352).

Ibarraran, Pablo and Darren Lubotsky, "Mexican immigration and self-selection: New evidence from the 2000 Mexican census," in "Mexican Immigration to the United States" University of Chicago Press 2007, pp. 159–192.

Imberman, Scott A., Adriana D. Kugler, and Bruce I. Sacerdote, "Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees," *American Economic Review*, May 2012, *102* (5), 2048–82.

Iregui, Ana Maria, "Efficiency Gains from the Elimination of Global Restrictions on Labour Mobility," in George J. Borjas and Jeff Crisp, eds., *Poverty, International Migration and Asylum*, Palgrave Macmillan, 2005, pp. 211–238.

Jack, W. and T. Suri, "Risk Sharing and Transaction Costs: Evidence from Kenya's Mobile Money Revolution," *Amer. Econ. Rev.*, 2013, *104* (1), 183–223.

Jasso, Guillermina and Mark R Rosenzweig, "Sponsors, sponsorship rates and the immigration multiplier," *International Migration Review*, 1989, pp. 856–888.

Jayachandran, Seema, "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, 2006, *114* (3), 538–575.

Jr, Richard H Adams and Alfredo Cuecuecha, "The economic impact of international remittances on poverty and household consumption and investment in Indonesia," 2010.

Kanbur, Ravi and Hillel Rapoport, "Migration selectivity and the evolution of spatial inequality," *Journal of Economic Geography*, 2005, *5* (1), 43–57.

Kandel, William A., "U.S. Family-Based Immigration Policy," Technical Report, Congressional Research Service 2016.

Kennan, John and James R. Walker, "The Effect of Expected Income on Individual Migration Decisions," *Econometrica*, 2011.

Kleemans, Marieke and Jeremy Magruder, "Labor Market Changes in Response to Immigration: Evidence from Internal Migration Driven by Weather Shocks," *The Economic Journal*, forth.

Klein, Paul and Gustavo Ventura, "TFP Differences and the Aggregate Effects of Labor Mobility in the Long Run," *The B.E. Journal of Macroeconomics*, 2007, *7* (1).

Kosec, Katrina, Valerie Mueller, and Joyce Chen, "Temporary and permanent migrant selection: Theory and evidence of ability-search cost dynamics," 2015.

Ligon, E., J. Thomas, and T. Worall, "Informal Insurance Arrangements with Limited Commitment: Theory and Evidence from Village Economies," *Rev. Econ. Stud.*, 2002, *69* (1), 209–244.

Lucas, Robert EB and Oded Stark, "Motivations to remit: Evidence from Botswana," *Journal of Political Economy*, 1985, *93* (5), 901–918.

Marchiori, Luca, Jean-Francois Maystadt, and Ingmar Schumacher, "The Impact of Weather Anomalies on Migration in sub-Saharan Africa," *Journal of Environmental Economics and Management*, 2012.

Massey, Douglas S, "Economic development and international migration in comparative perspective," *The Population and Development Review*, 1988, pp. 383–413.

_ , Luin Goldring, and Jorge Durand, "Continuities in transnational migration: An analysis of nineteen Mexican communities," *American Journal of Sociology*, 1994, *99* (6), 1492–1533.

Mayda, Anna Maria, "International migration: A panel data analysis of the determinants of bilateral flows," *Journal of Population Economics*, 2010, *23* (4), 1249–1274.

McKenzie, David and Hillel Rapoport, "Self-selection patterns in Mexico-US migration: the role of migration networks," *The Review of Economics and Statistics*, 2010, *92* (4), 811–821.

_ , Caroline Theoharides, and Dean Yang, "Distortions in the international migrant labor market: evidence from Filipino migration and wage responses to destination country economic shocks," *American Economic Journal: Applied Economics*, 2014, *6* (2), 49–75.

_ , Steven Stillman, and John Gibson, "How important is selection? experimental vs. non-experimental measures of the income gains from migration," *Journal of the European Economic Association*, 2010, *8* (4), 913–945.

Missirian, Anouch and Wolfram Schlenker, "Asylum Applications and Migration Flows," *American Economic Review*, May 2017, *107* (5), 436–40.

Morduch, Jonathan, "Risk, Production, and Saving: Theory and Evidence from Indian Households." PhD dissertation, Harvard University 1993.

Morten, Melanie, "Temporary migration and endogenous risk sharing in village india," Technical Report, National Bureau of Economic Research 2016.

Moses, Jonathon W. and Bjorn Letnes, "The Economic Costs to International Labor Restrictions: Revisiting the Empirical Discussion," *World Development*, 2004.

_ **and** _ , "If People Were Money: Estimating the Gains and Scope of Free Migration," in George J. Borjas and Jeff Crisp, eds., *Poverty, International Migration and Asylum*, Palgrave Macmillan, 2005, pp. 188–210.

Munshi, Kaivan, "Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market," *The Quarterly Journal of Economics*, 2003, *118* (2), pp. 549–599.

Noy, Ilan, "The macroeconomic consequences of disasters," *Journal of Development Economics*, 2009, *88* (2), 221–231.

Orrenius, Pia M, "The Role of Family Networks, Coyote Prices and the Rural Economy in Migration from Western Mexico," *Federal Reserve Bank of Dallas Research Paper*, 1999, (99-10), 2–11.

_ **and Madeline Zavodny**, "Self-selection among undocumented immigrants from Mexico," *Journal of Development Economics*, 2005, *78* (1), 215–240.

Ortega, Francesc and Giovanni Peri, "The effect of income and immigration policies on international migration," *Migration Studies*, 2013, *1* (1), 47–74.

Ouattara, B. and E. Strobl, "Hurricane Strikes and Local Migration in US Coastal Counties," *Economics Letters*, 07 2014, *124* (1), 17–20.

Passel, Jeffrey S. and Roberto Suro, "Rise, Peak, and Decline: Trends in U.S. Immigration 1992-1994," Technical Report, Pew Hispanic Center 2005.

Pedersen, Peder J, Mariola Pytlikova, and Nina Smith, "Selection and network effects–Migration flows into OECD countries 1990–2000," *European Economic Review*, 2008, *52* (7), 1160–1186.

Pelham, Brett and Gerver Torres, "One-Quarter of the World's Population May Wish to Migrate," Technical Report, Gallup 2008.

Rasmussen, Tobias N., "Macroeconomic Implications of Natural Disasters in the Caribbean," IMF Working Papers 04/224 December 2004.

Redstone, Ilana and Douglas S. Massey, "Coming to Stay: An Analysis of the U.S. Census Question on Immigrants' Year of Arrival," *Demography*, 2004, *41* (4), pp. 721–738.

Rosenzweig, M. and K. Wolpin, "Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Assets in Low-Income Countries: Investments in Bullocks in India," *J. Polit. Econ.*, April 1993, *101* (2), 223–244.

Rosenzweig, Mark and Oded Stark, "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India," *Journal of Political Economy*, 1989, *97* (4), 905–926.

Roy, Andrew Donald, "Some thoughts on the distribution of earnings," *Oxford Economic Papers*, 1951, *3* (2), 135–146.

Sjaastad, Larry A, "The costs and returns of human migration," *Journal of Political Economy*, 1962, *70* (5, Part 2), 80–93.

Stark, Oded, *The migration of labor*, Basil Blackwell, 1991.

_ **and David Levhari**, "On Migration and Risk in LDCs," *Economic Development and Cultural Change*, 1982, *31* (1), 191–96.

Stecklov, Guy, Paul Winters, Marco Stampini, and Benjamin Davis, "Do conditional cash transfers influence migration? A study using experimental data from the Mexican progresa program," *Demography*, 2005, *42* (4), 769–790.

Strobl, Eric, "The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties," *Review of Economics and Statistics*, 05 2011, *93* (2), 575–589.

_ **and Frank Walsh**, "The Re-Building Effect of Hurricanes: Evidence from Employment in the US Construction Industry," *Economics Bulletin*, 2009, *29* (4), 3059–3066.

Taylor, J Edward, "Undocumented Mexico–US migration and the returns to households in rural Mexico," *American Journal of Agricultural Economics*, 1987, *69* (3), 626–638.

Theoharides, Caroline, "Manila to Malaysia, Quezon to Qatar: International Migration and the Effects on Origin-Country Human Capital," 2016.

