THE UNIVERSITY OF CHICAGO

Subnational Fiscal Impacts of Extreme Cyclone Exposure: Evidence from the Philippines

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Abstract

What is the subnational fiscal impact of natural disasters in the Philippines? Using meteorological data, I reconstruct the extreme exposure of tropical cyclones for each province in the Philippines during 2001-2021. I exploit random within-province year-to-year variation in cyclone strikes with a dynamic two-way fixed effect panel model to identify the causal effect of environmental disasters on local fiscal dynamics. Also, this paper examines different post-disaster fiscal responses for governments of different levels. The major findings are: (1) wind exposure generally induces a drop in government spending (for all levels of governments) and an increase in deficit (for the provincial-level), despite showing some nonlinearity under extremely high wind velocity. (2) There is a persistent significant negative impact of storm exposure on tax revenue, with lower level governments may suffer more. (3) An increase in storm exposure reduces the provincial-level investment activities.

1 Introduction

Developing Asia is one of the most disaster-prone areas in the world (ADB 2013a, ADBI 2013), and the Philippines ranked the 4^{th} most-affected country from 2000 to 2019 according to the long-term Climate Risk Index (Eckstein et al., 2021) and the 9^{th} the most affected country from extreme weather events in the 2020 World Risk Index. Because of the destructive and uncertain nature of natural disasters (NDs), they challenge local governments' ability to deal with emergencies and impose economic shocks (Miao et al., 2020, PFR). Such exogenous shocks unanticipated by local governments often require emergency funding in the short run and induce costs for reconstruction in the long run.

According to Table (2), meteorological NDs are the most frequent type of NDs in the Philippines. Philippines lies in the Pacific Typhoon Belt and, as a result, experiences 21 typhoons each year on average (the National Disaster response plan of the Philippines; Villacin, 2017). For example, Typhoon Haiyan (2013) affected 16 million people in 14 provinces with 7,354 lives lost, with total economic damage estimated to be 10 billion dollars (EM-DAT; Guha-Sapir et al., 2016). Therefore, I specifically focus on meteorological NDs in this research with the measure of extreme cyclone exposure and to estimate the corresponding subnational fiscal impacts.

The subnational fiscal effects of NDs are important for two reasons. First, local government units (LGUs) are essential providers of public goods and services and direct responders to local natural disasters. Second, there is subnational heterogeneity across the Philippines, and some provinces are more disaster-prone than others. Understanding subnational fiscal impacts help to make domestic policies and appropriate budgetary plans.

In this paper, I will discuss four research questions: (i) What is the subnational fiscal impact of natural disasters in the Philippines? While answering this question, this research particularly cares about local fiscal resilience and how local government units (LGUs) redistribute social resources post disasters. (ii) How are provincial fiscal resources from different levels of government impacted? (iii) What is the underlying mechanism that leads to the post-disaster fiscal dynamics? (iv) What is the possible heterogeneity of fiscal impacts caused by different intensities of disasters? This research answers the first two questions with estimated causality and tries to cast insights on the question (iii) and (iv).

To accurately measure the intensity and size of natural disasters, this research will utilize grid-level satellite data from IBTrACS, which contains the most complete global collection of tropical cyclones available. I will reconstruct grid-level yearly sustainable wind velocity using data from IBTrACS and collapse the grid-level speed to the provincial level. This reconstruction of wind speed could provide more precise records of the intensity of extreme cyclone exposure with higher resolution than other widely used data sources, such as EM-DAT, which is self-reported and endogenous to the economic condition of a country (Hsiang and Jina, 2014). I compile a panel data set of 76 provinces[1] in the Philippines over 20 years to conduct an empirical analysis of the subnational effects at the provincial level. There are two sources for the total fiscal resources in a province: one is the fiscal resources from the provincial government, and the other is from the municipality/city governments. Examining the fiscal impacts of NDs on different fiscal resources helps to understand how different levels of LGU share the financial burden differently post-disaster.

This dataset provides measures of intensity of NDs, which is an important contribution as governments response with different mechanisms for NDs of various severity. Most high frequency and low severity disasters are within the capability of government reserves or contingency budgets regarding natural disasters, and they would not be a financial burden on local governments. However, for low frequency and high severity disasters, sovereign risk transfer is required as emergency funding to cope with the unexpected consequence (Villacin, 2017). Therefore, I will also consider the possible heterogeneity caused by the different intensities of disasters.

The impact of extreme cyclone exposure on the local fiscal system is estimated with a dynamic Two-way Fixed Effect (TWFE) panel setting with distributed lags. The general framework is introduced by Deschênes and Greenstone (2007) and applied by Hsiang and Jina (2014) to identify the effect of random weather events and cyclone impacts, respectively. I include the distributed lags to measure the post-storm fiscal dynamics. In addition, I incorporate both time and individual fixed effects to address concerns related to endogeneity and other possible omitted-variable bias. To analyze the impact on the local fiscal system, I follow the framework of Jerch et al. (2020). For the empirical analysis, I first analyze subna-

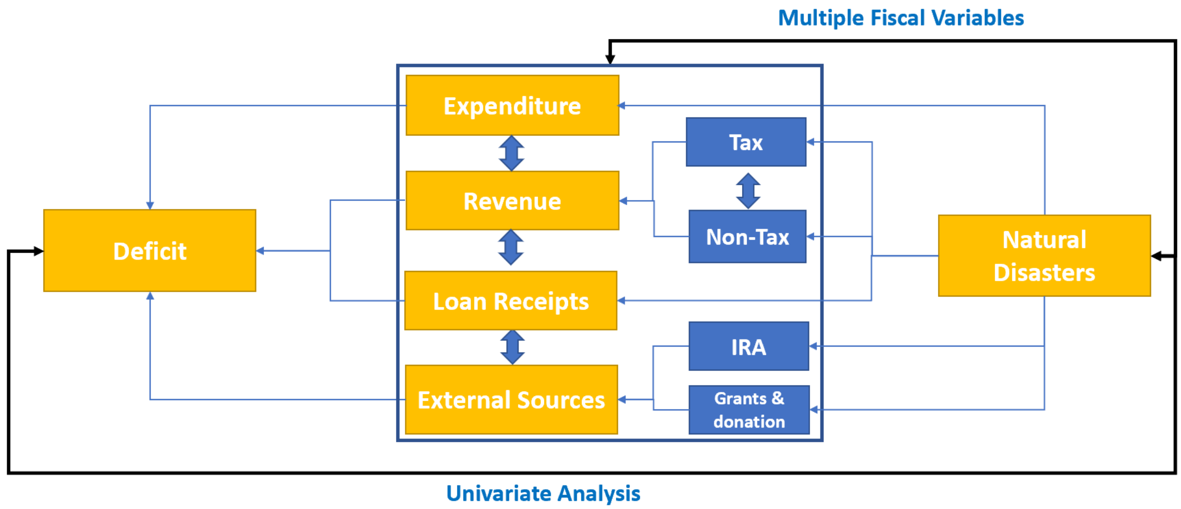
[1] Note that 5 provinces were dropped because of missing data problems or there is a change in administrative divisions during the past years.

tional impacts on the local deficit. Then I dissect the local deficit into a six-variable system and analyze the impact of NDs on each of the components. For each fiscal variable, I conduct TWFE regression for each of them from three sources: (1) the total fiscal resources for a provincial government; (2) the fiscal resources directly managed by a provincial government; (3) the part collected from municipality/city governments. The framework of the empirical analysis is shown in the flow chart, Figure (1).

The major findings in the thesis are: (1) wind exposure generally induces a drop in government spending (for all levels of governments) and an increase in deficit (for the provincial level), despite showing some nonlinearity under extremely high wind velocity. (2) There is a persistent significant negative impact of storm exposure on tax revenue, with lower-level governments may suffer more. (3) An increase in storm exposure reduces the provincial-level investment activities. My research provides empirical evidence for theoretical discussion of post-disaster fiscal dynamics, especially at the subnational level. Additionally, this research reveals the possible tremendous effect of natural disasters like cyclones on the particularly vulnerable fiscal system of less developed countries such as the Philippines, and it is an innovative attempt to conduct an empirical analysis on developing countries using such high-resolution satellite data.

The rest of the paper is organized as follows: section 2 introduces the background of this paper, from the distribution of natural disasters to the fiscal structure in the Philippines; section 3 is the literature review of previous research on the impacts of NDs; section 4 introduces the panel dataset of 76 provinces in the Philippines from 2001 to 2021. Specifically, in this section I describe how I reconstruct grid-level sustainable wind velocity, collapse the grid-level data to provincial level, and merge it with the fiscal data to create a desirable panel dataset. Section 5 shows the empirical setting of a dynamic TWFE model with distributed lags, and I estimate the empirical result in section 6 with discussions of important findings; finally, in section 7, I summarize the thesis.

