

Vulnerability and Resilience against Natural Disasters in Central Vietnam

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Abstract: We investigate the impacts of natural disasters (henceforth called disaster impact) on Central Vietnam's regional GDP growth per capita. We use provincial data on disaster damages for nineteen provinces and cities in Vietnam's Central Region from the Vietnam Disaster Management Authority (VDMA). The Statistical Yearbook of Each Province in the Region (SYEP) provides three state, private, and foreign capital datasets. The General Statistics Office of Vietnam (GSOV) provides data on local vulnerabilities and resiliencies. Since GDP per capita is also a measure of resiliency, we write the estimation model as a system of equations to account for the possible feedback effects. This system calls for three-stage least squares (3SLS) estimations. The results showed that vulnerabilities exacerbate the disaster impact, while resiliencies help reduce this impact on regional GDP per capita growth. Regarding the feedback effect, GDP per capita does lessen the disaster impact. Last, we suggest strategies for local governance to reduce vulnerability and increase resilience.

Keywords: growth, GDP per capita, vulnerabilities, resiliencies, local governance.

JEL classification: O40, Q54.

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1. Introduction

Natural disasters often wreak havoc on production and the environment, adversely affecting sustainable development, especially in Central Vietnam. Hence, reducing local vulnerabilities and increasing resiliency against disasters should be prioritized in local governance. The Central Vietnam Region comprises the Central Coastal Region and Central Key Economic Region (Central Coastal Area), and the Central Highland Region (henceforth called Central Highland Area).

Readers might still remember Typhoon Ketsana, which landed in Quang Nam on September 29, 2009, with a wind speed of 144 km per hour. The typhoon brought floods in Vietnam, killed 179 people, and caused total damage of 16.07 trillion VND (896.1 million US dollars).

There are disagreements on the word "vulnerability." Oxford Online Dictionary defines vulnerability as:

"...the quality or state of being exposed to the possibility of being harmed or attacked, either physically or emotionally."

We adapted this definition in our paper and did not encounter conflicts in defining resilience. Accordingly, there are two main types of disaster resilience.

- (i) Inherent resilience is the built-in strength of an individual, a building, or a road to deal with disasters.
- (ii) Adaptive resilience is the ability of consumers, producers, communities, and states to adapt to and recover from repeated disasters, including the shocks and stresses caused by any disaster.

Our paper investigates the impacts of vulnerability and resilience on losses caused by natural disasters (henceforth called disaster losses) in a two-way causality framework between regional GDP growth per capita (henceforth called regional growth) and natural disasters in Central Vietnam. It also discusses the importance of local governance in disaster response.

The General Statistics Office of Vietnam (GSOV) provides data on local vulnerabilities, such as the percentage of children under five years old registered in the population, unemployment rates, and infant mortality rates, as well as data on local resiliencies, such as the percentage of trained workers in the labor force, the proportion of housing area built by professional enterprises, and the percentage of health insurance coverage in the population.

Section 2 of this article reviews existing research. Section 3 analyzes methodology and data. Section 4 reports the results. Section 5 discusses local governance and concludes.



2. Existing Research

2.1. Vulnerability

According to the United Nations summary of risk reduction, the frequency and the magnitude of natural disasters have risen (Ingirige et al. 2015, 1-3). As a result, the total damage caused by natural disasters has increased to \$2.5 trillion, affecting mostly developing countries (De Bono 2013, 1-6; Storrier 2018, 14). Due to these rising losses, there is an increasing need for local decision-makers, practitioners, and community members to assess their communities' disaster vulnerability and resilience better.

This section presents research examining vulnerability as a social condition or a measure of the resilience of population groups when confronted by disaster (Cutter, Boruff, and Shirley 2003, 242-261). There are general agreements on the facts that populations living in a disaster-frequent area are not affected equally (Bolin 2006, 1-4).

Factors affecting a person's vulnerability depend on socioeconomic status, such as income, unemployment, household composition, minority status, and vehicle access. The poor are more vulnerable to all-natural disasters, as are racial and ethnic minorities, children, the elderly, and disabled people (Morrow 1999, 1-18). Vulnerability can reflect the local governance and public health policies (Krieger 2006, 355-361). Vulnerability is also evident at any stage of a disaster cycle preparedness, response, recovery, and mitigation (Morrow 1999, 1-18).

Concerning local governance, communities with socially vulnerable populations were slow to recover even without heavy damage, but vulnerable communities experiencing heavy damage were slowest to recover (Flanagan et al. 2011, 34-36). A study in Georgia showed significant spatial clustering and increased rates of extreme heat-related mortality and emergency department visits in areas of high social vulnerability (Adams et al. 2016, 1-3). Data analyses were applied to understand hurricane-related deaths in the US better (Lavery 2017, 1-8). Research using such an approach with health and environmental data reported the database as a significant predictor of asthma emergency department rates, with the strength of prediction varying across counties in the study areas (Kolling et al. 2017).