Townsend, R., "Risk and Insurance in Village India," *Econometrica*, May 1994, *62* (3), 539–591.

Udry, C., "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria," *Rev. Econ. Stud.*, 1994, *61* (3), 495–526.

van der Mensbrugghe, Dominique and David Roland-Holst, "Global Economic Prospects for Increasing Developing-Country Migration into Developed Countries," *United Nations Development Programme Human Development Research Paper*, 2009, (50).

Walmsley, Terrie L. and L. Alan Winters, "Relaxing the Restrictions on the Temporary Movement of Natural Persons: A Simulation Analysis," *Journal of Economic Integration*, 2005, *20* (4), pp. 688–726.

Weerdt, Joachim De and Kalle Hirvonen, "Risk Sharing and Internal Migration," *Economic Development and Cultural Change*, 2016.

Winters, Paul, Alain De Janvry, and Elisabeth Sadoulet, "Family and community networks in Mexico-US migration," *Journal of Human Resources*, 2001, pp. 159–184.

Woodruff, Christopher and Rene Zenteno, "Migration networks and microenterprises in Mexico," *Journal of Development Economics*, 2007, *82* (2), 509–528.

World Bank Group, "Migration and Remittances: Recent Developments and Outlook," World Bank Group Migration and Development Brief 26 2016.

Wozniak, Abigail, "Are College Graduates More Responsive to Distant Labor Market Opportunities?," *Journal of Human Resources*, 2010, *45* (3), 944–970.

Yang, Dean, "Why do migrants return to poor countries? Evidence from Philippine migrants' responses to exchange rate shocks," *The Review of Economics and Statistics*, 2006, *88* (4), 715–735.

_ , "Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002," *B.E. Journal of Economic Analysis and Policy (Advances)*, 2008, *8* (1).

_ , "International Migration, Remittances and Household Investment: Evidence from Philippine Migrants' Exchange Rate Shocks," *The Economic Journal*, 2008, *118* (528), 591–630.

_ , "Risk, migration, and rural financial markets: Evidence from earthquakes in El Salvador," *Social Research*, 2008, pp. 955–992.

_ **and Claudia Martinez**, "Remittances and poverty in migrants' home areas: Evidence from the Philippines," *International Migration, Remittances and the Brain Drain Washington DC: World Bank*, 2006, pp. 81–121.

_ **and HwaJung Choi**, "Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines," *World Bank Econ. Rev.*, 2007, *21* (2), 219–248.

Zavodny, Madeline, "Welfare and the locational choices of new immigrants," *Economic Review-Federal Reserve Bank of Dallas*, 1997, p. 2.

Tables and Figures

Figure 1: The Effect of Negative Income Shocks on Migration Probability

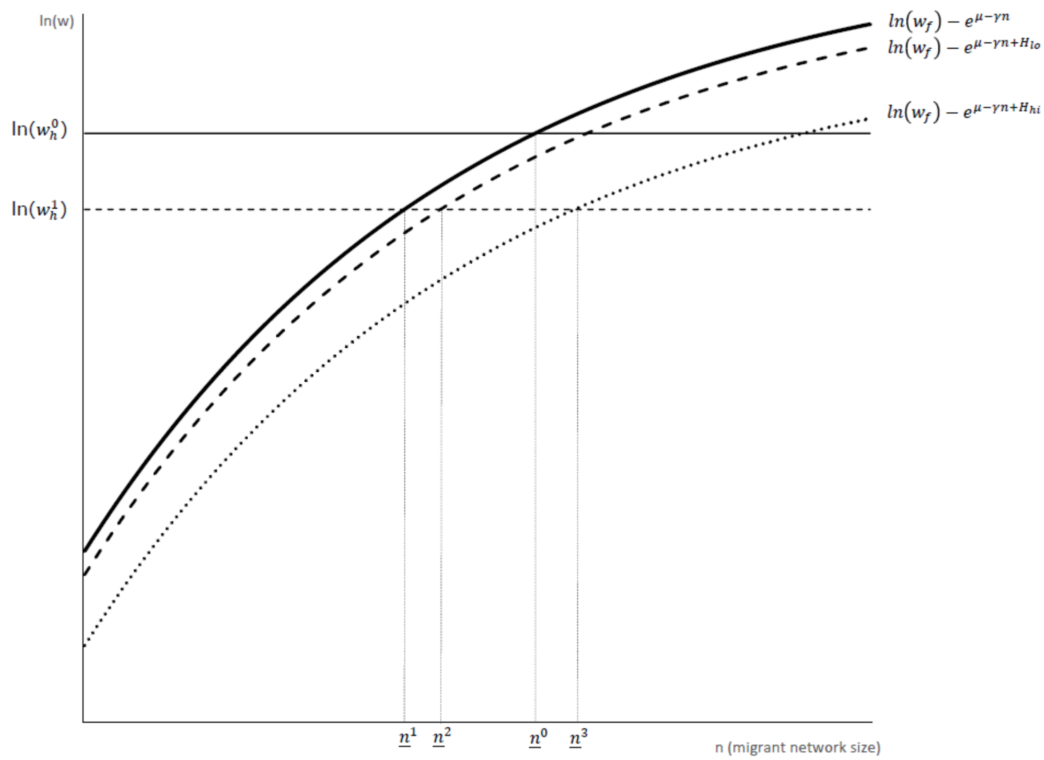
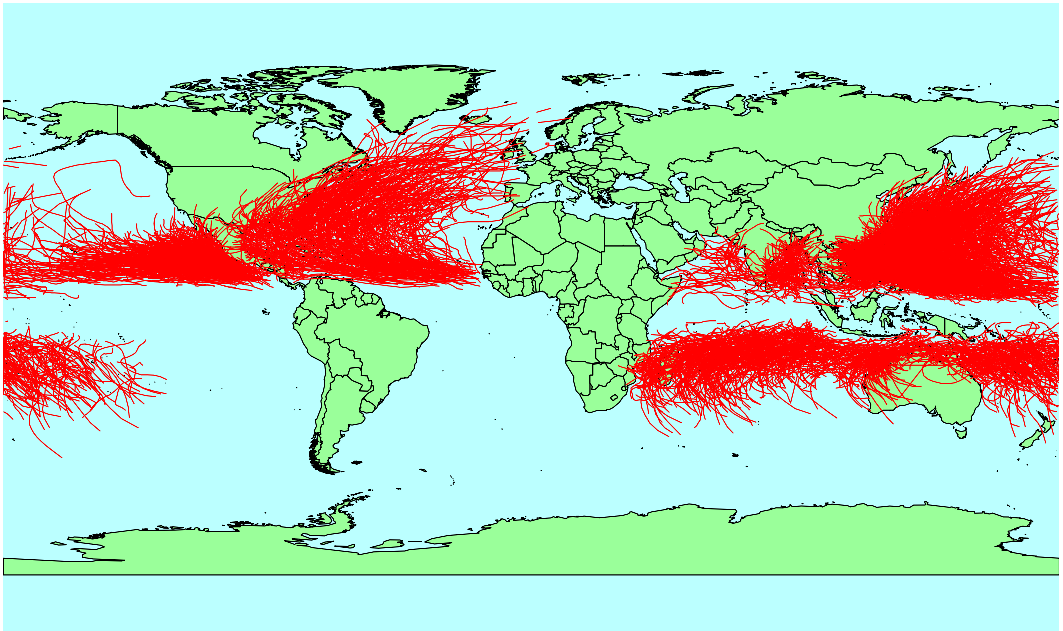
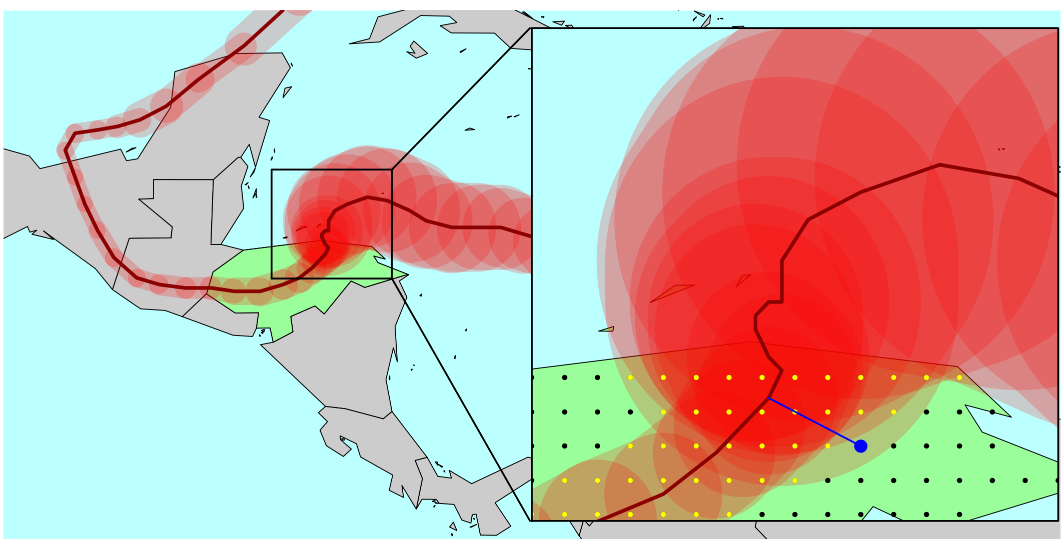


