Pareto Seminar Paper

The Effect Of Extreme Climate Events On Migration In Mexico

Ludwig-Maximilians-Universität München

Luca Veh

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Abstract

This seminar paper studies the effect of extreme weather events on medium-term internal migration in Mexican municipalities. Using individual-level census micro data from IPUMS International for the years 2010, 2015, and 2020, I construct municipality-level measures of inter-municipal migration over five-year periods. These data are combined with government records on disaster declarations from Mexico's National Center for Disaster Prevention (CENAPRED), which capture severe climate-related events.

By exploiting within-municipality variation over time, I estimate two-way fixed effects models that regress migration outcomes on disaster exposure. A range of specifications are explored including some that control for time-invariant municipal fixed effects, common state and national fixed effects and time-varying socioeconomic and crime-related factors. The results indicate that, on average, additional disaster exposure is associated only with small and statistically insignificant changes in medium-term net migration. Because the Mexican government has only started to collect data on medium-term migration very recently (since 2010) and only as part of the census that is collected every five years, statistical power is not strong enough to make confident claims about causal effects. This highlights the need for higher-frequency migration data to better assess the effects of climate-related shocks on medium and long-run migration outcomes.

Overall, the findings suggest that extreme weather events, as captured by the official disaster declarations, do not lead to large or systematic changes in medium-term internal migration patterns across Mexican municipalities.

Contents

1 Introduction

1.1 Motivation and Research Question

Mexico is among the countries most exposed to extreme climate events in the Americas. Its geographic location between the Pacific and Atlantic basins places it directly in the path of tropical cyclones. In addition, large internal climatic variation makes many regions vulnerable to droughts, floods, wildfires, and heatwaves. Over the past two decades, Mexico has suffered from frequent and often severe extreme weather events, that not only have high economic but also high social costs. According to Mexico's National Institute of Statistics and Geography (INEGI), economic losses from extreme weather disasters regularly amount to billions of pesos annually. The National Center for Disaster Prevention (CENAPRED) documents this consistent exposure to extreme weather events and climate-related disasters (CENAPRED (2024)).

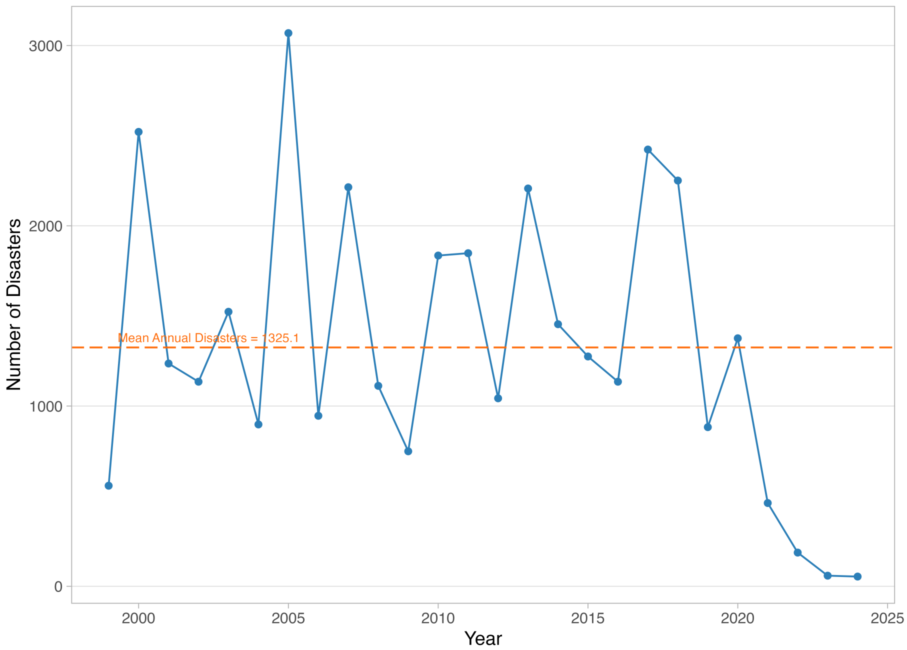


Figure 1: Number of Disasters per Year

Beyond direct economic losses, extreme climate events shape demographic patterns by disrupting livelihoods, damaging infrastructure, and altering local labor markets. The Internal Displacement Monitoring Centre (IDMC) reports that Mexico experiences tens of thousands of new disaster-related displacements each year, driven primarily by storms and floods (IDMC (2023)).

