Taken by Storm: Hurricanes, Migrant Networks, and U.S. Immigration

Online Appendix

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A Theoretical Framework

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.[1] A subset of the literature explicitly takes account of migration fixed costs.[2] 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.

A.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. Let the fixed cost of migration be lower when an individual has a larger migrant network, meaning $C' < 0$. 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

[1] 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, Docquier and Rapoport (2001), Feliciano (2005), Chiquiar and Hanson (2005), Orrenius and Zavodny (2005), Clark, Hatton and Williamson (2007), Ibarraran and Lubotsky (2007), Beine, Docquier and Rapoport (2008), Dolfin and Genicot (2010), McKenzie and Rapoport (2010), Akee (2010), Abramitzky, Boustan and Eriksson (2012), Ortega and Peri (2013), Bertoli, Moraga and Ortega (2013), and Bertoli, Fernández-Huertas Moraga and Keita (2016).

[2] 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, Detragiache and Vishwanath (1996), Chiquiar and Hanson (2005), Ibarraran and Lubotsky (2007), Gathmann (2008), McKenzie and Rapoport (2010), Grogger and Hanson (2011), Bertoli, Moraga and Ortega (2013), Belot and Hatton (2012), Bertoli and Rapoport (2015), Kennan and Walker (2011), Kosec, Mueller and Chen (2015), and Boustan et al. (2017). Empirical studies on the association between pre-existing migrant stocks and subsequent migration flows include Winters, De Janvry and Sadoulet (2001), Clark, Hatton and Williamson (2007), Pedersen, Pytlikova and Smith (2008), Zavodny (1997), Hanson and McIntosh (2012), McKenzie and Rapoport (2010), Collins (1997), Collins and Wanamaker (2015), and Orrenius and Zavodny (2005).

$\gamma > 0$. Now, the condition for migration can be written as:

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

In this set-up, we can represent the individual's choice graphically. In Figure A.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 (A.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 (A.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 $\ln\left(w_h^1\right)$.

A.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 A.1. Within the population of those who had not migrated prior to the negative shock, 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.

A.3 Negative home shock affects migration costs

The hurricane's effect becomes ambiguous if the negative shock to the home economy does affect migration costs. 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:

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

It now becomes possible for a negative shock to either increase or decrease migration. These possibilities are also represented in Figure A.1. A negative shock now also leads the curved line (the left hand side of inequality A.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 A.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 $\underline{n}^3$.

A.4 Migrant networks provide insurance

Now consider the possibility that migrants can provide insurance in the form of remittances in response to negative shocks such as hurricanes.

In the context of our theoretical framework, we can represent the insurance provided by the migrant network as replacing a fraction of home-area income losses caused by a negative shock. The income loss due to a negative shock is the difference between pre- and post-shock home wages, $\ln\left(w_h^0\right) - \ln\left(w_h^1\right)$. Let $\alpha(n)$ be the fraction of this loss that is replaced by migrant remittances. Let $\alpha' > 0$, to represent that the extent of insurance (the fraction of the loss replaced) is larger when the migrant network is larger (as a share of home country population). This is sensible, because when migrant networks are larger, more individuals in the home country should have a migrant social network member, and the financial burden of supporting disaster-affected home-country residents can be spread across more migrants.

After remittances from migrants in the wake of a negative shock, the relevant measure of well being in the home country is log wages plus remittances, $\ln\left(w_h^1\right) + \alpha(n)\left[\ln\left(w_h^0\right) - \ln\left(w_h^1\right)\right]$. Log wages plus remittances are presented graphically in Figure A.2 as the upward-sloping heavy dashed line between the horizonal lines at $\ln\left(w_h^1\right)$ and $\ln\left(w_h^0\right)$.[3] It is now the intersection of this line with the foreign net wage function that determines the threshold network size above which people in the home country choose to migrate, in this case $\underline{n}^4$. New migration occurs for individuals with migrant networks in the range of $\underline{n}^4$ to $\underline{n}^0$.

This range is smaller than the range of new migrants if their migrant networks did not send remittances in response to negative shocks (that range is $\underline{n}^1$ to $\underline{n}^0$). Therefore, the possibility of migrants sending shock-coping remittances attenuates the effect of shocks on new migration. The attenuation can be arbitrarily large. As $\alpha(n)$ approaches 1, new migration in response to home-country shocks goes to zero.

A.5 In sum

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 reduce ability to pay migration fixed costs. Migrants' ability to send remittances in response to negative shocks introduces further ambiguity, potentially attenuating further any positive migration response to hurricanes.

[3] For the purpose of this figure, we have specified $\alpha(n)$ as a logistic function bounded between $\ln\left(w_h^1\right)$ and $\ln\left(w_h^0\right)$.

Figure A.1: Negative Shocks and Migration

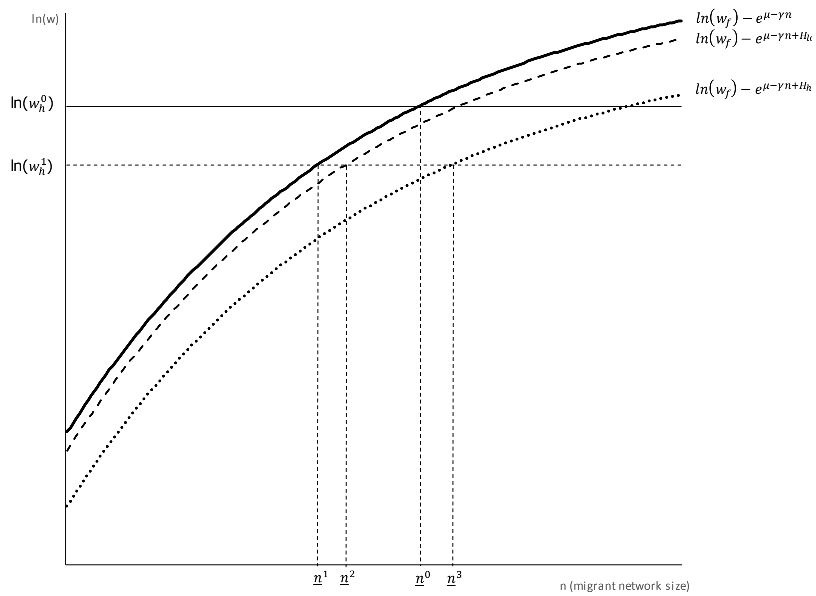
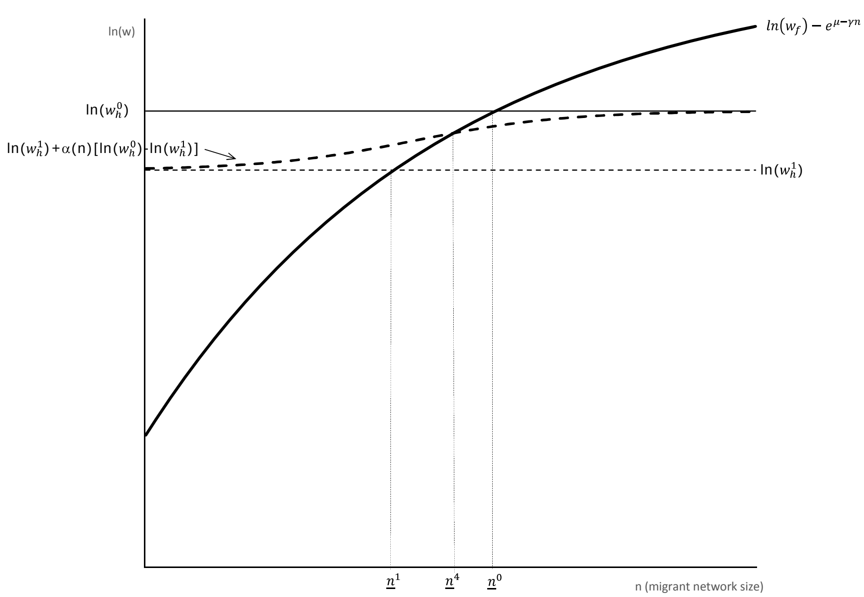


