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In the Eye of the Storm:
Gendered Impacts of Climate Change in Africa.

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ABSTRACT

This dissertation explores the climate change and gender inequality nexus with a focus on Africa. The research question is: Is climate change likely to exacerbate gender inequality across countries and time? The two complementary hypotheses are H1: Countries with higher climate change impacts will show greater gender inequality than those with lower climate change impacts; and H2: The intensity of the impact of climate change on gender inequality increases over time. To test such hypotheses, I employ a multiple cross-country regression model. The study examines various dimensions of gender inequality circa 2010 and circa 2019. The dependent variables are the reproductive health index and the gender gaps in average years of schooling, enrollment rates, and labor force participation. Independent variables include disaster frequency (accumulated over 10 years), GDP per capita, agricultural dependency, dependency ratio, urbanization rate, extreme poverty rate, and civil wars. I formulate a core model with these variables, augmented models with additional variables and perform robustness checks. The key findings reveal that disaster frequency counterintuitively narrows the average years of schooling gap, while it worsens reproductive health. Additionally, agricultural dependency and the dependency ratio emerge as significant factors influencing most dimensions of gender inequality. Extreme poverty, GDP per capita, and civil wars also have explanatory power for certain gender inequality variables.

Key words: Climate change, gender inequality, natural disasters, climate impacts, developing economies

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LIST OF ABBREVIATIONS

African Institute for Security Studies and the Peace and Security Council	ISS-PSC
African Union	AU
European Institute for Gender Equality	EIGE
Food and Agriculture Organization	FAO
Gender in Geopolitics Institute	GGI
Gender Inequality Index	GII
Gender-Based Violence	GBV
Gross Domestic Product	GDP
Intergovernmental Panel on Climate Change	IPCC
International Labour Organization	ILO
International Monetary Fund	IMF
International Organization for Migration	IOM
International Union for Conservation of Nature	IUCM
National Aeronautics and Space Administration	NASA
Notre Dame Global Adaptation Initiative	ND-GAIN
Ordinary Least Squares	OLS
United Nations	UN
United Nations Department of Economic and Social Affairs	UN DESA
United Nations Development Program	UNDP
United Nations Economic Commission for Africa	UNECA
United Nations Educational, Scientific and Cultural Organization	UNESCO
United Nations Entity for Gender Equality and the Empowerment of Women	UN Women
World Bank	WB
World Economy Forum	WEF
World Health Organization	WHO
World Meteorological Organization	WMO

LIST OF VARIABLES

Reproductive health index	health
Average years of schooling gap	g_school
Enrollment ratio gap	g_enroll
Labor force participation gap	g_labor
Disaster frequency (10-year accumulation)	disaster10
Disaster frequency (5-year accumulation)	disaster5
GDP per capita	gdp_pc
Agriculture’s contribution to GDP	agri_gdp
Land devoted to agriculture	agri_land
Age dependency ratio	dependency
Urbanization rate	urban
Extreme poverty rate	poverty
Civil war	c_war
Climate change vulnerability	cc_vul
Landlocked	landlock
Mobility rate	mobility
Access to water	water
Female political empowerment	politics

1. INTRODUCTION

Climate change, undeniably one of the most pressing global challenges of our time, has been carefully examined by scholars and experts. In particular, the exploration of inequalities linked to this phenomenon has gained increasing attention in the academic field. Research has examined the disproportionate effects of climate change on diverse groups, which result in heightened disparities in education, wealth or health, among other areas. However, while vertical inequalities –disparities across groups over the income distribution– have attracted significant attention, the study of horizontal inequalities –disparities between different groups or communities– has received comparatively less scrutiny. Even so, there is a common agreement of the discernible inequity in the distribution of climate change consequences across diverse social groups.

Along these lines, there is a notable gap in the scholarship in one of the key facets of horizontal inequality: gender. What is more, while detailed climate data has been collected over the years, sex-disaggregated data has not been consistently integrated –the so-called "gender data gap"–, hindering the documentation and analysis of climate effects on gender (WEF, 2020). Emerging literature offers theoretical frameworks and real-life analyses. These, in turn, enable the identification of mechanisms of transmission and impacts, laying the foundation for targeted interventions and policies to address the specific causes and impacts of climate change on women.

The significance of this study lies in its potential to contribute to the emerging literature by offering a deeper understanding of the intersection between climate change and gender inequality. It does so particularly through the utilization of quantitative methodologies, a less common approach within the field. Moreover, the intensification of climate change in recent years emphasizes the urgency of exploring its gendered consequences. By examining these dynamics, this study aims to provide an initial mapping of the gendered effects of climate change through a statistical lens. In doing so, it can pave the way for future research efforts and informed policy formulation.

This dissertation is structured as follows. Section 2 deals with the nexus between climate change and gender inequality conducting a literature review, and discussing its core concepts, the theoretical framework and the geographical focus on Africa. It also formulates the research's hypotheses. Section 3 explains the methodology and the data collection methods. It also describes the regression analysis approach and the construction of the models. Section 4 provides the econometric analysis and discussion of the climate change-gender inequality models, together with a robustness check. Finally, Section 5 offers a summary of the findings, along with an exploration of its limitations and suggestions for future research efforts.

2. THE CLIMATE CHANGE-INEQUALITY NEXUS

2.1. Conceptualizing Climate Change

Climate change refers to long-term shifts in temperatures and weather patterns (IPCC, 2023). The IPCC states that climate change manifests across various phenomena, notably through alterations in meteorology, heightened frequency and intensity of natural disasters, and ecological shifts. This encompasses rising temperatures, modified precipitation patterns, elevated sea levels, and the proliferation of extreme weather events. Institutions like the IPCC or US's NASA provide data-based evidence of the intensification of these phenomena. In fact, according to the IPCC (2023), the climate crisis is rapidly intensifying, marked by a rising frequency and global expansion of droughts, floods, and heat waves across both hemispheres. NASA (2024) further states that some of those natural events are happening even faster than scientists previously envisaged.

