



**THE INEQUALITY EFFECTS OF NATURAL
DISASTERS: EVIDENCE FROM THAILAND**

BY

MR. ANNOP JAEWISORN

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
MASTER OF ECONOMICS
(INTERNATIONAL PROGRAM)
FACULTY OF ECONOMIC
THAMMASAT UNIVERSITY
ACADEMIC YEAR 2020
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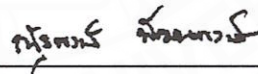
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THE INEQUALITY EFFECTS OF NATURAL DISASTERS:
EVIDENCE FROM THAILAND

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ABSTRACT

This study explores the effects of natural disasters on inequalities in Thailand – both income and expenditure inequality – at a micro level. The analysis uses a unique survey panel and remote-sensing dataset constructed for the objectives of this research. It contains provincial inequality measures and other economic and social indicators based on the Thailand Household Survey during the period between 1992 and 2019. Besides, the remote-sensing data on natural disaster is received from several sources using GIS software. Employing a panel fixed effects estimation, the key finding of this study shows that natural disasters significantly decrease household income and expenditure inequality as measured by the Gini index. These results are robust across heterogeneity of the samples, lagged effects of natural disasters, outliers, and an alternative inequality measure. The effect on income inequality is mainly driven by droughts, while the effect on expenditure inequality is mainly driven by flood events.

Keywords: Natural disasters, Remote-sensing data, Inequality, Thailand.

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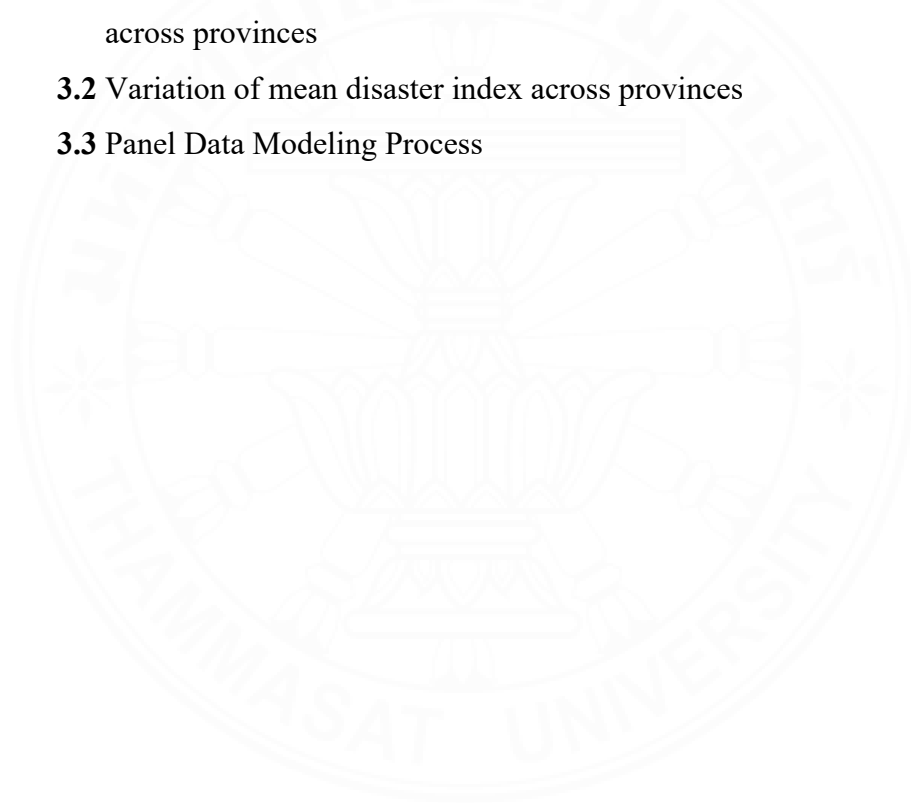


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CHAPTER 1

INTRODUCTION

1.1 Statement of Problem

Natural disasters have been growing in frequency and severity on a global scale. Every year, the disasters such as storms, earthquakes, floods, droughts, and other natural hazards cause more than thousands of deaths, over hundred thousand of injuries, and many billions of dollars losses all over the world (Dilley et al., 2005). While these incidents seem to become more and more relevant in the near future in a world where the climate-related natural events are expected to increase as a result of global warming.

Natural disasters have an equalizing power. Forest fires destroy the homes of the wealthy and the poor alike. Hurricanes cause problems on both cruise ships and old automobiles. Earthquakes devastate towns, affecting those in the surrounding area. Natural disasters, on the other hand, have a polarizing power. In other words, income and wealth determine how and who is affected by the disasters; the degree to which individuals, insurers, nonprofits, and governments are able to help; and who recovers and to what extent.

Regardless of the level of economic development, the natural catastrophe results in economic and human losses. The earthquake in Haiti in 2010 and Hurricane Harvey in 2017, for example, shown that both rich and poor countries are vulnerable to such disasters, which have long-term effects on human welfare and economic development. However, due mainly to distinctions in the exposures and vulnerability to disasters, these effects may vary across countries, territories, cultures, and individuals (Clark et al., 1998). Meanwhile, natural disasters frequently have a negative impact on household income and expenditure, increasing in poverty and inequality might be one of the important following issues (Dercon, 2004; Masozera et al., 2007; Thomas et al., 2010; Mottaleb et al., 2013). Some researchers found that poor households appear to be more vulnerable to natural disasters in both the response and recovery phases, and countries that are more vulnerable to disasters may experience higher poverty and inequality than those who are not, especially in undeveloped and developing countries where the majority of poor people live. (Peacock et al., 1997; Fothergill and Peek, 2004;

Blaikie et al., 2004; and Krueger and Perri, 2009). Nevertheless, some argue that catastrophic natural disasters will cause negative effects on economic activity even more in highly developed countries due to the higher value of losses. This raises the question: "How do natural disasters truly affect inequality?".

Thailand has frequently been cited as a country with rapid economic growth and high job employment, but with a persistent problem of high- and increasing-income inequality (Deolalikar, 2002; Kakwani and Krongkaew, 2000). On average, the inequality in Thailand was significantly higher than other East Asian and Pacific Rim countries in 1976, and it increased even further with sustained economic growth, reaching a value of 0.515 in 1996. (Jeong, 2008). Recently, Thailand has been scored 90.2 on the Gini coefficient in the Credit Suisse Research Institute's 2018 Global Wealth Report (also the Gini index). This makes Thailand become the country with the highest level of income inequality in ASEAN, and one of the 4 worst on the world chart. Meanwhile, Thailand has been affected by a number of natural disasters, including earthquakes, floods, tropical storms, and drought. For instance, notable disasters in Bangkok include the devastating floods of 2010 and 2011, which negatively impacted over 7 million people and devastated the capital and its surrounding region. Therefore, the main objective of this study is to investigate the impact of natural disasters on inequality in Thailand.

There are, however, only a few studies that have been researched on the relationship between natural disasters and income inequality, especially in Thailand. Additionally, up until now, the majority of studies on the impact of natural disasters have relied on the Emergency Events Database (EM-DAT), developed by the Centre for Research on the Epidemiology of Disasters (CRED), which contains results derived from outcome-based data. This database has been critiqued by several scholars that it might suffer from the selection bias problem, and endogeneity problem (Felbermayr and Gröschl, 2014). Moreover, they are hardly to be disaggregated into micro-level analysis of economic and social conditions such as inequality. Noy (2009) and Cavallo et al. (forthcoming) suggest that for causal empirical research, comprehensive physical disaster severity measures would be superior to the EM-DAT dataset. Therefore, this study fulfils this gap by using the physical intensity dataset (remote-sensing data) in the analysis instead.

1.2 Objectives

1. To investigate the effect of natural disasters on income and expenditure inequality in Thailand.
2. To investigate the effect of each type of natural disaster on income and expenditure inequality in Thailand.



CHAPTER 2

REVIEW OF LITERATURES

This chapter presents literature reviews on the relationship between income inequality and natural disasters, including the determinants of income inequality. The first part, 2.1, discusses the theoretical frameworks. Section 2.2 examines the previous empirical studies on the relationship between income inequality and natural disasters. The last section, 2.3, presents an overview of natural disasters and income inequality in Thailand.

2.1 Theoretical Frameworks

Theories that fully explain natural catastrophes' underlying economic processes are rare. Only a few studies have explored the relationship between income inequality and natural disasters in details. They often refer to it as a component of economic loss and risk exposure frameworks.

2.1.1 The Relationship Between Natural Disasters and Economic Losses

Natural disasters, in general, are seen as exogenous shocks that disrupt the (macro)economic cycle by reducing available inputs, which typically results in changes in output and consumption patterns. They have a variety of effects on the economic system, and determining the "cost" of it is difficult. Several scholars, including Pelling et al. (2002), Lindell and Prater (2003), Cochrane (2004), and Rose (2004), address disaster effect typologies. Typically, these typologies differentiate between direct and indirect losses.

“Direct losses” are the instant effects of a disaster. Direct losses are frequently divided into two types: direct market losses and direct non-market losses (also known as losses that are difficult to define, though non-market losses are not often intangible). Market losses are losses incurred in products that are exchanged on markets and whose values are readily visible. Many events result in direct market losses in

properties, such as damage to the building infrastructure and consumer products. The cost of restoring or replacing the lost or disabled properties may be used to calculate these losses. Thus, direct market losses can be measured by accessing observable prices and remaining inventories of physical damages that can be identified (as reported, for example, in the EM-DAT database or insurance sector databases) or modeled (using, e.g., simplified techniques or disaster models of the insurance company; see Ranger et al., 2011).

Meanwhile, “indirect losses” are those that are incurred by the disaster's aftermath rather than the incident itself. In some contexts, indirect costs are described differently (Hallegatte and Przulski, 2010). Controversial problems can arise along the edges of these concepts, causing debate within hazard societies: where do the direct and indirect cost categories meet? Business interruption is a topic that is often discussed, as it may be classified as direct or indirect damage, or it may be considered into a separated group. The expression "indirect losses" is mostly used as a metaphor for "output losses," i.e., the decrease of economic output triggered by the event, for capital-destroying disasters (such as floods, earthquakes, and storms). The cost of business interruption due to fluctuations of water or power supply, as well as the longer-term effects of maintenance and capital destruction, are both examples of output losses.

The following principles have often been used to help in identifying indirect losses: indirect damages occur as a result of secondary impacts, not as a result of the disaster itself. Indirect damages are incurred when assets are destroyed or when businesses are disrupted. Apart from this principle, costs are indirect whether they cover a longer time period, a broader geographic scale, or an economic field unrelated to the disaster. Additionally, secondary losses or indirect losses can be market or non-market in scope (see Government of Queensland, 2002). Occasionally, disasters have non-monetary indirect effects, most notably the effect on poverty or inequality, the loss in revenue, or the rise in the country's national debt.

The distinction between catastrophe situations with varying rebuilding rates exemplifies why indirect damages are critical. There is a significant gap in terms of welfare in a situation in which all direct casualties could be recovered in some months by an efficient reconstruction mechanism versus one in that

reconstruction is costly and takes more than a year. Welfare effects are much greater in the latter situation with the same number of direct casualties, and this should be considered.

In the case of natural disasters and their effect on inequalities, the loss from natural hazards may be either direct (or first-order) consequences or subsequent indirect (second-order) effects on the allocation and use of capital within a community (Euston and Kumari, 2018).

Economic welfare losses from disasters are typically characterized in terms of lost consumption, which is a significant part and a strong proxy for welfare losses¹ related to economic factors. The figure 2.1 illustrates how to calculate consumption losses as a result of asset and production losses. It essentially depicts a post-disaster scenario. The region ABD represents the case where only production losses are measured. What is frequently referred to as the indirect loss is the number of instantaneous output losses. However, reconstructing needs in the case of a catastrophe would require a large portion of remaining output to be dedicated to reconstruction. In other words, the money spent to reconstruct affected building cannot be used to construct new buildings or to maintain the remaining ones. This reconstruction output is incorporated into overall output and does not reflect a reduction in output. However, it is a "forced" investment, in comparison to the standard "investment—consumption" trade-off. As a result, it results in a loss of welfare, which is quantified as region BCD. This is referred to as direct cost. The number of production losses and reconstruction output is what cannot be used for consumption or non-reconstruction investment, and is depicted in this section as "total losses," as shown in region ABC.

The total cost, in this model, is calculated as the aggregate of the indirect cost (i.e., the loss in the economy's total value added as a result of the event) and the direct cost (i.e., some part of remaining value added that must be allocated to reconstruction rather than usual consumption). Thus, consumption losses can be estimated easily by adding capital and production losses. As previously stated, it is dependent on the objective of the analysis whether or not any of the cost components must be used in the calculation.

¹ In a utilitarian framework, consumption is more important than output and production.

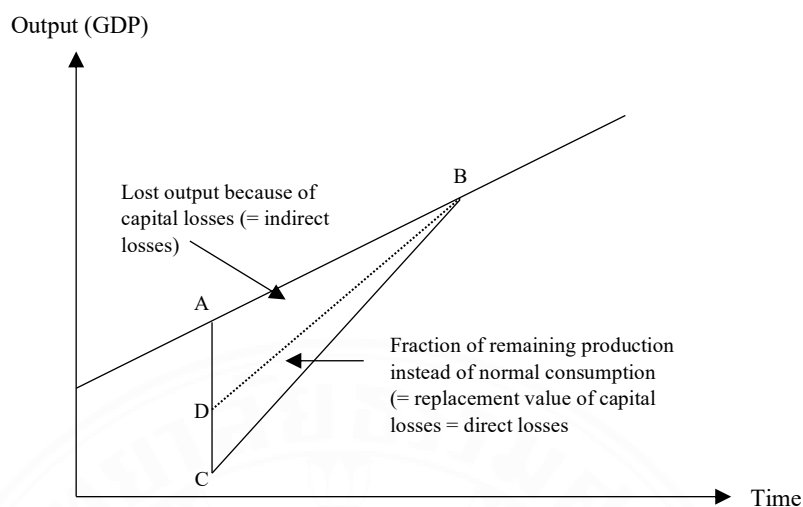


Figure 2.1 Direct losses, indirect losses, and “total” losses from “The economics of natural disasters: concepts and methods.” by Hallegatte and Przulski. (2010). The World Bank.

Figure 2.1 depicts a simplistic scenario in which production is fixed. In this situation, reconstruction requirements cannot be met by expanded demand alone; they must be met at the cost of other consumption and expenditure. Figure 2.2 illustrates another scenario in which there is limited production flexibility in the manufacturing process: capital destruction results in a decrease in production; however, unaffected capital can increase its own production to compensate, for example, by increasing work hours for employees in unaffected areas. In fact, there are gross indirect losses and gross indirect benefits as a result of the reconstruction's stimulatory effect (see area BEF in Figure 2.2). However, a portion of the remaining output is now used for reconstruction rather than regular use, but at a lower rate than in the lack of production flexibility.