Figure 2: Hurricane Best Tracks: 1980-2004



Source: Unisys Weather data (http://weather.unisys.com/hurricane/) processed in R.

Figure 3: Hurricane Mitch over Honduras



Source: Unisys Weather data (http://weather.unisys.com/hurricane/) processed in R.

Table 1: Summary Statistics

	Mean	Std. Dev.	Percentile					N	Source
			10	25	50	75	90		
Hurricane Index (H_{jt})	0.00392	0.02288	0	0	0	0	0.00064	3,895	Unisys
Hurricane Index ((H_{jt} >0)	0.02385	0.05204	0.00001	0.00014	0.00190	0.01903	0.07686	641	Unisys
1980 Population	21,617,238	96,381,174	43,388	238,299	2,923,111	11,095,449	38,124,000	159	UN, Census IDB
As a Proportion of 1980 Population:									
Annual Migrants (m_{jt})	0.00176	0.00287	0.00004	0.00010	0.00038	0.00199	0.00597	2,150	Census IPUMS
Annual Immigrants (m_{jt}^{LPR})	0.00144	0.00340	0.00001	0.00005	0.00022	0.00125	0.00456	2,573	DHS
Annual Non-Immigrant Entries ($m_{jt}^{\text{non-imm}}$)	0.06108	0.22277	0.00019	0.00059	0.00413	0.02086	0.10580	2,200	DHS
Annual Immediate Family Immigrants ($m_{jt}^{LPR,\text{immed}}$)	0.00051	0.00109	0	0.00002	0.00009	0.00046	0.00174	2,573	DHS
Annual Family-Sponsored Immigrants ($m_{jt}^{LPR,\text{fam}}$)	0.00047	0.00138	0	0	0.00003	0.00030	0.00147	1,476	DHS
1980 Stock of Immigrants ($s_{j,1980}$)	0.0150	0.0272	0.00019	0.00038	0.00248	0.01452	0.05618	142	Census IPUMS
1980 Stock of Citizen Immigrants ($s_{j,1980}^{\text{citizen}}$)	0.0058	0.0118	0.00004	0.00009	0.00068	0.00393	0.02005	142	Census IPUMS
1980 Stock of Non-Citizen Immigrants ($s_{j,1980}^{\text{non-cit}}$)	0.0093	0.0161	0.00012	0.00023	0.00163	0.00960	0.03025	142	Census IPUMS

Notes: All statistics constructed using publicly-available data to avoid confidentiality issues, which explains the loss in sample size when the source is "Census IPUMS." See Section A of the Online Appendix for details on creation of hurricane index. The second row shows summary statistics for the hurricane index conditional on it being greater than zero. "Immediate Family" refers to parents, children, or spouses of U.S. citizens—these admissions are uncapped. "Family-Sponsored" immigrants are those whose admissions are capped, but who enter through family sponsorship. Census data obtained from IPUMS-USA (https://usa.ipums.org/usa/acs.shtml). DHS data obtained from electronic copies of the *Yearbook of Immigration Statistics* (1996-2004) and *Statistical Yearboook of the Immigration and Naturalization Service* (prior to 1996). UN data obtained from the United Nations Statistics Division (https://unstats.un.org/). Census IDB data obtained from the Census Bureau's International Data Base (https://www.census.gov/population/international/data/idb).

Table 2: The Effect of Hurricanes on Migration, 1980-2004

Outcome:	m_{jt}	m_{jt}
HI_{jt}	0.0040**	-0.001
	(0.0020)	(0.0010)
$HI_{jt} \times s_{j,1980}$		0.1163**
		(0.0451)
Country-Years	3,900	3,900
R^2	0.4319	0.4409
Countries	159	159

Notes: Each column refers to an OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). HI_{jt} refers to the hurricane index for country j in year t. $s_{j,1980}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. m_{jt} refers to the estimated immigrant inflows to the U.S. from country j in year t. $s_{j,1980}$ and m_{jt} are constructed using restricted-access data from the Census Bureau's Research Data Center. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 3: The Effect of Hurricanes on Migration by Age Group, 1980-2004

	Age group of m_{jt}											
	0 to 12	0 to 12	13 to 17	13 to 17	18 to 24	18 to 24	25 to 44	25 to 44	45 to 64	45 to 64	65 and older	65 and older
HI_{jt}	0.0014*	-0.0007*	0.0006	0.0004	0.0009	-0.0005	0.001	-0.0004	0.0002	0.0006	-0.0001	-0.0005
	(0.0007)	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0003)	(0.0007)	(0.0004)	(0.0004)	(0.0006)	(0.0002)	(0.0004)
$HI_{jt} \times s_{j,1980}$		0.0481***		0.0057		0.0329*		0.0306**		-0.0083		0.0072
		(0.0138)		(0.0076)		(0.0185)		(0.0150)		(0.0076)		(0.0047)
Country-Years	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900
R^2	0.2293	0.2461	0.1794	0.1798	0.2953	0.3010	0.3123	0.3155	0.1884	0.1906	0.1359	0.1403
Countries	159	159	159	159	159	159	159	159	159	159	159	159

Notes: Each column refers to an OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). HI_{jt} refers to the hurricane index for country j in year t. $s_{j,1980}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. m_{jt} refers to the estimated immigrant inflows to the U.S. from country j in year t. $s_{j,1980}$ and m_{jt} are constructed using restricted-access data from the Census Bureau's Research Data Center. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 4: The Effect of Hurricanes on Migration by Citizenship of Stock, 1980-2004

Outcome:	m_{jt}	m_{jt}
HI_{jt}	-0.001	-0.0005
	(0.0010)	(0.0009)
$HI_{jt} \times s_{j,1980}$	0.1163**	
	(0.0451)	
$HI_{jt} \times s^{citizen}_{j,1980}$		0.4044*
		(0.2245)
$HI_{jt} \times s^{\text{non-cit}}_{j,1980}$		-0.1444
		(0.1661)
Country-Years	3,900	3,900
R^2	0.4409	0.4429
Countries	159	159
p-value: $\pi_2 = \pi_3$		0.154

Notes: Each column refers to an OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (4) and (5). HI_{jt} refers to the hurricane index for country j in year t. $s_{j,1980}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. m_{jt} refers to the estimated immigrant inflows to the U.S. from country j in year t. $s_{j,1980}$ and m_{jt} are constructed using restricted-access data from the Census Bureau's Research Data Center. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 5: The Effect of Hurricanes on Migration—Comparing Census and DHS Data

Inflow Type:	Census		DHS LPR		DHS non-imm.	
Years:	1980 to 2004		1982 to 2004		1983 to 2004	
Outcome:	m_{jt}	m_{jt}	m^{LPR}_{jt}	m^{LPR}_{jt}	$m^{\text{non-imm}}_{jt}$	$m^{\text{non-imm}}_{jt}$
$HI_{j,t,t-1}$	0.0046**	-0.0012	0.0023	-0.0035	0.2193***	-0.0627
	(0.0021)	(0.0016)	(0.0040)	(0.0039)	(0.0788)	(0.0689)
$HI_{j,t,t-1} \times s_{j,1980}$		0.1235***		0.1266***		5.7883**
		(0.0427)		(0.0402)		(2.3536)
Prop. of Census Inflows		1		2.47		50.51
Country-Years	3,800	3,800	2,600	2,600	2,200	2,200
R^2	0.4426	0.4475	0.2954	0.2966	0.4485	0.4495
Countries	156	156	156	156	156	156