Figure 1: Working Flow of Empirical Analysis I



2 Background

2.1 Natural Disasters in the Philippines

Notice that certain types of disasters are more frequent than disasters of other types in the Philippines. Disasters can be categorized into four groups: hydrological (floods and landslides), meteorological (storms), climatological (droughts), geophysical (earthquakes, volcanic activities, and dry mass movement). Governments have somewhat different procedures to deal with different types of disasters. Next, from Figure (10), the NDs are heterogeneously distributed across the Philippines in terms of the types and frequencies of NDs. Therefore, this research will add two sets of control dummies later: 1) Disaster types; 2) Geographical dummies of provinces.

The intensity of disasters is also important. When a disaster is of high frequency but low severity, LGUs mainly rely on risk retention; however, if the disaster is of low frequency and high severity, risk transfer is demanded (Villacin, 2017). One possible way to measure the intensity of natural disasters is based on the total damage induced. However, Miao et al. points that economic damage might be endogenous to fiscal variables, as it is associated with local human exposure and their socio-economic conditions. Second, economic direct damage is less accurately recorded in poorer areas. Thus, the current paper will use satellite data from Earthdata to gain specific measures of the intensities, sizes and types of natural disasters, and this innovative source of data will enable us to overcome some data limitation of previous research.

2.2 Fiscal Structure in the Philippines

This section provides a brief outline of the local fiscal structure and definitions of the fiscal variables.

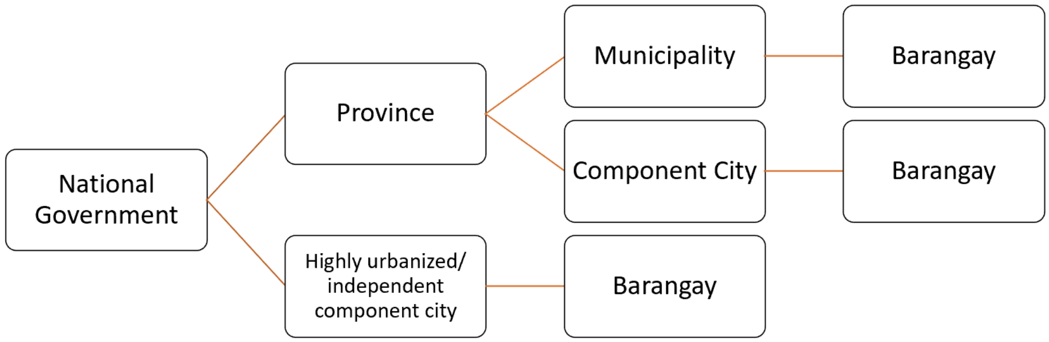
2.2.1 Fiscal decentralization

A higher degree of fiscal decentralization is related to a more responsive reaction post-disaster, Escaleras and Register (2012) find a significant negative relationship between the degree of decentralization and disaster-related deaths with cross-country data. Similarly, Skidmore and Toya (2013) found that countries with more decentralized governments experience fewer disaster-induced fatalities. Since the radical reform induced by the 1991 Code, the Philippines has become more decentralized than before, which increases the emergency responses post-disaster.

The Philippines is highly fiscal decentralized, and each LGU is relatively independent. According to Uchimura and Suzuki (2012), the structure of local governments in the Philippines is shown in Figure (2). As for the structure of local governments in the Philippines, in comparison to the political subordinate relationship, there is almost no fiscal affiliation among different levels, according to Uchimura and Suzuki (2012). The transfer of the national government will be directly conveyed to each level of LGUs as in Figure (2). This is different from some countries where subsidies will first be transferred to a provincial government and then to its lower level of governments. In this research, I will not directly examine how the fiscal impacts of NDs can be moderated by fiscal decentralization. I will try to provide some empirical evidence about the subnational fiscal impact of NDs on a highly fiscal decentralized country and cast insight into the interaction of different levels of governments by examining NDs' impacts on various fiscal sources.

Figure 2: Structure of local governments

Source: Uchimura and Suzuki (2012)



2.2.2 Fiscal variables

The fiscal variables of interest are listed in Figure (3). Notice that for revenue (also named total local sources), I will investigate tax and non-tax revenue specifically.

For transfer (or named as total external sources), I focus on Internal Revenue Allotments (IRA) and grants/donations/aids (abbreviated as grants). IRA is unconditional fiscal transfers directly distributed from the national internal revenue taxes collected to each LGU according to a certain formula. The share of the transfer is related to the land size, population, and socio-economic condition of each province/municipality/city. The majority of transfer consists of IRA and accounts for 40 percent of the national internal revenue taxes collected[2] (Uchimura and Suzuki, 2012). The second component of transfer, grants, include the following terms: both domestic and foreign grants and donations, subsidy from government-owned or -controlled corporations, gain on foreign exchange and sale of assets and investment, premiums on bonds payable, and other subsidy income.

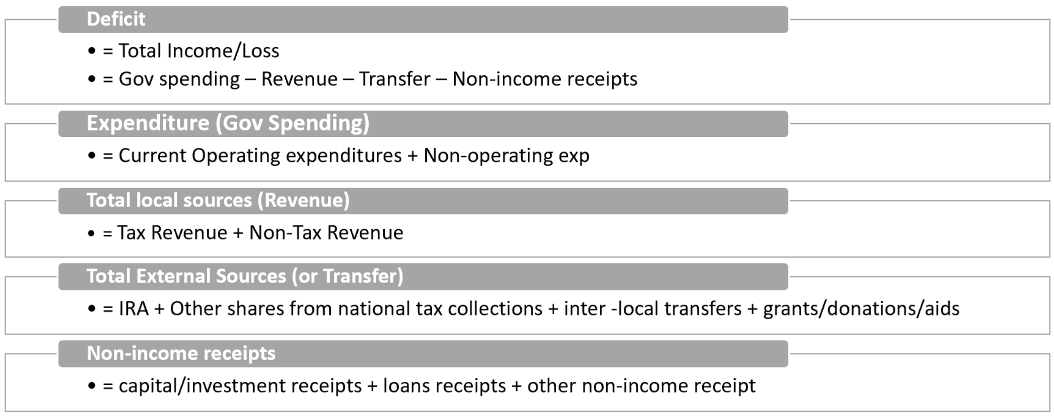
As for non-income receipts, I will only consider loan receipts because I do not have data of other sub-categories of non-income receipts before 2009 and this terms takes over 90% of the total non-income receipts. Loan receipts include the subtotal of acquisition of loans and issuance of bonds.

Deficit is a linear combination of the fiscal terms introduced earlier, and it is defined as the difference between the spending of local governments and the sum of revenue, transfers,

[2]The total amount distributed is based on the collection of national internal revenue taxes in the third year preceding the current one(Uchimura and Suzuki, 2012).

and non-income receipts. The sub-components of each fiscal variable is listed in Figure (3) as well.

Figure 3: Fiscal Variables



2.3 Disaster Response

In terms of the post-disaster fiscal reaction: a minimum 5% from estimated regular income sources is required to be set aside for the Local Disaster Risk Reduction and Management Fund (DRRMF). However, most LGUs still maintain it at exactly 5 percent. LGUs cannot access the National Government's National DRRMF if they have duplicate funding from other sources (including grants and donations, insurance proceeds) or government-owned or -controlled corporations (GOCC). In addition, LGUs should exhaust their internal resources first before they access the NDRRMF.

Measuring the intensity of disasters is also important as it helps to understand the underlying mechanism, because that governments respond with different procedures to NDs of various severity as time elapses. According to Figure (4), LGUs deal with disasters of various intensities in the short-run (for emergency funding) and the long-run (for reconstruction) differently. When a disaster is of high frequency but low severity, LGUs mainly rely on risk retention, including government reserves, contingency budgets or funds, and relevant credit. However, if the disaster is of low frequency and high severity, risk transfer is demanded to manage the post-disaster impact. Specifically, LGUs need sovereign risk transfer from the national government as the emergency funding in the short-run and receive insurance of

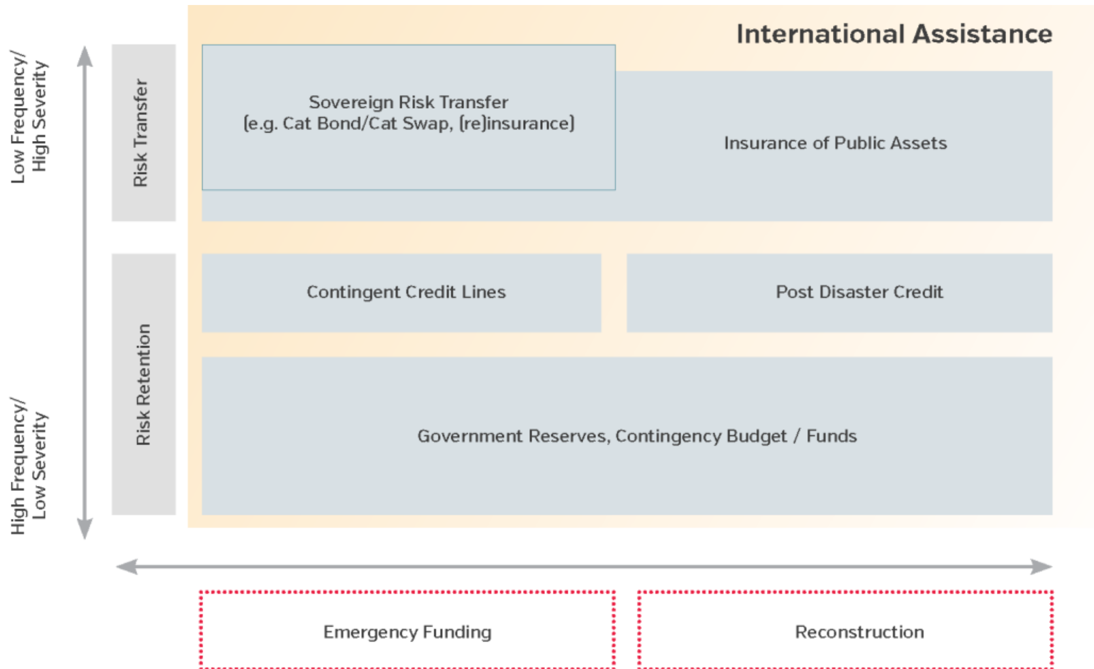


Figure 4: Risk layering framework

Source: World Bank (2017)

public assets to support post-disaster reconstruction in the long (Villacin, 2017). Hence, according to the risk layering framework above, we might expect the fiscal impact of a ND varies among both different intensities and different time scopes.

