

Rivera, John Paolo R.; Miral, Ramona Maria L.; Ruiz, Mark Gerald C.

Working Paper

Estimating the impacts of climate change on fiscal health in the Philippines: Designing a policy toward a climate-resilient fiscal sector

PIDS Discussion Paper Series, No. 2024-34

Provided in Cooperation with:

Philippine Institute for Development Studies (PIDS), Philippines

Suggested Citation: Rivera, John Paolo R.; Miral, Ramona Maria L.; Ruiz, Mark Gerald C. (2024) : Estimating the impacts of climate change on fiscal health in the Philippines: Designing a policy toward a climate-resilient fiscal sector, PIDS Discussion Paper Series, No. 2024-34, Philippine Institute for Development Studies (PIDS), Quezon City, <https://doi.org/10.62986/dp2024.34>

This Version is available at:

<https://hdl.handle.net/10419/311723>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

DISCUSSION PAPER SERIES NO. 2024-34

Estimating the Impacts of Climate Change on Fiscal Health in the Philippines: Designing a Policy toward a Climate-Resilient Fiscal Sector

*John Paolo R. Rivera, Ramona Maria L. Miral,
and Mark Gerald C. Ruiz*



The PIDS Discussion Paper Series constitutes studies that are preliminary and subject to further revisions. They are being circulated in a limited number of copies only for purposes of soliciting comments and suggestions for further refinements. The studies under the Series are unedited and unreviewed. The views and opinions expressed are those of the author(s) and do not necessarily reflect those of the Institute. The Institute allows citation and quotation of the paper as long as proper attribution is made.

CONTACT US:

RESEARCH INFORMATION DEPARTMENT
Philippine Institute for Development Studies

18th Floor, Three Cyberpod Centris - North Tower
EDSA corner Quezon Avenue, Quezon City, Philippines

publications@pids.gov.ph
(+632) 8877-4000

<https://www.pids.gov.ph>

Estimating the Impacts of Climate Change on Fiscal
Health in the Philippines: Designing a Policy toward
a Climate-Resilient Fiscal Sector

John Paolo R. Rivera
Ramona Maria L. Miral
Mark Gerald C. Ruiz

PHILIPPINE INSTITUTE FOR DEVELOPMENT STUDIES

December 2024

Abstract

We explored the fiscal impacts of climate-related phenomena in the Philippines and offer policy recommendations for creating a climate-resilient economy. By employing a three-pronged empirical approach (i.e., time series, panel data, cross-section analyses), we probed on the nuanced interplay of climate shocks, fiscal health, and economic sustainability. Time series analysis highlighted how structural vulnerabilities, reliance on climate-sensitive sectors, and socio-economic inequalities exacerbate long-term scarring effects on growth. Panel data analysis emphasized temperature's acute impact on government consumption expenditure, contrasting with the mixed fiscal effects of rainfall and storms, shaped by mitigation measures and fiscal structures. Cross-section analysis elucidated further how local government units' fiscal resilience depends on external revenues, pre-allocated funds, and disaster severity. Findings revealed the need for region-specific fiscal responses, diverging from established scholarly literature due to the Philippines' decentralized disaster management and reliance on local institutions. Our policy recommendations include establishing a climate resilience fund, integrating climate-responsive budgeting, reinforcing risk transfer mechanisms, incentivizing green investments, and empowering local governments to manage adaptation funds. Additionally, investing in climate research, data-driven decision-making, and public awareness campaigns is critical. Aligning climate finance with long-term development plans and the 2030 Agenda for Sustainable Development ensures resilience is embedded within the broader development strategy. These steps aim to prepare the Philippines for climate-induced risks while fostering sustainable growth, mitigating fiscal shocks, and ensuring economic stability.

Keywords: climate change, climate resiliency, fiscal balance, fiscal health, sustainability

Table of Contents

1. Introduction	1
1.1. Rationale	4
1.2. Research question.....	5
1.3. General and specific objectives	5
1.4. Scope and limitation	5
1.5. Significance of the study.....	7
2. Literature review	7
2.1. Macroeconomic impacts of rapid climate change.....	8
2.2. Fiscal impacts of rapid climate change	8
2.3. Impacts of rapid climate change in the Philippines.....	9
2.4. Research gap	10
3. Methodology.....	12
3.1. Data requirements	12
3.2. Empirical strategy	13
4. Results and discussion	17
4.1. National level time series regression model.....	17
4.2. Regional level panel data regression model	21
4.3. LGU level cross-sectional regression model	27
5. Conclusions and recommendations.....	31
5.1. Key findings.....	31
5.2. Policy recommendations.....	32
6. References.....	34
7. Appendix	41

List of Figures

Figure 1. Global land-ocean temperature index (in temperature anomaly C).....	2
Figure 2. Observed annual average mean surface air temperature of the Philippines (in °C).2	
Figure 3. Heat index 35 in the Philippines. Heat index 35 in the Philippines.....	3
Figure 4. Total disaster risk reduction expenditure (2015-2022, in billion PHP).....	4
Figure 5. Climate-macroeconomic literature map with research gap.	11
Figure 6. Empirical strategy.....	14
Figure 7. OIRF and FEVD of total revenue.....	17
Figure 8. OIRF and FEVD of total expenditure.	20
Figure 9. Local government expenditure, by region (in million PHP).	28

List of Tables

Table 1. Selected climate-macroeconomic literature matrix with methodologies.	11
Table 2. Data availability mapping and variable description.	12
Table 3. Variable description and a-priori expectations (national level).	15
Table 4. Variable description and a-priori expectations (regional level).	16
Table 5. 1. Panel data model with mean temperature as exogenous variable.	22
Table 5. 2. Panel data model with mean rainfall as exogenous variable.....	23
Table 5. 3. Panel data model with severe storm as exogenous variable.	24
Table 5. 4. Panel data model with drought as exogenous variable	26
Table 6. Summary statistics	28
Table 7. Cross-sectional regression results for expenditure.	29
Table 8. Cross-sectional regression results for revenue.....	29
Table 9. Pairwise correlations of variables from the cross-section analysis.....	30

List of Abbreviations

ADB	Asian Development Bank
ARDL	Autoregressive Distributed Lag
ASEAN	Association of Southeast Asian Nations
BARMM	Bangsamoro Autonomous Region in Muslim Mindanao
BEH	Bündnis Entwicklung Hilft
BLGF	Bureau of Local Government Finance
BSP	Bangko Sentral ng Pilipinas
BTr	Bureau of Treasury
CALABARZON	Cavite, Laguna, Batangas, Rizal, Quezon Province
CAR	Cordillera Administrative Region
CCRIF	Caribbean Catastrophe Risk Insurance Facility
CH ₄	Methane
CLRM	Classical Linear Regression Model
CO ₂	Carbon dioxide
COA	Commission on Audit
CPEIR	Climate Public Expenditure and Institutional
CPI	Consumer Price Index
DA	Department of Agriculture
DBM	Department of Budget and Management
DepEd	Department of Education
DILG	Department of Interior and Local Government
DOH	Department of Health
DOLE	Department of Labor and Employment
DOST	Department of Science and Technology
DOTr	Department of Transportation
DPWH	Department of Public Works and Highways
DRR	Disaster Risk Reduction
DRRM	Disaster Risk Reduction and Management
DSWD	Department of Social Welfare and Development
EC	European Commission
EM-DAT	Emergency Events Database
EMDEs	Emerging Markets and Developing Economies
ENSO	El Nino Southern Oscillation
EU	European Union
FE	Fixed Effects
FEVD	Forecast Error Variance Decomposition
GDP	Gross Domestic Product
GFCE	Government Final Consumption Expenditure
GFI	Government Financial Institutions
GHG	Greenhouse Gases
GMM	Generalized Method of Moments
GOCC	Government-Owned and Controlled Corporation
GVA	Gross Value Added
HEI	Higher Education Institutions
IMF	International Monetary Fund
LBP	Land Bank of the Philippines
IRA	Internal Revenue Allotment
LGU	Local Government Unit
LP	Local Projections

MIMAROPA	Mindoro, Marinduque, Romblon, Palawan
MLGU	Municipal Local Government Unit
NASA	National Aeronautics and Space Administration
NCR	National Capital Region
NDRRM	National Disaster Risk Reduction and Management
NEDA	National Economic and Development Authority
NIA	National Irrigation Administration
NG	National Government
NGS	National Geographic Society
NIR	Negros Island Region
OCD	Office of Civil Defense
ODA	Official Development Assistance
OIRF	Orthogonal Impulse Response Function
OLS	Ordinary Least Squares
PAGASA	Philippine Atmospheric, Geophysical and Astronomical Services Administration
PDP	Philippine Development Plan
PDSI	Palmer Drought Severity Index
PhilHealth	Philippine Health Insurance Corporation
PHP	Philippine Peso
PSA	Philippine Statistics Authority
RA	Republic Act
RCEP	Regional Comprehensive Economic Partnership
RE	Random Effects
SDG	Sustainable Development Goals
SOCCSKSARGEN	South Cotabato, Cotabato Province, Sultan Kudarat, Sarangani, General Santos City
SWS	Social Weather Stations
TOT	Terms of Trade
UCAR	University Corporation for Atmospheric Research
UN	United Nations
USD	United States Dollar
VAR	Vector Autoregression
WB	World Bank
WMO	World Meteorological Organization

Estimating the Impacts of Climate Change on Fiscal Health in the Philippines: Designing a Policy toward a Climate-Resilient Fiscal Sector

John Paolo R. Rivera^{}, Ramona Maria L. Miral^{**}, Mark Gerald C. Ruiz^{***}*

1. Introduction

Climate is defined as the average weather conditions (e.g., temperature, humidity, and rainfall patterns) for a particular location over an extended period (from months to thousands or millions of years) (World Meteorological Organization [WMO] n.d.). In contrast to weather (i.e., the atmosphere's state, including temperature, pressure, wind, humidity, precipitation, cloud cover, among others) (Deschênes and Greenstone 2007), that can suddenly shift because it is influenced by latitude, altitude, and local and regional geography (National Geographic Society [NGS] n.d.), climate changes over longer periods. Hence, as the World Bank [WB] (2023) and United Nations [UN] (n.d.) defined, climate change is the significant variations and long-term shifts of average weather conditions, temperature, and weather patterns (i.e., becoming warmer, wetter, or drier over several years or longer). As such, it is the longer-term trend that distinguishes climate change from natural weather variability.

While temperature fluctuations naturally occur as part of the phenomenon (e.g., changes can be natural because of solar activity or large volcanic eruptions) (Deschênes and Greenstone 2007), recent decades have seen significant global warming and rapid climate change (UN n.d.). With consensus, such was driven by the ever-increasing human activities since the first industrial revolution due to the burning of fossil fuels like coal, oil, and gas (Lynas et al. 2021; UN n.d.). These human activities resulted to changes in the atmospheric composition either directly or indirectly, via emissions of gases or particles, or via atmospheric chemistry, respectively (WB 2023).

The continued burning of fossil fuels to power the economy generates greenhouse gas (GHG) emissions that act like a blanket wrapped around the Earth, trapping the sun's heat, and raising global temperatures (Denchak 2022). According to UN (n.d.), the major GHG causing rapid climate change include carbon dioxide (CO₂) and methane (CH₄) emanating from the use of gasoline for driving vehicles, or coal for heating a building. Moreover, clearing land and clearing forests also generate CO₂. Furthermore, agriculture, oil, and gas operations are major sources of CH₄ emissions (Charabi 2021; Xiaoli et al. 2016). Energy, industry, transport, buildings, agriculture, and land use are among the main sectors contributing to GHG emissions (Lamb et al. 2021; van Vuuren et al. 2017).

To illustrate, from Figure 1, there is a steeper increase in global land-ocean temperature from 1966 to 2021 than from 1901 to 1965. Such translates to a faster rise in sea levels and more extreme weather events, like super typhoons and heatwaves (Pun et al. 2023; Carrington 2022). These have varied impacts on health, education, labor, agriculture, and government finance, among others (Gagliardi et al. 2022; Talukder et al. 2021; Malhi et al. 2021).

Meanwhile, the Philippines mirrors global trends by also recording increases in annual temperatures, as seen in Figure 2. Annual temperature demonstrated steeper increments from

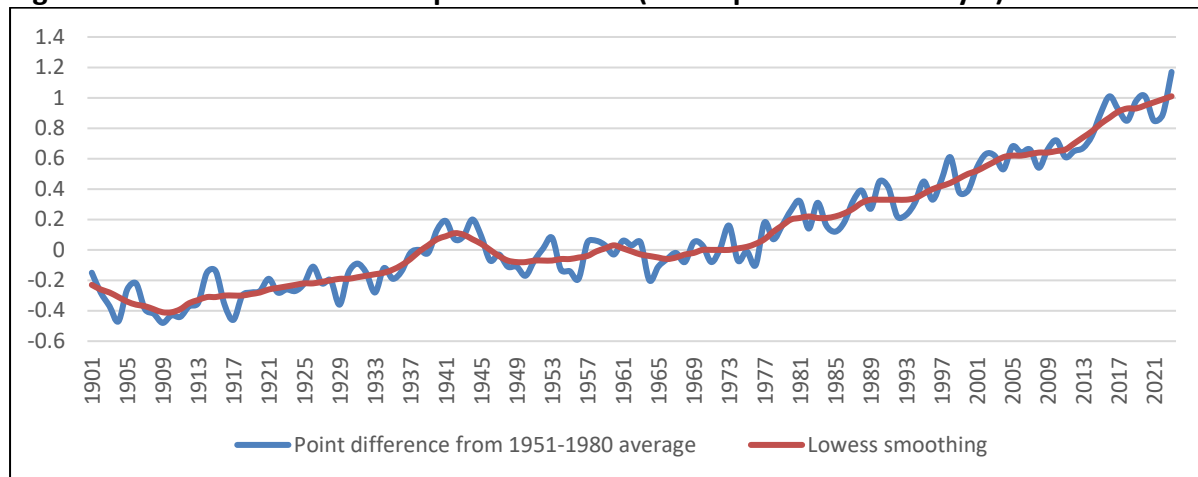
^{*} Senior Research Fellow, Philippine Institute for Development Studies. Email: jrivera@pids.gov.ph

^{**} Research Analyst II, Philippine Institute for Development Studies. Email: rmiral@pids.gov.ph

^{***} Research Specialist, Philippine Institute for Development Studies. Email: mrui@pids.gov.ph

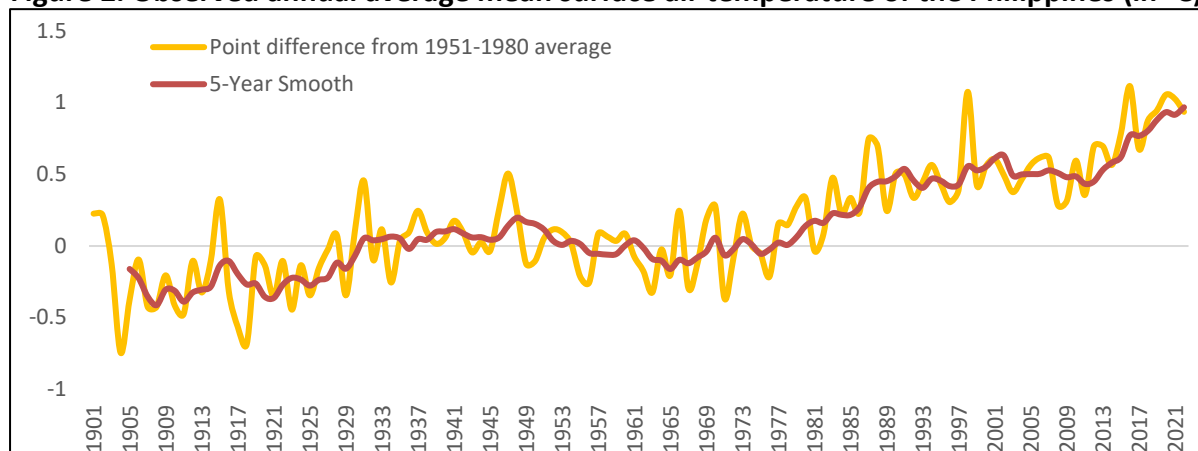
1966 to 2023 than from 1901 to 1965. Similarly, the Heat Index 35, which records the number of days that the daily temperature rises above 35°C for a given year, shows higher readings for the years between 2013 and 2021 than in previous periods, as seen in Figure 3. In fact, in 2024, the hottest day on record in Metro Manila (also referred to as the National Capital Region [NCR]) was also reported at 38.8°C in April 29, exceeding the previous peaks of 38.6°C in 1915 and 2021 (Mendoza 2024). This is reinforced by more recent reports of record-breaking temperatures in the Philippines (Millard 2024; Lee-Brago 2020).

Figure 1. Global land-ocean temperature index (in temperature anomaly C).



Source: National Aeronautics and Space Administration (2024).

Figure 2. Observed annual average mean surface air temperature of the Philippines (in °C).



Source: World Bank (2023); Authors' calculations.

Rising temperatures prompted government agencies in the Philippines to take precautionary measures. For instance, the Department of Health (DOH¹) sounded an alarm against heat-related illnesses (Cabalza 2024; Espina 2024) and the Philippine Health Insurance Corporation (PhilHealth) increased benefits by 30 percent for the same reason² (Montemayor 2024; Barro II 2024). Meanwhile, the Department of Education (DepEd³) allowed schools to suspend

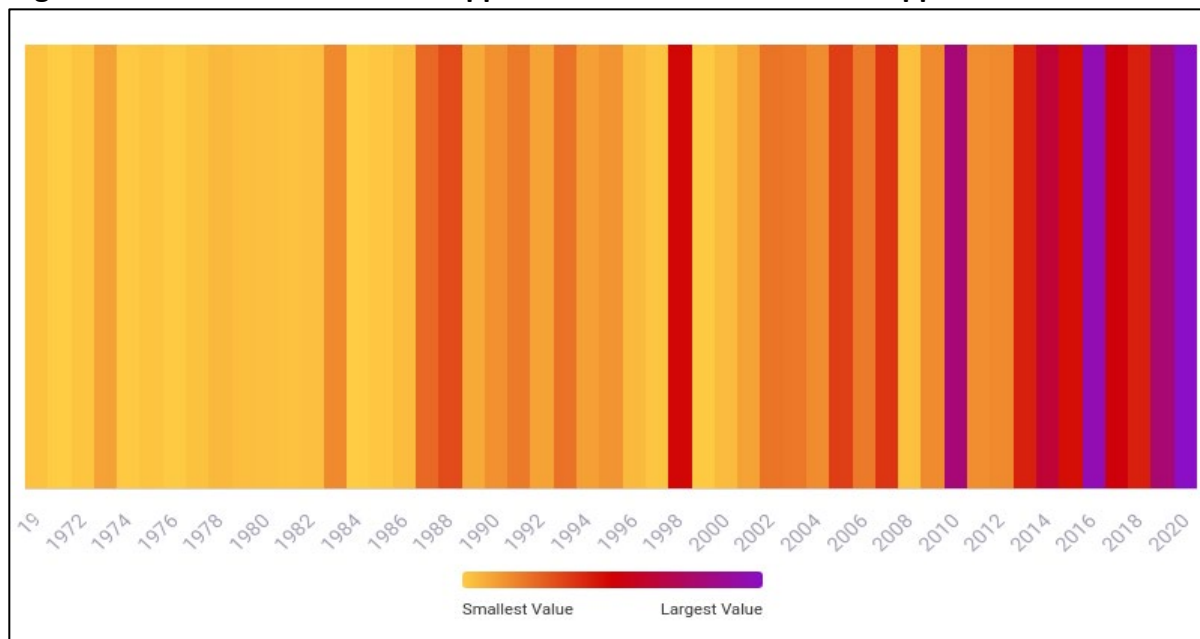
¹ DOH is the Philippines' health policy and regulatory institution. Meanwhile, the Philippine Health Insurance Corporation (PhilHealth) is an attached agency of DOH – a government-owned and controlled corporation (GOCC) that administers the economy's health insurance program.