These transformations extend beyond the environmental sphere, permeating social, economic, and political domains. As such, climate change becomes a multi-dimensional phenomenon, recognized for its exacerbation of preexisting inequalities and vulnerabilities (IPCC, 2023). This disproportionately affects fragile and marginalized communities, nations and regions. Countries' socio-economic development, especially in the Global South[1], faces substantial challenges attributed to climate change (UNDP, 2023b). This struggle is primarily driven by a heavy reliance on climate-sensitive sectors like forestry and agriculture, coupled with limited adaptive capacities. Concurrently, at the local level, millions of households face extreme vulnerability due to their reliance on natural resources and exposure to disasters, making them susceptible to adverse impacts (*idem*).

2.2. Conceptualizing Gender Inequality

Gender inequality constitutes a pervasive social issue with multifaceted dimensions. The EIGE defines this concept as "the legal, social and cultural situation in which sex and/or gender determine different rights and dignity for women and men, which are reflected in their unequal access to or enjoyment of rights, as well as the assumption of stereotyped social and cultural roles." It extends along reproductive health, education, and economic and political participation, reflecting the multiple ways in which individuals' opportunities and choices are shaped by their gender identity, with more or less subtle systemic biases that affect every facet of life (UNDP, 2023a). It entails poorer health outcomes, characterized by higher female mortality rates and inadequate access to quality healthcare services. It also undermines educational outcomes, including lower enrollment rates, reduced educational attainment, and fewer years of schooling for women and girls. Moreover, it hampers political empowerment, resulting in limited representation of women in politics and decision-making processes.

[1] According to the UNCTAD´s definition, the Global South encompasses developing and least developed countries (LDCs), while the Global North comprises developed countries.

And beyond the overt disparities in incomes, employment opportunities, and access to resources, gender inequality encompasses the complex interplay of power dynamics and socio-cultural norms. It influences dynamics within families, labor markets, economic and political realms, power structures, decision-making processes, and social gender relations (EIGE, *n.d.*).

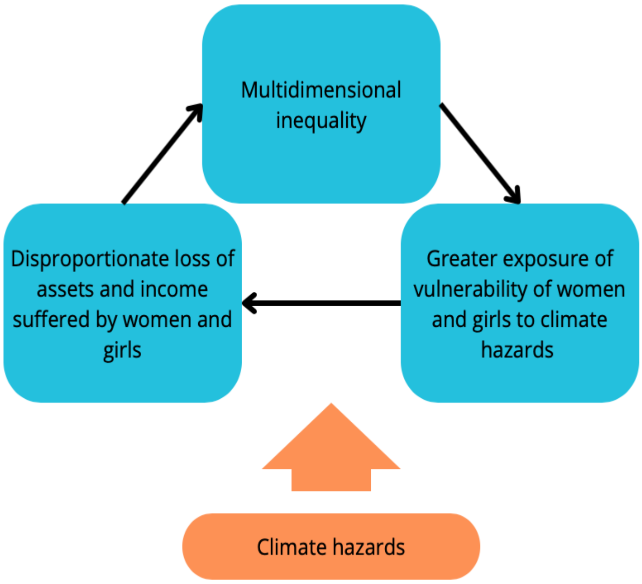
Overall, gender inequality impacts the status of women and girls across all facets of society, spanning both public and private domains. And although there has been notable progress in recent decades, it has been predominantly centered on the Global North, leaving the Global South struggling with challenges in advancing gender equality policies and social reforms in many instances.

2.3. The Nexus

Climate change is neither symmetric nor gender neutral. Several studies and reports already link climate change with the widening of existing gender inequalities. Literature substantiates the hypothesis of the gendered effects of climate change through empirical evidence, case studies, and theoretical frameworks. There is evidence demonstrating that the multiple dimensions of inequality, such as gender, "underlie a situation where disadvantaged groups are more exposed and susceptible to climate hazards [...], and, as a result, inequality is exacerbated" (UN DESA, 2016). According to a 2023 study by the ISS-PSC of the African Union (AU), gender inequality causes women to be poorer, have less education and have greater exposure to health risks, rendering them especially vulnerable to climate changes. Further findings reveal how women, especially those in developing communities and regions, bear a high burden of climate-induced adversities, facing increased risks related to food security, health, displacement, and economic stability (UNWomen & IUCN, 2022; UNDP, 2023b). Oxfam (2022b) maintains that "during and after extreme weather events, they [women and girls] are at increased risk of violence and exploitation". In a worst-case climate scenario, as many as 158 million women and girls globally may be pushed into poverty by 2050 as a direct result of climate change (UN Women, 2023a). Therefore, there is a growing consensus regarding the role of climate change in exacerbating women's inequality, poverty, and insecurity.

Before continuing with the analysis, it is fundamental to stress that climate change does not create gender inequalities, but rather intensifies the existing ones. UNDP (2023b), UN Women (2022b), Oxfam (2023) and many other institutions emphasize the intersection of gender inequalities with climate risks and vulnerabilities, which worsen existing gender disadvantages. Women face an increased vulnerability to climate change owing to their historical disadvantages, like differences in workloads, restricted access to decision-making processes and environmental and economic resources, and limited rights (UNDP, 2023b). Figure 1 summarizes this vicious cycle, reflecting how climate change does not originate gender inequalities, but rather contributes to and intensifies them. Whilst originally built by UN DESA (2016) to encompass all disadvantaged groups, I have adapted it so that it reflects the case of women and girls. It reflects how pre-existing multidimensional inequalities lead to an increased exposure and vulnerability of women and girls to the effects of climate change. As a result, they suffer disproportionate losses of income and assets (physical, financial, human and social) when natural hazards actually hit them. Consequently, inequality worsens, and the cycle perpetuates with greater force.

Figure 2.1. Climate change - inequality vicious cycle. Focus group: women and girls.



Source: Own adaptation from UN DESA (2016)

Finally, a notable contribution to my work within the emerging quantitative research on the climate change-gender inequality nexus is Eastin's (2018), which examines the intersection of climate change and gender *equality*. His research covers a broader sample than mine, including most developing states worldwide, employing ordered-logistics models. Specifically, he finds that increases in temperature deviations and occurrences of climatic disasters are linked to declines in women's economic and social rights. This impact is particularly notable in autocracies with high agricultural dependence and lower economic development levels.