Based on these observations, a group of researchers at the U.S. Centers for Disease Control and Prevention has developed a Social Vulnerability Index (SVI) to help scholars researching in the U.S. (Flanagan et al. 2011, 34-36). Their SVI index is divided into four categories.

- (i) Socioeconomic status: income, unemployment, education.
- (ii) Household composition: Old age, young age, disability, single-parent household.
- (iii) Minority status: ethnicity, language fluency.
- (iv) Housing and transportation: house structure, means of transportation.

The validation of SVI in disaster management by several U.S. state and local governments, as well as several private sector organizations, includes:

- mapping fire outbreaks and vulnerability metrics to target aid during emergencies (Lue and Wilson 2017, 409-426),
- hazard mitigation planning studies (Horney et al. 2015, 802-818),

- adult physical inactivity (An and Xiang 2015, 751-760; Gay et al. 2016, 121-130); and
- study social vulnerability and physical hazards (e.g., sea level rise, flooding, tornadoes, volcanic risk, house fires), hazard awareness, rural/urban differences, migrant and refugee populations, and health status (e.g., youth fitness).

Other projects validated SVI before the authors officially published the 2018 paper. For example, a post-Katrina recovery paper on the floods in New Orleans, Louisiana, found that damaged communities were slow to recover with a socially vulnerable population (Flanagan et al. 2011, 34-36). Research on extreme heat in Georgia showed significant spatial clustering and increased rates of mortality and emergency department visits in areas of high social vulnerability (Adams et al. 2016, 1-3). Following a series of hurricanes in 2017, the SVI database was applied to media-reported data on the number of deaths to understand hurricane-related fatalities better (Lavery 2017, 1-8). A study coupling data from the SVI database with health and environmental data reported the database as a significant predictor of asthma emergency department rates, with the strength of prediction varying across counties in the research area (Kolling et al. 2017, 1-12). An independent study that validates several social vulnerability indices finds that the SVI database compares well to other indices, especially concerning explaining property damage and deaths (Bakkensen et al. 2017, 982-1004).

2.2 Resilience

United Nations International Strategy for Disaster Reduction (UNISDR) has defined community resilience as

“... the ability of a system, community, or society exposed to hazards to resist, absorb, accommodate to, and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions...”

Understanding resilience from community stakeholder perspectives can help implement measures to reduce the disaster impact on the community in general, saving lives and personal property (Jones and Tanner. 2017, 229-243). These stakeholders need inclusive and equitable methods to understand their vulnerabilities and resiliencies and assess the disaster losses (Kuecker and Hartley 2021, 85-102). A more transparent and accurate approach to measuring resilience can help communities effectively utilize scarce resources to counter disaster losses (Jones 2019, 1-4). A straightforward explanation of the measure also helps local leaders implement disaster mitigation measures that decrease their vulnerability and increase their resilience (Morshed and Ameen, 2020, 595-630).

For the last twenty years, researchers have examined local resilience, which is the ability of local identities to withstand or respond to disaster losses to explain the impact of disasters on communities (Norris et al. 2008, 127-140). International development agencies and donor organizations have also realized the benefit of developing resilience assessment tools with greater inclusivity. They can help local identities develop intervention strategies, improve local governance, and hold local businesses accountable (Jones 2019, 1-4)

Several definitions of local community exist in the existing research. However, they are usually classified as entities within geographic boundaries and as shared outcomes concerning

adversity (Norris et al. 2008, 127-150). We follow Ostadtaghizadeh et al. (2015, 1-6) to define a local community as

“...a group of people with diverse characteristics who are linked by social ties, share common perspectives, and engage in joint action in geographical locations or settings...”

This definition focuses on the capacity of a local community to work together and engage in disaster risk reduction activities by pooling knowledge, experience, and actions towards the common goal of a resilient community in geographical-based populations like wards, villages, neighborhoods, towns, and districts.

Resilience, in general, is divided into two categories: inherent and adaptive. Inherent resiliencies are strong characteristics built into an individual or structure, such as a grown-up person and a professionally built house. Adaptive resiliencies refer to the ability of an individual or community to learn from past events and improve their preparedness to cope with subsequent adversities, such as building cyclone-resistant material after a hurricane occurs or training workers to deal with adversity after facing adversity.