The intensity of disasters is also important. From Figure (4), I can see how LGUs deal with disasters of various intensity in the short-run (for emergency funding) and the long-run (for reconstruction) differently. When a disaster is of high frequency but low severity, LGUs mainly rely on risk retention, including government reserves, contingency budgets or funds, and relevant credit. However, if the disaster is of low frequency and high severity, risk transfer is demanded to manage the post-disaster impact, and LGUs need sovereign risk transfer as the emergency funding in the short-run, and receive insurance of public assets to support post-disaster reconstruction in the long (Villacin, 2017). Hence, according to the risk layering framework, I might expect the fiscal impact of a natural disaster varies among both different intensities and different time scopes.

3 Literature Review

Previous literature mainly focuses on the fiscal impact of NDs at the country level (Noy and Nualsri, 2011; Cavallo et al.), 2013). Even for research on the sub-national effects, the majority is about developed countries (Hsiang and Jina, 2014; Noy et al., 2021; Jerch et al., 2020) with limited discussion of developing countries (Noy and Vu, 2020; Miao et al., 2020). Additionally, only a few papers have examined the post-disaster local public finance dynamics, which measures how the fiscal impacts of NDs change and accumulate as time goes by after they occur.

Moreover, Jerch et al. (2020, NBER) suggests unclear fiscal effects of NDs. On the one hand, a ND can improve fiscal outcomes in the long term for local governments because it can stimulate economic activities that offset immediate fiscal shocks. Researchers who hold this point often cite the theory of creative destruction by Schumpeter that dismantling established capital can make way for improved productivity and production for an economy. On the other hand, a ND can deteriorate fiscal conditions in both the long run and short run. Because a ND generates direct costs on local governments through reconstruction and assistance payments, and brings indirect costs by disrupting local revenue sources and increasing the cost of public debt.

Precisely, this financial burden of emergency responses and assistance could increase government spending, and this increase could be financed by intergovernmental transfers from the central or federal governments in both China and the U.S. (Miao et al., 2018; Miao et al., 2020). Through these intergovernmental transfers, fiscal impacts may expand across all levels of government, and the extent of such expansion can vary with the fiscal structure, especially the degree of fiscal decentralization, of an economy. Meanwhile, increasing expenditure brings up governments' demand for extra funding, and as a result, local governments may borrow more and have a higher cost of public debt. By contrast, the impact of tax revenue, a major source of local revenue sources, is somewhat ambiguous. Because shrinking tax bases and the structure of local tax bases can bring opposite effects and cancel each other out, it is not yet clear what is the subnational fiscal impact in the Philippines. Following the framework of Jerch et al. (2020, NBER) that analyzes the local public finance dynamics under hurricane shocks, this research fills this gap.

Measuring the intensity of disasters is also important as it helps to understand the underlying mechanism, because that governments respond with different procedures to NDs of various severity as time elapses. Previous literature uses either a composite index or dummy variable to characterize the intensity of NDs. For example, Miao et al.(PFR, 2020). created a composite disaster intensity index based on data from EM-DAT, which is a weighted sum of different disaster intensity indexes. Cavallo et al. (ReStat, 2013) encode the disaster dummy variable equal to 1 if death toll surpasses a certain quantile. We do not use the total damage caused by a disaster to denote the intensity of NDs because total damage is endogenous to local economic development (Miao et al., 2020), and the missing data problems of damage can be a severe problem in poor areas. In addition, EM-DAT does not provide data that are objective enough, because it is self-reported by governments themselves and endogenous to the economic condition of an economy (Hsiang and Jina, 2014). Hsiang and Jina use a more accurate measure by reconstructing cyclones exploiting the high-resolution satellite data from IBTrACS, and their measures are more detailed and exogenous measures of ND intensities, and I construct my dataset using the same techniques as their research.

4 Data

4.1 Data Source

This research creates a panel dataset for 76 provinces in the Philippines from 2001 - 2021 with data from the five sources below:

- Fiscal Data: Bureau of Local Government Finance
- Storm wind exposure data: the author reconstruct sustainable wind velocity at the grid level using storm information from International Best Track Archive for Climate Stewardship (IBTrACS).
- Socio-economic controls: Philippine Statistics Office
- Political variable controls: Commission on Elections
- Tourism: Department of Tourism

The fiscal data are my dependent variables; the storm wind exposure data constructed by the author contains information of the exogenous shock; and other data sources allow me to control variation caused by different industrial structures, socio-economic conditions, and local election results. Specific control variables include types of NDs, political controls, socio-economic variables, tourism data, geographical dummies, and other controls.

For fiscal variables, this research considers deficit and the six-variable system of fiscal variables, including government spending, tax revenue, non-tax revenue, IRA, grants, and loan receipts. Aside from the total fiscal resources for each province, I dissect their total fiscal resources (for simplicity, total level) into fiscal resources directly managed by a provincial government (provincial level) and the part collected from lower-level governments (municipalities and cities belonging to the province, MC level).

In this research, to measure the influence of storms over the whole Philippines, I construct sustainable wind speeds using data from IBTrACS (Knapp et al., 2010; Knapp et al., 2018). The IBTrACS project contains the most complete global collection of tropical cyclones available. It merges recent and historical tropical cyclone data from multiple agencies to create a unified, publicly available, best-track dataset. It provides tracks of cyclones at the $0.3° \times 0.3°$ grid level. I will introduce the details of data processing in Section 4.2.

Five provinces are to be deleted from the sample. Because there were changes in the administrative division over these years or a large proportion of missing data in those provinces. I include the names of provinces in our sample in the Appendix.

4.2 Reconstruct Storms

IBTrACS provides the maximum sustainable wind for tracks of cyclone centers at the $0.3° \times 0.3°$ grid level. To reconstruct the sustainable wind velocity Vs for each $0.3° \times 0.3°$ grid of the Philippines from 2001 to 2021, I follow the meteorological model of Boose et al. (2004):

$$Vs = F\left(v_m - \frac{S\,(1 - sin\ T)\, v_h}{2}\right) \times \left[(R_m/R)^B\, exp\left(1 - (R_m/R)^B\right)\right]^{1/2} \tag{1}$$

The explanation of parameters and variables in (1) are as below:

- F: the scaling parameter for effects of friction (water = 1.0 and land = 0.8).

- v_m: the maximum sustainable wind velocity over water anywhere in the hurricane. The maximum sustained wind speeds for tropical cyclones are the highest surface winds occurring within the circulation of the system.
- S: the scaling parameter for asymmetry (due to forward motion of storm, =1.0).
- T: clockwise angle between the forward path of hurricane and a radial line from hurricane center to a point P, which is the location of a given grid here.
- v_h: the forward velocity of the hurricane.
- R_m: the radius of maximum winds.
- R: radial distance from the hurricane center to point P (calculated by the longitude and latitude).
- B: the scaling parameter controlling the shape of the wind profile curve (1.2 – 1.5).
- v_g: the peak wind gust velocity. (gust, in meteorology, a sudden increase in wind speed above the average wind speed).
- G: the gust factor (water = 1.2, land = 1.5).

I present the distribution of the grid-level reconstructed maximal sustainable wind velocity of the Philippines from 2001 to 2021 in Figure (5).

4.3 Collapse Data

After reconstructing the wind speed for each grid using the meteorological model in (1), I then calculate the annual highest sustainable wind velocity for each grid. Next, when I collapse the sustainable wind speed V_s from the grid level to the province level, I first filter grids with wind speed above 20 km/h, otherwise, I assign zero to the grid. Next, I get the average and maximum of the yearly-maximal sustainable wind speeds in each province and name the latter as max V_s (the former is not presented in this thesis). The interpretation of a one-unit change in max V_s would be a one-kilometer-per-hour increase in stormwind exposure because max V_s only captures variation in sustainable wind speeds above 20 km/h.