2.4. Case Selection

To determine the geographical scope of this study, I looked at metrics for climate change vulnerability[2] and gender inequality across global regions. The goal was to select the most representative region for further investigation. The following table summarizes them:

[2] Climate change vulnerability is defined by the IPCC as "a function of the character, magnitude and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity".

Table 2.1. Climate change vulnerability and gender inequality by global regions*

	Vulnerability to climate change (ND-GAIN)		Gender inequality (GII)	
Groups of economies	**2010**	**2019**	**2010**	**2019**
Developed	0,310	0,301	0,306	0,247
Developing: Americas	0,393	0,398	0,437	0,388
Developing: Asia and Oceania	0,431	0,427	0,472	0,421
Developing: Africa	0,497	0,499	0,602	0,573

Source: ND-GAIN and UNCTAD, respectively. Vulnerability to climate change index ranges between 0-1 with higher values indicate higher vulnerability. Gender inequality index ranges between 0-1 with higher values indicate higher inequality. **Countries follow the division by UNCTAD´s classification.*

According to these metrics, Africa is the most affected global region in terms of both climate change and gender inequality. There is ample evidence highlighting its vulnerability to the adverse impacts of climate change profoundly influencing its socio-economic structure, alongside its persistent and severe gender inequaflity challenges.

In particular, the IPCC (2023) highlights that Africa emerges as the continent bearing the highest brunt of climate change impacts. UNECA (2023) reports that periods of droughts and flooding in Africa are intensifying, and that several other natural disasters will not only be more extreme but also more recurrent. And while Africa's contribution to global warming is minimal, of around 10% (WMO, 2023), the continent is disproportionately affected by it. Nowadays, out of the 20 most threatened countries by climate change, 17 are situated in Africa (UNECA, 2023).

In terms of gender inequality, UNDP states that Africa is the global region with the highest gender inequality levels. This fact is well reflected by UNDP's Gender Inequality Index (GII), which is used as one of the main gender inequality indexes.[3] Socially, discriminatory practices such as early marriage, prevalent in many African countries, perpetuate gender inequality. For instance, in West Africa, 44% of women aged 20 to 24 are married before 15 (GGI, 2021). These marriages often lead to girls dropping out of school, widening the education gap between genders and hindering the country's

[3] This index reflects gender-based disadvantages in different dimensions: reproductive health, empowerment and the labor market. Sub-section 3.3. further explores it.

development. Economically, women face barriers to participation, reflected in a wage gender gap of about 30% and limited integration into formal economic sectors (*idem*). This economic exclusion also hinders women's empowerment. Overall, women in Africa frequently experience heightened vulnerability to climate change owing to their social roles, economic conditions, and restricted access to resources (ISS African Studies, 2023).

2.5. Research Question and Hypotheses

Building upon this prevailing consensus, this study seeks to empirically test the nexus between climate change and gender inequality. My research question is: *Is climate change likely to exacerbate gender inequality across countries and time?* This research question posits not only that gender dynamics play a crucial role in shaping individuals' vulnerability to the adverse effects of climate change, but also asserts that this impact varies across different countries. Moreover, it postulates that since climate change worsens over time, it is likely that its impact on gender inequality will increase. Guided by this central question, the proposed complementary hypotheses of the study are the following:

H1: Countries with higher climate change impacts will show greater gender inequality than those with lower climate change impacts.

H2: The intensity of the impact of climate change on gender inequality increases over time.

3. METHODOLOGY

This research employs a mixed-methods approach to address the research question and the two hypotheses. Qualitative research has been utilized to gather theoretical data for exploratory purposes and for identifying themes and patterns within the climate change-gender inequality nexus. This allowed to identify the metrics to be used in the quantitative analysis, involving the creation of a database, the design of statistical models and the discussion of the results.

Particularly, this work employs econometric regression analysis to investigate the connection between climate change and gender disparities. Given the intricacies of the nexus between natural disasters to gender inequality, the use of quantitative analysis becomes imperative. To test H1 and H2, I employ a number of Ordinary Least Squares (OLS) cross-country regressions for the periods of c. 2010 and c. 2019. OLS is a preferred method for providing estimates of the coefficients that represent the strength and direction of the relationship between the independent and dependent variables, allowing for clear interpretation of the results. I further incorporate country dummy variables to address outliers originating from specific countries, which can influence the outcome independently of the primary variables under examination.

Finally, and as previously mentioned, the research explores the climate change-gender inequality nexus at two different points in time, circa 2010 and 2019. This aims to study how, as climate change intensifies annually, the results should be more impactful and significant closer to the present. By spanning a nearly 10-year interval between measurements, the study also captures the evolving effects over time while mitigating potential distortions caused by external contextual factors. Opting for 2019 as the ending year allows to avoid any potential distortions caused by the COVID-19 pandemic.

3.2. Data Collection

This study relies on both qualitative and quantitative data sources. Qualitative sources encompass reports, studies, and theoretical descriptions relevant to the topics explored in this paper. This research draws from a diverse array of reputable sources, including the United Nations Development Programme, the United Nations Entity for Gender Equality and the Empowerment of Women, Oxfam, and the World Economic Forum, all of which offer valuable insights and data on gender inequality and climate change. Regarding information on Africa, key sources include the African Institute for Security Studies and the United Nations Economic Commission for Africa. On the other hand, quantitative data sources provide statistical datasets across various domains of interest, including economic, social, environmental, and political dimensions. Sources include the World Bank, the International Monetary Fund, the International Labour Organization, the World Health Organization, and V-Dem.

To examine the influence of climate change on gender inequality in Africa, I have assembled a cross-country dataset comprising 47 African countries out of a total of 54. The remaining countries could not be incorporated due to insufficient data.

3.3. Econometric Models

In the following lines I introduce the core econometric model, presenting the chosen variables and explaining their roles within the proposed framework.[4] The core specification model for the regression analysis is outlined in *Equation 1*. Later, this model is expanded by incorporating additional explanatory variables.