Since people who are temporarily displaced often return to their original homes, short-term migration caused by weather related displacement incidents are well documented. Meanwhile, long term migration patterns are often more complex. Permanent migration decisions are influenced by a multitude of factors and distinguishing extreme weather from

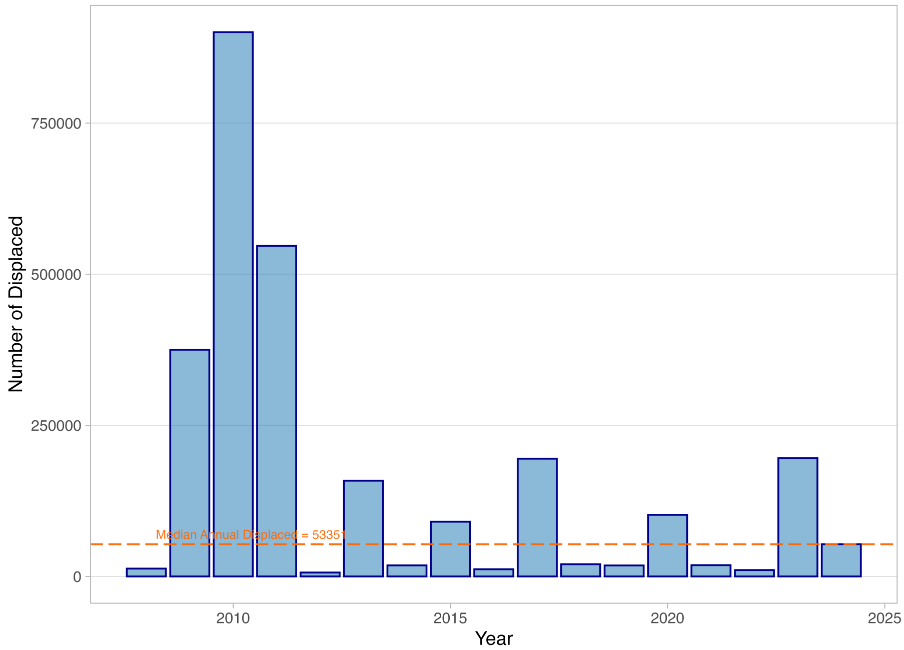


Figure 2: Number of Displaced People per Year

other push-factors becomes much more difficult in the long run. Municipalities within Mexico experience heterogeneous exposure to climate hazards and differ significantly in adaptive capacity, economic structure, and institutional strength. Still, understanding the relationship between disasters and long-term migration is crucial, not only for improving disaster-risk management but also for informing climate adaptation and regional development policy.

This seminar paper examines how extreme climate events affect medium-term internal migration patterns. The estimation strategy leverages a panel of individual-level movement data from 2005 to 2020 that was created using data from the 2010, 2015 and 2020 Mexican Census. Using data for this extended study period of 15 years increases the likelihood of estimating coefficients that are independent from the effects of cyclical trends and short-term displacement. In addition, data on the amount of yearly disasters is provided by the Center of Disaster and Risk Prevention (CENAPRED).
To answer the research question, how extreme weather events influence medium-term migration patterns, the identification strategy employs a fixed-effects regression model. This makes it possible to control for time-invariant municipality fixed effects, aswell as municipality-invariant period- (i.e. the 5-year census-intervals) fixed effects.

2 Data

2.1 Migration Data

The migration data used in this paper was sourced from the Mexican Population and Housing Census for the years 2000, 2010, 2015 and 2020. Specifically of interest was the long-form survey that was administered to approximately 10% of households and included an extended questionnaire with information relevant for inter-municipal migration flows. The sampling process, i.e. the process of selecting which household received the extended questionnaire is based on multistage probability sampling with slight differences in the exact methodology between the three rounds. The actual data used was downloaded from the IPUMS International Database (IPUMS International (2010, 2015, 2020)). This greatly facilitated geographic matching with the other data and ensures standardized variable naming across censuses.

During pre-processing, rows with invalid municipality codes, missing information on their municipality of residence five years ago, and missing information on the demographic data were removed. This lowered the amount of observations to around 42 million individual-level observations for the three census-iterations 2010, 2015, and 2020.