² DOH registered 77 incidents of heat-related illnesses in the first four months of 2024, comprising of individuals aged 12 to 21. A fraction resulted in deaths, but the number is undetermined (Cabalza 2024, Montemayor 2024).

³ DepEd is the Philippines' government institution that holds authority over public and private basic educational institutions.

classes⁴ (Parungao 2024), while the Department of Labor and Employment (DOLE⁵) reiterated measures for the prevention and control of heat stress in workplaces⁶ (Patinio 2024). The extreme heat also resulted in agricultural damage worth at least PHP 4.9 billion by April 2024, as reported by the Department of Agriculture (DA⁷) (Santos 2024).

Figure 3. Heat index 35 in the Philippines. Heat index 35 in the Philippines.



Source: World Bank Climate Change Knowledge Portal via CEIC Data (2024).

Scholarly literature provided evidence that rapid climate change has exacerbated the occurrence of floods, droughts, and storms that impacts economies (Bilal and Känzig 2024; Tovar Mora et al. 2022; Hallegatte et al. 2016; Thomas and López 2015). The Philippines has been identified as one of the most disaster-prone economies in the world (Bollettino et al. 2020; Jha et al. 2018). This is also reported in the World Risk Report by Bündnis Entwicklung Hilft [BEH] (2023), which considers the vulnerability and capacity to respond of 193 economies. Such standing translates to contributions in disaster-related expenses, as illustrated in Figure 4.

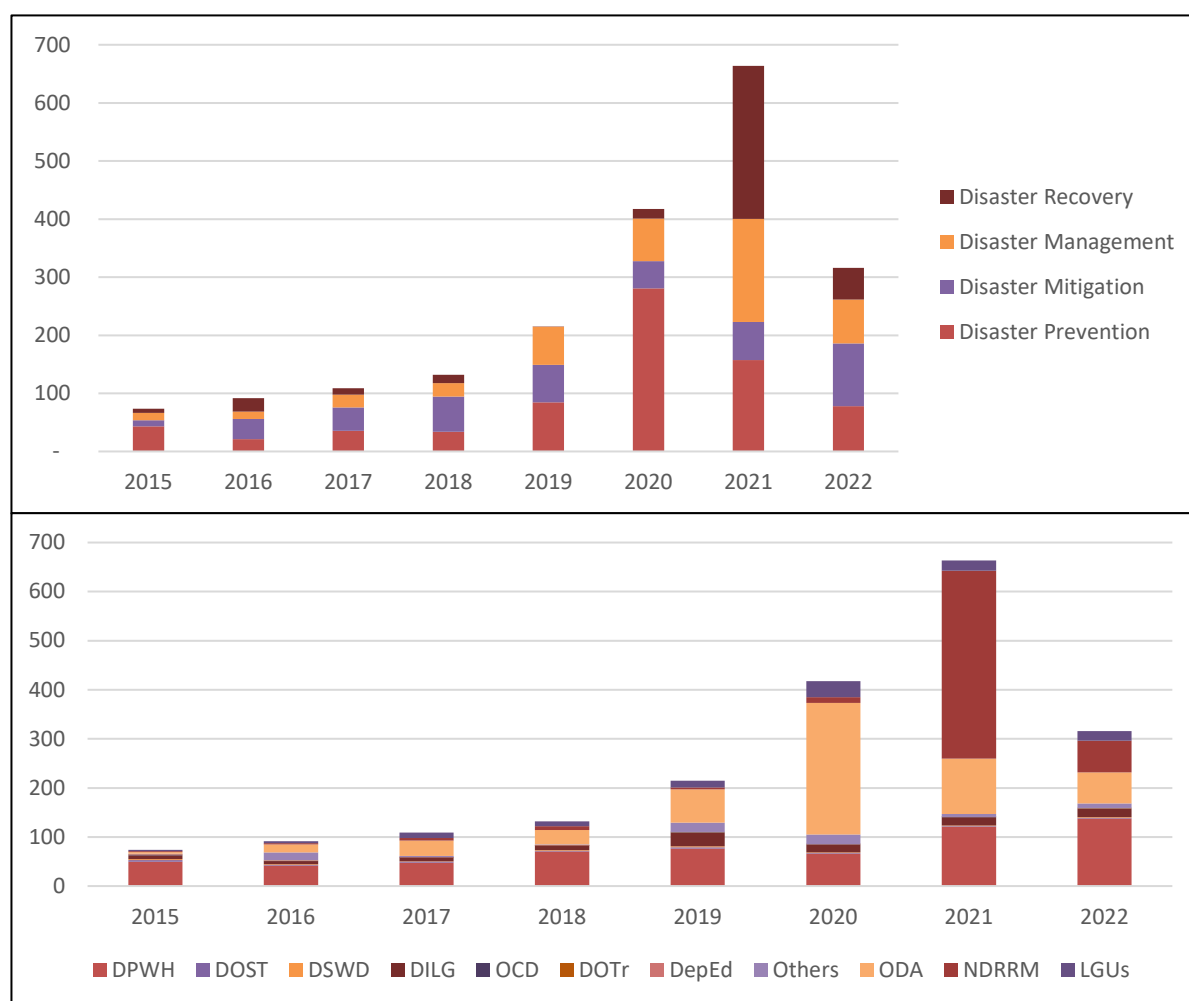
⁴ DepEd released an official statement in April 2024, emphasizing the provisions of Department Order 037 of 2022. These are guidelines on the cancellation of classes due to natural disasters, power outages and interruptions, and other calamities.

⁵ DOLE is the Philippines' government entity for the promotion of employment and the protection of workers' welfare.

⁶ Labor Advisory No. 08 of 2023 enumerated measures ensuring the safety and health of workers exposed to extreme heat. It directs employers to assess risks, disseminate information on heat stress, and formulate procedures and information networks in case of emergencies.

⁷ DA is the Philippines' government entity for agricultural development in the economy.

Figure 4. Total disaster risk reduction expenditure (2015-2022, in billion PHP).



Note: Above (by expenditure type); Below (by government agency); PHP = Philippine Peso, DPWH = Department of Public Works and Highways, DOST = Department of Science and Technology, DSWD = Department of Social Welfare and Development, DILG = Department of Interior and Local Government, OCD = Office of Civil Defense, DOTr = Department of Transportation, ODA = Official Development Assistance, NDRRM = National Disaster Risk Reduction and Management, LGUs = local government units.

Source: Commission on Audit (COA), Department of Budget and Management (DBM), and National Economic and Development Authority (NEDA) via Philippine Statistics Authority [PSA] (2023).

1.1. Rationale

The effects of rapid climate change have become a major discourse due to its uncertain path and significant consequences (Duarte Santos et al. 2022; Lindwall 2022; Fesenfeld and Rinscheid 2021; European Commission [EC] n.d.). At the macroeconomic front, Cevik and Jalles (2023) highlighted the uneven effects of rapid climate change on the growth and inflation of advanced and developing economies. Armas et al (2024) focused on Philippine regions⁸ and

⁸ As of June 2024, there are 18 political-geographical divisions in the Philippines, namely: NCR, Cordillera Administrative Region (CAR), Region I (Ilocos), Region II (Cagayan Valley), Region III (Central Luzon), Region IV-A (CALABARZON [Cavite, Laguna, Batangas, Rizal, Quezon Province]), Region IV-B (MIMAROPA [Mindoro, Marinduque, Romblon, Palawan]), Region V (Bicol), Region VI (Western Visayas), Negros Island Region (NIR), Region VII (Central Visayas), Region VIII (Eastern Visayas), Region IX (Zamboanga Peninsula), Region X (Northern Mindanao), Region XI (Davao), Region XII (SOCCSKSARGEN [South Cotabato, Cotabato Province, Sultan Kudarat, Sarangani, General Santos City]), Region XIII (Caraga), and the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM). These regional divisions classify, for administrative purposes, the provinces (which are also comprised of municipalities, component cities, or highly urbanized cities), each with respective LGUs. Note that historical data used in this study may not yet reflect the updated regional classification, given the newly created NIR through Republic Act (RA) No. 12000.

probed the effects of temperature shocks on growth, inflation, and related indicators. Meanwhile, Fuje et al (2023) explained the impacts of extreme weather events on fiscal health. However, a research gap remains – to probe further on the effects of climate-related phenomena, particularly on the Philippine fiscal picture. This is the gap that we aim to bridge in this study. We hypothesize that *there exists a negative causal relationship between climate-related phenomena and fiscal health in the Philippines.*

1.2. Research question

In probing on the effects of climate-related phenomena on fiscal health in the Philippines, we statistically explain public finances or fiscal health represented by viable measures using climate-related phenomena represented by feasible metrics. Hence, we pose the research question: *how do climate-related phenomena affect fiscal health in the Philippines?*

Addressing this research question will generate two outcomes: (1) provide empirical evidence on the causal relationship between climate-related phenomena and fiscal health specifically for the Philippines; and (2) provide answers to this follow up question: *how can development strategies that are affected by rapid climate change be recalibrated to ensure fiscal viability, resiliency, and sustainability?*

1.3. General and specific objectives

In addressing the abovementioned research question, our overarching objective is *to statistically determine whether the construct extent of the impact of climate change causally affects the construct public finances, represented by viable metrics mentioned above.* That is, we aim to statistically quantify the effects of extreme weather incidents (e.g., severe storms, severe drought), temperature shocks, and precipitation levels on government revenues and expenditures.

Our overarching objective is supported by the following specific objectives:

1. At the multivariate level, using national and regional data, we aim to develop models explaining government revenues and expenditures. This will allow us to compare national and regional analysis.
2. At the policy level, we aim to consolidate policy recommendations on determining how to build, utilize, and maximize public funds in preparing for, recovering from climate-related phenomena, and creating a climate-resilient economy

1.4. Scope and limitation

By touching on the topic of climate change as one of the anchors of our study, we note that we are referring to rapid climate change. Climate naturally does change over an extended period (UN n.d.). However, it is the rapid change in climate that is causing disruptions in human activities, political, social, environmental, and economic systems we depend on (Rocha et al. 2022) that serves as context of our study. By rapid climate change, we subscribe to the definition of Holmes et al. (2011) wherein “rapid, or abrupt, climate change is regarded as a change in the climate system to a new state following the crossing of a threshold. It generally occurs at a rate exceeding that of the change in the underlying cause” (p. 157).

Our constructs are measured as follows. On one hand, we measure fiscal health using government revenues and expenditures. While there are other plausible variables to represent our constructs, we are limited to variables whose data is complete, consistent, and accessible whether unrestricted access, by request, or under subscription. These are all readily available or computable from the Philippine Statistics Authority (PSA), Bangko Sentral ng Pilipinas (BSP), Bureau of Treasury (BTr), and Bureau of Local Government Finance (BLGF).

On the other hand, we measure climate-related phenomena using extreme weather incidents (e.g., severe storms, severe drought), temperature shocks, and precipitation levels. These variables were chosen as they are readily available or computable from secondary sources such as The International Disaster Database – Emergency Events Database (EM-DAT), Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), and are computable using established methodologies (Becker and Mauro 2006; Fuje et al. 2023). As climate-related variables tend to be scarce and are prone to measurement issues, availability and processability, with support from literature, played a vital role in the choice of variables.

Because we are utilizing time series data, following the caveats underscored by Rivera and Tullao Jr. (2023), a longer period is needed to undertake time series analysis. However, data is sourced from multiple agencies. Hence, we are constrained by data consistency. For instance, despite PSA and/or BSP having monthly or quarterly data for our variables of interest, but PAGASA only has annual data, the common unit of analysis will prevail, most likely annual. Likewise, even if BSP has available time series from 1950 but EM-DAT has 1990 as earliest, the shorter timeframe will be used. Similarly, even if BSP has 2023 as latest data point and BTr only have until 2021, the less recent year will be followed.

Consequently, Rivera and Tullao Jr. (2023) emphasized the constraints on: (1) the number of variables that can be included in the empirical model to conserve degrees of freedom; and (2) the unit of analysis of empirical analysis (i.e., instead of a more granular unit of time like monthly or quarterly, annual will be used). Due to impediments in the access to and availability of disaggregated, consistent, and granular data, we make use of what is admissible for time series analysis. As such, not all variables used in the national-level regression can be used for regional-level regression due to availability. That is, while there are national level data available, it does not follow that regional level data are also available.

Likewise, while the time series data for regional analysis may not be that long, a panel data econometric analysis serves as an alternative. Following Cevik and Jalles (2023) and Armas et al. (2024) who used local projections (LP), fixed effects (FE), random effects (RE), and Generalized Method of Moments (GMM) panel data model prove to be a viable alternative.

We also recognize and anticipate the impacts of aggregation bias⁹ limiting our time series and panel data analysis. Hence, a cross-sectional analysis was also conducted. While it also has its advantages and disadvantages (Maier et al. 2023; Taris et al. 2021; Rindfleisch et al. 2008), the methodologies and interdisciplinary approaches implemented are geared towards supplementing and validating analysis (Shome et al. 1996).

⁹ Refers to the error arising from making inferences about an individual on the bases of aggregated data (Wang et al. 2021; Smith and Campbell Jr. 1978; Gupta 1971).

1.5. Significance of the study

Being an economy that is susceptible to the adverse impacts of rapid climate change (BEH 2023; Bollettino et al. 2020; Jha et al. 2018), this study augments understanding on the climate-macroeconomy nexus by discussing the impacts of climate-related variables on fiscal health on two fronts: (1) knowledge perspective and (2) policy perspective.

From a knowledge perspective, this study will contribute to scholarly literature on economy-specific discourse on the effects of rapid climate change on fiscal health, particularly for the Philippines. While there have been studies on such topic, most focused on the real economy (Cevik and Jalles 2023; Mukherjee and Ouattara 2021; Kahn et al. 2021) and fiscal policy using global data (Fuje et al. 2023). Of equal importance, through this study, we also contribute to existing Philippine literature on the effects of rapid climate change on the macroeconomy, building on the work done by Tanay et al. (2023), Domingo and Manejar (2023), Suh and Pomeroy (2020), Bayudan-Dacuycuy and Baje (2019), Abrigo and Brucal (2019), Stromberg et al. (2011), and Lu and Herbosa (2011).

From a policy perspective, salient findings derived from the empirical analysis allow for policy implications. Through this study, we can provide policymakers basis on determining how to build, utilize, and maximize public funds in preparing for, recovering from climate-related phenomena, and creating a climate-resilient economy. Likewise, we can also provide recommendations on how development strategies that are affected by rapid climate change be recalibrated to ensure fiscal viability, resiliency, and sustainability. Policy may also call for greater support for disaster preparedness and climate change adaptation so the Philippines, as well as other less developed economies, to confront rapid climate change.

Outcomes will benefit not only the government but also the private sector, households, and individuals as they can better navigate the political, social, environmental, and economic systems we all depend on. Similarly, this will also benefit the academe and the research community in continuing the pursuit for greater understanding of how rapid climate change not only affects the natural environment but also the macroeconomy. Validation of earlier results and generation of new knowledge build the credibility of the basis of policy. This will in turn generate confidence in crafting policies and interventions.

2. Literature review

Scholarly research on global warming and rapid climate change has been existent as early as the 1930s (Weart 2008). Over the years, concerns about the said issue escalated due to this externality's unprecedentedly large, complex, and uncertain impact (Tol 2009). In fact, according to Poushter et al. (2022), 75 percent of respondents in a global survey deemed rapid climate change as a major threat to their economy. Meanwhile, in a report by the Social Weather Stations [SWS] (2024), 87 percent of Filipino adults agreed that they have personally experienced the impacts of climate change in recent years. This is due to the increasingly evident effects, which extend beyond direct impacts like rising temperatures and affect various economic sectors (Rocha et al. 2022; Lindwall 2022). Hence, it is imperative to explicate the work scholars have done in relation to the economic impacts of rapid climate change. In the context of our study, we review scholarly literature on the climate's impact on the fiscal sector.

2.1. Macroeconomic impacts of rapid climate change

Scholarly literature argues that the impacts of several types of climate shocks on economic growth and fiscal health are not yet fully explored and understood. To shed light on this research agenda, we begin with the study of Tol (2009) underscoring that the impact of climate change over a century is comparable to economic growth over a few years with impacts encompassing “the indirect effects of climate change on economic development; large-scale biodiversity loss; low-probability, high-impact scenarios; the impact of climate change on violent conflict; and the impacts of climate change beyond 2100” (p. 29).

Following the discourse, Auffhammer (2019), focusing on Asia, provided an overview of how economists think about climate change impacts. By emphasizing on the concept of social cost of carbon, a mapping from physical climate impacts to economic damages (i.e., damage function) is obtained. This is supported by a mapping of weather/climate into GDP growth rates and a discussion of mitigation measures, both physical and economic, and policy challenges.

Meanwhile, Kahn et al. (2021) probed the larger-scale economic effects of climate change. They determined that the variable deviations of temperatures from historical norms had a negative effect on per-capita economic growth; and precipitation had no significant impact on per-capita economic growth. Moreover, Mukherjee and Ouattara (2021) found that the variable temperature shocks had an upward pressure on prices.

On the other hand, the study of Breckenfelder et al. (2023) drew on economic research to identify some key medium- and long-run economic implications of climate change to explore implications for growth, innovation, inflation, financial markets, fiscal policy, and several socio-economic outcomes for economies in the European Union (EU). Results revealed that climate change results to income divergence across individuals, sectors, and regions; adjustment in energy markets; greater inflation variability; financial markets stress; increased innovation; amplified migration; and expanding public debt.

In continuing the discourse from Auffhammer (2019), Bilal and Känzig (2024) estimated the macroeconomic damages of rapid climate change using damage functions in a neoclassical growth model. They found that these damages are six times larger than previously thought and that a 1°C rise in global temperature contracts world Gross Domestic Product (GDP) by 12 percent with business-as-usual warming results to a 29 percent present welfare loss and a social cost of carbon of USD 1,065 per ton. Similarly, Felbermayr et al. (2022) found that storms, excessive precipitation, and cold spells indeed reduce the growth of economic activity visibly in the emission of night light at the local level. These negative effects do not tend to last long and generally cause positive spillovers in neighboring areas.

2.2. Fiscal impacts of rapid climate change

From the macroeconomic impacts of rapid climate change, we focus on fiscal impacts. We begin with the study of Barrage (2020) who probed on the fiscal consequences of rapid climate change. Results found that it affects “the cost of existing government services (e.g., disaster assistance) and the need for publicly provided anticipatory adaptation (e.g., sea walls)” (p. 107). From a dynamic general equilibrium climate-economy model with distortionary taxation and government expenditures, accounting for fiscal impacts can expand welfare benefits of efficient climate policy by up to 30 percent. Business-as-usual climate change requires increases in income tax rates and raises the marginal cost of growing public funds.

Similarly, Gagliardi et al. (2022) assessed fiscal risks from climate change by analyzing the fiscal implications of acute physical risks from climate change through stylized stress tests for selected EU member economies. Their results revealed that extreme weather and climate events pose risks to debt sustainability thus necessitating large-scale, rapid, and immediate climate mitigation and adaptation measures to suppress the inauspicious economic and fiscal effects of potentially more frequent extreme weather events, thus dampening economic exposure, vulnerability, and debt sustainability risks (Gagliardi et al. (2022)).

Meanwhile, Fuje et al. (2023) probed this issue driven by the increasing frequency of climate-induced disasters that disproportionately disrupt and damage economies, particularly those from the emerging markets and developing economies (EMDEs). By analyzing the macro-fiscal implications of three common climate disasters (i.e., droughts, storms, floods) as well as using a combination of macroeconomic data and comprehensive ground and satellite disaster indicators spanning the past thirty years across 164 economies, they found that across EMDEs, drought negatively impacts economic growth and government revenues due to the erosion of tax bases. Consequently, government expenditures do not increase following a drought. Meanwhile EMDEs' economic growth slows down after a storm, but government expenditure increases due to reconstruction and clean-up efforts. In contrast to advanced economies, they experience negligible growth and fiscal consequences from climate-induced shocks.