Notes: Each column within a panel refers to an OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). Outcomes in columns 3-6 obtained from electronic copies of the *Yearbook of Immigration Statistics* (1996-2004) and *Statistical Yearboook of the Immigration and Naturalization Service* (prior to 1996). HI_{jt} refers to the hurricane index for country j in year t. $HI_{j,t,t-1}$ is the moving average of the hurricane index in year t and year $t-1$ for country j. See Section B of the Online Appendix for details of construction. LPR: legal permanent resident; "non-imm:" non-immigrant. "Prop. of Census Inflows" calculated by multiplying the estimated coefficients by each country's specific $HI_{j,t,t-1}$ in a given year and $s_{j,1980}$, summing them across country-years, then dividing by the same calculation made using the results from the second "Census" column. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 6: The Effect of Hurricanes on LPR Entries—DHS Data

		Immediate Relatives of U.S. Citizen (Uncapped)					Capped		
Type of LPR Admission:	Total	Parents	Spouses	Children	Parents, Spouses, and Children	Refugee	Family Sponsored	Employer Sponsored	Diversity Lottery
$HI_{j,t,t-1}$	-0.0035	-0.0002	-0.0007	-0.0007	-0.0014	0.0003	-0.0019	0.0001	-0.0001
	(0.0039)	(0.0003)	(0.0006)	(0.0008)	(0.0014)	(0.0002)	(0.0029)	(0.0002)	(0.0003)
$HI_{j,t,t-1} \times s_{j,1980}$	0.1266***	0.0130*	0.0150**	0.0234	0.0457**	-0.0013	0.1630**	-0.0225***	-0.0005
	(0.0402)	(0.0069)	(0.0065)	(0.0167)	(0.0189)	(0.0027)	(0.0660)	(0.0054)	(0.0044)
Country-Years	2,600	2,600	2,600	2,600	2,600	2,600	1,500	1,500	1,500
R^2	0.2966	0.1609	0.197	0.12	0.1435	0.3309	0.1667	0.4223	0.4218
Years	1982 to 2004	1982 to 2004	1982 to 2004	1982 to 2004	1982 to 2004	1982 to 2004	1992 to 2004	1992 to 2004	1992 to 2004
Countries	156	156	156	156	156	156	156	156	156

Notes: Each column within a panel refers to an OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). Outcomes obtained from electronic copies of the *Yearbook of Immigration Statistics* (1996-2004) and *Statistical Yearboook of the Immigration and Naturalization Service* (prior to 1996). HI_{jt} refers to the hurricane index for country j in year t. $HI_{j,t,t-1}$ is the moving average of the hurricane index in year t and year $t-1$ for country j. See Section B of the Online Appendix for details of construction. LPR: legal permanent resident. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 7: Robustness

	m_{jt}	m_{jt}	m_{jt}	m_{jt}	m_{jt}	m_{jt}	m_{jt}	m_{jt}	m_{jt}	m_{jt}
HI_{jt}	-0.0010	-0.0018*	0.0124	0.0094	-0.0045	-0.0034	-0.0010	-0.0028	-0.0012	0.0541
	(0.0010)	(0.0010)	(0.0175)	(0.0064)	(0.0030)	(0.0034)	(0.0010)	(0.0021)	(0.0022)	(0.0334)
$HI_{jt} \times s_{j,1980}$	0.1163**	0.1199***	0.1213**	0.1001***	0.1249***	0.1175***	0.1159**	0.1291***	0.1032**	0.1094***
	(0.0451)	(0.0453)	(0.0494)	(0.0369)	(0.0462)	(0.0428)	(0.0451)	(0.0483)	(0.0399)	(0.0331)
$HI_{jt} \times HHI_{j,1980}$		0.3709								-0.0122
		(0.2488)								(0.0088)
$HI_{jt} \times \log(\text{Real GDP Per Capita})_{j,1980}$			-0.0015							-0.0049
			(0.0020)							(0.0033)
$HI_{jt} \times \log(\text{Population})_{j,1980}$				-0.0802						-0.1165
				(0.0517)						(0.0717)
$HI_{jt} \times [\text{Remittances as a Prop. of GDP}_{j,1980}]$					-0.0474					-0.2181**
					(0.0700)					(0.1040)
$HI_{jt} \times \mathbb{1}[\text{Missing: Remittances as a Prop. of GDP}_{j,1980}]$					0.0040					0.0034
					(0.0030)					(0.0043)
$HI_{jt} \times [\text{Domestic Credit as a Prop. of GDP}_{j,1980}]$						-0.0015				0.0026
						(0.0061)				(0.0088)
$HI_{jt} \times \mathbb{1}[\text{Missing: Domestic Credit as a Prop. of GDP}_{j,1980}]$						0.0038				0.0126**
						(0.0038)				(0.0064)
$HI_{jt} \times [\text{Land Area (mil. sq. km)}_{j,1980}]$							-0.0014			0.0102
							(0.0041)			(0.0080)
$HI_{jt} \times [\text{Distance to U.S. (mil. km)}_{j,1980}]$								0.1952		0.2579
								(0.1618)		(0.1686)
$HI_{jt} \times [\text{Prop. stock in non-U.S. destinations}_{j,1990}]$									0.0055	-0.0117
									(0.0068)	(0.0079)
$HI_{jt} \times \mathbb{1}[\text{Missing: Prop. stock in non-U.S. destinations}_{j,1990}]$									0.0004	-0.0122**
									(0.0029)	(0.0056)
Country-Years	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900
R^2	0.4409	0.4412	0.4413	0.4422	0.4423	0.4424	0.4409	0.4412	0.4412	0.4495
Countries	159	159	159	159	159	159	159	159	159	159

Notes: Each column within a panel refers to a different OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equation (8). Domestic Credit as Prop. of GDP and Remittances as a Prop. of GDP are averages of non-missing data from 1970 through 1980. HI_{jt} refers to the hurricane index for country j in year t. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

For Online Publication: Online Appendix

Table A1: List of Countries in Sample

Afghanistan	French Polynesia	Nigeria
Algeria	Gabon	Niue
Angola	Gambia	Oman
Anguilla	Ghana	Pakistan
Antigua & Barbuda	Grenada	Panama
Argentina	Guadeloupe	Papua New Guinea
Aruba	Guatemala	Paraguay
Australia	Guinea	Peru
Bahamas	Guinea-Bissau	Philippines
Bahrain	Guyana	Qatar
Bangladesh	Haiti	Reunion
Barbados	Honduras	Rwanda
Belize	Hong Kong	Samoa
Benin	India	Sao Tome & Principe
Bermuda	Indonesia	Saudi Arabia
Bhutan	Iran	Senegal
Bolivia	Iraq	Seychelles
Botswana	Israel	Sierra Leone
Brazil	Ivory Coast	Singapore
British Virgin Islands	Jamaica	Solomon Islands
Brunei	Japan	Somalia
Burkina Faso	Jordan	South Africa
Burma (Myanmar)	Kenya	South Korea
Burundi	Kiribati	Sri Lanka
Cambodia	Kuwait	St. Helena
Cameroon	Laos	St. Kitts-Nevis
Canada	Lebanon	St. Lucia
Cape Verde	Lesotho	St. Vincent & the Grenadines
Cayman Islands	Liberia	Sudan
Central African Republic	Libya	Suriname
Chad	Macau	Swaziland
Chile	Madagascar	Syria
China	Malawi	Taiwan
Colombia	Malaysia	Tanzania
Comoros	Maldives	Thailand
Congo	Mali	Togo
Cook Islands	Martinique	Tokelau
Costa Rica	Mauritania	Tonga
Cuba	Mauritius	Trinidad & Tobago
Cyprus	Mexico	Tunisia
Democratic Republic of Congo (Zaire)	Micronesia	Turkey
Djibouti	Mongolia	Turks & Caicos Islands
Dominica	Montserrat	Uganda
Dominican Republic	Morocco	United Arab Emirates
East Timor	Mozambique	Uruguay
Ecuador	Namibia	Vanuatu
Egypt	Nauru	Venezuela
El Salvador	Nepal	Vietnam
Equatorial Guinea	Netherlands Antilles	Wallis & Futuna Islands
Ethiopia	New Caledonia	Western Sahara
Falkland Islands	New Zealand	Yemen
Fiji	Nicaragua	Zambia
French Guiana	Niger	Zimbabwe

Notes: See Section 4 for details on sample selection.