Equation 3.1. Core model

$$g_{ineq} = \beta_0 + \beta_1 \cdot disaster10 + \beta_2 \cdot gdp\_pc + \beta_3 \cdot agri\_gdp + \beta_4 \cdot dependency + \beta_5 \cdot urban + \\ + \beta_6 \cdot poverty + \beta_7 \cdot c\_war + e$$

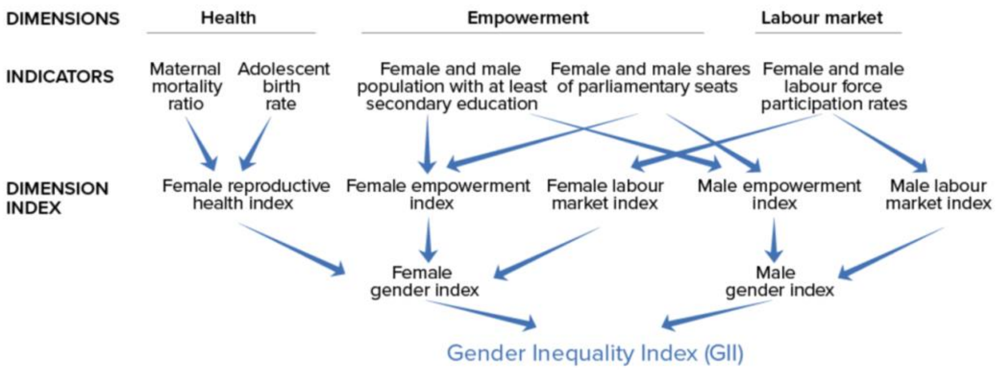
[4] Please, consult Table 4 in Annex I for a comprehensive overview and detailed description of the selected variables. In the same Annex, correlation matrices are also available for reference.

Source: Own creation

a) Dependent Variables

Dependent variables capture different dimensions of gender inequality. The choice of these variables is informed by the Gender Inequality Index (GII) developed by the UNDP, which stands as one of the most widely utilized indicators of gender inequality across academic and policy domains. Below is an image detailing the dimensions of this index:

Figure 3.2. Gender Inequality Index (GII)



Source: UNDP

Since nuances may be ignored when solely assessing the overall GII, this research has focused on analyzing the three separate dimensions that comprise index. Therefore, our dependent variables measuring gender inequality (*g_ineq*) are: the female reproductive health index (*health*); the average years of schooling gap (*g_schoo*l) and the enrollment gap in primary education (*g_enroll*)[5]; and the labor force participation rate gap (*g_labor*). Before continuing, it must be highlighted that including the gender income gap as an additional dependent variable was considered, given its interest and relevance in measuring gender inequality. However, it was not possible owing to data limitations.

The ***reproductive health index*** *(health)* is a key measure of gender inequality built from the adolescent fertility rate and maternal mortality. Thus, the higher the index, the worse women's reproductive health. Reproductive health (or its lack thereof) is a key driver of disparities between men and women. The transmission mechanisms are the following:

[5] This gender inequality dimension was modified from the original GII. The variable for secondary education attainment was not utilized given the lack of data availability, and parliamentary seats were also excluded due to its lack of connection to climate change phenomena.

On the one hand, the adolescent fertility rate in low- and middle-income countries presents a severe impediment to development and can lead to school dropout, lost productivity, and the intergenerational transmission of poverty, enlarging the gender inequality gap (UNESCO, 2012). Its link to climate change stems from the unique challenges women and girls encounter in climate-affected environments, often resulting in the exploitation of their bodies that lead to unintended and early pregnancies. For instance, women and girls face heightened vulnerability to sexual exploitation, particularly amidst food shortages. There are cases where male food vendors, farmers, and landowners have taken advantage of resource scarcity, coercing women and adolescents into exchanging sex for food (UN Women, 2023a). Similarly, when families are unable to meet basic needs, child marriage rates increase significantly (Warren et al., 2023).

On the other hand, numerous studies highlight the detrimental connection between climate change and maternal mortality. Sorensen et al. (2018) proved that women tend to suffer higher rates of chronic malnutrition and have a heightened sensitivity to climate-induced food and nutrition insecurity, especially during pregnancy. Blakstad and Smith (2020) conclude that women giving birth during or in the period following a natural disaster have an increased risk of adverse reproductive outcomes, including preeclampsia, bleeding, delivery complications and, in many instances, death. Furthermore, infectious diseases, many of which are exacerbated by climate change, have serious consequences on maternal health (*idem*). For instance, rising temperatures and changes in rainfall patterns contribute to increased malaria transmission in sub-Saharan Africa. Consequently, pregnant women in West, Central, East, and Southern Africa are estimated to face a nearly 50% mortality rate from malaria infections, attributed to their weakened immune systems (Awiti, 2022).

Average years of schooling gap *(g_school)* and ***enrollment ratio gap*** *(g_enroll).*[6] Due to underlying socio-economic factors, women and girls usually face lower school outcomes than men in terms of enrollment, years of schooling and attainment. Compounding this disadvantage, it is usually women and girls who bear a disproportionate burden in collecting essentials like food, water, wood or fuel for their households and communities. With climate change events destroying natural resources or making them scarce, women and girls are forced to walk longer distances to obtain them (UNWomen, 2022a; UNWomen, 2022b). This heightened responsibility leads to added strain on them, who may have to forgo schooling to assist in managing this amplified workload (*idem*). Thus, women's and girls' disposable time to get formal education is reduced, ultimately widening the educational gap between women and men. Moreover, child marriages and early pregnancies often result in a significant dropout rate among girls from schools (Girls Not Brides, 2020).

[6] Both gaps are built as the female/male ratio.

Labor participation gap *(g_labor).*[7] Similar to the mechanisms affecting schooling, the continual necessity to procure increasingly scarce natural resources diminishes available time for engaging in the *public* sphere's employment –meaning out-of-home, paid jobs. Moreover, during climate change events, women are usually the first ones to leave paid work to care for their family or community (Ghosh, 2021). However, incorporating the variable of female labor participation adds complexity, as its impact on gender inequality is ambiguous. On the one hand, a higher female labor participation rate could potentially reduce gender inequality and income disparity. However, it is important to note that in many African economies, a significant portion of female labor participation occurs within informal sectors, which may not necessarily contribute positively to overall gender equality particularly regarding income.

b) Independent Variables

Among the following independent variables, some are associated with climate change effects. Others function as supplementary control variables that provide explanatory insights into the gender inequality variables under examination.