Table 1 reports summary statistics aggregated across census rounds. A similar table with summary statistics for each census-round can be found in table 3 in the appendix. Summary statistics on the migration outcomes are reported in panel A. Note that a "N" of 6975 indicates that data is available for all 2325 (IPUMS harmonized) municipalities for the three census rounds. Across time, on average in- and out-migration balances out, leading to an average net migration of 0. Rates were calculated by dividing absolute migration numbers by population size at the time where the census data was collected.

2.2 Demographic Data

The census data that was additionally used to extract key demographic variables that serve as controls in the regressions below. During pre-processing, invalid municipality codes were removed and municipality level, weighted means of relevant variables, such as age, literacy-rate, male/female ratio, etc. were calculated. Where it was necessary, means were weighted with their respective weights (contained in the perwt variable in the data) make sure that they represent the overall Mexican population accurately. Summary statistics for the demographic data are provided in Panel C of Table 1.

2.3 Disaster Data

The National Center for Prevention of Disasters (CENAPRED) publishes data on the number of emergencies, disasters and climatic contingencies for every year and municipality in an "Atlas Declaratorias"CENAPRED (2024). This information is collected trough analysis of the government's official newspaper, which among other things publishes any declarations of emergency for one or more municipalities by the federal government. Such a declaration of emergency follows the presence of a severe disturbing natural agent in certain municipalities or delegations of one or more federal entities (i.e. municipalities, states, etc.), whose damage exceeds the local financial and operational capacity. Declaring this emergency is necessary in order to be able to access resources of the financial instrument for the care of natural disasters, such as the Natural Disasters Fund. The key advantage of using this data is that it offers a very powerful and convenient count of disastrous weather events on a municipality level. Moreover, since it only records those weather that were deemed by local authorities to have such a large impact that they could not handle it themselves and required federal help, the data indirectly also filters for weather events that had a significant impact on local municipalities. On the other hand this preselection of weather events also makes clean inference more difficult. In addition to the information that is relevant for this analysis, the data might also reflect administrative capacity to request and obtain a declaration from the federal government in the first place, hidden political incentives, eligibility rules and the efficiency of coordination between local and federal governments. During estimation this might lead coefficients to pick up a combination of actual disaster-information, local capacity and attractiveness of reporting.

The data is available from 2000 to 2024 on a municipality level. During pre-processing the current municipality codes used by the CENAPRED data are matched to the harmonized version used by IPUMS. As IPUMS combines some municipalities to maintain a harmonized structure across multiple census rounds, a some information is lost here. Furthermore, the disaster data are aggregated to five year intervals, to match the census time intervals. This means that the effect of all events recorded e.g. during 2001 and 2005 are attributed to the 2005 census. As the census in 2005 captures all movement between 2000 and 2005, the idea behind this is that events recorded between 2000 and and 2005 also influence migration in this time period. This of course is an oversimplification - a tropical storm that hit land on the 31st December of 2005 may very well only start having an effect on migration in 2006 or later. This potential problem is further addressed section 3.4. Figure 3 illustrates how the disaster data is aggregated to the census intervals (highlighted in blue).

2.4 Crime Data

In addition to extreme weather events, the main driver of displacement and short-term migration in Mexico is violent crime IDMC (2023). A key indicator for crime is inferred from the amount of homicides in a municipality that is published by the National Institue of Statitics (INEGI) INEGI (2025). As with the disaster data, the crime data is also aggregated to the five year-census intervals.

2.5 Data merging

After pre-processing the data (i.e. removing NAs, transforming and matching geographic data, where necessary) the datasets for migration, disasters, demographics and crime were merged into two datasets: Firstly, a municipality-node dataset, that contains one entry for each node (=municipality) and census year combination. This dataset is used to estimate the two-way fixed effects estimation models. Secondly, a municipality-edge dataset that