A Construction of the Hurricane Index

The damage caused by hurricanes depends on the intensity of the hurricane (in particular, wind speed). In addition, hurricanes should cause more damage if they strike in more populated areas. An index H_{jt} for country j in year t that has these features is as follows:

$$H_{jt} = \frac{\sum_i \sum_s x_{isjt}}{N_{jt}}$$

where x_{isjt} is a measure of person i's "affectedness" by hurricane s in country j, year t. Affectedness is summed over hurricanes and over individuals, and then divided by total population N_{jt}.

We define a person's hurricane "affectedness" in a particular storm is a nonlinear function of the wind speed to which the individual was exposed.[35] There is no data source for individual-level hurricane affectedness (x_{isjt}), and so we approximate the numerator in the hurricane index H_{jt} by estimating wind speeds at evenly-spaced points on a country's land area, and combining this with population estimates at these points.

The first step in this process is the creation of a 0.25 by 0.25 degree grid of latitude and longitude points that fall inside large countries and 2.5 minute by 2.5 minute latitude and longitude points that fall inside small countries.[36] Then, we predict the wind speed of each hurricane segment (a connected set of points from the best tracks) using a model from Dilley et al. (2005):

$$pw_{gjst} = \mathbb{1}\{w_{gjst} > 33\}\left[33 + (w_{gjst} - 33)\left(1 - \frac{d_{gjst}}{prad_{gjst}}\right)\right] \tag{9}$$

Here, pw_{gjst} is the predicted wind speed (in knots) felt at grid point g in country j from storm s, w_{gjst} is the actual wind speed recorded at the beginning of the storm segment from the best track, d_{gjst} is the distance between the grid point and the storm segment, and $prad_{gjst}$ is the predicted radius of the hurricane segment, where we only calculate pw_{gjst} for grid points for which $d_{gjst} < prad_{gjst}$.[37]

As an example of a pw_{gjst} calculation, consider Figure 3, which shows both

[35] The pressure exerted by winds is commonly modeled in climatology as rising in the square of wind speed (Emanuel, 2005).

[36] "Large" countries are defined as those that have at least two 0.25 by 0.25 degree grid points, and "small" countries are defined as the converse of this large set of countries. Country delineations are provided by the `maptools` package in *R*.

[37] $prad_{gjst}$ is calculated based on a model of wind-speed decay given distance from the hurricane, as in Dilley et al. (2005).

the best track for Hurricane Mitch and its radius of hurricane-force winds. The black grid points are points in Honduras that did not experience hurricane-force winds, while the yellow grid points did experience such winds. Consider the grid point highlighted in blue, $g*$. We first calculate the shortest distance between this point and the nearest storm segment from the Hurricane Mitch best track, represented by the blue line from the point to the storm best track. This distance is $d_{g*,Honduras,Mitch,1998}$. Then, since this distance is less than the predicted radius ($prad_{g*,Honduras,Mitch,1998}$) of the closest storm segment—represented by the red width surrounding the storm best track—we proceed to calculating $pw_{g*,Honduras,Mitch,1998}$ using Equation (9), where wind speed also comes from this nearest storm segment.

The effect of hurricane s at grid point g in country j during year t is then:

$$x_{gjst} = \mathbb{1}\{pw_{gjst} > 33\}\left[\frac{(pw_{gjst} - 33)^2}{(w^{max} - 33)^2}\right]$$

where w^{max} is the maximum wind speed observed in the dataset (166.65 knots). Finally, to aggregate this information up to a population-weighted, country-year level, we utilize the 1990 gridded population data for each 0.25 degree and 2.5 minute grid point from Columbia University's Socioeconomic Data and Applications Center (SEDAC).[38] This allows us to create the final hurricane index H_{jt} for country j in year t:

$$H_{jt} = \frac{\sum_g \sum_s x_{gsjt} N_{g,1990}}{\sum_g N_{g,1990}}$$

where $N_{g,1990}$ is the grid point's population 1990 given from SEDAC. That is, we sum up a measure of how affected each country grid point is by each storm across storms to get each grid point's affectedness, then take a weighted sum of these grid points (by population), to obtain the intensity-weighted hurricane events per capita measure.

Three additional issues merit mention with respect to the construction if H_{jt}. First, 1990 is the earliest date for which we have access to worldwide gridded population from SEDAC. Since our sample period is 1980 to 2004, there is the potential for our estimate to reflect reverse causality created by hurricane-induced migration from grid points affected in the 1980s. In this case, within-country areas most likely to be hit by hurricanes would receive weights that are too low, creating values of H_{jt} that are also too low. This reverse causality would generate a downward bias on our estimated effect of hurricanes on emigration, making our estimates conservative. Second, because of a lack of reliable wind speed information in the best tracks,

[38] http://sedac.ciesin.columbia.edu/data/collection/gpw-v3

we only have H_{jt} for countries affected by North Indian basin hurricanes starting in 1981 and South Indian and South Pacific basin hurricanes starting in 1983. We therefore drop any observations from countries affected by North Indian hurricanes prior to 1981 and any countries affected by southern hemisphere hurricanes prior to 1983. Finally, the hurricane season in the southern hemisphere starts in November. For ease of comparison within year across countries, we include hurricanes from November and December in the following year's hurricane index for countries in the southern hemisphere.

B Census Bureau: 1980 Stocks and 1980-2004 Inflows

In order to estimate migration inflows, we construct retrospective estimates using the 2000 Census and 2005 through 2015 ACS 1-year files. This methodology utilizes the combination of questions that asks survey respondents where they were born and what year they came to live in the United States. Aggregating person weights by country of birth and year of entry within a given survey thus generates a set of initial country-year migration inflow estimates for all years before the survey. That is,

$$M_{jt}^{\text{survey}} = \sum_{i \in \text{survey}} \left[\mathbb{1}\{\text{Person } i \text{ is from country j}\} \times \mathbb{1}\{\text{Person } i \text{ entered in year } t\} \times pwgt_i^{\text{survey}} \right]$$

where i is an individual respondent to a given survey (2000 Census, 2005 ACS, 2006 ACS, ..., 2015 ACS) and $pwgt_i$ is that individual's person weight assigned by that survey. Given the sheer sample size of the 2000 Census, we use these aggregated estimates to infer migration inflows for the years 1980 through 1999. In order to extend our annual sample to 2004 while retaining relatively low levels of noise in our estimates, we average the estimates generated by the 11 ACS surveys from 2005 through 2015 for the years 2000 to 2004:

$$M_{jt} = \begin{cases} M_{jt}^{\text{2000 Census}} & \text{if } t \leq 1999 \\ \frac{1}{11} \sum_{r=2005}^{2015} M_{jt}^{\text{ACS year } r} & \text{if } 2000 \leq t \leq 2004 \end{cases}$$

Given this methodology, the key advantage of access to confidential data comes in estimating migration inflows from small countries. Use of smaller Census samples available publicly can generate accurate estimates of migrant inflows for large countries with many immigrant survey respondents that appear consistent across surveys. However, small countries, many of which are heavily affected by hurricanes, often either contain relatively few observations per year of entry or are aggregated into categories like "Other Caribbean" in publicly available data. This would generate substantial imprecision in the annual migration estimates. The 1-in-6 count provided by the confidential 2000 Census and aggregation of multiple ACS surveys alleviates this issue.

