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Impact of Natural Disasters on Economic Development: A Comparative Study Between Middle-Income and High-Income Countries

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ABSTRACT

Natural disasters usually slow down economic growth due to their numerous effects. The goal of this research is to investigate the impact of natural disasters on the GDP and HDI of high- and middle-income countries. For this reason, data from 20 countries, split into two groups: high-income and middle-income, over 25 years (1999–2023), were studied. The study used the Hausman test and the Breusch-Pagan Lagrange Multiplier test to figure out which model specification was best: fixed effects or random effects. Following that, tests for multicollinearity, heteroskedasticity, and autocorrelation were run, and the FGLS regression models were estimated based on the results. The regression results showed that natural disasters have a substantial adverse impact on the GDP growth of middle-income countries, but they don't have any effect on high-income countries. Natural disasters also have an enormous and detrimental impact on the HDI of middle-income economies. But this result doesn't fit with the high-income countries. Unemployment, education, and the size of the population are also important factors that affect the economic growth of high- and middle-income countries. The government and policymakers, especially in middle-income countries, can use these results to make policy decisions and give greater resources to certain areas to lessen the damage that a natural disaster may cause.

1. Introduction

1.1. General Background

In recent years, climate change has significantly influenced ocean and atmospheric temperatures, which in turn increase the frequency, duration, and intensity of most natural disasters (Vernick, 2025). The climate crisis has not only amplified the scale of these events but has also made their effects more severe and far-reaching. In 2023 alone, natural disasters affected approximately 93.1 million people and resulted in 86,473 deaths globally (Zebra,

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2025). Beyond the immediate destruction, climate change is expected to further intensify environmental degradation and destabilise the socio-economic systems that rely on natural ecosystems, potentially leading to widespread population displacement. Alongside ecological challenges, many economies, particularly in low- and middle-income countries, face multi-dimensional vulnerabilities. These include persistent threats to food security and public health, economic slowdowns, high unemployment rates, low literacy rates, coastal flooding, and the degradation of land and freshwater resources (Warner et al., 2009).

Natural disasters, predominantly, have inadvertent effects on underdeveloped economies, which often lack the financial capacity and institutional expertise to manage the aftereffects of natural disasters (Warner et al., 2009). As a result, several residents of these countries then tend to migrate to seek refuge in some other developed country for safety and security, sometimes leading to social tensions and political unrest in host countries (Reuveny, 2007). For instance, the February 2023 earthquake, which took place in Turkey, caused extreme loss of life, with up to 50,000 lives being lost due to the earthquake, and millions more had to flee their respective countries as refugees to find shelter in surrounding countries. Due to such a large number of people entering Turkey as refugees from Syreia, it led to a massive increase in anti-refugee sentiment in Turkey (Center for Disaster Philanthropy, 2025).

Disasters have become increasingly deadly over the years, with an average of 40,000 to 50,000 lives lost annually worldwide over the past decade (Ritchie et al., 2022). That is a small percentage of all deaths worldwide, but disasters can have significantly larger effects on certain groups of people. One extreme event can kill tens of thousands to hundreds of thousands of people. In the 20th century, it wasn't uncommon for more than a million people to die each year. Along with this, natural disasters, on average, have cost the world 235.2 billion dollars in damages (UNDRR, 2024). Globally, natural disasters (NDs) result in massive losses, with an estimated direct cost of USD 2,908 billion over the 20 years from 1978 to 1997, averaging USD 145 billion per year. This represents a 68% increase in losses over this period. However, these figures underrepresent the true extent of the damage, as 63% of emergency disaster reports in the EM-DAT database do not include economic loss data and rarely capture environmental degradation (Sangha et al., 2020).

The economic repercussions stretch far beyond the immediate cost of recovery from the damages. Thousands of individuals lose their jobs, and small businesses, particularly in underdeveloped regions, often cease to operate permanently. For example, approximately 139,000 men and 31,000 women lost their jobs due to earthquakes in Syria (International Labour Organisation, 2024). Additionally, several indirect impacts remain underreported, such as the effects on the younger population of an economy. For instance, Venton et al. (n.d.) estimate that up to 175 million children will be affected by climate-related disasters. As vulnerable children in underdeveloped nations, their access to education and nutrition may be severely disrupted due to damaged infrastructure.

Subsequently, the way a country deals with natural disasters is largely dependent on how developed the country is. For example, developed countries generally deal with natural disasters through a combination of advanced planning, strong infrastructure, and effective response systems. They invest heavily in early warning technologies, enforce strict building codes to ensure structures can withstand disasters, and conduct regular public awareness campaigns and emergency drills. During a disaster, trained emergency personnel respond quickly with coordinated rescue and relief operations, often supported by technology like drones and satellite imaging. After the event, insurance systems, government aid, and mental health services help people recover, while policies are reviewed and updated to improve future preparedness (United Nations Climate Change Secretariat, 2020). This comprehensive approach emphasises prevention, rapid response, and long-term resilience. Due to being so developed, Japan has the extra resources to develop such technology, whereas other countries, such as Nigeria, do not have the resources and need to bear the brunt of Mother Nature and cannot do anything regarding the impact that a natural disaster will have (Useradmin, 2024). Hence, it is evident that natural disasters have multi-dimensional adverse impacts on an economy.