Additionally, in this case, the consumption loss is the number of direct (asset) and indirect (output) losses, necessitating the estimation of production losses. However, production losses include not only decreased input from effected resources, but also gains and losses in production from unaffected capital throughout

the economy. This complicates the calculation of production losses by relying on dynamic economic processes and trade-offs.

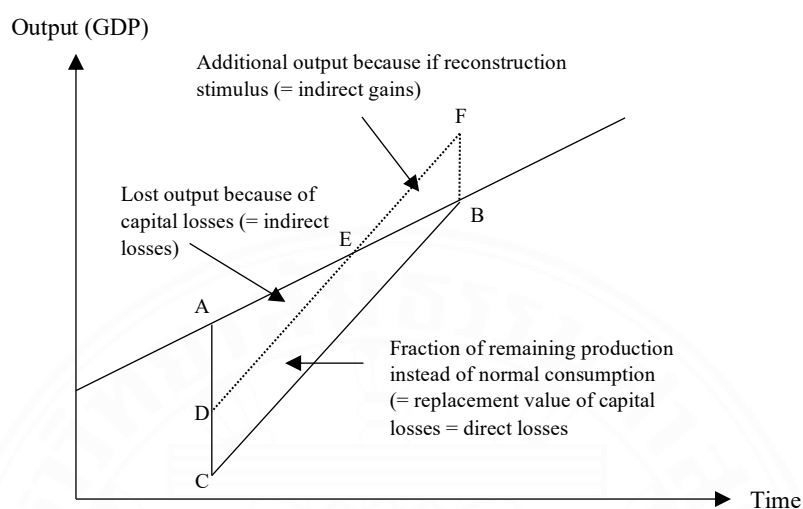


Figure 2.2 Direct losses, indirect losses, and “total” losses when there is a limited flexibility in the production process from “The economics of natural disasters: concepts and methods.” by Hallegatte and Przulski. (2010). The World Bank.

This conceptual framework implies that there could be either costs or benefits from natural disasters. Likewise, we could apply this to the income inequality conception generating losses and benefits aftermath. Hence, the impacts of natural disasters on income inequality are ambiguous.

2.1.2 Risk and Income Inequality

In his study, Sandmo (1971) demonstrates that when the output price is uncertain, a risk-averse producer (firm) generates less output than in a situation when the output price is certain. Specifically, once the producers face risk, they mitigate their exposure by reducing their allocation of limited capital to the risky option. The result appears to be true for a risk-averse agricultural household producing a single good (i.e., cash crops) in order to maximize the expected utility of revenue.

However, when considering risk-averse farmer households that be able to devote their limited capital (i.e., land) to a variety of risky return activities to optimize their expected utility of revenue, this households seem to have an optimal

resource distribution solution. The farmer households usually spread resources to a particular task until the marginal effect on expected revenue is approximately equal to the marginal effect on income risk weighted by household risk aversion. In other words, the household allocates a limited resource through several producing activities in such a way that the ratio of expected marginal revenue (marginal benefit) equals the ratio of marginal effect on income risk (marginal cost) for each pair of activities i and j :

$$\frac{d\bar{Y}/dX_i}{d\bar{Y}/dX_j} = \frac{d\sigma^2/dX_i}{d\sigma^2/dX_j} \quad i \neq j \quad (2.1)$$

where Y represents expected (total) farmer household return; σ^2 denotes (total) return risk (variance); and X_i, X_j denotes the quantity if resource X is given to activities, i and j , respectively. If the correlation between the returns on one risky income activity and other risky income activities is relatively low, the household can devote its limited resources to other risky return activities in order to reduce overall income risk.

Even in a world with only one activity, the Sandmo's result is not always true for farmer households that consume a large portion of their production and have problems with both consumption- and income-price risk. Finkelshtain and Chalfant (1991) demonstrate that lots of households, that are risk-averse and consume more than half of their production, are tending to increase their food production in order to mitigate against risky food prices.

Moreover, the presence of different environments in poor and unstable zones incentivizes households to diversify their revenue sources through zones where the return on activities is not strongly related (i.e., by migration) or within zones through non-harvest-dependent activities. By comparison, in zones with higher soil fertility and more consistent precipitation, households have greater incentives to specialize or diversify their revenue sources locally, including into activities related to harvesting production via input-output markets. Given these considerations, a natural disaster that reduces crop production could have a less unequalizing (or even equalizing) impact on income distribution in the poor and unstable area, where ex-ante prospects for low- and middle-income households to diversify their revenue risk are high.

However, in the real world, not everything is equal. In the case that credit and insurance markets are not perfect, wealthier households are in a better position to self-insure against specific income losses and participate in cropping strategies in order to reduce the risk from unexpected events. For example, they may invest in environment-improving technologies like land quality improvements, irrigation, and flood and erosion control. If the revenue diversification is costly, and uncertain, the wealthier households are more likely to be well positioned to diversify into non-crop activities. Therefore, assuming the requirement that households must self-finance this diversification, in light of the poor's liquidity and credit limitations may produce the opposite empirical result when compared to wealthier households.

2.1.3 Sources of Income Inequality

Amartya Sen may have been the first scholar (after Marx) who raised the issue of why one should study inequality seriously. He concurred with Marx that research on inequality should aim to identify the mechanisms that keep people from living the lives they 'have reason to enjoy', and that the trouble with inequality is that many people lack this choice (Sen, 2006, p. 35). Both accepted that the dilemma stems from a disproportionate allocation of wealth and its symbolic legitimization. They suggest a somewhat mechanistic origin for these systems and the oversimplified solution of redistribution.

However, Sen's approach has not been more explored by economists as it always sticks to methods that can't include a comprehensive view of inequality. From a microeconomic perspective, the determinants of the income distribution are mainly drawn from at least three approaches, and each has some benefits that are still important in today's research:

1. **Growth.** Kuznets (1955) proposed the Kuznets inverted-U hypothesis, which states that the disparity of income would begin to worsen in the beginning stages of economic development and change only later. According to the hypothesis, in the early stage of economic growth, potential investment options for those who do have money to spend improve. In other words, these additional investment options suggest that those who already have money have the potential to increase their capital. In contrast, the influx of cheap rural labor into cities leaves working-class wages

down, widening the income gap and rising economic inequality. When a nation begins to industrialize, the population moves from rural to urban regions, and people, such as farmers, continue to relocate in search of better-paying employment. However, as a consequence of this influx, there is a significant income gap between rural and urban areas, and the number of rural populations is declining as the number of urban populations rises. Hereafter, until a certain amount of average income is met and mechanisms consistent with industrialization, such as democratization and the creation of a welfare state, take place, economic inequality is supposed to decline. That is to say, society is supposed to prosper from the trickle-down impact and a rise in per capita wealth at this stage in economic growth would eventually decrease inequality.

2. *Human capital.* The human capital theory is neoclassical economics' core analytical method for explaining various individual's earning profiles (Becker, 1964; Mincer, 1974). From two separate views, the human capital theoretical concept is used to analyze the mechanism of ability formation. On the one hand, this method, which is focused on a constrained maximization model, takes into consideration of individual educational options. Individuals can engage in years of schooling over as many years as possible, according to this view, so that the return on investment is higher than most other financial investments. The size of this investment determines a worker's earning profile, which is influenced by two factors: personal skill and background characteristics such as gender, parental background, and wages. Becker, on the other hand, began his study of ability formation in firms by looking at various types of training, assuming a perfectly dynamic labor market (on-the-job, off-the-job, ...). He explained the critical distinction between specific and general training and demonstrated that, although it can be convenient for employers to commit to specific training investment, the burden for general training falls entirely on the hands of workers, as the possibility of free riding from other employers may render general training investment inefficient. Inequality results from a process of ability formation from all sides. In the case of individual educational options, inequality is determined by the amount of time spent in school, which is determined by both experience and individual characteristics; in the case of corporate training, inequality is determined by judgments made by both employers and employees.

3. *Inequality.* The basic concept is that inequality may be thought of as an autoregressive mechanism, in which past inequality influences current inequality. This is in line with a recent study by Brunori, Ferreira, and Peragine (2013), which looked into the influence of exogenous factors including past inequality, birthplace, gender, ethnicity, and family history on inequality. They discovered that these exogenous causes account for a significant portion of income inequality. Furthermore, there is a negative relationship between the inequality index and intergenerational mobility: the greater the degree of inequality, the less likely it is to change one's relative status in the social hierarchy. Of course, the relevance of these factors varies from country to country.

The focus of recent studies on income distribution in Thailand has relied on the relationship between economic growth and income inequality. Other factors, though, have been studied, and all of them have a major impact on Thailand's income disparities. Table 2.1 summarizes each of these determinants.

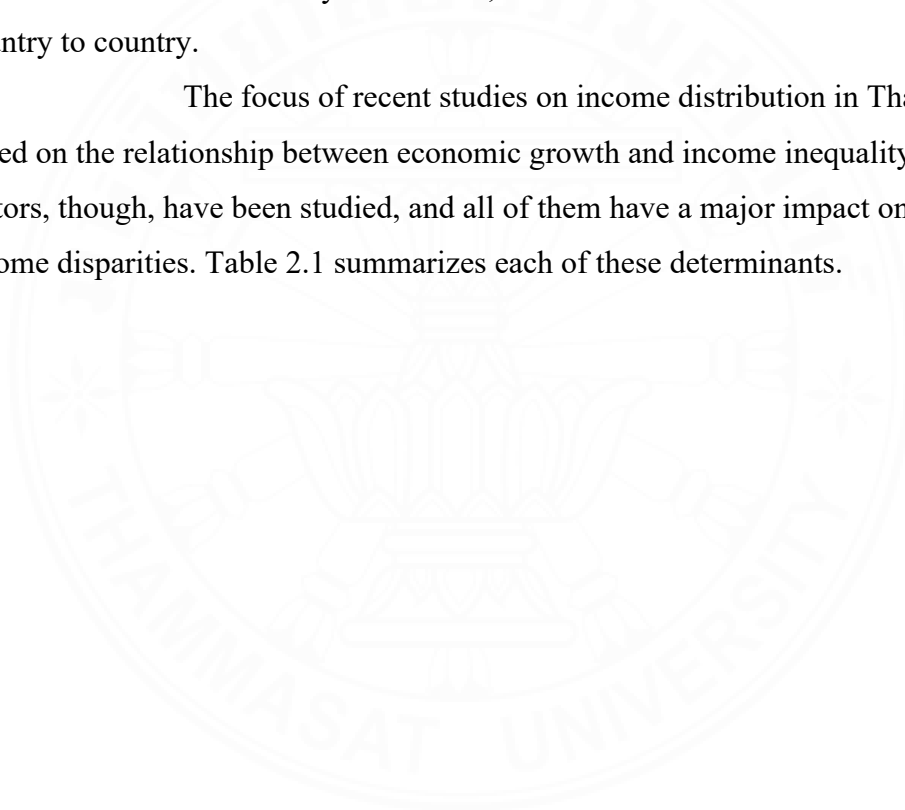


Table 2.1

Summary of the empirical studies: the determinants of income inequality in Thailand

Empirical Literature	Econometric Model	Study Periods	Determinant of Income Inequality*
Meesok (1979)	-	1962-1963 and 1975-1976	<ul style="list-style-type: none"> ▪ Economic growth
Fofack and Zeufack (1999)	Error component model (ECM)	1986-1996	<ul style="list-style-type: none"> ▪ Level of Education ▪ Land and property possession ▪ Transfer ▪ Concentration of income by area
Motonishi (2006)	OLS Fixed and random effects panel regression	1975-1998	<ul style="list-style-type: none"> ▪ Mean of monthly household income ▪ Proportion of insurance and interest expenditure ▪ Education level ▪ Proportion of agricultural households to non-agricultural household
Kurita and Kurosaki (2011)	Generalized Method of Moments (GMM) estimation	1988-2004	<ul style="list-style-type: none"> ▪ Inequality

Table 2.1

Summary of the empirical studies: the determinants of income inequality in Thailand (continued)

Empirical Literature	Econometric Model	Study Periods	▪ Determinant of Income Inequality*
Paweenawat (2014)	Weighted least squares (WLS) estimation	1992-2011	<ul style="list-style-type: none"> ▪ Variance of per capita income ▪ Variance of years of education ▪ Variance of number of children in households ▪ Variance of number of earners in households ▪ Age

Note: * selected only some important determinant (s) in each study. There may also be other determinants in the models.

Source: Author's Elaborations

2.2 Previous Economics Empirical Studies: The Impacts of Natural Disasters on Income Inequality

Economic analysis on the impacts of natural disasters has exploded in recent years. The primary and most compelling explanation is an increasing recognition of natural disasters' potential for devastation, as shown by the 2011 Tōhoku earthquake and tsunami in Fukushima, Japan and the 2012 super typhoon named Haiyan in the Philippines. Additionally, it is a product of a growing recognition that natural disasters are socioeconomic phenomena that have a variety of negative consequences for human well-being. However, their effect is likely to be different from country to country. In other words, the impact of natural disasters is usually determined by the nature of the incidents (i.e., level of precipitation, intensity of wind associated with a storm or magnitude of an earthquake) as well as features of the countries (i.e., level of development, location).

In the past few years, many projects have evaluated the impact of natural disasters on the short- and medium-term growth, the fiscal impact of disasters on international and financial flows, the impact on populations through migration and fertility choices, the impact on human capital, the role of political economy in shaping disasters' aftermaths, and on other various issues (Euston and Kumari, 2018). Surprisingly, despite the fact that this issue is affecting people all over the world, there are few studies on the impact of natural disasters on the disadvantaged and income distribution.

A disaster's impact is not equally distributed. Many cross-country studies demonstrate explicitly that wealthier countries can avoid or reduce the impacts of disasters more efficiently, and therefore bear a substantially lower cost (as a percentage of the size of their economy). The sources that tend to explain these cross-country disparities appear to be dependent on the countries' average incomes or per capita income (Kahn, 2005). The most obvious clarification is that, because preventive interventions are regarded as standard (or luxury) investment products. Thus, there will be countries with higher permanent income or capital that will devote more resources to preventing or reducing the impacts of disasters. Additionally, Escaleras et al. (2007) suggest that the level of democracy and transparency also accounts for a substantial

portion of the variation in the primary effects of similar natural hazards across countries, and it is well established that the level of democracy and transparency is also linked to average per capita income with a positive relationship.