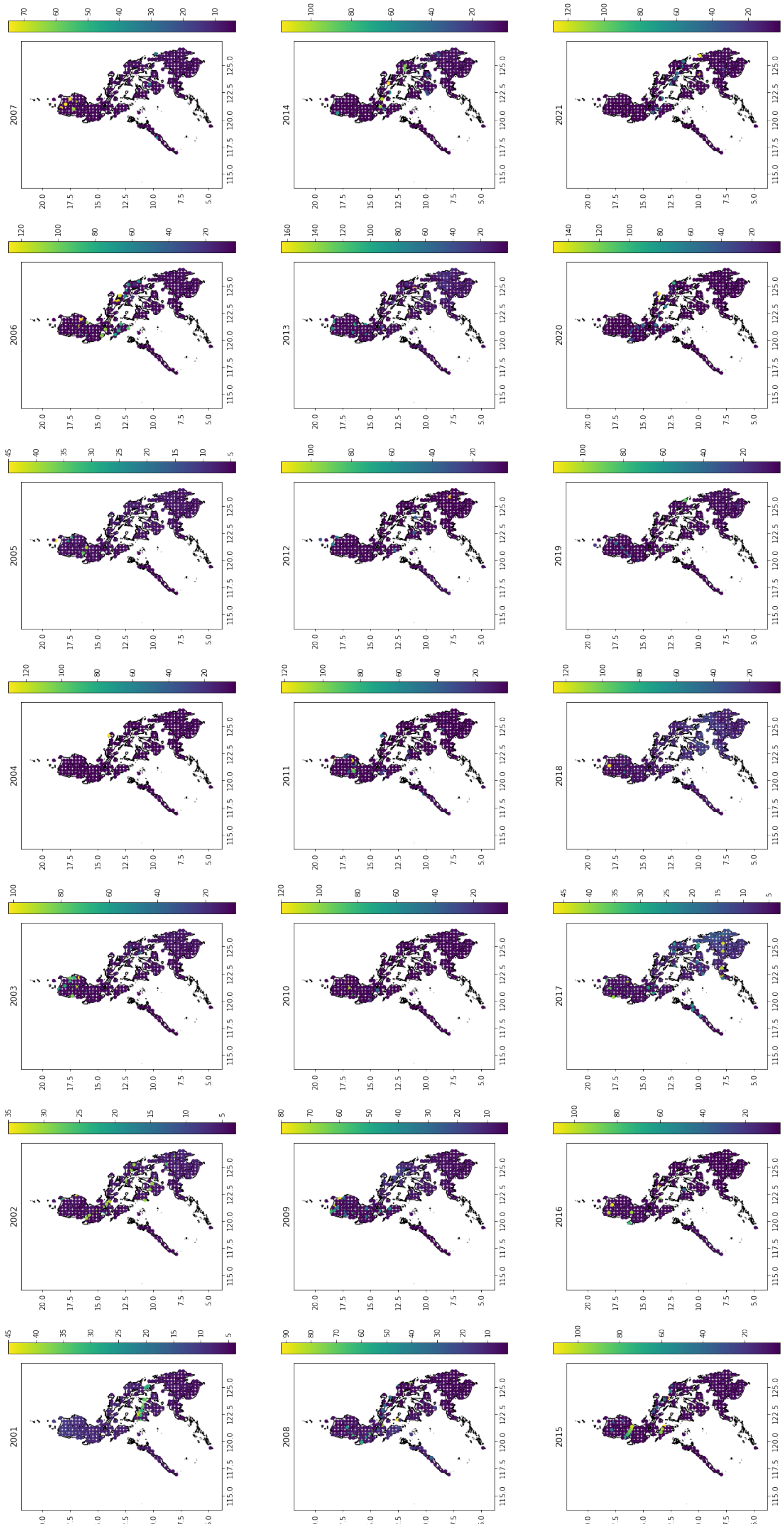


Figure 5: The Distribution of Reconstructed Grid-level V_s, 2001-2021

In terms of the choice of grid size, I can simulate at a higher resolution with a smaller grid of $0.1° \times 0.1°$, but there is a trade-off between the measurement error (higher when the size of the grid is smaller than that in the original dataset) and the error from averaging with larger grids. Thus, I stick to $0.3° \times 0.3°$ grids here, which is of the same resolution as the IBTrACS data.

There are two ways to collapse data to the provincial level: (1) collapse the grid-level data to the provincial level first, and then only keep the wind speed for a province if it is higher than a certain level. (2) Only keep the grid-level data if the speed is higher than a certain level, otherwise, let it equal zero; and after filtering the grid-level data, collapse the data to the provincial level. These two ways will generate different wind speeds at the provincial level as shown in Figure (6). If a province is evenly affected by relatively high but not extreme storms, then its provincial-level wind speed would be higher when collapsing with the method (1) and lower using the method (2). In this research, method (2) is a better way to collapse data, because it helps to characterize the consequences of extremely high storm exposure more accurately.

The summary statistics of the provincial level average maximal sustainable wind speed for grid-level speed above the threshold (Vs 20km/h) reconstructed by the author are presented in Table (1). From the table, the distribution of the reconstructed wind velocity is highly skewed: most provinces have zero exposure to extreme sustainable wind speeds annually, while in some extreme cases, the sustainable wind speed can be 165km/h. The distribution of the square of Vs is also shown. Notice that I include a separate column for Vs^2. Because I calculate the square of the Vs at the pixel level first and then collapse to the provincial level, the Vs^2 of a province might be different from a direct square of a provincial level Vs.

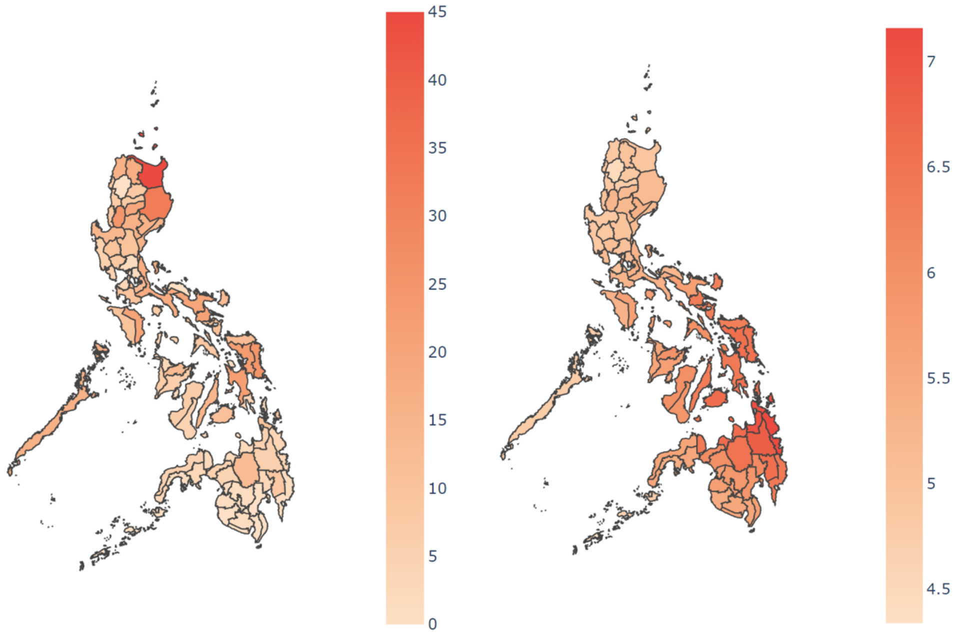


Figure 6: Sustainable wind speeds V_s under different ways of data collapse.
Left: Yearly average of the provincial level maximal sustainable wind speed for grid-level speed above the threshold ($V_s \geq 20$km/h). *Right*: Yearly average of the spatial average of the annual maximal sustainable wind speeds at $0.3° \times 0.3°$ grid level.

Table 1: Summary Statistics of Maximal V_s and V_s^2

	V_s	V_s^2
75%	0	0
90%	33.5	1181.25
95%	65	4225
99%	107	11450
max	165	27225
mean	8.62	609.63
std. dev	22.92	2225.64
Skewness	3.15	5.21
# of obs	1701	1701

5 Methodology

For the empirical setting, I will use a dynamic TWFE model with distributed lags. The general framework is introduced by Deschênes and Greenstone (2007) to identify the effect of random weather events, and I follow the application of Hsiang and Jina (2014) to characterize the dynamic impact of wind exposure on local fiscal conditions. The equation is as below:

$$y_{i,t} = \sum_{L=0}^{k} \beta_L \times Vs_{i,t-L} + \sum_{L=0}^{k} \psi_L \times Vs_{i,t-L}^2 + \gamma_i + \delta_t + \eta \times X_{i,t} + \epsilon_{i,t} \tag{2}$$

- y_{it}: deficit or one variable of the six-variable fiscal system of a province i at time t. y_{it} can be a variable of the total, provincial and MC levels.

- Vs_{it}: average wind speed in the province i at time t, which is a measure of storm wind exposure. There are multiple candidate measures of Vs_{it}, and in our later section I will present the result using max Vs (will explain soon) specifically. Occurrences of storms are often treated as exogenous in most related literature. Distributed lags of both Vs_{it} and Vs_{it}^2 are included to measure the post-storm fiscal dynamics.