Figure A.2: Negative Shocks and Migration, When Migrants Provide Insurance



B 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.[4] 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.[5] Then, we predict the wind speed of each hurricane segment (a connected set of points from the best tracks) using a model from Dilley, Chen and Deichmann (2005):

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

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 $d_{gjst} < prad_{gjst}$.[6]

As an example of a pw_{gjst} calculation, consider Figure B.1, which shows both 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 (B.1), where wind speed also comes from this nearest

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

[5] "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*.

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

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).[7] This allows us to create the final hurricane index H_{jt} for country j in year t:

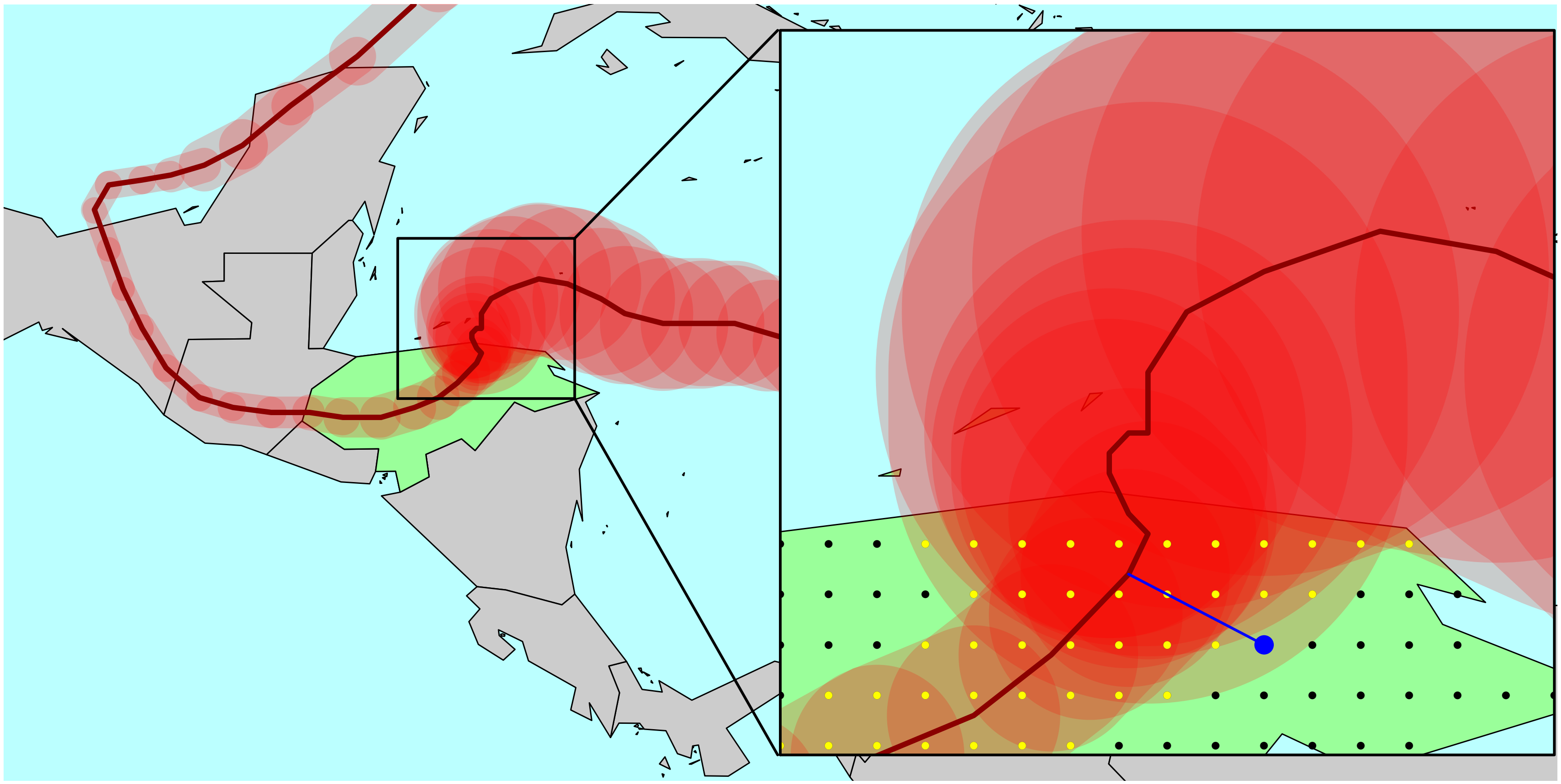
$$H_{jt} = \frac{\sum_g \sum_s x_{gsjt} N_{g,1990}}{\sum_g N_{g,1990}}$$

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, 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.

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

Figure B.1: Hurricane Mitch over Honduras



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

C 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 III.C, 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.[8] 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:

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

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.

[8]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.

D Income and Damages in Sending Countries

We establish here that the hurricane index captures events that have tangible, negative consequences in sending countries. 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.[9] Following Hsiang and Jina (2014), our regression specification is:

$$g_{jt} = \alpha + \sum_{\ell \neq -1, \ell = -5}^{10} \theta_\ell H_{j,t-\ell} + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \tag{D.1}$$

$$g_{jt} = \alpha + \sum_{\ell \neq -1, \ell = -5}^{10} \alpha_\ell H_{j,t-\ell} + \sum_{\ell \neq -1, \ell = -5}^{10} \alpha_\ell^{stock} (H_{j,t-\ell} \times s_{j,1980}) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \tag{D.2}$$

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

We add the α_ℓ coefficients from Equation (D.1) starting at ℓ =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 D.1, 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 (D.2) 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 D.2 shows that the impulse responses of GDP per capita implied by α_ℓ^{stock} coefficients does not contain any evidence of such an interaction.[10] Meanwhile, constructing the impulse response based on the α_ℓ coefficients from Equation (D.2) yields similar results to doing so without the stock interaction effect, as in Equation (D.1). 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.