The empirical study that does exist usually indicates that wealthier households are less vulnerable and would suffer losses disproportionately when compared to poorer households, both in terms of dollar amounts and as a share of their household income. However, determining the magnitude and relative impact of disasters on the poor cannot be evaluated by analyzing the distribution of costs and economic activity by studying at cross-country level, since the magnitude and impact could be more dependent on country-wide distinctions. For example, the difference in government ability and policies that may be indirectly associated with incomes rather than related to income directly (Euston and Kumari, 2018). In other words, these distinctions could lead to different conclusions. As such, country-level study in this area is warranted. Unfortunately, the data on how disasters affect households at different income levels within a country is scarce.

An important characteristic of natural disaster risk vulnerability is that millions of inhabitants are forced to live in hazard prone zones, which are often populated by the poor (e.g., Boustan et al., 2012). Kim (2012) claims that, on average, poor households are at least twice as vulnerable to natural hazards as middle- and high-income households worldwide, owing to a 26 percent higher concentration of hazard prone zones. Tesliuc and Lindert (2002) find evidence from Guatemala indicating that poor people are more vulnerable to natural shocks than the rich, but the opposite is true for man-made shocks. In their study, they discovered that natural shocks affect 35.4 percent of the poorest quantile, but just 21.2 percent to the richest quantile.

Bui et al. (2014) use the Vietnam Household Living Standard Survey to examine the impact of natural disasters on household income, expenditure, poverty, and inequalities. They found that the effect of a natural disaster on household income and expenditure is projected to be 6.9 percent and 7.1 percent reductions in Vietnamese household per capita income and expenditure, respectively. They argue that natural disasters impact negatively on Vietnam's expenditure, poverty, and inequality.

In contrast, Abdullah et al. (2016) establish that income disparity was reduced following Cyclone Aila in the Sundarbans area of Bangladesh in 2009. Another

paper published in Myanmar by Warr and Aung (2018) demonstrates that the cyclone decreased regional inequality, as the adversely impacted areas were relatively better off than the non-impacted areas both before and after the cyclone. Among the impacted areas, the cyclone's detrimental effect was greatest on richer households in actual term, but was greatest as a percentage of household spending on poorer households. Thus, they assume that the decrease in inequality in Myanmar between 2005 and 2010 is due to the fact that the reduction in inequality between regions outpaced the increase within regions.

Meanwhile, according to Feng et al. (2016), household income in China dropped by 14% as a result of the 2008 Sichuan earthquake, but income disparities remained unchanged. On the surface, these results may seem shocking, since one would expect natural disasters to have a negative relationship with income inequality. Table 2.2 summarizes the relevant empirical studies.

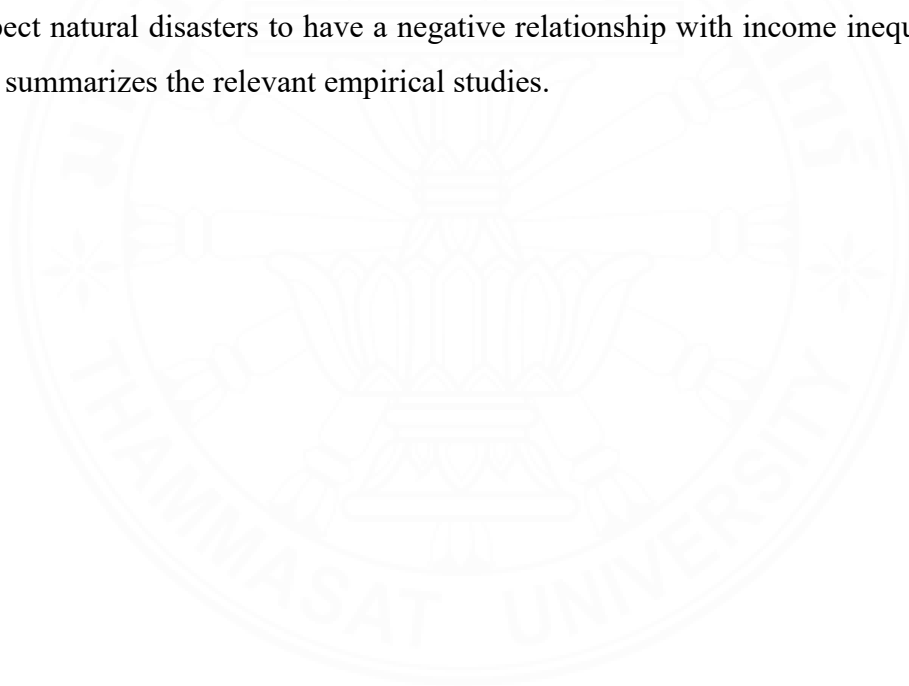


Table 2.2

Empirical studies on the impact of natural disasters on income inequality

Study Description	Date/Time Period	Sample/Methods	Results/Outcomes
Author: Tesliuc and Lindert (2002) Study area: Guatemala Natural disaster: Bunched shocks (D, Fl, H, Q)	Database used: Pilot LSMS survey module, QPES, ENCOVI Data Time period: 2000	Sample size: N = urban-2609, rural-3706, Guatemala City-921 Modeling technique: log linear multivariate regression model	Poor people are vulnerable to natural disasters and agricultural shocks when compared to rich people, bearing a higher portion of the cost. As a consequence of hazard incidents, 16% of income inequality is reduced, 11% of consumption inequality is increased, and 20% of overall poverty is increased.
Author: Yamamura (2015) Study area: 86 countries Natural disaster: D, Q, Ext, Fl, MMd, MMw, S, V, and Wf	Database used: SIDD, EM-DAT, WB Time period: 1965-2004	Modeling technique: OLS, Fixed-effects estimation	In the short run, natural disasters exacerbate income inequality, although this effect fades with time.
Author: Bui et al. (2014) Study area: Vietnam Natural disaster: S, Fl, L, Cw, and Ot	Database used: Household Living Standard Survey Time period: 1989 - 2008	Modeling technique: 2SLS regression, ATT, Bootstrap techniques	Natural disasters are expected to have a 6.9 percent and a 7.1 percent fall in Vietnamese household per capita income and expenditure, respectively. Additionally, it has been shown that it exacerbates expenditure, poverty, and inequality.

Table 2.2

Empirical studies on the impact of natural disasters on income inequality (continued)

Study Description	Date/Time Period	Sample/Methods	Results/Outcomes
Author: Abdullah et al. (2016) Study area: Bangladesh Natural disaster: Cyclone Ali	Database used: Household Surveys Time period: October 2009 and March 2010	Sample size: 249 households Modeling technique: One-way ANOVA	The poorest households raised their income by 16% as a result of new opportunities. Middle-class households have seen a small decline in income (by 4%), while the richest households have seen a 50% decrease in income after the cyclone.
Author: Feng et al. (2016) Study area: Sichuan, China Natural disaster: Earthquake	Database used: Household Survey Time period: 2007 (9 months before Q) and 2009 (15 months after Q)	Modeling technique: log linear multivariate regression model, Pair-wise comparisons	Household income decreased by 14% as a result of the disaster, but income disparities did not improve as a result of government support.
Author: Warr and Aung (2018) Study area: Myanmar Natural disaster: Cyclone Nargis	Database used: National Household Survey Time period: 2005-2010	Sample size: 18,000 households Modeling technique: Fixed- effects estimation	Cyclone reduce inequality between regions of Myanmar.

Table 2.2

Empirical studies on the impact of natural disasters on income inequality (continued)

Study Description	Date/Time Period	Sample/Methods	Results/Outcomes
Author: Keethiratne and Tol (2018) Study area: Sri Lanka Natural disaster: C, D, Epi, Fl, L, S, Ot	Database used: HIES, Disaster Management Centre of Sri Lanka Time period: 1990-2013	Modeling technique: OLS, Fixed-effects estimation, System GMM	Natural disasters and their immediate aftereffects reduce income inequalities per adult equivalent household. Meanwhile, non-seasonal agricultural and non-agricultural income inequality is reduced, but seasonal agricultural income inequality is increased.

Note: The acronyms used above are explained as follows: LSMS (Living Standard Measurement Survey), QPES (Qualitative Poverty and Exclusion Field Study), ENCOVI (Encuesta Nacional de Condiciones de Vida), SIID (Standardized Income Distribution Database), EM-DAT (Emergency Events Database), WB (World Bank), HIES (Household Income and Expenditure Survey), 2SLS (Two-Stage Least Square), ATT (Average Treatment Effect of the Treated), GMM (Generalizes Method of Moments), Natural Disasters - (D – Drought, Fl – flood, H – Hurricane, Q – Earthquake, Ext – Extreme Temperature, MMd – Mass Movement Dry, MMw – Mass Movement Wet, S – Storm, V – Volcano, Wf – Wildfire, L – Landslide, Cw – Cold Wave, C – Cyclone, Epi – Epidemics, Ot - Others)

Source: Author's Elaborations

2.3 Overview of Natural Disasters and Income Inequality in Thailand

2.3.1 Natural Disasters in Thailand

Thailand is situated between latitudes 6–12 North and 98–108 East. It covers a region of 513,115 square kilometers and has a population of more than 69 million people. Thailand's topography naturally divides the country into four regions: the north (which is vulnerable to floods, earthquakes, and forest fires); the central area (which is vulnerable to floods and earthquakes); the northeastern region (which is vulnerable to floods and droughts); and the south (which is prone to floods, tropical storms, and forest fires).

Floods, droughts, tropical storms, and forest fires are frequent natural hazards in Thailand. Whereas earthquakes are a rare occurrence. Generally, natural disasters that strike suddenly do the greatest harm to people and property. Rural areas tend to be the most prone to hazards as a result of underdeveloped facilities. Additionally, rural residents, who are mostly poor agriculturists, are unwilling to invest in infrastructure that would mitigate their exposure to disasters. The following are the most devastating natural disasters in Thailand:

1. Floods. Flooding, Thailand's most common natural disaster, happens during the monsoon season from June to September, having a negative effect on property more than any other form of disaster. In July 2011, Thailand experienced one of the deadliest floods in over half a century, resulting in 815 deaths, 45.7 U.S. billion dollars in economic losses, and devastation to 8,100 square miles of farmland. Flooding stretched through 65 provinces, affecting 13.6 million residents, and was especially severe in the country's central and northern regions. Parts of Bangkok were inundated with flood water when the floods reached the mouth of the Chao Phraya River, and even the Don Mueang airport's runway complex was almost submerged.

2. Droughts. Droughts arise periodically during the dry season of March–April, and they are becoming even stronger than they have ever been due to the global warming. The challenges are exacerbated by the increased demand for water for agricultural and industrial activities as a result of population growth and economic development. Droughts in Thailand are mostly caused by deforestation, which is combined with soil characteristics and a dry atmosphere. For instance, in 1998, the El

Nino effect exacerbated the issues. As a result, droughts threatened the whole nation to varying degrees. Drought-affected communities face water scarcity, especially for drinking, crop production, and livestock farming. Thailand is forecast to face the worst drought in at least four decades in 2020. Around half of the country's main basins are operating at less than 50% capacity. River flows are so low that saltwater from the ocean is infiltrating the river and contaminating drinking water (Bangkok Post, 2020).

3. Tropical Storms. Tropical storms coupled with flooding occur in Thailand between June and November, during the monsoon season. Although the entire country is susceptible to tropical storms, the Malay Peninsula's southern zone is particularly vulnerable. Of all tropical storms, 1989's typhoon 'Gay' was the most damaging storm. Typhoon Gay swept inland and crossed the southern portion of Chumphon province, destroying 602 lives and severely affecting property worth an approximate 480 U.S. million dollars.

4. Forest Fires. In general, forest fires in Thailand are fueled by humans who enter forest areas and then destroy them for crop cultivation. Northern Thailand is facing the worst forest fires in decades in 2020, resulting in severe air emissions in many regions. Experts report that about 20% of northern Thailand's overall forest area has been lost so far, resulting in irreplaceable biodiversity and biodiversity declines. The topic has persisted for ten years and has not been resolved.

5. Earthquakes. Thailand experiences a few earthquakes per year, all of which are of moderate magnitude. Thailand has a range of active faults that could trigger tremors, the majority of which are located in the north and west. However, these faults lack the capacity to generate significant earthquakes on the scale of those seen in the Ring of Fire or along tectonic plate boundaries.

Table 2.3 summarizes the number of incidents and the total cost of harm incurred by natural disasters in Thailand from 1989 to 2019, based on EM-DAT datasets. Droughts and floods are the two most common and dangerous natural hazards. There are 80 distinct incidents in which floods and droughts affected the region, causing destruction in excess of 45 billion dollars, killing over 2,000 and affecting more than 92 million.

Table 2.3

The value of losses caused by different kinds of disaster from 1989 to 2019

Disaster types	Number of disasters	Number of disasters with recorded damage	Total value of the damages ['000 US\$]	Number of deaths	Number of affected
Storm	33	14	879,600	850	4,829,693
Drought	12	5	3,725,500	0	41,982,602
Flood	68	38	45,753,162	2,924	51,326,875
Earthquake	4	2	1,062,000	8,347	76,053
Extreme temperature	2	0	0	17	1,000,000
Landslide	3	0	0	47	10,100
Wildfire	1	0	0	0	0
Epidemic	6	0	0	241	43373
Total	129	59	51,420,262	12,426	99,268,696

Source: Author's Elaborations based on EM-DAT Database

2.3.2 Income Inequality in Thailand

There is widespread agreement among scholars that Thai economic disparity has deteriorated steadily since the 1960s and continued to do so until the 1990s. However, scholarly debate persists about how it has progressed after the mid-1990s and the Tom Yum Kung or Asian Financial Crisis [following the 1990s].

In a recent study, Jenmana (2018) was able to map the development of Thailand's personal income disparity between 2001 and 2016 using a combination of surveys, administrative tax returns, and national accounts database. The research demonstrates that income inequalities in Thailand continue to be far greater than household surveys solely indicate.

In 2016, according to his study, the richest 10% of Thai people earned 53% of Thailand's national income, on average receiving around 2,900 U.S. dollar (100,000 Thai Baht) per month, and the top 1% of Thai citizens earned over 11,000 U.S. dollar (380,000 Thai Baht) per month. Meanwhile, the lower half of society

received just 13% of Thailand's national income and obtained an average of 150 U.S. dollar (5,000 Thai Baht) a month (see Table 4.2). This indicates that, on average, a person in the bottom 50% would have to work nearly four months to earn the richest 1%'s daily income, and one month to earn the richest 10%'s daily income.