- Vs_{it}^2: The square of Vs_{it}. This term is added to capture the nonlinearity in the change of fiscal variables. The possible nonlinearity is related to the underlying disaster response mechanism. For example, if the quadratic term indicates that a fiscal variable would first increase and then decrease as Vs_{it} increases, it might indicates that the responsibility of dealing with the storm shifts among different levels of governments for Vs_{it} withing different ranges.

- $\mathbf{z}_{it}$: a vector of control variables. In the benchmark setting, it includes basic socio-economic controls (including regional GDP per capita, population, etc), Tourism population, the level of fiscal decentralization. I included tourism population because this is a major industry in the Philippines and is highly susceptible to NDs such as storm wind exposure. Fiscal decentralization is measured by the ratio of government spending from MC level over that from the total level.

- α_i denotes the individual effects of province i, which is also called time-invariant heterogeneity. This term helps to capture the unobservable different attributes of different provinces. Including fixed effects (both α_i and γ_t) helps to resolve the possible endogeneity problem.

- γ_t: the time fixed effects at time t, also called cross-sectionally invariant heterogeneity. It controls for possible macro shocks (such as possible national-wide pandemics; national economic recession or crises that impact the fiscal system of the Philippines, etc)

- ϵ_{it}: idiosyncratic attributes of each province i at time t. I will assume that error terms of each province will be independent of those of other regions, but has serial correlation with error terms of provinces in the same region but of different time.

First, this model estimates the sign and size of β from this empirical setting, and whether such a change will exhibit nonlinearity that changes with Vs_{it}. Because it is ambiguous whether a storm will have a negative or positive impact on a fiscal variable, and For example, under the shock of one ND, the tax base of a province will be reduced by the destruction, however, the tax revenue can increase as well because of tax related to more reconstruction. Moreover, in a six-variable fiscal system, different fiscal variables may change with various sizes and thus the sum-up impact on provincial level deficit is unclear. Therefore, both the sign and size of β is important in our research. In addition, the nonlinearity captured by the quadratic term Vs_{it} can give hint on how the post-storm responsibility might shift among different levels of governments and some related mechanism.

Noticeably, readers should pay attention to the meaning of max V_s in our regression, and the interpretation here is related to the data processing procedure. I first derive the annually highest sustainable speed for each grid by reconstructing wind speeds using a meteorological model. Next, when I collapse the sustainable wind speed V_s from the grid level, I first filter grids with wind speed above 20 km/h, otherwise, I assign zero to the grid. Next, I get the average and maximum of the yearly-maximal sustainable wind speeds[3]. The interpretation of a one-unit change in max V_s would be an one-kilometer-per-hour increase in storm wind exposure, because max V_s only captures variation in sustainable wind speeds above 20 km/h.

[3] Both are derived, but currently only present the result using provincial-maximum of yearly-maximal sustainable wind speeds in this thesis

The occurrences of NDs, such as a storm, are generally exogenous to human behaviors. However, there are still some concerns related to possible endogeneity. First, though Hsiang and Jina (2014) mention that disaster-prone regions will gradually adapt to natural disasters with better disaster prevention and response mechanisms, reducing their loss under a ND compared with less experienced region. And from Figure (10), we do notice that the northern Philippines do face more frequent shocks of NDs (especially meteorological disasters) compared with the other regions. Meanwhile, northern Philippines is more economically-developed compared with the southern. Such correlation that the most disaster-prone regions are the most economically active provinces might brings a concern of endogeneity to our estimation. I address this issue by adding the terms of individual fixed effects α_i, and the intrinsic attributes of a region can be captured in this time-invariant heterogeneity.

Moreover, there might be concerns about the variation in timing. Macro shocks, including pandemic, economic recessions, and political events might occurs during certain years and affect the fiscal conditions of all provinces in the Philippines. These omitted variables are correlated with local fiscal conditions, and it is hard to observe and incorporate them directly into our model. Hence, I add a term of time fixed effect γ_t to address such a concern.

Moreover, this model (2) includes distributed lag terms to capture the post-storm fiscal dynamics, and this setting could help us to derive plots of time path in our later section. In my later empirical work, I choose three lags for both Vs and Vs^2. Because both information criteria of AIC and BIC suggests that there is no much difference in terms of how well the model fits the data among different numbers of lags, so I choose 3 here both to reduce the loss of data due to a larger number of lags and provides coefficients with higher statistical significance.

For the reasons above, a dynamic TWFE model with distributed lags would a be a appropriate choice for this research.

6 Empirical Results

I estimate the dynamic TWFE model with distributed lags in (2) for all six variables in our fiscal system. Specifically, I have checked the impact of stormwind exposure on the spending, IRA, tax revenue, non-tax revenue, loan receipt, and grants and donation of a provincial government, and how their linear combination, deficit, is affected. Aside from checking the subnational fiscal impacts of storm exposure for all the fiscal resources of a provincial government, we dissect the total-level fiscal resources into provincial-level fiscal resources and the MC-level fiscal resources collected from lower-level governments including municipalities and cities. By comparing the treatment effects of stormwind exposure on fiscal variables of various sources, my result casts insights on how different levels of administrative units might share their fiscal burden differently under natural disasters. All the fiscal variables are normalized by provincial population and measured by Philippine peso per capita (1 Philippine peso = 0.019 United States dollars).

Table (3), (4), and (5) show the empirical subnational impacts for fiscal resources from the total, provincial, and MC levels. The major findings from these Tables are: (1) An increase in stormwind exposure has a nonlinear effect on provincial government spending for fiscal resources from all levels of government. When the storm exposure is low, the government decreases its expenditure; and when the storm exposure is tremendously high, local governments will increase their expenditure in response to the high storm exposure (Figure (7)). (2) Similarly, as in Figure (8), there is a nonlinear effect of storm exposure on the deficit for the provincial level. (3) Despite the nonlinearity mentioned in (2) and (3), in most storms with maximal sustainable wind speeds below 99% quantile, wind exposure induces a drop in government spending (for all levels) and an increase in deficit (for the provincial level). (4) There is a persistent significant negative impact of storm exposure on tax revenue, and I plot the corresponding dynamic paths for all three fiscal resources after a unit increase in storm exposure. According to Figure (9), the MC level fiscal resources decrease more than that of the provincial level, indicating that the lower-level governments may suffer more in terms of tax revenue attainment post disasters. (5) An increase in storm exposure persistently reduces the investment activities for the provincial level fiscal resources measured by grants and donation.

6.1 Non-linear Effects on Government Spending

Figure (7) shows how the fiscal spending for all levels of government could change nonlinearly with an increase in stormwind exposure. For most storm exposure of maximal V_s between

33.5 km/h (90% quantile) to 107 km/h (99%), wind exposure will negatively affect government spending from all resources. Only in some extreme storms that even surpass the 99% quantile will wind exposure induce an increase in government spending. And in such extreme cases, MC governments share a higher fiscal burden because the change in fiscal spending is higher at the MC level compared with that of the provincial level. Hence, lower levels of administrative units suffer more in extreme cases when the max $V_s > 120$km/h.

However, despite there is non-linearity, most storms lie below the 99% contributes to a loss in local government spending for all levels. Therefore, in more general cases, high wind exposure to storms will induce a decrease in government spending, which is related to less provision of public services and goods and a reduction in capital or investment expenditures.

Also, the size of the effect is worth attention. The decrease in government spending will reach its peak for both the total and MC level at around the 95% quantile of maximal V_s (65km/h), and the drop in spending is more than 150 and 80 pesos per capita for the total and MC level respectively. In addition, at 95% quantile, the decline in provincial-level government spending surpasses 70 pesos per capita as well.

6.2 Non-linear Effects on Deficit

Similarly, there is a nonlinear effect of storm exposure on the deficit for the provincial level as in Figure (8). In most storms with maximal wind speeds below 99% (107km/h), wind exposure will increase the subnational deficit. Such an increase in deficit peaks when maximal V_s is around 50km/h. By contrast, in extreme storms when wind speeds surpass the 99% quantile, the provincial-level deficit will decrease.

Such nonlinearity might yield somewhat counter-intuitive results under extremely high wind exposure. It is related to the underlying mechanism of disaster responses of different levels of government. For example, if the wind speed below 99%, the provincial government is mainly in charge of the post-disaster reconstruction, and thus its deficit increases; however, when there is an extreme disaster surpasses the 99%, a higher level of government (the national government of the Philippines) steps in and will be primarily responsible for dealing with the storm, therefore decreasing the deficit of the provincial government.

