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Weathering the Storm: Weather Shocks and International Migrants from the Philippines

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***Weathering the storm:* Weather shocks and international migrants from the Philippines**

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Abstract

The growing literature on environmental migration presents conflicting results. While some find that natural disasters induce international migration, others discover a dampening effect. We aim to reconcile these differences by using a comprehensive list of weather shocks from the Philippines, a country prone to natural disasters and a major exporter of labor. We constructed a longitudinal provincial dataset (2005–2015) from an assemblage of administrative and survey datasets and tested linear, quadratic, and lagged models.

Our fixed-effects results are consistent with both strands in the literature with caveats. First, Filipinos are more likely to work abroad when they experience less-intense tropical cyclones and storm warning signal but are more likely to stay with a more damaging storm warning signal. Second, differential effects of weather shocks on international migration contingent on agriculture exists. Third, non-environmental factors such as economic (unemployment rate) and infrastructure (number of high schools) also push Filipinos abroad.

Keywords: Migration, Natural Disaster, Panel Dataset, Agriculture, OFWs

JEL classification: C33, C36, F22

1. Introduction

The Philippines has experienced the various manifestations of climate change over the past few decades, such as increase in temperature, rising sea-level and increase in frequency and higher intensity of typhoons (Philippine Atmospheric Geophysical and Astronomical Services Administration [PAGASA] 2011, Asian Development Bank [ADB] 2009). These climate hazards are projected to worsen. For example, the surface temperature in the Philippines is predicted to increase to as much as about 1.1°C by 2020 and 2.2°C by 2050. The country will also more likely experience extreme temperature events (more frequent days of temperatures exceeding 35°C) and extreme rainfall events (increase in the number of dry days and days with extreme rainfall) from 2020 to 2050. The vulnerability of the Philippines to climate change is arguably aggravated by its geographic location. As one of the countries within the Pacific Ring of Fire and along a typhoon belt, the Philippines has experienced a myriad of natural disasters, from frequent typhoons to drought, earthquakes, and volcanic eruptions. The latest reported catastrophe just happened early January of 2020 when Taal volcano erupted, which caused 625 seismic activities (184 were felt with earthquake intensities) as of January 14, dispersed ash, and generated plumes that reached about 1km high (Department of Science and Technology–Philippine Institute of Volcanology and Seismology [DOST–PHIVOLCS] 2020).

Natural disasters have several adverse effects, one of which is damage to assets and properties. For example, PAGASA (2011) reported that the five most destructive typhoons, which made landfall in the Philippines in the 1990s and in 2006, caused about PHP 46.8 billion (USD 924 million) of damage to property.

Destructive natural disasters not only cause physical damage but can also displace the population. In the literature, extreme weather events have an adverse impact on household welfare, and households can choose to adopt different risk-coping mechanisms, one of which is migration (Halliday 2006; Drabo and Mbaye 2011; Tse 2012; Kubik and Maurel 2016; Maurel and Tuccio 2016; Bohra-Mishra et al. 2017; Mahajan and Yang 2017). Migration (temporary or permanent) remains an important survival strategy for people facing natural disasters (Smith 2007). For example, in the Philippines, the Taal volcano eruption in the early 2020 resulted to DOST-PHIVOLCS strongly advising a total evacuation of the high-risk areas identified within the 14-km radius from Taal main crater (DOST–PHIVOLCS 2020). Intergovernmental Panel on Climate

Change (IPCC 2007) also identified rise in sea level, increase in cyclone intensity and drought events as the three environmental factors that often led to human migration.

It is important to differentiate between the types of migrants (internal versus international migrants) and types of environmental factors, because results may vary contingent on the choice of categories. Nonenvironmental influences on migration, as well as their interactions with the environmental factors, also must be considered. For example, Obokata et al. (2014) conducted a systematic review of empirical studies on climate change (such as natural disasters, drought, flooding, rising sea level, etc.) and international migration. The complex interactions of environmental and nonenvironmental (such as economic, political, and sociodemographic) factors and their impact on the migration decision of international migrants (as refugees or labor migrants) are highlighted in their review. The choice of methodology is also highly relevant, because proper identification method is crucial in capturing and isolating the impact of climate change on migration.

The main goal of this paper is to examine whether the various measures of natural disasters (such as type, frequency and intensity of typhoons, as well as public storm warning signals) and the damages they cause (including casualties and damage in pecuniary terms) contribute to the international migration of Filipino workers. We used a longitudinal dataset (2005–2015) that we constructed, controlling for different provincial characteristics, including the historical migration rate, income, sociodemographic characteristics, and institutions in place.

The Philippines is an important country to analyse in this context for two reasons. First, this country is a major contributor to global labor migration. The number of Filipino workers over the years keeps on increasing (Survey on Overseas Filipinos [SOF] 1993–2015) and the Philippines has been consistently one of the top origin countries of international migrants (International Organization for Migration [IOM] 2017).[1] Therefore, learning more about the factors, such as environmental factors, that push Filipinos to work abroad, can have a far-reaching impact, because it potentially affects not just the economy of the Philippines but also that of the destination countries. Second, as mentioned previously, the Philippines is frequented by natural disasters. PAGASA (2019) reports that from 1948 through 2018, more tropical cyclones entered the Philippine Area of Responsibility (an average of 20 annually) compared to other countries in the world.

[1] Authors' computation from SOF datasets and IOM website.

Our paper intends to add to the literature on environmental migration in the following ways. First, to the best of our knowledge, our paper is among the first studies, if not the very first, to analyse the relationship between natural disasters and international migration, using longitudinal data (2005–2015) from the Philippines. Also, its use of a panel dataset reveals a telling relationship, beyond what simple cross-sectional or time trend datasets can accomplish. Panel data analysis allows for a model that incorporates time-invariant fixed effects (such as unobserved provincial or regional characteristics). In effect, a panel data approach considers unobserved factors that are common to all farmers, for example, or a macro-shock that affects several provinces, such as price changes (Falco et al. 2018a).

Second, in the growing literature on environmental migration, the results are conflicting. While some authors find a positive correlation between migration and natural disasters (such as Cai et al. 2014; Baez et al. 2016, 2017; ; Chort and de la Rupelle 2016; Maurel and Tuccio 2016; Bohra-Mishra et al. 2017; Mahajan and Yang 2017), others find that weather shocks decrease migration (Halliday 2006; Tse 2012; Robalino et al. 2015; Gignoux and Menendez 2016 to cite a few). We aim to reconcile and explain these differences in the findings by using a more comprehensive list of weather shocks categorized by wind intensity and damage.

Third, we aim to appropriately identify the relationship of weather variation and international migration by considering different measures of weather events, using an assemblage of datasets, testing different model specifications, and performing different econometric strategies. Specifically, we use a total of 11 distinct datasets, such as administrative (weather warning system and frequency and intensity of typhoons), nationally representative household dataset, and provincial and regional datasets, to answer an important and relevant question on environmental migration. We recognize the importance of the interactions of both environmental and nonenvironmental factors in determining international migration—hence the use of myriad sets of data. We also use various econometric specifications and approaches to appropriately test our hypothesis and verify the robustness of our results, from using a linear model as our base analysis to examining a quadratic model, a lagged model, splitting the dataset into agricultural and non-agricultural provinces, and using interaction terms to formally test the heterogeneity in our results conditional on agricultural intensity. We also consider different combinations of weather events and control variables, as well as create different agricultural thresholds to identify agricultural provinces. We further test our hypothesis by using six distinct econometric strategies and clustering standard errors by province (ordinary least squares [OLS], random effects [RE], fixed effects [FE], 2-stage least squares [2SLS], instrumental variable fixed effects [IVFE] and instrumental variable random effects [IVRE]).

In the case of the Philippines, it is fitting to analyse the international migration response of Filipinos to weather variations over the years. In their review of the literature on environmental migration, Falco et al. (2018a) found that international migration is more of a long-run response to sustained weather events, while internal migration is more subject to short-term natural disasters. This is because households intending to migrate internationally often face a larger migration cost and would need more time to prepare to migrate, whereas households experiencing hazardous natural disasters may have to migrate internally immediately and perhaps temporarily. It is also more likely for households to strategize and distribute the risks that they face by allowing one or two members to migrate somewhere not exposed to similar adverse weather shocks, and since the entire Philippines is subject to a myriad of natural disasters quite regularly, this means migrating abroad. The migration response to weather variation is better seen and understood also by examining a longer time period than analysing just one period.

Our results are consistent with both strands in the literature on weather shocks and international migration with caveats. First, we find that there exists a positive correlation between low-intensity weather shocks (storm warning #1, tropical depression and typhoon) and migration, but this correlation diminishes as the wind intensifies. This is further supported by finding that a more-intense weather shock (storm signal #4) actually decreases migration. Second, we find that agriculture provides heterogeneity in the impact of weather shocks on migration. This supports the finding in the literature that agriculture is an important link between climate variables and migration. Since the rice yields of agricultural provinces are more adversely affected by a natural disaster, international migration is more likely to come from these provinces as well. Third, we find that the effect of weather shocks on income, similar to migration, is not as simple and straightforward as it appears; we also find a nonlinear relationship between weather variations and income. Finally, the local economic welfare and infrastructure positively affect international migration. In particular, as the provincial unemployment rate and the number of high schools increase, more Filipinos tend to migrate.

This paper is organized as follows. Section 2 presents a brief review of the literature related to our paper. Section 3 shows the discussion of our data and the descriptive statistics of the variables we are using in our paper. Section 4 focuses on the econometric strategies and models for testing our hypotheses, and section 5 presents a discussion of our results. Section 6 is the conclusion.

2. Related literature

In the literature on environmental migration, internal migration is often differentiated from international migration, which is subject to higher liquidity and credit constraints and therefore involves a more complex decision-making process. In this section we present the literature on weather shocks, internal migration, and international migration.

2.1 Weather variation and internal migration

The findings of the studies that examine the impact of natural disasters (such as hurricanes) and other climatic variables (such as precipitation and temperature shocks) on internal migration are dependent on the intensity of the weather shock and the post-disaster recovery efforts of the government and individuals. While some studies found that weather shocks induce internal migration (a positive correlation), such as Kubik and Maurel (2016), Gröger and Zylberberg (2016), Baez et al. (2017), Bohra-Mishra et al. (2017), other studies found that extreme weather variation and the post-disaster response of the government induce people to stay or return to their place of origin that was damaged by the natural disaster (a negative correlation), such as Tse (2012), Curtis et al. (2015) and Robalino et al. (2015).