Frequency of natural disasters *(disaster10).* This variable provides an approximation of climate change as it remains entirely exogenous to existing socio-economic and political processes. This ensures that any observed effects on gender equality are directly attributable to climate-related factors, rather than being influenced by other societal dynamics. *Disaster10* is calculated as the cumulative of disasters during the previous 10 years[8]. The rationale for this is twofold: i) the presence of lingering and cumulative effects; and ii) that country observations in both periods are circa 2010 or 2019, with a range of about three years. It is anticipated that countries experiencing higher frequencies of natural disasters will exhibit greater levels of gender inequality. Thus, *disaster10* is expected to exhibit a positive coefficient β_1 with *health* and a negative one with the rest of *g_ineq* variables.

Droughts *(drought)* and floods (*flood)* represent specific natural disasters with distinct relationships with gender inequality. Among the array of natural disasters, I have included them as variables for the augmented model in sub-section 4.1 due to their high occurrence and direct impacts on gender inequality across Africa.

Climate change vulnerability *(cc_vul).* It will be used as a variant of *disaster10*. Increased vulnerability leads to heightened impacts on a country's population, with women anticipated to suffer disproportionate consequences due to their heightened susceptibility to the effects of climate change.

[7] The gap is built as the female/male ratio.
[8] It encompasses disasters from 2000 to 2010, and from 2010 to 2019.

Thus, *cc_vul* is expected to have a positive coefficient β_1 with *health* and a negative one with the rest of *g_ineq* variables.

GDP per capita *(gdp_pc)* is a commonly utilized proxy to gauge the level of development within a country. A commonly held assumption in the development literature is that more developed countries are also likely to have greater respect for women's rights (WEF, 2022). Accordingly, it is anticipated that higher levels of GDP per capita will correspond to lower values of gender inequality. Thus, *gdp_pc* is expected to demonstrate a negative coefficient β_2 with *health* and a positive one with the rest of *g_ineq* variables.

Agricultural dependency. Women and girls carry a disproportionate unpaid work burden and rely heavily on climate-sensitive sectors for their livelihoods and on natural resources, while facing limited access to them (UNWomen & IUCN, 2022; Awiti, 2022). Particularly in low- and lower-middle-income countries, agriculture stands as a key employment sector for women (Oxfam, 2023; UN Women 2023a). Schalatek (2022) notes that sub-Saharan African women remain the primary producers in agriculture, many times in the informal sector, accounting for about 80% of sub-Saharan Africa's food production. Along these lines, it has been observed that African women are among the first groups to experience the effects of climate change on agricultural processes and production (ISS-PSC, 2023). Further, persistent inequalities compound the challenges faced by women farmers, rendering them more susceptible than their male counterparts to agricultural insecurity. These vulnerabilities not only constrain their income sources, but also compel them to bear an increased workload. This perpetuates a detrimental cycle, leaving women with less time to invest in education or pursue higher-wage employment opportunities (UNWomen, 2022a).

I incorporate two variants for agricultural dependency: agriculture´s contribution to GDP (*agri_gdp*, for the core model) and the percentage of agricultural land (*agri_land*, for the augmented model).[9] Both *agri_gdp* and *agri_land* are expected to yield a positive coefficient β_3 with *health* and a negative one with the rest of *g_ineq* variables.

The ***age dependency ratio*** *(dependency)* is anticipated to have a positive association with gender inequality, as higher dependency ratios imply that women are more likely to leave their jobs and education to care for family or community dependents (Li, S. 2020; Sharma, N. et al, 2016). Moreover, high dependency ratios can lead to strained healthcare systems potentially resulting in inadequate maternal care and to societal pressures on adolescent girls to marry and bear children early. Consequently, countries with higher dependency ratios are expected to exhibit higher levels of gender inequality. However, it is important to note the possibility of reverse causation from gender inequality

[9] *Agri_land* is also used by Eastin (2018).

measures, particularly those reflecting income and schooling, as evidence suggests that poorly educated (and poorer) girls tend to have more children (Pradhan, 2015). To address this issue *dependency* enters the regression equation with a 5-year lag. Therefore, *dependency* is expected to show a positive coefficient β_4 with *health* and a negative one with the rest of *g_ineq* variables.

The ***urbanization rate*** *(urban)* is anticipated to have a negative association with vulnerability to climate change, as countries with higher urbanization rates typically possess better infrastructure and are less exposed to the direct consequences experienced in rural landscapes (Oloke, O. and Akindele, N, 2023). Additionally, urbanization rate serves as a measure of a country's level of development, similar to GDP per capita. Consequently, *urban* is expected to demonstrate a negative coefficient β_5 with *health* and a negative one with the rest of *g_ineq* variables.

Extreme poverty rate *(poverty)*.[10] Climate change is known to disproportionately affect marginalized groups and individuals within society. Those who were already excluded find themselves particularly vulnerable to the impacts of climate change due to a combination of factors (IPCC, 2023). Living in areas with physical risks, such as marginal lands, coastal areas or dry regions exposes them to heightened vulnerabilities. Additionally, their livelihoods, like those of farmers, make them more sensitive to climate impacts. Most importantly, these groups often lack the necessary resources and decision-making power to adapt effectively. According to (Oxfam, 2022; UNDP, 2023b), poor communities are the first ones to be affected by climate change disasters and are also the ones that take the worst part of it. Women constitute a significant proportion within these communities (UNDP, 2023b). The poverty rate is associated with poorer female health outcomes, primarily because of limited financial resources and being overlooked in meeting family needs (Ralli, m. et al, 2021). Thus, *poverty* is expected to show a positive coefficient β_6 with *health.* For the remaining *g_ineq* variables, the coefficient might exhibit ambiguity since extreme poverty could impact both males and females regardless of gender.

Civil wars *(c_war)*. Civil wars can profoundly disrupt societal structures and exacerbate existing inequalities, including gender disparities (Buvinic, M. et al., 2013). The turmoil and violence associated with civil conflicts often disproportionately affect women and girls, leading to increased vulnerability and marginalization. Moreover, civil wars can have lasting socio-economic impacts, disrupting education systems, healthcare services, and economic opportunities, which can further perpetuate gender inequalities (*idem*). Thus, *c_war* is expected to show a positive coefficient β_7 with *health* and a negative one in relation to the rest of *g_ineq* variables.