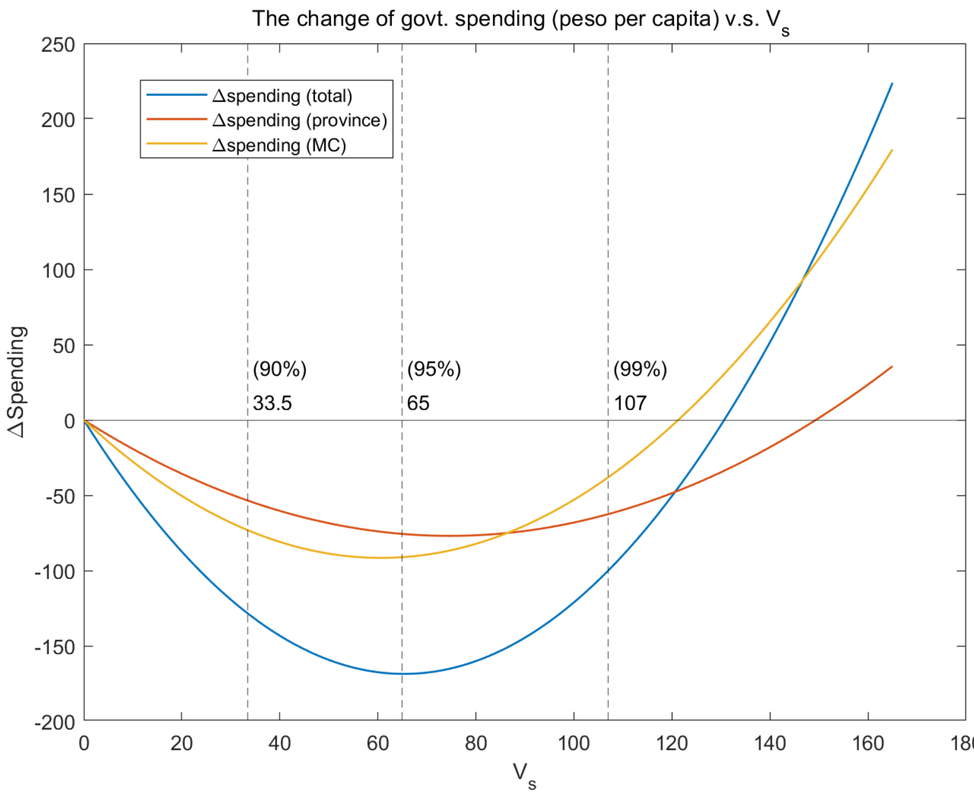


Figure 7: The nonlinear change of government spending (peso per capita) regarding V_s

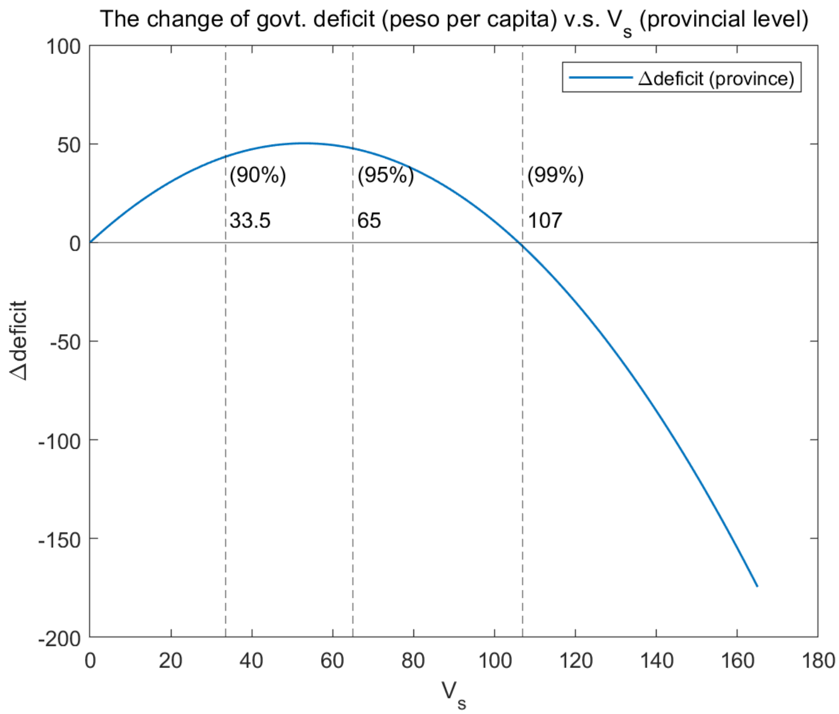


Figure 8: The nonlinear change of government deficit (peso per capita), provincial level

6.3 Dynamic Effects on Tax revenue

Figure (9) shows that there is a persistent significant negative impact of storm exposure on tax revenue. Specifically, there is a persistent decrease in tax revenue that peaks contemporarily for the total and MC levels, and one year later for the provincial level. This negative impact is persistent in the short run and will reverse to zero three years after the storm wind exposure.

In addition to the impact on tax for one-unit increase in wind exposure (an 1km/h increase in max V_s) in the left of Figure (9), I simulate the time path for tax revenue changes under a 95% maximal V_s (65km/h) on the right hand side of Figure (9).

6.4 Other findings

From Table (3), (4), and (5), I find that generally an increase in storm wind exposure has no statistically significant effects on IRA (inter-government transfer), non-tax revenue, and loan receipts from all fiscal resources. Though the coefficients are significantly negative for the square and the first lag term of maximal V_s regarding total-level non-tax revenue

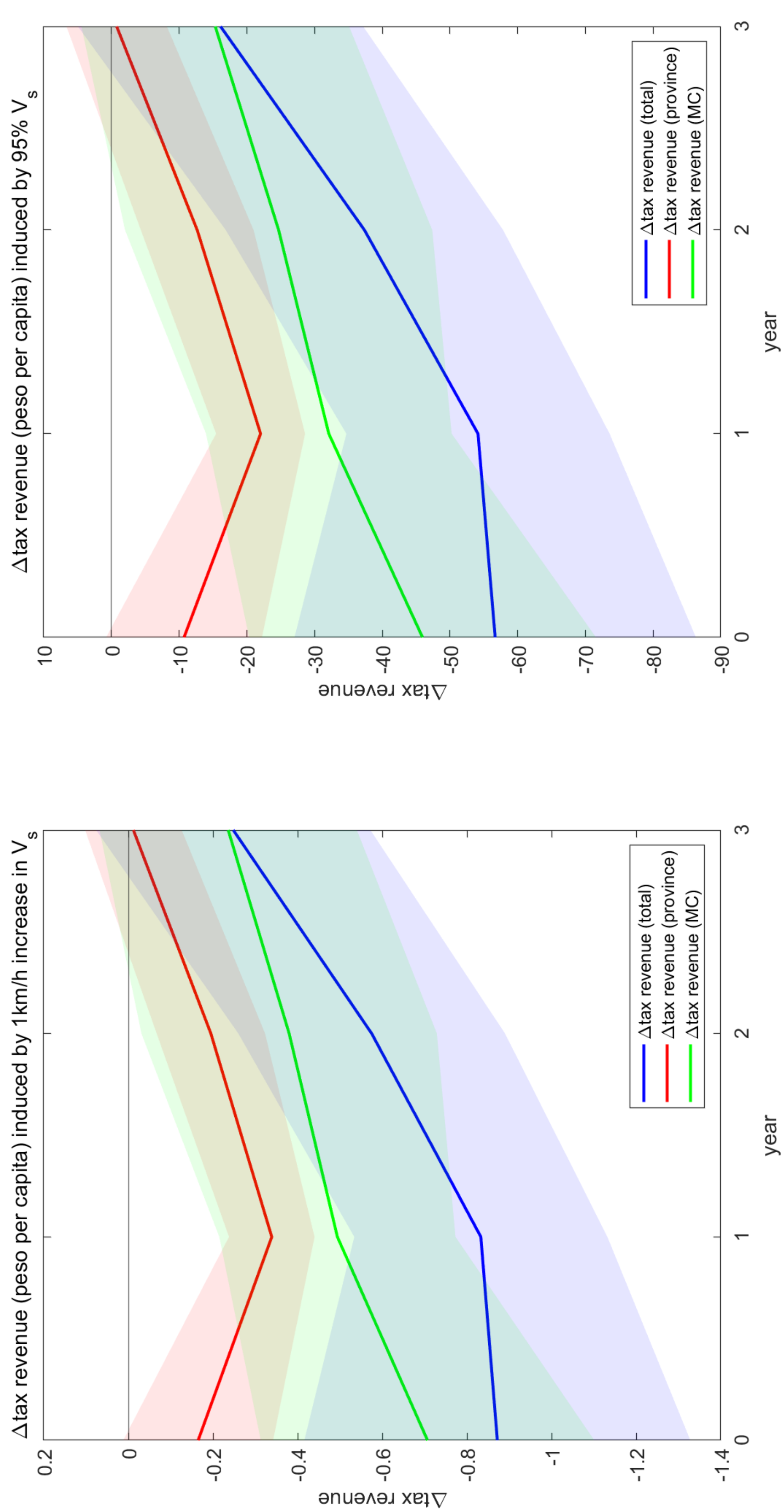


Figure 9: The dynamic changes in tax revenue (peso per capita) caused by a change in V_s

and provincial-level IRA, they are significant at margin and without similar effects in other periods and levels of governments, and thus conveying less convincing information.

Moreover, the coefficients of the first and second lags of the max V_s on the provincial-level grants and donations are significantly negative, indicating there is a persistent decrease in grants and donations at the provincial level after an increase in storm exposure. Recall the definition of grants and donation here is cash outflow from investing activities, and grant/loan the government gives to other entities. Thus, the increasing wind exposure of a wind persistently reduces the investment activities for the provincial level fiscal resources.

