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Weather Shocks and Economic Activity
Evidence from the Philippines

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Jeremy Smith (Head of the Department of Economics, University of Warwick) and Michael Ward (Head of the Department of Economics, Monash University)

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Weather Shocks and Economic Activity

Evidence from the Philippines

Marvin Pardillo

Abstract:

As global temperatures continue to rise, strategies to mitigate the adverse effects of weather shock events become crucial. While previous studies have analysed the effect of climatic variation on economic activity at the national level, there is a lack of understanding of the developmental effects of weather shocks at the subnational level. This study uses monthly night light data captured by Visible Infrared Imaging Radiometer Suite (VIIRS) and weather data to examine the effect of weather shock events at the municipal level in the Philippines. We find that excesses and shortages in monthly rainfall are associated with a decrease in the level of economic activity. We also find that lower temperatures are associated with an increase in the level of economic activity whereas higher temperatures are associated with a decrease in economic activity.

JEL Classification: Q54, Q58, R12

***Keywords*:** Philippines, rainfall shocks, temperature Shocks and night lights.

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Thanks to Pushkar Maitra as supervisor for this piece of work.

1. Introduction:

As global temperatures continue to increase at unprecedented rates, studies indicate weather shock events where we observe temperature and rainfall extremes, are likely to increase in both frequency and intensity (Hoegh-Guldberg, 2018). Compared to developed economies, low-income countries contribute substantially less to the increase in global air temperature and oceanic warming[2] (Wei et al., 2016). A dependence on agricultural-related output in these economies are likely to have disproportionate effects on poor households in rural areas, leaving them highly susceptible to increased variability in rainfall and temperature. As such, understanding the implications of climatic variability on rural households in the Philippines become imperative.

This paper aims to analyse the effect of weather shock events on economic activity at the municipal level in the Philippines. We use Visible Infrared Imaging Radiometer Suite (VIIRS) monthly night light data from the Philippines as a proxy for economic activity. We also use monthly rainfall and temperature data from 1986 to 2018 to construct a 30-year historical average for each month and municipality within the country. We define positive and negative shocks as deviations away from their respective historical average. Our paper contributes to the understanding of how climate change can adversely impact economic activity in the Philippines by analysing the effect weather shock events at the municipal level. To the best of our knowledge, we are the first to use VIIRS monthly night light data from the Philippines to analyse the effect of weather shock events on economic activity. We hope to build upon the growing body of research that have utilised night lights to make predictions on economic outcomes in low-income countries.

[2] Studies estimate that developed countries contribute approximately 61%, whilst developing countries contribute approximately 39% to rise in global temperatures (Wei et al., 2016).

2. Background

The Philippines is an archipelago state located in Southeast Asia, consisting of approximately 107 million people (World Bank, 2018). The country is separated into 17 Regions, 81 Provinces, 1,647 Municipalities and approximately 42,044 Barangays (PSA, 2018). The country is also divided into three main islands: Luzon, Visayas and Mindanao. With approximately 57% of the country's population, Luzon is the most populated of the three main groups. Approximately 23% of the population reside in Visayas and the remaining 20% residing in Mindanao (PSA, 2015). In the last decade, the Philippines have continued its transition from a predominantly agricultural economy, to an industrial one. The country continues to lag behind growth expectations with 16.6% of the population living below the national poverty line in 2018 (ADB, 2018). The agricultural sector continues to employ more than a quarter of the working population and sand contributes approximately 10% to national output (World Bank, 2018).

The Philippines are ranked as the third most exposed and economically vulnerable countries to extreme weather shock events such as typhoons, storm surges and landslides (Heintze et al., 2018 and Strobl, 2019). In the last three decades, the Philippines have experienced 565 weather shock events which have led to approximately $US 23 billion in damages (Jha, 2018). This inherent vulnerability is largely attributed to their geographical location, large coastal population, and exposure to El Niño and La Niña events. A study by the Global Facility for Disaster Reduction and Recovery (GFDRR) estimate that approximately 60% of the country's total land area is vulnerable to weather shock events and 74% of the population is exposed to their impacts (UNDRR, 2019). Weather shock events related to excessive rainfall arising from typhoons which cause flooding and landslides contribute to over 80% of natural disasters since 1970 (Jha, 2018). Historically, July and

August have proved to be particularly problematic. These months average three extreme rainfall shock events between 1948 and 2019. In the last decade, the country has been affected by six deadly typhoons and tropical storms:

1. Typhoon Ketsana & Parma (2009): $1.7 billion (USD) in damages
2. Tropical Storm Washi (2011): $97.8 million (USD)
3. Super Typhoon Haiyan: (2013): $2.98 billion (USD) in damages
4. Typhoon Koppu (2015): $313 million (USD) in damages
5. Super Typhoon Mangkhut: (2018) $3.77 billion (USD) in damages
6. Typhoon Vongfong (2020): $31.1 million (USD) in damages

While the Asian economic crisis hindered growth in the Philippines, exposure to frequent weather shock events are argued to play a key role in explaining why the country has failed to meet growth expectations achieved by neighbouring economies (Tolo, 2011). The ADB estimate that approximately 85.2% of the country's production sources are vulnerable to reoccurring weather shock events, posing significant long-term economic challenges (Martinico-Perez et al., 2018). Costs related to recovery efforts during typhoon seasons are approximately equivalent to 4% of the country's annual GDP (Vidal, 2013). The Food and Agricultural Organisation (FAO) also estimate that damages to the agricultural sector account for 74% of total damages or approximately $1.4 Billion USD (FAO, 2018). However, non-agricultural sectors are also highly susceptible to adverse climatic variations as they have negative spillover effects that hurt the wider economy. Weather shocks reduce output in the utilities sector as the supply of electricity is severely limited and unstable long after the event, reducing demand for services in the manufacturing and infrastructure sectors (Ang, 2014).