1.2. Literature Review

The influence of natural disasters on an economy is explored dynamically in the literature and previous research. A study, in the same realm, by Shabnam (2014) investigated the influence of natural disasters, specifically floods, on economic growth, emphasising the relevance of economic growth theories in mitigating these impacts regarding such occurrences. Analysis of a panel dataset encompassing 187 nations, monitored from 1960 to 2010, revealed that the incidence of individuals affected by natural disasters strongly influences GDP growth. Nonetheless, there seems to be an insignificant or nonexistent association between the death toll or fatality rate of a disaster and GDP growth, as demonstrated by the empirical model estimation. Another significant statistic is that for every one thousand individuals affected, each million floods reduces GDP per capita growth by 0.005%.

With a focus on both direct and indirect macroeconomic effects, Botzen et al. (2019) undertook a study to thoroughly evaluate the burgeoning literature regarding the economic consequences of natural disasters. The research demonstrated that natural disasters have profoundly severe consequences regarding various elements, particularly significant property loss in industrialised nations and numerous fatalities in developing nations. The level of development in a country has a considerable influence on how much of an impact it has. Natural disasters usually have negative impacts on the economy as a whole, but in highly developed countries like Japan, this effect is likely to be small for the larger economies because these countries are better able to handle detrimental output shocks. Nonetheless, these economic repercussions are frequently more severe and transformative in undeveloped, emerging, and less diversified nations.

From a different dimension, Hallegatte and Przyluski (2016) designed a study that aimed to propose a clear definition of the economic cost of a natural disaster and clarify the mechanisms that explain and determine these costs. The research found that it is exceedingly difficult to precisely determine the true 'cost' of a natural disaster, as the associated costs might fluctuate considerably based on the specific objectives and context of the evaluation. Second, there are significant uncertainties surrounding the estimation of indirect disaster costs, largely due to limited data availability and methodological shortcomings. Given the critical role these estimates play in policy and planning, obtaining accurate and unbiased assessments is essential, particularly for evaluating the cost-effectiveness and overall justification of investments in disaster prevention and preparedness.

Specifically for the region of Latin America, research conducted by Zapata and Madrigal (2009) analysed the economic repercussions of significant natural catastrophes over the past 35 years, utilising systematic evaluations performed by the United Nations Economic Commission for Latin America and the Caribbean (ECLAC). The findings of the study revealed that, although natural disasters are widely perceived as having purely negative effects, often associated with destruction, loss, and disruption, this perception overlooks the complexity of their long-term economic impacts. It is a prevalent fallacy that all consequences of natural disasters are intrinsically negative. In reality, while natural disasters typically cause significant short-term damage, their long-term effects on economic development can, in some cases, be more nuanced and may not always be entirely negative. This is due to the considerable deployment of resources for the reconstruction and development of infrastructure following large natural catastrophes, necessitating enormous financial investment and strategic planning. In conclusion, while natural disasters are often associated with significant negative consequences, their aftermath can also offer opportunities for economic recovery and long-term growth. By prioritising investments in disaster risk reduction, strengthening infrastructure resilience, and promoting comprehensive insurance coverage, governments can mitigate the adverse effects of such events. These efforts can help reduce future vulnerabilities, support faster recovery, and lay the groundwork for sustainable economic growth in the years to come.

A different study in the same context was conducted by Klomp and Valckx (2014) using the data for developed, developing, and mixed economies. The study's goal is to find out what the exact relationship is between natural disasters and their effects on the economy, and to see if these disasters have any effect at all. The study used t-tests and meta-regression analysis to find out that the type of natural disaster is the most important thing to look at when figuring out its economic effects. The negative and statistically significant parameter linked to the inverse standard errors suggests that, on average, natural disasters adversely affected per capita economic growth. This study shows that after these kinds of disasters, per capita output usually goes down in the economy. However, research also shows that there is a major flaw in the current body of literature. It shows that there is publication bias, which could make it harder to understand the real link between natural disasters and economic growth. Because of this bias, there may be too many studies that report more negative effects and not enough studies that report more neutral or even positive effects on the long-term economic effects of natural disasters.

Using a case study for the Wenchuan earthquake, 2008, another study by Xie et al. (2018) sought to examine the influence of dynamic economic resilience on the recovery process following disasters, specifically on its impact on the duration and size of economic losses. The data was assessed by dynamic computable general equilibrium (CGE) analysis. From the results, it was found that the most important factor for an economy is the reconstruction efforts that are made after a disaster occurs. Moreover, reducing the amount of time spent in the recovery from the disaster also plays a pivotal role in how the economy is impacted by the disaster. To effectively aid reconstruction planning, it is crucial to accurately assess potential BI (business interruption) losses. While shortening the recovery period is important, it is much more effective to increase investment in reconstruction and repairs and to accelerate the pace of recovery over time.