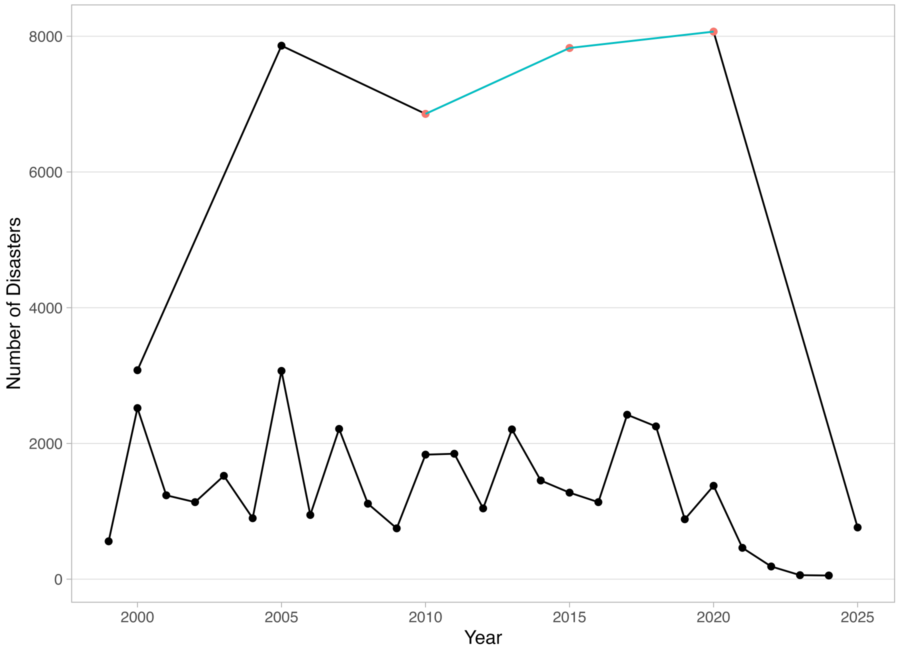


Figure 3: Disasters per Year and per Census Period

Table 1: Summary statistics (municipality-year level)

Variable	N	Mean (SD)	Median	Min	Max
Panel A: Migration outcomes					
Period Immigration	6975	2512.33 (11059.83)	344.00	0.00	276699.00
Period Emmigration	6975	2512.33 (13784.52)	386.00	0.00	483051.00
Net Immigration	6975	0.00 (8410.35)	-4.00	-219655.00	113326.00
Immigration Rate	6975	0.04 (0.03)	0.03	0.00	0.67
Emmigration Rate	6975	0.04 (0.05)	0.03	0.00	2.10
Net Immigration Rate	6975	-0.00 (0.06)	-0.00	-2.06	0.66
Panel B: Disaster exposure					
Total Unique Disasters (Period)	6975	3.79 (4.79)	2.00	0.00	86.00
Total Disasters (Period)	6975	3.26 (4.02)	2.00	0.00	78.00
Panel C: Controls					
Mean Income	6965	3313.14 (2378.09)	2941.76	34.95	39125.43
Mean Age	6975	30.99 (3.71)	30.66	20.24	48.91
Female Rate	6975	0.51 (0.02)	0.51	0.43	0.61
Literacy Rate	6966	0.86 (0.08)	0.88	0.42	1.00
Mean Years of Schooling	6966	6.08 (1.28)	6.01	2.07	12.62
Municipal Population	6975	51188.19 (200573.91)	12704.00	76.00	5413803.00
Population Density	6975	219.80 (719.69)	51.75	0.11	10714.21
Crime (Homicides)	6975	50.18 (411.69)	1.00	0.00	15140.00

Notes:
Unit of observation is municipality-year. N reports non-missing observations.

contains information about the amount of people who migrated from one municipality to another in a certain time span. This dataset is especially relevant for research into where migration flows. Due to the scope of this seminar paper this is not discussed further here, but offers an exciting opportunity for future research.

As always, when using public data, systematic (i.e. non-random) measurement error remains a concern. In the worst case this would lead to attenuation bias, i.e. coefficients are biased towards 0. Furthermore, if measurement error is spatially correlated (e.g. differential reporting across municipalities) estimates would suffer from non-classical bias.

3 Research Design

3.1 Conceptual Framework

To identify the medium run effect of extreme events on permanent in-and out migration in Mexican municipalities this seminar paper uses a municipality level panel data design. This approach exploits variation in exposure to extreme climate events within municipalities over time, while controlling for unobserved long-term heterogeneity across municipalities and common shocks across time periods.

The parameter of interest is the average effect of within-municipality variation in exposure to extreme climate events over a five-year period on net-migration rates, while holding time-invariant municipal characteristics and common period shocks constant. To identify this parameter the core identification strategy relies on a two-way fixed effects (TWFE) panel regression model, where migration outcomes are regressed on the (quasi-) **continuous** climate shock exposure variable. The main motivation for choosing the TWFE-regression model stems from two major concerns for the validity of the identification strategy. Firstly, municipalities may follow nation-wide long-run economic or demographic trajectories that could correlate with climate exposure and migration patterns, leading to omitted variables bias in the estimated coefficients. This is addressed by including municipality fixed effects (ρ_t) that capture any such national-level trends. Secondly, there are significant time-invariant differences across municipalities, concerning mainly geographic and long-term climate exposure factors. This is addressed by including municipality fixed effects (μ) that capture any such time-invariant factors.