3. Literature Review:

Related Literature on Night Lights:

There is a growing body of research that have used night light data to gain important insights into the level of development at disaggregated levels in low income countries (Henderson et al., 2012 , Mendelsohn et al., 2001 and Goldblatt et al., 2016). A common characteristic shared by rural areas in low-income countries is the lack of accounting systems that allow for effective data collection. This has previously made it difficult for researchers to make reliable inferences on the level of activity in these areas. Night light data overcomes this by providing regular and timely insights into the level of economic development in a given area. The level of luminosity emitted from these areas have been found to explain key economic indicators such as income and standard of living in rural areas, highlighting its practicality in understanding economic outcomes at highly disaggregated levels (Bhandari & Roychowdhury, 2011 and Henderson et al., 2012). Interestingly, night lights are also able to explain dimensions of human development at the local level as they were found to be positively correlated with education, health, and electricity consumption within rural areas (Bruederle & Hodler, 2018 and Addison, 2015).

Related Literature on Weather Shocks and Economic Outcomes:

In recent times, the International Monetary Fund (IMF) have increased their scope of interest to include the economic impact of climate change on developing economies. There is an overwhelming consensus amongst studies that suggest more frequent and intense weather shock events will have uneven implications on low-income countries such as the Philippines (Burke, et al., 2015). The IMF find that a 1° C increase in temperature across low-income countries with an average temperature of 25°, reduced growth by 1.2 percentage points (Acevedo, et al., 2018). On the other hand, a 1° C increase in temperatures in advanced economies[3] did not significantly affect output per capita, highlighting the inherent susceptibility of developing economies to fluctuations in temperature. Levels of productivity, labor supply and investment are also shown to be negatively related to increases in average temperatures (Burke, et al., 2015). A benchmark estimate suggests that compared to a world without climate change, approximately 40% of the world's poorest economies will experience a 75% decrease in average income by 2100 (Burke, et al., 2015). This is in contrast to high income countries who are predicted to experience slight gains as a result of a warmer climate (Burke, et al., 2015).

The Philippines are inherently exposed to rainfall shocks due to their large coastal population and exposure to El Niño and La Niña events. El Niño events where we observe significant shortages in rainfall, have negative effects on key economic indicators such as inequality, household income, consumption and health in the Philippines (Safir et al., 2018, Datt, 2003 & Roberts, 2009). Historically, Mindanao (South of the Philippines) have been unaffected by weather shock events. However, in the last decade, Typhoons Washi and Bopha caused approximately $3 billion USD in damage in 2011 and 2012, respectively. Such shocks have been shown to significantly reduce economic activity in the short term and hinder long term growth (Strobl, 2019)

4. Methodology and Overview:

The paper is organized as follows. First, we describe our data on rainfall, temperature, and night lights. We will then discuss our process in defining positive and negative weather shock events. Following this, we specify our empirical model in which we regress night lights

[3] A large majority of advanced economies are geographically located in cooler parts of the earth where the average temperature lies between 13 ° C and 15° C.

on positive and negative weather shock events. Finally, we present our empirical results and discuss potential implications of our findings on municipalities within the Philippines.

5. Data and Descriptive Statistics:

To analyse the effect of weather shock events on economic activity at the municipal level, we utilise monthly rainfall and temperature data provided by World Clim from 1986 to 2018. To estimate the level of economic activity at the municipal level, we use VIIRS monthly nighttime lights obtained from the Earth Observation Group (EOG) from 2016 to 2018. Table 1 presents the means and standard deviations of rainfall, temperature, and night light variables. Across all months between 1986 and 2018, the average rainfall and temperature across municipalities is 237mm and 30°C, respectively. Across municipalities over the 30-year period, we observe rainfall levels between 0.5mm to 1534mm while average monthly temperature levels ranged between 19°C to 36°C.

Table 1: Descriptive Statistics:

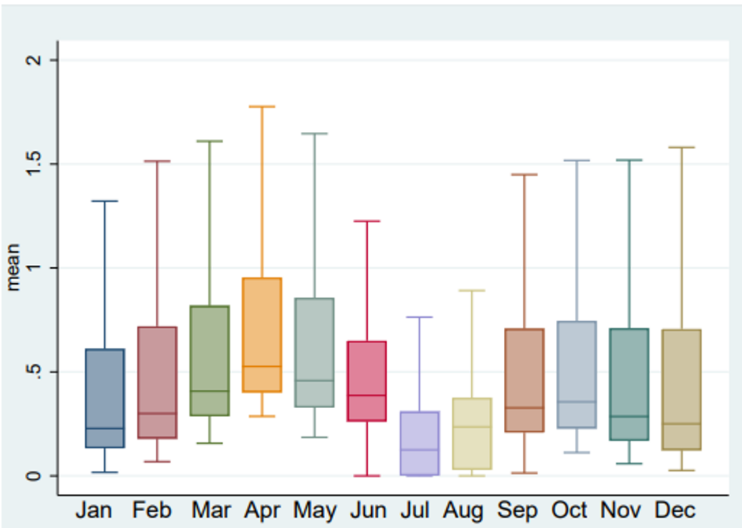
Variables	Observations	Mean	Std. Dev	Min	Max
Rainfall	59,184	237.28	185.07	0.51	1534.40
Temperature	59,184	30.77	1.92	18.85	36.13
Night lights	59,292	1.05	3.46	-0.20	66.28
Log(night lights)	59,292	0.43	0.56	-0.22	4.21