Despite this novel use of confidential data, a few concerns merit further consideration with this methodology. First, by using the 2000 Census and to look at inflows as far back as 1980, we are focusing on permanent migrants to the U.S.—those who remain living in the U.S. (or connected enough through repeated return trips) to be enumerated by the Census Bureau up to 20 years after arrival. As estimates from the 2000 Census roll forward from the starting point of 1980, underestimation due to death and re-migration give way to overestimation of permanent migrants due to the presence of more temporary migrants closer to the year 2000. Nonetheless, Passel and Suro (2005) find that this methodology tracks other migration estimates well for large countries in publicly available data, and thus we find its broader use with confidential data to be appropriate. Furthermore, as described in Section 4.3.2, we complement these estimates with data from the DHS that counts legal *permanent* resident entries *at the time of entry* in order to ensure that our results are robust to these concerns. In this sense, the results from the Census/ACS panel can be viewed as incorporating undocumented and temporary migrant response to hurricanes.

Second, as elucidated by Redstone and Massey (2004), in the presence of circular migration, the interpretation of year of entry provided by survey respondents in the Census is not clear. Specifically, in cases where immigrants reported multiple entries and exits in the New Immigrant Survey, Redstone and Massey (2004) find that 45 percent of immigrants report a "year that they came to live" that was not their first entry, and 54 percent of immigrants report a "year that they came to live" that was not their final entry.[39] The answers to this Census question appear to largely be a combination (across respondents) of first year of entry and the mental decision to make the United States their permanent home. Given the nature of our empirical strategy, we understand this as an issue of interpretation rather than bias. Any effect found on migrant inflows using the Census data should be interpreted as an effect on the decision to stay permanently in the U.S.—including both literal, one-time moves and the decision to turn repeated circular migration into permanent residency in the United States. Furthermore, remaining, pure noise created by inaccuracy in recalling year of entry causes larger standard errors in our coefficient estimates, making our estimates of precision conservative.

We also use access to the confidential, full version of the 1980 Census Long Form responses to construct a measure of immigrant stocks from each country in 1980, the base year of our analysis:

$$S_{j,1980} = \sum_{i \in 1980 \text{ Census}} \left[\mathbb{1}\{\text{Person } i \text{ is from country j}\} \times pwgt_i^{1980 \text{ Census}} \right]$$

These estimates have the advantage of producing more accurate stocks for small countries due to the large, 1-in-5 count sample size of the confidential data and do not suffer from either of the concerns of year-by-year migration estimates mentioned above.

[39]The wording "year you came to live in the U.S." used by Redstone and Massey (2004) exactly mimics the Census wording in order to make this comparison.

C Income and Damages in Sending Countries

Before moving to our main results, we first establish that our hurricane index captures events that have tangible, negative consequences in sending countries. In particular, we estimate the long-run response of incomes in sending countries to hurricane events, as in Hsiang and Jina (2014). We obtain year-by-year real GDP per capita estimates from the World Bank's World Development Indicators (WDI), enabling us to estimate the long-run effect of hurricanes on income.[40] Following Hsiang and Jina (2014), our regression specification is:

$$g_{jt} = \alpha + \sum_{\ell=-5}^{10} \alpha_\ell H_{j,t-\ell} + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \tag{10}$$

$$g_{jt} = \alpha + \sum_{\ell=-5}^{10} \alpha_\ell H_{j,t-\ell} + \sum_{\ell=-5}^{10} \alpha_\ell^{stock} (H_{j,t-\ell} \times s_{j,1980}) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \tag{11}$$

$$g_{jt} = \log(\text{Real GDP per capita})_{jt} - \log(\text{Real GDP per capita})_{j,t-1}$$

We add the α_ℓ coefficients from Equation (10) starting at $\ell = 0$ to unravel the impulse response of log real GDP per capita to the hurricane index (calibrated to $\sigma_H = 0.02$). The results are shown in Figure A1, where we see a robust, long-run effect. Ten years later, a one standard deviation increase in the hurricane index leads to 5 to 10 percent lower in GDP per capita. This kind of permanent economic impact buttresses the notion that hurricanes can cause the kind of permanent migration we observe.

We also estimate Equation (11) in order to determine whether the interaction between hurricanes in sending countries and immigrant stocks in the United States alters the impact of hurricanes on sending country economic activity. Figure A2 shows that the impulse responses of GDP per capita implied by α_ℓ^{stock} coefficients does not contain any evidence of such an interaction.[41] Meanwhile, constructing the impulse response based on the α_ℓ coefficients from Equation (11) yields similar results to doing so without the stock interaction effect, as in Equation (10). This strengthens our interpretation of $s_{j,1980}$ as a pure pull factor for potential migrants. That is, the stock operates as a network effect, facilitating migration as a response to hurricanes, but does not appear to alleviate damages at home to the point of dampening the push factor caused by hurricane-induced income losses.

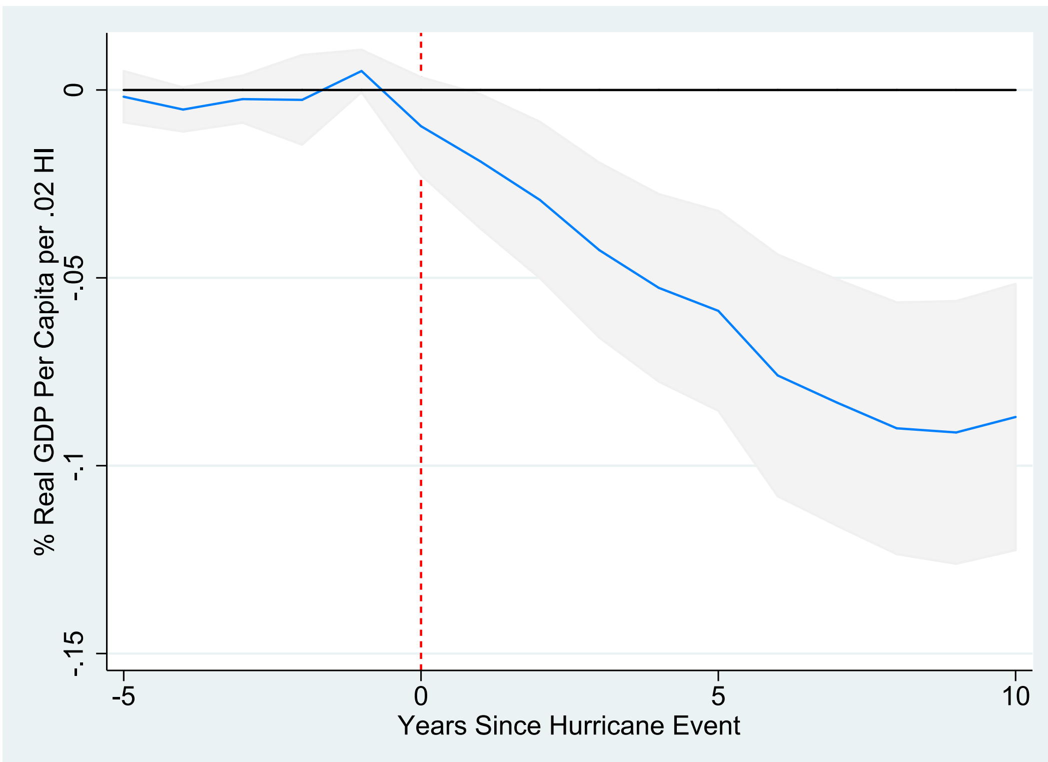
Another source of data on impact in sending countries is EM-DAT, as described

[40] See Table A3 for summary statistics.

[41] The impulse responses for the stock interaction effect are multiplied by the standard deviation of $s_{j,1980}$, 0.03 to retain consistency in units.