Complementing these results is from the study of Cevik and Jalles (2023) illustrating how growth and inflation in advanced and developing economies were affected differently by climate shocks, with results riding on income levels, state of the economy, and fiscal space. Edelman (2024) supported this finding by underscoring the impacts of climate change on government finances ranging from direct and immediate (e.g., disaster relief) to indirect and long term (e.g., sovereign creditworthiness) and include everything in between. As a matter of future research agenda, ways that rapid climate change poses risks to public finances requires repeated exploration to generate practical interventions to mitigate such risks.

Lastly, Miao et al. (2023) examined the effects of floods and hurricanes on government finances in the USA through a “novel event study model allowing for heterogeneous treatment effects” (p. 93). Results showed that a flood or hurricane presidential disaster declaration (PDD) reduces tax revenue but raises government spending and intergovernmental revenues. In addition, because hurricanes generate heavier consequences on both revenues and borrowing, results revealed disparate patterns of disaster-induced long-run fiscal impacts in economies with varying socioeconomic conditions. That is, economies with lower incomes or greater social vulnerability tend to experience tax revenue losses and engage in more borrowing after a PDD. Meanwhile, higher-income economies experience increased tax revenues and spending. They also receive more intergovernmental transfers than their poorer counterparts.

2.3. Impacts of rapid climate change in the Philippines

While climate change impacts have been discussed by scholarly literature in the Philippines, it has been discussed on a socio-economic, issue-specific, and sector-specific basis. For instance, Lu and Herbosa (2011) investigated epidemics, diseases, and health emergencies arising from natural disasters. Diarrhea, acute respiratory infection, measles, and malaria were listed as the most common communicable diseases following disasters and emergencies. Moreover, Stromberg et al. (2011) explored the link between climate-related mitigation and adaptation in quantifying the decrease in biofuel feedstock productivity due to climate change. Furthermore,

Bayudan-Dacuycuy and Baje (2019) established that rainfall shocks applied negative pressure on wages and income and subsequently chronic total and chronic food poverty. Lastly, Jha et al. (2018) used synthetic panel data regressions to provide evidence that typhoon-affected households are highly probable to become low income, although disasters can drive economic growth. Moreover, ameliorating household data with municipal fiscal data provided evidence that municipal local government units (MLGUs) in the country helped reduce poverty by allocating more fiscal resources to reinforce local resilience, while at the same time using additional funds from the national government (NG) for recovery and rehabilitation. All underscored the impact of rapid climate change on different fronts.

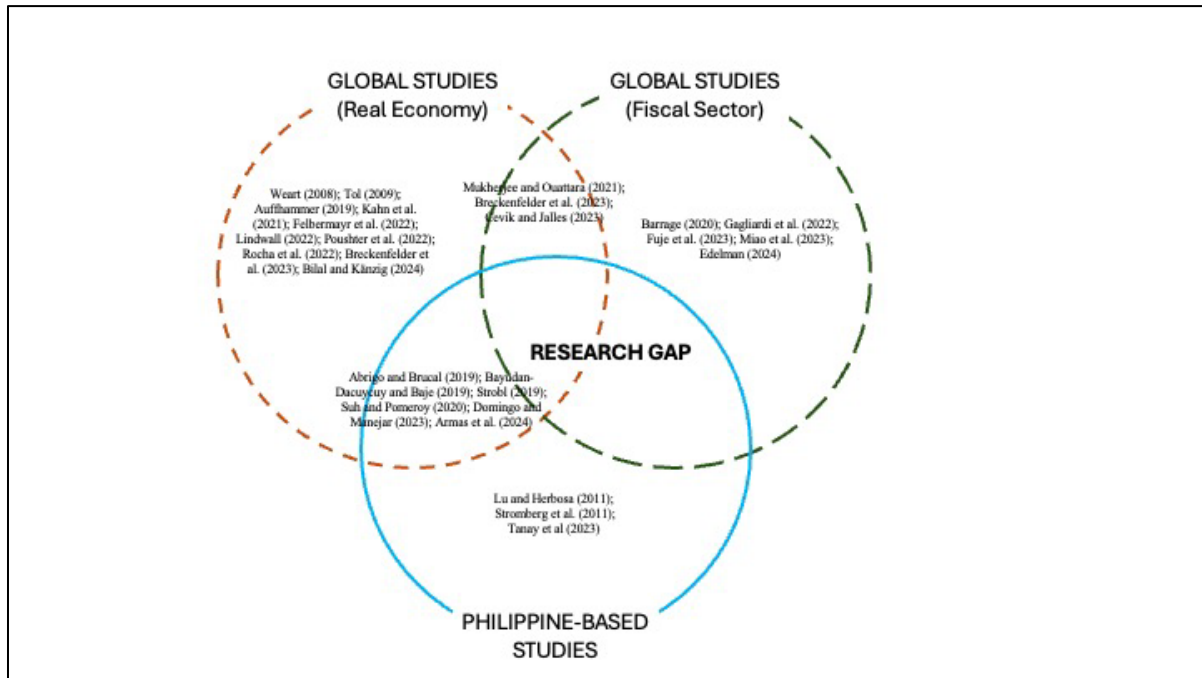
More recent studies such as that of Strobl (2019) found that the onslaught of typhoons have a significant negative, but short-lived impact on local economic activity in the Philippines. Local economic activity is measured by the intensity of light usage at night measured from satellites. Specifically, a key result was that frequent, low-damaging typhoons are likely to reduce local economic activity by around 1 percent, while atypical, but severe typhoons, will result to a reduction of up to nearly 3 percent. Similarly, a typhoon's severity of impacts will differ significantly between regions in the country. In terms of drought, Abrigo and Brucal (2019), using local-level data on public income and expenditures, precipitation, poverty incidence, and satellite-based night-light luminosity, supplemented these findings. They found that the Philippines allocates more national aid and transfers during droughts when damage is significantly higher and that extends to periods of higher-than-usual precipitation. However, they did not find significant relationship between national-to-local aid and local public finance and economic development to temper the adverse effects of extreme weather.

On the other hand, industry-specific studies were done by Suh and Pomeroy (2020) pointing out the negative impact of climate change on fisheries and select economic variables. Meanwhile, Tanay et al (2023) described how natural disasters caused disruptions in the delivery of health services. Domingo and Manejar (2023) meanwhile cited institutional platform and capacity, method application, profess inefficiency, monitoring and evaluation lapses, and poor and inadequate responses as loss and damage accounting issues in the country. Additionally, they pointed out that only direct impacts on infrastructure, property, and human life are often tracked and reported. Indirect consequences like productivity disruptions, intergenerational impacts, and other long-term damages required more attention. Finally, Armas et al. (2024) calculated that a decline in aggregate output by 0.37 percentage point results from a 1°C increase in the annual mean temperature.

2.4. Research gap

We have partially seen, from Figure 5 and Table 1, the state of scholarly literature on the climate-macroeconomy nexus. There is a noteworthy discourse on such topic spanning different EMDEs, advanced economies, regional economies, and the global economy. Scholarly literature has also focused on the real economy more than a specific economic sector. For instance, among others, Fuje et al. (2023) concentrated on the impact on fiscal variables using global data. Cevik and Jalles (2023) investigated the impact on real economy variables using country data. Armas (2024) ran a similar study on the real economy with a more localized context using Philippine regional data. Hence, there remains a scarce literature on the effects of rapid climate change on macroeconomic variables, particularly fiscal variables, in the Philippines as a research locale. We aim to bridge this gap.

Figure 5. Climate-macroeconomic literature map with research gap.



Source: Authors' illustration.

Table 1. Selected climate-macroeconomic literature matrix with methodologies.

Particulars / Author(s)	Kahn et al. (2021)	Abrigo and Brucal (2019)	Mukherjee and Ouattara (2021)	Cevik and Jalles (2023)	Fuje et al. (2023)	Armas et al. (2024)
Research locale	174 economies	Combined municipal- and city-level data	107 economies (80 developing and 27 developed)	173 economies	164 EMDEs and AEs	Philippines (all 17 regions)
Data type	Panel	Panel	Panel	Panel	Panel	Panel
Endogenous variable (Without transformations)	Real GDP per capita	Includes per capita income from local sources, per capita local government expenditure, poverty incidence, number of night-lights	Consumer Price Index (CPI)	CPI, economic growth	Real GDP growth, revenue, expenditure, primary balance	Output growth; other channels of economic activity such as crop production, livestock, fishing, manufacturing, services, real investment, and labor productivity in heat-exposed industries; inflation
Select exogenous variables (Without transformations)	Average temperature and precipitation	Rainfall, aid, internal revenue allotment (IRA), control variables	Temperature, population Real GDP, government	Climate shock (binary), number of deaths	Drought, extreme flood, and extreme storm (binary)	Temperature, occurrence of floods/storms, ENSO events

		spending, money supply	Set of control variables relevant to the dependent variable	Inflation, level of TOT, current account deficit, value added of agriculture as share of GDP, debt-to-GDP ratio, total population, GDP per capita, ODA in USD per capita		
Econometric procedure	Panel ARDL (Fixed effects [FE])	Regression with local projections (LP) and FE	Panel VAR (FE)	Regression with LP	Regression with LP	Regression with LP

Note: ARDL = Autoregressive Distributed Lag, CPI = consumer price index, ENSO = El Nino Southern Oscillation, GDP = growth domestic product, ODA = official development assistance, OLS = Ordinary Least Squares, TOT = terms of trade, USD = United States Dollar, VAR = Vector Autoregression

Source: Authors' compilation; Arranged from earliest to latest.

3. Methodology

In addressing our research question, we implement an econometric multivariate approach. For the earlier, we identify associations in climate and fiscal data using time series data analysis. For the latter, we build models illustrating the link between climate and fiscal factors using national and regional data subjected to both panel data and cross-section data analysis.

Our empirical findings shall then be used to develop guidelines for strategies and policy recommendations on the building, utilization, and maximization of public funds, in the face of climate-related phenomena – from preparation to recovery.

3.1. Data requirements

Our study has two constructs: (1) climate change; and (2) fiscal health. These constructs are represented by variables in Table 2 based on the work of Kahn et al (2019), Cevik and Jalles (2023), Fuje et al (2023), and Armas et al (2024). Secondary data shall be sourced from online sources used by previous studies and other alternative sources such as CEIC, IMF, WB, ADB, among others. Data collected will be converted to quarterly and annual formats spanning 2000 to 2023, where necessary and possible.

Table 2. Data availability mapping and variable description.

	Variable	Unit of measure	Initial Frequency	Periods available	Source	Availability	Basis	Can be used for	
								National models	Regional models
Climate	Storm	Occurrence	N/A	2000-2023	EM-DAT	Open access	Fuje et al. (2023); Cevik and Jalles (2023); Armas et al. (2024)	✓	✓
	Drought	Occurrence	N/A	2000-2023	EM-DAT	Open access	Fuje et al. (2023); Cevik and Jalles (2023);	✓	✓

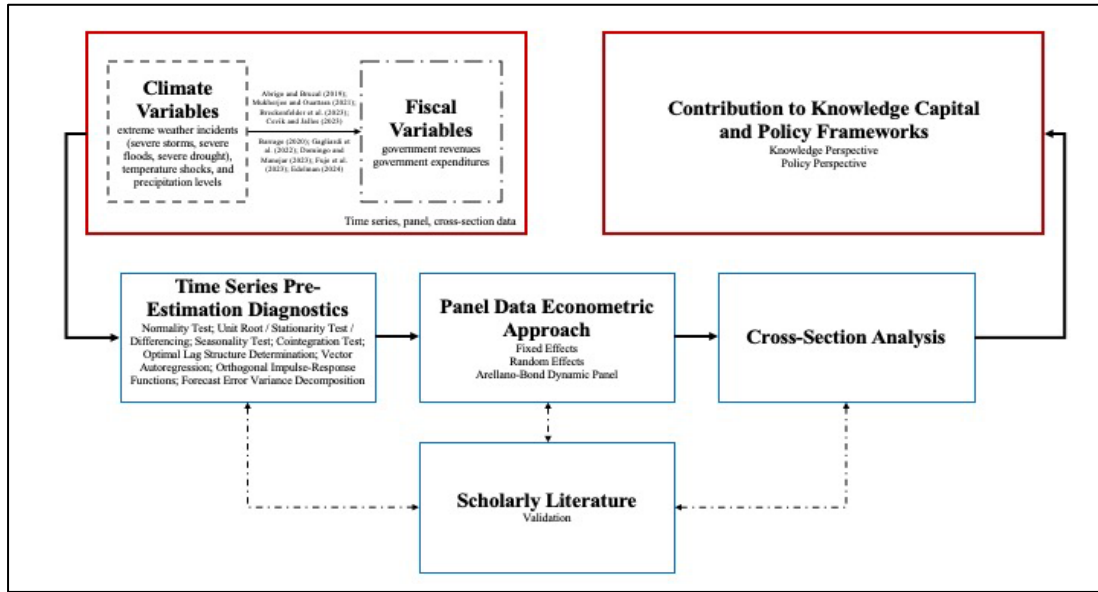
	Total deaths	Person	N/A	2000-2023	EM-DAT	Open access	Armas et al. (2024) Fuje et al. (2023); Cevik and Jalles (2023); Armas et al. (2024)	✓	✓
	Number affected	Person	N/A	2000-2023	EM-DAT	Open access	Fuje et al. (2023)	✓	✓
	Dates covered	Days	N/A	2000-2023	EM-DAT	Open access	Fuje et al. (2023); Cevik and Jalles (2023)	✓	✓
	Temperature	Celsius	Monthly averages	2000-2023	PAGASA	Requested	Armas et al. (2024)	✓	✓
	Precipitation	Amount in ml or inches	Monthly averages	2000-2023	PAGASA	Requested	Kahn et al. (2019)	✓	✓
Fiscal	Fiscal revenue	In million PHP	Monthly, quarterly	1985-2024, 2009-2024	BTr, BLGF	CEIC Data, DOF websites	Fuje et al. (2023)	✓	✓
	Public expenditure	In million PHP	Monthly, quarterly	1985-2024, 2009-2024	BTr, DBM, BLGF	CEIC Data, DOF websites	Fuje et al. (2023)	✓	✓
	Nominal GDP	In million PHP	Quarterly	1981-2024	PSA	CEIC Data	Fuje et al. (2023)	✓	✓
	CPI	2018=100	Monthly	1957-2024	PSA	CEIC Data	-	✓	✓
	Headline inflation	%	Monthly	1957-2024	PSA	CEIC Data	Fuje et al. (2023)	✓	✓
	TOT	%	Quarterly	2000-2024	PSA	CEIC Data	Fuje et al. (2023)	✓	
	Current account deficit	In million USD	Monthly	2005-2024	BSP	CEIC Data	Fuje et al. (2023)	✓	
	Gross Value Added (GVA) (Agriculture)	In million PHP	Quarterly	1981-2024	PSA	CEIC Data	Fuje et al. (2023)	✓	
	Debt-to-GDP ratio	%	Quarterly	1993-2024	BTr	CEIC Data	Fuje et al. (2023)	✓	
	Total population	Person	Annual	1960-2024	PSA	CEIC Data	Fuje et al. (2023)	✓	✓

BLGF = Bureau of Local Government Finance, BTr = Bureau of Treasury, DBM = Department of Budget and Management, EM-DAT = Emergency Events Database, PAGASA = Philippine Atmospheric, Geophysical, and Astronomical Services Administration, sUCAR = University Corporation for Atmospheric Research
Source: Authors' tabulation.

3.2. Empirical strategy

Figure 6 illustrates our empirical approach in estimating the impact of climate-related variables to fiscal health following the findings from our literature review. That is, we would be subjecting data indicated in Table 2 to time series data analysis, panel data analysis, and cross-section data analysis. While most studies tackle this topic at the national level (Botzen et al. 2019), we recognize the presence of aggregation bias as natural disasters such as typhoons and drought do not necessarily affect the entire economy per se. However, it affects the governance and financing dynamics in the entire economy. Hence, we want to empirically show that these assumptions do hold.

Figure 6. Empirical strategy.



Source: Authors' illustration.

3.2.1. National level time series regression model

Since we are using time series data, it is mandatory to perform diagnostics (Rivera and Tullao Jr. 2023, 2022, 2020; Diebold 2007; Enders 2004) such as: establish stationarity and optimal lag structure, among other pre-regression requirements.

Results of pre-regression diagnostics will help determine the appropriate Vector Autoregression (VAR) model specification following the functional relationship indicated by Equations 1.1 to 1.8 whose variable descriptions are indicated in Table 3.

$$\begin{aligned}
 NATGVEX_t &= f(SVDRGHT_t) + \varepsilon_{t1} & 1.1 \\
 NATGVEX_t &= f(SVFLOOD_t) + \varepsilon_{t2} & 1.2 \\
 NATGVEX_t &= f(SVSTORM_t) + \varepsilon_{t3} & 1.3 \\
 NATGVEX_t &= f(PRECIPT_t) + \varepsilon_{t4} & 1.4 \\
 NATGVEX_t &= f(TMPRTRE_t) + \varepsilon_{t5} & 1.5 \\
 SVFLOOD_t &= f(SVSTORM_t) + \varepsilon_{t6} & 1.6 \\
 SVSTORM_t &= f(PRECIPT_t) + \varepsilon_{t7} & 1.7 \\
 PRECIPT_t &= f(TMPRTRE_t) + \varepsilon_{t8} & 1.8
 \end{aligned}$$

The functional forms explaining government revenue are indicated in Equations 2.1 to 2.8.

$$\begin{aligned}
 NATGVRV_t &= f(SVDRGHT_t) + \varepsilon_{t1} & 2.1 \\
 NATGVRV_t &= f(SVFLOOD_t) + \varepsilon_{t2} & 2.2 \\
 NATGVRV_t &= f(SVSTORM_t) + \varepsilon_{t3} & 2.3 \\
 NATGVRV_t &= f(PRECIPT_t) + \varepsilon_{t4} & 2.4 \\
 NATGVRV_t &= f(TMPRTRE_t) + \varepsilon_{t5} & 2.5 \\
 SVFLOOD_t &= f(SVSTORM_t) + \varepsilon_{t6} & 2.6 \\
 SVSTORM_t &= f(PRECIPT_t) + \varepsilon_{t7} & 2.7 \\
 PRECIPT_t &= f(TMPRTRE_t) + \varepsilon_{t8} & 2.8
 \end{aligned}$$

Table 3. Variable description and a-priori expectations (national level).

	Variable	Description (from Table 2)	A-priori	Basis
Endogenous Variables	$NATGVEX_t$	National public expenditure	-	-
	$NATGVRV_t$	National fiscal revenue	-	-
Exogenous Variables	$SVDRGHT_t$	occurrence of severe drought	$+ (NATGVEX_t)$	Gagliardi et al. (2022)
			$0 (NATGVEX_t)$	Fuje et al. (2023)
			$- (NATGVRV_t)$	Gagliardi et al. (2022)
			$+/- (NATPFBL_t)$	Cevik and Jalles (2023); Edelman (2024)
			$+ (NATGVEX_t)$	Fuje et al. (2023)
	$SVFLOOD_t$	occurrence of severe flood	$- (NATGVRV_t)$	Gagliardi et al. (2022)
			$+/- (NATPFBL_t)$	Cevik and Jalles (2023); Edelman (2024)
			$+ (NATGVEX_t)$	Fuje et al. (2023)
	$SVSTORM_t$	occurrence of severe storm	$- (NATGVRV_t)$	Gagliardi et al. (2022)
			$+/- (NATPFBL_t)$	Cevik and Jalles (2023); Edelman (2024)

Source: Tabulated by the authors.

After estimating the VAR(p) model corresponding the abovementioned equations, the resulting orthogonal impulse response functions (OIRFs) and Forecast Error Variance Decompositions (FEVDs) were estimated to deepen analysis. We follow the empirical and analytical procedures implemented by Rivera and Tullao Jr. (2023, 2022, 2020).

3.2.2. Regional level panel data regression model

In estimating the impact of climate variables on fiscal variables at the regional level, we designate the fiscal variables: actual expenditures, based on figures from national data, and government final consumption expenditure (GFCE)¹⁰ as endogenous variables with climate variables: mean temperature, mean rainfall, occurrence of severe storms, and occurrence of droughts as exogenous variables.