In Vietnam, Gröger and Zylberberg (2016) found that households used urban labor migration as a coping mechanism after a substantial drop in their income brought about by a catastrophic typhoon. Curtis et al. (2015) interpreted the large in-migration flows to New Orleans, United States post–Hurricane Katrina from both displaced residents and newcomers as recovery migration, given the contribution of these migrants to the repopulation of the disaster-affected state.

Although hurricanes induce internal migration, the effect does not appear to be linear. For example, in Costa Rica, Robalino et al. (2015) found that while hydro-meteorological emergencies increase internal migration during 1995–2000, emergencies with severe consequences, such as casualties, lead to a decrease in migration. Heterogeneity in the results attributed to urbanization effects is also observed.

In addition, there also exists heterogeneity across age groups. Baez et al. (2016), which examined internal migration due to droughts and hurricanes in Northern Latin America and the Caribbean, found that youths are more vulnerable to either natural disaster and are more likely to migrate.

Kubik and Maurel (2016) examined how internal migration of rural households in Tanzania respond to weather-related shocks such as standardized precipitation evapotranspiration index, temperature and precipitation shocks. They find that weather shocks adversely affect income, which then translates to an increase in migration the following year by 13 percentage points, using an instrumental variable (IV) probit. They further find that households in the middle of the wealth distribution and whose incomes are highly dependent on agriculture are more likely to migrate.

In the Philippines, Bohra-Mishra et al. (2017) investigate the effects of climatic variations such as annual average, maximum and minimum temperatures, and precipitation values, and deaths from typhoons on aggregate interprovincial migration flows, using Census data in 2000 between two periods (five years and ten years). Their OLS estimates suggest that a 1-degree increase in temperature pushes up the emigration rate by 0.6 percentage points, while an increase in typhoon activity, represented by an increase in 1 percent in normalized death rates from typhoons, increases the emigration rate by 0.15 percentage points. Consistent with the previous studies, climate variables also have a significant negative effect on rice yields.

Tse (2012) analysed the effect of three of the most common natural disasters in Indonesia—earthquakes, volcanic eruptions and floods—on the household-level decision to migrate across provinces and districts between two successive years. Their findings suggest that earthquakes tend to reduce split-household migration and that floods reduce whole-household migration.

2.2 Weather variation and international migration

Some studies on environmental migration have focused on the impact of climatic variation, such as rainfall and temperature anomalies and climatological disasters, on international migration. The findings suggest heterogeneity in the effects of weather shocks conditional on education

(Drabo and Mbaye 2011), network of migrants (Mahajan and Yang 2017), location (Maurel and Tuccio 2016) and type of weather variation (Chort and de la Rupelle 2016, and Halliday 2006).

Drabo and Mbaye (2011) analyse the relationship between migration and natural disasters caused by climate change (such as meteorological, hydrological, and climatological disasters), using data from 88 countries from 1950 to 2010. Their findings suggest that natural disasters induce migration, but this is more pronounced among individuals with a higher level of education.

Mahajan and Yang (2017) examine the impact of hurricanes overseas on US immigration. The authors found that hurricanes experienced by the 159 countries (including the Philippines) included in the dataset increased the US migrant stock, and the impact was higher for countries with larger pre-existing stocks of US immigrants.

Maurel and Tuccio (2016) examined 226 countries from 1960–2000 to investigate climate-induced migration. Their findings suggest that climate anomalies (deviations of rainfall and temperature from their long-run mean values) affect urbanization, defined as the increase in the total number of urban workers relative to the total population through rural-urban migration. This internal migration has a dampening effect on urban wages, which then leads to international migration. In addition, they find that for developing countries, where rural households tend to be more vulnerable to climatic shocks, the likelihood of both urbanization and international migration due to climate shocks is greater compared to countries in richer regions.

Heterogeneity across environmental factors also exists in the literature. For example, Chortand de la Rupelle (2016), using the gravity model, found that drought causes more outmigration from Mexico to the US, while other climatic shocks, such as hurricanes, have no impact. Halliday (2006) investigates the migration response of households in El Salvador to exogenous income and wealth shocks measured as harvest and livestock loss, and damage caused by earthquakes. He finds that losses associated with agricultural shocks had a positive effect on migration; since households anticipated that losses from shocks yield low returns, these shocks tended to push people out of El Salvador. Earthquakes, however, had a negative effect on migration—such that households that endured larger amounts of damage were less likely to migrate. His findings suggest that households used migration as insurance.

2.3 Summary of review of literature

In summary, the impact of weather shocks on migration (internal or international) varies across countries and depends on the type of environmental factor and the post-disaster recovery efforts of the government and households, as well as the time period (short run or long run). We summarize our review of related literature in Appendix 1.0. In general, a more intense weather shock, such as earthquakes, tend to reduce migration and induce households to stay, while less intense climate shocks (like temperature and precipitation deviation) increase migration. A well-funded and systematic post-disaster grant improves productivity in the long run, which is then conducive for households to stay or to return.

We aim to contribute to the existing literature by examining whether Filipinos migrate or stay after they experience weather shocks (measured by intensity and wind damage of tropical cyclone, storm warning signal, and the ensuing casualties and damage), using longitudinal data. We also try to incorporate the roles of income and agriculture into our analysis. We estimate 11 main equations using a variety of econometric methods—fixed effects (FE), random effects (RE), ordinary least squares (OLS), two-stage least square (2SLS), and instrumental variable (IV) methods such as IVFE and IVRE.

3. Data and methodology

This section is divided into four subsections. In the first subsection, we discuss how we constructed the provincial longitudinal dataset for the years 2005–15. In the second through fourth subsections, we describe our dependent variables (income and migration), environmental factors (weather shocks), and the nonenvironmental factors (various provincial characteristics used as control variables).

3.1 Longitudinal dataset

We construct a panel dataset from the Labor Force Survey (LFS) from 2005 to 2015 at the provincial level to derive average household income and the stock of international migration. We average household income at the provincial level and count the stock of migrants from each household, aggregated by province.[2] In addition, we used volume of production of rainfed *palay*, or rice, derived from the Philippine Statistics Authority (PSA), at the provincial level to incorporate agriculture into our analysis of environmental migration.

We then merge this longitudinal dataset with weather shocks—measured by, again, the annual frequency of tropical cyclones (by category); the annual frequency of the public storm warning signal (PSWS) (by province); total casualties; and total amount of damage—provided by the Philippine Atmospheric Geophysical and Astronomical Services Administration (PAGASA) and the National Disaster Risk Reduction and Management Council (NDRRMC).

To control for the nonenvironmental factors (provincial characteristics) that also affect the average provincial household income, agricultural yields and the stock of international migrants originating from a province, we merge other datasets with our main LFS and weather shocks panel data.[3] We first consider the economic factors that affect both the income level and the decision to migrate such as the provincial unemployment rate (derived from LFS), poverty incidence, and access to electricity and water. The poverty incidence at the provincial level is taken from the Family Income and Expenditure Survey (FIES) estimates for the survey years 2003, 2006, 2009, 2012 and 2015, while the regional variable for access to electricity is derived from Philippine Yearbook (PY) 2005–2013 and Philippine Statistical Yearbook (PSY) 2015 and 2016. Access to an improved water source is derived from the National Demographic and Health Survey (NDHS) for the years 2003, 2008 and 2013.

We also include a sociodemographic factor such as the average provincial household size derived from PSA. The third set of nonenvironmental factors (total numbers of schools and hospitals, and enrolment rates) serves as a measure of infrastructure.[4] We use them as proxies for the disaster readiness and disaster resiliency of a province. The number of schools and hospitals are derived from the PY for the years 2005–10 and the PSY for the years 2011–2015, while the net participation rates in public and private elementary and secondary schools are derived from the PY 2011 for the years 2005–2009 and PSY 2015 and 2016 for the years 2010–2015.

[2] A panel dataset at the household level is not available. Therefore, we opted to construct a longitudinal dataset at the provincial level.
[3] For missing values, we use the values from the closest survey year.
[4] The available dataset limits us to regional variables for education and health infrastructure.

The last set of nonenvironmental factors pertains to location indicators (provincial and major islands dummy variables), which are derived from the Philippine Standard Geographic Codes (PSGC).

3.2 Dependent variables (migration, household income and rice yields)

There are three dependent variables of interest—total migration, average household income and volume of production of rainfed *palay* at the provincial level. The total stock of international migrants originating from a province is derived from the LFS for the years 2005–15, which contains information about the number of household members aged 15 years old and over who are considered to be overseas Filipino workers (OFWs) in two categories: overseas contract workers (OCWs) and workers other than OCWs. The total number of migrants, on average, at the provincial level across the 11 years (2005–15) is about 180 (Table 1). The highest number of migrants was 2,145 (National Capital Region [NCR]) in 2009, and the minimum number of migrants was zero (Batanes) in 2011.

Given that the LFS does not contain an explicitly defined income variable, the basic pay per day is used as a proxy for income. Respondents were asked how much their basic pay per day for their primary occupation (in cash) was. We aggregate this basic pay at the provincial level per year, then average it per province, and adjust for inflation using the Consumer Price Index (CPI) 2010 as the base. It can be gleaned from Table 1 that the average annual income (inflation-adjusted) was about PHP127,000 or about USD2,510.[5] The minimum annual income was recorded in 2008 at about PHP 33,600 (Negros Oriental), and the maximum was about PHP 2.5 million in 2005 (Tawi-Tawi).

We explore the important role of agriculture, as the link between climate change and migration, in environmental migration. Agriculture is linked with climate change due to its vulnerability to weather variations caused by climate change, and it can be linked with international migration because countries that rely mostly on agriculture for income are also the same origin countries of migration. For example, precipitation and rising temperature as indicators of climate change can adversely affect agricultural productivity and outputs, pushing individuals and households to migrate (Cai et al. 2016). Food insecurity through agriculture further links

[5] Using the average exchange rate in 2019 (PHP50.60 to USD1).

climate change and migration (Falco et al. 2018a). Therefore, we use volume of production of rainfed rice as another dependent variable impacted by our measures of weather shocks, given its obvious dependence on rainfall and its vulnerability to any climate anomalies. On average, there are about 52,170 metric tons of rainfed rice, with the province of Iloilo having the largest volume of production at 542,556 metric tons in 2012, and the national capital region (NCR) without any production at all for all the years 2005–2015. In addition, we divide provinces based on the volume of their production of rainfed rice, and create a binary variable "agriculture" with a value of 1 if a province belongs to the top 25% producers of rice, and 0 otherwise, following the strategy of Cai et al. (2014). To test the robustness of our results, we also used an alternative definition of agricultural dependence and identified the top 50% and bottom 50% producers of rice.