Table 2.4

Number of adults, thresholds, averages, and shares of national income of Thailand in 2016

Income groups	Number of adults	Threshold (monthly)		Average income (monthly)		Income share
		2017 THB	2017 USD	2017 THB	2017 USD	
Full populations	51,954,056	0.00	0.00	18,661	550	100%
Bottom 50%	25,977,028	0.00	0.00	4,941	146	13%
Middle 40%	20,781,622	8,613	254	15,707	463	34%
Top 10%	5,195,406	37,783	1,114	99,072	2,920	53%
incl. Top 1%	519,541	161,489	4,760	377,426	11,124	20%
Top 0.1%	51,954	609,716	17,970	1,426,474	42,042	8%
Top 0.01%	5,195	2,150,996	63,395	5,668,244	167,057	3%
Top 0.001%	520	8,679,363	255,802	24,329,051	717,037	1%

Source: Jenmana, T. (2018)

More recently, Thailand scored 90.2 on the Gini coefficient in the Credit Suisse Research Institute's 2018 Global Wealth Study (also the Gini index). Thailand became the ASEAN country with the highest wage disparities (see Figure 4.1), and one of the world's four worst performers (90.9), alongside Ukraine (95.5), Kazakhstan (95.2), and Egypt (95.2).

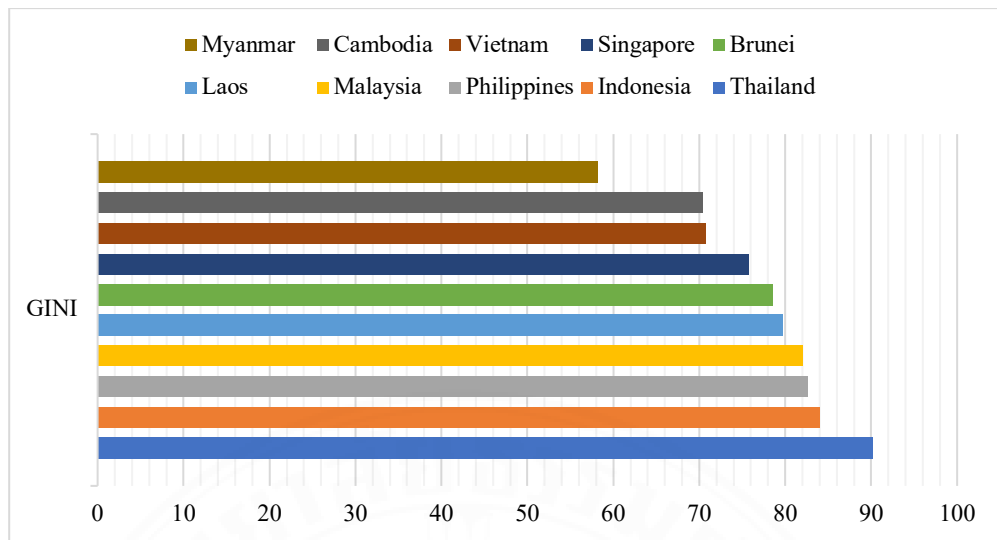


Figure 2.3 Rank of wealth inequality across ASEAN in 2018 from “Global Wealth Report” by Credit Suisse Research Institute database. (2018).

In the same direction, The Credit Suisse Report depicts the global wealth inequality as a wealth pyramid, with adults classified into four levels of wealth: (1) less than 10,000 U.S. dollars, (2) between 10,000 U.S. dollars and 100,000 U.S. dollars, (3) between 100,000 and 1,000,000 million U.S. dollars, and (4) more than 1,000,000 U.S. dollars.

Adults in Thailand are highly concentrated at the low end of the income scale. To be precise, 91.7 percent of adults have a wealth of less than \$10,000 U.S. dollars, 7.5 percent have a wealth of between 10,000 and 100,000 U.S. dollars, and 0.7 percent have a wealth of between 100,000 and 1 million U.S. dollars. Just 0.1 percent of the population has a net worth of more than one million dollars. This results in a Gini coefficient value of 90.2 for high income inequalities (see Table 2.5).

Table 2.5

Level of wealth inequality of adults in ASEAN in 2018

Country	Range of wealth distribution (U.S. dollars) of adults (%)				GINI score (%)
	Under 10,000	10,000 – 100,000	100,000 – 1 million	Over 1 million	
Thailand	91.7	7.5	0.7	0.1	90.2
Indonesia	85.5	13.7	0.8	0.1	84.0
The Philippines	89.0	10.2	0.7	0.1	82.6
Malaysia	60.6	36.2	3.0	0.2	82.0
Laos	93.6	5.9	0.5	0.0	79.7
Brunei	43.0	51.2	5.4	5.4	78.6
Singapore	13.8	38.2	44.0	4.0	75.8
Vietnam	93.1	6.6	0.3	0.0	70.8
Cambodia	94.8	5.0	0.3	0.0	70.4
Myanmar	98.9	1.1	0.0	0.0	58.2

Source: Author's Elaborations based on Credit Suisse Research Institute database

To conclude this, Thailand is one of the unique countries where most of its income is held by the top 10% of rich people in the country, while the majority of the population (poor and middle class) own less than 50 percent of the income of the whole country. In other words, even though Thailand has very rapid growth, it seems like all the growth is transferred to the rich rather than the poor or the middle-class population.

CHAPTER 3

DATA AND METHODOLOGY

This chapter mainly presents research methodology and data sources of the study. The organization is as follows; section 3.1 focuses on the model specification; section 3.2 presents the data sources; section 3.3 mainly explains the variable measurements and the last section, section 3.4, briefly examines the econometric procedures.

3.1 Model Specification

Theoretically speaking, according to Kuznets's inverted-U hypothesis, growth of an economy is a necessary condition in determining income inequality, but it is not an adequate condition alone. According to many previous empirical studies of the determinants of income inequality, this study thus includes other factors rather than income as independent variables since the sources of income inequality are considered to be complex and interlinked with others as well. In this research, therefore, the significance of education, number of earners, number of children, and money transfers are also included and inspected as the following details:

1. The mean of year of education. The mean of year of education of household head is included as explanatory variables according to human capital theory. Table 3.1 outlines the number of years spent by household heads obtaining each educational degree used in this study. The expected sign of coefficient of years of education is positive.

Table 3.1

The education years of the head of household

	Year of education
No education	0
Elementary	7
Secondary	12
Bachelor's degree	16
Vocational or technical	15
Higher education	18

Source: Author's Elaborations

2. The mean of number of children. Having children divides income in a household since it increases a greater number of household members. This would reduce per capita income in the household. According to the theory, families with a higher child count are thus more likely to have a higher degree of income inequality. Therefore, this variable is predicted to have a positive effect on the inequality variable. The number of children is measured on scales of zero to nine, and only children under the age of 15 are included.

3. The mean of number of children. Having children divides income in a household since it increases a greater number of household members. This would reduce per capita income in the household. According to the theory, families with a higher child count are thus more likely to have a higher degree of income inequality. Therefore, this variable is predicted to have a positive effect on the inequality variable. The number of children is measured on scales of zero to nine, and only children under the age of 15 are included.

4. The mean of number of earners. Given that household incomes can be raised by a rise in the number of income earners, a large number of income earners is thus expected to decrease income inequality. In other words, the coefficient of this variable is predicted to be negative. The Household Socio-Economic Survey has a selection number of earners from zero to nine.

5. The mean of money transfer. The log of monthly transfer money from both public and private sources is treated as an independent variable because it is widely cited as one mechanism for reducing income inequality in developing countries (See Fofack & Zeufack, 1999; Acosta et al, 2008). Thus, it is assumed that this variable would have a negative coefficient in the relationship with the inequality.

6. The mean of per capita income. The log of per capita income and its square are used to compare the level of economic growth and to search for the Kuznets hypothesis's inverted U-curve. According to Jeong (2008), if such a relationship occurs between mean per capita income and income disparities across cohorts, it is most likely a result of gaps in working positions, accessing to money credit, and urban-rural residential patterns across cohorts.

This study estimates the impact of natural disasters on income inequality in Thailand by using panel data for the period 1992–2019. The empirical model, including the variables relating to factors mentioned above, is thus specified as

$$INEQ_{it} = \beta_1 + \beta_2 \ln Y_{it} + \beta_3 (\ln Y_{it})^2 + \beta_4 EDU_{it} + \beta_5 CHI_{it} + \beta_6 EAR_{it} + \beta_7 \ln TRA_{it} + \beta_8 DIS_{it} + \varepsilon_{it} \quad (3.1)$$

where $INEQ_{it}$ = inequality index of area i at time t

Y_{it} = mean of monthly income of area i at time t

EDU_{it} = mean number of years of education of area i at time t

CHI_{it} = mean number of children of area i at time t

EAR_{it} = mean number of earners of area i at time t

TRA_{it} = mean of monthly transfers of area i at time t

DIS_{it} = natural disaster index of area i at time t

ε_{it} = error term of area i at time t .

Besides income inequality, according to previous empirical studies and dataset availability, expenditure inequality is measured as dependent variables as well, seeing whether the expenditure distribution would change in the same direction as the income distribution.

Moreover, since natural disasters are caused by a variety of different causes and have a variety of different effects, aggregating each type of disaster may be meaningless. Therefore, this study also disaggregates explanatory variables DIS_{it} into each specific type of natural disaster in the estimates as well.

3.2 Data Sources

There are two major sources of the data used in this study: household survey data and GeoMet data. Most of the variable data in this study is obtained from household survey data, which is ground data. Except for the data used to measure natural disaster variables is GeoMet data, which is remote sensing data from several sources.

3.2.1 Household Survey Data

The Household Socio-Economic Survey (HSES) was conducted by Thailand's National Statistical Office (NSO). Its aim has been to collect data on households' income, expenditures, and other characteristics. The survey is usually conducted two years at a time. Each time, a nationally representative sample is drawn and a questionnaire on household demographics, such as income, expenditure, education and relationships in households, is administered. The data can be segmented by province, and includes comprehensive income and expenditure data. As a result, data for each of the country's divisions is available. Since the number of provinces increased after 1992 from 73 to 76, and after 2011 from 76 to 77, the panel in this study is unbalanced.

This study makes use of pseudo panel data sets to create cohorts of households headed by members of the same provincial area and survey year. The sample size is approximately 17,000 to 38,000 households, covering heads of household in all provinces. The data spanning a period of 15 years (1992, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2007, 2009, 2011, 2013, 2015, 2017 and 2019) are employed. The number of available observations for estimate ranges from 1,065 to 1,141 cells.

One advantage of employing synthetic cohort data is that it enables the use of panel data estimation techniques, such as fixed effects, to account for unobservable variables. Additionally, the approach eliminates the attrition problem² associated with true longitude studies (Fofack & Zeufack, 1999). One possible source of concern in the study of this cohort data is the issue of measuring errors caused by small cell sizes. However, previous studies demonstrate that "sampling error" biases are negligible when there are at least 100–200 available observations per cell (Verbeek & Nijman, 1992, 1993). This concern is fulfilled by the panels built in this study because the datasets in this study contain at least 1,000 observations per cell.

3.2.2 Geophysical and Meteorological Database (GeoMet)

Empirically, disaster intensity is typically described in terms of the magnitude of its damage. To accomplish this, quantitative concepts are developed using objectively measurable criteria. When an incident meets the requirements of the criteria, it is classified as a "disaster" and entered into the database.

Felbermayr and Gröschl (2014) introduce, a new and comprehensive dataset, GeoMet, that includes exogenous measurements of physical disaster intensity. The data has been extracted from official geophysical or meteorological databases. The database includes data on the magnitude of all disaster incidents, as well as the month, year, and country in which they occurred. This data can be combined with the EM-DAT damage information. Additionally, it can be collapsed on a country-year, or even more specific level. The precise locations of the incidents allow this analysis to map disasters to particular areas using geographic information system (GIS) tools.

There are five types of natural disaster in this study: storms, floods, droughts, extreme temperatures, and earthquakes. Each type of natural disaster data is from different sources as the details are as follow:

1. Storms. Wind speed data is primarily derived from the International Best Track Archive for Climate Stewardship (IBTrACS) provided by The National Climatic Data Center of the National Oceanic and Atmospheric

² Attrition creates a problem of missing data, and can potentially have serious consequences when researchers use only data of responding individuals (Little and Rubin, 1987).

Administration (NOAA). NOAA collects databases of actual hurricane activities³, the positions (latitude and longitude) of hurricane centres at six-hourly intervals, and statistics on hurricane magnitude (wind speed in knots and barometric pressure). The data is derived from a number of sources, including reconnaissance aircraft, ships, and satellites.

2. Floods and Droughts. Precipitation data (millimeters) for measuring the intensity of floods and droughts are from Copernicus Climate Change Service (C3S) in ERA5 reanalysis, which is the fifth generation ECMWF atmospheric reanalysis of the world climate. The reanalysis brings together model data and findings from around the world to create a globally consistent and complete dataset. Total precipitations are expressed as monthly sums.

3. Extreme temperature events. Temperature data (kelvin) are also derived from the Copernicus Climate Change Service (C3S) in the ERA5 reanalysis, where monthly minimum and maximum air temperatures at two meters are measured using hourly two-meter air temperature data. The unit of temperature data are converted into degrees Celsius in this study.

4. Earthquakes. The seismic activity data comes from the Incorporated Institute for Seismology (IRIS), which records the magnitude measured by the Richter scale of any earthquake on the earth by the epicenter's latitude and longitude.

3.3 Variable Measurements

As mentioned above, most of the variable data in this study are provided by the Household Socio-Economic Survey. There are, however, two variables in the model that will be measured in this study due to the incomplete dataset: income and expenditure inequality index, and the natural disaster index.

³ Hurricanes, Typhoons, and Cyclones are symmetric. In the North Atlantic Ocean and Northeast Pacific, they are called hurricanes. But if the same type of disturbance takes place in the Northwest Pacific Ocean, it is known as a typhoon. And in the South Pacific and Indian Ocean, cyclone is the correct term.

3.3.1 Inequality Index

The three most frequently used inequality measurements are Gini, Theil's L (occasionally mentioned as the mean log deviation (MLD) measure), and Theil's T. Due to its simplicity of measurement, adaptability across various demographic groups, and dependence from sample size and economic scale, the Gini coefficient is the most commonly used indicator of inequality. The Gini coefficient is calculated as the difference between the income distribution and a uniform distribution corresponding to equality.

$$G = \frac{n+1}{n-1} - \frac{2}{n(n-1)\bar{Y}} \sum_{i=1}^n \rho_i Y_i \quad (3.1)$$

where ρ_i is the income rank of an individual i . ρ_i is equivalent to one for the richest people and increase for those with lower income. The Gini coefficient is between zero to one. The greater the inequality, the greater the Gini coefficient is.