Following Gujarati and Porter (2009) and the approach taken by Mendoza and Rivera (2017) and Rivera and See (2011), running regressions on panel data gives rise to concerns about unobserved effects (c_i), unmeasured effects that influence the dependent variables but are not directly observed. When these effects are correlated with identified independent variables, the model can be estimated using a fixed effects approach. Such an approach would control time-invariant individual-specific factors. On the other hand, when these effects are uncorrelated with the independent variables, a random effects approach would be more appropriate. This assumes that the unobserved effects are randomly distributed across individuals (Wooldridge 2001). Arellano-Bond linear dynamic models were also estimated for comparison.

To ensure data stationarity, Levin-Lin-Chu and Harris-Tzavalis tests were conducted (Levin et al. 2002; Harris and Tzavalis 1999). Subsequently, fixed and random effects models were estimated for both expenditure and GFCE, with the Hausman test determining the more appropriate model (Baltagi 2024). Additional explanatory variables were incorporated into the random effects models to enhance their explanatory power.

¹⁰ GFCE is defined by the PSA as "expenditures on consumption of goods and services incurred by general government either on collective services or on selected individual goods or services" (<https://openstat.psa.gov.ph/Metadata/2B5BRECE2>)

The functional forms explaining expenditures are indicated in Equations 3.1 to 3.12 whose variable descriptions are indicated in Table 4.

$$\begin{aligned}
REGGVEX_{it} &= f(TMPRTRE_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 3.1 \\
\Delta REGGVEX_{it} &= f(\Delta TMPRTRE_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 3.2 \\
\Delta^2 REGGVEX_{it} &= f(\Delta^2 TMPRTRE_{it}, c_{it}, \varepsilon_{it}) & 3.3 \\
REGGVEX_{it} &= f(PRECIPT_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 3.4 \\
\Delta REGGVEX_{it} &= f(\Delta PRECIPT_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 3.5 \\
\Delta^2 REGGVEX_{it} &= f(\Delta^2 PRECIPT_{it}, c_{it}, \varepsilon_{it}) & 3.6 \\
REGGVEX_{it} &= f(SVSTORM_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 3.7 \\
\Delta REGGVEX_{it} &= f(\Delta SVSTORM_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 3.8 \\
\Delta^2 REGGVEX_{it} &= f(\Delta^2 SVSTORM_{it}, c_{it}, \varepsilon_{it}) & 3.9 \\
REGGVEX_{it} &= f(SVDRGHT_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 3.10 \\
\Delta REGGVEX_{it} &= f(\Delta SVSTORM_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 3.11 \\
\Delta^2 REGGVEX_{it} &= f(\Delta^2 SVSTORM_{it}, c_{it}, \varepsilon_{it}) & 3.12
\end{aligned}$$

The functional forms explaining GFCE are indicated in Equations 4.1 to 4.12.

$$\begin{aligned}
REGGVGFCE_{it} &= f(TMPRTRE_{it}, c_{it}, \varepsilon_{it}) & 4.1 \\
\Delta REGGVGFCE_{it} &= f(\Delta TMPRTRE_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 4.2 \\
\Delta^2 REGGVGFCE_{it} &= f(\Delta^2 TMPRTRE_{it}, c_{it}, \varepsilon_{it}) & 4.3 \\
REGGVGFCE_{it} &= f(PRECIPT_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 4.4 \\
\Delta REGGVGFCE_{it} &= f(\Delta PRECIPT_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 4.5 \\
\Delta^2 REGGVGFCE_{it} &= f(\Delta^2 PRECIPT_{it}, c_{it}, \varepsilon_{it}) & 4.6 \\
REGGVGFCE_{it} &= f(SVSTORM_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 4.7 \\
\Delta REGGVGFCE_{it} &= f(\Delta SVSTORM_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 4.8 \\
\Delta^2 REGGVGFCE_{it} &= f(\Delta^2 SVSTORM_{it}, c_{it}, \varepsilon_{it}) & 4.9 \\
REGGVGFCE_{it} &= f(SVDRGHT_{it}, RGDP_{it}, CPI_{it}, c_{it}, \varepsilon_{it}) & 4.10 \\
\Delta REGGVGFCE_{it} &= f(\Delta SVSTORM_{it}, \Delta RGDP_{it}, \Delta CPI_{it}, c_{it}, \varepsilon_{it}) & 4.11 \\
\Delta^2 REGGVGFCE_{it} &= f(\Delta^2 SVSTORM_{it}, c_{it}, \varepsilon_{it}) & 4.12
\end{aligned}$$

Table 4. Variable description and a-priori expectations (regional level).

	Variable	Description (from Table 2)	A-priori	Basis
Endogenous Variables	$REGGVEX_t$	Regional public expenditure	-	-
	$REGGVGFCE_t$	Regional fiscal revenue	-	-
Exogenous Variables	$TMPRTRE$	mean temperature	$\frac{+ (REGGVEX_t)}{+ (REGGVGFCE_t)}$	Gagliardi et al. (2022), Fuje et al. (2023)
	$PRECIPT$	mean rainfall	$\frac{+ (REGGVEX_t)}{+ (REGGVGFCE_t)}$	
	$SVSTORM_t$	occurrence of severe storm	$\frac{+ (REGGVEX_t)}{+ (REGGVGFCE_t)}$	
	$SVDRGHT_t$	occurrence of severe drought	$\frac{+ (REGGVEX_t)}{+ (REGGVGFCE_t)}$	

Source: Tabulated by the authors.

Note that the above panel data equations have been stated following Wooldridge (2001) wherein a more general notation is used. The unobserved effect, c , and stochastic disturbance

term, ε , are included in the general function. Note further that our model specification took one climate-related variable at a time instead of grouping them in one functional form due to the perceived presence of severe multicollinearity (e.g., temperature explains precipitation, precipitation explains severe flood, severe storm explains severe floods) and simultaneity bias (e.g., precipitation and temperature have feedback effects, severe storm and precipitation have feedback effects). Note that temperature influences precipitation (Irwindi et al. 2023; Trenberth 2011); precipitation can explain severe storms (Sousounis and Little 2017); and severe storms create severe floods (Williams et al. 2020).

2.2.3. LGU level cross-sectional regression model

In estimating the impact of the severity of a storm on fiscal variables, the total expenditure and total revenues of the LGUs in the affected regions during the i^{th} storm were assigned to be the explained variables, while total damage, severe storm, and mean temperature in the i^{th} storm were included as explanatory variables. This modelling also employed a multi-stage regression procedure, in which the predicted values in the prior econometric model were taken as the regressor variable in the next. The functional forms explaining regional local expenditure are indicated in Equations 5.1 to 5.3 below.

$$SVSTORM_i = f(TMPRTRE_i) + \varepsilon_{i1} \quad 5.1$$

$$DAMAGES_i = f(SVSTORM_i) + \varepsilon_{i2} \quad 5.2$$

$$REGGVEX_i = f(DAMAGES_i) + \varepsilon_{i3} \quad 5.3$$

The functional forms explaining regional local revenue are indicated in Equations 6.1 to 6.3 below.

$$SVSTORM_i = f(TMPRTRE_i) + \varepsilon_{i1} \quad 6.1$$

$$DAMAGES_i = f(SVSTORM_i) + \varepsilon_{i2} \quad 6.2$$

$$REGGVRV_i = f(DAMAGES_i) + \varepsilon_{i3} \quad 6.3$$

Following Irwindi et al. (2023), Williams et al. (2020), Sousounis and Little (2017), and Trenberth (2011), the set of models above are specified in such a way that severe storm is a function of mean temperature. Total damage can be explained by storm severity. Finally, the fiscal variables are a function of total damages.

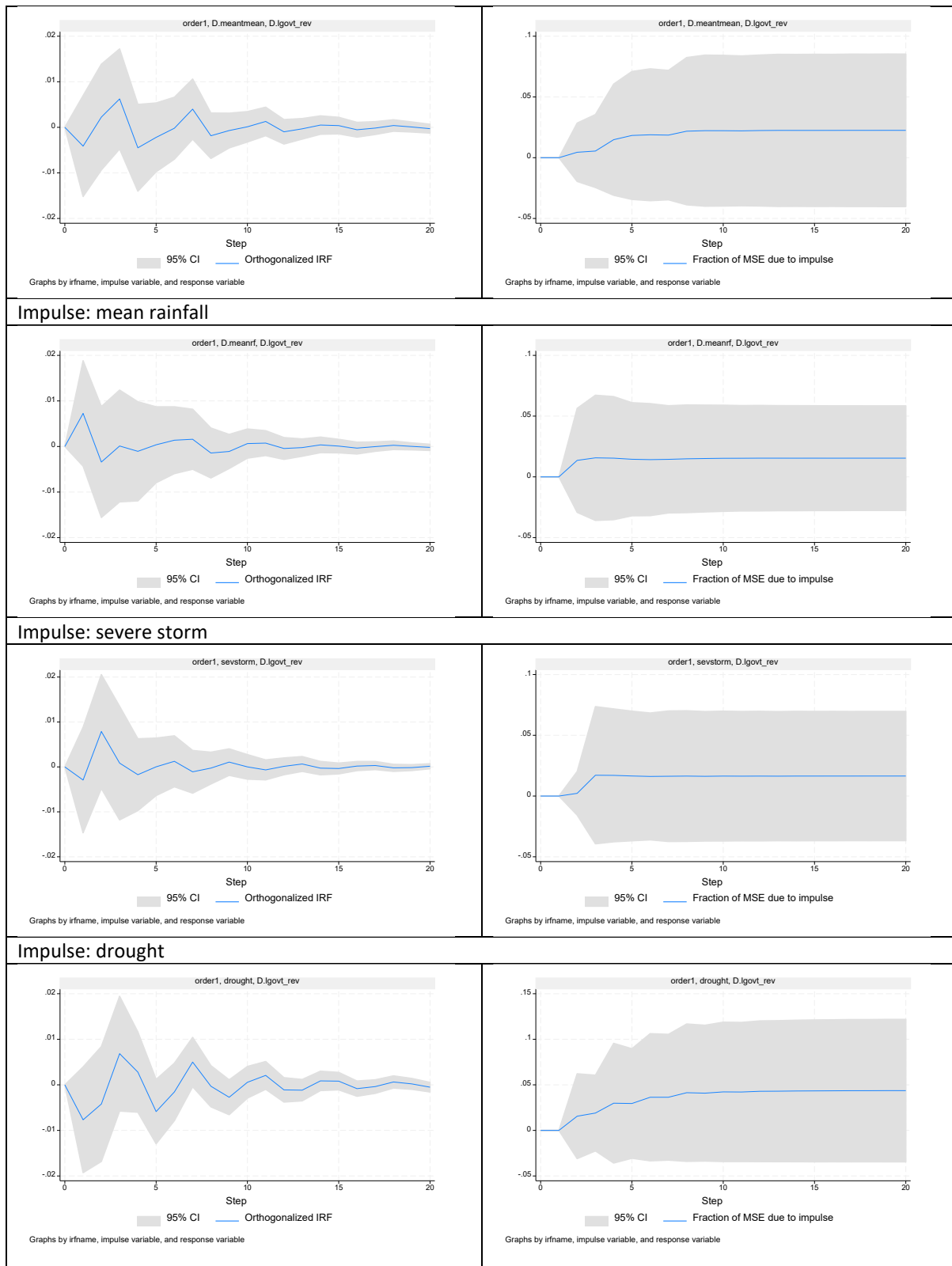
4. Results and discussion

4.1. National level time series regression model

We only report the resulting OIRFs and FEVDs after estimating the VAR(p) model included in Appendix 1. Overall, the estimates of the VAR(p) model indicate statistically significant impacts of climate-related variables on government revenues. While such is contrary to a-priori expectations and findings from scholarly literature, such results may be due to the aggregation of data that confounds the existence of statistical relationship, which might be seen at a granular, disaggregated, and localized context. However, the accompanying OIRFs and FEVDs may give us valuable information on the economy's ability to absorb shocks from climate-related variables and how such variations are transmitted throughout the economy.

Figure 7. OIRF and FEVD of total revenue.

Impulse: mean temperature



Note: Left panels show the OIRF while those on the right panels are the FEVD

Source: Authors' illustration

Hence, we underscore our findings of the post-estimation results from our VAR(p) model. Figure 7 illustrates the OIRF and FEVD with total revenue as response variable and climate

variables are impulse. Meanwhile, Figure 8 illustrates the OIRF and FEVD with total expenditures as response variable and climate variables are impulse

Following the analysis of Rivera and Tullao Jr. (2023, 2022, 2020), we can see from Figure 7 (left panel) the OIRFs illustrating the response of government revenues to temperature, rainfall, severe storm, and drought. A positive shock to government revenues from all climate-related variables at $t = 0$ is absorbed after at least 10 quarters until such reaction dissipates, and government revenues stabilizes. This indicates that climate-related variables create a short- to medium-run shock to government revenues that dissolves in about 2.5 years. That is, holding other factors constant, the impact of movements in climate-related variables on government revenues this quarter will soften approximately in the next 2.5 years.

On the other hand, in Figure 7 (right panel), the FEVDs show that variations (movements) in government revenues caused by climate-related variables start at around $t = 1$ with a positively and almost negligible percentage variation (<0.01 per cent) and will continue to increase until approximately $t = 2$ to $t = 4$ and then stabilize afterwards. However, notice that the variations trace an almost flat line. This illustrates the leisurely response of government revenues to shocks arising from climate-related variables. That is, variations to government revenues caused by climate-related variables are seemingly slow. This may explain why the economy takes time before it can absorb climate-related shocks.

Meanwhile, we can see from Figure 8 (left panel) the OIRFs illustrating the response of government expenditures to temperature, rainfall, severe storms, and drought. A positive shock to government expenditures from all climate-related variables at $t = 0$ is absorbed after at least 12 quarters until such reaction dissipates, and government expenditures stabilize. This indicates that climate-related variables create a short- to medium-run shock to government expenditures that dissolves in about three years. That is, holding other factors constant, the impact of movements in climate-related variables on government expenditures this quarter will soften approximately in the next three years.

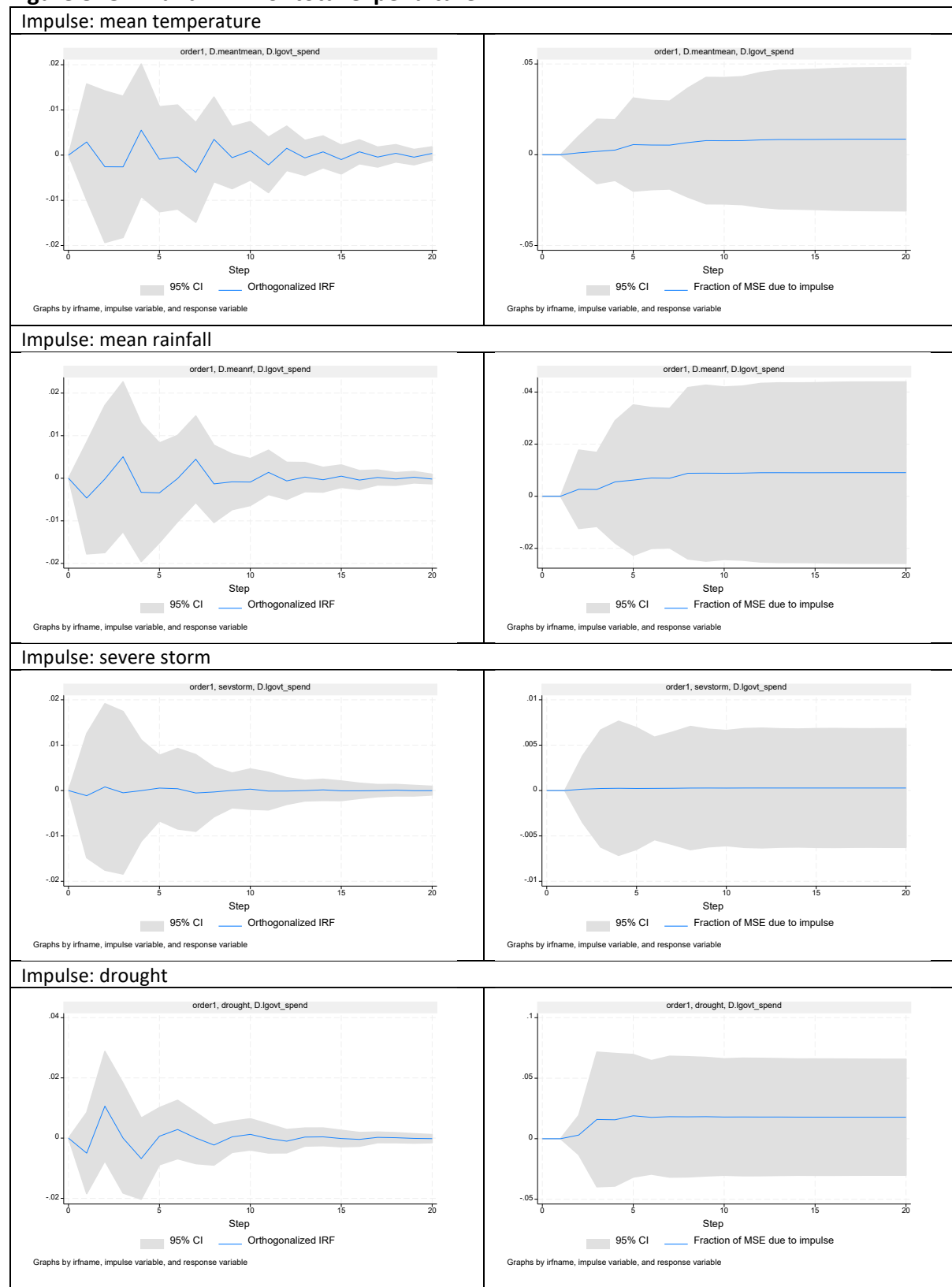
On the other hand, in Figure 8 (right panel), the FEVDs show that variations (movements) in government expenditures caused by climate-related variables start at around $t = 1$ with a positively and almost negligible percentage variation (<0.01 per cent) and will continue to increase until approximately $t = 2$ and then stabilize afterwards. However, notice that the variations trace an almost flat line. This illustrates the leisurely response of government expenditures to shocks arising from climate-related variables. That is, variations to government expenditures caused by climate-related variables are seemingly slow. Like government revenues, this may also explain why the economy takes time before it can absorb climate-related shocks. That is, given climate-related disruption, government expenditures take more time to normalize than government revenues.

Note that the OIRFs and FEVDs are interpreted aggregated and may not reflect the narrative at a localized context. Should localized and disaggregated data be available, the same analytical approach can be done to probe on the length of absorption time and depth of variation.

However, such results paint a picture of how the economy responds to impulses emanating from the movement of climate-change variables – while the economy can absorb shocks emanating from changes in temperature, rainfall, storms, and droughts, the damages and disruptions caused by changes in climate change variables linger in the economy for quite a

long time even if the calamity is over. That is, the long-lasting damages and disruptions from these calamities persist due to the following structural, economic, and social factors.

Figure 8. OIRF and FEVD of total expenditure.



First, the Philippines is an agricultural economy that is highly sensitive to temperature changes, erratic rainfall, and droughts. Rapid climate change disrupts planting and harvest cycles, depletes stocks, and damages agricultural infrastructure resulting to prolonged recovery for farmers. Droughts and floods reduce productivity in subsequent seasons, compounding income losses and creating a cascading effect on food security and inflation. Moreover, frequent typhoons and environmental degradation discourage tourism in vulnerable areas, particularly during peak seasons, reducing revenues and livelihood opportunities.

Second, the Philippines lack infrastructure designed to withstand climate shocks, such as resilient road networks, flood-control systems, and climate-proof public buildings. Damage to critical infrastructure (i.e., transportation, energy, communication) disrupts supply chains, economic activities, and public services. Also, post-disaster reconstruction and rehabilitation are hampered by bureaucratic inefficiencies prolonging economic disruptions.