3.3 Environmental factors (weather shock variables)

Four sets of weather shock variables at the provincial level, from 2005 to 2015, obtained from the NDRRMC, are considered in this paper: (1) frequency of tropical cyclones by type and intensity; (2) frequency of public storm warning signal issued by PAGASA (categorized into wind intensity and damage); (3) total cost of damages caused by tropical cyclones per year per province; and (4) total casualties caused by tropical cyclones per year per province (summation of dead, injured or missing persons).

Tropical cyclones are categorized, based on intensity, as a (1) tropical depression (TD) with sustained surface winds of 61 kilometres per hour (kph) or less; (2) tropical storm (TS) with sustained winds of 62 to 88 kph; (3) severe tropical storm (STS) with winds of 89 to 117 kph; (4) typhoon with winds of 118 to 220 kph; and (5) super typhoon with winds of more than 220 kph (Table 2).

In addition, the annual frequency of the public storm warning signal (PSWS) raised by the PAGASA for the years 2005–15, at the provincial level, was also used. There are five possible PSWSs that can be raised by the PAGASA before a tropical cyclone lands: (1) PSWS #1 raised for a tropical cyclone with winds 30 to 60 kph expected to land within the next 36 hours (no expected to very light wind damage); (2) PSWS #2 for a tropical cyclone with winds 61 to 120 kph expected within the next 24 hours (light to moderate wind damage); (3) PSWS #3 for a tropical cyclone with winds of 121 to 170 kph expected within the next 18 hours (moderate to heavy wind damage); (4) PSWS #4 for a tropical cyclone with winds of 171 to 220 kph expected within the next 12 hours (heavy to very heavy wind damage); and (5) PSWS #5 for a tropical cyclone with winds of more than 220 kph expected within the next 12 hours (very heavy to widespread wind damage). It is important to note that when PAGASA issues a PSWS number, its corresponding meteorological conditions do not yet prevail in the locality and it is possible that the storm warning signal is upgraded or downgraded. Therefore, it is possible that a PSWS #3 will be downgraded to PSWS #1 or that the typhoon will not make a landfall at all.

Table 2 presents the descriptive statistics for weather shock variables. The frequency of tropical depressions and severe tropical storms ranges from only 0 to 2 at the provincial level, on average over the span of 11 years from 2005 to 2015, while tropical storms and typhoons hit a province, at the maximum, five times over the same time period. There was no super typhoon classified by the NDRRMC at the provincial level from 2005 to 2015.

The average annual casualties attributed to tropical cyclones were 66 at the provincial level while the annual cost of damages due to tropical cyclones, adjusted using the CPI 2010 as the base, amounted to about PHP 316 million (USD 6 million), on average, over the 11-year period (2005–15). The destructive typhoon Haiyan (*Yolanda*), which had a maximum sustained wind speed of 205kph, made landfall in the Leyte province in November 2013. This had caused catastrophic devastation, with more than 22,000 casualties (dead, missing and injured) and about USD 1 billion of damages in Leyte in 2013 (Table 2 maximum values for total casualties and total damages).

On average, the raising of weather storm signal #1 at the provincial level was the most frequent; at least one PSWS #1 was raised in a province per year. All the other storm signals (PSWS #2 to #4) were raised less than one time, on average, per province for the same period, while the PAGASA did not raise the PSWS #5 at all.

3.4 Nonenvironmental factors (provincial characteristics)

There are six major sets of control variables used in this paper to capture the nonenvironmental factors that impact the provincial migration rate, household income, and agricultural production: (1) unemployment rate; (2) number of schools and hospitals, and net participation rate in public and private primary and secondary schools as measures of infrastructure; (3) poverty level, and percentage of households with access to water and electricity as measures of income level of the province; (4) historical migration rate in 2003; (5) average household size as a measure of sociodemographic characteristic of the province; and (6) indicators for location such as provincial and major islands dummies. The descriptive statistics of these control variables can be gleaned from Table 2.

The unemployment rate from the LFS, defined as the number of individuals within a province who are unemployed, divided by the number of both employed and unemployed persons (or the labor force) within a province, was used as one of the control variables for the years 2005–2015. Table 2 shows that the provincial mean unemployment rate is 5.3 percent, which is somewhat close to the prevailing national unemployment rate (Philippine Statistical Authority [PSA] 2017a).

The historical migration rate in 2003, derived from the LFS, is controlled for to account for the possible effect of networking on migration in the years that followed.[6] Table 2 suggests that the average migration rate was about 1 percent of the provincial population. In terms of the sociodemographic characteristic of a province, the average household size is about five.

3.4.1 Infrastructure

The number of schools and hospitals (both public and private), as well as enrolment rates in primary and secondary levels (both public and private) at the regional level, are used as infrastructure variables. On average, there are about five times more public elementary schools than public secondary schools at the regional level across years. The net participation rate in public and private primary schools is higher than the net participation rate in public and private secondary schools. On average, the proportion of enrolees 7–12 or 6–11 years old to the population of the same age is 89 percent at the regional level across years, while that for enrolees 13–16 years old is 60 percent. For hospitals, on average, there are more private hospitals (about 58) than public hospitals (about 39).

[6] The migrant's network refers to family and friends who have already migrated to the migrant's destination area and make it easier for the migrant to adjust. In some cases, the network provides financial assistance.

3.4.2 Measures of income

We use poverty incidence and access to utility services such as water and electricity as measures of the income level of a province. The provincial mean poverty incidence is about 34 percent from 2005 to 2015 (Table 2). On average, about 74 percent of households have access to electricity in a region across the same time period while about 90 percent of households have access to an improved water source (Table 2). An improved water source is defined by the NDHS as a pipe connection on household premises, public tap/standpipe, protected dug well, tube well or borehole, semi-protected dug well, protected spring, rain, or bottle.

3.4.3 Location variables

Variables for the 80 provinces and the three main island groups (Luzon, Visayas, and Mindanao) are also included.[7] Among the regions, Region 3 (Central Luzon) has the most observations on average (at 0.09 percent), while among the main island groups, Luzon has the most (at 47.6 percent).

4. Empirical model

We divide our empirical analysis into two sections. The first one depicts the migration models while the second section presents the income models.

4.1 Migration econometric models

This section focuses on depicting the relationship of weather shocks and international migration, which we model in three ways—linear, quadratic and lagged linear. We also incorporate agriculture into the analysis by adding interaction terms to examine the heterogeneity between provinces that are the top producers of rainfed *palay* and the bottom producers.

[7] The PSGC Codes Legend Spreadsheet contains the PSGC followed for the analysis. To ensure matching of the LFS using the PSGC provincial codes across time (2005–15), we assumed regional demarcations (17) prior to the formation of the Negros Island Region. As per the PSGC Summary of Changes (March 2017) spreadsheet of PSA, it was only in 2015 that a province was transferred to another region.

4.1.1 Linear migration model

The main goal of this research is to examine the impact of weather shocks on the international migration of workers, analysed at the provincial level and depicted in the following reduced-form equation (1):

$$LMigration_{pt} = \delta_0 + \delta_1 TC_{jpt} + \delta_2 PSWS_{kpt} + \delta_3 LCasualty_{pt} + \delta_4 LDamage_{pt} + \delta_5 Prov_{pt} + \lambda_p + \upsilon_t \quad (1)$$

where $p=1,2,\ldots,80$ is the index for the province; t = 2005, 2006,…2015 is the index for year; $LMigration_{pt}$ represents the annual number of migrants originating from province p at time t in log form[8]; TC_{jpt} is the j*th* tropical cyclone {$j=1$ for tropical depression, $j=2$ for tropical storm, $j=3$ for severe tropical storm, $j=4$ for typhoon, $j=5$ for super typhoon}; $PSWS_{kpt}$ is the kth annual frequency of the public storm warning signal {$k=1$ for PSWS#1, $k=2$ for PSWS#2, $k=3$ for PSWS#3, $k=4$ for PSWS#4, $k=5$ for PSWS#5}; $LCasualty_{pt}$ measures the annual casualties (dead/missing/injured) due to tropical cyclones in log form; $LDamage_{pt}$ refers to the annual total cost of damages due to tropical cyclones adjusted to the consumer price index (CPI) in 2010 to account for inflation in log form; $Prov_{pt}$ is the set of provincial or regional characteristics that vary over time (unemployment rate, number of schools and hospitals, enrolment rates, poverty incidence, access to water and electricity, and historical migration rate); λ_p is the province's fixed effect; and υ_t is the error term that varies over time. Year, provincial and major island dummies are also included in all models.

Weather-induced migration can be interpreted as a risk-coping mechanism such that the risks experienced by household members are distributed across various locations. Therefore, the null hypothesis that we want to reject is that weather shocks do not affect the decisions of the households to migrate or the stock of international migrants, analysed at the provincial level (δ_1=0, δ_2=0, δ_3=0, δ_4=0). We predict that the more damaging a natural disaster is, the more Filipinos are induced to work elsewhere. However, we recognize the possibility that the impact of weather shocks on international migration is not linear or that the impact is contingent on the intensity of

[8] Migration variable is transformed into a logarithmic form, in particular, log(x+1) to accommodate for zero values. This transformation applies to all our log-transformed variables.

a tropical cyclone. For example, it is possible that the more severe a natural disaster is, the more likely it is for households and individuals to stay in the Philippines instead. In the next section, we discuss this possibility by considering a quadratic relationship between weather shocks and international migration.

The treatment of λ_p, which represents the unobserved time-invariant provincial characteristics (fixed effects), determines the econometric strategy to be used to test equation (1). If these provincial fixed effects are uncorrelated with each independent variable, including the weather shocks, then the random effects (RE) model is used; otherwise, the fixed effects (FE) model is the appropriate estimation model. We assume that the cultural norms and even preferences of the populace can be related to how they respond to a natural disaster. Their resilience and risk-mitigating strategies can affect the number of casualties and even the cost of damages, which we measure as weather variables, in which case, the FE model is more appropriate. The ordinary least squares (OLS) estimation method is also used for the robustness test. We focus on the FE model in this paper, but all RE and OLS regression results are displayed in Appendix 1.1 to 14b.3.

4.1.2 Quadratic migration model

We explore the possibility that the impact of weather shocks on migration is not linear and that their relationship depends on the severity, type and frequency of a natural disaster. For example, there could be a positive correlation between the weather shocks and international migration when the natural disaster is less intense, and a negative correlation when the weather shock is more severe (a parabolic relationship).