The unit of analysis are municipality-period observations, where periods correspond to three five-year census intervals (2005-2010, 2010-2015 and 2015-2020). This extended time period allows the estimation of coefficients that are less sensitive to cyclical trends. As outlined in section 2.1. the migration outcomes are constructed by aggregating origin-destination flows from Mexican census micro data into municipality-level measures of in-, out- and net-migration. The climate data that is originally observed in smaller time intervals is aggregated to fit the five-year periods of the census, to ensure appropriate temporal alignment with the migration data.

3.2 Estimation Strategy

The main estimating regression is the following two-way-fixed-effects model:

$$NetMigration_{it} = \beta ClimateShock_{it} + \gamma X_{it} + \mu_i + \rho_t + \epsilon_{it}$$

where $NetMigration_{it}$ is the net (in-) migration (i.e. amount of in migrants - amount of out migrants) for municipality i in period t, $ClimateShock_{it}$ is the continuous climate shock variable, indicating the amount of extreme weather events, X_{it} is a vector of time-varying controls including population size, income, age, literacy and crime, μ_i are municipality fixed effects that capture time-invariant local characteristics like geography and long-run climate risks, ρ_t are period (5-year) fixed effects that capture national-level

trends in migration, overall economic conditions and policy that affects all municipalities and ϵ_{it} is an idiosyncratic error term.
Standard errors are clustered at the municipality level to account for serial correlation in climate exposure and migration outcomes within municipalities across time periods. Allowing and controlling for both heteroskedasticity and autocorrelation within municipalities (across time) reduces the risk that standard errors are underestimated. In addition Table X in the Appendix reports results with Standard Errors computed using Conley (1999) to account for spatial correlation in the error term across neighboring municipalities. This might be relevant, since large scale extreme weather events (such as tropical cyclones) often disrupt regional (not only municipal) outcomes. Migration responses to these disasters might thus exhibit spillover effects because of e.g. shared labor markets or infrastructure across municipality borders.

3.3 Key identifying assumptions

The key identifying assumption of the TWFE-model outlined above is that, conditional on municipality fixed effects, year fixed effects and observed time-varying controls, there are no unobserved time-varying factors within municipalities that affect migration and are correlated with extreme weather exposure. Formally this means that strict exogeneity is required:

$$E[\epsilon_{it}|ClimateShock_{i,t}, X_{it}] = 0 \ \ \forall t \in 2010, 2015, 2020$$

This condition rules out unobserved shocks that vary both over time and within municipalities and are correlated with disaster exposure. Potential violations arise if municipal government implement policy changes that for example improve their capacity of handling extreme weather events or increase investment in preventive measures. If these policy changes also influence migration patterns (e.g. investment in the municipality makes it more attractive for in-migration) strict exogeneity is violated. In words of the classical parallel trends assumption, the exogeneity assumption also implies that municipalities, that experienced more or fewer extreme weather events in a given year, relative to their average, would have had the similar migration outcomes as other municipalities, in the absence of climate exposure, conditional on FEs and controls.
In order to be able to interpret the climate shock coefficient as constant marginal effect, assumptions about the linearity and homogeneity of the functional-form are necessary. This implies that one extra climate shock has the same marginal effect on all municipalities and the effect remains roughly constant over time. If this does not hold, then β does not represent a constant marginal effect but rather a weighted average effect of a marginal change in disaster exposure.
It should be noted that, the approach outlined above differs significantly from the standard TWFE approach with a binary treatment variable, that unless very strict criteria are met, suffers from negative weighting problems and bias (Goodman-Bacon 2021). In standard TWFE models treatment is usually binary and represents the occurrence of a one-time shock. The treatment used in this paper is modeling climate exposure as a (quasi-) continuous and recurrent shock-variable. This mitigates the concerns related to heterogeneous treatment timing in different geographic regions. The literature on TWFE-models with continuous shock-variables is unfortunately not yet as sophisticated as the

literature about TWFE-models with binary shock variables. Future research may uncover different challenges for these models that will need to be considered.
Although the usual concerns about bias do not directly apply here, the estimates should be interpreted as reduced-form effects that capture the combined influence of the actual direct physical risk of the climate events, economic losses and also indirect social responses to climate shocks. Although information about the reason for migration is provided for some iterations of the mexican census, the amount of observations where this was actually reported do not provide enough statistical power for estimation.
One of the issues that is due to the periodical nature of census-migration data is that the disaster data has to be aggregated to five year intervals. This makes interpretation more difficult, as the data only provides information about how migration and disasters happened "sometime in the last five years", not when exactly. A tropical storm towards the end of a time period could for example have considerable consequences for migration in the next time period. The interpretation of the coefficients should thus be seen as capturing the average medium-run effects of disasters on migration, rather than short-term effects. A model specification that includes a coefficient for lagged effects is discussed in the evaluation of the regression results in part 4.