[10] Extreme poverty is defined as living below the International Poverty Line, which is $2.15 per day in 2017 prices.

Landlocked *(landlock).* The most vulnerable countries to climate change are the landlocked developing countries (Loe, J., 2022; FAO, 2014). Therefore, this dummy variable is expected to show a positive coefficient with *health* and a negative one with the rest of *g_ineq* variables.

Access to water *(water).* As already mentioned, women are usually in charge of collecting natural resources for their households and communities. In particular, the task of water collection is notably one of their most challenging responsibilities, with women being predominantly responsible for water collection in two out of every three households (WHO & UNICEF, 2023). Climate change events destroy natural resources or make them scarce, forcing women and girls to walk longer distances to obtain them. This reduces women's and girls' disposable time to get formal education or work in paid employment (*idem*). Thus, *water* is expected to show a negative coefficient with *health* and a negative one with the rest of *g_ineq* variables.

Mobility gap *(mobility).* Socio-cultural norms often impose greater mobility restrictions on women compared to men, leading to adverse consequences during climate change events. Cultural norms related to gender sometimes limit the ability of women to make quick decisions on whether to move to safer grounds in disaster situations until it is too late. Similarly, a gendered socio-cultural ethos does not encourage girls to learn skills such as swimming and tree climbing that help people to survive during floods (UNDP, 2023b). Women are also at higher risk of involuntary immobility and being left behind while caring for households and children. Their limited mobility confines them to vulnerable areas, where educational opportunities or income sources are compromised by the impacts of climate change (IOM, 2023). Moreover, climate-induced migration can aggravate existing gender disparities and introduce women to heightened vulnerabilities (IOM, 2023). Consequently, *mobility* is expected to yield a positive coefficient with *health* and a negative one with the rest of *g_ineq* variables.

Female political empowerment *(politics)* is proven to reduce income inequality, as women's participation in politics often advocates for egalitarian policies (Gloor et al, 2022; Mavisakalyan and Tarverdi, 2019). Further, their unique understanding of the challenges they face in the wake of climate impacts positions them as key actors in shaping effective responses (Gloor et al, 2022). Their local, cultural, and environmental knowledge, as well as survival strategies, play a fundamental role in fostering recovery and resilience (UNDP, 2023b; UNDP, 2017). Therefore, it is expected that *politics* will exhibit a negative coefficient with *health* and a negative one with the rest of *g_ineq* variables.

4. OUTCOMES AND DISCUSSION

4.1. Core and Augmented Models

I have conducted tests on the core specification model for each gender inequality variable. The gross outputs for each model can be found in Annex II.[11] I have also tested the augmented models by incorporating additional variables into the analysis. Through their inclusion, these models aim to capture more facets of the studied nexus. Tables 2 and 3 display the findings from the core and a selection of augmented models that estimate the gendered effects of climate change across 47 African countries for c. 2010 and c. 2019, respectively. Moreover, regressions (1a), (2a), (5a) and (6a) are included to show the links between the independent variables and on existing gender inequality without the impact of climate change.

[11] Additionally, correlation matrices are included in Annex I. They have been studied for mitigating collinearity issues by avoiding the simultaneous inclusion of highly correlated variables on the right-hand side of the regression equation.

Table 3.1. Results of the core and selected augmented models (2010)

	Reproductive health index			**Average years of schooling gap**			**Enrollment rate gap**	**Labor force participation gap**
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**	**(3)**	**(4)**
Disaster frequency (10y)		5.796 [0.063]*	6.113 [0.05]**		0.00775 [0.025]**	0.0074 [0.038]**	−0.001 [0.5]	0.003 [0.487]
GDP per capita	−70.226 [0.579]	−123.3 [0.329]	−138.648 [0.269]	0.039 [0.829]	−0.035 [0.796]	−0.044 [0.753]	−0.0005 [0.996]	−0.344 [0.063]*
Agriculture (GDP)	357.762 [0.027]**	373.8 [0.018]**	379.278 [0.018]**	−0.932 [0.0002]***	−1.008 [4.43e-07]***	−0.965 [3.15e-06]***	−0.405 [0.0005]***	−0.385 [0.084]*
Dependency ratio	359.713 [0.041]**	298.02 [0.085]*	131.626 [0.496]	−0.428 [0.088]*	−0.461 [0.02]**	−0.416 [0.077]*	−0.115 [0.342]	0.346 [0.162]
Urbanization rate	−136.356 [0.29]	−105.56 [0.401]	−12.604 [0.932]	−0.229 [0.217]	−0.241 [0.084]*	−0.181 [0.292]	−0.142 [0.115]	−0.081 [0.878]
Extreme poverty rate	−54.893 [0.595]	−35.38 [0.725]	−51.671 [0.604]	0.182 [0.221]	0.153 [0.173]	0.153 [0.181]	0.053 [0.46]	0.345 [0.021]**
Civil war	77.507 [0.1]*	80.538 [0.079]*	84.326 [0.07]*	0.036 [0.59]	0.052 [0.295]	0.061 [0.235]	−0.085 [0.01]**	−0.079 [0.226]
Landlocked			−43.888			−0.038		

			[0.347]			[0.486]		
Access to water			−209.18			0.083		
			[0.112]			[0.579]		
All models use 47 observations								
Adjusted-R2	0.496	0.527	0.541	0.41	0.682	0.672	0.405	0.363
S.E. of regression	115.853	112.256	110.564	0.166	0.122	0.124	0.0798	0.162

Source: Own database. Data sources can be found in Table A.1.