As shown in the literature, while some authors find that there is a positive correlation between weather shocks and migration (Halliday 2006; Drabo and Mbaye 2011; Cai et al. 2014; Chort and de la Rupelle 2016; Maurel and Tuccio 2016; Mahajan and Yang 2017), others find that weather shocks lower the propensity to migrate (Halliday 2006; Tse 2012; Robalino et al. 2015; Gignoux and Menendez 2016). Several mechanisms that are cited in the literature could explain why weather shocks negatively affect migration.

The first mechanism is that there could be an increase in the productivity of agricultural land after a natural disaster, due to soil fertility and an improved labor productivity that resulted from the need to rebuild damaged infrastructures; this then could induce individuals and households to stay and not migrate. Flooding in Pakistan in 2010, which affected an area of about 160,000 km^2 and covered around 0.75 million hectares of cultivated land, improved the soil fertility due to the natural deposit of fine mud and silt (Ahmad 2011). Gignoux and Menendez (2016) found in Indonesia a positive long-term impact (after 6–12 years) of earthquakes on productivity (through reconstituted farm assets and improved infrastructures) due to external aid, which then resulted in reduced urban migration in the long run. Their study highlighted the need for well-designed post-disaster interventions when physical assets are adversely affected.

The second mechanism is that the severe and widespread damage to assets and agricultural outputs brought about by a natural disaster may result in financial and borrowing constraints that could limit financial resources needed for migration. In effect, a natural disaster could result in liquidity constraints, which preclude migration (Tse 2012).

Given that in the literature, we find both positive and negative correlation between weather shocks and migration, we also consider a quadratic relationship between these two:

$$LMigration_{pt} = \sigma_0 + \sigma_1 TC_{jpt} + \sigma_2 TC_{jpt}^2 + \sigma_3 PSWS_{kpt} + \sigma_4 PSWS_{kpt}^2 + \sigma_5 LCasualty_{pt} + \sigma_6 LCasualty_{pt}^2 + \sigma_7 LDamage_{pt} + \sigma_8 LDamage_{pt}^2 + \sigma_9 Prov_{pt} + \lambda_p + \mu_t \quad (2)$$

The variables in equation (2) follow the same definitions as those identified in equation (1); only the specification changes.

4.1.3 Lagged migration model

We consider the possibility that a decision to migrate internationally involves a more complex household decision process and thus would require more time and more financial resources. Therefore, we also examine the effect of weather and control variables in the previous time period (at time *t-1*) on migration in the current period (at time *t*):

$$LMigration_{pt} = \pi_0 + \pi_1 TC_{jpt-1} + \pi_2 PSWS_{kpt-1} + \pi_3 LCasualty_{pt-1} + \pi_4 LDamage_{pt-1} + \pi_5 Prov_{pt-1} + \lambda_p + \xi_{t-1} \quad (3)$$

All variables in equation (3) follow the same definitions as those in equation (1).

4.1.4 Migration and agricultural provinces

We also incorporate into our analysis the role of agriculture. In particular, we examine whether heterogeneity in the impact of weather shocks on international migration exists between provinces that are the top producers, and provinces that are the bottom producers, of rainfed rice. We have weather shocks interact with indicators for agriculture productivity. We first identify the provinces that are the top 25% producers and compare them with the bottom 75%. Then we compare the top 50% producers with the bottom 50%.

$$LMigration_{pt} = \beta_0 + \beta_1 TC_{jpt} + \beta_2 PSWS_{kpt} + \beta_3 LCasualty_{pt} + \beta_4 LDamage_{pt} + \beta_5 agri_{lpt} + \beta_6 TC_{jpt} * agri_{lpt} + \beta_7 PSWS_{kpt} * agri_{lpt} + \beta_8 LCasualty_{pt} * agri_{lpt} + \beta_9 LDamage_{pt} * agri_{lpt} + \beta_{10} Provchar_{pt} + \lambda_p + \varepsilon_t \quad (4)$$

where *l* = *1, 2* {*1* = top 25% agricultural production; *2* = top 50% agricultural production} while the rest of the variables follow the definitions in equation (1). We predict that there is a differential impact of weather shocks conditional on whether the province is identified as an agricultural province and test the null hypotheses $\beta_6 = 0;\ \beta_7 = 0;\ \beta_8 = 0;\ \beta_9 = 0$.

4.2 Income econometric models

We also consider the possibility that weather shocks affect migration through household income first, which we averaged at the provincial level. Therefore, we first regress average provincial household income on weather shocks for the first stage, and on the second stage we regress international migration against the estimated income.

We follow the same specifications used for the preceding migration models to depict the relationship of weather shocks and average household income—linear, quadratic, and lagged linear income models (equations 5–7 below).

$$LY_{pt} = \gamma_0 + \gamma_1 TC_{jpt} + \gamma_2 PSWS_{kpt} + \gamma_3 LCasualty_{pt} + \gamma_4 LDamage_{pt} + \gamma_5 Prov_{pt} + \lambda_p + \eta_t \quad (5)$$

$$LY_{pt} = \phi_0 + \phi_1 TC_{jpt} + \phi_2 TC_{jpt}^2 + \phi_3 PSWS_{kpt} + \phi_4 PSWS_{kpt}^2 + \phi_5 LCasualty_{pt} + \phi_6 LCasualty_{pt}^2 + \phi_7 LDamage_{pt} + \phi_8 LDamage_{pt}^2 + \phi_9 Prov_{pt} + \lambda_p + \varrho_t \quad (6)$$

$$LY_{pt} = \varphi_0 + \varphi_1 TC_{jpt-1} + \varphi_2 PSWS_{kpt-1} + \varphi_3 LCasualty_{pt-1} + \varphi_4 LDamage_{pt-1} + \varphi_5 Prov_{pt-1} + \lambda_p + \omega_{t-1} \quad (7)$$

where LY_{pt} is the measure of average household income per province in logarithmic form, and the rest of the variables follow the definition discussed for equation (1). We use FE econometric strategy to test all income equations, consistent with our migration strategy, but we also use RE and OLS models, and all the regression results are displayed in the Appendix section.

We again recognize that agriculture is an important link between international migration and weather shocks, as we discussed earlier in the review of the literature. Therefore, we also consider the volume of rainfed rice production per province in log form ($LAgri_{pt}$) as an alternative measure of income (equation 8 below). In addition, similar to our migration strategy, we examine the possible heterogeneity between agriculture provinces (the top 50% producers of rainfed rice) and non-agricultural provinces (the bottom 50%) by including terms that describe weather shocks interacting with indicators for agricultural intensity (*agri_50*), depicted in equation (9) below.

$$LAgri_{pt} = \varphi_0 + \varphi_1 TC_{jpt} + \varphi_2 PSWS_{kpt} + \varphi_3 LCasualty_{pt} + \varphi_4 LDamage_{pt} + \varphi_5 Prov_{pt} + \lambda_p + \varpi_t \quad (8)$$

$$LY_{pt} = \zeta_0 + \zeta_1 TC_{jpt} + \zeta_2 PSWS_{kpt} + \zeta_3 LCasualty_{pt} + \zeta_4 LDamage_{pt} + \zeta agri\_50_{pt} + \zeta_6 TC_{jpt} * agri\_50_{lpt} + \zeta_7 PSWS_{kpt} * agri\_50_{lpt} + \zeta_8 LCasualty_{pt} * agri\_50_{pt} + \zeta_9 LDamage_{pt} * agri\_50_{pt} + \zeta_{10} Prov_{pt} + \lambda_p + \vartheta_t \quad (9)$$

For the second stage regression, we simply regress the total number of international migrants in log form ($LMigration_{pt}$) originating from province p at time t on either average household income (LY_{pt}) or volume of production of rainfed rice ($LAgri_{pt}$) both in log form, depicted in equations (10) and (11), respectively, below.

$$LMigration_{pt} = \chi_0 + \chi_1 LY_{ipt} + \chi_2 Prov_{pt} + \lambda_p + \psi_t \quad (10)$$

$$LMigration_{pt} = \alpha_0 + \alpha_1 LAgri_{pt} + \alpha_2 Prov_{pt} + \lambda_p + \tau_t \tag{11}$$

All the weather and provincial variables identified in equations (8) through (11) are the same variables included in equation (1) above.

5. Results

We discuss our regression results in this section, divided into two subsections – migration results and income results.

5.1 Impact of weather shocks on migration

To reiterate, to analyse the impact of weather shocks on international migration, we estimate a linear model (equation 1), quadratic model (equation 2) and lagged linear model (equation 3) using FE. We also consider whether agriculture plays a role in the migration response of Filipinos to weather shocks (equation 4). The results of our migration analyses, displayed in Tables 3.1 and 3.2, are discussed below.

5.1.1 Results for linear migration model

Table 3.1 Column 1 presents the results of estimating the linear reduced-form model of migration (equation 1), using the fixed effects (FE) method.[9] We regress international migration (in logarithmic form) on the four measures of weather shocks at the provincial level over the 11-year period (2005–2015), and we control for provincial and regional characteristics, time invariant unobserved provincial characteristics, or time fixed effects, and cluster the robust standard errors by province.

We find that the weather shock variables, the total cost of damage (adjusted for inflation and measured annually in log form) due to tropical cyclones and the annual frequency of public storm warning signal #1 (PSWS #1), positively affect international migration. However, we find

[9] We also estimate all our migration equations (1–4), using random effects (RE) and OLS. Individual weather events and their various combinations are also used, and the results are all displayed in Appendix 1.1 to Appendix 4b.3.

that the magnitude of the coefficients varies. The effect of total cost of damages on migration is marginal: as the total cost of damages increases by 10 percent, international migration increases by only 0.04 percent, or as total cost of damages increases by about PHP32 million (USD630,000), on average, international migrants increase by only about 7.[10] In comparison, typhoon Haiyan with recorded USD1 billion damage in Leyte province would result in 14 international migrants. The impact of PSWS#1, however, is a little bigger: as the frequency of PSWS #1 (tropical cyclone or TC with 30–60 kph winds with little expected wind damage) increases by 1 more, international migration increases by about 1.3 percent (or an increase of about 2 migrants, on average, if PSWS#1 increases by 1).

The impact of an extreme weather event such as the annual frequency of PSWS #4 (TC with 171–220 kph winds and heavy to very heavy damage) on international migration is negative and substantial. In particular, as the annual frequency of PSWS #4 increases by 1 more, international migration decreases by about 5.7 percent, which translates to a decrease of about 10 international migrants, on average, if PSWS#4 increases to 1.

5.1.2 Results for the quadratic migration model

The results using a linear model, thus far, indicate that while PSWS#1 positively affects international migration, a stronger warning signal (PSWS #4) negatively affects international migration, therefore, we explore the possibility that the impact of a weather variable on migration is nonlinear, and we estimate equation (2), shown earlier.