Third, calamities displace households, particularly in coastal and low-lying areas, leading to unemployment and income losses. The slow pace of resettlement and rehabilitation worsens economic vulnerabilities. Businesses in disaster-prone areas forced to close permanently or operate at reduced capacity due to destroyed assets and/or disrupted supply chains. Hence, households and businesses resort to borrowing to recover from losses, leading to long-term debt burdens that reduce future investments and consumption.

Fourth, a significant portion of the Philippine population lives below or near the poverty line, making them highly susceptible to climate shocks (Albert et al. 2024). Post-disaster recovery is challenging for them due to limited savings and insurance coverage. Vulnerable groups (e.g., women, children, indigenous communities) bear the brunt of climate-related disruptions, exacerbating inequalities. Similarly, disasters disrupt classes, with school facilities serving as evacuation centers or also suffering physical damage. These result to learning losses impacting future productivity. Prolonged health impacts, such as malnutrition, waterborne diseases, and heat-related illnesses, strain public health systems and reduce labor force productivity.

Fifth, the Philippine government often reallocates funds from planned projects to disaster response and recovery, delaying economic development and infrastructure investments. Rising public debt from disaster-related borrowing constrains fiscal space for future climate adaptation and mitigation programs. Also, despite strong legal frameworks like Republic Act (RA) 9729 (Climate Change Act) and RA 10121 (Philippine Disaster Risk Reduction and Management Act), implementation is inconsistent due to capacity limitations and governance issues.

Finally, unsustainable practices like illegal logging, mining, and overfishing worsen the impacts of climate shocks, compromising the environment's ability to recover. For example, mangrove deforestation amplifies storm surge impacts. Degraded watersheds worsen flooding and drought conditions. Rapid urbanization without adequate planning leads to increased vulnerability in cities evidenced by flooding in NCR.

4.2. Regional level panel data regression model

Table 5 presents the panel data estimation results using regional data. Table 5.1 is for mean temperature, Table 5.2 for mean rainfall, Table 5.3 for severe storm, and Table 5.4 for drought as exogenous variables with government expenditure and GFCE as endogenous variables.

Table 5. 1. Panel data model with mean temperature as exogenous variable.

Y_{it}	Model type	Stationarity	X_{it}	Coefficients	p
Expenditure	Fixed/Random Effects Regression	Level – Random R ² : 0.8360	Mean temperature	5.513103	0.575
			Regional GDP	0.0001328	0.000
			CPI	1.919779	0.007
		1 st Difference – Random R ² : 0.0060	Mean temperature	8.779038	0.731
			Regional GDP	0.0000194	0.689
			CPI	1.479005	0.709
	Arellano Bond	2 nd Difference – Fixed R ² : 0.0063	Mean temperature	18.6386	0.511
			Regional GDP	-	-
			CPI	-	-
		Level	Expenditure (1 lag)	0.3584802	0.000
			Mean temperature	23.70352	0.470
			Regional GDP	-0.0000343	0.407
GFCE	Fixed/Random Effects Regression	Level – Fixed R ² : 0.0285	Mean temperature	95.69058	0.000
			Regional GDP	-	-
			CPI	-	-
		1 st Difference – Random R ² : 0.2873	Mean temperature	2.113717	0.299
			Regional GDP	0.0000568	0.000
			CPI	-0.0874349	0.820
	Arellano Bond	2 nd Difference – Fixed R ² : 0.0295s	Mean temperature	3.213189	0.001
			Regional GDP	-	-
			CPI	-	-
		Level	GFCE (1 lag)	1.029233	0.000
			Mean temperature	1.521029	0.321
			Regional GDP	0.0000114	0.000
			CPI	-0.0433699	0.117

Source: Tabulated by the authors.

From Table 5.1, all iterations for mean temperature revealed a direct variation on government expenditures and GFCE consistent with Gagliardi et al. (2022) and Fuge et al. (2023) who provided evidence of a strong relationship between climate-related factors and specific categories of government spending. That is, the higher the temperature, the higher the GFCE. However, it was found to have a statistically significant impact on GFCE only suggesting that temperature variations are likely to impact specific types of government spending more directly than aggregate expenses. This can be explained by the following reasons.

First, public services and adaptation costs have a direct link. Higher temperatures may require increased spending on public goods and services like healthcare (e.g., addressing heat-related illnesses), disaster management, and infrastructure adaptation to cope with heat-related impacts. Likewise, NG may incur higher costs for energy (e.g., cooling public buildings) or water management systems directly affecting GFCE. As per PSA, since GFCE measures

government consumption expenditures on goods and services (excluding investments), the observed relationship reflects immediate and recurrent costs tied to climate adaptation.

Second, temperature may have limited influence on broader expenditures. Other forms of government expenditures (e.g., capital expenditures or transfers) may not be as sensitive to temperature changes, as they are typically driven by long-term policy priorities or investment projects that may not directly respond to short-term temperature fluctuations. Moreover, broader government spending might take longer to adjust to temperature-driven needs due to budgeting cycles or political processes, limiting statistical significance in aggregate measures.

Third, GFCE reflects the immediate operational budget for running public services and government operations. This category of spending is likely more responsive to temperature increases compared to broader fiscal measures, which might include investment or subsidies that are less directly tied to temperature variations.

Statistically, the insignificance of results may be traced to measurement sensitivity. GFCE data may be more granular and sensitive to temperature variations compared to aggregated measures of government expenditures. This could make GFCE more likely to show statistically significant results. Likewise, the specific allocation of GFCE may include areas highly affected by temperature (e.g., emergency response, healthcare), leading to significant statistical results, whereas broader government spending might dilute this effect.

Table 5. 2. Panel data model with mean rainfall as exogenous variable.

Y_{it}	Model type	Stationarity	X_{it}	Coefficients	p
Expenditure	Fixed/Random Effects Regression	Level – Random R^2 : 0.8367	Mean rainfall	-.0083297	0.951
			Regional GDP	.0001341	0.000
			CPI	1.941525	0.007
		1 st Difference – Random R^2 : 0.0048	Mean rainfall	.0060273	0.957
			Regional GDP	.0000184	0.705
			CPI	1.625416	0.680
	Arellano Bond	2 nd Difference – Fixed R^2 : 0.0012	Mean rainfall	-.0349574	0.767
			Regional GDP	-	-
			CPI	-	-
		Level	Expenditure (1 lag)	0.3485704	0.001
			Mean rainfall	-0.0535865	0.743
			Regional GDP	-0.0000383	0.354
GFCE	Fixed/Random Effects Regression	Level – Random R^2 : 0.8706	CPI	3.223107	0.013
			Mean rainfall	-0.0122991	0.751
			Regional GDP	0.0001719	0.000
		1 st Difference – Random R^2 : 0.2880s	CPI	-0.3203205	0.002
			Mean rainfall	0.0055277	0.598
			Regional GDP	0.0000577	0.000
	Arellano Bond	2 nd Difference – Fixed R^2 : 0.0027s	CPI	-0.1683759	0.663
			Mean rainfall	-0.0050213	0.322
			Regional GDP	-	-
		Level	CPI	-	-
			GFCE (1 lag)	1.028814s	0.000
			Mean rainfall	-0.003957	0.656
			Regional GDP	0.0000116	0.000
			CPI	-0s.0343366	0.198

Source: Tabulated by the authors.

From Table 5.2, mean rainfall was statistically insignificant in influencing government expenditure and GFCE in any of the eight iterations, which is counterintuitive with Gagliardi et al. (2022) and Fuje et al. (2023). However, several models showed negative impact of rainfall on both expenditure and GFCE, suggesting that as rainfall increases, spending decreases. This can be explained by the following reasons.

First, rainfall has indirect and varied effects (i.e., localized, sector-specific impacts). Unlike temperature, which can broadly and consistently impact sectors like health and energy, rainfall's effects are more localized and sector-specific, such as in agriculture or flood-prone areas. This variability dilutes the measurable impact on aggregate spending like GFCE. The insignificance can also be ascribed to the fact that rainfall can have both beneficial (e.g., boosting agricultural output) and detrimental (e.g., flooding) effects. These mixed impacts might offset each other in the aggregated data resulting to statistical insignificance.

Second, excessive or insufficient rainfall may lead to infrastructure investments or disaster recovery spending. However, these are usually part of capital expenditures than GFCE. The immediate operational spending reflected in GFCE does not capture these delayed or one-time expenses. Also, NG may already have mechanisms in place to adjust spending based on seasonal rainfall patterns, minimizing the observable impact in annual or quarterly data.

Third, rainfall may reduce the need for certain expenditures such as in regions where rainfall enhances agricultural productivity. That is, NG may spend less on subsidies, disaster relief, or food assistance programs, particularly if rainfall is within normal or favorable ranges. Also, increased rainfall may reduce demand for cooling energy resulting to lower operational costs for government facilities. Such can explain the negative coefficients implying a potential cost-saving relationship.

Fourth, in areas with drainage systems and/or irrigation networks, the negative effects of rainfall are mitigated allowing them to reduce spending. Also, areas that have adapted to varying rainfall patterns may experience minimal fiscal disruptions from changes in precipitation rendering its statistically insignificant impact.

Fifth, rainfall-induced expenditures, such as disaster response, might fall under capital spending or transfers, which are not part of GFCE. Governments may prioritize temperature-related expenditures (e.g., heatwaves, energy costs) over rainfall impacts further reducing the observable effect of rainfall on GFCE.

Statistically, we suspect that rainfall data might have more variability reducing its explanatory powers in econometric models. It may also be possible that negative coefficients could reflect coincidental correlations rather than direct causal relationships, especially if other omitted variables (e.g., economic cycles, governance quality) impact spending.

Table 5. 3. Panel data model with severe storm as exogenous variable.

Y_{it}	Model type	Stationarity	X_{it}	Coefficients	p
Expenditure	Fixed/Random Effects Regression	Level – Random R^2 : 0.8374	Occurrences of severe storms	-19.43197	0.296
			Regional GDP	0.0001347	0.000
		1 st Difference – Random	CPI	2.348629	0.004
			Occurrences of severe storms	-6.506637	0.720

GFCE	Fixed/Random Effects Regression	R ² : 0.0061	Regional GDP	0.0000188	0.699
			CPI	2.04893	0.618
		2 nd Difference – Fixed R ² : 0.0085	Occurrences of severe storms	-23.59914	0.438
			Regional GDP	-	-
		Level – Random R ² : 0.8712	CPI	-	-
			Occurrences of severe storms	1 (1.894095)	1 (0.740)
			Regional GDP	2 (-12.66914)	2 (0.216)
			CPI	0.0001836	0.000
		1 st Difference – Random R ² : 0.1356	CPI	-0.3263863	0.002
			Occurrences of severe storms	1 (-2.698415)	1(0.187)
			Regional GDP	2 (-1.007212)	2 (0.776)
			CPI	0.0000554	0.000
		2 nd Difference – Fixed R ² : 0.0148	CPI	0.0620282	0.877
			Occurrences of severe storms	1 (-3.436289)	1 (0.028)
			Regional GDP	2 (1.837064)	2 (0.520)
			CPI	-	-

Source: Tabulated by the authors.

From Table 5.3, severe storm was statistically insignificant in influencing government expenditure and GFCE. This is counterintuitive with Gagliardi et al. (2022) and Fuje et al. (2023). This can be explained by the following reasons.

First, this may be due to temporal mismatch in data and lagged fiscal response. Severe storms require significant government expenditures on disaster relief, infrastructure repair, and emergency services. However, these expenditures might occur in subsequent periods (e.g., months or years after the storm) rather than immediately, leading to an apparent statistical insignificance in contemporaneous data. While severe storms can slow down economic and spending activities in the short term, the recovery phase might see increased spending, balancing out the aggregate impact over time.

Second, severe storms often result in capital expenditures (e.g., rebuilding infrastructure, constructing flood defenses) rather than GFCE, which primarily captures operational spending on goods and services. Also, a significant portion of storm-related expenditures can be transfer payments (e.g., financial aid to affected populations), which are not under GFCE.

Third, as expected, this may be due to regional and localized impacts. Severe storms typically have concentrated geographic impacts, affecting only specific regions. In national-level data, localized impacts may not appear statistically significant. Meanwhile, with decentralized governance, LGUs may bear storm-related spending, further diluting the impact on government expenditure and GFCE.

Fourth, NG often invest in proactive mitigation measures (e.g., early warning systems, evacuation plans) reducing the need for significant reactive spending after storms. Hence, a reduced or statistically insignificant relationship between storms and spending. Likewise, pre-allocated funds for disaster response may cushion the fiscal impact, making it less observable in aggregate spending data.

Fifth, severe storms disrupt government operations, supply chains, and project timelines, delaying spending activity. However, this slowdown does not necessarily reduce spending. It shifts expenditures to future periods; hence, appearing insignificant in the short-term analysis.

NG may also redirect funds from planned projects to storm-related activities, causing no net change in spending instead a realignment of expenditure not captured in GFCE.

Statistically, other concurrent economic factors (e.g., global economic conditions, unrelated fiscal policies) might overshadow the impact of severe storms, making their effect on government spending appear insignificant.

Table 5. 4. Panel data model with drought as exogenous variable.

Y_{it}	Model type	Stationarity	X_{it}	Coefficients	p
Expenditure	Fixed/Random Effects Regression	Level – Random R^2 : 0.8419	Occurrences of drought	53.39418	0.098
			Regional GDP	.0001356	0.000
			CPI	2.037048	0.004
		1 st Difference – Random R^2 : 0.0987	Occurrences of drought	103.5766	0.001
			Regional GDP	-1.70e-06	0.971
			CPI	4.809033	0.215
		2 nd Difference – Fixed R^2 : 0.0697	Occurrences of drought	131.7304	0.020
			Regional GDP	-	-
			CPI	-	-
		Level – Random R^2 : 0.8706	Occurrences of drought	-2.666059	0.761
			Regional GDP	0.0001714	0.000
			CPI	-0.3096984	0.002
GFCE	Fixed/Random Effects Regression	1 st Difference – Random R^2 : 0.2881	Occurrences of drought	2.018075	0.519
			Regional GDP	0.000063	0.000
			CPI	-0.1854239	0.639
		2 nd Difference – Fixed R^2 : 0.0023	Occurrences of drought	-2.218454	0.362
			Regional GDP	-	-
			CPI	-	-

Source: Tabulated by the authors.

From Table 5.4, droughts posted positive impacts on expenditure and negative coefficients for GFCE. This is also inconsistent with Gagliardi et al. (2022) and Fuje et al. (2023). Like temperature, rainfall, and severe storms, drought also slow down spending activity. This underscored more concentrated impact on actual government spending, with government-owned and controlled corporations (GOCCs), government financial institutions (GFIs), among others. We construed the following reasons.

First, drought impacts both capital spending and operational spending. On one hand, droughts require significant infrastructure investments, such as irrigation systems, water storage facilities, and drought-resilient agricultural projects. These are classified as capital expenditures contributing to the increase in total government expenditure but not GFCE. Also, NG may prioritize long-term mitigation strategies, such as funding renewable energy projects (e.g., solar-powered water pumps) that increase expenditures. On the other hand, operational government activities, reflected in GFCE, may decrease during droughts as government offices, schools, and other public services face operational disruptions and resource limitations.

Second, droughts may shift fiscal response burden from GFCE to quasi-government entities, such as GOCCs and GFIs, which provide funding or infrastructure development. For example, the National Irrigation Administration (NIA) or Land Bank of the Philippines (LBP) may take the lead in addressing drought-related challenges driving expenditures outside GFCE. GFIs may also issue loans or transfer funds to affected sectors (e.g., farmers), which are not captured in GFCE but are part of broader NG expenditure.

Third, drought has a concentrated effect on agriculture, water supply, and rural economies requiring targeted interventions like subsidies for farmers, emergency water distribution, and agricultural insurance payouts. These expenses fall under transfer payments or subsidies instead of GFCE. This results to a negative coefficient for GFCE and a positive one for total expenditure. Meanwhile, NG services not related to drought response may slow down during drought reducing GFCE and increasing total expenditures due to targeted spending elsewhere.

Fourth, operational activities may be deferred during droughts as NG focus on addressing immediate crises (e.g., food or water shortages). Realigning funds can reduce current GFCE levels. As mentioned earlier, droughts often have concentrated geographic impacts, leading to significant localized spending. This may not proportionally increase aggregate operational spending, which is spread across broader categories in GFCE.

Statistically, the positive coefficients for total government expenditure may reflect a reallocation from other areas of spending to drought-related priorities, which do not necessarily show up in GFCE. Droughts can also disrupt government operations, slow down economic activity, and reduce tax revenues prompting austerity measures in operational spending.

4.3. LGU level cross-sectional regression model

Table 6 shows the descriptive statistics of the variables for the cross-sectional analysis. Expenditure refers to the total quarterly spending (total current operating expenditures and non-operating expenditures) of LGUs in the regions affected by the storm i . On the other hand, revenue is the sum of the total current operating income and non-income receipts. Total damage¹¹ is the “value of all economic losses directly or indirectly due to the disaster”. It can be noted that the maximum value of USD 10 billion, according to the data, is Typhoon Haiyan¹². Severe storm¹³ is equal to one if storm i is tagged as a severe storm, based on the formula employed by Fuje et al. (2023); zero otherwise. Mean temperature pertains to the average recorded temperature. Lastly, the regional CPI is the average consumer price index in the affected regions in the quarter when the i^{th} storm occurred. Appendix 2 contains the dataset used while Appendix 3 indicates the Stata commands used for replication purposes.

Exploring the total expenditure of local government units in regional aggregates, the three regions with the highest total spending are NCR, Region IVA (CALABARZON) and Region III (Central Luzon). It should be noted that these are not all for disaster- or calamity-related spending. These include spending on other social services, economic services, debt service (if any), among others. Regardless, variation in spending across these regions may reflect the differences in the demand for public services. It might also provide an idea as to the varying costs of implementing the different government programs, whichever are more prioritized in

¹¹ See <https://doc.emdat.be/docs/data-structure-and-content/emdat-public-table/>.

¹² Typhoon Haiyan, also known in the Philippines as Super Typhoon Yolanda, was one of the most powerful tropical cyclones ever recorded. It is one of the deadliest typhoons on record in the Philippines (Singer 2014).

¹³ As defined by Fuje et al. (2023), a storm is categorized as severe “if the number of deaths plus 30 percent of the affected population makes up at least one percent of the total population.”

the localities. The choropleth of the 10-year average shows that this may have been generally the trend over the past decade.

Table 6. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
expenditure	117	40835.462	39866.084	1412.32	236526.8
revenue	117	41442.656	33504.497	1783.358	196377.13
total damage	86	227.339	1093.496	.005	10000
severe storm	117	.077	.268	0	1
mean temperature	117	27.037	1.156	23.261	29.011
regional CPI	117	93.586	12.712	68.54	124.633

Source: Authors' computations

Figure 9. Local government expenditure, by region (in million PHP).

a. 2023 regional local expenditure

b. 10-year average annual expenditure (2014-2023)



Source: BLGF (2023).

Table 7 shows the multi-stage regression¹⁴ estimated results from the cross-section analysis. The first regression (column 1) puts mean temperature as the explanatory variable and the occurrence of a severe storm being the explained variable. This however yielded statistically insignificant results. The second step (column 2) looks at the relationship between the predicted values for severe storm from the previous model on total damages attributed to the storm. The result shows a positive and significant relationship, at the 10 percent. The severity of a storm is associated with higher total estimated damage. The third column examines the effect of damage on local government expenditure. The estimation yielded insignificant results which suggest that it may not be the economic losses per se that outright and solely triggers an immediate rise in spending. That is, the use of other resources including disaster risk reduction (DRR)-related funds may then be attributed to other considerations in episodes of disasters.

¹⁴ The estimation procedure were done with cognizance CLRM violations and corrective measures.