Note that, for completeness, we can construct similar graphs for our main outcome of interest, migration m_{jt}. Figures and thus show the results of estimating Equations (D.1) and (D.2) with m_{jt} as the outcome. Because our primary outcome of interest is migration flows, we do not cumulate responses in this case, and instead directly plot the resulting coefficients. As seen from the estimates of θ_ℓ in Figure D.3, the only detectable migration response to hurricanes appears in the year of the hurricane itself. This justifies our use of a specification without lags in the hurricane index in Equations (1) and (2). Splitting this effect into its interaction through previous migrant stock and a direct, level effect, Figure D.4 further reveals that this "Year 0" response is entirely driven by the interaction effect. The lack of response prior to a given hurricane event serves as another placebo test. The data fail to reject the null hypothesis of no pre-trends.

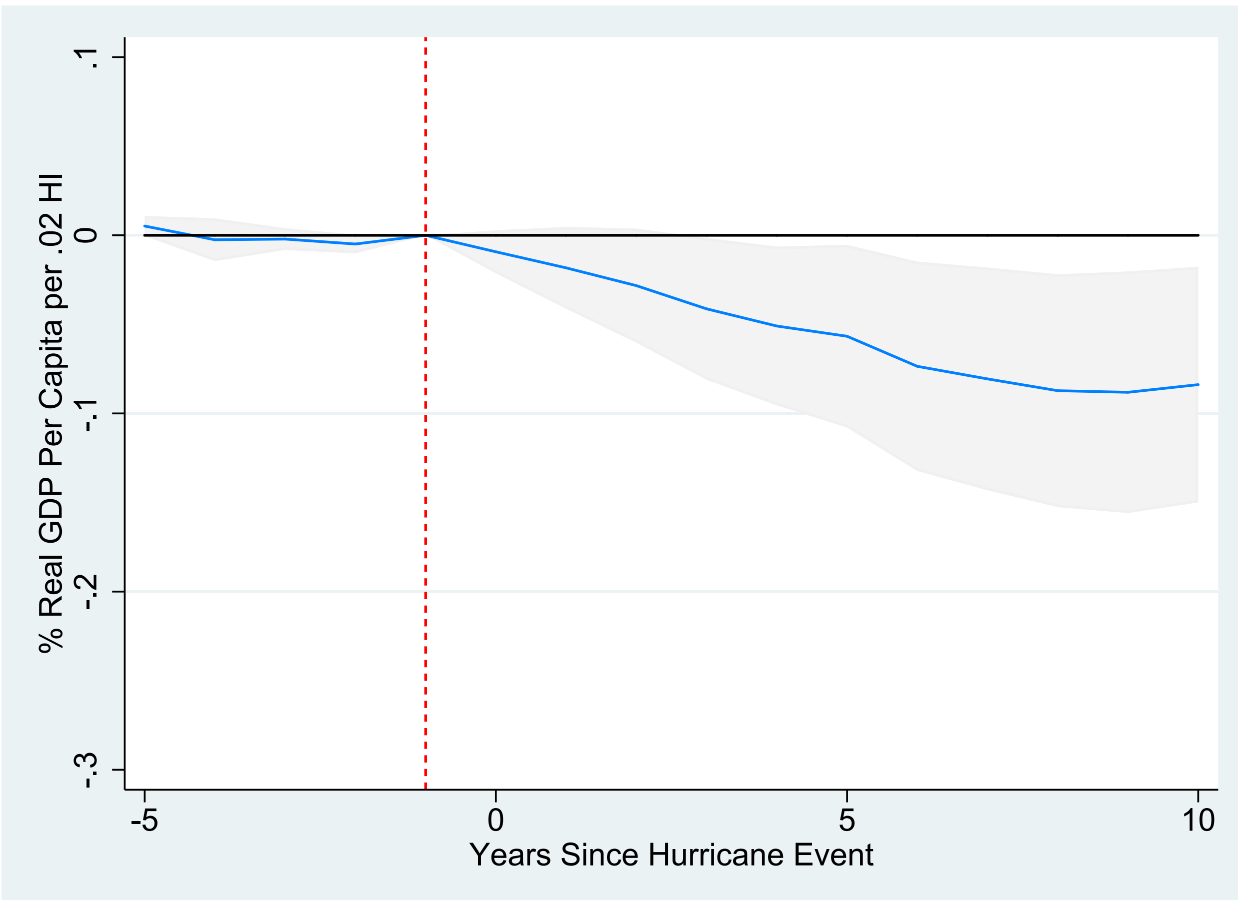
Another source of data on impact in sending countries is EM-DAT, as described in Section III.

[9] See Table E.1 for summary statistics.

[10] 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.

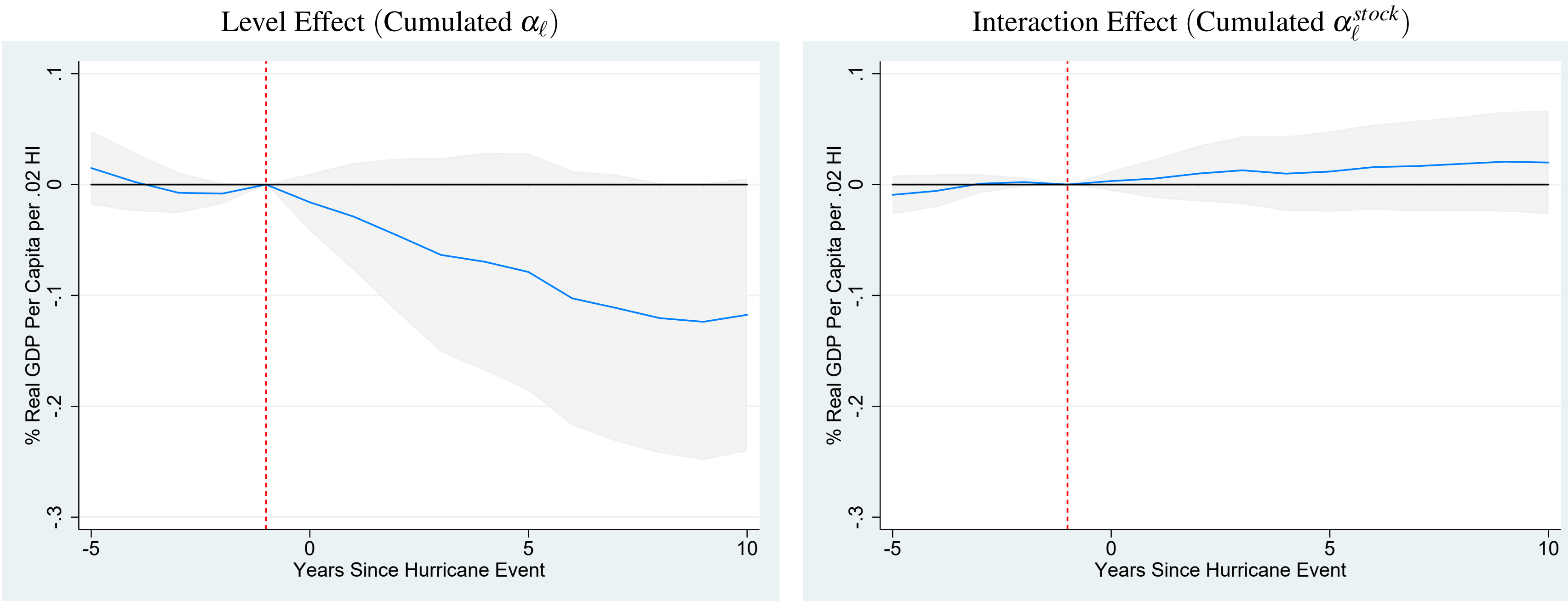
Table D.1 presents results from estimating Equations (1) and ((2)) with damages as a proportion of 1980 real per capita GDP, as well as deaths, injuries, and total number of people affected as a proportion of 1980 population due to meteorological disasters as outcomes. Table D.1 shows a strong, robust 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 (D.2), we find no evidence of a stock interaction effect that mitigates the effect of hurricanes on sending country damages.