1.3. Literature Gap and Rationale of the Study

Notwithstanding comprehensive studies on the economic consequences of natural disasters, numerous gaps persist in the current literature. The absence of comparison studies between middle-income and high-income countries constrains the comprehension of the economic impacts of natural catastrophes across varying socioeconomic tiers. Much study about the effects of natural catastrophes predominantly emphasises macroeconomic variables, such as GDP or economic growth, frequently neglecting more comprehensive measurements of human development, such as the Human Development Index (HDI). This limited perspective may result in an inadequate comprehension of the comprehensive impact of a calamity on a nation's entire growth. Furthermore, there is a significant deficiency in comparison analysis regarding the effects of natural disasters on GDP vs their effects on HDI, constraining a thorough comprehension of how these events influence both economic performance and total human welfare.

Along with filling in the gaps in the literature, the study on the effect of natural disasters on an economy is important because natural disasters have profound, often devastating, impacts on economies worldwide, yet the extent and nature of these effects are not always well understood. By analysing how disasters influence economic growth and human development, this study can inform better disaster management strategies, economic resilience policies, and investment in recovery efforts. In light of the escalating frequency and severity of extreme weather events attributable to climate change, comprehending these effects is crucial for both developed and developing economies to enhance their readiness and resilience. This research is particularly necessary as it can guide policymakers in making informed decisions about risk mitigation, infrastructure planning, and recovery processes to minimise long-term economic setbacks and enhance national resilience. Therefore, the objective of the study is to examine the impact of natural calamities on the economic growth and human development of a country, contrasting the data for high-income and middle-income nations..

2. Materials and Methodology

2.1. Research Aim and Objectives

The research aim of this study is to evaluate the impact of natural disasters on economic development. To measure the influence on economic development, two dimensions were considered, including economic growth and human development. Moreover, for a dynamic analysis, two panels: high-income countries and middle-income countries, were examined. The research aim is divided into multiple objectives, stated as follows. The study analyses the impact of natural disasters on the following:

- Economic growth of high-income countries
- Economic growth of middle-income countries
- Human development in high-income countries
- Human development in middle-income countries

2.2. Research Hypotheses

The hypotheses given below are assumed in the study to assess the objectives.

- No significant impact of damage caused by natural disasters on economic growth in high-income countries
- No significant impact of damage caused by natural disasters on economic growth in middle-income countries
- No significant impact of damage caused by natural disasters on the human development index in high-income countries
- No significant impact of damage caused by natural disasters on the human development index in middle-income countries

2.3. Data

This study seeks to examine the effects of natural disasters on a nation's progress and human development. To achieve this objective, secondary data from other countries has been utilised to evaluate the empirical data. The nations have been categorised into two segments: middle-income and high-income. The middle-income nations comprise Bangladesh, Brazil, India, Indonesia, Iran, the Philippines, South Africa, Turkiye, Vietnam, and Zimbabwe. The high-income nations comprise Australia, Canada, France, Germany, Italy, Japan, South Korea, New Zealand, the United Kingdom, and the United States. The countries were categorised as middle-income and high-income according to World Bank data, which classed them based on per capita income. The selection of nations was contingent upon a combination of random sampling, the availability of data for the chosen variables, and the frequency of natural catastrophes occurring in each country from 2001 to 2023.

2.4. Description of Variables

The collected data is analysed using regression analysis. For the same, Gross Domestic Product Growth Rate (GDP growth) and the Human Development Index (HDI) were considered as the dependent variables, and the GDP damage caused by the natural disasters is considered as the key independent variable. Additionally, education, unemployment, population, and sanitation are the controlled variables. The description of the variables is given as follows.

2.4.1. Dependent Variables

- Gross Domestic Product growth rate (GDP): The GDP growth rate measures the annual percentage increase in a country's total economic output. It reflects the health of an economy, typically expressed as a percentage (*Glossary | DataBank*, n.d.-a). A positive GDP growth indicates economic expansion, while a negative value signals contraction. For example, a GDP growth rate of 3% would mean the economy has grown by 3% compared to the previous year.
- Human Development Index (HDI): HDI is an index that shows how well people are doing in important areas of human development, like life expectancy, education, and quality of life. The HDI is measured by taking the geometric mean of the above-mentioned parameters (each of which is measured from a scale of 0-1) (United Nations, n.d.). For example, 0.5 would mean achieving halfway between the lowest and highest possible outcomes in each development dimension.

2.4.2. Independent and Controlled Variables

Natural Disaster (DISASTER): The occurrence of a natural disaster is indicated by the GDP Damage caused by that disaster. “Damage to GDP refers to a reduction in a country's Gross Domestic Product (GDP), which is the total value of goods and services produced within a country's borders during a specific period, often a year.” Hence, the percentage (%) of GDP damage is considered to measure the natural disasters (Lafeiullee et al., 2021).

Education (EDUC): In the model, education is measured by the Gross Secondary School Enrolment Ratio. Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Secondary education completes the provision of basic education that began at the primary level, and aims at laying the foundations for lifelong learning and human development, by offering more subject- or skill-oriented instruction using more specialised teachers. Gross Secondary School Enrolment Ratio is measured as the percentage of population in the 5-year age group immediately following primary education (*Glossary | DataBank*, n.d.-b).