The FE regression results displayed in Table 3.1 (Column 2) and the Wald test results for the joint significance of the coefficients of weather shocks displayed in Table 5 (Panel A) are consistent with the baseline linear model results discussed previously. While a less intense weather variable such as storm warning PSWS#1 (30–60kph) marginally and positively affects international migration, variables that measure relatively more intense weather such as a severe tropical storm (89–117kph) and storm warning PSWS#4 (171–220kph) negatively affect international migration. In addition, we find the total damage cost again to marginally induce migration.

[10] This is similar to saying that a PHP3.2 million increase in total damages could result to an increase of only about 1 international migrant.

In particular, we find that an increase in the annual frequency of PSWS #1 by 1 more would lead to an increase in international migration by about 2.2 percent (Table 5, Panel A, Column 7).[11] The impact of this weather shock on international migration becomes negative after the households experienced three PSWS#1.[12]

Total damage cost again marginally increases migration. Similar to the findings when we ran our baseline regression, as the total cost of damages increases by 10 percent, international migration marginally increases by about 0.04 percent.

However, we find that if severe tropical storms increase by 1 more, international migration decreases by about 4 percent, while if PSWS#4 increases by 1 more, international migration decreases by about 5 percent (Table 5, Panel A, Columns 3 and 10, respectively). Although the relationship of severe tropical storm and international migration is U-shaped, the turning point is close to zero (at 0.18) suggesting that this weather shock almost never induces migration. PSWS#4, on the other hand, never increases international migration.

The result for PSWS#4 is consistent with our baseline regression and the slightly higher magnitude in its coefficient relative to that of a severe tropical storm also reflects our prediction that a more intense weather shock has a dampening effect on migration. These results are consistent with the findings on the negative impact of extreme climatic variable on migration (Gignoux and Menendez 2016, Robalino et al. 2015, Tse 2012, and Halliday 2006).

5.1.3 Results for lagged migration model

Given that in the literature, international migration is seen as more of a long-run response to sustained weather events (Falco 2018a, for example) and given the liquidity constraints associated with working abroad, we explore the lagged or delayed effects of weather shocks on international migration and estimate equation (3) above using FE model.

The results displayed in Table 3.1 Column 3 are consistent with our linear and quadratic migration regressions, depicted in Table 3.1 Columns 1 and 2, respectively. We find that as Filipino experience weather shocks like tropical depression (<61kph) and typhoon (118–220kph) the previous year, they are more likely to migrate the following year. However, they are more

[11] Applying the equation dlog(y)/dx = $(\beta_1 + 2\ \beta_2)*100$ if $y = \beta_1 x + \beta_2 x^2$ (Wooldridge, 2006).
[12] Applying the equation $x = \left|\beta_1/2\beta_2\right|$ to compute for the turning point (Wooldridge, 2006).

likely to migrate when they experience tropical depression (at 5%) than when they experience a relatively more intense weather shock such as typhoon (at 2%). PSWS#4 (171-220kph) has a consistent negative impact on international migration, at about 5 percent.

5.1.4 Migration response of households from agricultural provinces

Given that agriculture plays an important role in the literature on environmental migration, we also examine the migration response of households in agricultural provinces, or those provinces that primarily depend on rainfed rice, and estimate equation (4) above.

The coefficients of interaction terms suggest that regardless of how we define an agricultural province, individuals from those provinces that belong to the top 25% and top 50% producers of rainfed rice are 5 percent and 4 percent more likely to migrate abroad, relative to those in the bottom 75% and 50%, respectively, when the frequency of typhoons increases (Table 3.2, Columns 1 and 2). We can conjecture that agricultural provinces are more vulnerable to typhoons and therefore are adversely affected by a weather shock, which induces international migration. Our results are consistent with the existing literature on agriculture and environmental migration (Cai et al., 2016 and Falco et al., 2018a, for example).

5.2 Impact of weather shocks on income

We also test the role of income in environmental migration, which we measure two-ways for robustness – as average household income and as rainfed rice yields. We presume that climatic shocks affect the migration response of Filipinos through their income. We estimate our income equations, depicted in the empirical model section, by using linear, quadratic, and lagged linear models (equations 5–7, shown previously). We also incorporate agriculture into our income analysis (equations 8 and 9, shown previously).[13] All the results of our income regressions are discussed below.

[13] The complete regression results for all income equations, including the coefficients and statistical significance of all control variables, using individual weather shocks and their different combinations, are displayed in Appendixes 5.1–9b.3.

5.2.1 Results for the linear income model

Our fixed effects (FE) regression results show that a tropical depression (<61kph), tropical storm (62–88kph), and typhoon (118–220kph) increase income (average annual household income adjusted using CPI 2010 in logarithmic form), but the positive effect diminishes as the wind intensifies (Table 4.1, Column 1). For example, while a tropical depression increases income by about 3%, a tropical storm increases it by about 2% and a typhoon increases it by only 1%, given the same increment in the frequency of the weather shock (increase of 1 more).

5.2.2 Results for the quadratic income model

Our baseline income results show that although weather shocks tend to increase average household income, this is at a decreasing rate. Therefore, similar to our migration strategy, we also explore the possibility that the relationship between income and weather shocks is quadratic.

The FE results of estimating the impact of weather shocks on income by using a quadratic specification are displayed in Table 4.1 (Column 2), while the Wald results of testing the joint significance of income and income squared are presented in Table 5 (Panel B). We find that as tropical storms (62–88kph) increase by 1 more, the average inflation-adjusted household income increases by 2% (Table 5, Panel B, Column 2). On average, this means that as tropical storms increase by 1, average household income increases by about PHP3,000 only or USD60.

5.2.3 Results for lagged income

We also consider the possibility that both environmental and nonenvironmental factors (weather shocks and other provincial control variables) have a lagged or a one-year delayed effect on household income. The FE results of estimating lagged income equation (7) suggest that while a less intense weather shock such as a tropical depression increases income, a more intense weather variable like PSWS#4 has an adverse effect on household income (Table 4.1, Column 3). In particular, if a tropical depression increases by 1 more, income increases by about 2%, while if PSWS#4 increases by 1 more, income decreases by about 3%.

5.2.4 Results for agricultural production

When we use volume of agricultural production per province (in logarithmic form) instead of average household income as the dependent variable, we find that while PSWS#3 (121–170 kph) positively affects rainfed rice production, the number of casualties in log form decreases it (Table 4.2, Column 1). In particular, as total casualties increase by 10%, rainfed rice production decreases by about 0.2%, or as the number of people who are dead, missing, and injured due to a tropical storm increases by about 7, on average, the volume of rice production decreases by about 104 metric tons, on average. However, as PSWS#3 increases by 1 more, the volume of rice production increases by about 4% (or by about 2,100 metric tons).

The estimated annual per capita rice consumption in the Philippines is about 100kg, which suggests that a metric ton of rice can feed about 9 Filipinos a year.[14] As such, as PSWS#3 increases by 1 more, the resulting approximate increase in rice yields (2,100 metric tons) can feed about 19,266 Filipinos annually (PSA, 2017b). In terms of revenues to rice producers, this increase in production can be roughly translated to PHP 30 million based on 2010 average monthly farmgate price of rice (Bureau of Agricultural Statistics, 2010).[15]

5.2.5 Income vulnerability of households from agricultural provinces

Similar to our strategy in analysing the direct impact of weather shocks on migration, we also examine whether heterogeneity exists in the impact of weather shocks on income between the top 50% provinces in terms of production of rainfed rice (*palay*) and the bottom 50% producers (Table 4.2, Column 2). The coefficient of the interaction term suggests that provinces that depend on agriculture as a source of income are more vulnerable to the adverse effects of weather shocks. In particular, the top 50% producers actually earn 8% less, relative to the bottom producers, when the frequency of an intense public storm warning signal (PSWS#4) increases.

5.3 Impact of weather shocks on migration through income

We also perform a two-stage regression analysis and assume that weather shocks affect

[14] 1 metric ton = 1,000kg.
[15] The 2010 average monthly farmgate price of rice was P14.40/kg.

migration only through income. After estimating and running regressions for each of our income equations, we perform the corresponding second-stage regressions and estimate equations (10) and (11) by using instrumental variable fixed effects (IVFE). Our results, all displayed in Appendix 10.1 to 14b.3, suggest that regardless of how we measure income (inflated-adjusted average household income and volume of agricultural production), it does not statistically impact migration after weather shocks are used as instruments.[16] It is possible that weather shocks affect migration not only through income but also through other channels such as political unrest, violence, or even health (Nandi et al. 2018). Therefore, we focus on reduced-form equation instead and regress migration against weather shocks directly as we have discussed in section 5.1 above.

5.4 Nonenvironmental factors (other control variables)

In the existing studies on weather shocks and migration, nonenvironmental factors and their interaction with environmental factors are deemed as important as climate variables (Mahajan and Yang, 2017; Maurel and Tuccio, 2016; Baez et al., 2016; Obokata et al, 2014; Drabo and Mbaye, 2011 to cite a few). Therefore, we also analyse the impact of several economic and sociodemographic factors, location, infrastructure and human capital on the decision of Filipinos to migrate and work abroad, and on their income and agricultural production.

5.4.1 Results for control variables of migration regressions

We find that across the various specifications that we used to examine the impact of weather shocks on international migration, the unemployment rate consistently and positively affects international migration.[17] We also find that the proportion of households with access to electricity has a dampening effect on migration, albeit marginally.

In addition, in our lagged migration model, our results show that as the total number of private and public secondary schools in a region increases by 10 in the previous year, international

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[16] We also estimate the second-stage equations by using other instrumental variable methods, such as instrumental variable random effects (IVRE) and two-stage least squares (2SLS). The results are shown in Appendix 10.1–14b.3. Similar to migration and income regressions, we focus on IVFE, assuming that the fixed effects and all independent variables, including weather shocks, are correlated.

[17] The complete regression results, including the coefficients and statistical significance of all control variables for all econometric specifications for both migration and income equations, are all displayed in Appendix 1.1 through Appendix 14b.3 for the purpose of brevity.

migration increases by about 0.6 percent in the succeeding year. This means that as the number of high schools increases by about 10, on average, the number of international migrants the following year increases by about 1. This suggests that, keeping everything else constant, an improvement in human capital marginally induces international migration.

5.4.2 Results for control variables of income regressions

We find that, similar to our migration results, the impact of regional number of high schools also positively affects income whether we use the linear or quadratic econometric specifications (Appendixes 1.3 and 2.3). We can conjecture that an improvement in infrastructure reflects the economic welfare of a province, and in this case, may translate to better education and improved income of the populace.