In addition, subjective resilience comprises an individual's self-assessment of possible risks. It results in the individual purchasing health insurance for his family members and property insurance for his house. Objective resilience comes from local

government, and donor agencies from relief and developmental sources have increasingly required a more disaster assessment at multiple stages of the community resilience assessment.

A group of researchers developed a community disaster resilience (CDR) based on these observations (Tariq et al. 2021, 1-12). Their set includes both subjective and objective indicators of resilience. Ideally, we can develop a set of CDR indexes drawn from different stages of stakeholder-led assessments. This approach allows researchers to use interviews, focus groups, and local government officials to be involved in defining what resilience means to them and then asks them to select measures from a library of indicators to determine how resilience is measured thus allowing customization of the resilience assessment tools according to their needs (Tariq et al. 2021, 36-48). However, due to time constraints, we can only draw a list of available variables from the General Office of Statistics of Vietnam (GOSV) for this paper.

3. Data and Methodology

3.1 Data

The Vietnam Disaster Management Authority (VDMA) provides data on disaster losses in 19 Central provinces and cities from 1998 to 2019. Figure 1 shows these disaster lossé.

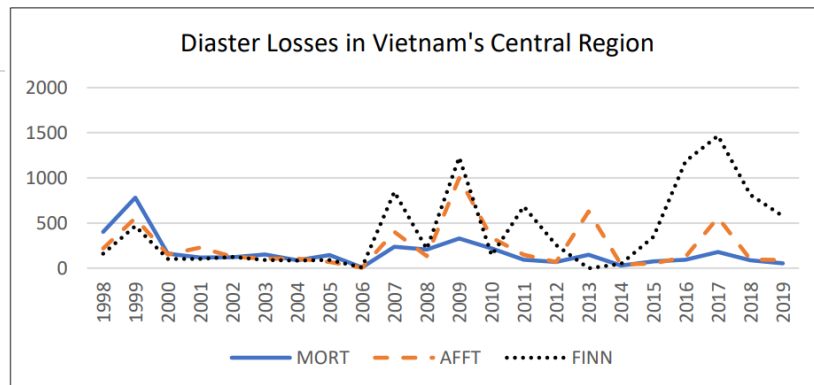


Figure 1. Three Types of Disaster Losses in Vietnam's Central Region

Source: author construct based on VDMA data

Disaster losses comprise mortalities (MORT), affected (AFFT), and financial damage (FINN). The data set on missing people has very few observations, so we excluded it from our model.

Based on the above literature, we employed several variables from GOSV to measure vulnerability in our paper: unemployment rate (UNEMP) to represent economic vulnerability, infant mortality rates (IMORT) to describe physical vulnerability, and percentage of self-built houses to total houses (SELFH) to represent structural vulnerability. Our paper also utilizes the above indicators to choose among the available variables three datasets in GSOV to measure resilience: percentage of trained workers (TRAINW) to total employment to present human-capital resilience, percentage of professionally built houses to total houses (PROH) to represent inherent resilience, and percentage of health-insurance individuals to total population (HINSU) to represent adaptive resilience.

The Statistical Yearbook of Each Province in the Region (SYEP) provides three datasets on state, private, and foreign capital. We sum these three datasets to form a measure of physical capital. Datasets on provincial GDG per capita in current Vietnamese Dong and the GDP index in 2010 constant Vietnamese Dong from GOSV Vietnamese Dong. We combine these datasets with the GDP deflator in 2015 US dollars provided by the U.S. Department of Agriculture to convert all financial variables into 2015 constant US dollars. There are missing observations, so we use binary dummy variables to control them.

3.2 Methodology

Model (1) contains a system of equations to account for the possible feedback effects among the variables:

$$PERCA_{i,t} = \alpha_1 LOSS_{i,t} + \sum_{k=1}^K \alpha_k LOSS_{i,t-k} + \beta X_{i,t} + q_i + s_t + \varepsilon_{i,t} \quad (1.1)$$

$$LOSS_{i,t} = \varphi Z_{i,t} + \theta PERCA_{i,t} + \sum_{l=1}^L \gamma_l Z_{i,t-l} + v_i + w_t + \omega_{i,t} \quad (1.2)$$

where *PERCA* is the growth of per capita GDP, which is the ratio of real GDP to population, and *LOSS* is the ratio of damage caused by disasters to population. *X* and *Z* are two vectors of potential control variables that might affect the system's dependent variables. Subscript *i* is the provincial index, and subscript *t* is the time index, with *k* and *l* being the numbers of lagged periods. The last three variables in each equation are the provincial-specific effect, time-specific effect, and idiosyncratic disturbances.