Unemployment (UNEMP): “Unemployment refers to the percentage of the labour force that is actively seeking work but unable to find employment” (OECD, 2024). It is a key economic indicator of a country's labour market health, typically measured on a scale from 0% to 100%. A 0% unemployment rate indicates full employment, while higher rates suggest greater economic challenges. For example, an unemployment rate of 5% would mean that 5% of the labour force is actively looking for but unable to find jobs.

Population (POP): The rate at which the number of people living in a country, territory, or specific geographic area increases or decreases over a certain period of time. In demographic terms, it reflects the percentage change in the total population, typically over a year, due to births, deaths, and migration. It can be calculated for the entire population or for specific sex and/or age groups. Usually expressed as an annual percentage, this measure helps understand how fast or slow a population is expanding or shrinking, though it may be influenced by data limitations or estimation methods (Ritchie et al., 2023).

Sanitation (SANI): "People using at least basic sanitation services (% of population)" are considered the indicator of sanitation in the study. People who have access to private bathrooms that are cleaner are included in the percentage of people who use at least basic sanitation services. This includes both people who have good sanitation and people who need basic services. Improved facilities often include vented improved pit latrines, composting toilets, or pit latrines with the right slabs. They also include flush or pour-flush toilets that are connected to sewage systems, septic tanks, or pit latrines" (Neal, 2024).

2.5. Data Analysis Methodology

This section of methodology shows the correlation analysis and multicollinearity to finalise the variables, along with model specification, and the diagnostic tests conducted. All the statistical tests and models are run on STATA 18 software.

2.5.1. Correlation Analysis

"Correlation is a statistical metric that quantifies the degree of linear relationship between two variables, indicating their simultaneous variation at a consistent pace" (Discovery, n.d.). The absolute value of correlation coefficients ranges from 0 to 1. The closer the coefficient is to one, the stronger the link. Correlation coefficients among the independent variables for both models and panels have been computed and assessed in this study. To prevent multicollinearity, variables should not exhibit correlation coefficients exceeding 0.8 (Kim, 2019). Hence, if the correlation is higher between two variables, then one of the variables is eliminated based on relevance. The following tables represent the correlation coefficients for all the models considered in the study. Four models are analysed in the framework to assess the impact of natural disasters on economic growth and human development in middle-income and high-income countries. It can be seen that none of the correlation coefficients is greater than 0.8, hence, considering all the independent variables in the respective regressions.

Table 1. "Correlation matrix of independent variables for the model with GDP as the dependent variable (Middle-income countries)"

Variables	(1)	(2)	(3)	(4)	(5)
(1) DISASTER	1.000				
(2) EDUC	-0.103	1.000			
(3) UNEMP	-0.128	0.242	1.000		
(4) HDI	-0.213	0.697	0.291	1.000	
(5) POP	0.069	-0.177	-0.023	-0.174	1.000

Table 2. "Correlation matrix of independent variables for the model with HDI as the dependent variable (middle-income countries)"

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) DISASTER	1.000					
(2) EDUC	-0.103	1.000				
(3) UNEMP	-0.128	0.242	1.000			
(4) GDP	-0.181	0.037	-0.209	1.000		
(5) POP	0.069	-0.177	-0.023	0.058	1.000	
(6) SANI	-0.117	0.650	0.221	-0.063	-0.269	1.000

Table 3. "Correlation matrix of independent variables for the model with GDP as the dependent variable (High-income countries)"

Variables	(1)	(2)	(3)	(4)	(5)
(1) DISASTER	1.000				
(2) EDUC	0.053	1.000			
(3) UNEMP	-0.019	-0.082	1.000		
(4) HDI	0.067	0.233	-0.355	1.000	
(5) POP	0.052	0.452	-0.106	0.205	1.000

Table 4. "Correlation matrix of independent variables for the model with HDI as the dependent variable (High-income countries)"

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) DISASTER	1.000					
(2) EDUC	0.053	1.000				
(3) UNEMP	-0.019	-0.082	1.000			
(4) GDP	-0.004	0.127	-0.205	1.000		
(5) POP	0.052	0.452	-0.106	0.175	1.000	
(6) SANI	0.151	0.202	-0.372	0.152	0.097	1.000

2.5.2. Multicollinearity

"Multicollinearity is a statistical phenomenon where several independent variables in a model exhibit a high degree of correlation among themselves." Two variables are considered perfectly collinear whenever the correlation coefficient is precisely +1.0 or -1.0. The test was performed by executing a VIF analysis and examining the average VIF. If the mean VIF were to be greater than 5, then multicollinearity would exist (Paul, 2006). For the model where GDP is the dependent variable, the mean VIFs for middle-income and high-income countries' models are 1.45 and 1.19, respectively. Similarly, for the framework with HDI as the dependent variable, the mean VIFs are 1.34 and 1.18, respectively. Hence, for all the models, the mean VIF is lower than 5, implying that the problem of multicollinearity does not exist in the study.