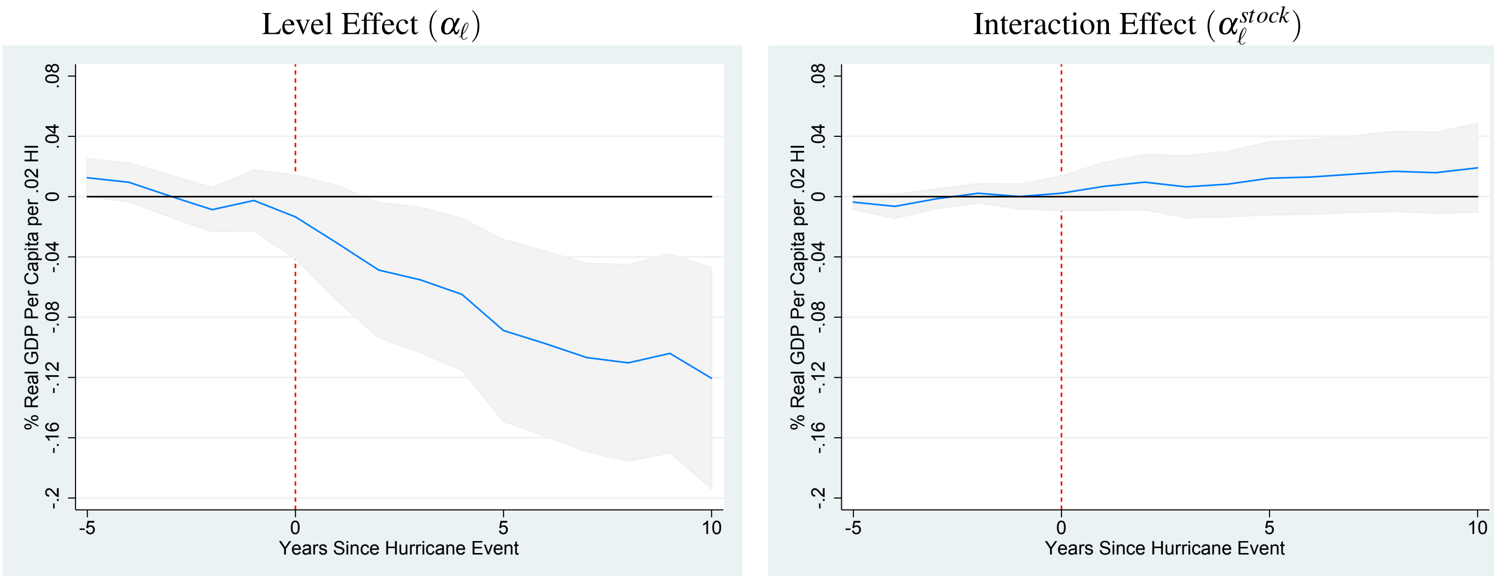
in Section 4. Table A2 presents results from estimating equations (3) and (4) with damages as a proportion of 1980 real per capita GDP, as well as deaths, injuries, and total number of people affected as a proportion of 1980 population due to meteorological disasters as outcomes. Table A2 shows a strong, robust effect of hurricanes on damages reported in potential sending countries. A one standard deviation increase in hurricane incidence in a given year corresponds to a 7.80 percent increase in damages as a proportion of 1980 GDP. As with our results from estimating Equation (11), we find no evidence of a stock interaction effect that mitigates the effect of hurricanes on sending country damages.

Figure A1: Long Run Effect of Hurricanes on GDP Per Capita (α_ℓ)



Notes: This figure represents an impulse response function generated by adding the coefficients α_ℓ that are estimated using Equation (10) before being multiplied by the standard deviation of the hurricane index. $K = 0$ indicates that the specification used to generate these estimates did not include any auto-regressive terms for log GDP growth.

Figure A2: Long Run Effect of Hurricanes on GDP Per Capita, with Stock Interaction ($K = 0$)



Notes: Each figure represents an impulse response function generated by adding the coefficients α_ℓ (Left Panel) and α_ℓ^{stock} (Right Panel) that are estimated using Equation (11) before being multiplied by the standard deviation of the hurricane index and, in the case of the Right Panel, the standard deviation of the 1980 immigrant stock as a proportion of 1980 sending country population. $K = 0$ indicates that the specification used to generate these estimates did not include any auto-regressive terms for log GDP growth.

Table A2: The Effect of Hurricanes on Sending Country Damages, 1980-2004

			As Proportion of 1980 Population					
Outcome:	$\frac{\text{Damages}}{\text{1980 GDP}}$	$\frac{\text{Damages}}{\text{1980 GDP}}$	Deaths	Deaths	Injured	Injured	Affected	Affected
HI_{jt}	3.8980***	4.2642***	0.0004**	0.0002	0.0009	0.0004	0.3492***	0.3465**
	(1.0114)	(1.5097)	(0.0002)	(0.0001)	(0.0007)	(0.0005)	(0.1132)	(0.1390)
$HI_{jt} \times s_{j,1980}$		-8.4283		0.0040		0.0128		0.0625
		(21.5619)		(0.0042)		(0.0158)		(2.3058)
Country-Years	3900	3900	3900	3900	3900	3900	3900	3900
R^2	0.0987	0.0987	0.0443	0.0466	0.1193	0.1194	0.0878	0.0878
Countries	159	159	159	159	159	159	159	159

Notes: Each column refers to a different OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). Outcome variables obtained from the Center for Research on Epidemiology of Disasters International Disaster Database. HI_{jt} refers to the hurricane index for country j in year t. $s_{j,1980}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. $s_{j,1980}$ is constructed using restricted-access data from the Census Bureau's Research Data Center. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

D Control Variables and their Sources

This section describes the sources and construction of control variables, used both to test robustness of the results found in Table 2 and to highlight mechanisms. Summary statistics for these variables are presented below in Table A3. Note that we have not been given permission to publish summary statistics on $HHI_{j,1980}$ (described below).

D.1 GDP Per Capita: Avakov (2015)

Avakov (2015) provides real GDP per capita estimates for the 159 land areas in our sample, including those that were not yet countries in 1980. These data allow us to assess robustness of our results to the inclusion of GDP per capita as a control, as well as how the interaction between migration networks and hurricanes change with sending country income.

D.2 World Bank World Development Indicators (WDI)

Beyond GDP per capita, we seek to assess robustness against a bevy of sending country characteristics that could mitigate the relationship between hurricanes, migrant networks, and migration to the U.S. The WDI aggregates many of these variables into one database, including remittances as a proportion of GDP and domestic credit as a proportion of GDP for 142 of the 159 countries in our sample. Because these variables are often missing for a given country in the year 1980, we employ a country-level average from 1970 to 1980 (throwing out missing observations) for these variables.

D.3 United Nations Population Division (UNDP): non-U.S. Immigrant Stocks

The UNDP estimates the stock of immigrants from a majority of our sending countries living in various destination countries starting in 1990. They construct this data by combining governmental estimates of immigration and emigration from each country.[42] These estimates allow us to test whether the primacy of the U.S. as a destination for a given source country affects our results. That is, if a source country is well-connected in multiple destination countries, the model presented in Section 2 implies that its hurricane-induced migrants would split their locational decisions between these countries.

D.4 Land Area and Distance to the U.S.

Proximity and the absence of undamaged land mass available within country can facilitate hurricane-induced migration to the U.S. In order to both understand the magnitude of these mechanisms and ensure they are not wholly driving our results,

[42] For example, the DHS data is used to generate immigrant stock estimates for the United States. The data can be found at https://esa.un.org/unmigration/.

Table A3: Summary Statistics of Control Variables

			Percentile						
	Mean	Std. Dev.	10	25	50	75	90	N	Source
1980 Real GDP Per Capita	8,158	14,776	903	1,554	3,983	9,094	18,691	159	Avakov (2015)
log Real Meteorological Monetary Damages	1.44149	3.81300	0	0	0	0	9.11451	2,983	CRED
Meteorological Monetary Damages per 1980 GDP	0.00001	0.00019	0	0	0	0	$<$0.00001	2,975	CRED
Meteorological Disaster Deaths per 1980 Population	0.00001	0.00009	0	0	0	0	$<$0.00001	2,975	CRED
Meteorological Disaster Injuries per 1980 Population	0.00005	0.00191	0	0	0	0	$<$0.00001	2,975	CRED
Meteorological Disaster Affected Persons per 1980 Population	0.00732	0.05602	0	0	0	0	0.00062	2,975	CRED
g_{jt}: Real GDP per capita growth	0.00142	0.15438	-0.15265	-0.06430	0.01186	0.07772	0.14715	3,221	WDI
Remittances as a Perc. of GDP (1970-1980 Average)	3.54	9.79	0.04	0.22	0.84	2.93	6.49	74	WDI
Dom. Credit as a Perc. of GDP (1970-1980 Average)	21.82	15.75	6.10	12.94	18.90	28.26	40.18	104	WDI
Non-U.S. Stock of Immigrants as Prop. of 1980 Population	0.11464	0.18869	0.00959	0.01724	0.05316	0.12502	0.30538	158	UNDP
Land Area (sq. km)	591,653	1,431,563	360	5,130	108,430	581,540	1,280,000	159	*R* `maptools`
Distance from Capital City to D.C. (km)	9,051	4,150	2,936	5,837	9,968	12,391	13,906	159	*R* `maptools`

Notes: Historical real GDP data obtained from Avakov (2015). CRED data obtained from the Center for Research on Epidemiology of Disasters International Disaster Database. WDI data obtained from the World Bank. *R* `maptools` contains land area, and is also used to calculate Distance to Washington D.C.

we construct two measures. The first the log of land area in squared kilometers and the second is the distance from each country's capital city to the U.S.—meant to mimic distance measures used in standard trade gravity models (e.g., Feenstra et al., 2001). Each is constructed using data available in the `maptools` package in *R* (distance to Washington D.C. is calculated using this package after obtaining latitude and longitude coordinates of capital cities from Google Maps).[43] For a subset of countries without land area information available in this package, we employ land area information provided in the WDI.