5.1 VIIRS Monthly Nightlight Data:

Since 2010, there have been advances in night light data imagery that have facilitated new methods of collecting and studying night light data. New sensors such as VIIRS have offered higher quality spatial, temporal, and radiometric resolution. Prior to averaging, the data is filtered to reduce the level of noise due to stray light, lightning, lunar illumination, and cloud cover. Similarly, electric lighting caused by fires and flares are also filtered out. The monthly night light images span the globe from 75N latitude to 65S. They are produced in 15 arc-second geographic grids and are made available in geotiff formats as a set of 6 tiles containing average radiance values and numbers of available observations.

To construct our monthly average level of night lights, we combine monthly VIIRS night lights data from with a Philippines shapefile that consists of administrative information regarding municipal boundaries. The zonal statistics command within Quantum Geographical Information System (QGIS) allow us to assign monthly night light levels to each municipality between 2016 to 2018. After taking the logarithm[4] of our values for night lights and pooling all municipalities, we observe a mean level of night lights of 0.43 between 2016 and 2018 (see Table 1 above). We find that the months of July and August report significantly lower values of night lights as shown in Figure 1.1(a) below. As discussed in section 2, this aligns with historically susceptible months where rainfall shocks occur the most. This may provide preliminary evidence to suggest a negative relationship between rainfall shocks and the level of the night lights across municipalities.

Figure 1.1 (a): Night lights between 2016 and 2018 across all municipalities:



[4] We also add 1 prior to taking the logarithm to avoid undefined values of night lights.

5.2 WorldClim Temperature and Rainfall Data:

Using approximately 60,000 weather stations around the world, Worldclim have compiled spatially interpolated monthly climate data at high spatial resolutions. The dataset has been shown to provide accurate measures of rainfall and temperature which are largely attributed to a high-quality network of weather station data and satellites. The dataset performs particularly well in measuring temperature and rainfall levels. Global cross-validation correlations were higher than 0.99 for temperature and humidity and approximately 0.86 for rainfall (Fick & Hijmans, 2017). For our analysis, we combine rainfall and temperature data from WorldClim with shapefiles containing administrative information regarding subnational boundaries. Similar to our construction of monthly night lights, we utilise the zonal statistics command within QGIS to assign monthly average temperature and rainfall levels to each municipality between 1986 to 2018. Figure 1.1 (b) and Figure 1.1 (c) below present boxplots for temperature and rainfall over a 30-year period. Figure 1.1 (b) presents a large variation in median rainfall within the year. Pooling all municipalities together, the monthly median rainfall ranges between approximately 80mm to 300mm in April and July, respectively. The months of July and August present the most volatility in terms of rainfall within the year. Over a 30-year period, rainfall levels in July and August ranged between 140mm to 630mm. Figure 1.1 (c) indicates that there is less variation in median temperatures within the year. After pooling all municipalities, monthly temperatures lie between 28°C and 32°C.

Figure 1.1(b): Rainfall from 1988 to 2018:

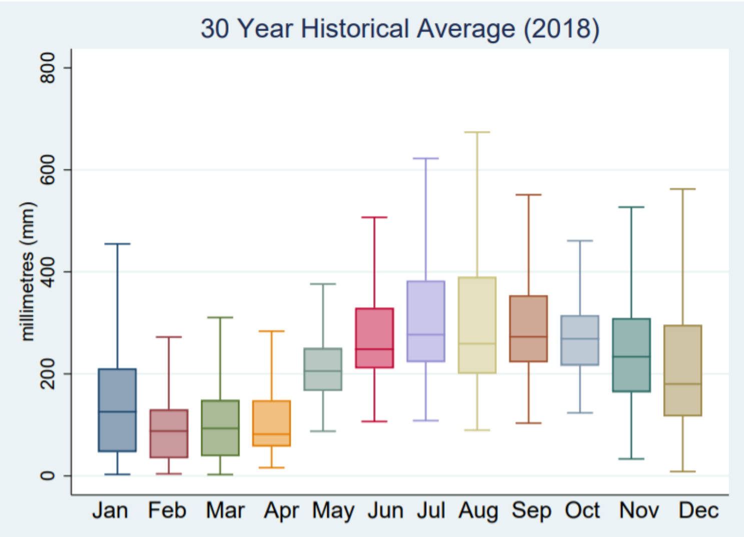


Figure 1.1(c): Temperature from 1988 to 2018:

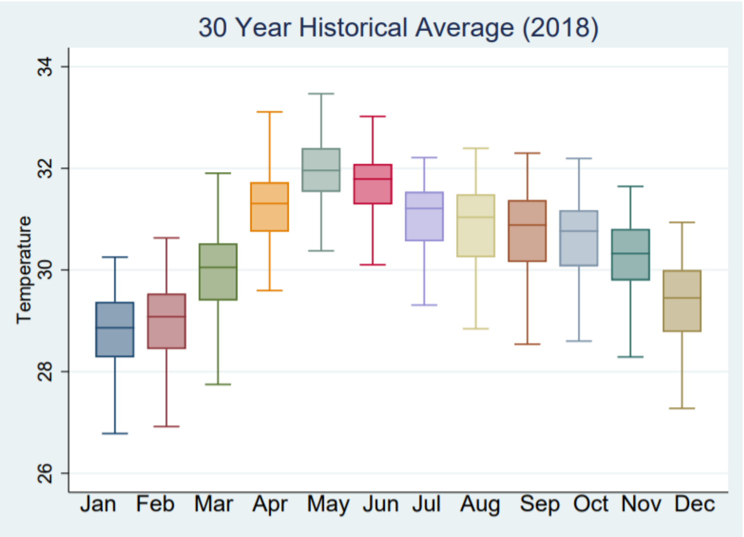


Figure 1.2 (a) and figure 1.2 (b) below presents the frequency of rainfall levels in the months of July and August over a 30-year period (1988 to 2017) across all municipalities in the Philippines. After pooling rainfall levels across all municipalities, we observe that both distributions for rainfall in these months are skewed to the right which may suggest that July and August are particularly problematic months where excess levels of rainfall occur the most.

Figure 1.2(a): Rainfall in July between 1988 and 2017

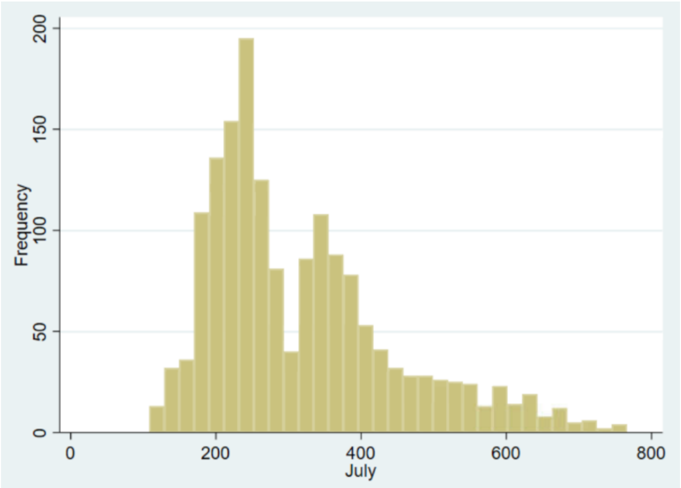
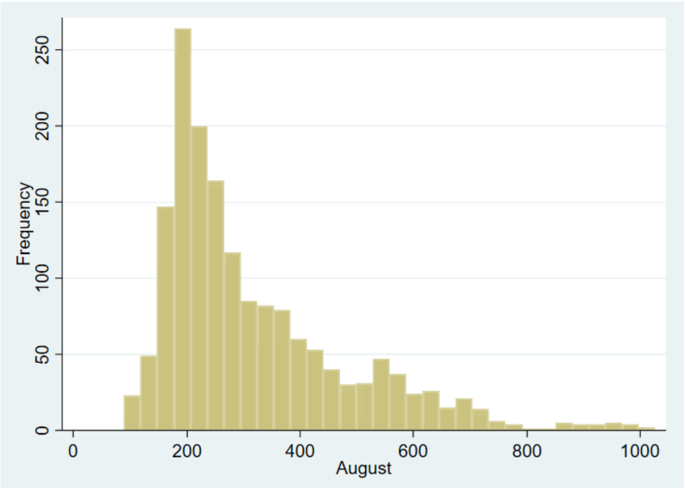


Figure 1.2(b): Rainfall in August between 1988 and 2017



5.2. Defining Weather Shock Events:

For our analysis, we construct temperature and rainfall shocks as independent variables denoted by z_{dmy}^{t} and z_{dmy}^{r} respectively in our regression equation. To do so, we calculate the 30-year historical average levels of rainfall and temperature for all municipalities and months in the Philippines between 2016 and 2018. For example, to calculate the 30-year historical level of rainfall for the month of May in 2018, we calculate the average level of rainfall for all months of May between 1988 and 2017 for all municipalities. Similarly, to calculate the 30-year historical average temperature for the month of May in 2017, we take the average levels of temperature for the months of May from 1987 to 2016 for all municipalities. We also calculate the standard deviation for each month and municipality between respective 30-year periods. Next, for each municipality and month, we define a rainfall and temperature shock as follows. First, we construct our z-score formula to determine deviations away from our 30-year historical averages for rainfall and temperature. For each month between 2016 and 2018, we input actual observations of rainfall and temperature for each municipality. This allows us to compare actual levels of rainfall and temperature in each municipality to their respective historical monthly average. The standardised measure for rainfall and temperature is calculated as follows:

$$z_{dmy}^{r} = \frac{Rf_{dmy} - \mu_{dmy}}{\sigma_{dmy}} \tag{1}$$

$$z_{dmy}^{t} = \frac{T_{dmy} - \mu_{dmy}}{\sigma_{dmy}} \tag{2}$$

T_{dmy} denotes the temperature in a municipality *d* in a month *m* and year *y*. Rf_{dmy} denotes the temperature in a municipality *d* in a month *m* and year *y*. A municipality in a given month and year will observe a rainfall shock if z_{dmy}^{r} < -1 or z_{dmy}^{r} > 1. Similarly, a municipality will observe a temperature shock if z_{dmy}^{t} < -1 or z_{dmy}^{t} > 1. Temperature z-scores above 1 indicate positive shocks, indicating temperature levels above their historical monthly average. On the other hand, temperature z-scores below -1 indicate negative shocks where temperature levels are below their historical monthly average. Similarly, a rainfall shock is defined to be a positive shock if z-scores are greater than 1, indicating excess levels of rainfall compared to the historical monthly average. Finally, negative shocks are defined by z-scores less than -1, indicating shortages in rainfall levels when compared to the monthly historical average. As shown in Table 2 below, after pooling monthly level of rainfall in each municipality between 1986 to 2018, we observe that the intensity of rainfall shocks ranges from -2.423 and 4.128. Similarly, after pooling monthly level of rainfall in each municipality between 1986 to 2018, we observe that the intensity of rainfall shocks ranges from -4.670 and 4.593. We define and categorise intensities of shocks in section 6.5 of the paper.