2.5.3. Model Specification

The following equations were used to figure out how natural disasters affect GDP and HDI. For the group of middle-income countries and the group of high-income countries, both models are estimated separately.

$$GDP_{it} = a_0 + a_1\, DISASTER_{it} + a_2\, EDUC_{it} + a_3\, UNEMP_{it} + a_4\, HDI_{it} + a_5\, POP_{it} + e_{it}$$

$$HDI_{it} = b_0 + b_1\, DISASTER_{it} + b_2\, EDUC_{it} + b_3\, UNEMP_{it} + b_4\, GDP_{it} + b_5\, POP_{it} + b_6\, SANI_{it} + u_{it}$$

Panel data have been utilised to estimate these models. Regression models applicable to panel data include fixed effects, random effects, and pooled OLS. Fixed-effects models examine the impact of temporal variations in factors on a result, while accounting for invariant traits. The fixed effects approach is appropriate when unobserved individual-specific heterogeneity is present and may correlate with the independent variables, enabling a consistent estimate by accounting for time-invariant traits. Random effects are employed to address variability and disparities among distinct entities or persons within a broader population. The random effects model is employed when unobserved individual-specific effects exist but are presumed uncorrelated with the explanatory variables, facilitating more efficient estimates by utilising both within- and between-individual variance. Pooled OLS is a technique for estimating the parameters of a linear regression model utilising panel data, which integrates cross-sectional and time-series observations. Pooled OLS is suitable when there are no unobserved individual-specific effects or when such effects are presumed to be uncorrelated with the explanatory variables. The Hausman test and Breusch-Pagan LM test are utilised to select among these three models (Wooldridge, 2009).

2.5.4. Hausman Test

The Hausman Test is an econometric tool used to figure out whether Fixed Effects (FE) or Random Effects (RE), or Pooled OLS estimators are better for a regression analysis. It looks at how individual effects are related to the independent factors that affect the choice of the right model (Baltagi, 2014). “The null hypothesis for our Hausman test says that random effects are always the same”. In the middle-income panel model with GDP as the dependent variable, the Hausman test yields a p-value of 0.016, leading to the rejection of the null hypothesis and suggesting the selection of the fixed effect model. In the same panel, the p-value for the HDI model is greater than 0.05 (p-value = 0.548). As a result, the null hypothesis stands, which means there isn't enough evidence to tell the difference between random effects and pooled OLS. The p-value for the GDP model in high-income countries is 0.044, which means that the null hypothesis is not true and the fixed effects model is chosen. The p-value for the HDI model in high-income nations is 0.061. The null hypothesis cannot be rejected because the value is greater than 0.05. This means that fixed effects are not consistent. Because of this, the Breusch-Pagan LM test is done next to choose between the random effects model and the pooled OLS model.

2.5.5. Breusch Pagan LM Test

“The Breusch-Pagan test is a statistical method used to determine the difference between the pooled OLS model and the random effects model” (Adekeye et al., 2006). The null hypothesis says that random effects are not consistent. The p-values for the Hausman test for both panels under the HDI models are greater than 0.05. This means that either the random effects model or the pooled OLS model should be used. The p-values for the Breusch-Pagan LM test for both nation panels are less than 0.05, so the null hypothesis for the inconsistent random effects model is not true. As a result, both models have been considered to be random effects models.

2.6. Diagnostics

2.6.1 Autocorrelation

Autocorrelation quantifies the similarity of a time series to its historical values across various time intervals (Wooldridge, 2009). Unlike regular correlation, which looks at the relationship between two different variables, autocorrelation focuses on how values at one time point relate to earlier ones (Jung, 2005). The Wooldridge test to detect autocorrelation has been conducted for both FE and RE models. There is no autocorrelation in the Woolridge test's null hypothesis. For all four models, the p-values for the Wooldridge test are less than 0.05, which means that the null hypothesis is not true. So, the regression models possess certain autocorrelation.

Table 5. "P-values for the Wooldridge test for Autocorrelation"

Dependent Variable	P-values for the Wooldridge Test	
	Middle-income countries	High-income countries
GDP	0.0134	0.0099
HDI	0.0000	0.0000

2.6.2. Heteroskedasticity

Heteroskedasticity happens when the residuals' variability is different for different observed values. To find out if the variance of the residuals is different across a range of measured values, you look at the heteroskedasticity. Heteroskedasticity is more likely to happen in regression models that include a lot of different values. This is because the big differences between the smallest and largest values can make the error variance uneven. The Fixed Effects model uses the Modified Wald test to find heteroskedasticity, and the Random Effects model uses the LM test, the Wald test, and the log likelihood tests (Team, 2024). The null hypothesis for all of the tests listed above is that there is no heteroskedasticity. If the p-value is less than 0.05, the null hypothesis is rejected, which means that heteroskedasticity is present. The p-value for both models is 0.000 for countries with high incomes. The p-value for both models is also 0.000 for low- and middle-income countries. So, it can be denoted that the null hypothesis is false and that all four models have heteroskedasticity.

2.7. Correction for Autocorrelation and Heteroskedasticity

When the error terms don't have the same variance, or heteroskedasticity, the Feasible Generalised Least Squares (FGLS) estimator is a way to find out how two variables are related in regression analysis. It adjusts for the issues of autocorrelation and heteroskedasticity to give more accurate and reliable estimates (Kumar et al., 2021). Since all the regression models in the study were diagnosed with the problem of heteroskedasticity and autocorrelation, the FGLS models are estimated in every equation as a corrective framework.