*Significance levels indicated by: * p < .01, ** p< .001, *** p < .0001*

Table 3.2. Results of the core and selected augmented models (2019)

	Reproductive health index			**Average years of schooling gap**			**Enrollment rate gap**	**Labor force participation gap**
	(5a)	**(5b)**	**(5c)**	**(6a)**	**(6b)**	**(6c)**	**(7)**	**(8)**
Disaster frequency (10y)		0.159	0.641		0.0083	0.00712	−0.003	0.003
		[0.935]	[0.745]		[0.0197]**	[0.038]**	[0.178]	[0.447]
GDP per capita	−32.614	−53.334	−56.547	0.037	0.023	−0.002	−0.027	−0.346
	[0.758]	[0.513]	[0.492]	[0.812]	[0.876]	[0.989]	[0.741]	[0.019]**
Agriculture (GDP)	191.047	246.093	231.958	−0.562	−0.613	−0.583	−0.288	0.126

	[0.192]	[0.033]**	[0.053]*	[0.012]**	[0.004]***	[0.007]***	[0.015]**	[0.562]
Dependency ratio	422.318	308.016	226.17	−0.482	−0.579	−0.52	0.026	0.099
	[0.003]***	[0.007]***	[0.09]*	[0.019]**	[0.004]***	[0.027]**	[0.814]	[0.607]
Urbanization rate	−27.409	−13.23	−12.48	−0.034	−0.042	0.034	−0.08	0.013
	[0.786]	[0.866]	[0.894]	[0.819]	[0.763]	[0.835]	[0.32]	[0.926]
Extreme poverty rate	3.083	31.645	23.219	0.143	0.15	0.095	−0.008	0.334
	[0.969]	[0.606]	[0.707]	[0.231]	[0.184]	[0.389]	[0.896]	[0.004]***
Civil war	−1.837	−15.756	−6.235	0.024	0.038	0.027	−0.081	−0.066
	[0.959]	[0.581]	[0.831]	[0.648]	[0.448]	[0.575]	[0.006]***	[0.199]
Landlocked			12.219			−0.056		
			[0.709]			[0.33]		
Access to water			−115.52			0.037		
			[0.18]			[0.802]		
All models use 47 observations								
Adjusted-R2	0.408	0.655	0.656	0.361	0.429	0.48	0.325	0.516
S.E. of regression	104.495	79.774	79.605	0.154	0.146	0.139	0.325	0.138

Source: Own database. Data sources can be found in Table A.1.

*Significance levels indicated by: * p < .01, ** p< .001, *** p < .0001*

The significance of *disaster10* in accounting for *health* in 2010 in (1b) and (1c), and the lack thereof in 2019 in (5b) and (5c) may be attributed to different factors. These could include improvements in post-disaster health response mechanisms implemented between the two time periods, differences in the types or severity of disasters experienced, or shifts in socio-economic and healthcare infrastructure that influenced women's access to reproductive health services.

The significance of *disaster10* regarding *g_school* in 2010 for (2b) and (2c), and in 2019 for (6b) and (6c) yields interesting findings. Surprisingly, the relationship shows a positive sign, indicating a slight reduction in the gap, contrary to my initial assumption. Moreover, its coefficient increases between both years. This unexpected outcome could stem from omitted variables, such as "anti-gender bias" educational policies or external aid. To shed light on this paradox, further research is warranted.

There is evidence of *agri_gdp* and *c_war* intensifying *g_enroll* in models (3) and (7). The lack of significance for *disaster10* for this *g_ineq* variable means that there is no evidence of climate change exacerbating gender inequality in enrollment rates. This may suggest that the disruptions caused by natural disasters likely affected immediate education access for both boys and girls, thereby maintaining the existing gap in the short term.

There is evidence in models (4) and (8) that the level of development (*gdp_pc*) and *poverty* account for *g_labor*. *Agri_gdp* is also significant in model (4). However, after controlling for those broader socio-economic factors, there is no evidence that *disasters10* exacerbate *g_labor*. Therefore, while natural disasters may impact overall economic conditions, their direct effect on the gender gap in labor force participation may be relatively limited compared to other structural factors.

The agricultural dependence (*agri_gdp*) is particularly significant with a negative effect, as expected. Its explanatory power in 7 out of the 8 dependent variables[12] suggests an important role for *agri_gdp* in accounting for existing *g_ineq*, after controlling for climate change.

Finally, *dependency* proves to be significant in both years for *health* and *g_school*. *C_wars* exhibit significance in the *g_enroll* in both years, with a negative sign of the coefficient as expected. Conversely, *poverty* is significant for *g_labor* in both years but exhibits an unexpected positive sign. This discrepancy may be attributed to factors such as informal employment opportunities or access to social welfare programs, leading to unaccounted outcomes in labor participation rates.

To test H1, I look for the significance of *disaster10* in both 2010 and 2019 cross-country regressions, as the interest is on the explanatory power of such variable; whereas to test for H2, I compare the outcomes with 2010 and 2019 and check for an increase in the coefficient of *disaster10* (i.e., a higher intensity) in those cases where there is significance.

There is overall support for H1 and H2, although the results also indicate that the evidence for a link is not consistent across all variables. The significance of *disaster10* in certain models suggests that there is indeed a relationship between climate change and gender inequality, but this relationship

[12] Specifically, in models (1b), (1c), (2b), (2c), (3), (4), (5b), (5c), (6b), (6c) and (7). The only variable for which agricultural dependence did not prove to be significant is *g_labor_19*, in (8).

may not be uniform across all dimensions of gender inequality or across different time periods. Therefore, H1 holds valid when examining the nexus between climate change and *health*, and to some extent, *g_school*. Ultimately, H2 holds valid for *g_school*.

Regarding the augmented models, in most cases across both time periods, the additional independent variables[13] only marginally improved the standard error (S.E.) of the regression, failing to yield significant coefficients; moreover, they just marginally improved the significance of *disaster10*. Only in (1c), (2c) and (6c) *disaster10* remained significant. Interestingly, its significance and S.E. improve for (1c), while they worsen for (2c) and (6c). Lastly, *disaster10* does not show significance in (5c).

4.2. Alternatives and Robustness

The main purpose of this section is to check the robustness of *disaster10*, our preferred variable to capture the impact of climate change.

This can be done in two ways. First, by looking at any changes in the significance of its coefficient across time (2010 vs. 2019). For a result to be robust, the significance of the coefficient and its sign need to be the same in both periods. And, secondly, by looking at changes in significance when alternative climate change variables are used, in particular, *disaster5*. For a result to be robust, the significance of the coefficient of the alternative needs to be kept and its sign needs to match that of the coefficient of *disaster10*. Also, I will comment on how robust the key independent variables in both exercises are.