Table 2: Summary Statistics for Rainfall and Temperature Shocks:

Variable	Observations	Mean	Std. Dev	Min	Max
Rainfall Shocks	59,184	0.14	0.94	-2.42	4.13
Temperature Shocks	59,184	0.15	1.50	-4.70	4.59

5.3 Empirical Specification

We used a fixed effect regression model at the month and year level to estimate the following equations:

(3) $lml_{dmy} = \beta_0 + \beta_1 posrf_{dmy} + \beta_2 negrf_{dmy} + \varepsilon_{dmy}$

(4) $lml_{dmy} = \beta_0 + \beta_1 post_{dmy} + \beta_2 negt_{dmy} + \varepsilon_{dmy}$

(5) $lml_{dmy} = \beta_0 + \beta_1 posrf_{dmy} + \beta_2 negrf_{dmy} + \beta_3 post_{dmy} + \beta_4 negt_{dmy} + \varepsilon_{dmy}$

(6) $lml_{dmy} = \beta_0 + \beta_1 posrf2_{dmy} + \beta_2 negrf2_{dmy} \beta_3 posrf3_{dmy} + \beta_4 negrf3_{dmy} + \varepsilon_{dmy}$

(7) $lml_{dmy} = \beta_0 + \beta_1 post2_{dmy} + \beta_2 negt2_{dmy} \beta_3 post3_{dmy} + \beta_4 negt3_{dmy} + \varepsilon_{dmy}$

Our dependent variable lml_{dmy} is captured by VIIRS and denotes our measure for economic activity in a given municipality d, month m and year y. On the right-hand side of our equations we use positive and negative temperature and rainfall shocks in a given municipality, month, and year as independent variables. These independent regressors are dummy variables that take the value of 1 in the case of a weather shock event and 0 otherwise. Positive and negative rainfall shocks are denoted by $posrf_{dmy}$, $negrf_{dmy}$ respectively. Similarly, positive and negative temperature shocks are denotated by $post_{dmy}$ and $negt_{dmy}$ respectively. Standard errors are clustered at the municipal level to allow for correlation between municipalities and is denoted by ε_{dmy}. We also isolate the effects of shock intensity in equations (6) and (7). To do so, we create a series of dummies that categories different intensity levels for both temperature and rainfall. We use rainfall and temperature levels between -1 and 1 as a reference category for both negative and positive shocks in our interpretations.

We include fixed effects (group dummies) to control for any systematic differences between municipalities. Month and year fixed effects are included to control for differences in rainfall and temperature levels in particular months and years. In other words, we account for climatic seasonality and control for normal variations in weather across months and years. By doing so, we hope to minimise the threat of omitted variable bias and isolate changes in the level of night lights to weather shock events.

6. Results

Our data set consists of 36 observations (i.e. 3 years of data between 2016 and 2018) for 1,647 municipalities. By including municipality, (d), month (m) and year (y) fixed effects, our regression estimates can be interpreted as the average effect of rainfall and temperature shocks on economic activity across all municipalities, within a given month and year.

6.1 Rainfall Shocks and Night lights:

The main results of our analysis are presented in Table 3. In our first specification, we define a negative rainfall shocks as rainfall levels below a z-score of -1 and positive rainfall shock as rainfall levels above a z-score of 1. Our estimations indicate that negative rainfall shocks are associated with an increase in economic activity across all municipalities within a given month, and year. On the other hand, positive rainfall shocks are associated with a decrease in the level of economic activity. Shortages in rainfall are associated with a 0.93% increase in the level of economic activity whereas excesses in rainfall are associated with a 3.81% decrease in economic activity across all municipalities in a given month and year. Both results are statistically significant at the 1% level. These results are summarised in Table 3 below.

Table 3: Rainfall Shocks with z < -1 and z > 1.

Variables	Night lights
Negative Rainfall Shock	0.0093***
	(0.0017)
Positive Rainfall Shock	-0.0381***
	(0.0031)
Constant	0.2466***
	(0.0036)
Observations	57,645
R-squared	0.9112

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

6.2 Temperature Shocks and Night lights:

We similarly define negative temperature shocks as temperature levels below a z-score of -1 and positive temperature shocks as temperature levels above a z-score of 1. Our regression estimates indicate that a negative temperature shocks are associated with an increase in the level of economic activity. On the other hand, positive temperature shocks are associated with a decrease in the level of economic activity. We find that negative temperature shocks are associated with a 0.41% increase in economic activity whereas positive temperature shocks are associated with a 0.65% decrease in the level of economic activity across all municipalities within a given month and year. Both results are statistically significant at the 1% significance level. These results are summarised in Table 4 below.

Table 4: Fixed Effects of Temperature with z < -1 and z > 1.