3. Results

3.1. Descriptive Analysis

Table 6 represents the descriptive statistics of all the variables considered in the research. Descriptive statistics are important because they help people understand and summarise data and provide a clear picture of a dataset's characteristics. It can be depicted that the average GDP growth for middle-income countries (m=4.139, sd=4.356) is greater than the average GDP growth of high-income countries (m=1.969, sd=2.532).

However, the range of GDP growth for middle-income countries (39.189) is also greater than the range of GDP growth for high-income countries (21.827), implying a wider spread of data in the middle-income panel. Similarly, on average, the HDI of middle-income countries (m=0.658, sd=0.095) is lower than the average HDI for high-income countries (m=0.906, sd=0.027), while the range of HDI in middle-income countries (0.455) is higher than the range of HDI in high-income countries (0.138). Moreover, as expected, the average GDP damage due to natural disasters is higher in middle-income countries (m=0.336, sd=0.794) as compared to the high-income countries (m=0.229, sd=0.815). Additionally, the range of GDP damage in middle-income countries (8.304) is lower than the range of GDP damage in high-income countries (11.581), demonstrating a higher dispersion of data for high-income countries. Amongst the controlled variables, the average education level (m_M = 75.631, m_H = 110.799) and average measure of sanitation (m_M = 66.687,m_H = 99.593) are lower in the middle-income countries as compared with the high-income countries. On the contrary, the average unemployment rate ($m_M = 8.274$, $m_H = 6.075$) and population growth ($m_M = 1.252$, $m_H = 0.633$) are higher in middle-income countries in comparison to high-income countries. Lastly, the range of education ($r_M = 148.369$, $r_H = 122.87$), unemployment ($r_M = 27.839$, $r_H = 10.152$), and sanitation ($r_M = 87.813$, $r_H = 0.412$) is higher in middle-income countries, depicting a lower spread in high-income countries. On the other hand, the range of population level of middle-income countries (2.395) is lower than the range of the population level of high-income countries (4.786).

Table 6 . "Results for Descriptive statistics of the variables considered in the study"

Variable	Country	Mean	Standard Deviation	Minimum	Maximum
GDP	Middle-Income	4.139	4.356	-17.669	21.52
	High-Income	1.969	2.532	-10.36	11.467
DISASTER	Middle-Income	0.336	0.794	-0.114	8.19
Variable	**Country**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
DISASTER	High-Income	0.229	0.815	-0.885	10.696
EDUC	Middle-Income	75.631	23.516	-30.436	117.933
	High-Income	110.799	23.243	92.503	215.373
UNEMP	Middle-Income	8.274	5.792	0.999	28.838
	High-Income	6.075	2.344	2.351	12.683
HDI	Middle-Income	0.658	0.095	0.414	0.869
	High-Income	0.906	0.027	0.814	0.952
POP	Middle-Income	1.252	0.379	0.161	2.556
	High-Income	0.633	0.627	-1.854	2.932
SANI	Middle-Income	66.687	20.816	11.448	99.261
	High-Income	99.593	0.476	99.588	100

3.2. Regression Analysis

Table 7 represents the regression results for the model where GDP is the dependent variable. It can be seen from the table that the damage (DISASTER) caused by natural disasters in middle-income countries significantly impacts GDP, as the p-value is less than 0.01. There exists a negative impact of natural disasters on the GDP growth of middle-income countries. This implies that if the GDP damage caused by natural disasters in middle-income countries increases by one percent, the GDP growth rate will significantly fall by 1.09 percent. On the contrary, natural disasters do not significantly impact GDP in high-income countries, as the p-value (0.95) is even greater than the 10 percent level of significance. Amongst the controlled variables, it can be observed that the p-values for education (EDUC) in middle-income (0.7) and high-income (0.145) countries are higher than 0.1, indicating that there is no significant impact of education on GDP growth when other drivers are constant. However, the unemployment rate significantly influences the GDP growth rate in both panels, with a p-value of zero. Therefore, for every 1 percent increase in unemployment in middle-income countries GDP growth rate will fall significantly by 0.201 percent. This impact is higher in high-income countries. For high-income countries, a one percent increase in the unemployment rate leads to a significant decrease in GDP growth by 0.302 percent. The observation that the p-value for HDI in middle-income countries (0.291) is higher than 0.1 implies that HDI has no significant impact on GDP. Contrarily, the p-value for HDI in high-income countries (0.000) is less than 0.01; therefore, it has a significant impact on GDP. Thus, for an increase of 1 unit in HDI, the GDP growth rate reduces by a significant 26.418 percent. Similarly, population growth significantly impacts GDP growth in high-income countries (p-value = 0.017) but not in the middle-income countries (p-value = 0.154). Therefore, if the population growth rate increases by one percent, GDP growth increases by 0.64 percent in high-income countries.