7 Conclusion

This paper reconstructs provincial level annually maximal sustainable wind velocity using $0.3° \times 0.3°$ grid-level data in the Philippines from 2001 to 2021, and estimate the subnational fiscal impacts of extreme storm exposure with a dynamic TWFE effect model for fiscal variables from three sources.

The major findings in the thesis are: (1) An increase in storm wind exposure has a nonlinear effect on provincial government spending for fiscal resources. When the storm exposure is low, the government decreases its expenditure; and when the storm exposure is tremendously high (higher than 99% quantile), local governments will increase their expenditure in response to the high storm exposure. (2) Similarly, there is a nonlinear effect of storm exposure on deficit for the provincial level. (3) Despite the nonlinearity mentioned in (2) and (3), in most storms with maximal sustainable wind speeds below 99% quantile, wind exposure induces a drop in government spending (for all levels of governments) and an increase in deficit (for the provincial-level). (4) There is a persistent significant negative impact of storm exposure on tax revenue, with lower level governments may suffer more. (5) An increase in storm exposure reduces the provincial-level investment activities measured by grants and donation.

These empirical results provide empirical evidence of the subnational fiscal impact of NDs in the Philippines. First, this estimation would inform us about the local fiscal resilience. Second, previous literature suggests that there is an ambiguous effect of a ND on tax revenue, and my finding provides the empirical evidence of a persistent decrease in tax revenue post-disasters. Additionally, this research suggests that provincial fiscal resources from different levels of government can be impacted differently, and specifically, lower-level governments can persistently suffer more from a cyclone. Moreover, this research cast insights into the possible underlying mechanism that leads to the post-disaster dynamics by exploring the nonlinearity with a quadratic term of maximal V_s. I find that even for the same level of government, the change in the same fiscal variable could be different because of the nonlinearity. My research suggests that though there is a decrease in government expenditure and an increase in deficit when the storm is not of extreme large size, these two fiscal variables could change differently under an extreme cyclone. This result implies that governments may have different procedures when confronting disasters of different intensities, and fiscal burdens can shift among different levels of government then.

This research is limited and can be extended by future work in certain ways. First, in the discussion of nonlinearity, I only include quadratic forms, but there can be other forms of nonlinearity, such as a saturated form with dummy variables for wind speeds within different bins in future research. Second, future research can include other measures of cyclones or other types of NDs. Third, future research can investigate more about the underlying data generating process of fiscal variables, and decide the right forms for them (such as whether to use the log form data, aggregate level data, or per capita level data). Last, by better incorporating the nonlinearity and the interaction among different levels of governments, future research can provide more insights on how different levels of government shares the fiscal burden differently post disasters.

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A Appendix

A.1 Acknowledgement

I would express my gratitude to my thesis advisor Amir Jina for instructing and supporting me throughout this research.

I also want to thank Elizabeth Huppert and Sanja Miklin who are my preceptors of my second and first year respectively in MACSS program.

Moreover, this research proposal is a further step based on my previous research project during my summer internship at the Economic Research and Regional Cooperation Department, Asian Development Bank (ADB) . I would express my gratitude to Dr. Yothin Jinjarak to allow me to conduct further research using data from ADB.

Finally, I want to thank my parents and other family members for their support.

A.2 Administrative Units

The name list of the provinces in our dataset is as below, and samples with administrative changes are excluded.

Abra, Agusan Del Norte, Agusan Del Sur, Aklan, Albay, Antique, Apayao, Aurora, Basilan, Bataan, Batanes, Batangas, Benguet, Biliran, Bohol, Bukidnon, Bulacan, Cagayan, Camarines Norte, Camarines Sur, Camiguin, Capiz, Catanduanes, Cavite, Cebu, Compostela Valley, Cotabato, Davao Del Norte, Davao Oriental, Eastern Samar, Guimaras, Ifugao, Ilocos Norte, Ilocos Sur, Iloilo, Isabela, Kalinga, La Union, Laguna, Lanao Del Norte, Lanao Del Sur, Leyte, Maguindanao, Marinduque, Masbate, Misamis Occidental, Misamis Oriental, Mountain Province, Negros Occidental, Negros Oriental, Northern Samar, Nueva Ecija, Nueva Vizcaya, Occidental Mindoro, Oriental Mindoro, Palawan, Pampanga, Pangasinan, Quezon, Quirino, Rizal, Romblon, Samar, Sarangani, Siquijor, Sorsogon, South Cotabato, Southern Leyte, Sultan Kudarat, Sulu, Surigao Del Sur, Tarlac, Zambales, Zamboanga Del Norte, Zamboanga Del Sur, Zamboanga Sibugay

A.3 Graphs and Tables

Table 2: Summary Statistics of different types of disasters

Variable	Mean	Std. Dev.	Min	Max
Meteorological	1.347	1.265	0	7
Hydrological	0.350	0.658	0	4
Climatical	0.040	0.196	0	1
Geophysical	0.021	0.147	0	2
Observations	N = 1444	n = 76	T = 19	

Numbers of different types of disasters for each province in the Philippines from 2001-2019 (data source: EM-DAT)

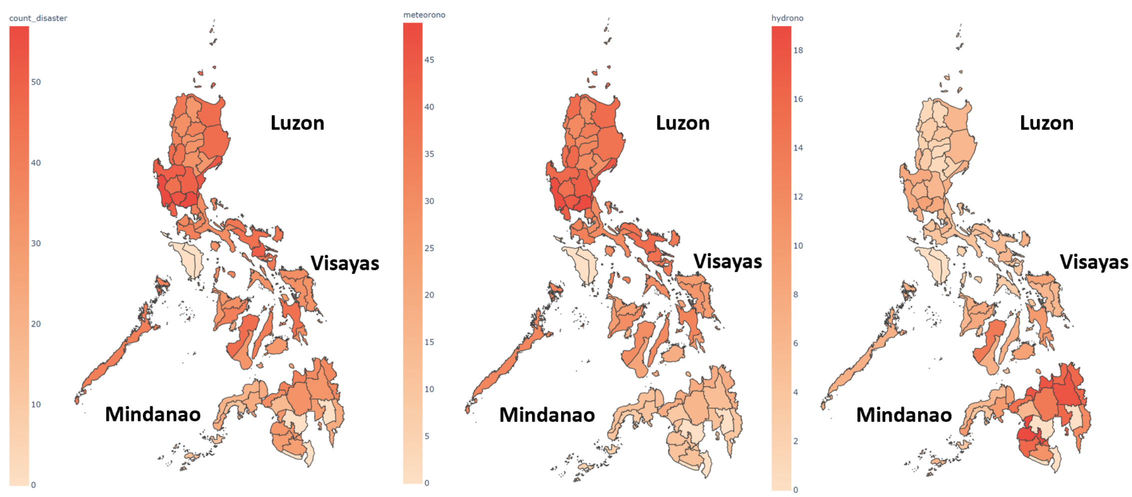

Figure 10: Natural Disasters in the Philippines, 2001-2019

This graph is made using information from EM-DAT. From Let to right, it shows the distribution of the number of: all disasters; meteorological disasters; hydrological disasters

Table 3: Fiscal Impacts of Maximal wind speed (total level)

	(1) Spending	(2) IRA	(3) Tax	(4) Non-tax	(5) Loan Receipt	(6) Grants&Donation	(7) Deficit
max V_s	-5.161*	-3.217	-0.872+	0.687	-0.108	-0.217	3.374
	(1.905)	(2.181)	(0.456)	(0.477)	(0.662)	(0.305)	(3.918)
max V_s^2	0.0395*	0.0213	0.00640	-0.00743+	-0.00262	0.00211	-0.0352
	(0.0160)	(0.0170)	(0.00627)	(0.00398)	(0.00645)	(0.00269)	(0.0458)
L1 max V_s	-0.859	-4.503	-0.833*	0.509	-0.738	-0.188	1.603
	(3.736)	(2.870)	(0.299)	(0.619)	(0.740)	(0.480)	(2.917)
L1 max V_s^2	-0.00224	0.0302	0.00619	-0.00465	0.00542	0.00175	-0.0211
	(0.0345)	(0.0271)	(0.00449)	(0.00522)	(0.00605)	(0.00456)	(0.0196)
L2 max V_s	-2.572	-3.235	-0.575+	-0.0678	-0.475	-0.0929	1.832
	(3.364)	(3.395)	(0.315)	(0.590)	(0.628)	(0.258)	(1.485)
L2 max V_s^2	0.0126	0.0229	0.00334	0.00123	0.00377	0.000743	-0.0247
	(0.0319)	(0.0360)	(0.00414)	(0.00559)	(0.00517)	(0.00307)	(0.0144)
L3 max V_s	-1.691	-2.718	-0.248	-0.0219	-0.271	0.290	3.245
	(2.641)	(2.999)	(0.324)	(0.529)	(0.400)	(0.562)	(1.911)
L3 max V_s^2	-0.00199	0.0139	0.00249	0.00228	0.000835	-0.00184	-0.0341+
	(0.0247)	(0.0283)	(0.00538)	(0.00603)	(0.00339)	(0.00497)	(0.0169)
Population	-0.00278**	-0.00303**	0.000438**	-0.000231	-0.0000687	-0.00000695	0.000848
	(0.000875)	(0.00102)	(0.000136)	(0.000132)	(0.0000436)	(0.0000693)	(0.000561)
GDP per capita	0.00384	-0.000353	0.00383*	0.00165	0.00149	0.000388	-0.0000825
	(0.0105)	(0.0133)	(0.00171)	(0.00231)	(0.000961)	(0.000618)	(0.00950)
Avg. Unemploy	87.88	133.3	-44.69*	16.93	8.415	7.245	90.63
	(94.44)	(89.90)	(17.74)	(25.41)	(6.000)	(5.151)	(95.21)
Tourism Pop.	630.6+	727.7	28.43+	88.39*	40.24	-14.98+	-219.5
	(316.4)	(475.1)	(13.73)	(32.66)	(35.35)	(8.389)	(196.6)
Fiscal Decen.	1795.0	4801.6**	-2.261	81.09	-404.3**	-37.76	-2569.4**
	(2541.2)	(1518.2)	(312.4)	(340.3)	(124.4)	(72.66)	(716.3)
Constant	4937.0*	2943.8*	-122.7	320.1	272.8+	4.593	-443.8
	(1828.7)	(1078.8)	(322.3)	(379.4)	(142.4)	(148.7)	(1720.7)
N	1139	1139	1139	1139	1139	1139	1139