4 Results

Table 2 displays the results of four different specifications. Model 1 is a simple pooled OLS regression. Compared to the full specification the coefficient of total disasters (main coefficient) is positive. This suggests that there might be large omitted heterogeneity between municipalities which the simple model fails to control for. This provides strong motivation to include fixed effects. Model 2 includes both municipality and year fixed effects but no control variables. The goal of this specification is to avoid bias from controlling with variables that are themselves part of a potential causal pathway through which disasters induce migration. Including them changes the interpretation of the coefficient from an estimation of the total effect of disasters on migration to a direct effect conditional on local economic conditions. As suggested by Dell et al. (2014) this is especially a concern for income. At the same time this model relies entirely on within-municipality variation, assuming that there are no time-varying municipality level confounders. Leaving out the controls thus likely introduces bias from omitted variables, thus potentially violating the strict exogeneity assumption. Model 3 is the main regression specification that includes both fixed effects, as well as a full set of controls. According to this model, the overall average ceteris paribus effect of an additional disaster on net migration, using only within-municipality, over-time derivations, net of common year shocks and conditional on control variables is -29.21. This means that on average c.p. an additional disaster is associated with 29.21 more people leaving a municipality than enter it. The effect is not statistically significant. Model 4 adds a total disasters coefficient, lagged by one (5-year) time period. This can be interpreted as lagged response to disasters that happened in the previous 5-year period. This coefficient is also not statistically significant.

Table 3 and 4 in the Appendix outline more model specifications that aim to address different problems. For the sake of brevity, independent of the specification and the

Table 2: Main Results

Dependent Variable:	Net Immigration			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-115.2			
	(360.6)			
Total disasters (period)	35.31	4.603	-29.21	-40.61
	(111.8)	(27.67)	(28.82)	(36.09)
Municipal population			0.0486	0.0492
			(0.0339)	(0.0342)
Mean income			0.2432**	0.2473**
			(0.0990)	(0.0997)
Average age			-182.4*	-178.1*
			(95.40)	(96.06)
Female share			-13,188.3***	-12,918.0***
			(4,635.0)	(4,555.0)
Literacy rate			7,561.0***	7,324.0***
			(1,932.7)	(1,903.5)
Urbanization rate			512.7	512.1
			(748.3)	(743.3)
Crime rate (homicides)			-0.6376	-0.6298
			(1.091)	(1.096)
Total disasters (lag 1)				-40.18
				(59.11)
Fixed-effects				
Municipality FE		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
Fit statistics				
Observations	6,975	6,975	6,965	6,965
R^2	0.00028	0.84391	0.84883	0.84892

Clustered (Municipality FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

outcome (migration) variable, the average effect of total disasters is never statistically significant. This implies that on average there is no direct medium-term effect of extreme weather events, as measured by the Atlas Declaratorias, on net migration in Mexican municipalities. At the same time it should be noted that standard errors are very high across specifications. Unfortunately the limited data on medium-term migration does not seem to provide enough power to make reliable inference, so all coefficients should be interpreted with caution.

5 Conclusion

This paper examines whether extreme weather events influence medium-term internal migration patterns in Mexico. Combining individual-level census micro data with municipality-level disaster declarations, I estimate the relationship between exposure to severe climate-related events and inter-municipal migration over five-year periods. The empirical strategy exploits within-municipality variation over time and controls for unobserved municipal heterogeneity, common period shocks, and a set of time-varying controls. Across a range of specifications, I find no statistically significant evidence that disaster exposure systematically affects medium-term net migration at the municipality level. While point estimates are small relative to average migration flows, standard errors are large. These results suggest that, on average, extreme weather events do not induce large permanent migration flows across municipalities, at least as measured by official disaster declarations and census-based migration outcomes.