Table 7. "Cross-sectional time-series FGLS regression results considering GDP as the dependent variable"

Dependent Variable (GDP)		
Independent Variables	**Middle-income**	**High-income**
DISASTER	**-1.09****** **(**0.338) 0.001	**-0.012** (0.184) 0.950
EDUC	**0.006** (0.016) 0.700	**0.011** (0.007) 0.145
UNEMP	**-0.201***** (0.047) 0.000	**-0.302***** (0.068) 0.000
HDI	**4.166** (3.944) 0.291	**-26.418****** (6.143) 0.000
POP	**1.002** 0.703 0.154	**0.64**** (0.269) 0.017
Constant	**1.716** (2.284) 0.453	**26.156****** (5.63) 0.000

*Standard errors in parentheses and p-value below standard errors; ***p<0.01, **p<0.05, *p<0.1*

Table 8 depicts the results of regression estimation for the model where HDI is the dependent variable. Similar to the impact on GDP growth, natural disasters significantly influence HDI in middle-income (p-value = 0.001) countries but not high-income countries (p-value = 0.226). Natural disasters negatively affect HDI in middle-income countries. Hence, a one percent increase in the GDP damage due to natural disasters leads to a fall in HDI by 0.009 units. Amongst the controlled variables, all of them are significant in both panels, with most of the p-values lying below 0.01, except population in high-income countries, which is significant at 5 percent. Education and population have a positive impact on HDI in middle-income and high-income countries. A one unit increase in education leads to a rise in HDI by 0.001 units in middle-income countries but has no impact in high-income countries. Moreover, for every one percent increase in population growth, the HDI increases by 0.018 percent in middle-income countries and 0.005 percent in high-income countries. However, unemployment, GDP, and sanitation positively impact HDI in middle-income countries but negatively influence HDI in high-income countries. So, a one percent increase in unemployment leads to an increase in HDI in middle-income countries by 0.001 units but a decrease in HDI in high-income countries by 0.005 units. Similarly, a one percent increase in GDP growth rate leads to an increase in HDI in middle-income countries by 0.002 units but a decrease in HDI in high-income countries by

0.02 units. Lastly, a one percent increase in sanitation leads to a rise in HDI in middle-income countries by 0.004 units but a decrease in HDI in high-income countries by 0.010 units.

Table 8. "Cross-sectional time-series FGLS regression results considering HDI as the dependent variable"

Dependent Variable (HDI)		
Independent Variables	**Middle-income**	**High-income**
DISASTER	**-0.009***** (0.003) 0.001	**0.002** (0.002) 0.226
EDUC	**0.001***** (0.000) 0.000	**0.000***** (0.000) 0.001
UNEMP	**0.001***** (0.000) 0.000	**-0.005***** (0.001) 0.000
GDP	**0.002***** (0.001) 0.000	**-0.020***** (0.001) 0.000
POP	**0.018***** (0.006) 0.003	**0.005**** (0.003) 0.050
SANI	**0.004***** (0.000) 0.000	**-0.010***** (0.003) 0.004
Constant	**0.324***** (0.013) 0.000	**1.899***** (0.339) 0.000

*Standard errors in parentheses and p-value below standard errors; ***p<0.01, **p<0.05, *p<0.1*

4. Discussion

As seen in the results, natural disasters often cause a greater GDP impact in middle-income countries than in high-income countries. Although a lot is then dependent on how prepared and adaptable the economies are, there are strong safety nets in place for wealthier countries. The primary support comes from the government, who quickly step in to help rebuild and keep businesses and communities afloat by giving financial support (Devdiscourse, 2025). This kind of immediate response helps soften the economic blow. Additionally, developed countries have better infrastructure, widespread insurance coverage, and well-developed emergency systems. So even when disasters cause damage, these countries can recover more quickly and get back on their feet (Nguyen et al., 2025). On the other hand, middle-income countries don't have the same resources, and the damage lingers on, as when disaster strikes, they struggle to mobilise enough money and support.

Investment drops, exports can get hit hard, especially if key infrastructure like ports or tourist spots are damaged, and there's not enough government spending to fill the gap (Adam & Bevan, 2020; Nguyen et al., 2025). The economy never fully catches up to where it would have been without the disaster, and hence, the recovery takes longer. So, the impact of natural disasters on GDP is deeper and lasts longer for middle-income countries, whereas on the other hand, high-income countries can cushion the blow and recover faster (Naoaj, 2023). The Human Development Index (HDI) of middle-income countries is also impacted by natural disasters in a much bigger way when compared to high-income countries, mainly because of differences in resources, vulnerability, and recovery capacity (Akram et al., 2022). Due to disasters in middle-income countries, years of progress in health, education, and living standards, which are key parts of HDI, cannot be quickly reversed. Since countries often have limited social protection, weaker infrastructure, and less access to quality healthcare and education, when disaster strikes, setbacks are deeper and recovery is slow (Admin, 2024; Oreggia, n.d.).

Studies indicate that a single disaster can erase as as two years' worth of progress in human development in the affected areas, with poverty and inequality rising sharply after the event (Oreggia, n.d). Since middle-income countries also tend to have more people living in disaster-prone areas and they have higher poverty rates, this makes they more exposed and less able to cope with the disasters (Admin, 2024; World Bank Group, 2021). In contrast to high-income countries, which have stronger institutions, better emergency response, and more resources to rebuild quickly, hence, the long-term impact on HDI is minimal (Akram et al., 2022; Susan Chacko, 2024). That's why the HDI drop is much more significant and lasting in middle-income countries after natural disasters.