In addition, we find a positive lagged effect of net participation rate in public and private secondary schools on average household income at the province level. This is consistent with the findings mentioned previously, that the number of high schools in a region positively impacts income.

6. Discussion

The results in our paper, presented in the preceding section, are consistent with those in the literature that found a positive association between weather shocks and migration (Baez et al. 2016, 2017; Gröger and Zylberberg 2016; Kubik and Maurel 2016; Maurel and Tuccio 2016 to cite a few) when we use less-intense weather variables but are also consistent with those that found a negative correlation when we use more damaging and intense weather shocks (for example, Halliday 2006; Tse 2012; Robalino et al. 2015; Gignoux and Menendez 2016).

Our first major result shows that in three of our migration specifications (linear, quadratic, and lagged linear), we find that an intense weather shock such as a public storm warning signal #4 (PSWS#4), defined as a tropical cyclone with expected 171–220kph winds that could incur heavy to very heavy damage, negatively affects international migration. However, less-intense weather shocks such as a tropical depression (<61kph) and a PSWS#1 (30–60kph) induce international migration. One possible reason identified in the literature is that while a more damaging natural disaster results in liquidity constraints and damage to assets, which preclude international migration, weather shocks that are less intense actually benefit the households through increased precipitation and improved income, which then induces migration.[18] This conjecture is supported by the negative correlation that we found between PSWS#4 and average household income when we used lagged income specification and the positive correlation between less-intense weather variables (tropical depression and tropical storm) by using the linear income model. It is also possible that the decision of Filipinos to stay after experiencing the negative effect of an intense weather shock can be attributed to other factors than income such as an adverse health outcome or a well-funded post-disaster government aid.

Our second main finding is that there is a decreasing change in international migration as the wind intensity of a tropical cyclone increases. For example, the increase in international migration, when tropical depression increases, is higher than when a more intense tropical cyclone, such as a typhoon, increases and when the wind intensity and damage become very severe (PSWS#4) the international migration starts to decrease after a turning point. To put it in another way, although the correlation between international migration and less-intense weather shocks is positive, the marginal rate of change is actually decreasing. These results support the argument that weather shocks and international migration have a non-linear relationship (parabolic) as attested to by the different conflicting findings, contingent on the intensity of a climatic variable, in the literature on environmental migration discussed above.

Our third finding pertains to the role of agriculture in environmental migration. The migration response of households in agricultural provinces (those that depend on rainfed rice) is more susceptible to weather variation relative to households from non-agricultural provinces. This is consistent with the findings in the literature that focus on migration and weather shocks in the context of agriculture (Feng et al. 2010; Cai et al. 2014; Falco 2018a, 2018b to cite a few). In addition, official reports from the Philippine weather agency confirm the vulnerability of agricultural households. In particular, PAGASA (2011) reports that the most destructive typhoons in the Philippines consistently damaged the agricultural sector the most (PHP34 billion or about US$ 683 million worth of damages).

Our fourth result pertains to the nonenvironmental factors that we considered. Our results

[18] There has been a series of drought-causing El Niño events in the Philippines. PAGASA (2011) identified six of these events, starting in the 1960s.

suggest that the local unemployment rate (provincial) induces international migration. Education also positively affects international migration; an improved infrastructure (a greater number of high schools) is conducive to migration.

7. Conclusion

This paper aims to contribute to the growing literature on international migration and natural disasters by using a provincial longitudinal dataset from the Philippines (2005–2015), merging a myriad of administrative and survey datasets (about 11 sources), using a more comprehensive list of weather shocks by intensity and damage, and performing a rigorous set of econometric strategies. The Philippines is a very interesting country to analyse for two main reasons. First, its location in the Pacific Ring of Fire makes it susceptible to natural disasters. Second, the Philippines is a major exporter of international labor (IOM, 2017). Specifically, we examined the impact of the various environmental factors (such as types and intensity of tropical cyclones and public storm warning signal as well as the resulting casualties and damage) and nonenvironmental factors (economic and sociodemographic) on international migration and income over a period of time. We also considered the interaction between the environmental and nonenvironmental factors to determine the differential impact of weather shocks contingent on agriculture. That is, we also explored whether agriculture serves as an important link between weather shocks and international migration.

Our paper is able to capture the differential results found in the literature, which we found to be contingent on the intensity and the expected damage of the climatic variable. The results, thus far, suggest that weather shocks induce migration up to a certain threshold, after which migration decreases due to the adverse effect of the natural disaster on income and agricultural yields. There are also factors other than income that could make households stay or return after a natural calamity, as studied in the literature (Gignoux and Menendez, 2016; Nandi et al. 2018). For example, Filipinos could decide not to migrate if their health has been compromised or if the Philippine government has a well-instituted post-disaster recovery plan, which creates an environment conducive to staying. Our results also show that households from agricultural provinces are more susceptible to weather variations and that an economic factor (unemployment rate), infrastructure (number of high schools) and education (high school enrolment rates) also positively affect international migration.

The research on natural disaster and migration has become more relevant in the face of recent climate-related and climate-altering calamities. Our research is particularly timely with the recent eruption of Taal volcano in the Philippines, which, after only three days, already displaced about 54,000 individuals and resulted to severe physical damages – approximately PHP75 million or USD1.5 million of agricultural damages (NDRRMC, 2020; Department of Agriculture, 2020). This natural disaster also may result to a certain degree of food insecurity in the neighboring provinces that rely on the agricultural produce from the towns in Taal. This food shortage could then lead to price inflation. More importantly, the welfare of the 12,370 families who had to migrate and temporarily live in 244 evacuation centres (as reported by NDRRMC) should be the priority of the Philippine government. The roles of pre-disaster risk-mitigation measures and post-disaster recovery plans of the government are very crucial at this point.

We hope that this paper could help policymakers understand better the relationship of weather calamities and human migration in the long-run. Since we find that intense weather shocks have a damaging effect on income and agricultural production and Filipinos are less likely/able to migrate, it would help if the government has in place a well-instituted and systematic post-disaster aids and grants that would make staying or returning a productive process. It would also be interesting to study the long-term impact of this Taal eruption on the propensity of families to migrate and leave the area as well as the response of the government when the data becomes available. More research is necessary also at the household level and on internal migration.

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Table 1 Descriptive statistics of dependent variables

Variable	Variable definition	Mean (Std. Dev.)	Min[1] (Max)	Source	Level	Available years
Total number of migrants	All household members aged 15 years old and over are asked whether or not they are an overseas Filipino worker falling under the categories: (1) OCW and (2) workers other than OCW.	180.27 (258.80)	0 (2,140)	LFS (2005–15)	Province	2005-2015
Inflation-adjusted average annual pay	Average annual household income per province adjusted using CPI 2010 as base.	126,963.3 (243,864.5)	33,620.34 (2,545,950)	LFS (2005–15)	Province	2005-2015
Volume of agricultural production	Volume of production of rainfed palay in metric tons	52,168.9 (71,066.92)	0 (542,556)	PSA OpenSTAT	Province	2005-2015

Notes: [1]For the total number of migrants, minimum of 0 corresponds to Batanes (2011) and maximum of 2,145 is NCR (2009). For the inflation-adjusted average annual pay, minimum corresponds to Negros Oriental (2008) and maximum to Tawi-tawi (2005). CPI = consumer price index; LFS = Labor Force Survey; OCW = overseas contract worker.

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Natural disasters/shock variables							
Total annual number of tropical cyclones (TC) by classification at the provincial level					NDRRMC (2005–15)	Province	2005-2015
Tropical depression	TC with < 61 kph sustained surface winds	879	0.143 (0.382)	0 (2)			
Tropical storm	TC with 62-88 kph sustained surface winds	879	0.543 (0.809)	0 (5)			
Severe tropical storm	TC with 89-117 kph sustained surface winds	879	0.085 (0.345)	0 (2)			
Typhoon	TC with 118-220 kph sustained surface winds	879	1.063 (1.132)	0 (5)			
Super typhoon	TC with > 220 kph sustained surface winds	879	0 (0)	0 (0)			
Annual total casualties (dead/missing/injured)	Counts of people dead missing and injured in the specified province due to TC	879	66.020 (821.98)	0 (22,005)	NDRRMC (2005–15)	Province	2005-2015
Inflation-adjusted annual total cost of damages (in millions)	Damages (agriculture, infrastructure and private property) due to TC adjusted using CPI 2010	879	316.70 (2,032.87)	0 (52,031)	NDRRMC (2005–15)	Province	2005-2015
Annual frequency that public storm warning signal (PSWS) was raised in a province					PAGASA (2005–15)	Province[2]	2005-2015
PSWS #1	TC with 30-60 kph winds, without expected damage to very light damage, expected within the next 36 hours	879	1.255 (1.364)	0 (8)			
PSWS #2	TC with 61-120 kph winds, with light to moderate damage, expected within the next 24 hours	879	0.675 (1.016)	0 (7)			
PSWS #3	TC with 121-170 kph winds, with moderate to heavy damage, expected within the next 18 hours	879	0.429 (0.740)	0 (4)			
PSWS #4	TC with 171-220 kph winds, with heavy to very heavy damage, expected within the next 12 hours	879	0.047 (250)	0 (3)			
PSWS #5	TC with >220 kph winds, with very heavy to widespread damage, expected within the next 12 hours	879	0 (0)	0 (0)			

Notes: kph = kilometres per hour; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Service Administration; CPI = consumer price index; NDRRMC = National Disaster Risk Reduction and Management Council.

[2]Data from PAGASA manually encoded from annual tropical cyclone reports—the language of the report poses some level of ambiguity with respect to where some PSWS affected which province (Example: PSWS #1 was raised in Northern Mindanao—hence counted all provinces in Northern Mindanao, and so on).