Moreover, total expenditure, which covers the quarter that the calamity occurred, involves spending in other sectors or programs of the government apart from the disaster-related government operations. This may also reflect disbursement issues in government, as mentioned by Abrigo and Brucal (2019, p.20) with respect to national-to-local aid and transfers which may be utilized on such disaster-related response, relief operations, rehabilitation and recovery, among other activities. Furthermore, if total damage includes direct and indirect economic losses, some insights from Domingo and Manejar (2023) on loss and damage accounting issues can be put into light. Underreporting is also recognized by the EM-DAT.

Lastly, considering the CPI in the affected localities can be associated with a positive and significant effect on spending. A change in prices is a factor in the corresponding higher funding requirements and the cost of providing public services.

Table 7. Cross-sectional regression results for expenditure.

Variables	(1) severe storm	(2) $\ln(\text{total damages})$	(3) $\ln(\text{expenditure})$
mean temperature	-0.00340 (0.0271)		
$\widehat{\text{severe storm}}$		123.0* (63.76)	
$\ln(\widehat{\text{total damages}})$			-0.0952 (0.159)
regional CPI			0.0290*** (0.00686)
Constant	0.169 (0.734)	-6.843 (5.000)	7.761*** (0.844)
Observations	117	86	117
R-squared	0.000	0.034	0.156

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

Source: Authors' computations

Table 8 shows the empirical results for local government revenues. Similarly, the total damages yielded statistically insignificant results. This implies that total revenue may not necessarily be influenced or affected by the computed total damage brought by a storm. While a severe storm and its associated damage are detrimental economic activity and therefore affecting government revenue, income and receipts of government units may come from various streams. Aside from local sources, LGUs have their share of national taxes. Other external sources include inter-local transfers (subsidies that came from other LGUs), as well as other extraordinary receipts which may be in the form of foreign and domestic grants, donations, or aid. LGUs may also acquire loans and borrowings as part of their total receipts.

Table 8. Cross-sectional regression results for revenue.

Variables	(1) severe storm	(2) $\ln(\text{total damages})$	(3) $\ln(\text{revenue})$
mean temperature	-0.00340 (0.0271)		
$\widehat{\text{severe storm}}$		123.0* (63.76)	
$\ln(\widehat{\text{total damages}})$			-0.0552 (0.133)

regional CPI			0.0287*** (0.00642)
Constant	0.169 (0.734)	-6.843 (5.000)	7.784*** (0.784)
Observations	117	86	117
R-squared	0.000	0.034	0.189

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

Source: Authors' computations

Probing further, Table 9 shows positive pairwise correlations between storm severity and total damage, which are expected. More importantly, expenditure and revenue are significantly correlated with total damage at the one percent and five percent level respectively. This suggests that a degree of correlation between damages and the fiscal variables may be established but may not be enough to show a significant effect on the latter.

Table 9. Pairwise correlations of variables from the cross-section analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) $\ln(\text{expenditure})$	1.000					
(2) $\ln(\text{revenue})$	0.954 (0.000)	1.000				
(3) $\ln(\text{total damages})$	0.298 (0.005)	0.274 (0.011)	1.000			
(4) severe storm	0.103 (0.267)	0.110 (0.238)	0.438 (0.000)	1.000		
(5) mean temperature	0.036 (0.701)	0.017 (0.855)	-0.185 (0.089)	-0.015 (0.875)	1.000	
(6) regional CPI	0.392 (0.000)	0.433 (0.000)	0.109 (0.319)	0.006 (0.946)	-0.034 (0.718)	1.000

p-values in parentheses.

Source: Authors' computations

Overall, evidence from the empirical method reveal that storms may not straightaway and outright adversely impact the fiscal situation among LGUs in the Philippines. The study sought to develop a model explaining government revenues and expenditures from the lens of climate-related phenomena. The multi-step regression modelled in this paper provided an idea as to the relationship between climate-related variables and revenues and expenditure. In terms of revenues, previous literature (Tol 2009; Auffhammer 2019; Kahn et al. 2021; and Felbermayr et al. 2022) states that natural disasters may cause a disruption in economic activity. The expectation therefore is the associated economic losses would pose a negative effect on revenue. While the negative coefficient is consistent in this aspect, it did not provide for a statistically significant result. This may adhere to Strobl (2019) in terms of the negative impact being short-lived. The negative sign also concurs with Fuje et al (2023); however, it is worth noting that external and other sources of income and receipts represent a significant chunk of LGU revenue, and this is not an unusual circumstance. Considering the prospect of exhausting initial resources, this might be somehow aiding the fiscal situation at the local level. Moreover, the results may be more in accord with Miao et al (2023), where the reduced revenue and elevated spending is attributed to the presidential disaster declaration.

The empirical findings allude to the way government disaster risk reduction and management (DRRM) spending is operated in the Philippines. Severe storms and bringing forth the economic losses brought by these natural calamities solely may not outright induce higher

spending. A budgeted process means there is already an allocated amount for disaster-related expenditure, as with other sectoral public services. However, severity of a calamity may warrant a government action which would then, in effect, cue the release and use of the NDRRM funds. In addition, expenditure includes the provision of other government services in that specific quarter when the severe storm occurred. Still, the negative coefficient may point to disruptions in the delivery of public services caused by severe disasters (Tanay et al 2023). When there is a warranted need for more resource requirements to deliver these services to the constituents, which subsequently leads to access to additional funding to utilize, these disasters make the provision of government services more costly which also seeps into the fiscal space of the government (Jha et al 2018; Barrage 2020 Cevik and Jalles 2023).

5. Conclusions and recommendations

Our study investigated the fiscal impacts of rapid climate change that can disrupt human activities and socio-economic systems. Fiscal health has been measured through government revenues and expenditures, while climate-related phenomena were captured using extreme weather events, temperature shocks, and precipitation levels. Data sources include PSA, BSP, BTr, BLGF, PAGASA, and EM-DAT, ensuring availability, consistency, and methodological support. Despite this, we remain cognizant that our analysis is constrained not only by data limitations but by the peculiarities and nuances of climate studies.

We have seen that while most climate change studies have employed time series analysis, it requires consistent data across sources, resulting in an annual unit of analysis due to mismatches in data granularity and temporal coverage. Variables are limited to those with complete, consistent, and processable data, impacting the depth of empirical analysis and regional disaggregation. While national-level data is available, regional-level data often lacks the same temporal and variable coverage, limiting the scope of regional analyses.

To address these limitations, we have implemented a three-pronged empirical approach – time series analysis, panel data analysis, and cross-section analysis to step-by-step capture the nuances of climate-related data at the macroeconomic and geographic levels. We then cross-validated our empirical findings with what scholarly literature has established. We addressed our research question and research objectives by determining how climate-related phenomena affect fiscal health in the Philippines. We saw that each approach done offered a different implication brought about by nuances in the approach and peculiarities of data driven by aggregation and disaggregation. These approaches mitigate potential aggregation bias and data limitations, ensuring a robust and interdisciplinary analytical framework. Being cognizant of these limitations, our methodologies are designed to maximize data utility and validity, providing a nuanced understanding of the relationship between climate change and fiscal health while carefully interpreting results within the context of data constraints.

5.1. Key findings

First, from our time series analysis, we have seen that the persistent economic disruptions caused by climate shocks in the Philippines stem from a combination of structural vulnerabilities, reliance on climate-sensitive sectors, weak infrastructure resilience, and socio-economic inequalities. While the economy can absorb short-term shocks, the cumulative and cascading effects of damages, exacerbated by slow recovery efforts and environmental degradation, create long-lasting scarring that impedes sustainable growth. Addressing these

challenges requires a shift toward proactive climate adaptation, improved governance, and investments in resilient infrastructure and sustainable practices.

Second, our panel data analysis indicated that the significant impact of temperature on GFCE likely arises because GFCE captures immediate operational and adaptation expenditures that are directly and acutely influenced by temperature variations. Other government expenditures might either adjust more slowly or not reflect temperature-driven spending as directly. Meanwhile, the statistically insignificant relationship between mean rainfall and government expenditure and GFCE likely arises from the localized, indirect, and sometimes beneficial effects of rainfall, combined with effective mitigation measures and the nature of GFCE, which may not fully capture rainfall-induced spending. The negative coefficients in some models suggest that favorable rainfall conditions could lead to cost savings, particularly in agriculture or energy, but these effects are not strong enough to be statistically significant. Similarly, the statistical insignificance of severe storms on government expenditure and GFCE is likely due to temporal mismatches (i.e., delayed spending), the nature of storm-related expenditures (i.e., capital or transfers rather than operational spending), and the localized or decentralized nature of storm impacts. Furthermore, proactive disaster preparedness and mitigation measures may reduce the observable fiscal impact of storms, while statistical limitations or competing factors could obscure their influence in econometric models. Finally, the positive coefficients for total expenditure and negative coefficients for GFCE reflect how droughts shift government spending toward capital projects and non-GFCE activities, such as subsidies or financial transfers, while operational expenditures slow down. The involvement of GOCCs, GFIs, and targeted interventions explains the concentrated fiscal response, highlighting the structural nuances of how governments manage drought impacts.

Third, our cross-section analysis, specifically a multi-step regression model, revealed a more consistent findings with respect to scholarly literature (Tol 2009; Auffhammer 2019; Strobl 2019; Kahn et al. 2021; Felbermayr et al. 2022; Fuje et al. 2023; Miao et al. 2023) highlighted the disruption of economic activity by natural disasters, which is expected to negatively affect LGUs' fiscal resilience is supported by external revenue sources and pre-budgeted allocations. Severe storms' fiscal impacts are more pronounced when disaster severity necessitates additional funding, which places pressure on the government's fiscal space and increases the cost of public service provision. These findings provide a nuanced understanding of how climate-related variables interact with local government finances, highlighting the importance of pre-allocated funds and external support in mitigating fiscal shocks.

Across our empirical analysis, our findings do not fully concur with scholarly literature stemming from differences in regional contexts and institutional structures. Scholarly literature may have captured areas where government responses to climate-related disasters are more centralized or uniformly affect revenues and/or expenditures. In the Philippine context, the response to climate-related disasters may involve more reliance on GOCCs and localized institutions, reducing NG's role while increasing broader expenditure. It can be construed that adaptation measures disproportionately burden operational budgets within the NG and LGUs.

5.2. Policy recommendations

Our key findings derived from our empirical approach allowed us to craft development strategies and to consolidate policy recommendations on how to build, utilize, and maximize public funds in preparing for and recovering from climate-related phenomena, as well as creating a climate-resilient Philippine economy.

5.2.1. Establish a climate resilience fund

First, we recommend establishing a climate resilience fund using frameworks from existing climate funds (e.g., Green Climate Fund) as models. With the objective of creating a dedicated fund specifically for climate resilience, including risk mitigation, emergency response, and recovery from climate-related disasters, the NG can allocate a percentage of the national budget to this fund annually and secure contributions from private sector partnerships, international donors, and climate-focused grants. This will be anchored on ensuring that funds are accessible for both immediate disaster relief and long-term climate resilience initiatives.

5.2.2. Strengthen climate-responsive budgeting and transparent allocation

Second, a Climate Public Expenditure and Institutional Review (CPEIR) process, assessing and reporting on climate-related spending across government agencies can be considered. This will spur a transparent, accountable reporting system on how funds are utilized and outcomes achieved. Through a budget mechanism that earmark funds for sectors and regions most vulnerable to climate impacts (e.g., agriculture, coastal communities, urban informal settlements), climate risk considerations can be integrated directly into the national budget and local government allocations and ensuring effective and proactive spending on resilience.

5.2.3. Reinforce insurance and risk transfer mechanisms

Third, learning from the Caribbean Catastrophe Risk Insurance Facility (CCRIF) that protects critical sectors and provide quick, post-disaster liquidity, it is necessary to reinforce insurance and risk transfer mechanisms. Economic agents can use insurance to spread and mitigate financial risks associated with climate-related events. The NG can implement public insurance policies for critical infrastructure, agriculture, and vulnerable populations, potentially in partnership with international insurers. In creating a shared regional resilience buffer, the Philippines may explore catastrophe bonds or risk-pooling schemes with Association of Southeast Asian Nations (ASEAN) and the Regional Comprehensive Economic Partnership (RCEP) member economies.

5.2.4. Incentivize green investments and climate-resilient infrastructure

Fourth, the NG must direct investments towards projects that both mitigate climate risks and enhance economic resilience. This can be done by offering tax breaks and financial incentives for private companies to invest in green infrastructure (e.g., flood control systems, renewable energy) and sustainable practices. Alternatively, NG can channel funds toward building resilient public infrastructure such as elevated roads, flood-resilient housing, and decentralized energy sources. This can be done by establishing green bonds and climate-friendly financing models through government partnerships with financial institutions to fund such projects.

5.2.5. Engage LGUs in fund utilization for climate adaptation

Fifth, LGUs must be empowered to manage funds effectively for community-level climate adaptation measures. This can be done by increasing LGUs' access to funding for climate action and streamline their ability to deploy these funds in response to local vulnerabilities. The NG can also provide capacity-building programs to ensure that LGUs can assess climate risks,

create resilience plans, and efficiently manage funds. Such steps facilitate the creation of an incentive structure for LGUs to adopt innovative adaptation practices.

5.2.6. Create a culture of evidenced-based policy research in disaster preparedness

Sixth, with data science and modern analytical tools, a culture of evidence-based policies must be nurtured to improve disaster preparedness and increase public awareness on climate adaptation and resilience. NG can direct funds toward climate research institutions, forecasting technology, and climate modeling to create accurate, localized climate projections. It may also be vital to launch education and awareness programs to help communities prepare for and adapt to climate impacts, especially in vulnerable regions. Synergy among NG agencies, LGUs, higher education institutions (HEIs), think tanks, and research centers to disseminate findings that inform policies, infrastructure planning, and emergency preparedness programs.

5.2.7. Integrate climate finance into long-term development plans

Not limited to the Philippine Development Plan (PDP), there is a need for NG to ensure that climate finance is part of the broader sustainable development strategy for the Philippines. By doing so, the Philippines can align its national and local climate resilience goals with the UN Sustainable Development Goals (SDGs) to ensure that climate action is part of all development efforts. By developing a climate-resilient development plan that merges development goals with climate adaptation priorities, supported by long-term financial planning, NG and LGUs would be compelled to regularly evaluate and adjust policies and funding allocations based on climate impact assessments, international best practices, and progress on SDG targets.

Through these policy steps, the Philippines can build a climate-resilient economy that is better prepared for, and able to recover from, climate-related events while ensuring sustainable economic growth.

6. References

- Abrigo, M. R. M., and A. Brucal. 2019. *National-to-local aid and recovery from extreme weather events: Evidence from the Philippines*. ADB Economics Working Paper Series No. 598. Asian Development Bank. <https://dx.doi.org/10.22617/WPS190576-2>.
- Albert, J. R. G., R. M. Briones, and J. P. R. Rivera. 2024. *Wealth creation for expanding the middle class in the Philippines*. PIDS Discussion Paper Series No. 2024-10. Philippine Institute for Development Studies. <https://doi.org/10.62986/dp2024.10>.
- Armas, J. C. A., R. J. L. Asi, D. R. L. Mandap, and G. R. L. Moral. 2024. *Macroeconomic effects of temperature shocks in the Philippines: Evidence from impulse responses by local projections*. BSP Discussion Paper Series No. 02. Bangko Sentral ng Pilipinas. <https://www.bsp.gov.ph/Pages/MediaAndResearch/PublicationsAndReports/Discussion%20Papers/DP202402.pdf> (accessed August 11, 2024).
- Auffhammer, M. 2019. *The (economic) impacts of climate change: Some implications for Asian economies*. ADBI Working Paper Series No. 1051. Asian Development Bank Institute. <https://www.adb.org/sites/default/files/publication/543321/adbi-wp1051.pdf> (accessed August 12, 2024).
- Baltagi, B. H. 2024. Hausman's specification test for panel data: Practical tips. *Advances in Econometrics* 46: 13-24. <https://doi.org/10.1108/S0731-905320240000046002>.

- Barrage, L. 2020. The fiscal costs of climate change. *AEA Papers and Proceedings* 110: 107-112. <https://www.aeaweb.org/articles?id=10.1257/pandp.20201082> (accessed August 12, 2024).
- Barro II, D. 2024. Solon calls for another 30% increase in PhilHealth benefits. *Manila Bulletin*. <https://mb.com.ph/2024/8/10/solon-calls-for-another-30-increase-in-phil-health-benefits> (accessed August 11, 2024).
- Bayudan-Dacuycuy, C., and L. Baje. 2019. When it rains, it pours? Analyzing the rainfall shocks-poverty nexus in the Philippines. *Social Indicators Research* (145): 67-93. <https://doi.org/10.1007/s11205-019-02111-1>.
- Becker, T., and P. Mauro. 2006. *Output drops and the shocks that matter*. IMF Working Paper No. 06/172. International Monetary Fund. <https://www.imf.org/external/pubs/ft/wp/2006/wp06172.pdf> (accessed August 12, 2024).
- Bilal, A., and D. R. Känzig. 2024. *The macroeconomic impact of climate change: Global vs. local temperature*. NBER Working Paper No. 32450. National Bureau of Economic Research. <https://www.nber.org/papers/w32450> (accessed August 12, 2024).
- Bollettino, V., T. Alcayna-Stevens, M. Sharma, P. Dy, P. Pham, and P. Vinck. 2020. Public perception of climate change and disaster preparedness: Evidence from the Philippines. *Climate Risk Management* 30: 100250. <https://doi.org/10.1016/j.crm.2020.100250>.
- Botzen, W. J. W., O. Deschenes, and M. Sanders. 2019. The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy* 13(2): 167-188. <https://doi.org/10.1093/reep/rez004>.
- Breckenfelder, J., B. Mackowiak, D. Marques, C. Olovsson, A. Popov, D. Porcellacchia, and Glenn Schepens. 2023. *The climate and the economy*. European Central Bank Working Paper Series No. 2793. <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2793~7969efec4f.en.pdf> (accessed August 12, 2024).
- Bündnis Entwicklung Hilft (BEH). 2023. *World Risk Report 2023*. https://weltrisikobericht.de/wp-content/uploads/2024/01/WorldRiskReport_2023_english_online.pdf (accessed August 11, 2024).
- Cabalza, D. 2024. DOH warns heat-related illness can kill; 7 dead since January. *The Philippine Daily Inquirer*. <https://newsinfo.inquirer.net/1937327/doh-warns-heat-can-kill-7-dead-since-january> (accessed on August 11, 2024).
- Carrington, D. 2022. Revealed: how climate breakdown is supercharging toll of extreme weather. *The Guardian News*. Guardian News & Media Limited. <https://www.theguardian.com/environment/2022/aug/04/climate-breakdown-supercharging-extreme-weather> (accessed August 11, 2024).
- Cevik, S., and J. T. Jalles. 2023. *Eye of the storm: The impact of climate shocks on inflation and growth*. IMF Working Paper 23/87. International Monetary Fund. <https://www.imf.org/en/Publications/WP/Issues/2023/04/28/Eye-of-the-Storm-The-Impact-of-Climate-Shocks-on-Inflation-and-Growth-532661> (accessed August 11, 2024).
- Charabi, Y. 2021. Digging deeper into cutting methane emissions from the oil and gas industry in the era of volatile prices. *Mitigation and Adaptation Strategies for Global Change* 26(6). <https://doi.org/10.1007/s11027-021-09948-3> (accessed August 11, 2024).
- Denchak, M. 2022. *Fossil fuels: The dirty facts*. National Resource Defense Council. <https://www.nrdc.org/stories/fossil-fuels-dirty-facts> (accessed August 11, 2024).