The Gini coefficient is widely used for inequality measure, and it satisfies the principle of transfer. However, it is not transfer sensitive because of its dependence on rank rather than income. On the contrary, the Theil index is additively decomposable and transfer sensitive. Therefore, this study measures household inequality by other proxies as alternative dependent variables as well: the Theil's L; and Theil's T, which can be written as follows:

$$Theil_L = \frac{1}{n} \sum_{i=1}^n \ln \left(\frac{\bar{Y}}{Y_i} \right) \quad (3.2)$$

$$Theil_T = \frac{1}{n} \sum_{i=1}^n \frac{\bar{Y}}{Y_i} \ln \left(\frac{\bar{Y}}{Y_i} \right) \quad (3.3)$$

Theil's L and Theil's T values range between 0 and ∞ (or 1 if normalized), where zero indicates an equal distribution and a higher value indicates a greater degree of inequality. A distinguishing characteristic of the latter indices is their complete decomposition. For instance, inequality can be segmented according to demographic classes, income sources, or other dimensions, which can be beneficial for policy implications.

3.3.2 Natural Disaster Index

In order to identify the natural disaster index, following the work of Felbermayr and Gröschl (2014), this analysis makes use of the conducting concept of Geophysical and Meteorological database or to be called GeoMet. Five types of natural disasters as mentioned above are selected based on the data availability: earthquakes, storms, floods, droughts, and extreme temperatures. Measuring the intensities associated with specific disasters using the Felbermayr and Gröschl's measurement scales can be modified as follows:

- **Earthquakes⁴:** Richter scale within a single earthquake scaled by land area.
- **Storms:** maximum total wind speed⁵ in knots scaled by land area.
- **Floods:** maximum positive difference in monthly rainfall from long run (1992 – 2019) monthly mean scaled by land area.
- **Droughts⁶:** one if precipitation falls 25 percent⁶ below the long run (1992–2019) monthly precipitation mean for three sequential months, or at least five months per year, scaled by land area.
- **Extreme temperatures:** maximum absolute difference in monthly temperature from long run (1992 – 2019) monthly mean scaled by land area.

The authors then obtained annual aggregates at the country level from these monthly or event-level observations by using the corresponding maximum intensities recorded each year and for each country as the disaster intensity measure. This study repeats the process of measuring natural disaster intensities by using plain

⁴ The data contains earthquakes on land and those that happened right off the coastline of a specific province.

⁵ Due to the incomplete dataset at provincial level, storms in this study do not include tornadoes, winter and summer storms.

⁶ According to Felbermayr and Gröschl's work, droughts are defined as one if precipitation in three consecutive months, or at least five months per year, is 50% or less than the long run (1992–2019) monthly precipitation mean, and zero otherwise, by land area. But since the data mostly does not match with the data reported in Thailand (See Climate Change and Disaster Center, Rangsit University, 2020), thus the 25% below long run (1992 – 2019) monthly precipitation mean scale is measured instead to capture the severe drought events in Thailand.

disaggregated maximum intensity values for each type of disaster to create a new indicator at the provincial level known as composite natural disaster index. The study also uses each disaggregated intensity of natural disasters to access the relationship between natural disasters and inequality by type of disaster.

Repeatedly, as mentioned before, the advantages of using GeoMet data is resolving the problem that the data on damage and selection criteria for inclusion of incidents in the report as disasters can be related to GDP of a country (the higher GDP losses, the higher possibility the events to be included as disaster in the dataset). Additionally, natural disasters, as measured by geophysical or meteorological intensity scales, include variance that is plausible exogenous to economic or social outcomes, and thus can be used as an instrumental variable in a variety of empirical research. Moreover, it allows us to analyze the data at micro-level, which the widely used dataset as EM-DAT database would not be able to do. Table 3.2 represents the primary statistics of all types of natural disasters used in this study.

Table 3.2

The physical strength of natural disasters in Thailand

Disaster Type	Physical Magnitude			
	Mean	Std. Dev.	Minimum	Maximum
Storm	2.414	8.145	0	60
Flood	1.552	0.558	0.299	4.250
Drought (dummy)	0.330	0.471	0	1
Earthquake	0.128	0.687	0	5.7
Extreme temperature	0.226	0.719	0.020	6.497

Source: Author's Elaborations based on satellite data

The Figures 3.1 and 3.2 illustrate the variation of the Gini index of mean income inequality, as well as the variation of the mean disaster index, across Thailand's provinces, respectively (See variation of mean of each type of disaster across provinces in Appendix C, Figure C-I). There appears to be an approximately negative

relationship between natural disasters and income inequality, implying that natural disasters may help reduce income inequality in Thailand.

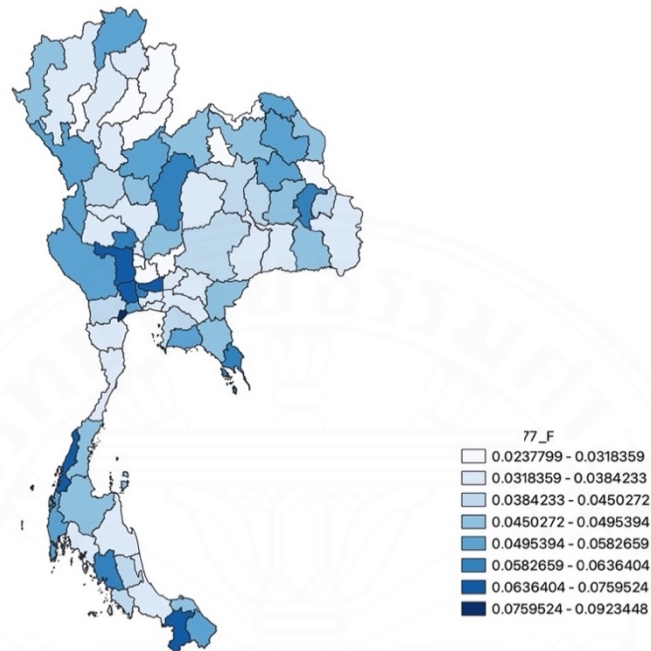


Figure 3.1 Variation of mean income inequality measured by the Gini index across provinces

Source: Author's calculation

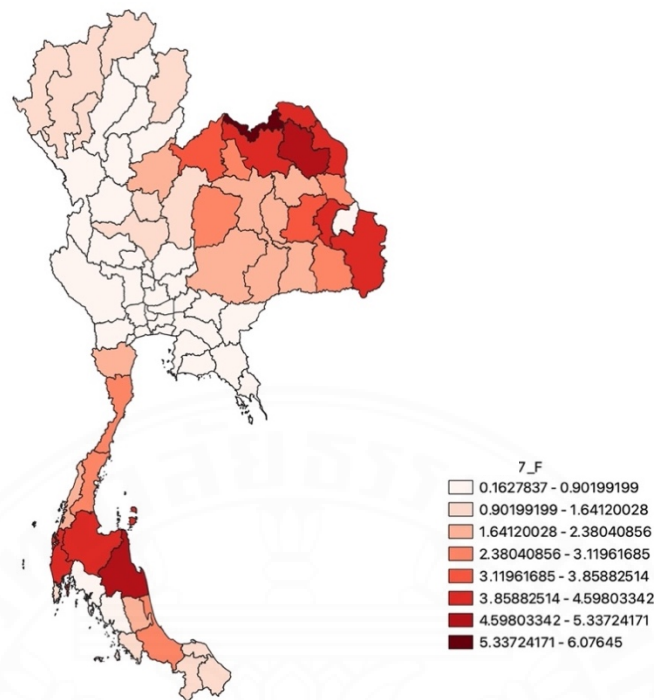


Figure 3.2 Variation of mean disaster index across provinces

Source: Author's calculation

3.4 Econometric Procedures

The basic model of panel data consists of a fixed effects model and a random effects model. A fixed effects model explores whether the intercept differs between groups or time periods, while a random effects model examines whether the error variance variable varies between individuals or time periods. The fundamental distinction between fixed and random effects is the significance of dummy variables. For fixed effects, a parameter measured using a dummy variable is included in the intercept, while error components are included in the intercept for random effects. Thus, the fixed effects and random effects models have the following functional equations.

$$\text{Fixed effect model:} \quad y_{it} = (\alpha_i + u_i) + x_{it}\beta + v_{it} \quad (3.4)$$

$$\text{Random effect model:} \quad y_{it} = \alpha_i + x_{it}\beta + (u_i + v_{it}) \quad (3.5)$$

where u_i is a fixed or random effect particular to an individual or time span that is not included in the estimation, and errors are independent identically, $v_{it} \sim iid(0, \sigma^2)$.

In the fixed effect model, the individual specific is assumed to be time invariant and is treated as a component of the intercept. The correlation between α_i and other regressors is allowed, so the OLS assumption is not violated. It can be estimated by least square dummy variable (LSDV) regression and within effects estimation methods. The details of the panel fixed effect method can be shown in the following forms. Suppose the population model in vector form is

$$Y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it} \quad (3.6)$$

Or in the scalar form;

$$Y_{it} = \beta_1 + \beta_2 x_{2it} + \dots + \beta_k x_{kit} + \alpha_i + \varepsilon_{it} \quad (3.7)$$

Here, a time-constant to error is added as

$$u_{it} = \alpha_i + \varepsilon_{it} \quad (3.8)$$

If α_i is correlated with x , OLS will be biased, since α_i is part of error term. Thus, in the panel data, the unobserved fixed effect can be differenced out as;

$$\begin{aligned} y_{it} - y_{it-1} &= (\beta_1 - \beta_1) + \beta_2(x_{2it} - x_{2it-1}) + \\ &\quad \dots + \beta_k(x_{kit} - x_{kit-1}) + (\alpha_i - \alpha_i) + \\ &\quad (\varepsilon_{it} - \varepsilon_{it-1}) \end{aligned} \quad (3.9)$$

or it can be written as;

$$\Delta y_{it} = \beta_2 \Delta x_{2it} + \dots + \beta_k \Delta x_{kit} + \Delta \varepsilon_{it} \quad (3.10)$$

This equation shows that the correlation between the x and error term does not exist, thus there is no bias or this method can yield consistent estimator of β . We can extend this method for more periods; however, this method cannot be used in the case of unbalanced panel data. Fixed effects estimation is an alternative method to first

differences estimation since it considers the deviation from the average cross-sectional group mean over time;

$$y_{it} - y_{it-1} = \beta_2(x_{2it} - \bar{x}_{2it-1}) + \dots + \beta_k(x_{kit} - \bar{x}_{kit-1}) + (\varepsilon_{it} - \bar{\varepsilon}_{it}) \quad (3.11)$$

From this method, the mean of α_i will be α_i , hence, if we subtract the mean α_i will be differenced out in the same way as doing first differences method.

A random effect, on the other hand, assumes that there is no correlation between an individual effect and any regressor and then estimates the error variance to the group. Therefore, u_i is an individual specific random heterogeneity or a part of the composite error term. When a covariance structure of an individual i is known, random effects is estimated using generalized least squares (GLS). While when a covariance structure of an individual i is not known, random effects is estimated using the feasible generalized least squares (EGLS).

In most cases, the fixed effects model seems to be more appropriate since it is more likely that unobserved variables are correlated with the independent variable. To determine whether to apply fixed effects or random effects, the Hausman test is applied, if the Hausman test is rejected, fixed effects should be applied. If not, random effects should be applied instead.

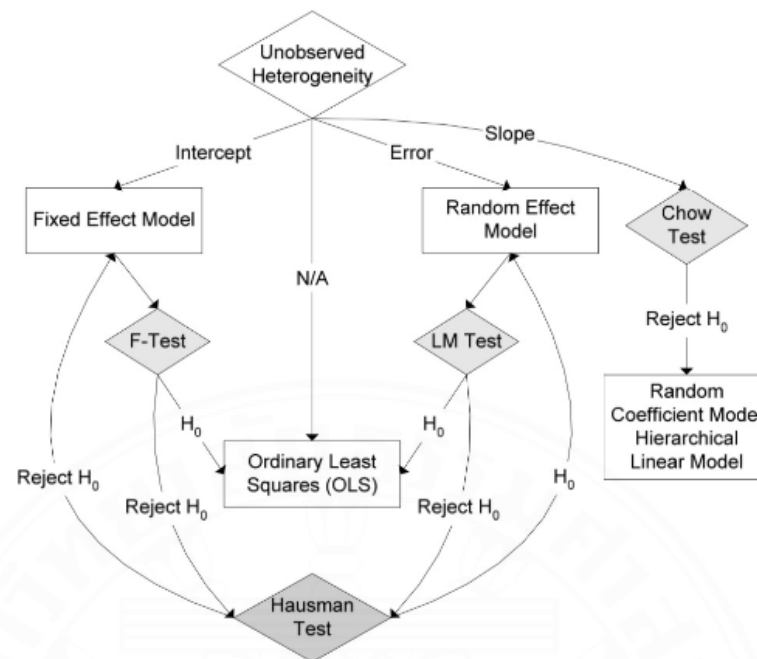


Figure 3.3 Panel Data Modeling Process from “Practical guides to panel data modeling: a step-by-step analysis using stata” by Park. (2011). Public Management and Policy Analysis Program, p. 1-52.

Further result checks, including heterogeneity across samples, lagged effects of disasters, and outliers are also employed in this study.

CHAPTER 4

FINDINGS AND DATA ANALYSIS

This chapter shows all the essential results of the study. The baseline results are presented in section 4.1 and the results of the inequality effects of each type of natural disaster are displayed in the following section, 4.2. Further, the results consistency checks are in the last section, 4.3, including several models: heterogeneity checks across the samples; lagged effects of natural disaster; outliers; and alternative dependent variables.

4.1 Baseline Results

Results of the baseline model are given in Table 4.1. The table compares regressions by using different dependent variables. In columns (1) and (2) the income Gini index is treated as a dependent variable, while in columns (3) and (4) the expenditure Gini index is treated as a dependent variable. The columns (1) and (3) are the results of the estimation without time fixed effect, and the columns (2) and (4) present the results of the estimation with time fixed effect. Each column summarizes the results using the sum of physical intensity measurement for natural disasters that happened in a specific province and a specific year scaled by log land area of affected provinces to take into account the fact that such disasters would have varying inequality effects in provinces with varying geographical extents. Additionally, for the comparison purpose, the estimations make use of standardized values for the different types of natural disasters.

The results show a significant negative effect of natural disasters that happened in the same year of the survey on income and expenditure inequality measured by the Gini index. To be more specific, a one-unit increase in the standard deviation of the disaster index reduces income inequality by 0.003 unit (column 2) on average over a year. Similarly, the model predicts that a one-unit increase in standard deviation of the disaster index lowers the expenditure inequality by 0.002 unit (column 4) on average over a year.