Figure D.1: Long Run Effect of Hurricanes on GDP Per Capita (Cumulated θ_ℓ)



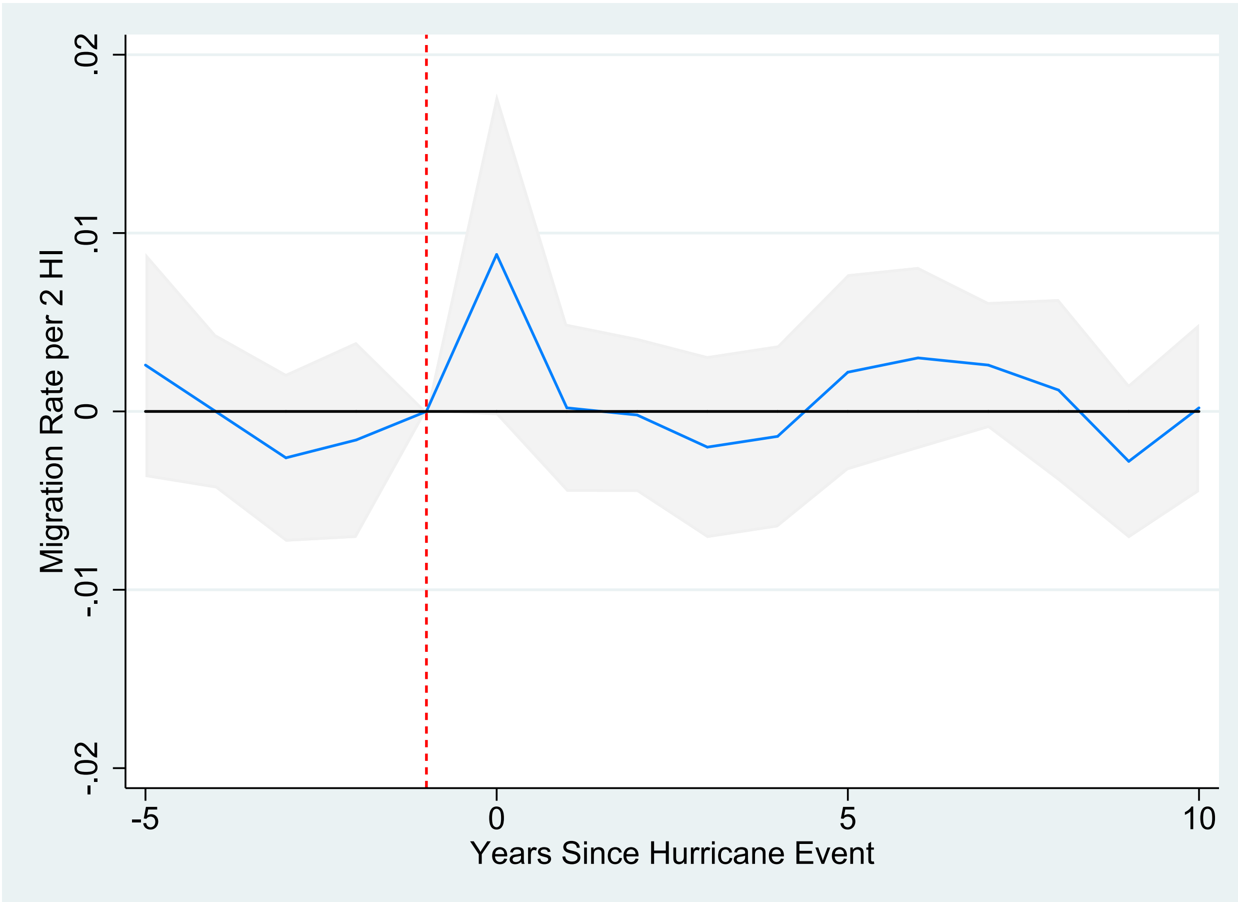
Notes: This figure represents an impulse response function generated by adding the coefficients α_ℓ that are estimated using Equation (D.1) before being multiplied by the standard deviation of the hurricane index.

Figure D.2: Long Run Effect of Hurricanes on GDP Per Capita, with Stock Interaction