- Department of Education (DepEd). 2022. *Guidelines on the cancellation or suspension of classes and work in schools in the event of natural disasters, power outages/power interruptions, and other calamities*. DepEd Order No. 037. 2022.
- Department of Labor and Employment (DOLE). 2023. *Safety and health measures to prevent and control heat stress at the workplace*. Labor Advisory No. 08. 2023.
- Deschênes, O., and M. Greenstone. 2007. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review* 97 (1): 354–385. <https://doi.org/10.1257/aer.97.1.354>.
- Diebold, F. 2007. *Elements of forecasting* (4th ed.). Thomson South-Western.
- Domingo, S. and A. Manejar. 2023. *Study on Climate Change and Disaster Related Loss and Damage Accounting*. Philippine Institute for Development Studies Discussion Paper Series No. 2023-47. <https://pids.gov.ph/publication/discussion-papers/study-on-climate-change-and-disaster-related-loss-and-damage-accounting> (accessed November 28, 2024).
- Duarte Santos, F., P. Lopes Ferreira, and J. S. T. Pedersen. 2022. The climate change challenge: A review of the barriers and solutions to deliver a Paris solution. *Climate* 10(5): 75. <https://doi.org/10.3390/cli10050075>.
- Edelman, B. 2024. Fiscal risks of climate change. *The Governance Brief* 55: 1-15. <https://www.adb.org/sites/default/files/publication/940096/governance-brief-055-fiscal-risks-climate-change.pdf> (accessed August 12, 2024).
- Enders, W. 2003. *Applied economic time series* (2nd ed.). John Wiley & Sons, Inc.
- Espina, Z. E. 2024. DOH warns of heat-related illnesses due to ‘dangerous’ heat indices. *Manila Bulletin*. <https://mb.com.ph/2024/4/2/doh-warns-of-heat-related-illnesses-due-to-dangerous-heat-indices> (accessed August 11, 2024).
- European Commission. n.d. *Consequences of climate change*. https://climate.ec.europa.eu/climate-change/consequences-climate-change_en (accessed August 11, 2024).
- Felbermayr, G., J. Gröschl, M. Sanders, V. Schippers, and T. Steinwachs. 2022. The economic impact of weather anomalies. *World Development* 151: 105745. <https://doi.org/10.1016/j.worlddev.2021.105745>.
- Fesenfeld, L. P., and A. Rinscheid. 2021. Emphasizing urgency of climate change is insufficient to increase policy support. *One Earth* 4(3): 411-424. <https://doi.org/10.1016/j.oneear.2021.02.010>.
- Fuje, H., J. Yao, S. Choi, and H. Mighri. 2023. Fiscal impacts of climate disasters in emerging markets and developing economies. IMF Working Paper 23/261. International Monetary Fund. <https://www.imf.org/en/Publications/WP/Issues/2023/12/15/Fiscal-Impacts-of-Climate-Disasters-in-Emerging-Markets-and-Developing-Economies-542408> (accessed August 11, 2024).
- Gagliardi, N., P. Arévalo, and S. Pamies. 2022. *The fiscal impact of extreme weather and climate events: Evidence for EU countries*. European Commission Discussion Paper 168. https://economy-finance.ec.europa.eu/system/files/2022-07/dp168_en.pdf (accessed August 11, 2024).
- Gujarati, D. N., and D. C. Porter. 2009. *Basic econometrics* (5th edition). New York: McGraw-Hill.
- Gupta, K. L. 1971. Aggregation bias in linear economic models. *International Economic Review* 12(2): 293-305. <https://doi.org/10.2307/2525689>.
- Hallegatte, S. et al. 2016. Shockwaves: Managing the impacts of climate change on poverty. *Climate Change and Development Series*. World Bank Group. <https://openknowledge.worldbank.org/server/api/core/bitstreams/aa3a35e0-2a20-5d9c-8872-191c6b72a9b9/content> (accessed August 11, 2024).

- Harris, R. D. F., and E. Tzavalis. 1999. Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of Econometrics* 91(2): 201-226. [https://doi.org/10.1016/S0304-4076\(98\)00076-1](https://doi.org/10.1016/S0304-4076(98)00076-1).
- Holmes, J., J. Lowe, E. Wolff, and M. Srokosz. 2011. Rapid climate change: lessons from the recent geological past. *Global and Planetary Change* 79(3-4): 157-162. <https://doi.org/10.1016/j.gloplacha.2010.10.005>.
- Irwandi, H., M. S. Rosid, and T. Mart. 2023. Effects of climate change on temperature and precipitation in the Lake Toba region, Indonesia, based on ERA5-land data with quantile mapping bias correction. *Scientific Reports* 13(2542). <https://doi.org/10.1038/s41598-023-29592-y>.
- Jha, S., A. Martinez, P. Quising, Z. Ardaniel, and L. Wang. 2018. *Natural disasters, public spending, and creative destruction: A case study of the Philippines*. ADBI Working Paper Series No. 817. Asian Development Bank Institute. <https://www.adb.org/sites/default/files/publication/408351/adbi-wp817.pdf> (accessed August 11, 2024).
- Kahn, M. E., K. Mohaddes, R. N. C. Ng, M. H. Pesaran, M. Raissi, and J-C. Yang. 2021. Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics* 104: 105624. <https://doi.org/10.1016/j.eneco.2021.105624>.
- Lamb, W. F., et al. 2021. A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. *Environmental Research Letters* 16(7): 073005. <https://iopscience.iop.org/article/10.1088/1748-9326/abee4e> (accessed August 11, 2024).
- Lee-Brago, P. 2020. 2019 second hottest year on record — WMO. *The Philippine Star*. <https://www.philstar.com/headlines/2020/01/20/1986228/2019-second-hottest-year-record-wmo> (accessed August 11, 2024).
- Levin, A., C-F. Lin, and C-S. J. Chu. 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics* 108(1): 1-24. [https://doi.org/10.1016/S0304-4076\(01\)00098-7](https://doi.org/10.1016/S0304-4076(01)00098-7).
- Lindwall, C. 2022. *What are the effects of climate change?* Natural Resources Defense Council. <https://www.nrdc.org/stories/what-are-effects-climate-change> (accessed August 11, 2024).
- Lu, J. L. D., and T. J. Herbosa. 2011. Epidemics, diseases, and health emergencies in the aftermath of natural disasters in the Philippines. *Acta Medica Philippina* 45(3): 60-68. <https://doi.org/10.47895/amp.v45i3.6148>.
- Lynas, M., B. Z. Houlton, and S. Perry. 2021. Greater than 99% consensus on human caused climate change in the peer-reviewed scientific literature. *Environmental Research Letters* 16(11): 114005. <https://iopscience.iop.org/article/10.1088/1748-9326/ac2966> (accessed August 11, 2024).
- Maier, C., J. B. Thatcher, V. Grover, and Y. K. Dwivedi. 2023. Cross-sectional research: A critical perspective, use cases, and recommendations for IS research. *International Journal of Information Management* 70: 102625. <https://doi.org/10.1016/j.ijinfomgt.2023.102625>.
- Malhi, G.S., M. Kaur, and P. Kaushik. 2021. Impact of climate change on agriculture and its mitigation strategies: A review. *Sustainability* 13(3): 1318. <https://doi.org/10.3390/su13031318>.
- Mendoza, J. E. 2024. Record-high heat in NCR a ‘glaring symptom’ of global crisis – Legarda. *The Philippine Daily Inquirer*. <https://newsinfo.inquirer.net/1936792/record-high-heat-in-ncr-a-glaring-symptom-of-global-crisis-legarda> (accessed August 11, 2024).

- Mendoza, R. R., and J. P. R. Rivera. 2017. The effect of credit risk and capital adequacy on the profitability of rural banks in the Philippines. *Scientific Annals of Economics and Business* 64(1): 83-96. <https://doi.org/10.1515/aicue-2017-0006>.
- Miao, Q., M. R. M. Abrigo, Y. Hou, & Y. Liao. 2023. Extreme weather events and local fiscal responses: Evidence from U.S. counties. *Economics of Disasters and Climate Change* 7: 93-115. <https://doi.org/10.1007/s41885-022-00120-y>.
- Millard, R. 2024. El Niño could make 2024 hotter than record 2023. *The Philippine Star*. <https://www.philstar.com/headlines/climate-and-environment/2024/01/13/2325548/el-nio-could-make-2024-hotter-record-2023> (accessed August 11, 2024).
- Montemayor, M. T. 2024. PhilHealth benefits for heat-related illnesses increase by 30%. *Philippine News Agency*. <https://www.pna.gov.ph/articles/1224396> (accessed August 11, 2024).
- Mukherjee, K., and B. Ouattara. 2021. Climate and monetary policy: Do temperature shocks lead to inflationary pressures? *Climatic Change* 167(32). <https://doi.org/10.1007/s10584-021-03149-2>.
- National Geographic Society (NGS). n.d. *Weather*. <https://education.nationalgeographic.org/resource/resource-library-weather/> (accessed August 11, 2024).
- Parungao, A. 2024. School heads can suspend in-person classes due to heat – DepEd. *The Philippine Daily Inquirer*. <https://newsinfo.inquirer.net/1926344/fwd-deped-on-class-suspensions-due-to-high-heat> (accessed August 11, 2024).
- Patinio, F. 2024. DOLE reminds employers of safety measures for heat stress. *Philippine News Agency*. <https://www.pna.gov.ph/articles/1221350> (accessed August 11, 2024).
- Philippine Statistics Authority (PSA). 2023. *Disaster mitigation posted the highest DRR expenditure at PhP 107.97 billion in 2022*. <https://psa.gov.ph/content/disaster-mitigation-posted-highest-drr-expenditure-php-10797-billion-2022> (accessed August 12, 2024).
- Poushter, J., M. Fagan, and S. Gubbala. 2022. *Climate change remains top global threat across 19-country survey*. Pew Research Center. <https://www.pewresearch.org/global/2022/08/31/climate-change-remains-top-global-threat-across-19-country-survey/> (accessed August 12, 2024).
- Pun, I-F., H-H. Hsu, I-J. Moon, I-I. Lin, and J-Y. Jeong. 2023. Marine heatwave as a supercharger for the strongest typhoon in the East China Sea. *npj Climate and Atmospheric Science* 6(128). <https://doi.org/10.1038/s41612-023-00449-5>.
- Republic Act 9729. 2009. *Climate Change Act of 2009*. Manila, Philippines: Congress of the Philippines.
- Republic Act 10121. 2010. *Philippine Disaster Risk Reduction and Management*. Manila, Philippines: Congress of the Philippines.
- Republic Act 12000. 2024. *Negros Island Region Act*. Manila, Philippines: Congress of the Philippines.
- Rindfleisch, A., A.J. Malter, S. Ganesan, and C. Moorman. 2008. Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of Marketing Research* 45(3): 261-279. <https://doi.org/10.1509/jmkr.45.3.261>.
- Rivera, J. P. R., and K. G. T. See. 2011. The impact of carbon emissions on birth rates and death rates in ASEAN+3. *SJCC Management Research Review* 1(1): 13-37. https://animorepository.dlsu.edu.ph/faculty_research/8747/ (accessed November 30, 2024).
- Rivera, J. P. R., and T. S. Tullao Jr. 2020. Investigating the link between remittances and inflation: Evidence from the Philippines. *South East Asia Research* 28(3): 301-326. <https://doi.org/10.1080/0967828X.2020.1793685>.

- Rivera, J. P. R., and T. S. Tullao Jr. 2022. Estimating the impact of selected macroeconomic indicators on remittance inflows in the Philippines. *Journal of Southeast Asian Economies* 39(3): 273-290. <https://bookshop.iseas.edu.sg/publication/7832> (accessed August 16, 2024).
- Rivera, J. P. R., and T. S. Tullao Jr. 2023. *Inclusivity of factor flows in a labor-surplus economy: Experience of the Philippines*. PIDS Discussion Paper Series No. 2023-32. Philippine Institute for Development Studies. <https://doi.org/10.62986/dp2023.32>.
- Rocha, J., S. Oliveira, C. M. Viana, and A. I. Ribeiro. 2022. Chapter 8 - Climate change and its impacts on health, environment, and economy. *One Health*: 253-279. <https://doi.org/10.1016/B978-0-12-822794-7.00009-5>.
- Santos, J. 2024. El Niño's damage to Philippines' agri swells to P4.39 billion; 85,232 farmers, fishers affected. *Manila Bulletin*. <https://mb.com.ph/2024/4/25/el-nino-s-damage-to-philippines-agri-swells-to-p4-39-billion-85-232-farmers-fishers-affected> (accessed August 11, 2024).
- Shome, P., C. J. Moreno, and K. Rao. 1996. Quantitative and qualitative methods to social science enquiry: Econometric methods and interdisciplinarity. *Economic and Political Weekly* 31(30): PE87–PW92. <http://www.jstor.org/stable/4404442>.
- Singer, M. 2014. 2013 State of the climate: record-breaking Super Typhoon Haiyan. *Climate.gov*. <https://www.climate.gov/news-features/understanding-climate/2013-state-climate-record-breaking-super-typhoon-haiyan>.
- Smith, B., and J. M. Campbell Jr. 1978. Aggregation bias and the demand for housing. *International Economic Review* 19(2): 495-505. <https://doi.org/10.2307/2526315>.
- Social Weather Station (SWS). 2024. *87% of Filipino adults have personally experienced the impacts of climate change in the past three years*. <https://www.sws.org.ph/swsmain/arteldisppage/?artcsyscode=ART-20240222063121> (accessed August 12, 2024).
- Sousounis, P. J., and C. M. Little. 2017. Climate change impacts on extreme weather. *Air Worldwide*. <https://www.insurance.wa.gov/sites/default/files/2019-10/air-climate-change-impacts-on-extreme-weather.pdf> (accessed August 16, 2024).
- Strobl, E. 2019. *The impact of typhoons on economic activity in the Philippines: Evidence from nightlight intensity*. ADB Economics Working Paper Series No. 589. Asian Development Bank. <https://dx.doi.org/10.22617/WPS190278-2>.
- Stromberg, P. M., M. Esteban, and A. Gasparatos. 2011. Climate change effects on mitigation measures: The case of extreme wind events and Philippines' biofuel plan. *Environmental Science & Policy* 14(8): 1079-1090. <https://doi.org/10.1016/j.envsci.2011.06.004>.
- Suh, D., and R. Pomeroy. 2020. Projected economic impact of climate change on marine capture fisheries in the Philippines. *Frontiers in Marine Science* 7(232). <https://doi.org/10.3389/fmars.2020.00232>.
- Talukder, B., G. W. van Loon, K. W. Hipel, S. Chiotha, and J. Orbinski. 2021. Health impacts of climate change on smallholder farmers. *One Health* 13: 100258. <https://doi.org/10.1016/j.onehlt.2021.100258>.
- Tanay, M. A., J. Quiambao-Udan, O. Soriano, G. Aquino, and P. M. Valera. 2023. Filipino nurses' experiences and perceptions of the impact of climate change on healthcare delivery and cancer care in the Philippines: a qualitative exploratory survey. *ECancer Medical Science* 9(17): 1622. <https://doi.org/10.3332/ecancer.2023.1622>.
- Taris, T. W., S. R. Kessler, and E. K. Kelloway. 2021. Strategies addressing the limitations of cross-sectional designs in occupational health psychology: What they are good for (and what not). *Work & Stress* 35(1): 1-5. <https://doi.org/10.1080/02678373.2021.1888561>.

- Thomas, V., and R. López. 2015. *Global increase in climate-related disasters*. ADB Economics Working Paper Series No. 466. Asian Development Bank. <https://www.adb.org/sites/default/files/publication/176899/ewp-466.pdf> (accessed August 11, 2024).
- Tol, R. S. J. 2009. The economic effects of climate change. *Journal of Economic Perspectives* 23(2): 29–51. <https://www.aeaweb.org/articles?id=10.1257/jep.23.2.29> (accessed August 12, 2024).
- Tovar Mora, C. E., Y. Wu, and T. Zheng. 2022. *Stress testing the global economy to climate change-related shocks in large, interconnected economies*. International Monetary Fund. <https://www.elibrary.imf.org/view/journals/001/2022/189/article-A001-en.xml> (accessed August 11, 2024).
- Trenberth, K. E. 2011. Changes in precipitation with climate change. *Climate Research* 47:123–138. https://www.int-res.com/articles/cr_oa/c047p123.pdf (accessed August 16, 2024).
- United Nations (UN). n.d. *What is climate change?* Climate Action. <https://www.un.org/en/climatechange/what-is-climate-change> (accessed August 11, 2024).
- van Vuuren, D P., et al. 2017. Energy, land-use, and greenhouse gas emissions trajectories under a green growth paradigm. *Global Environmental Change* 42: 237–250. <https://doi.org/10.1016/j.gloenvcha.2016.05.008>.
- Wang, Z., C. Yang, H. Yuan, and Y. Zhang. 2021. Aggregation bias in estimating log-log demand function. *Production and Operations Management* 30(11): 3906–3922. <https://doi.org/10.1111/poms.13488>.
- Weart, S. R. 2008. *The discovery of global warming*. Harvard University Press. <https://doi.org/10.2307/j.ctt6wpmv8>.
- Williams, L., M. J. B. Arguillas, and F. Arguillas. 2020. Major storms, rising tides, and wet feet: Adapting to flood risk in the Philippines. *International Journal of Disaster Risk Reduction* 50: 101810. <https://doi.org/10.1016/j.ijdrr.2020.101810>.
- Woolridge, J. 2001. *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.
- World Bank Climate Change Knowledge Portal. n.d. *Heat Index* 35. <https://climateknowledgeportal.worldbank.org/country/philippines/heat-risk> (accessed August 11, 2024).
- World Bank (WB). 2022. *Philippines: Climatology*. World Bank Climate Change Knowledge Portal for Development Practitioners and Policy Makers. <https://climateknowledgeportal.worldbank.org/country/philippines/climate-data-historical> (accessed August 11, 2024).
- World Bank (WB). 2023. *What is climate change?* Climate Change Knowledge Portal for Development Practitioners and Policy Makers. <https://climateknowledgeportal.worldbank.org/overview> (accessed August 11, 2024).
- World Meteorological Organization (WMO). n.d. *Climate*. <https://wmo.int/topics/climate> (accessed August 11, 2024).
- Xiaoli, C., D. J. Tonjes, and D. Mahajan. 2016. Methane emissions as energy reservoir: Context, scope, causes and mitigation strategies. *Progress in Energy and Combustion Science* 56: 33–70. <https://doi.org/10.1016/j.pecs.2016.05.001>.

7. Appendix

Appendix 1. National level VAR(p) model results

Summary of VAR(p) results for government revenue.

Impulse	Response	Coefficient	p
L1.D.meantmean	D.ln(total revenues)	-0.012	0.567
L2.D. meantmean		-0.015	0.530
L3.D. meantmean		0.016	0.468
L1.D.meanrf	D.ln(total revenues)	0.000	0.424
L2.D. meanrf		0.000	0.510
L3.D. meanrf		0.000	0.675
L1.D.sevstorm	D.ln(total revenues)	-0.017	0.358
L2.D.sevstorm		0.018	0.358
L3.D.sevstorm		0.008	0.684
L1.drought	D.ln(total revenues)	-0.018	0.540
L2.drought		-0.046	0.124
L3.drought		0.001	0.978

Lag order selection: 3

Order of integration: 1

Source: Authors' estimates

Summary of VAR(p) results for government expenditures.

Impulse	Response	Coefficient	p
L1.D.meantmean	D.ln(total spending)	0.010	0.743
L2.D. meantmean		0.001	0.973
L3.D. meantmean		-0.028	0.304
L1.D.meanrf	D.ln(total spending)	-0.000	0.477
L2.D. meanrf		-0.000	0.440
L3.D. meanrf		0.000	0.667
L1.D.sevstorm	D.ln(total spending)	-0.005	0.844
L2.D.sevstorm		-0.004	0.871
L3.D.sevstorm		-0.001	0.967
L1.drought	D.ln(total spending)	-0.026	0.483
L2.drought		0.040	0.285
L3.drought		0.022	0.562

Lag order selection: 3

Order of integration: 1

Source: Authors' estimates

Appendix 2. Cross-sectional dataset.