However, these findings should be interpreted with caution. The use of the government's data on disaster declarations may not be able to distinguish between physical exposure and institutional or political factors that vary over time within municipalities. As a result, the estimates should be viewed as reduced-form associations rather than precise causal effects.

Promising paths of future research include the collection and inclusion of higher-frequency migration data, calculation of alternative measurements for extreme weather events, as well as their economic and demographic impact.

A Appendix

Table 3: Summary statistics by period

		2010		2015		2020	
Variable	N	Mean	SD	Mean	SD	Mean	SD
Panel A: Migration outcomes							
Period Immigration	6975	2600.62	11840.52	2366.81	9924.28	2569.55	11328.86
Period Emmigration	6975	2600.62	16216.00	2366.81	12275.78	2569.55	12510.66
Net Immigration	6975	0.00	9945.73	0.00	7758.42	0.00	7290.55
Immigration Rate	6975	0.04	0.04	0.04	0.04	0.04	0.03
Emmigration Rate	6975	0.04	0.06	0.04	0.06	0.04	0.03
Net Immigration Rate	6975	0.00	0.07	0.00	0.07	0.00	0.04
Panel B: Disaster exposure							
Total Unique Disasters (Period)	6975	3.34	4.03	4.47	5.92	3.57	4.09
Total Disasters (Period)	6975	2.95	3.63	3.37	4.46	3.47	3.91
Panel C: Controls							
Mean Income	6965	1335.24	878.84	3809.61	1818.96	4796.70	2553.13
Mean Age	6975	29.64	3.49	30.96	3.57	32.37	3.56
Female Rate	6975	0.51	0.02	0.51	0.02	0.51	0.02
Literacy Rate	6966	0.84	0.09	0.87	0.07	0.88	0.07
Mean Years of Schooling	6966	5.53	1.20	6.09	1.20	6.62	1.21
Municipal Population	6975	48154.90	192540.95	51424.47	199927.82	53985.18	208959.46
Population Density	6975	204.90	677.19	221.34	727.47	233.17	752.39
Crime (Homicides)	6975	32.80	235.92	48.03	275.08	69.71	613.68

Notes:
Unit of observation is municipality-year. Cells report means and standard deviations. N is the number of non-missing observations.

Table 4: Alternative Model Specifications

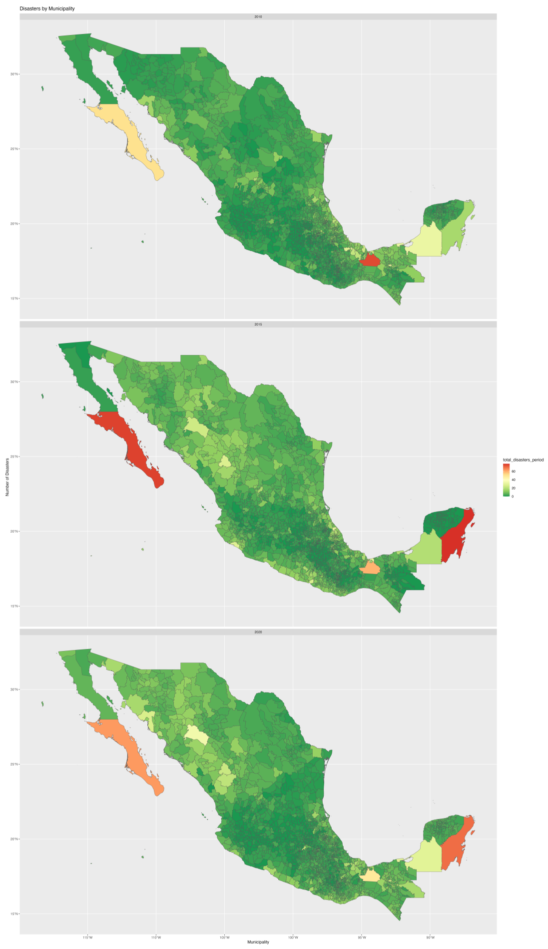
Dependent Variable:	Net Immigration		
Model:	(1)	(2)	(3)
Variables			
Total disaster (lead 1)	128.2*		
	(71.02)		
Municipal population	0.0523	0.0516	0.0328
	(0.0349)	(0.0335)	(0.0341)
Mean income	0.2481**		0.2403**
	(0.0999)		(0.0938)
Average age	-159.6	-181.1*	-202.5**
	(97.93)	(95.57)	(97.98)
Female share	-11,841.1***	-12,461.8***	-12,803.2***
	(4,455.1)	(4,601.5)	(4,896.6)
Literacy rate	5,982.4***	3,784.1	6,577.4***
	(1,945.9)	(2,498.4)	(1,868.3)
Urbanization rate	556.2	756.3	676.3
	(739.8)	(744.1)	(766.5)
Crime rate (homicides)	-0.6317	-0.5663	-0.8142
	(1.099)	(1.096)	(0.9282)
Total disasters (period)		-25.69	-7.523
		(29.37)	(29.58)
Fixed-effects			
Municipality FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE-Year FE			Yes
Fit statistics			
Observations	6,965	6,966	6,959
R^2	0.84984	0.84819	0.86089