Variable	Variable definition	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Control variables						
Unemployment rate	Unemployed/labour force within province	0.053 (0.028)	0 (0.173)	LFS (2005–15)	Province	2005-2015
Infrastructure at the regional level						
Total number of elementary public schools		2,405 (712)	511 (3,644)	PY (2005–09), DedEd (2010–15)	Region	2005-2015
Total number of secondary public schools		444 (147)	206 (818)	PY (2005–09), DedEd (2010–15)	Region	2005-2015
Total number of public hospitals		39 (16)	9 (70)	PY (2005-15)	Region	2005-2015
Total number of private hospitals		58 (46)	5 (192)	PY (2005-15)	Region	2005-2015
Net participation rate in public and private elementary schools	Proportion of the number of enrollees 7–12/6–11 years old to same age population	89 (8)	70 (103)	PY (2011), PSY (2015, 2016)	Region	2005-2015
Net participation rate in public and private secondary schools	Proportion of the number of enrollees 13–16 years old to same age population	60 (10)	30 (81)	PY (2011), PSY (2015, 2016)	Region	2005-2015
Measures of income						
Poverty incidence	Proportion of families/individuals with per capita income or expenditure less than the per capita poverty threshold to the total number	34.381 (17.167)	0 (74)	FIES (2005–15)	Province	2003 for 2005 2006 for 2006-2008, 2009 for 2009-2011, 2012 for 2012-2014, 2015
Percentage of households with access to electricity	Percentage of region with connections (potential/actual)	74.38 (17.364)	22 (100)	PY (2005–13), 'Status of Energization', PSY (2015, 2016)	Region	2005-2015
Percentage of households with access to improved water source	Percentage of households within province with access to improved water source (based on the definition of NDHS)	89.537 (12.5)	21.2 (100)	NDHS (2003, 2008, 2013)	Province	2003 for 2005-2007, 2008 for 2008-2012, 2013 for 2013-2015
Historical migration (2003)	(Migration per province/ N per province)*100	1.087 (0.671)	0.19 (3.03)	LFS (2003)	Province	2003

Variable	Variable definition	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Agricultural intensity indicators						
Agricultural dummy variable (50% cutoff)	= 1 if a province belongs to the top 50% rainfed palay producing provinces in a certain year	0.495 (0.500)	0 (1)	PSA OpenSTAT	Province	2005-2015
Agricultural dummy variable (25% cutoff)	= 1 if a province belongs to the top 25% rainfed palay producing provinces in a certain year	0.243 (0.429)	0 (1)	PSA OpenSTAT	Province	2005-2015
Demographic						
Average household size	Average number of members in a household	4.591 (0.255)	3.000674 (6.052722)	PSA	Region (2006) Province (2009, 2012, 2015)	2006 for 2005-2008 2009 for 2009-2011 2012 for 2012-2014 2015

Notes: CPH = Census of Population and Housing; DepEd = Department of Education; FIES = Family and Income Expenditure Survey; LFS = Labor Force Survey; NDHS = National Demographic and Health Survey; PSA = Philippine Statistics Authority; PSGC == Philippine Statistics Geographic Classification; PY = Philippine Yearbook; PSY = Philippine Statistical Yearbook.

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Provincial dummies							
Ilocos Norte	= 1 if Ilocos Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Ilocos Sur	= 1 if Ilocos Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
La Union	= 1 if La Union province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Pangasinan	= 1 if Pangasinan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Batanes	= 1 if Batanes province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Cagayan	= 1 if Cagayan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Isabela	= 1 if Isabela province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Nueva Vizcaya	= 1 if Nueva Vizcaya province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Quirino	= 1 if Quirino province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Bataan	= 1 if Bataan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Bulacan	= 1 if Bulacan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Nueva Ecija	= 1 if Nueva Ecija province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Pampanga	= 1 if Pampanga province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Tarlac	= 1 if Tarlac province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Zambales	= 1 if Zambales province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Aurora	= 1 if Aurora province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Batangas	= 1 if Batangas province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Cavite	= 1 if Cavite province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Laguna	= 1 if Laguna province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Quezon	= 1 if Quezon province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Rizal	= 1 if Rizal province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Albay	= 1 if Albay province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Camarines Norte	= 1 if Camarines Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Camarines Sur	= 1 if Camarines Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Catanduanes	= 1 if Catanduanes province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Masbate	= 1 if Masbate province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Sorsogon	= 1 if Sorsogon province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Aklan	= 1 if Aklan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Antique	= 1 if Antique province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Capiz	= 1 if Capiz province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Iloilo	= 1 if Iloilo province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Negros Occidental	= 1 if Negros Occidental province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Guimaras	= 1 if Guimaras province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Bohol	= 1 if Bohol province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Cebu	= 1 if Cebu province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Negros Oriental	= 1 if Negros Oriental province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Siquijor	= 1 if Siquijor province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Eastern Samar	= 1 if Eastern Samar province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Leyte	= 1 if Leyte province	879	0.114 (0.106)	0 (1)	PSA, PSGC	Province	2005-2015
Northern Samar	= 1 if Northern Samar province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Samar (Western Samar)	= 1 if Samar (Western Samar) province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Southern Leyte	= 1 if Southern Leyte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Biliran	= 1 if Biliran province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Zamboanga Del Norte	= 1 if Zamboanga Del Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Zamboanga Del Sur	= 1 if Zamboanga Del Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Zamboanga Sibugay	= 1 if Zamboanga Sibugay province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Bukidnon	= 1 if Bukidnon province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Camiguin	= 1 if Camiguin province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Lanao Del Norte	= 1 if Lanao Del Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Misamis Occidental	= 1 if Misamis Occidental province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Misamis Oriental	= 1 if Misamis Oriental province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Davao Del Norte	= 1 if Davao Del Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Davao Del Sur	= 1 if Davao Del Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Davao Oriental	= 1 if Davao Oriental province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Compostela Valley	= 1 if Compostela Valley province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Cotabato (North Cotabato)	= 1 if Cotabato (North Cotabato) province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
South Cotabato	= 1 if South Cotabato province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Sultan Kudarat	= 1 if Sultan Kudarat province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Sarangani	= 1 if Sarangani province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
National Capital Region	= 1 if National Capital Region province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Abra	= 1 if Abra province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Benguet	= 1 if Benguet province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Ifugao	= 1 if Ifugao province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Kalinga	= 1 if Kalinga province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Mountain Province	= 1 if Mountain Province province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Apayao	= 1 if Apayao province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Basilan	= 1 if Basilan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Lanao Del Sur	= 1 if Lanao Del Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Maguindanao	= 1 if Maguindanao province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Sulu	= 1 if Sulu province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Tawi-Tawi	= 1 if Tawi-Tawi province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Agusan Del Norte	= 1 if Agusan Del Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Agusan Del Sur	= 1 if Agusan Del Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
Surigao Del Norte	= 1 if Surigao Del Norte province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Surigao Del Sur	= 1 if Surigao Del Sur province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Marinduque	= 1 if Marinduque province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Occidental Mindoro	= 1 if Occidental Mindoro province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Oriental Mindoro	= 1 if Oriental Mindoro province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Palawan	= 1 if Palawan province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Romblon	= 1 if Romblon province	879	0.125 (0.111)	0 (1)	PSA, PSGC	Province	2005-2015
Major island group dummies							
Luzon	= 1 if Luzon island group	879	0.476 (0.500)	0 (1)	PSA, PSGC	Major island group	2005-2015
Visayas	= 1 if Visayas island group	879	0.199 (0.400)	0 (1)	PSA, PSGC	Major island group	2005-2015
Mindanao	= 1 if Mindanao island group	879	0.325 (0.469)	0 (1)	PSA, PSGC	Major island group	2005-2015
Year dummies							
2005	= 1 if year 2005	879	0.091 (0.288)	0 (1)		Province	2005-2015
2006	= 1 if year 2006	879	0.091 (0.288)	0 (1)		Province	2005-2016
2007	= 1 if year 2007	879	0.091 (0.288)	0 (1)		Province	2005-2017
2008	= 1 if year 2008	879	0.091 (0.288)	0 (1)		Province	2005-2018

Table 2 Descriptive statistics of independent variables

Variable	Variable definition	N	Mean (Std. Dev.)	Min (Max)	Source	Level	Available years
2009	= 1 if year 2009	879	0.091 (0.288)	0 (1)		Province	2005-2019
2010	= 1 if year 2010	879	0.091 (0.288)	0 (1)		Province	2005-2020
2011	= 1 if year 2011	879	0.091 (0.288)	0 (1)		Province	2005-2021
2012	= 1 if year 2012	879	0.091 (0.288)	0 (1)		Province	2005-2022
2013	= 1 if year 2013	879	0.091 (0.288)	0 (1)		Province	2005-2023
2014	= 1 if year 2014	879	0.090 (0.286)	0 (1)		Province	2005-2024
2015	= 1 if year 2015	879	0.091 (0.288)	0 (1)		Province	2005-2025

Table 3.1 The impact of weather shocks on migration (Fixed effects)

Specification	Baseline	Quadratic	Lag
	(1)	(2)	(3)
Dependent variable	Migration	Migration	Migration
Tropical depression	0.0160	0.0733	
	(0.0196)	(0.0609)	
Tropical storm	-0.0127	-0.0152	
	(0.0106)	(0.0194)	
Severe tropical storm	-0.0325	0.00877	
	(0.0199)	(0.0985)	
Typhoon	-0.000246	0.0117	
	(0.0101)	(0.0223)	
Total damage cost	0.00385**	0.00451	
	(0.00146)	(0.00577)	
Total casualties	-0.000897	-0.00989	
	(0.00580)	(0.0143)	
PSWS #1	0.0127*	0.0299**	
	(0.00729)	(0.0149)	
PSWS #2	-0.0107	0.00273	
	(0.00943)	(0.0161)	
PSWS #3	-0.0123	-0.0261	
	(0.0119)	(0.0275)	
PSWS #4	-0.0572**	-0.00874	
	(0.0273)	(0.0739)	
Tropical depression squared		-0.0448	
		(0.0409)	
Tropical storm squared		0.00234	
		(0.00566)	
Severe tropical storm squared		-0.0245	
		(0.0489)	
Typhoon squared		-0.00242	
		(0.00477)	
Total damage cost squared		-3.96e-05	
		(0.000297)	
Total casualties squared		0.00162	
		(0.00237)	
PSWS #1 squared		-0.00403	
		(0.00251)	
PSWS #2 squared		-0.00341	
		(0.00354)	
PSWS #3 squared		0.00659	
		(0.00991)	
PSWS #4 squared		-0.0228	
		(0.0267)	
Tropical depression (lag)			0.0485**
			(0.0214)
Tropical storm (lag)			-0.0116
			(0.0119)
Severe tropical storm (lag)			-0.0180
			(0.0225)
Typhoon (lag)			0.0186*
			(0.00968)
Total damage cost (lag)			-0.000765
			(0.00113)
Total casualties (lag)			-0.00851
			(0.00597)
PSWS #1 (lag)			0.00536
			(0.00857)
PSWS #2 (lag)			-0.00320
			(0.0106)
PSWS #3 (lag)			-0.0181
			(0.0147)
PSWS #4 (lag)			-0.0526*
			(0.0284)
Control variables	X	X	
Control variables (lag)			X
Year dummies	X	X	X
Constant	4.950**	4.937**	5.490***
	(1.989)	(1.957)	(1.782)
Observations	859	859	779
R-squared	0.589	0.592	0.333