The Akaike Information Criteria (AIC) procedure shows that the two-legged values are the most appropriate model. The augmented Granger Causality test indicates two-way causality in the system. The modified endogeneity test reveals that *PERCA* is endogenous, so the three-stage least squares estimation (3SLS) is used. The instrumental variables (IVs) are from the data lagged values. The System Generalized Method of Moments (SGMM) procedures control lagged dependent variable problems and obtain the IVs for the 3SLS estimations. We then interact the datasets on vulnerabilities and resiliencies with the dataset on disaster impact to see the feedback effects among these variables. Partial

derivatives of these variables with disaster impact will provide their effects on regional growth.

We start with all available variables and then gradually eliminate the ones with high multicollinearity. The preliminary tests confirm no heteroskedasticity or autocorrelation problems. To avoid multicollinearity further, the vulnerability and resilience systems are estimated separately because some variables are opposite, for example, *SELFH* and *PROH*. Since *PERCA* is also a measure of resilience, this is the direct -impact variable in this equation. Vulnerability and resilience variables interact with *PERCA* to find the indirect effects of these variables on *LOSSES*. Each type of loss is also estimated in a separate system to avoid multicollinearity.

4. Results

Table 1 reports the results for all three vulnerability variables. Panel (1.1) is with *PERCA* as the dependent variable, and Panel (1.2) is for each type of *LOSSES* as the dependent variable.

Table 1. Effects of Vulnerability on Growth and Disaster Losses

Panel (1.1) Dependent variable: Growth of per capita income			
Variable	PERCA (MORT)	PERCA (AFFT)	PERCA (FINN)
UNEMP	-0.28** (.036)	-0.22** (.034)	-0.13*** (.009)
UNEMP1	-0.14** (.029)	-0.11** (.035)	-0.03** (.045)
UNEMP2	-0.06* (.079)	-0.03* (.063)	-0.01* (.054)
COM-UNEMP	-0.48** (.031)	-0.36** (.028)	0.17 ** (.046)
IMORT	-0.24** (.026)	-0.11** (.028)	-0.12** (.014)
IMORT1	-0.12** (.041)	-0.13** (.042)	-0.10* (.065)
IMORT2	0.05** (.039)	-.003* (.031)	-0.04 (.038)
COM-IMORT	-0.41** (.042)	-0.27** (.029)	-0.26** (.012)
SELFH	-0.31** (.039)	0.28*** (0.008)	0.15** (.028)
SEFH1	-0.12** (.046)	0.14** (.017)	0.06*** (.001)
SELFH2	-0.04** (.37)	0.05** (.29)	0.03** (.025)
COM-SELFH	-0.47** (.036)	0.47** (.028)	0.24** (.015)
CAPITAL	0.33** (.029)	0.35*** (.006)	0.45** (.032)
INITIAL GDP	-0.07** (.032)	-0.06*** (.001)	-0.05** (.024)
Panel (1.2) Dependent variable: Ratio of loss measure to population			
Variable	MORT	AFFT	FINN
UNEMP*PERCA	0.09** (.022)	0.08** (0.41)	0.11*** (.006)
IMORT*PERCA	0.11** (.031)	0.15** (.021)	-0.12** (.048)
SELH*PERCA	-0.12** (.017)	-0.21** (.033)	0.23** (.022)
PERCA	-0.07** (.031)	-0.06** (.018)	-0.08*** (.003)
INFRASTRUCTURE	-0.14** (.023)	-0.13*** (.009)	-0.12** (.039)
INTEREST RATE	0.075** (.042)	0.05*** (.002)	0.07** (.045)
p-value for F-test	0.002	0.000	0.006
Average RMSE	0.143	0.125	0.162
p-value for AR (1)	0.315	0.276	0.307
p-value for AR (2)	0.323	0.298	0.271
Notes: ***, **, * indicate the significant level at 1, 5, and 10 percent, respectively, with p-values in parentheses. The p-value for AR(1) and p-value for AR(2) are from Arellano-Bond test for AR(1) and AR(2) in first differences and second differences, respectively.			

UNEMP1 is UNEMP lagged one period, UNEMP2 is UNEMP lagged two periods and COM-UNEMP is the composite effect.

Taking the most complicated case of the unemployment rate (UNEMP), which indirectly increases the losses of disasters since UNEMP lowers the per capita income, making a household poorer, holding other variables constant, we have:

$$\text{LOSS} = B2 (\text{UNEMP} * \text{PERCA})$$

$$(\text{LOSS} / \text{PERCA}) = B2 \text{ UNEMP}$$

Differentiating (LOSS/PERCA) with respect to UNEMP yields:

$$d[(\text{LOSS} / \text{PERCA})] / d(\text{UNEMP}) = B2.$$

Hence, B2 measures the percentage increase in disaster losses due to an increase in the unemployment rate by one percent, which adversely affects the growth of per capita.