Clustered (Municipality FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

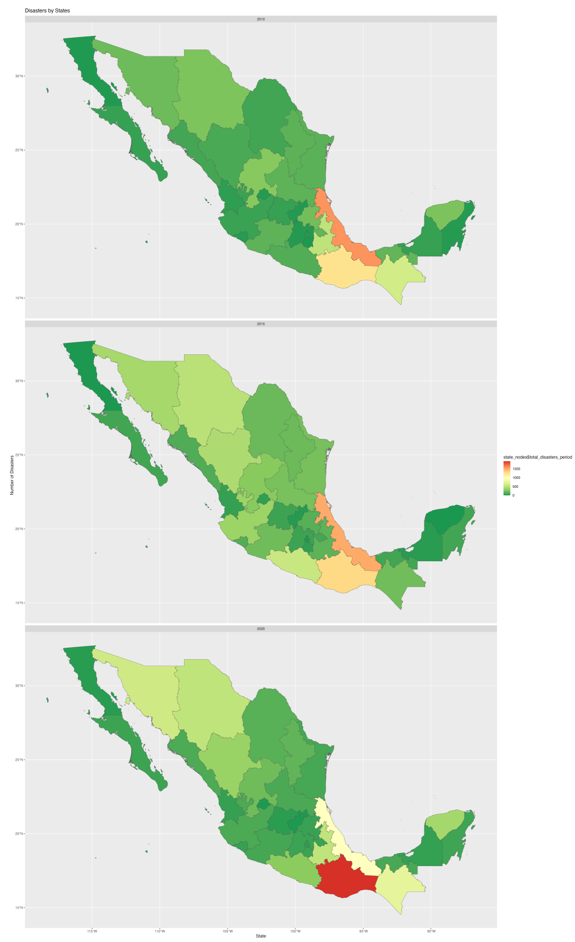
Table 5: Alternative Model Specifications

Dependent Variable:	Net Immigration				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Total disasters (period)	-0.4727	38.12	59.22	-29.21	-29.21
	(29.52)	(45.55)	(45.36)	(28.82)	(28.82)
Total disasters (lag 1)	-18.58		49.37		
	(52.42)		(43.16)		
Total disaster (lead 1)		147.9*	166.7**		
		(78.67)	(77.70)		
Municipal population		0.0340	0.0341	0.0486	0.0486
		(0.0344)	(0.0344)	(0.0339)	(0.0339)
Mean income		0.2460***	0.2468***	0.2432**	0.2432**
		(0.0947)	(0.0945)	(0.0990)	(0.0990)
Average age		-184.8*	-185.9*	-182.4*	-182.4*
		(97.92)	(98.23)	(95.40)	(95.40)
Female share		-11,859.3**	-11,914.3**	-13,188.3***	-13,188.3***
		(4,754.1)	(4,751.2)	(4,635.0)	(4,635.0)
Literacy rate		6,057.6***	5,992.8***	7,561.0***	7,561.0***
		(1,804.5)	(1,814.5)	(1,932.7)	(1,932.7)
Urbanization rate		744.4	741.5	512.7	512.7
		(767.4)	(770.8)	(748.3)	(748.3)
Crime rate (homicides)		-0.8054	-0.8131	-0.6376	-0.6376
		(0.9402)	(0.9392)	(1.091)	(1.091)
Fixed-effects					
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
geolevel1-Year FE		Yes	Yes		
Fit statistics					
Observations	6,975	6,959	6,959	6,965	6,965
R^2	0.84393	0.86152	0.86159	0.84883	0.84883

Clustered (Municipality FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*



(a) Disasters in Municipalities



(b) Disasters in States

Figure 4: Spatial distribution of disasters at different administrative levels

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