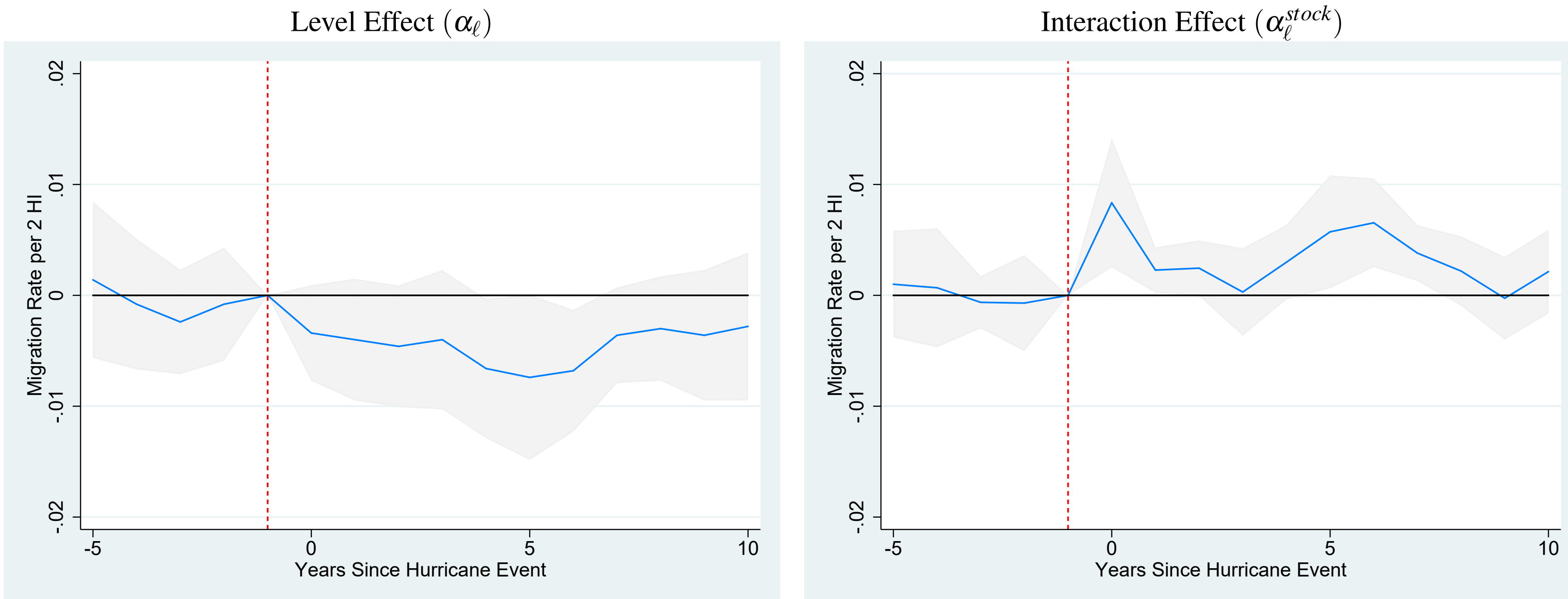
Notes: Each figure represents an impulse response function generated by adding the coefficients α_ℓ (Left Panel) and α_ℓ^{stock} (Right Panel) that are estimated using Equation (D.2) before being multiplied by the standard deviation of the hurricane index and, in the case of the Right Panel, the standard deviation of the 1980 immigrant stock as a proportion of 1980 sending country population.

Figure D.3: Long Run Effect of Hurricanes on Migration (θ_ℓ)



Notes: This figure plots the coefficients that are estimated using Equation (D.1) before being multiplied by 100 times the standard deviation of the hurricane index.

Figure D.4: Long Run Effect of Hurricanes on Migration, with Stock Interaction



Notes: This figure plots the coefficients that are estimated using Equation (D.2) (Bottom Panel) before being multiplied by 100 times 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.

Table D.1: 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
Hurricane Index(t)	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)
Hurricane Index(t) $\times$		-8.4283		0.0040		0.0128		0.0625
1980 Proportional Immigrant Stock		(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 (1) and (2). Outcome variables obtained from the Center for Research on Epidemiology of Disasters International Disaster Database. "Migrants" and "1980 Proportional Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

E 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 3 and to highlight mechanisms. Summary statistics for these variables are presented below in Table E.1. Note that we have not been given permission to publish summary statistics on $HHI_{j,1980}$ (described below).

E.1 GDP Per Capita: Avakaov (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.

E.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 1979 (throwing out missing observations) for these variables.

E.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.[11] 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 I implies that its hurricane-induced migrants would split their locational decisions between these countries.

E.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, 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, Markusen and Rose (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).[12] For a subset of countries without land area information available in this package, we employ land area information provided in the WDI.

[11] 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/.

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

Table E.1: Summary Statistics of Control Variables

	Mean	Std. Dev.	Percentile 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 Prop. of 1980 GDP (1970-1980 Average)	3.54	9.79	0.04	0.22	0.84	2.93	6.49	74	WDI
Dom. Credit as Prop. of 1980 (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.

E.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.[13] 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.

E.6 Restricted-Access Census Bureau: 1980 Immigrant 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:

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

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.

E.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:

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

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

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

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

E.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 E.2 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 E.2: Predicting $s_{j,1980}$, the 1980 Proportional Stock

	$s_{j,1980}$
1980 Immigrant 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 (1) and (2). Outcome variables obtained from sources described in Section E. "1980 Proportional Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center.* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

F Robustness of Stock-by-Citizenship Results

This section combines Equations (3) with (6) to test the robustness of the results presented in Table 5. That is, it estimates

$$m_{jt} = \pi_0 + \pi_1 H_{jt} + \pi_2 (H_{jt} \times s_{j,1980}^{\text{citizen}}) + \pi_3 (H_{jt} \times s_{j,1980}^{\text{non-cit}}) + \pi_c (H_{jt} \times c_j) + \eta_j + \delta_t + \phi_j t + \varepsilon_{jt} \quad \text{(F.1)}$$

This estimating equation modifies Equation (3) by adding an additional set of interaction terms with time-invariant control variables. Online Appendix Section E (above) details the construction of each of these variables. Table F.1 displays the results of estimating Equation (F.1) with each individual control variable as well as with the complete set. The estimated coefficients $\hat{\pi}_2$ and $\hat{\pi}_2$ remain stable. The p-vales from the test that $\pi_2 = \pi_3$ are shown in the bottom row. They show that there appears to be a robust effect of the citizen stock of immigrants itself, as opposed to the many factors it may additionally proxy for. When the "kitchen sink" set of controls is included, this result is only strengthened.

Table F.1: Robustness

	Outcome for all columns: Migrants(t) as a Prop. of 1980 Population									
Hurricane Index(t)	-0.0005	-0.0014*	0.0181	0.0080	-0.0013	-0.0019	-0.0005	-0.0016	0.0011	0.0665***
	(0.0009)	(0.0009)	(0.0173)	(0.0050)	(0.0021)	(0.0027)	(0.0010)	(0.0019)	(0.0028)	(0.0239)
Hurricane Index(t) $\times$	0.4044*	0.4191*	0.4396*	0.3615*	0.4173*	0.3377*	0.4040*	0.4042*	0.5172*	0.6559***
1980 Proportional Citizen Immigrant Stock	(0.2245)	(0.2266)	(0.2552)	(0.2030)	(0.2329)	(0.2023)	(0.2243)	(0.2266)	(0.2976)	(0.2502)
Hurricane Index(t) $\times$	-0.1444	-0.1491	-0.1631	-0.1311	-0.1388	-0.0773	-0.1449	-0.1300	-0.2225	-0.2736
1980 Proportional Non-Citizen Immigrant Stock	(0.1661)	(0.1663)	(0.1854)	(0.1541)	(0.1685)	(0.1593)	(0.1663)	(0.1653)	(0.2132)	(0.1941)
Hurricane Index(t) $\times$		0.0046***								-0.0088
Immigrant Concentration Index		(0.0017)								(0.0058)
Hurricane Index(t) $\times$			-0.0021							0.0023
log(1980 Real GDP Per Capita)			(0.0020)							(0.0566)
Hurricane Index(t) $\times$				-0.0664*						-0.0664
log(1980 Population)				(0.0400)						(0.0566)
Hurricane Index(t) $\times$					-0.1111					-0.3682***
[1970s Remittances as Prop. of GDP]					(0.0775)					(0.1149)
Hurricane Index(t) $\times$					0.0011					-0.0030
$\mathbb{1}$[Missing: Remittances]					(0.0023)					(0.0048)
Hurricane Index(t) $\times$						-0.0024				0.0032
[1970s Dom. Credit as Prop. of GDP]						(0.0058)				(0.0076)
Hurricane Index(t) $\times$						0.0022				0.0122**
$\mathbb{1}$[Missing: Dom. Credit]						(0.0030)				(0.0055)
Hurricane Index(t) $\times$							-0.0015			-0.0082
[Land Area (mil. sq. km)]							(0.0040)			(0.0110)
Hurricane Index(t) $\times$								0.1144		0.1667
[Distance to U.S. (mil. km)]								(0.1670)		(0.1729)
Hurricane Index(t) $\times$									-0.0085	-0.0273***
[1990 Prop. non-U.S. Emigrant Stock]									(0.0094)	(0.0091)
Hurricane Index(t) $\times$									-0.0021	-0.0124***
$\mathbb{1}$[Missing: non-U.S. Emigrant Stock]									(0.0035)	(0.0046)
Country-Years	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900
Countries	159	159	159	159	159	159	159	159	159	159
p-value: Equal Interaction Effect of Citizen and Non-Citizen Proportional Stock	0.1540	0.1430	0.1660	0.1630	0.1590	0.2400	0.1540	0.1650	0.1460	0.0365