Table 4.1

Inequality effects of natural disasters (1992-2019)

Independent variable	Dependent variable			
	Gini income		Gini expenditure	
	(1)	(2)	(3)	(4)
$\log(Y)_{i,t}$	0.072*** (0.008)	0.158*** (0.009)	0.022** (0.007)	0.070*** (0.007)
Number of years of education $_{i,t}$	-0.012*** (0.003)	-0.006** (0.003)	0.002 (0.002)	-0.001 (0.002)
Number of children $_{i,t}$	0.122*** (0.013)	0.059*** (0.013)	0.073*** (0.002)	0.022** (0.010)
Number of earners $_{i,t}$	-0.002 (0.011)	-0.019* (0.010)	0.008 (0.009)	-0.011 (0.008)
$\log(Transfer)_{i,t}$	-0.011*** (0.002)	-0.005 (0.004)	-0.001 (0.002)	0.001 (0.003)
Disaster Index $_{i,t}$	-0.003** (0.001)	-0.003** (0.001)	-0.002** (0.001)	-0.002** (0.001)
Time fixed effect	No	Yes	No	Yes
Number of observations	1,141	1,141	1,141	1,141
Adjusted R^2	0.067	0.279	0.015	0.201

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors in brackets. Unbalanced panel with 77 provinces. The variable $\ln Y_{it}^2$ is dropped out because the Kuznets hypothesis does not hold with this dataset.

Source: Author's calculation

In the case of a negative effect on income inequality, this could be explained that the rich people are affected by natural disasters more than the poor people. In other words, rich people take a disproportionate share of direct disaster losses at a higher level when compared to poor people. Even if poor people are more vulnerable to natural disasters than rich people, since they live at a subsistence level and have few material possessions, their losses would be less than those of the wealthy. While, rich people can suffer a greater loss of income-generating capital assets as a result of destruction and selling as a coping strategy. Moreover, if the vulnerable group like poor people are mostly employed in unskilled or low-skilled labor jobs, they can

diversify their sources of income in the aftermath of a disaster in an easy way. Therefore, while rich people may suffer from profit losses, disasters may provide a better opportunity for the poor. This appears to be a one-of-a-kind case in Thailand, as the richest Thais receive a much larger share of income when compared to the poor. (See the estimation of natural disaster effects on income in Appendix B, Table B-II).

Meanwhile, in the case of negative effects of natural disasters on expenditure inequality, this could be due to the fact that the rich and poor people in the country disproportionately spend less after the disasters, with poor people spending less in proportion compare to the rich, or it could be that only the rich are forced to lower their expenditure to cope with the disasters, while the poor have more limitation in reducing their daily expenditure.(See the estimation of natural disaster effect on expenditure in Appendix B, Table B-II).

Other control variables show statistically significant effects on income inequality as expected in Chapter 3, except the transfers which show insignificant effect. To be more specific, on average, a one-percentage-point increase in monthly income raises income inequality by 0.002 unit; a one-year increase in the number of education years lowers income inequality by 0.012 unit; a one-person increase in the number of children raises income inequality by 0.059 unit; and a one-person increase in the number of earners lowers income inequality by 0.002 unit. Meanwhile, the Kuznets hypothesis does not hold with this dataset.

In another case, the effect of the other control variables on expenditure inequality is mostly as expected in Chapter 3, with the exception of the effect of number of years of education, number of earners, and money transfers, which are insignificant. Precisely, on average, a one-percentage-point increase in monthly income increases the expenditure inequality by 0.001 unit; and a one-person increase in the number of children raises the income inequality by 0.022 unit.

4.2 Effects by Type of Disaster

To capture the different effects of each natural disaster type on the inequalities in Thailand, Table 4.2 summarizes the regression results for storms, floods, droughts, earthquakes, and extreme temperatures. The disasters are disaggregated by

choosing the highest intensity measure recorded in each province for that year. All measurements of intensity are scaled by the log of land area of the province in which a natural disaster happened. Similarly, to the disaster index, the estimates use the standardized values for the different disaster types for comparison purpose.

The natural disaster types are introduced separately in column (1) to (5), and then combined in column (6). Only some natural disaster types have a statistically significant effect on income inequality measured by the Gini index either if entered separately or together into the regressions. In this case, there are storms and droughts. Specifically, a one-unit increase in the standard deviation of droughts increases the income inequality by 0.003 unit on average, while a one-unit increase in the standard deviation of floods lowers the income inequality by 0.003 unit. When province and time fixed effects are included, the coefficients of control variables are nearly identical to those in Table 4.1.

Not surprisingly, droughts lead to higher income inequality because they are mostly relevant to the agricultural sector and rural areas where most poor people live in Thailand. While earthquakes and extreme temperatures are not statistically significant since they are not intensively concerned as harmful disasters in Thailand. In contrast, storms have a strong effect on lowering income inequality, since they usually impact the great portions of the economy which are mostly owned by rich people. Interestingly, floods, which are recognized as one of the worst and most frequent natural disasters that happened in Thailand (especially in 2011), are not statistically significant in affecting income inequality. This is possible if the household's income is not affected by flooding or if their income is affected in the same proportion between poor and rich people.

Table 4.2

Income inequality effects of natural disaster by type of disaster (1992-2019)

Dependent variable: GINI income

Type of disaster	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
Wind speed _{<i>i, t</i>}	-0.003** (0.001)					-0.003** (0.001)
Flood _{<i>i, t</i>}		-0.002 (0.002)				-0.002 (0.002)
Drought _{<i>i, t</i>}			0.003* (0.002)			0.003** (0.002)
Earthquake _{<i>i, t</i>}				-0.001 (0.001)		-0.001 (0.001)
Δ temperature _{<i>i, t</i>}					0.001 (0.001)	0.0004 (0.001)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,141	1,141	1,141	1,141	1,141	1,141
Adjusted R^2	0.279	0.277	0.279	0.277	0.276	0.281

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces. Control variables are included as of Table 4.1 column 1 but not reported.

Source: Author's calculation

On the other hand, Table 4.3 shows that most natural disaster types in this study have a statistically significant negative effect on expenditure inequality measured by the Gini index either if entered separately or together into the regressions except for the earthquakes. Meanwhile, with the exception of droughts, that have a positive effect on expenditure inequality, all other types have a significant negative impact on expenditure inequality. Note, however, that droughts are events that are mostly savage to farmers who are usually considered poor in Thailand. After province and time fixed effects are included, the coefficients of control variables are nearly identical to those in Table 4.1.

Similar to the income inequality effect in the case of storms and droughts, but the floods and extreme temperatures turn out to be statistically significant in reducing the expenditure inequality here as well. The floods have the strongest effect, followed by droughts, extreme temperatures, and storms, respectively. To be more precise, a one-unit increase in the standard deviation of droughts increases the expenditure inequality by 0.003 unit on average, while a one-unit increase in the standard deviation of floods, extreme temperatures, and storms lowers the expenditure inequality on average by 0.004, 0.002, and 0.002 unit, respectively. This may roughly imply that natural disasters are more sensitive to affecting the rich's expenditure when compared to the poor.

Table 4.3

Expenditure inequality effects of natural disaster by type of disaster (1992-2019)

Dependent variable: GINI expenditure

Type of disaster	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
Wind speed _{<i>i, t</i>}	-0.002*					-0.002*
	(0.001)					(0.001)
Flood _{<i>i, t</i>}		-0.003**				-0.004**
		(0.001)				(0.001)
Drought _{<i>i, t</i>}			0.002			0.003**
			(0.001)			(0.001)
Earthquake _{<i>i, t</i>}				-0.001		-0.001
				(0.002)		(0.001)
Δ temperature _{<i>i, t</i>}					-0.002*	-0.002*
					(0.001)	(0.001)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,141	1,141	1,141	1,141	1,141	1,141
Adjusted R^2	0.189	0.191	0.187	0.186	0.188	0.196

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces. Control variables are included as of Table 4.1 column 1 but not reported.

Source: Author's calculation

It is important to compare the estimates in Table 4.2 to data from a well-known disaster in Thailand. In particular, significant flooding occurred in Thailand at the end of July 2011 during the monsoon season. These floods spread throughout Thailand's northern, northeastern, and central provinces, especially along the Mekong and Chao Phraya River basins. When the estimate is evaluated using unique data⁷ from only 2011 flooding case, the findings in Table 4.4 indicate that the 2011 flood had a statistically important negative effect on income inequality. Thus, it is possible that only a very severe flood could have an effect on income inequality.

Table 4.4

Inequality effects of 2011 flooding in Thailand, OLS estimate

Independent variable	Dependent variable: Δ GINI income
$\Delta \log(Y)_{i,t}$	0.447*** (0.053)
Δ Number of years of education $_{i,t}$	-0.534** (0.212)
Δ Number of children $_{i,t}$	-0.101 (0.082)
Δ Number of earners $_{i,t}$	-0.515** (0.143)
$\Delta \log(Transfer)_{i,t}$	-0.248 (0.212)
Δ Flood $_{i,t}$	-0.007** (0.003)
Time fixed effect	Yes
Number of observations	76
R^2	0.521

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets.

Source: Author's calculation

⁷ The data variables are transformed into percentage changes.

4.3 Further Result Checks

To further test the robustness of the estimates, several alternative and additional estimations are applied in this study including: (1) heterogeneity across samples, (2) lagged effects of natural disasters, (3) outliers and (4) alternative dependent variables.

4.3.1 Heterogeneity across samples

As in developing countries, real estate ownership is a common indicator of wealth, and it can also serve as a source of non-labor income and as a form of collateral for debt. Therefore, this disaggregated data estimate will be crucial in confirming the previous results. The findings for model estimated on income and expenditure inequality effects of natural disasters when the data are disaggregated by tenure or dwelling/land ownership status are presented in Table 4.5. The findings show that natural disasters only have a negative impact on the income and expenditure inequalities of ownership of dwelling/land assets. This relationship, however, vanishes in the category that does not own real estate. As a result, this clearly shows that natural disasters impact rich people rather than poor people in Thailand. Furthermore, this could imply that natural disasters only have a statistically significant impact on the incomes of wealthy people.

Table 4.5

Inequality effects of natural disasters by sample (1992-2019): disaggregation by ownership of real estate

Dependent variable	Gini Income		Gini Expenditure	
	Either own dwelling or land	Neither own dwelling nor land	Either own dwelling or land	Neither own dwelling nor land
$\log(Y)_{i,t}$	0.175*** (0.009)	0.087*** (0.014)	0.072*** (0.007)	0.078*** (0.009)
Number of years of education $_{i,t}$	0.000 (0.003)	-0.014*** (0.003)	0.002 (0.002)	-0.017*** (0.002)
Number of children $_{i,t}$	0.072*** (0.014)	0.023 (0.011)	0.039** (0.012)	-0.006 (0.011)
Number of earners $_{i,t}$	-0.032** (0.011)	-0.036** (0.010)	-0.013 (0.009)	-0.056*** (0.010)
$\log(\text{Transfer})_{i,t}$	-0.006 (0.004)	0.001 (0.003)	0.003 (0.003)	-0.008** (0.003)
Disaster Index $_{i,t}$	-0.003* (0.002)	0.001 (0.002)	-0.002** (0.001)	-0.002 (0.002)
Time fixed effect	Yes	Yes	Yes	Yes
Number of observations	1,141	1,131	1,140	1,131
Adjusted R^2	0.307	0.162	0.205	0.096

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces.

Source: Author's calculation

According to the results in Table 4.6, in order to fully confirm these results, the estimate of income and expenditure effects of natural disasters disaggregated by ownership of dwelling/land assets are approximately estimated. The result firmly shows that only the negative effects of natural disasters are statistically significant on the income and expenditure of the group that owns real estates in Thailand. This means that when natural disasters strike, the income of wealthy people is affected the most compared to the poor in the case of Thailand.

Table 4.6

*Income and expenditure effects of natural disasters by sample (1992-2019):
disaggregation by ownership of real estate*

Dependent variable	Log Income		Log Expenditure	
	Either own dwelling or land	Neither own dwelling nor land	Either own dwelling or land	Neither own dwelling nor land
Number of years of education $_{i,t}$	0.070*** (0.010)	0.129*** (0.006)	0.048*** (0.008)	0.093*** (0.006)
Number of children $_{i,t}$	0.094* (0.050)	0.091** (0.039)	0.173*** (0.041)	0.110** (0.034)
Number of earners $_{i,t}$	0.285*** (0.038)	0.362*** (0.034)	0.256*** (0.031)	0.300*** (0.030)
$\log(\text{Transfer})_{i,t}$	0.159*** (0.013)	0.050*** (0.010)	0.105*** (0.010)	0.040*** (0.008)
Disaster Index $_{i,t}$	-0.009* (0.005)	-0.006 (0.006)	-0.009** (0.004)	-0.006 (0.006)
Time fixed effect	Yes	Yes	Yes	Yes
Number of observations	1,141	1,131	1,141	1,131
Adjusted R^2	0.885	0.752	0.899	0.755

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces.

Source: Author's calculation

4.3.2 Lagged Effects of Disasters

To test the robustness of the results, the estimates also use the previous years' measurements of natural disaster index as control variables. Overall, the results show in Table 4.7 are similar to the one found in Table 4.1 in term of significance and sign. Moreover, the results show that natural disasters seem to have only a short - medium term effect on both income and expenditure inequality of Thailand, and disappear in the long run.

Table 4.7*Inequality and natural disasters, lags (1992–2019)*

Independent variable	Dependent variable	
	GINI income	GINI expenditure
Disaster Index _{<i>i, t</i>}	-0.004** (0.001)	-0.003** (0.001)
Disaster Index _{<i>i, t-1</i>}	-0.005** (0.001)	-0.001 (0.001)
Disaster Index _{<i>i, t-2</i>}	-0.003** (0.001)	-0.002 (0.001)
Disaster Index _{<i>i, t-3</i>}	-0.003** (0.001)	-0.002** (0.001)
Disaster Index _{<i>i, t-4</i>}	-0.002 (0.001)	0.0001 (0.001)
Disaster Index _{<i>i, t-5</i>}	0.0003 (0.001)	0.0001 (0.001)
Time fixed effect	Yes	Yes
Number of observations	1,138	1,138
Adjusted R^2	0.291	0.191

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces. Control variables are included as of Table 4.1 column (1) but not reported.

Source: Author's calculation

4.3.3 Outliers

As mentioned above, in 2011, there was a devastating flood that happened in Thailand. It is possible that the negative effect on inequality could be mainly derived from this flood event and its aftereffects. Thus, in order to see whether this argument is true and to confirm the previous results, the data for the year 2011 and the years after are excluded. Table 4.8 shows that the results are still the same in terms of significance and sign with the baseline results.