Variables	Night lights
Negative Temperature Shock	0.0041
	(0.0030)
Positive Temperature Shock	-0.0065***
	(0.0021)
Constant	0.2391***
	(0.0035)
Observations	57,645
R-squared	0.9106

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

6.3 Combining the effect of rainfall and temperature shocks:

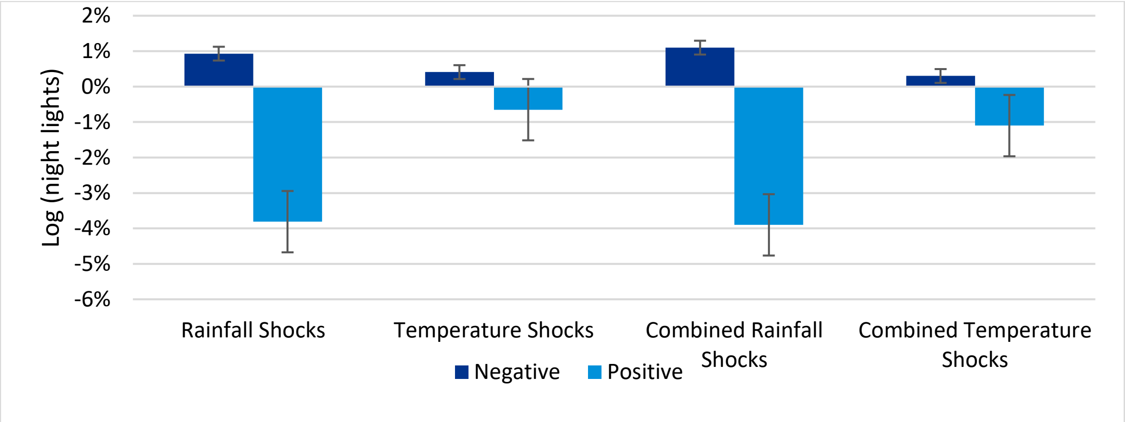
We also respecify our regression equation to test the combined effect of positive and negative temperature and rainfall shocks. This may be useful in identifying the joint effect of shocks on the level of economic activity across municipalities. Positive and negative temperature and rainfall shocks are defined the same as the preceding sections. Our results indicate negative rainfall shocks are associated with a 1.1% increase in economic activity by and positive rainfall shock is associated with a decrease of 3.9%. Negative temperature shocks are associated with a 0.3% increase in economic activity whereas positive temperature shocks are associated with a 1.1% decrease in economic activity. All results are significant at the 1% significance level. This is shown in Figure 3 and Table 5 below.

Table 5: Rainfall and temperature shocks with z-scores between -1 and 1

Variables	Night lights
Negative Rainfall Shock	0.011***
	(0.002)
Positive Rainfall Shock	-0.039***
	(0.003)
Negative Temperature Shock	0.003
	(0.003)
Positive Temperature Shock	-0.011***
	(0.002)
Constant	0.251***
	(0.004)
Observations	57,645
R-squared	0.911

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

Figure 3: Joint effect of rainfall and temperature shocks



6.4 Linear Combination Test:

To better understand the relationship between our independent regressors, we conduct a linear combination tests to check for symmetry between the effect of negative and positive shocks. First, we conduct a linear combination test[5] for rainfall shocks. Our null hypothesis is that positive and negative rainfall shocks have symmetric effects whereas our alternative hypothesis is that they have asymmetric effects. Our test results indicate a significantly significant difference between our estimators, and we conclude that the effects of positive and negative rainfall shocks are asymmetric. Similarly, we conduct a linear combination tests to check for symmetry between the effect of negative and positive temperature shocks. Our null hypothesis is that positive and negative temperature shocks have symmetric effects whereas our alternative hypothesis is that they have asymmetric effects. Our test results indicate a significantly significant difference between our estimators and we conclude that effect of positive and negative temperature shocks are asymmetric.

6.5 Intensity of Shocks:

In our discussion so far, we have treated rainfall and temperature shocks defined by a z-scores close to 1 the same as temperature or rainfall shocks defined by z-scores close to 4. For example, it is unlikely that rainfall shocks defined by a z-score close to 1 has the same effect as rainfall shocks defined by a z-score close to 4. Similarly, it is unlikely that temperature shocks defined by a z-score close to 1 has the same effect as temperature shocks defined by a z-score close to 3. As such, we want to distinguish between the effect of different shock intensities on the level of economic activity across all municipalities. To

[5] To conduct our test, we let β1 and β2 denote positive and negative rainfall shocks, respectively. SE (β_1) and SE (β_2) denote the corresponding standard errors. The t-test for the difference between our two regression coefficients is given by $t = \frac{\widehat{\beta_1} - \widehat{\beta_2}}{SE(\widehat{\beta_1}) - SE(\widehat{\beta_2})} \sim t_{df}$

isolate the effect of different shock intensities, we create a series of dummies that categorise different intensity levels for both temperature and rainfall. We use rainfall and temperature levels between -1 and 1 as a reference category for both negative and positive shocks in our interpretations. That is, we define z-scores between -1 and 1 as “normal” levels of temperature and rainfall. Next, we define “moderate” negative shocks are defined by z-scores between -1 and -2 and “high” negative shocks are defined by z-scores between -2 and -3. We also define “extreme” negative shocks as z-scores less than -3. On average, extreme shortages in rainfall shocks indicate drought conditions where we observe approximately 0mm to 5mm of monthly rainfall[6] and extreme negative temperature shocks indicate temperatures between 24° C and 26° C. In the positive direction, we define “moderate” positive shocks as z-scores between 1 and 2 and “high” positive shocks as z-scores between 2 and 3. Finally, we define “extreme” positive shocks as z-scores above 3. On average, extreme positive rainfall shocks indicate flooding due to typhoons and storms where we observe rainfall levels between 650mm to 1200mm of monthly rainfall[7] and extreme positive temperature shocks indicate temperatures typically above 34° C.