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 Equation (F.1). 1970s Domestic Credit as Prop. of GDP and 1970s Remittances as a Prop. of GDP divide averages of non-missing data of Domestic Credit and Remittances from 1970 through 1979 by 1980 GDP. "Migrants," "1980 Proportional Citizen Immigrant Stock," and "1980 Proportinal Non-Citizen Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

G 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 I assume. Table G.1 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 G.1: The Effect of Future Hurricanes on Migration—Placebo Test, 1980-2004

	As a Prop. of 1980 Population	
	Migrants(t)	Migrants(t)
Hurricane Index($t+1$)	0.0017	0.0028
	(0.0015)	(0.0020)
Hurricane Index($t+1$) $\times$		-0.0266
1980 Proportional Immigrant Stock		(0.0281)
Country-Years	3,900	3,900
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 (1) and (2). "Migrants" and "1980 Proportional Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

H TPS Responses to Hurricane Mitch

The following table displays the sensitivity of our main results to dropping Honduras and Nicaragua, countries that were granted TPS status in response to Hurricane Mitch.

Table H.1: Hurricane Mitch Robustness

	Full Sample		Dropping Mitch-Affected	
Panel A: Census, 1980-2004				
Hurricane Index(t)	0.0040**	-0.001	0.0040**	-0.0011
	(0.0020)	(0.0010)	(0.0020)	(0.0010)
Hurricane Index(t) $\times$		0.1163**		0.1170**
1980 Proportional Immigrant Stock		(0.0451)		(0.0452)
Country-Years	3,900	3,900	3,800	3,800
R^2	0.4319	0.4409	0.4247	0.4341
Countries	159	159	157	157
Panel B: DHS non-immigrant, 1983-2004				
	Full Sample		Dropping Mitch-Affected	
Hurricane Index($t,t-1$)	0.2193***	-0.0627	0.2197***	-0.0608
	(0.0788)	(0.0689)	(0.0788)	(0.0699)
Hurricane Index($t,t-1$) $\times$		5.7883**		5.7541**
1980 Proportional Immigrant Stock		2.3536		2.3647
Country-Years	2,200	2,200	2,200	2,200
R^2	0.4485	0.4495	0.4489	0.4498
Countries	156	156	154	154
Panel C: DHS LPR, 1982-2004				
	Full Sample		Dropping Mitch-Affected	
Hurricane Index($t,t-1$)	0.0023	-0.0035	0.0024	-0.0034
	(0.0040)	(0.0039)	(0.0040)	(0.0039)
Hurricane Index($t,t-1$) $\times$		0.1266***		0.1254***
1980 Proportional Immigrant Stock		(0.0402)		(0.0408)
Country-Years	2,600	2,600	2,500	2,500
R^2	0.2954	0.2966	0.2957	0.2969
Countries	156	156	154	154

Notes: Outcome for each specification is the estimated migrant inflows to the U.S. from a given country in year t as a proportion of that country's 1980 population. 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 (1) and (2). Outcomes in Panels B and C obtained from electronic copies of the *Yearbook of Immigration Statistics* (1996-2004) and *Statistical Yearboook of the Immigration and Naturalization Service* (prior to 1996). "Hurricane Index($t,t-1$)" refers to the average of a hurricane index for a given country across years t and $t-1$. "1980 Proportional Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center. LPR: legal permanent resident; "non-imm:" non-immigrant. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

I Analysis With Publicly-Available Data

The following table displays the results of estimating Equations (1) and (2) using publicly-available data from the Census Bureau. The large differences in coefficient and standard error estimates display the importance of using restricted-access Census data for the main analyses presented in this paper.

Table I.1: The Effect of Hurricanes on Migration, Public Data, 1980-2004

	As a Prop. of 1980 Population	
Outcome, Estimated from Public Data:	Migrants(t)	Migrants(t)
	(1)	(2)
Hurricane Index(t)	0.0016	0.0003
	(0.0015)	(0.0019)
Hurricane Index(t)$\times$		0.0267
Public-Data 1980 Proportional Immigrant Stock		(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 (1) and (2). "Public-Data 1980 Proportional Immigrant Stock" refers to the immigrant stock from a given country living in the U.S. in 1980 as a proportion of that country's 1980 population, estimated from IPUMS-USA (Ruggles et al., 2019). "Migrants" refers to the estimated immigrant inflows to the U.S. from a given country in year t as a proportion of that country's 1980 population, estimated from IPUMS-USA as well. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

J The Role of Small Countries

This section complements Section I in demonstrating that the primary results in the paper—contained in Table 3—are driven by smaller countries in our sample. These are countries for whom 1980 stocks and migration inflows can only be measured accurately using RDC or DHS data. However, this section also shows that these primary results are not driven by a very small number of these countries.

Table J.1 demonstrates how the result from Column 2 in Table 3 changes with population weighting and within sub-samples of countries defined by quartiles of 1980 population. When no lags of the hurricane index are included (Panel A), as in Equation (2), weighting by 1980 population eliminates the effect. In this specification, India and China receive almost one-half of the total weight in the regression, and the effects in these countries do not appear to be large. However, when we weight by log 1980 population instead, the effect is essentially identical to that found in Table 3 (reproduced in the Column 1 here for convenience). Columns 4-7 show that the effect is driven by countries in the bottom quartile by population. We also produce results that add an additional lag in the hurricane index to the model estimated in Equation (2). These results (in Panel B), largely mirror those in Panel A, but also show a lagged interaction effect response in the second population quartile.