D.5 Damages: Center for Research on Epidemiology of Disasters (CRED)

In order to verify that our independent hurricane index corresponds to immediate damages in potential sending countries on a level that could prompt immigration to the United States, we use data from EM-DAT: the Center for Research on Epidemiology of Disasters (CRED) International Disaster Database.[44] These estimates include monetary damages in nominal USD and the number of deaths, injuries, and total number of people affected by meteorological disasters in a given country and year. The sources of disaster impact data include national governments, UN agencies, non-governmental organizations, insurance companies, research institutes, and the media. In order to put the monetary damages in real terms (2010 USD), we employ the U.S. GDP deflator from the World Bank's World Development Indicators. The use of these data allow us to establish something akin to a "first stage" effect, that our objective hurricane index corresponds to monetary and human damages felt on the ground in potential sending countries. Additionally, we report damages as a proportion of 1980 real GDP. We obtain the denominator from Avakov (2015), who collects historic data for land masses small enough to cover our entire country sample.

D.6 Restricted-Access Census Bureau: 1980 Herfindhal Concentration Index

In theory, we may expect that immigrant communities that are particularly concentrated in U.S. areas that are close to hurricane-hit countries—Miami, for example—are particularly suited to absorb hurricane-induced inflows. In order to test whether our stock interaction effect is solely driven by such concentrated communities, we construct a Herfindhal-style concentration index:

$$HHI_{j,1980} = \sum_{c} \left(\frac{S_{jc,1980}}{\sum_c S_{jc,1980}} \right)^2$$

[43] Source data for the `maptools` project is available from https://github.com/nasa/World-Wind-Java/tree/master/WorldWind/testData/shapefiles.

[44] http://www.emdat.be

where c represents a U.S. county and $S_{jc,1980}$ is the number of immigrants from country j living in county c in 1980. Note that the denominator is the same as $S_{j,1980}$ in this paper's notation. The ability to construct this variable at the granular, county level comes from access to restricted-use Census Bureau data.

D.7 Populations: United Nations and U.S. Census Bureau International Data Base

Finally, in order to make country-year observations comparable, we use population data from the set of potential sending countries in our base year, 1980. For this, we used data publicly available data from the United Nations and the U.S. Census Bureau's International Data Base, which between them cover our entire sample. For most of the countries in our sample, estimates of the 1980 population were available from both sources, in which case we took a simple average. These 1980 population estimates are then used as denominators for our final migration inflow outcome variables and our 1980 stock estimates:

$$m_{jt} \equiv \frac{M_{jt}}{N_{j,1980}}$$
$$s_{j,1980} \equiv \frac{S_{j,1980}}{N_{j,1980}}$$

m_{jt} is our main outcome of interest from the data constructed using confidential data from the U.S. Census Bureau.

D.8 Predicting the 1980 Stock

We motivate the potential need for these predetermined control variables by using them to predict our interacting variable of interest: $s_{j,1980}$. Table A4 presents the result from this exercise. Unsurprisingly, countries that are closer to the U.S. had higher proportional immigrant stocks in 1980. Somewhat surprisingly, larger countries, countries with more concentrated immigrant populations, and larger countries also featured higher immigrant stocks in 1980. Real GDP per capita, our best indicator for development, has a positive, but not statistically significant effect on 1980 proportional stocks.

Table A4: Predicting $s_{j,1980}$, the 1980 Proportional Stock

	$s_{j,1980}$
1980 Herfindhal Concentration Index (divided by one million)	-0.0360*
	0.0183
Log 1980 Real GDP Per Capita	0.0015
	0.0017
Log 1980 Population	-0.0068***
	0.0022
Remittances as a Prop. of GDP (average in 1970's)	-0.0123
	0.0237
Domestic Credit as a Prop. of GDP (average in 1970's)	0.0079
	0.0063
Land Area (millions of Sq. KM)	0.0020*
	0.0011
Distance from Capital City to D.C. (millions of KM)	-2.3294***
	0.6525
1990 Proportional Stock in non-U.S. countries	0.0451
	0.0316
Indicator: Missing Remittances as Prop. of GDP	-0.002
	0.0042
Indicator: Missing Domestic Credit as a Prop. of GDP	0.0094**
	0.0045
Indicator: Missing p_stock1990 in non-US countries	-0.0098*
	0.0055
Countries	159
R^2	0.4776

Notes: Each column refers to a different OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). Outcome variables obtained from sources described in Sectionsubsec:Control-Variables. $s_{j,1980}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. $s_{j,1980}$ is constructed using restricted-access data from the Census Bureau's Research Data Center. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

E Placebo Tests

In order to verify that the results presented above are not just the result of spurious statistical noise, we test the following model:

$$m_{jt} = p_0 + p_1 H_{j,t+1} + p_2(H_{j,t+1} \times s_{j,1980}) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt}$$

We should not expect hurricanes in the future to affect current migration if they are unexpected, exogenous events, as the theoretical considerations laid out in Section 2 assume. Table A5 presents the result of this test, and demonstrates that we cannot reject the hypotheses that $p_1 = 0$ or $p_2 = 0$. This buttresses the notion that H_{jt} is causing migration through the negative income and asset shock channels that we propose.

Table A5: The Effect of Future Hurricanes on Migration—Placebo Test, 1980-2004

Outcome:	m_{jt}	m_{jt}
$H_{j,t+1}$	0.0017	0.0028
	(0.0015)	(0.0020)
$H_{j,t+1} \times s_{j,1980}$		-0.0266
		(0.0281)
Country-Years	3900	3900
R^2	0.4273	0.4277
Countries	159	159

Notes: Each column refers to a different OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). HI_{jt} refers to the hurricane index for country j in year t. $s_{j,1980}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. m_{jt} refers to the estimated immigrant inflows to the U.S. from country j in year t. $s_{j,1980}$ and m_{jt} are constructed using restricted-access data from the Census Bureau's Research Data Center. See Section B of the Online Appendix for details of construction. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

F Analysis With Publicly-Available Data

The following table displays the results of estimating Equations (3) and (4) using publicly-available data from the Census Bureau. The large differences in coefficient and standard error estimates display the importance of using more detailed data for the main analyses presented in this paper.

Table A6: The Effect of Hurricanes on Migration, Public Data, 1980-2004

Outcome:	m_{jt}^{public}	m_{jt}^{public}
HI_{jt}	0.0016	0.0003
	(0.0015)	(0.0019)
$HI_{jt} \times s_{j,1980}^{public}$		0.0267
		(0.0343)
Country-Years	2,215	2,215
R^2	0.3917	0.3921
Countries	97	97

Notes: Each column refers to a different OLS specification with a constant term, country fixed effects, year fixed effects, and country-specific time trends along with the variables displayed. Standard errors clustered at the country level. See Equations (3) and (4). HI_{jt} refers to the hurricane index for country j in year t. $s_{j,1980}^{public}$ refers to the immigrant stock from country j in the U.S. in 1980 as a proportion of country j's 1980 population. m_{jt}^{public} refers the immigrant inflows to the U.S. from country j in year t as a proportion of country j's 1980 population. See Section B of the Online Appendix for details of construction. $s_{j,1980}^{public}$ and m_{jt}^{public} constructed using publicly-available data from IPUMS-USA (https://usa.ipums.org/usa/acs.shtml). * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$