Table 4.8

Inequality effect of natural disasters, excluding possible outliers (1992–2009)

Independent variable	Dependent variable	
	Gini income	Gini expenditure
$\log(Y)_{i,t}$	0.143*** (0.011)	0.068*** (0.010)
Number of years of education $_{i,t}$	-0.008** (0.003)	0.003 (0.003)
Number of children $_{i,t}$	0.039** (0.014)	0.012 (0.013)
Number of earners $_{i,t}$	-0.027** (0.011)	-0.011 (0.011)
$\log(\text{Transfer})_{i,t}$	-0.001 (0.005)	0.006 (0.003)
Disaster Index $_{i,t}$	-0.004** (0.002)	-0.003** (0.002)
Time fixed effect	Yes	Yes
Number of observations	757	757
Adjusted R^2	0.222	0.165

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces. The variable $\ln Y_{it}^2$ is dropped out because the Kuznets hypothesis does not hold with this dataset.

Source: Author's calculation

4.3.4 Alternative Dependent Variables

To check if the results hold for various inequality measures, the Theil's L index⁸ is used as an alternative measurement of income and expenditure inequality of Thailand. As shown in Table 4.9, the fixed effects model produces similar results in terms of significance and sign, thus confirming the results as shown in Table

⁸ This study has also tried to treat Theil's T index as one of the alternative dependent variables, but the effect of natural disasters turns out to be statistically insignificant. See details in Appendix B, Table B-I.

4.1. In other words, natural disasters reduce income and expenditure inequalities not only measured by the Gini coefficient, but also by the Theil index.

Table 4.9

Inequality effect of natural disasters, using Theil index as an alternative dependent variable (1992–2019)

Independent variable	Dependent variable	
	Theil income	Theil expenditure
$\log(Y)_{i,t}$	0.270*** (0.015)	0.075*** (0.009)
Number of years of education $_{i,t}$	-0.011** (0.004)	0.002 (0.003)
Number of children $_{i,t}$	0.091*** (0.021)	0.022* (0.013)
Number of earners $_{i,t}$	-0.022 (0.017)	-0.011 (0.011)
$\log(Transfer)_{i,t}$	-0.012** (0.001)	0.001 (0.004)
Disaster Index $_{i,t}$	-0.004* (0.002)	-0.002* (0.001)
Time fixed effect	Yes	Yes
Number of observations	1,141	1,141
Adjusted R^2	0.278	0.198

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces. The variable $\ln Y_{it}^2$ is dropped out because the Kuznets hypothesis does not hold with this dataset.

Source: Author's calculation

CHAPTER 5

CONCLUSION AND LIMITATION

5.1 Conclusion

The occurrence of natural disasters generally affects people's living conditions, whether they are rich or poor. This study explores the impact of natural disasters on income and expenditure inequality in Thailand at provincial level using a new dataset called GeoMet (remote-sensing data). The study was constructed as a unique panel dataset for 15 years (1992-2019). Employing panel fixed effects as the key empirical estimation technique, the findings show that natural disasters are statistically significant in decreasing provincial level income and expenditure disparities as measured by the Gini index.

These results are robust and consistent across heterogeneity of the samples, lagged effects, outliers, and alternative inequality measure – Theil index. Hence, it could be clarified that rich people are affected by natural disasters more than poor people. In other words, rich people pay a disproportionate share of direct disaster losses at a higher rate when compared to poor people. Despite the fact that the poor are more vulnerable to natural disasters than the rich, when the poor maintain a subsistence lifestyle and have fewer financial possessions, their misfortunes would be less intense. Rich people can lose more money through their capital assets losses due to destruction and profit reduction, resulting in a more serious situation. Moreover, given that the poor are mostly engaged in low-skilled or unskilled labor jobs, they could simply diversify their sources of income in the aftermath of a natural disaster. Therefore, while rich people can lose a lot of money, disasters may provide better opportunities for poor people.

Meanwhile, in the case of expenditure inequality, the results are possibly because both rich and poor people are disproportionately forced to spend less after the disaster matches, where poor people reduce their spending less in proportion compared to rich people leading by higher reducing in income, or there might be only the rich who are forced to lower their expenditure as poor have more limitation in reducing their

daily expenditure. These kinds of situation could lead to decreasing in expenditure inequality.

Moreover, to capture the effect of each type of natural disaster, the disaggregated disaster intensity measures for storms, floods, droughts, earthquakes, and extreme temperatures are applied in this study as well. Interestingly, the results show that storms have a negative effect on income inequality, and droughts have a positive effect on income inequality. Meanwhile, floods, storms, and extreme temperatures significantly reduce expenditure inequality, and drought significantly increases household expenditure inequality. These results show us that the most vulnerable people here are the people who are mostly related to drought events. This warrants government policies to take care of the poor as the first priority, especially the poor farmers who are usually considered to be affected by droughts the most, and to protect rich and middle-income people from damage with an appropriate measure.

The findings however seem to be unique cases for Thailand as Thai richest receive much higher share of income when compared to the poor. Further, Thailand is just only one of a number of countries struggling with the varying effects of natural disasters and issues of income inequality. Thailand is a middle-income country where it primarily relies on exports. The industrial and service sectors play an important integral part in Thailand's gross domestic product. Therefore, it could not represent other countries which have different contexts compared to Thailand. Additionally, a reduction of disparity as a consequence of higher damages to rich people does still not completely represent real distributive justice. In other words, reducing inequality does not mean that poor people do not suffer from natural disasters. Thus, changes in inequality in response to natural disasters should be interpreted cautiously.

5.2 Limitation

The data used in this study is not employed every year, due to the lack of the available data of the Household Survey Data (HSES) which is mostly conducted every two years at a time. Therefore, some natural disasters in some years that might have a significant effect on the inequalities may not be captured in this study. Further, the smaller level analysis, such as Amphoe (district) or Tambon (sub-district), would

be more precise and useful because natural disasters are sometimes caused by the microclimate of a specific area.

In addition, more specific types of disaster studies may be more beneficial, particularly for policy recommendations, because the data can be specifically cleaned and searched for the determinants of the dependent variable(s) that may have unique effects depending on the type of disaster. Also, a greater number of types of natural disaster(s) could be added as well.

Moreover, the possible internal migration of an individual or household as a result of a natural disaster, which may have explained the decrease in inequality, is not captured in this study. Lastly, the effects of climate change, which tend to be more intense in the near future, could lead to more severe disasters after a period of time as well. In other words, the more severe disasters could also lead to different conclusions from this study. These would be the limitations of this study. Therefore, this analysis could be replicated with better data or estimation techniques as a research avenue in the future.



REFERENCES

Books and Book Articles

- Aoki, M., OAKI, M. A., Greif, A., & Milgrom, P. (2001). *Toward a comparative institutional analysis*. MIT press.
- Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., & Arnold, M. (2005). *Natural disaster hotspots: a global risk analysis*. The World Bank.
- Little Roderick, J. A., & Rubin Donald, B. (1987). *Statistical analysis with missing data*. Hoboken, NJ: Wiley.

Articles

- Abdullah, A. N. M., Zander, K. K., Myers, B., Stacey, N., & Garnett, S. T. (2016). A short-term decrease in household income inequality in the Sundarbans, Bangladesh, following Cyclone Aila. *Natural Hazards*, 83(2), 1103-1123.
- Acosta, P., Calderon, C., Fajnzylber, P., & Lopez, H. (2008). What is the impact of international remittances on poverty and inequality in Latin America?. *World Development*, 36(1), 89-114.
- Amable, B. (2003). *The diversity of modern capitalism*. Oxford University Press on Demand.
- Autor, D. H., Kerr, W. R., & Kugler, A. D. (2007). Does employment protection reduce productivity? Evidence from US states. *The Economic Journal*, 117(521), F189-F217.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2), 277-297.
- Becker, G. S. (1964). *Human Capital*, New York: Columbia University Press for the National Bureau of Economic Research.
- Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (2014). *At risk: natural hazards, people's vulnerability and disasters*. Routledge.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1), 115-143.

- Boustan, L. P., Kahn, M. E., & Rhode, P. W. (2012). Moving to higher ground: Migration response to natural disasters in the early twentieth century. *American Economic Review*, 102(3), 238-44.
- Brunori, P., Ferreira, F. H., & Peragine, V. (2013). Inequality of opportunity, income inequality, and economic mobility: Some international comparisons. In *Getting development right* (pp. 85-115). Palgrave Macmillan, New York.
- Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). x *Applied Economics*, 46(15), 1751-1766.
- Cavallo, E., Galiani, S., Noy, I., Pantano, J., forthcoming. Catastrophic Natural Disasters and Economic Growth. *Review of Economics and Statistics*.
- Clark, G. E., Moser, S. C., Ratick, S. J., Dow, K., Meyer, W. B., Emani, S., ... & Schwarz, H. E. (1998). Assessing the vulnerability of coastal communities to extreme storms: the case of Revere, MA., USA. *Mitigation and adaptation strategies for global change*, 3(1), 59-82.
- Cochrane, H. (2004). Economic loss: myth and measurement. *Disaster Prevention and Management: An International Journal*.
- Deaton, A., & Paxson, C. (1994). Intertemporal choice and inequality. *Journal of political economy*, 102(3), 437-467.
- Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics*, 74(2), 309-329.
- Deolalikar, A. B. (2003). Poverty, growth, and inequality in Thailand. In *Poverty, growth, and institutions in developing Asia* (pp. 247-272). Palgrave Macmillan, London.
- Escaleras, M., Anbarci, N., & Register, C. A. (2007). Public sector corruption and major earthquakes: a potentially deadly interaction. *Public Choice*, 132(1-2), 209-230.
- Estevez-Abe, M., Iversen, T., & Soskice, D. (2001). Social protection and the formation of skills: a reinterpretation of the welfare state. *Varieties of capitalism: The institutional foundations of comparative advantage*, 145, 145-183.
- Euston, Q., & Kumari, S. S. (Eds.). (2018). *Economics of Natural Disasters*. World Scientific.
- Felbermayr, G., & Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of development economics*, 111, 92-106.
- Feng, S., Lu, J., Nolen, P., & Wang, L. (2016). The effect of the Wenchuan earthquake and government aid on rural households. *IFPRI book chapters*, 11-34.

- Finkelshtain, I., & Chalfant, J. A. (1991). Marketed surplus under risk: Do peasants agree with Sandmo?. *American Journal of Agricultural Economics*, 73(3), 557-567.
- Fofack, H., & Zeufak, A. (1999). Dynamics of income inequality in Thailand: Evidence from household pseudo-panel data. *The World Bank*, Washington DC, 1-35.
- Fothergill, A., & Peek, L. A. (2004). Poverty and disasters in the United States: A review of recent sociological findings. *Natural hazards*, 32(1), 89-110.
- Goldin, C., & Katz, L. F. (2007). Long-run changes in the US wage structure: narrowing, widening, polarizing (No. w13568). *National Bureau of Economic Research*.
- Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *American economic review*, 99(2), 58-63.
- Government of Queensland, Guidance on the Assessment of Tangible Flood Damages. (Sep 2002). *The State of Queensland (Department of Natural Resources and Mines) 2002*.
- Guidetti, G., & Rehbein, B. (2014). Theoretical approaches to inequality in economics and sociology: A preliminary assessment. *Transcience (2014) Vol, 5*.
- Hallegatte, S., & Przulski, V. (2010). *The economics of natural disasters: concepts and methods*. The World Bank.
- Jenmana, T. (2018), 'Democratisation and the Emergence of Class Conflict: Income Inequality in Thailand, 2001-2016'. *World Inequality Lab*.
- Jeong, H. (2008). Assessment of relationship between growth and inequality: micro evidence from Thailand. *Macroeconomic Dynamics*, 12(S2), 155-197.
- Just, R. E., & Zilberman, D. (1983). Stochastic structure, farm size and technology adoption in developing agriculture. *Oxford Economic Papers*, 35(2), 307-328.
- Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *Review of economics and statistics*, 87(2), 271-284.
- Kakwani, N., & Krongkaew, M. (2000). Analysing poverty in Thailand. *Journal of the Asia Pacific Economy*, 5(1-2), 141-160.
- Karim, A., & Noy, I. (2016). Poverty and natural disasters—a qualitative survey of the empirical literature. *The Singapore Economic Review*, 61(01), 1640001.
- Keerthiratne, S., & Tol, R. S. (2018). Impact of natural disasters on income inequality in Sri Lanka. *World Development*, 105, 217-230.
- Kim, N. (2012). How much more exposed are the poor to natural disasters? Global and regional measurement. *Disasters*, 36(2), 195-211.

- Krueger, D., & Perri, F. (2009). How do households respond to income shocks?. Technical Report, University of Minnesota.
- Kurita, K., & Kurosaki, T. (2011). Dynamics of growth, poverty and inequality: a panel analysis of regional data from Thailand and the Philippines. *Asian Economic Journal*, 25(1), 3-33.
- Kuznets, S. (1955). Economic growth and income inequality. *The American economic review*, 45(1), 1-28.
- Lindell, M. K., & Prater, C. S. (2003). Assessing community impacts of natural disasters. *Natural hazards review*, 4(4), 176-185.
- Masozera, M., Bailey, M., & Kerchner, C. (2007). Distribution of impacts of natural disasters across income groups: A case study of New Orleans. *Ecological Economics*, 63(2-3), 299-306.
- Meesook, O. A. (1979). Income, consumption and poverty in Thailand, 1962/63 to 1975/76.
- Mills, M., Blossfeld, H. P., Klijzing, E., Blossfeld, H. P., Mills, M., & Kurz, K. (2005). Globalization, uncertainty and youth in society. *Globalization, Uncertainty and Youth in Society*, 1-24.
- Mincer, J. (1974). *Schooling Experience and Earnings*. New York: Columbia.
- Motonishi, T. (2006). Why has income inequality in Thailand increased?: An analysis using surveys from 1975 to 1998. *Japan and the World Economy*, 18(4), 464-487.
- Mottaleb, K. A., Mohanty, S., Hoang, H. T. K., & Rejesus, R. M. (2013). The effects of natural disasters on farm household income and expenditures: A study on rice farmers in Bangladesh. *Agricultural Systems*, 121, 43-52.
- Newberg, D. N., & Stiglitz, J. E. (1981). The theory of commodity price stabilization.
- North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge university press.
- Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development economics*, 88(2), 221-231.
- Noy, I., & Karim, A. (2013). *Poverty, inequality and natural disasters—A survey*.
- OECD. (2012). *Divided we stand: Why inequality keeps rising*. OECD Publishing.
- Pachauri, R. K., & Reisinger, A. (2008). *Climate change 2007. Synthesis report. Contribution of Working Groups I, II and III to the fourth assessment report*. Cambridge University Press, Cambridge.