Conversely, Unemployment significantly impacts GDP and HDI across income levels due to interconnected mechanisms. Unemployment directly lowers labour input, shrinking economic output. Studies show that a 1% rise in unemployment reduces GDP by 0.39% in Western Balkan countries (Kukaj, 2018) and negatively correlates with growth in Sub-Saharan Africa (Abraham & Nosa, 2018). Furthermore, during crises, earnings decline more sharply than employment, particularly in manufacturing-heavy economies with strict labour regulations. This reduces consumer spending and aggregate demand. Additionally, countries with larger manufacturing sectors and smaller export bases experience steeper GDP declines from unemployment shocks (*Open Knowledge Repository*, n.d.).

Subsequently, health, education, and living standards are directly undermined by unemployment, which in turn increases the poverty rate, core HDI components. In middle-income countries, HDI scores are further lowered as joblessness reduces household capacity to invest in health and education. Research confirms unemployment's negative effect on HDI (Sumaryoto et al., 2021). Sometimes, even when GDP grows, the high unemployment correlates with lower HDI, indicating non-inclusive growth (e.g., in Botswana and South Africa) (Ihensekhien & Aisien, 2018). The inconsistency across income levels simultaneously reduces economic output (GDP) and human capital development (HDI) through diminished productivity, increased poverty, and constrained access to essential services (Aji et al., 2024). Therefore, considering all the factors, there is a higher negative impact of natural disasters on the middle-income economies.

5. Conclusion

This study looks at how natural disasters affect GDP and HDI in middle- and high-income countries using panel data and different models. This study uses panel data econometric methods to look at how natural disasters affect GDP and HDI in middle- and high-income countries. It also looks at statistical issues like multicollinearity, heteroskedasticity, and autocorrelation. Australia, Canada, France, Germany, Italy, Japan, Korea, Rep. (i.e., South Korea), New Zealand, the United Kingdom, and the United States are all high-income countries. Bangladesh, Brazil, India, Indonesia, Iran (Islamic Rep.), the Philippines, South Africa, Turkiye, Viet Nam, and Zimbabwe are all middle-income countries. We have gathered and examined data from all of these countries from 1999 to 2023. We used the FGLS model to estimate the results after performing diagnostic tests like multicollinearity, autocorrelation, and heteroskedasticity. The results showed that damage to GDP from natural disasters has a major adverse impact on both GDP and HDI in middle-income countries, but not on GDP or HDI in high-income countries. Natural disasters and unemployment have an enormous impact on both GDP and HDI. However, the effects are not the same in middle- and high-income countries because they have different levels of resilience, resources, and institutional strength. Middle-income countries are more affected by natural disasters because their infrastructure is weaker, they have less money to fall back on, and they take longer to recover. This means that their economies lose income for longer and their people develop more slowly. These disasters can undo years of progress in education, health, and living standards, especially where poverty is high and social protection is minimal.

Hence, due to disasters in middle-income countries, years of progress in health, education, and living standards, which are key parts of HDI, can quickly be reversed. On the other hand, high-income countries, with stronger safety nets, insurance systems, and disaster response mechanisms, recover faster and avoid long-term damage. Unemployment, however, negatively affects both GDP and HDI across all income levels by reducing economic output, lowering consumer spending, and increasing poverty. It weakens households' ability to invest in health and education, thus hurting long-term development. In both income groups, unemployment constrains growth and undermines human well-being, demonstrating its powerful dual impact on economic and social indicators. Overall, the disparity in impact highlights the critical need for stronger resilience and inclusive recovery strategies, especially in middle-income countries.

6. Limitations and Policy Implications

Although this investigation offers valuable insights, it is imperative to acknowledge specific constraints in order to contextualise the results. The study's limitation is that it only examined 10 countries from both middle and high-income countries. Nevertheless, a greater number of countries could be included on both ends to obtain more generalised and precise results. Additionally, a more detailed analysis could have been conducted for each group of countries. Subsequently, the analysis does not account for other substantial economic shocks, including financial crises, pandemics, or political disruptions, which may have impacted GDP and HDI either independently or in conjunction with natural catastrophes. The data may be obscured by the excluded factors, which complicates the isolation of the unique impact of natural disasters. Finally, the scope of comparative insights is restricted by the exclusion of low-income countries in this study. Incorporating them could expose more profound disparities in resilience and vulnerability to natural disasters.

Apart from the drawbacks, this study gives useful insights to governments, policymakers, and research scholars. Governments can use the results to lay down disaster-specific policies, make the economy more resilient, and include disaster risk reduction in their long-term development plans. Policymakers may adopt economic and social policies that are more specific, use resources more effectively, and allocate funds into vital sectors like education, healthcare, and jobs, especially in middle-income nations that are likely to have disasters. The study also points out structural weaknesses that need to be resolved by making early warning systems and preparedness better. Researchers can use these results to look into the long-term effects on society and the economy, and include low-income countries in their studies. Also, development agencies can utilise the information to help create customised programs to increase resilience and make effective policy changes based on a country's income level and level of risk.

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