Interpretations of other variables are in the same manner. The signs of the control variables are as expected.

Table 2 reports the results for the resilience variables.

Table 2. Effects of Resilience on Growth and Disaster Losses

Panel (1.1) Dependent variable: growth of per capita GDP			
Variable	PERCA (MORT)	PERCA (AFFT)	PERCA (FINN)
TRAINW	0.78** (.017)	0.35*** (.005)	0.19** (.029)
TRAINW1	0.25** (.042)	0.19** (.031)	0.05** (.029)
TRAINW2	0.12* (.076)	0.11* (.068)	0.04* (.082)
COM-TRAINW	1.15** (.031)	0.65** (.028)	0.28** (.028)
PROH	0.72** (.01)	0.42** (.033)	0.51** (.014)
PROH1	0.14** (.031)	0.12** (.045)	0.12** (.043)
PROH2	0.03* (.063)	0.037* (.079)	0.13** (.038)
COM-PROH	-0.89** (.021)	0.58** (.031)	-0.75 (.217)
HINDU	0.19** (.039)	0.11*** (.007)	0.13* (.083)
HINSU1	0.15** (.026)	0.12*** (.003)	0.08* (.061)
HINSU2	0.12* (.059)	0.05* (.068)	0.96** (.046)
COM-HINSU	-1.46** (.031)	-0.28** (.025)	0.21* (.055)
CAPITAL	0.31*** (.004)	0.32** (.048)	0.34** (.033)
INITIAL GDP	-0.06** (.029)	-0.07** (.041)	-0.08*** (.005)
Panel (1.2) Dependent variable: Ratio of loss measure to population			
Variable	MORT	AFFT	FINN
TRAINW	-0.07** (.022)	-0.08** (.043)	-0.11** (.039)
PROH	-0.12** (.031)	-0.15** (.031)	-0.18*** (.004)
HINSU	-0.16** (.047)	-0.19*** (.003)	-0.20** (.028)
PERCA	-0.06*** (.001)	-0.07** (.035)	-0.08** (.041)
INFRASTRUCTURE	-0.15** (.036)	-0.13** (.050)	-0.14** (.042)
INTEREST RATE	0.05* (.064)	0.02** (.012)	0.07** (.044)
p-value for F-test	0.006	.003	0.009
Average RMSE	0.206	0.218	0.184
p-value for AR (1)	0.276	0.312	0.251
p-value for AR (2)	0.247	0.301	0.324
Notes: ***, **, * indicate the significant level at 1, 5, and 10 percent, respectively, with p-values in parentheses. The p-value for AR(1) and p-value for AR(2) are from Arellano-Bond test for AR(1) and AR(2) in first differences and second differences, respectively.			

The results indicate that all vulnerability variables adversely affect regional growth or disaster losses. For example, the estimated coefficient of the variable UNPEM*PERCA in Panel (1.2) is 0.09 for MORT, implying that a one-percent increase in the unemployment rate indirectly increases the possibility of MORT rate by 0.09 percent through the decrease in growth of per capita GDP.

5. Local Governance and Conclusion

5.1 Implication on Local Governance

We believe that the most important aspect of local governance regarding sustainable development is fighting corruption. Since natural disasters destroy the environment for sustainable development, and corruption activities favor the groups who pay them over others, they create inequality in per capita income and unemployment, decreasing local resilience and exacerbating their vulnerability.

Voice and accountability reflect local residents participating in policy-making processes, as well as freedom of expression, freedom of association, and a free media. They will improve the local communities' trust in the government, making it easier to encourage them to buy disaster insurance and health insurance.

Stringing the rules of laws prevents business violations of environmental codes will reduce the impact of natural disasters on economic growth.

Concerning political stability, tracking criminal activities and encouraging resident communities to help each other can improve political stability and foster local peace.

Improvement of regulatory quality focuses on developing institutions and tools to assess, consult, design, deliver, and monitor regulatory policy. This will help reduce the infant mortality rate and increase the quality of life for other residents, especially in healthcare businesses.

5.2 Conclusion

This paper investigates the feedback effects of vulnerability and resilience on disaster losses and economic growth in Central Vietnam. All three measures of vulnerability reduce economic growth and exacerbate disaster losses, whereas resilience measures improve economic growth and mitigate the adverse effects of disasters. Due to data limitations, the impact interpretations should be in directions rather than in magnitudes. We hope this research helps local governments improve their disaster preparedness and local governance in sustainable development.

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