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 3.2 The impact of weather shocks on migration (Fixed effects)

Specification	Interaction [top 25%] (1)	Interaction [top 50%] (2)
Dependent variable	Migration	Migration
Tropical depression	0.0163	0.00860
	(0.0215)	(0.0227)
Tropical storm	-0.0146	-0.0112
	(0.0123)	(0.0151)
Severe tropical storm	-0.0223	-0.0128
	(0.0217)	(0.0284)
Typhoon	-0.0122	-0.0195
	(0.0114)	(0.0137)
Total damage cost	0.00387**	0.00390*
	(0.00169)	(0.00199)
Total casualties	-0.000629	0.000853
	(0.00711)	(0.00961)
PSWS #1	0.0159**	0.0185*
	(0.00771)	(0.0104)
PSWS #2	-0.0105	-0.00989
	(0.0105)	(0.0133)
PSWS #3	-0.00427	-0.000585
	(0.0143)	(0.0183)
PSWS #4	-0.0451**	-0.0212
	(0.0224)	(0.0308)
Agri25 (dummy; top 25%)	-0.00968	
	(0.0685)	
Agri25 × tropical depression	0.0191	
	(0.0489)	
Agri25 × tropical storm	0.00610	
	(0.0174)	
Agri25 × severe tropical storm	-0.0404	
	(0.0328)	
Agri25 × typhoon	0.0495***	
	(0.0186)	
Agri25 × total damage cost	1.92e-05	
	(0.00200)	
Agri25 × total casualties	0.000533	
	(0.0128)	
Agri25 × PSWS #1	-0.0103	
	(0.0136)	
Agri25 × PSWS #2	-0.00803	
	(0.0176)	
Agri25 × PSWS #3	-0.0309	
	(0.0274)	
Agri25 × PSWS #4	-0.0634	
	(0.0922)	
Agri50 (dummy; top 50%)		0.00277
		(0.0489)
Agri50 × tropical depression		0.0188
		(0.0362)
Agri50 × tropical storm		-0.00198
		(0.0166)
Agri50 × severe tropical storm		-0.0375
		(0.0347)
Agri50 × typhoon		0.0368**
		(0.0164)
Agri50 × total damage cost		0.000399
		(0.00228)
Agri50 × total casualties		-0.00467
		(0.0122)
Agri50 × PSWS #1		-0.00858
		(0.0124)
Agri50 × PSWS #2		0.00108
		(0.0156)
Agri50 × PSWS #3		-0.0190
		(0.0219)
Agri50 × PSWS #4		-0.0521
		(0.0499)
Control variables	X	X
Year dummies	X	X
Constant	5.082**	5.040**
	(2.008)	(1.978)
Observations	859	859
R-squared	0.593	0.592

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 4.1 The impact of weather shocks on income (Fixed effects)

Specification	Baseline (1)	Quadratic (2)	Lag (3)
Dependent variable	Income	Income	Income
Tropical depression	0.0296**	0.0523	
	(0.0137)	(0.0373)	
Tropical storm	0.0224***	0.0273**	
	(0.00848)	(0.0135)	
Severe tropical storm	-0.0244	-0.0680	
	(0.0150)	(0.0503)	
Typhoon	0.0121*	0.0166	
	(0.00629)	(0.0135)	
Total damage cost	0.000475	0.00471	
	(0.00102)	(0.00389)	
Total casualties	-5.14e-05	0.00864	
	(0.00377)	(0.00774)	
PSWS #1	-0.00412	0.000906	
	(0.00502)	(0.0117)	
PSWS #2	0.00615	-0.00750	
	(0.00684)	(0.0123)	
PSWS #3	0.000617	0.0245	
	(0.00859)	(0.0253)	
PSWS #4	0.00184	0.0110	
	(0.0209)	(0.0485)	
Tropical depression squared		-0.0188	
		(0.0227)	
Tropical storm squared		-0.00233	
		(0.00416)	
Severe tropical storm squared		0.0266	
		(0.0267)	
Typhoon squared		-0.00200	
		(0.00326)	
Total damage cost squared		-0.000235	
		(0.000203)	
Total casualties squared		-0.00116	
		(0.00125)	
PSWS #1 squared		-0.000991	
		(0.00204)	
PSWS #2 squared		0.00391	
		(0.00252)	
PSWS #3 squared		-0.00966	
		(0.0104)	
PSWS #4 squared		0.00200	
		(0.0265)	
Tropical depression (lag)			0.0219*
			(0.0128)
Tropical storm (lag)			-0.00600
			(0.00661)
Severe tropical storm (lag)			-0.00103
			(0.0169)
Typhoon (lag)			-0.00858
			(0.00558)
Total damage cost (lag)			0.000158
			(0.000794)
Total casualties (lag)			0.00171
			(0.00385)
PSWS #1 (lag)			0.00491
			(0.00522)
PSWS #2 (lag)			-0.00281
			(0.00600)
PSWS #3 (lag)			0.00379
			(0.00843)
PSWS #4 (lag)			-0.0344*
			(0.0188)
Control variables	X	X	
Control variables (lag)			X
Year dummies	X	X	X
Constant	11.70***	11.77***	9.684***
	(1.205)	(1.260)	(0.945)
Observations	859	859	779
R-squared	0.963	0.963	0.362

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 4.2 The impact of weather shocks on income (Fixed effects)

Specification	Agriculture (1)	Interaction [top 50%] (2)
Dependent variable	Agriculture	Income
Tropical depression	-0.00791	0.0394**
	(0.0390)	(0.0176)
Tropical storm	0.0103	0.0295**
	(0.0106)	(0.0113)
Severe tropical storm	-0.0145	-0.0126
	(0.0301)	(0.0296)
Typhoon	-0.00317	0.00696
	(0.0142)	(0.00866)
Total damage cost	0.00149	0.000952
	(0.00142)	(0.00140)
Total casualties	-0.0160*	0.00120
	(0.00892)	(0.00509)
PSWS #1	0.0160	-0.000682
	(0.0104)	(0.00995)
PSWS #2	0.00415	0.0103
	(0.00960)	(0.00825)
PSWS #3	0.0430**	0.00854
	(0.0204)	(0.0123)
PSWS #4	0.0284	0.0545*
	(0.0441)	(0.0281)
Agri25 (dummy; top 25%)		
Agri25 × tropical depression		
Agri25 × tropical storm		
Agri25 × severe tropical storm		
Agri25 × typhoon		
Agri25 × total damage cost		
Agri25 × total casualties		
Agri25 × PSWS #1		
Agri25 × PSWS #2		
Agri25 × PSWS #3		
Agri25 × PSWS #4		
Agri50 (dummy; top 50%)		0.0387
		(0.0312)
Agri50 × tropical depression		-0.0179
		(0.0237)
Agri50 × tropical storm		-0.0141
		(0.0148)
Agri50 × severe tropical storm		-0.0177
		(0.0307)
Agri50 × typhoon		0.00515
		(0.0132)
Agri50 × total damage cost		-0.000807
		(0.00149)
Agri50 × total casualties		-0.00103
		(0.00760)
Agri50 × PSWS #1		-0.00376
		(0.0104)
Agri50 × PSWS #2		-0.00811
		(0.0142)
Agri50 × PSWS #3		-0.00745
		(0.0158)
Agri50 × PSWS #4		-0.0836**
		(0.0345)
Control variables	X	X
Year dummies	X	X
Constant	12.42***	11.72***
	(2.516)	(1.242)
Observations	859	859
R-squared	0.142	0.963

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 5 Wald tests on the differential impact of weather shocks

Panel A (on migration)	Tropical depression	Tropical storm	Severe tropical storm	Typhoon	Total damage cost	Total casualties	PSWS #1	PSWS #2	PSWS #3	PSWS #4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Wald test of joint significance of coefficients for weather shocks and weather shocks squared										
F-statistic	0.73	0.44	2.63	0.14	3.17	0.25	2.07	1.08	0.56	6.3
p-value	0.483	0.6436	0.0783	0.8693	0.0476	0.7804	0.1326	0.3458	0.5729	0.0029
Marginal effects	-0.0163	-0.01052	-0.04023*	0.00686	0.0045892**	-0.00665	0.02184+	-0.00409	-0.01292	-0.05434***
B. Wald test of joint significance of coefficients for weather shocks and weather shocks × Agri25										
F-statistic	0.63	0.77	2.17	3.58	3.75	0.00	2.12	1.11	1.25	2.67
p-value	0.5369	0.4668	0.1213	0.0325	0.028	0.9961	0.1267	0.3361	0.291	0.0755
Marginal effects	0.0354	-0.0085	-0.0627+	0.0373**	0.0038892**	-9.6E-05	0.0056+	-0.01853	-0.03517	-0.1085*
C. Wald test of joint significance of coefficients for weather shocks and weather shocks × Agri50										
F-statistic	0.48	0.74	1.95	2.52	3.91	0.14	1.93	0.5	0.91	1.73
p-value	0.6212	0.4788	0.1492	0.0872	0.024	0.8681	0.1525	0.6057	0.4062	0.1843
Marginal effects	0.0274	-0.01318	-0.0503+	0.0173*	0.004299**	-0.003817	0.00992	-0.00881	-0.019585	-0.0733

Panel B (on income)	Tropical depression	Tropical storm	Severe tropical storm	Typhoon	Total damage cost	Total casualties	PSWS #1	PSWS #2	PSWS #3	PSWS #4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Wald test of joint significance of coefficients for weather shocks and weather shocks squared										
F-statistic	2.02	3.54	1.38	1.25	0.73	0.62	0.47	2.01	0.47	0.27
p-value	0.1395	0.0337	0.2565	0.2928	0.4838	0.5387	0.6268	0.1405	0.6271	0.7659
Marginal effects	0.0147	0.02264**	-0.0148	0.0126	0.00424	0.00632	-0.001076	0.00032+	0.00518	0.015
B. Wald test of joint significance of coefficients for weather shocks and weather shocks × Agri50										
F-statistic	2.86	3.99	2.02	1.15	0.24	0.03	0.49	0.79	0.24	2.95
p-value	0.0634	0.0224	0.1393	0.3214	0.7862	0.9721	0.6138	0.4568	0.7858	0.0583
Marginal effects	0.0215*	0.0154**	-0.0303+	0.01211	0.000145	0.00017	-0.004442	0.00219	0.00109	-0.0291*

**** p<0.01, ** p<0.05, * p<0.1, + p<0.15*