Quarter	Disaster type	Disaster subtype	Event name	Total deaths	No. injured	No. affected	Total. affected	Severe storm	Mean temp.	Mean rainfall	RCPI	Revenue	Expenditure	Total damage (in USD)
2009q2	Storm	Tropical cyclone	Typhoon "Emong" (Chanom)	77	53	400954	401007	0	26	338	77	14391	10372	30
2009q2	Storm	Tropical cyclone	Typhoon "Dante" (Kujira)	29	8	383457	383465	0	28	396	75	1783	1412	26
2009q2	Storm	Tornado					100	0	28	355	69	1818	1700	0
2009q3	Storm	Tropical cyclone	Tropical Storm "Feria" (Nangka)	16	5	110400	110405	0	28	328	76	36175	30498	4
2009q3	Storm	Tropical cyclone	Tropical Storm "Isang" (Molave)	5	1	248057	248058	0	28	519	78	14873	13384	
2009q3	Storm	Tropical cyclone	Typhoon Morakot (Kiko)	26	18	94211	94229	0	25	608	78	11170	9584	25
2009q3	Storm	Tropical cyclone	Tropical storm Labuyo (Dujan)	1		95700	95700	0	28	289	75	16394	13218	
2009q3	Storm	Tropical cyclone	Tropical depression Maring	15		388373	388373	0	28	429	78	14184	12522	6

2009q3	Storm	Tropical cyclone	Tropical Depression Nando	3	3	48330	48333	0	25	472	77	12748	10669	
2009q3	Storm	Tropical cyclone	Tropical storm "Ondoy" (Ketsana)	501	529	4901234	4901763	1	27	397	76	33708	28383	237
2009q4	Storm	Tropical cyclone	Typhoon "Pepeng" (Parma)	512	207	4478284	4478491	1	26	254	78	89763	96023	585
2009q4	Storm	Tropical cyclone	Tropical storm "Mirinae" (Santi)	39	20	802155	802175	0	27	166	78	76486	82260	15
2009q4	Storm	Tropical cyclone	Tropical depression "Urduja"	4	13	48129	48142	0	27	214	74	13002	15487	0
2009q3	Storm	Tropical cyclone	Goni (Jolina)	14	10	221412	221422	0	28	173	73	23839	18416	3
2010q3	Storm	Tropical cyclone	Typhoon Conson (Basyang)	146	91	585383	585474	0	28	334	80	30483	25526	9
2010q3	Storm	Tropical cyclone	Tropical storm Ester (Dianmu)	31		1045	1045	0	28	334	80	29306	25124	
2010q4	Storm	Tropical cyclone	Typhoon Megi (Juan)	35	42	2008984	2009026	0	25	270	81	18348	21395	276
2011q2	Storm	Tropical cyclone	Typhoon Bebang (Aere)	37	11	430081	430092	0	28	294	81	34998	31571	31
2011q2	Storm	Tropical cyclone	Tropical storm "Dodong" (Sarika)	9	1	1151	1152	0	28	329	84	31525	28261	
2011q2	Storm	Tropical cyclone	Tropical storm "Meari" (Falcon)	20	4	1700085	1700089	0	28	308	84	40363	36437	13
2011q3	Storm	Tropical cyclone	Tropical storm Juaning (Nock-ten)	84	53	1108171	1108224	0	27	374	82	54985	49620	63
2011q3	Storm	Tropical cyclone	Typhoon "Kabayan" (Muifa)	11	5	8418	8423	0	27	435	85	29511	29075	0
2011q3	Storm	Tropical cyclone	Typhoon Mina (Nanmadol)	43	37	403193	403230	0	27	434	83	46628	42825	34
2011q4	Storm	Tropical cyclone	Typhoon Quiel (Nalgae)	25	12	1113763	1113775	0	25	240	85	24141	25302	3
2011q3	Storm	Tropical cyclone	Typhoon Pedring (Nesat)	103	91	3030755	3030846	0	27	421	83	53128	47845	344
2011q4	Storm	Tropical cyclone	Tropical Storm Ramon (Banyan)	11	6	75632	75638	0	27	284	81	33194	38680	
2011q4	Storm	Tropical cyclone	Tropical storm Washi (Sendong)	1439	6071	1144229	1150300	0	27	282	81	27843	31284	38
2011q2	Storm	Tropical cyclone	Typhoon Chedeng (Songda)			446907	446907	0	28	229	81	35207	30926	0
2011q2	Storm	Tropical cyclone	Tropical Storm Haima (Egay)					0	27	232	81	86003	74093	
2012q3	Storm	Tropical cyclone	Tropical storm Gener (Saola)	58	35	949051	949086	0	27	483	85	63399	55764	10
2012q3	Storm	Tropical cyclone	Typhoon Kai-Tak	4				0	26	679	87	42085	37296	3
2012q3	Storm	Tropical cyclone	Typhoon Igme (Tembin)	11	1	5606	5607	0	27	604	86	5293	3958	0
2012q3	Storm	Tropical cyclone	Typhoon Lawin (Jelawat)	4		7921	7921	0	28	540	85	14886	14719	
2012q4	Storm	Tropical cyclone	Typhoon Son Tinh (Ofel)	36	19	108021	108040	0	28	206	86	74653	88382	1
2012q3	Storm	Tropical cyclone	Typhoon Karen	1		1234	1234	0	28	753	87	20013	19784	
2012q4	Storm	Tropical cyclone	Tropical Storm Marce (Gaemi)			322	322	0	27	166	87	11494	14593	
2012q4	Storm	Tropical cyclone	Typhoon Bopha	1901	2666	6243998	6246664	1	28	176	85	3838	4794	898
2012q4	Storm	Tropical cyclone	Tropical storm Wukong (Quinta)	24	3	241603	241606	0	28	220	85	36956	47959	6
2013q1	Storm	Tropical cyclone	Tropical storm Auring	1		10597	10597	0	28	168	85	12416	8072	
2013q2	Storm	Tropical cyclone	Typhoon Rumbia	7	4	3592	3596	0	29	172	86	25662	22868	1
2013q3	Storm	Tropical cyclone	Tropical storm Utor (Labuyo)	18	7	395723	395730	0	28	486	88	18279	14779	32
2013q3	Storm	Tropical cyclone	Typhoon Usagi (Odette)	5		72696	72696	0	27	454	88	45770	37349	
2013q1	Storm	Tropical cyclone	Tropical depression Crising (Shanshan)	6	4	262880	262884	0	27	204	85	40669	27158	2
2013q4	Storm	Tropical cyclone	Tropical storm Nari (Santi)	20	154	871601	871755	0	26	181	89	20415	23079	97
2013q4	Storm	Tropical cyclone	Typhoon Haiyan (Yolanda)	7354	28689	16078181	16106870	1	28	231	88	21691	25112	10000
2013q4	Storm	Tropical cyclone	Typhoon Krosa (Vinta)	4		220443	220443	0	24	121	89	13951	15930	5
2014q1	Storm	Tropical cyclone	Tropical Depression Agaton (Lingling)	79	86	1148621	1148707	0	27	244	88	22945	13812	13
2014q1	Storm	Tropical cyclone	Tropical storm Basyang (Kajiki)	6		47740	47740	0	26	312	89	26288	14288	3

2014q3	Storm	Tropical cyclone	Typhoon Rammason (Glenda)	111	1250	4653716	4654966	1	28	374	92	48284	43808	821
2014q3	Storm	Tropical cyclone	Typhoon Henry (Matmo)	2		683	683	0	28	313	91	19748	16219	
2014q3	Storm	Tropical cyclone	Tropical storm Fung-Wong (Mario)	22	16	2052141	2052157	0	28	469	92	27865	26994	76
2014q3	Storm	Tropical cyclone	Typhoon Kalmaegi (Luis)	4	1	431085	431086	0	27	401	92	53975	47867	19
2014q4	Storm	Tropical cyclone	Tropical storm 'Sinlaku' (Queenie)	12		4695	4695	0	28	280	90	40128	46992	
2014q4	Storm	Tropical cyclone	Typhoon 'Hagupit' (Ruby)	18	916	4149484	4150400	1	27	308	91	76494	91820	114
2014q4	Storm	Tropical cyclone	Tropical storm 'Jangmi' (Seniang)	72		578549	578549	0	28	268	90	43666	50788	18
2015q1	Storm	Tropical cyclone	Tropical storm 'Amang' (Mekkhala)	2		21687	21687	0	26	159	91	22728	12157	1
2015q2	Storm	Tropical cyclone	Typhoon' Maysak'			2761	2761	0	29	106	91	15982	12675	
2015q2	Storm	Tropical cyclone	Typhoon Noul (Dodong)	2		523	523	0	28	98	91	5195	3928	0
2015q3	Storm	Tropical cyclone	Typhoon Chan-Home	5		10800	14100	0	25	564	92	14241	12025	1500
2015q3	Storm	Tropical cyclone	Tropical cyclone Linfa (Egay)			55567	55567	0	25	595	92	13232	10958	2
2015q3	Storm	Tropical cyclone	Typhoon 'Soudelor' (Hanna)			3843	3843	0	28	220	91	28079	17159	
2015q3	Storm	Tropical cyclone	Typhoon Goni (Ineng)	40	24	318359	318383	0	25	564	92	14241	12025	30
2015q4	Storm	Tropical cyclone	Typhoon Koppu (Lando)	51	83	2898507	2898590	0	26	278	92	67771	78824	211
2015q4	Storm	Tropical cyclone	Typhoon Mujigae	2		3500	3500	0	25	293	93	23985	25636	1
2015q4	Storm	Tropical cyclone	Typhoon Melor (Nona)	46	24	287227	287251	0	28	220	91	63216	75377	135
2016q3	Storm	Tropical cyclone	Typhoon Butchoy (Nepartak)	2	2	3357	3359	0	28	384	94	26537	20056	
2016q3	Storm	Tropical cyclone	Typhoon Ferdie (Meranti)			16648	16648	0	28	461	92	13128	9275	5
2016q4	Storm	Tropical cyclone	Typhoon Karen (Sarika)			52270	52270	0	27	360	94	54102	59900	11
2016q4	Storm	Tropical cyclone	Typhoon Lawin (Haima)	8		981154	981154	0	26	337	94	57686	63916	51
2016q3	Storm	Storm (General)	Typhoon Carina (Nida)			8809	8809	0	27	360	93	51298	36669	
2016q4	Storm	Tropical cyclone	Tropical storm Marce (Tokage)			14309	14309	0	28	356	94	26806	29810	
2016q3	Storm	Tropical cyclone	Typhoon Helen (Megi)			1559	1559	0	28	521	94	11446	9152	
2016q4	Storm	Tropical cyclone	Typhoon 'Nina' (Nock-Ten)	24		1893404	1893404	0	27	417	93	37083	40693	104
2017q2	Storm	Tropical cyclone	Tropical depression 02W (Crising)	10	10	850	860	0	29	135	94	10255	7261	2
2017q3	Storm	Tropical cyclone	Typhoon Nesat & Haitang			7339	7339	0	27	413	96	59891	49270	0
2017q3	Storm	Tropical cyclone	Typhoon 'Doksuri'	26		7465	9110	0	28	388	95	35459	30851	5
2017q4	Storm	Tropical cyclone	Typhoon 'Damrey' / 'Ramil'	6		305	305	0	27	444	96	30528	38785	
2017q4	Storm	Tropical cyclone	Typhoon 'Lan'/'Paolo'	9		163349	163349	0	28	244	96	51537	56551	3
2017q3	Storm	Tropical cyclone	Tropical storm 'Pakhar'/'Jolina'					0	26	383	96	31195	22929	
2017q4	Storm	Storm (General)	Storm 'Tembin' (Vinta)	58		871757	923757	0	28	212	95	19244	21025	50
2017q4	Storm	Storm (General)	Tropical storm 'Kai-Tak' (Urduja)	91	78	1861250	1861328	0	28	373	96	50013	55230	72
2018q1	Storm	Tropical cyclone	Agaton (01W)	3	9	83908	83917	0	27	203	98	42292	19053	12
2018q1	Storm	Tropical cyclone	Tropical storm 'Basyang' (Sanba)			254859	254859	0	27	285	98	47546	22306	3
2018q3	Storm	Tropical cyclone	Typhoon Mangkut (Ompong)	84	138	3800000	3800138	1	23	1016	101	25363	7814	32
2018q3	Storm	Tropical cyclone	Tropical Storm Yagi	5		1709511	1709511	0	26	638	101	87385	51567	19
2018q4	Storm	Tropical cyclone	Typhoon 'Yutu' (Rosita)	12	2	253298	253300	0	25	169	102	47357	52958	305
2018q4	Storm	Tropical cyclone	Tropical depression 'Usman'	182	105	1015958	1016063	0	27	276	102	39080	52111	107
2019q1	Storm	Tropical cyclone	Tropical depression 'Amang' (01W)			13160	13160	0	27	285	101	6430	3409	
2019q3	Storm	Tropical cyclone	Tropical cyclone 'Danas'	4		2000	2000	0	25	603	102	21304	14221	377
2019q3	Storm	Tropical cyclone	Tropical cyclone 'Podul'	2	2	61500	61502	0	28	565	103	16789	13432	

2019q4	Storm	Tropical cyclone	Tropical cyclone 'Kalmaegi' (Ramon)			3000	3000	0	28	252	105	16503	19497	
2019q4	Storm	Tropical cyclone	Tropical cyclone 'Nakri'	19	3	670	673	0	25	311	103	8832	9364	36
2019q4	Storm	Tropical cyclone	Tropical cyclone 'Kammuri' (Tisoy)	4	318	2305075	2647558	0	26	214	104	77031	85320	109
2019q4	Storm	Tropical cyclone	Tropical cyclone 'Phanfone' (Ursula)	63	369	3296877	3297246	0	26	237	103	43229	52378	16
2020q2	Storm	Tropical cyclone	Tropical Cyclone 'Vongfong' (Ambo)	5	169	578571	578740	0	26	198	104	42719	26857	31
2020q4	Storm	Tropical cyclone	Tropical depression 'Ofel'	3		250	250	0	28	425	107	87532	102616	0
2020q4	Storm	Tropical cyclone	Typhoon 'Goni' (Rolly)	31	399	3355995	3356394	0	26	411	107	117569	162984	503
2020q4	Storm	Tropical cyclone	Typhoon 'Molave' (Quinta)	31	40	888375	888415	0	28	426	107	107141	119750	87
2020q4	Storm	Tropical cyclone	Typhoon 'Ulysses' (Vamco)	111	85	514824	514909	0	27	432	106	50968	92136	421
2020q4	Storm	Tropical cyclone	Tropical depression 'Vicky' (Krovanh)	9	2	36030	36032	0	26	422	106	20315	24998	2
2021q1	Storm	Severe weather		6		37830	37830	0	27	367	110	36559	17729	
2021q1	Storm	Tropical cyclone	Tropical storm 'Djuan' (Auring)	5	2	272451	272453	0	27	501	109	17752	8690	3
2021q2	Storm	Tropical cyclone	Tropical cyclone 'Surigae'	9		15000	15000	0	28	199	110	36545	25702	20
2021q3	Storm	Tropical cyclone	Tropical cyclone 'Conson' (Jolina)	17	24		24	0	28	327	110	110252	106296	
2021q4	Storm	Tropical cyclone	Tropical cyclone 'Lionrock' (Lannie)	3		8048	8048	0	28	207	112	27200	32125	0
2021q4	Storm	Tropical cyclone	Tropical cyclone 'Kompasu' (Maring)	59	5	1140534	1140539	0	26	274	111	178714	215056	76
2021q4	Storm	Tropical cyclone	Typhoon 'Rai' (Odette)	457	1371	10607625	10608996	1	28	304	110	88222	105263	915
2022q2	Storm	Tropical cyclone	Tropical storm 'Megi' (Agaton)	346	8	2298780	2298788	0	28	253	115	57844	43819	42
2022q3	Storm	Tropical cyclone	Tropical Cyclone 'Ma-On' (Florita)			7616	7616	0	26	310	118	94323	52254	
2022q3	Storm	Storm surge	Tropical cyclone 'Noru' (Karding)	17	52	913893	913945	0	28	389	118	56154	38334	57
2022q4	Storm	Tropical cyclone	Tropical depression 'Maymay'					0	24	354	120	61916	71099	
2022q4	Storm	Tropical cyclone	Storm 'Nalgae' (Paeng)	158	103	3323188	3323291	0	28	247	119	149651	236527	46
2023q2	Storm	Tropical cyclone	Tropical Depression 'Amang'			136149	136149	0	29	160	123	71387	55748	0
2023q2	Storm	Tropical cyclone	Typhoon 'Mawar'	1	1	30500	30501	0	28	184	122	79706	62105	
2023q3	Storm	Tropical cyclone	Tropical cyclone 'Doksuri' (Egay)	39	171	5385066	5385237	1	28	348	124	196377	170236	284
2023q4	Storm	Tropical cyclone	Typhoon 'Koinu'			275	275	0	26	237	124	11943	13632	
2023q4	Storm	Tropical cyclone	Tropical storm 'Jelawat' (Kabayan)	1				0	28	239	125	67128	82146	0

Appendix 3. Stata do file.

```

*transform the variables for revenue, expenditure, and damage
gen revenue = (tot_rev_q + tot_nonirec_q)/1000000
gen expenditure = (tot_coexp_q + tot_nonexp_q)/1000000
*revenue in million PHP
*expenditure in million PHP
gen totaldamageadjustedus = totaldamageadjusted000us/1000
gen totaldamageus = totaldamage000us/1000
*damage in million USD
gen ln_revenue = ln(revenue)
gen ln_expenditure = ln(expenditure)
gen ln_totaldamageadjustedus = ln(totaldamageadjustedus)
gen ln_totaldamageus = ln(totaldamageus)
*Stepwise regression
*severe storm = f(mean temperature)

```

```

*damages = f(severe storm_hat)
*expenditure and revenue = f(damages_hat, cpi)
reg sevstorm meantmean, robust
predict sevstorm_yhat, xb
reg ln_totaldamageus sevstorm_yhat, robust
predict damages_yhat, xb
reg ln_expenditure damages_yhat rcpi, robust
drop sevstorm_yhat damages_yhat
reg sevstorm meantmean, robust
predict sevstorm_yhat, xb
reg ln_totaldamageus sevstorm_yhat, robust
predict damages_yhat, xb
reg ln_revenue damages_yhat rcpi, robust
*correlation matrix
pwcorr ln_expenditure ln_revenue ln_totaldamageus sevstorm meantmean rcpi,
sig
estat vif
*normality of residuals
quietly reg ln_expenditure damages_yhat rcpi, robust
predict r, resid
kdensity r, normal
pnorm r
drop r
quietly reg ln_revenue damages_yhat rcpi, robust
predict r, resid
kdensity r, normal
pnorm r

*generate the descriptive statistics
sum expenditure revenue totaldamageus sevstorm meantmean rcpi
*ransform revenue, expenditure and total damage
gen ln_revenue = ln(revenue)
gen ln_expenditure = ln(expenditure)
gen ln_totaldamageadjustedus = ln(totaldamageadjustedus)
gen ln_totaldamageus = ln(totaldamageus)
*Run the stepwise regression for expenditure
*First stage: severe storm and mean temperature
reg sevstorm meantmean, robust
predict sevstorm_yhat, xb
*Second stage: total damage and severe storm
reg ln_totaldamageus sevstorm_yhat, robust
predict damages_yhat, xb
*Third stage: expenditure, total damage, and regional cpi
reg ln_expenditure damages_yhat rcpi, robust
*Run the stepwise regression for revenue
*First stage: severe storm and mean temperature
reg sevstorm meantmean, robust
predict sevstorm_yhat, xb

*Second stage: total damage and severe storm
reg ln_totaldamageus sevstorm_yhat, robust
predict damages_yhat, xb
*Third stage: revenue, total damage, and regional cpi
reg ln_revenue damages_yhat rcpi, robust
*Correlation matrix
pwcorr ln_expenditure ln_revenue ln_totaldamageus sevstorm meantmean rcpi,
sig
*Variance inflation factors for the independent variables
reg ln_expenditure damages_yhat rcpi, robust
estat vif
reg ln_revenue damages_yhat rcpi, robust

```

```
estat vif
*Normality of residuals
reg ln_expenditure damages_yhat rcpi, robust
predict r, resid
kdensity r, normal
pnorm r
drop r
reg ln_revenue damages_yhat rcpi, robust
predict r, resid
kdensity r, normal
pnorm r
drop r
```