6.5.1 Intensity of Rainfall Shocks:

Rainfall Shortages:

We use rainfall levels with a z-score between -1 and 1 as a reference category to interpret the intensity of negative rainfall shocks. Our estimations indicate that moderate shortages in the level of rainfall are associated with an increase in the economic activity. However, high shortages in rainfall are associated with a decrease in the level of economic

[6] Negative shocks are defined by historical averages for each month, year, and municipality. As such, levels of rainfall and temperature that define negative shock intensity differ depending on the municipality, month, and year.
[7] Positive shocks are defined by historical averages for each month, year, and municipality. As such, levels of rainfall and temperature that define positive intensity differ depending on the municipality, month, and year.

activity. Both results are statistically significant at the 1% and 5% level, respectively. As shown in Table 7, our results indicate that a moderate shortage in rainfall, is associated with an increase of 0.95% increase in economic activity it across all municipalities within a given month and year. On the other hand, we estimate that a high shortage in rainfall has an opposite effect. Our results indicate that a high shortage in rainfall is associated with a decrease in economic activity by 1.39% holding all else constant. This result is significant at the 5% level.

Excess Rainfall:

Next, we consider the intensity of positive shocks on the level of economic activity on municipalities in the Philippines. Our estimations indicate that a moderate and high excess in the level of rainfall is associated with a decrease in economic activity. Interestingly, we find that an extreme excess or flooding caused by typhoons and storm surges is associated with an increase in the level of night lights or activity. Our results indicate that a moderate excess in rainfall is associated with a decrease of 4.12% decrease in economic activity whereas a high excess in rainfall is associated with a decrease of 2.24%. Interestingly, extreme levels of rainfall or flood are associated with an increase in night lights by 2.63%. All results are statistically significant at the 1% level.

Table 7: Rainfall intensity

Variables	**Night lights**
Rainfall shocks with a z-score between -1 and -2	0.0095***
	(0.0017)
Rainfall shocks with a z-score between -2 and -3	-0.0139*
	(0.0080)
Rainfall shocks with a z-score between 1 and 2	-0.0411***
	(0.0033)
Rainfall shocks with a z-score between 2 and 3	-0.0224***
	(0.0042)
Rainfall shocks with a z-score above 3	0.0264***
	(0.0030)

Constant	0.2462***
	(0.0036)
Observations	57,645
R-squared	0.9113

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.5.2 Intensity of Temperature Shocks:

Cooler temperatures:

We similarly use temperature levels between -1 and 1 as a reference category for our interpretations. Given that our regression returns some statistically insignificant estimates, we focus our interpretation on the sign of our coefficients rather than their magnitude. Our estimation indicates that cooler weather, at all intensities, are associated with an increase in the economic activity. Our results regarding cooler temperatures confirm our hypotheses as well as previous literature regarding the positive effects of cooler temperatures on productivity in south east Asian countries. These results are shown in Table 8 below.

Warmer temperatures:

Conversely, we find that all temperatures above a normal range, are associated with a decrease in the level of night lights. Our results indicate that moderately warmer temperatures are associated with a decrease of 0.37% in the level of night lights. This is statistically significant at the 10% level. We also find that high temperatures are associated with a decrease in economic activity by 1.81%. This result is statistically significant at the 5% level. Further, we find that extreme temperatures are associated with a decrease in night lights. We find this result is statistically insignificant. However, the direction of the coefficient confirms previous literature regarding the negative effects of warmer temperatures on productivity. These results are shown in Table 8 below.

Table 8: Temperature Intensity

Variables	Night lights
Temperature Shocks with a z-score between -1 and -2	0.0002
	(0.0035)
Temperature Shocks with a z-score between -2 and -3	0.0072
	(0.0062)
Temperature Shocks with a z-score below -3	0.0090
	(0.0061)
Temperature Shocks with a z-score between 1 and 2	-0.0038*
	(0.0023)
Temperature Shocks with a z-score between 2 and 3	-0.0181***
	(0.0045)
Temperature Shocks with a z-score above 3	-0.0009
	(0.0043)
Constant	0.2383***
	(0.0035)
Observations	57,645
R-squared	0.9106

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

7. Discussion:

Our findings indicate that the Philippines are relatively more susceptible to adverse effects arising from positive temperature shocks and rainfall shocks in both directions. These key findings of our analysis are discussed in the context of previous literature and current mitigation strategies. In doing so, we hope to further illuminate potential implications arising from climatic variability in the Philippines and comparable economies.

7.1 Temperature Shocks and Economic Activity:

Our findings support previous studies that find a negative association between temperature and economic activity. We find strong evidence to suggest that warmer temperatures have an adverse effect on the level of economic activity in the Philippines. Our results support studies by the IMF who estimate that a 1°C increase in temperature in low-income countries with an average temperature of 25°C reduced productivity by 1.2 percentage points (Acevedo, et al., 2018). We also find that adverse effects on the level of economic activity increase with shock intensity. We observe that moderate positive temperatures are associated with a decrease of 0.37% in the level of economic activity whereas high positive temperature shocks were associated with a decrease by 1.81%. We suspect that the reduction in economic activity can largely be attributed to a dependance on agricultural output and physical labour. This contention supports evidence that finds that the level of labour supplied decreases drastically once temperature levels breach the 30°C mark (Burke, et al., 2015). Higher temperatures are also likely to increase stress on livestock, laborers and raise production costs (Sutton et al., 2018). The Department of Primary Industries and Regional Development find that the health and quality of poultry and swine decrease sharply at temperatures above 21.0°C and 27.0°C and (DPIRD, 2018 & Yap, 2018) Considering the importance of farmers, livestock, swine, and poultry to national output and food stability, we believe increased variability in temperatures pose significant challenges to agricultural production, costs, and health of labourers in the sector.