To provide further insight into the role of small countries, we drop progressively larger sets of countries (starting with the smallest in terms of 1980 population) from our analysis. Table J.2 displays these results. The Census Bureau's rounding rules do not permit us to disclose the exact number of countries we drop in each column, but this exercise was done in a systematic way, with the number of dropped countries increasing from left to right in the table (the number of dropped countries has been rounded to the nearest ten in the table, and cannot be specified below 15). The point estimate on the migrant stock interaction term becomes smaller when more and more of the small countries are dropped from the sample. This pattern is consistent with results in Appendix Table A7: the small countries provide key identifying variation. But the result is not contingent on the presence in the sample of only a handful of countries, only disappearing when the smallest 20 countries (approximately) are dropped from the sample (Column 4 of the table).

Finally, Table J.3 sorts the 159 countries in our sample by 1980 population. It demonstrates that the smallest countries in the sample tend to have significant "leverage" in our main regression specifications, with high mean values in the hurricane index. Among the smaller countries, there is variation in the population share of prior migrants, providing additional variation for identifying heterogeneity in the impact of hurricanes.

Table J.1: Alternate Weighting and Unweighted Effect by 1980 Population Quartile

Panel A: No lags in Hurricane Index	Outcome for all columns: Migrants(t) as a Prop. of 1980 Population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hurricane Index(t)	-0.0010	-0.0002	-0.0010	-0.0012	0.000	-0.0010	-0.0001
	(0.0010)	(0.00020)	(0.00080)	(0.00210)	(0.00060)	(0.00450)	(0.0003)
Hurricane Index(t) $\times$	0.1163**	0.0092	0.1087**	0.1240**	-0.0027	-0.0623	-0.0228
1980 Proportional Immigrant Stock	(0.0451)	(0.0162)	(0.0422)	(0.0520)	(0.0071)	(0.1808)	(0.0536)
Weight	None	1980 Population	Log 1980 Population	None	None	None	None
Quartile	All	All	All	1st	2nd	3rd	4th
Country-Years	3,900	3,900	3,900	1,000	1,000	1,000	1,000
Panel B: One lag in Hurricane Index	Outcome for all columns: Migrants(t) as a Prop. of 1980 Population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hurricane Index(t)	-0.0011	-0.0003	-0.0011	-0.0012	-0.0001	-0.0013	0.0000
	(0.0010)	(0.0003)	(0.0008)	(0.0022)	(0.0005)	(0.0049)	(0.0004)
Hurricane Index($t-1$)	-0.0009	-0.0006	-0.0009	-0.0005	-0.0016***	0.0007	0.0007
	(0.0008)	(0.0006)	(0.0008)	(0.0019)	(0.0006)	(0.0054)	(0.0006)
Hurricane Index(t) $\times$	0.1175***	0.0117	0.1103***	0.1242**	0.0029	-0.0812	-0.0380
1980 Proportional Immigrant Stock	(0.0450)	(0.0157)	(0.0419)	(0.0520)	(0.0067)	(0.1819)	(0.0652)
Hurricane Index($t-1$) $\times$	0.0150	0.0171	0.0180	-0.0021	0.0871***	-0.1792	-0.1550
1980 Proportional Immigrant Stock	(0.0135)	(0.0548)	(0.0157)	(0.0217)	(0.0080)	(0.1725)	(0.1129)
Weight	None	1980 Population	Log 1980 Population	None	None	None	None
Quartile	All	All	All	1st	2nd	3rd	4th
Country-Years	3,900	3,900	3,900	1,000	1,000	1,000	1,000

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 Equation (2). "Migrants" and "1980 Proportional Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table J.2: Dropping Small Countries

Panel A: No lags in Hurricane Index	Outcome for all columns: Migrants(t) as a Prop. of 1980 Population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hurricane Index(t)	-0.0010	-0.0015*	-0.0007	-0.0003	-0.0002	-0.0001	-0.0005	-0.0005
	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0004)	(0.0004)
Hurricane Index(t) $\times$	0.1163**	0.1283***	0.0719***	0.0390	0.0477	0.0592	0.0421*	0.0395
1980 Proportional Immigrant Stock	(0.0451)	(0.0468)	(0.0260)	(0.0319)	(0.0353)	(0.0381)	(0.0254)	(0.0297)
Country-Years	3,900	3,800	3,600	3,500	3,400	3,300	3,200	3,000
Dropped Countries	0	<15	<15	20	20	30	30	40

Panel B: One lag in Hurricane Index	Outcome for all columns: Migrants(t) as a Prop. of 1980 Population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hurricane Index(t)	-0.0011	-0.0016*	-0.0008	-0.0004	-0.0003	-0.0002	-0.0007	-0.0007
	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0004)	(0.0005)
Hurricane Index($t-1$)	-0.0009	-0.0009	-0.0008	-0.0008	-0.0010	-0.0008	-0.0011	-0.0012
	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0010)	(0.0009)	(0.0009)	(0.0008)
Hurricane Index(t) $\times$	0.1175	0.1298***	0.0754***	0.0427	0.0506	0.0617*	0.0442**	0.0417*
1980 Proportional Immigrant Stock	(0.0450)	(0.0467)	(0.0257)	(0.0312)	(0.0340)	(0.0364)	(0.0214)	(0.0242)
Hurricane Index($t-1$) $\times$	0.0150	0.0170	0.0242	0.0378	0.0217	0.0197	0.0167	0.0176
1980 Proportional Immigrant Stock	(0.0135)	(0.0142)	(0.0210)	(0.0362)	(0.0390)	(0.0390)	(0.0411)	(0.0493)
Country-Years	3,900	3,800	3,600	3,500	3,400	3,300	3,200	3,000
Dropped Countries	0	<15	<15	20	20	30	30	40

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 Equation (2). "Migrants" and "1980 Proportional Immigrant Stock" constructed using restricted-access data from the Census Bureau's Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table J.3: Sample Countries Sorted by Population