Provincial level average maximal sustainable wind speed for grid-level speed above the threshold ($V_s \geq 20$km/h)

Lx denotes the lag term for x periods ago, $x = 1, 2, 3$.

Standard errors in parentheses: + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$

Table 4: Fiscal Impacts of Maximal wind speed (provincial level)

	(1) Spending	(2) IRA	(3) Tax	(4) Non-tax	(5) Loan Receipt	(6) Grants&Donation	(7) Deficit
max V_s	-2.061*	-1.983	-0.165	0.296	0.0804	-0.122	0.888
	(0.893)	(1.192)	(0.177)	(0.302)	(0.509)	(0.187)	(1.509)
max V_s^2	0.0138	0.0140	0.00124	-0.00486	-0.00230	0.00126	-0.00744
	(0.00949)	(0.0110)	(0.00237)	(0.00292)	(0.00482)	(0.00176)	(0.0165)
L1 max V_s	-0.709	-3.081+	-0.339**	0.272	-0.439	-0.451+	1.896+
	(1.548)	(1.711)	(0.101)	(0.352)	(0.508)	(0.238)	(0.948)
L1 max V_s^2	0.00248	0.0245	0.00261*	-0.00317	0.00276	0.00352	-0.0179*
	(0.0140)	(0.0159)	(0.00119)	(0.00328)	(0.00430)	(0.00213)	(0.00836)
L2 max V_s	-1.226	-2.252	-0.195	0.105	-0.236	-0.259+	1.402
	(1.308)	(1.640)	(0.128)	(0.336)	(0.643)	(0.146)	(0.969)
L2 max V_s^2	0.00727	0.0184	0.000762	-0.00216	0.00450	0.00260	-0.0161
	(0.0129)	(0.0179)	(0.00127)	(0.00355)	(0.00551)	(0.00207)	(0.00981)
L3 max V_s	-1.349	-1.963	-0.0120	-0.350	0.0312	0.0252	1.740
	(0.973)	(1.462)	(0.114)	(0.388)	(0.487)	(0.123)	(1.166)
L3 max V_s^2	0.00447	0.0134	-0.000448	0.00382	0.000561	0.000978	-0.0201+
	(0.0100)	(0.0143)	(0.00157)	(0.00490)	(0.00370)	(0.00116)	(0.0106)
Population	-0.00146**	-0.00152*	-0.0000739+	-0.000257*	-0.0000125	-0.0000286	0.000649*
	(0.000462)	(0.000584)	(0.0000387)	(0.0000941)	(0.0000307)	(0.0000171)	(0.000241)
GDP per capita	0.00210	0.000758	0.00103	0.000479	0.00104	-0.0000303	-0.000231
	(0.00431)	(0.00639)	(0.000629)	(0.00124)	(0.000643)	(0.000323)	(0.00400)
Avg. Unemploy	36.64	62.20	-16.79+	-3.698	9.614+	1.533	20.06
	(40.23)	(54.32)	(9.360)	(13.16)	(5.156)	(1.429)	(36.56)
Tourism Pop.	333.4+	397.9	6.985	22.25+	44.70	-11.72*	-119.3
	(186.5)	(328.8)	(4.152)	(11.58)	(35.94)	(5.034)	(134.2)
Fiscal Decen.	-3728.5**	656.8	-83.27	-355.3*	-613.8**	-130.5	-2893.7**
	(742.1)	(635.7)	(54.34)	(141.8)	(91.77)	(83.50)	(925.8)
Constant	5050.3**	2114.3+	223.1*	637.1**	313.2*	130.9+	847.4
	(629.3)	(1113.2)	(87.34)	(180.9)	(116.7)	(63.39)	(979.5)
N	1132	1139	1139	1135	1139	1139	1139

Provincial level average maximal sustainable wind speed for grid-level speed above the threshold ($V_s \geq 20$km/h)

Lx denotes the lag term for x periods ago, $x = 1, 2, 3$.

Standard errors in parentheses: + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$

Table 5: Fiscal Impacts of Maximal wind speed (MC level)

	(1) Spending	(2) IRA	(3) Tax	(4) Non-tax	(5) Loan Receipt	(6) Grants&Donation	(7) Deficit
max V_s	-3.020*	1.616	-0.707+	0.411	-0.188	-0.0952	2.486
	(1.286)	(1.928)	(0.394)	(0.333)	(0.333)	(0.238)	(2.646)
max V_s^2	0.0249*	-0.00883	0.00517	-0.00277	-0.000317	0.000846	-0.0277
	(0.00870)	(0.0178)	(0.00458)	(0.00286)	(0.00333)	(0.00233)	(0.0317)
L1 max V_s	0.0187	0.683	-0.494+	0.251	-0.299	0.263	-0.293
	(2.209)	(2.302)	(0.279)	(0.485)	(0.349)	(0.425)	(2.284)
L1 max V_s^2	-0.00609	-0.00372	0.00358	-0.00162	0.00266	-0.00177	-0.00328
	(0.0211)	(0.0216)	(0.00355)	(0.00438)	(0.00299)	(0.00382)	(0.0155)
L2 max V_s	-1.409	-0.621	-0.380	-0.161	-0.239	0.166	0.429
	(2.291)	(2.557)	(0.349)	(0.513)	(0.307)	(0.192)	(1.081)
L2 max V_s^2	0.00589	-0.00321	0.00258	0.00327	-0.000733	-0.00186	-0.00860
	(0.0203)	(0.0221)	(0.00377)	(0.00449)	(0.00264)	(0.00211)	(0.0102)
L3 max V_s	-0.434	-0.962	-0.236	0.332	-0.302	0.265	1.505
	(1.898)	(2.440)	(0.304)	(0.351)	(0.297)	(0.561)	(1.107)
L3 max V_s^2	-0.00577	0.00128	0.00294	-0.00162	0.000273	-0.00282	-0.0140
	(0.0168)	(0.0229)	(0.00461)	(0.00298)	(0.00278)	(0.00498)	(0.0103)
Population	-0.00132*	0.000406	0.000512**	0.0000274	-0.0000562*	0.0000217	0.000200
	(0.000479)	(0.000288)	(0.000107)	(0.0000609)	(0.0000246)	(0.0000637)	(0.000356)
GDP per capita	0.00171	0.00618	0.00280*	0.00101	0.000455	0.000418	0.000149
	(0.00660)	(0.00491)	(0.00128)	(0.00121)	(0.000482)	(0.000388)	(0.00568)
Avg. Unemploy	50.65	46.48	-27.90*	20.32	-1.199	5.711	70.57
	(60.23)	(47.35)	(10.80)	(13.79)	(4.624)	(4.357)	(62.24)
Tourism Pop.	297.1+	-63.94	21.45	66.38+	-4.467	-3.252	-100.3
	(140.3)	(67.94)	(13.60)	(31.14)	(5.767)	(4.909)	(66.13)
Fiscal Decen.	5544.7**	1050.6+	81.01	430.9+	209.5*	92.74+	324.4
	(1867.6)	(515.8)	(275.0)	(224.0)	(72.22)	(45.07)	(508.1)
Constant	-117.4	-848.1	-345.9	-297.9	-40.41	-126.4	-1291.2
	(1414.4)	(688.6)	(269.6)	(232.9)	(88.50)	(133.7)	(1030.4)
N	1139	1139	1139	1139	1139	1139	1139

Provincial level average maximal sustainable wind speed for grid-level speed above the threshold ($V_s \geq 20$km/h)

Lx denotes the lag term for x periods ago, $x = 1, 2, 3$.

Standard errors in parentheses: + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$