- Park, H. M. (2011). Practical guides to panel data modeling: a step-by-step analysis using stata. Public Management and Policy Analysis Program, Graduate School of International Relations, International University of Japan, 1-52.
- Paweenawat, S. W., & McNown, R. (2014). The determinants of income inequality in Thailand: A synthetic cohort analysis. *Journal of Asian Economics*, 31, 10-21.
- Peacock, W. G., Morrow, B. H., & Gladwin, H. (Eds.). (1997). *Hurricane Andrew: Ethnicity, gender, and the sociology of disasters*. Psychology Press.
- Pelling, M., Özerdem, A., & Barakat, S. (2002). The macroeconomic impact of disasters. *Progress in Development Studies*, 2(4), 283-305.
- Ranger, N., Hallegatte, S., Bhattacharya, S., Bachu, M., Priya, S., Dhore, K., ... & Herweijer, C. (2011). An assessment of the potential impact of climate change on flood risk in Mumbai. *Climatic change*, 104(1), 139-167.
- Reardon, T., & Taylor, J. E. (1996). Agroclimatic shock, income inequality, and poverty: Evidence from Burkina Faso. *World Development*, 24(5), 901-914.
- Rose, A., & Miernyk, W. (1989). Input-output analysis: the first fifty years. *Economic Systems Research*, 1(2), 229-272.
- Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. *The American Economic Review*, 61(1), 65-73.
- Sen, A. (2006). Conceptualizing and measuring poverty. *Poverty and inequality*, 30-46.
- Tesliuc, E., & Lindert, K. (2002). Vulnerability: A quantitative and qualitative assessment. *Guatemala Poverty Assessment Program*, 1-91.
- Thomas, T., Christiaensen, L., Do, Q. T., & Trung, L. D. (2010). *Natural disasters and household welfare: evidence from Vietnam*. The World Bank.
- Warr, P., & Aung, L. L. (2018). Poverty and inequality impact of natural disasters: Myanmar, 2005 to 2010 (No. 2018-15).
- Verbeek, M., & Nijman, T. (1992). Can cohort data be treated as genuine panel data? *Empirical Economics*, 17, 9-23.
- Verbeek, M., & Nijman, T. (1993). Minimum MSE estimation of a regression model with fixed effects from a series of cross-sections. *Journal of econometrics*, 59, 125-136.
- Yamamura, E. (2015). The impact of natural disasters on income inequality: analysis using panel data during the period 1970 to 2004. *International Economic Journal*, 29(3), 359-374.

Other Materials

Bangkok Post (2020, February 8) Thailand tackles worst drought in 40 years. Accessed May 5, 2020 from <https://www.bangkokpost.com/business/1853069/thailand-tackles-worst-drought-in-40-years>.

Centre for Research on the Epidemiology of Disasters. (2018). Natural Disaster 2018.

Climate Change and Disaster Center, Rangsit University. (2020). 177 Years of Drought in Thailand [database].

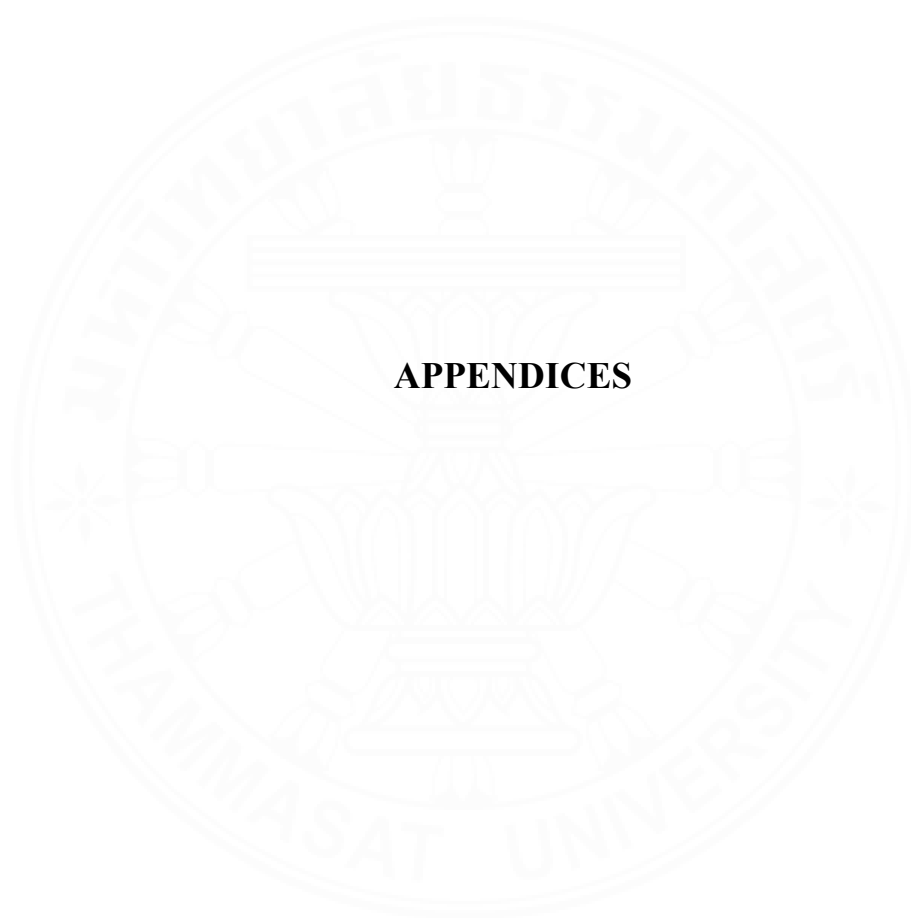
Credit Suisse Research Institute. (2018). Global Wealth Report.

Copernicus Climate Change Service (C3S). (2017): ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service Climate Data Store (CDS). Accessed December 24, 2020 from <https://cds.climate.copernicus.eu/cdsapp#!/home>.

Incorporated Institute for Seismology. (2020). IRIS Earthquake Browser [database].

Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann. (2010). The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data.

Knapp, K. R., H. J. Diamond, J. P. Kossin, M. C. Kruk, C. J. Schreck. (2018). International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4. NOAA National Centers for Environmental Information. Accessed December 22, 2020 from <https://doi.org/10.25921/82ty-9e16>.



Appendix A

Table A-I

Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Disaster Index	1.228	2.153	0.093	15.907
Wind speed	0.620	2.098	0	1.404
Flood	0.423	0.166	0.073	1.504
Drought	0.089	0.128	0	0.382
Earthquake	0.032	0.032	0	1.404
Δ temperature	0.063	0.207	0.007	2.032
Gini income	0.436	0.055	0.262	0.620
Theil L income	0.331	0.089	0.116	0.716
Theil T income	0.389	0.162	0.119	1.662
Gini expenditure	0.346	0.043	0.226	0.498
Theil L expenditure	0.203	0.058	0.088	0.426
Theil T expenditure	0.227	0.074	0.097	0.891
$\log(Y)$	8.493	0.575	6.535	9.790
$\log(Transfer)_{i,t}$	6.298	1.242	3.291	8.612
Number of years of education	8.526	1.077	4.187	12.343
Number of children	0.799	0.264	0.206	1.615
Number of earners	1.887	0.229	1.264	2.902

Source: Author's calculation

Table A-II

Variable's definition and source

Variable	Definition	Source
Disaster Index	Sum of disaster intensity	Remote-sensing data
Gini Index	Inequality index measured by Gini Coefficient.	Household Socio-Economic Survey
Theil Index	Inequality index measured by Theil index.	Household Socio-Economic Survey
Wind speed	Maximum wind speed in knots for tropical storms.	International Best Track Archive for Climate Stewardship (IBTrACS)
Flood	Maximum positive difference in total precipitation over the long run mean.	Copernicus Climate Change Service (C3S)
Drought	Dummy equal one if precipitation falls 25 percent below the long run monthly precipitation mean for three sequential months, or at least five months per year.	Copernicus Climate Change Service (C3S)
Earthquake	Maximum Richter scale for earthquakes.	Incorporated Institute for Semiology (IRIS)
Δ temperature	Maximum absolute difference in monthly temperature from long run mean.	Copernicus Climate Change Service (C3S)
Education	Number of years of education of household head.	Household Socio-Economic Survey
Earner	Number of earners of household.	Household Socio-Economic Survey
Children	Number of children of household.	Household Socio-Economic Survey
Transfer	Transfer money received by household	Household Socio-Economic Survey

Source: Author

Appendix B

Table B-I

Inequality effect of natural disasters using Theil's T index as alternative dependent variable

Independent variable	Dependent variable	
	Theil's T income	Theil's T expenditure
$\log(Y)_{i,t}$	0.495*** (0.030)	0.090*** (0.013)
Number of years of education $_{i,t}$	-0.032** (0.009)	0.002 (0.004)
Number of children $_{i,t}$	0.138** (0.043)	0.012 (0.020)
Number of earners $_{i,t}$	-0.021 (0.036)	-0.003 (0.017)
$\log(\text{Transfer})_{i,t}$	-0.050*** (0.013)	0.002 (0.006)
Disaster Index $_{i,t}$	-0.002 (0.006)	-0.001 (0.002)
Time fixed effect	Yes	Yes
Number of observations	1,141	1,141
Adjusted R^2	0.173	0.132

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets. Unbalanced panel with 77 provinces. The variable $\ln Y_{it}^2$ is dropped out because the Kuznets hypothesis does not hold with this dataset.

Source: Author's calculation

Table B-II

Disaster effects on income and expenditure

Independent variable	Dependent variable	
	Log income	Log expenditure
Number of years of education _{<i>i, t</i>}	0.058*** (0.009)	0.048*** (0.008)
Number of children _{<i>i, t</i>}	0.053 (0.044)	0.104** (0.037)
Number of earners _{<i>i, t</i>}	0.259*** (0.036)	0.227*** (0.031)
$\log(\text{Transfer})_{i, t}$	0.156*** (0.012)	0.119*** (0.011)
Disaster Index _{<i>i, t</i>}	-0.010** (0.005)	-0.010** (0.004)
Time fixed effect	Yes	Yes
Number of observations	1,141	1,141
Adjusted R^2	0.893	0.897

Note: ***, **, * represent significant level at 1%, 5%, and 10%, respectively. Robust standard errors are in brackets.

Source: Author's calculation

Appendix C

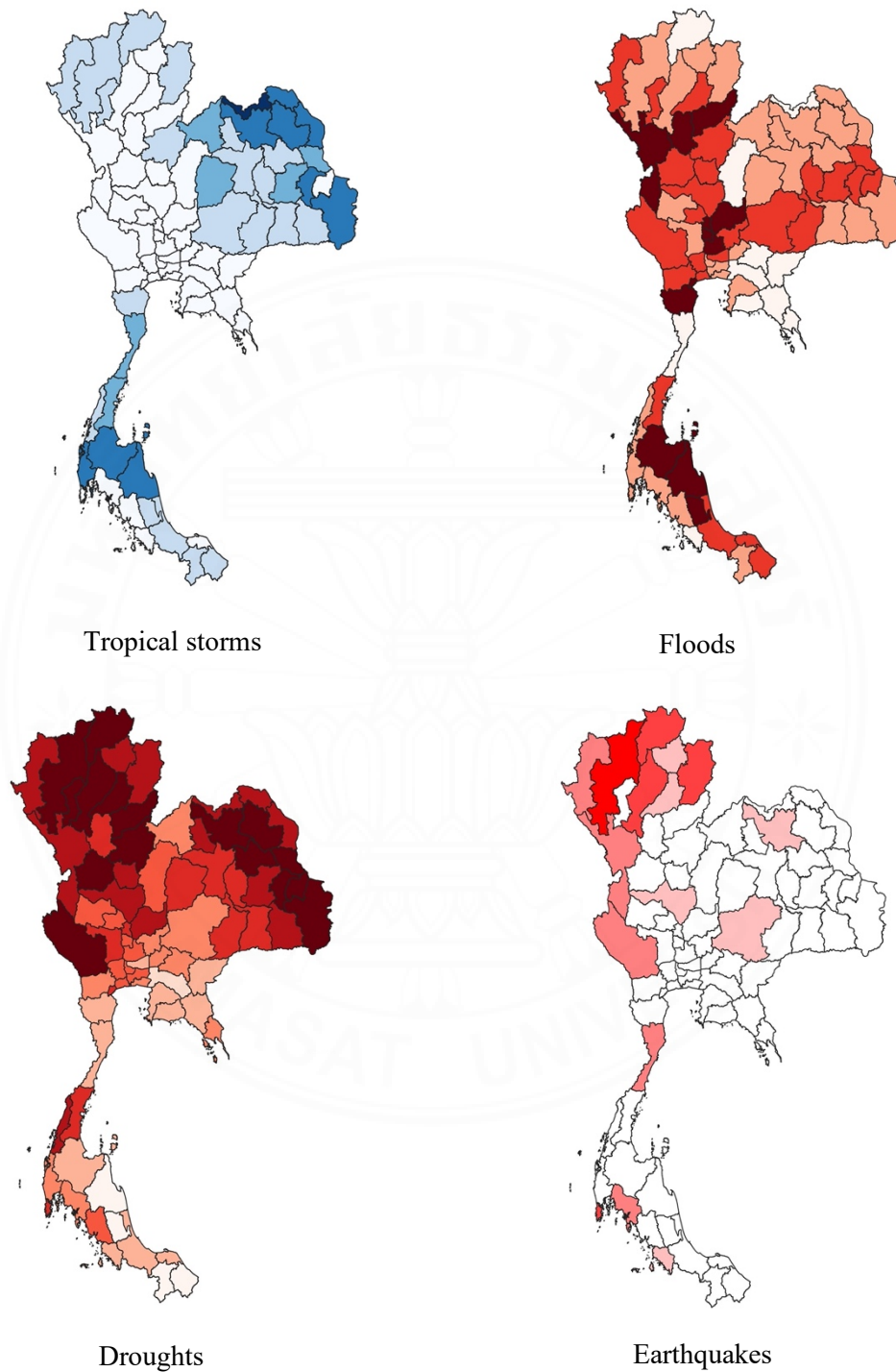
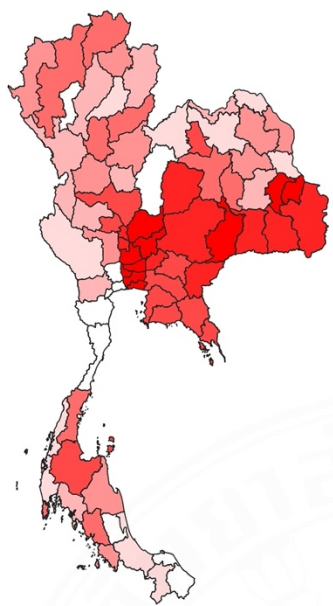


Figure C-1 Variation of mean of each type of disaster across provinces

Source: Author's calculation



Extreme temperature

Figure C-I Variation of mean of each type of disaster across provinces (*continued*)

Source: Author's calculation

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