Country	1980 Population	Mean Hurricane Index 1980–2004	1980 Proportional Immigrant Stock [a]
Tokelau	1,553	0.0001	0.0515
Falkland Islands (Malvinas)	1,856	0	0.2155
Niue	3,402	0.0214	—[b]
St. Helena	5,899	0	—[b]
Anguilla	6,607	0.0199	0.0605
Turks and Caicos Islands	7,495	0.0114	0.0507
Nauru	7,599	0	0.0105
British Virgin Islands	11,001	0.0160	0.6836
Wallis and Futuna	11,016	0.0003	—[b]
Montserrat	11,845	0.0200	0.0912
Cayman Islands	16,623	0.0264	0.0578
Cook Islands	17,817	0.0003	0.0090
St. Kitts and Nevis	43,388	0.0210	0.0438
Kiribati	56,023	0	0.0025
Bermuda	56,067	0.0170	0.1413
Aruba	59,999	0.0001	0.0403
Seychelles	64,817	0	0.0074
French Guiana	67,801	0	0.0006
Antigua & Barbuda	69,424	0.0299	0.0562
Dominica	74,600	0.0034	0.0386
Micronesia	75,024	0.0003	—[b]
Grenada	89,584	0.0072	0.0804
Tonga	92,407	0.0054	0.0732
Sao Tome & Principe	94,512	0	—[b]
St. Vincent & the Grenadines	99,323	0.0063	0.0358
Vanuatu	116,213	0.0224	—[b]
St. Lucia	120,231	0.0087	0.0126
Western Sahara	137,458	0	0.0017
New Caledonia	140,633	0.0350	0.0010
Belize	144,284	0.0037	0.0992
French Polynesia	151,299	0.0015	0.0054
Maldives	153,593	0	0.0033
Samoa	157,298	0.0109	—[b]
Netherlands Antilles	172,296	0.0003	0.0269
Brunei	189,135	0	0.0041
Bahamas	210,210	0.0199	0.0675
Qatar	226,422	0	0.0046
Solomon Islands	230,691	<0.0001	—[b]
Equatorial Guinea	238,299	0	0.0004
Barbados	250,375	0.0089	0.1141
Macau	251,005	0.0122	0.0112
Cape Verde	299,019	0	0.0336
Martinique	325,459	0.0012	0.0030
Comoros	326,678	0.0006	0.0006
Guadeloupe	328,678	0.0381	0.0025
Djibouti	343,060	0	0.0005
Bahrain	353,735	0	0.0020
Suriname	359,850	0	0.0038
Bhutan	429,390	0	0.0053

Reunion	509,259	0.0179	0.0008
Timor-Leste	568,946	<0.0001	0.0004
Swaziland	607,418	0	0.0012
Gambia	628,415	0	0.0006
Fiji	634,881	0.0241	0.0131
Cyprus	657,838	0	0.0132
Gabon	720,141	0	<.0001
Guyana	768,140	0	0.0667
Guinea-Bissau	803,589	0	0.0002
Botswana	949,005	0	0.0006
Mauritius	964,869	0.0163	0.0007
United Arab Emirates	1,007,555	0	0.0006
Namibia	1,035,391	0	0.0002
Trinidad & Tobago	1,087,911	0.0001	0.0616
Oman	1,169,927	<0.0001	0.0003
Lesotho	1,332,988	0	0.0001
Kuwait	1,370,632	0	0.0033
Mauritania	1,539,525	0	0.0003
Mongolia	1,672,445	0	0.0001
Congo	1,735,761	0	0.0001
Liberia	1,874,816	0	0.0017
Panama	1,974,814	0	0.0306
Jamaica	2,180,542	0.0208	0.0908
Jordan	2,235,174	0	0.0093
Central African Republic	2,311,433	0	<0.0001
Costa Rica	2,323,776	<0.0001	0.0128
Singapore	2,414,214	0.0001	0.0021
Togo	2,673,175	0	0.0002
Lebanon	2,753,241	0	0.0194
Uruguay	2,923,111	0	0.0047
Nicaragua	3,026,750	0.0012	0.0145
Papua New Guinea	3,030,944	<0.0001	0.0002
Libya	3,069,342	0	0.0022
New Zealand	3,147,183	0.0001	0.0039
Paraguay	3,185,226	0	0.0010
Sierra Leone	3,257,631	0	0.0006
Laos	3,272,042	0.0007	0.0157
Honduras	3,519,165	0.0005	0.0106
Benin	3,588,043	0	0.0001
Israel	3,732,547	0	—[b]
Burundi	4,212,187	0	0.0001
Guinea	4,471,424	0	0.0002
Chad	4,517,575	0	<0.0001
El Salvador	4,615,483	<0.0001	0.0205
Hong Kong	5,058,392	0.0172	0.0157
Rwanda	5,140,312	0	<0.0001
Bolivia	5,405,100	0	0.0025
Haiti	5,587,661	0.0036	0.0165
Senegal	5,590,117	0	0.0001
Zambia	5,693,800	0	0.0003
Dominican Republic	5,761,285	0.0068	0.0288
Somalia	5,941,631	<0.0001	0.0001
Niger	5,963,859	0	0.0004
Malawi	6,247,395	0	0.0001

Tunisia	6,375,640	0	0.0005
Burkina Faso	6,570,515	0	<0.0001
Cambodia	6,793,898	0.0001	0.0027
Mali	6,801,635	0	<0.0001
Guatemala	6,825,347	0.0004	0.0093
Zimbabwe	7,229,519	0.0001	0.0005
Angola	7,421,478	0	0.0001
Ecuador	7,914,966	0	0.0112
Ivory Coast	8,429,406	0	0.0001
Yemen	8,519,761	<0.0001	0.0004
Madagascar	8,718,880	0.0053	0.0001
Cameroon	8,844,030	0	0.0002
Syria	8,848,002	0	0.0025
Cuba	9,741,318	0.0071	0.0633
Saudi Arabia	9,932,392	<0.0001	0.0016
Ghana	10,977,531	0	0.0007
Chile	11,095,449	0	0.0033
Mozambique	12,122,316	0.0008	<0.0001
Uganda	12,284,744	0	0.0003
Iraq	13,443,098	0	0.0023
Malaysia	13,646,914	<0.0001	0.0008
Afghanistan	14,112,360	0	0.0003
Nepal	14,498,764	0	0.0001
Sudan	14,600,904	0	0.0002
Australia	14,708,323	0.0001	0.0025
Venezuela	14,932,161	<0.0001	0.0021
Sri Lanka	15,044,572	0.0001	0.0004
Kenya	16,299,302	0	0.0004
Peru	17,311,920	0	0.0033
Taiwan	17,848,320	0.0564	0.0042
Tanzania	18,670,128	0	0.0002
Algeria	19,140,632	0	0.0002
Morocco	19,642,988	0	0.0005
Canada	24,511,056	0.0003	0.0344
Colombia	26,782,940	<0.0001	0.0055
Zaire	27,684,130	0	<0.0001
Argentina	28,244,966	0	0.0024
South Africa	29,164,364	0	0.0006
Burma	33,905,584	0.0014	0.0003
Ethiopia	35,638,836	0	0.0002
South Korea	37,787,544	0.0073	0.0077
Iran	39,299,124	0	0.0031
Egypt	43,783,092	0	0.0010
Turkey	44,476,880	0	0.0012
Thailand	47,197,448	0.0001	0.0012
Philippines	47,843,828	0.0263	0.0107
Vietnam	54,306,296	0.0037	0.0044
Mexico	69,350,248	0.0010	0.0316
Nigeria	74,263,440	0	0.0003
Bangladesh	81,826,248	0.0036	0.0001
Pakistan	82,601,704	0.0002	0.0004
Japan	115,912,104	0.0239	0.0019
Brazil	121,402,072	0	0.0003
Indonesia	147,907,968	<0.0001	0.0002

India	691,926,656	0.0007	0.0003
China	985,918,656	0.0013	0.0003

[a]Estimated using publicly available data from IPUMS-USA (Ruggles et al., 2019).
[b]Country's 1980 immigrant stock not avaiable in IPUMS-USA.

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