7.2 Rainfall Shocks and Economic Activity:

We also find strong evidence to indicate that the Philippines are prone to rainfall shocks. Our results also indicate that the impact of positive rainfall shocks have substantially larger effects than those due to positive or negative temperature shocks. This may capture the country's inherent susceptibility to tropical storms, typhoons and flooding which impact approximately 60% of total land area and 74% of population who reside in these areas (UNDRR, 2019). Excluding moderate shortages in rainfall, we find that positive and negative rainfall shocks at all intensities, are associated with a decrease in the level of economic activity across municipalities within a given month and year. Interestingly however, our results indicate that extreme excesses in rainfall due to flooding caused by typhoons have a positive effect on night lights. In line with previous studies, we suspect that this could be due lights emitted from rescue lights and aid efforts (Skoufias, et al., 2019). Similar to our discussion of temperature shocks, we suspect that rainfall shocks expose the country's dependence on agricultural output. This susceptibility to rainfall shortages was evident in 2016 when extreme rainfall shortages affected approximately 40% of the country. With over 400,000 farmers adversely impacted by the drought, a total of 16 provinces, 65 municipalities declared a state of calamity and reported over $327 million in agricultural production losses (Sutton, et al., 2019). In response, the Department of Agriculture (DAO) paid approximately $70 million USD[8] in insurance claims to farmers who were severely affected by the drought (PCIC, 2018). Our findings regarding positive rainfall shocks also support previous studies that find a negative association between rainfall shocks and economic outcomes. Excess rainfall during typhoon season costs are approximately equivalent to 4% of the country's annual GDP. (Vidal, 2013). We suspect that our results regarding positive and negative rainfall shocks capture the country's inherent susceptibility to rainfall variability, potentially highlighting a reliance on agricultural output as a predominant means of income.

7.4 Potential Implications:

In the last decade, the Philippines have continued its transition from a predominantly agricultural economy, to an industrial one. However, compared to Japan and Hong Kong, the Philippines' economy still relies heavily on agricultural activity, limiting their ability to accelerate their transition into a services-based economy. The agricultural sector employs 26% of the total working population and contributes approximately 10% of the national GDP (World Bank, 2019). Concerningly, low income households in rural areas are most likely bear

[8] This was a 75% increase in the total paid out in the previous year (PCIC,2018)

the brunt of weather shock events. These households account for 20% of all workers in the agricultural sector and rely on farm related labour for almost 72% of their household income (World Bank, 2019). Reductions in agricultural output due to weather shock events are likely to have disproportionate repercussions on poor households as they place upward pressure on food prices and decrease the demand for labour in the sector. Losses in the sector may also have spillover effects that negatively impact non-agricultural sectors. Lower levels of agricultural production due to weather shock events are likely to reduce output in the manufacturing sector as demand for equipment, machinery and materials required in the farming process fall. This is also likely to place downward pressure on household incomes in non-agricultural sectors. Based on the economic structure of the Philippines and the results of our paper, we hypothesise that weather shock events are likely to have a direct effect on the agricultural sector as well as wider indirect effects on the wider economy.

Limitations of Study:

The main limitations of our study are attributed to missing night light, rainfall, and weather data for municipalities across the country. Between 2016 and 2018, there were 876 instances in which we are unable to obtain records of night light data within a municipality. We note a clear pattern across the months of July and August which account for 763 of 876 of missing data records. We do not observe a clear pattern across municipalities. An immediate disadvantage of this is our inability to measure changes in economic activity due to rainfall and temperature shocks. Similarly, between 1986-2018 period, not all municipalities recorded temperature and rainfall data. We find 1116 instances in which we do not obtain monthly records of rainfall levels and 383 instances where we do not have records of monthly temperatures across all municipalities. Another limitation to our study is the applicability of night light data to municipalities within the Philippines. While our use of VIIRS night light data is a substantial improvement from the traditional DMSP dataset, we acknowledge that there are shortcomings related to the detectability of lights emitted from rural areas. Previous studies find that night lights may pose challenges in capturing rural activity (Gibson, 2020) and are likely to perform optimally in urbanized areas and non-agricultural sectors. We believe that further investigation and research into the practicality of night lights in rural areas may be required to further strengthen the validity of our findings.

Conclusion:

This study's aim was to be able to determine the effect of weather shock events on the level of activity at the municipality level. We collected 30 years of historical monthly average temperature and rainfall from the WorldClim and assigned their values to their respective municipalities. For the years between 2016 and 2018, we compare monthly average levels of temperature and rainfall to their respective 30-year historical average. We use deviations (shocks) away from the historical average to determine the impact of rainfall/temperature shocks on night lights which we proxy for economic activity. We also find strong evidence to indicate that the Philippines are prone to rainfall shocks in both directions. Our findings support previous studies that have found a negative association between excesses and shortages in rainfall. We also found negative temperature shocks to be associated with an increase in economic activity whereas positive temperature shocks were associated with a decrease in the level of economic activity. Based on the economic structure of the Philippines and the results of our paper, we hypothesise that weather shock events are likely to have a direct effect on the agricultural sector as well as wider indirect effects on the wider economy.

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