Independent variables are robust across time, although such robustness is not uniform across all models. *Disaster10* exhibits a consistent relationship in sign with all *g_ineq* variables, retaining statistical significance only for *g_school* in (2b), (2c), (6b) and (6c). Thus, robustness of this variable is contingent on its use accounting for *g_school*. Regarding the other independent variables, *gdp_pc* also displays consistency for *g_labor* in (4) and (8) in direction and significance, which is improved. *Agri_gdp* maintains its direction and significance, except for model (8), where it is no longer significant. However, significance worsens in (5c), (6a) and (6c) with respect to (1c), (2a) and (2c), respectively. This indicates a partial robustness of the variable. *Dependency* retains its significance for *health* and *g_school*, maintaining the same sign. *Urban* remains non-significant, with changes in sign between 2010 and 2019 models. *Poverty* remains significant for *g_labor*, with no changes in sign between years, rendering it robust for such *g_ineq* variable. *C_war* maintains consistent direction with the *g_ineq* variables, except for *health*, and retains and even improves significance for *g_enroll*.

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[13] *Drought*, *flood*, *mobility* and *politics* were also tested in the augmented model, but they did not prove to be significant.

I now explore alternative variables for the model. Specifically, I replace (i) *disaster10* with a shorter accumulation of 5 years (*disaster5*); and (ii) *disaster10* with *cc_vul*. [14] Table 4 and Table 5 display the results for 2010 and 2019, respectively:

[14] *Agri_gdp* was replaced by *agri_land*. However, it did not prove to be significant, and thus is not included in the tables.

Table 3.3. Alternative specifications (2010)

	Reproductive health index		Average years of schooling gap		Enrollment rate gap		Labor force participation gap	
	(9a)	**(9b)**	**(10a)**	**(10b)**	**(11a)**	**(11b)**	**(12a)**	**(12b)**
Disaster frequency (5y)	−1.894 [0.63]		−0.007 [0.122]		0.004 [0.194]		0.011 [0.071]*	
Climate change vulnerability		568.474 [0.213]		−0.122 [0.838]		−0.008 [0.983]		−1.137 [0.107]
GDP pc	−24.788 [0.83]	−23.328 [0.832]	0.095 [0.507]	0.016 [0.91]	−0.044 [0.619]	−0.014 [0.873]	−0.401 [0.027]**	−0.378 [0.029]**
Agriculture (GDP)	455.509 [0.002]***	341.45 [0.044]**	−1.028 [5.73e-07]***	−0.97 [7.98e-05]***	−0.407 [0.0004] ***	−0.4 [0.004]***	−0.411 [0.057]*	−0.135 [0.59]
Dependency ratio	440.065 [0.006]***	324.342 [0.066]	−0.326 [0.101]	−0.376 [0.108]	−0.151 [0.202]	−0.129 [0.348]	0.321 [0.174]	0.511 [0.056]*
Urbanization rate	−40.803 [0.749]	8.433 [0.943]	−0.368 [0.018]**	−0.203 [0.261]	−0.093 [0.318]	−0.135 [0.141]	0.02 [0.915]	−0.209 [0.237]
Extreme poverty rate	−49.907 [0.583]	−69.921 [0.441]	0.124 [0.281]	0.123 [0.307]	0.055 [0.43]	0.058 [0.424]	0.328 [0.022]**	0.31 [0.033]**
Civil war	82.277 [0.055]*	71.91 [0.08]*	0.066 [0.208]	0.06 [0.277]	−0.094 [0.005]***	−0.085 [0.012]**	−0.108 [0.099]*	−0.073 [0.238]
All models use 47 observations								
Adjusted R-squared	0.611	0.624	0.659	0.634	0.399	0.393	0.38	0.433
S.E. regression	101.84	100.116	0.126	0.131	0.08	0.081	0.159	0.152

Source: Own database. Data sources can be found in Table A.1.
*Significance levels indicated by: * p < .01, ** p< .001, *** p < .0001*

Table 3.4. Alternative specifications (2019)

	Reproductive health index		Average years of schooling gap		Enrollment rate gap		Labor force participation gap	
	(13a)	**(13b)**	**(14a)**	**(14b)**	**(15a)**	**(15b)**	**(16a)**	**(16b)**
Disaster frequency (5y)	−8.627 [0.0095]***		−0.003 [0.636]		3.91e-05 [0.991]		0.005 [0.416]	
Climate change vulnerability		940.098 [0.009]***		0.25 [0.677]		−0.362 [0.316]		−1.68 [0.003]***
GDP pc	−0.637 [0.994]	−10.939 [0.897]	0.035 [0.815]	0.031 [0.835]	−0.05 [0.579]	−0.058 [0.518]	−0.302 [0.049]**	−0.464 [0.001]***
Agriculture (GDP)	215.328 [0.067]*	64.838 [0.606]	−0.599 [0.005]***	−0.639 [0.006]***	−0.268 [0.034]**	−0.214 [0.111]	0.137 [0.551]	0.137 [0.479]
Dependency ratio	376.905 [0.001]***	161.296 [0.236]	−0.407 [0.038]**	−0.464 [0.055]**	−0.066 [0.566]	0.0179 [0.898]	0.227 [0.242]	0.431 [0.042]**
Urbanization rate	−111.662 [0.18]	1.89 [0.982]	−0.056 [0.7]	−0.023 [0.876]	−0.042 [0.628]	−0.069 [0.438]	0.083 [0.579]	−0.194 [0.141]
Extreme poverty rate	88.458 [0.199]	−3.548 [0.956]	0.103 [0.402]	0.075 [0.518]	0.002 [0.982]	0.013 [0.852]	0.355 [0.005]***	0.276 [0.009]***
Civil war	−14.07 [0.633]	−22.635 [0.435]	0.019 [0.71]	0.016 [0.745]	−0.065 [0.041]**	−0.69 [0.026]**	−0.117 [0.027]**	−0.102 [0.03]**
All models use 47 observations								
Adjusted R-squared	0.627	0.628	0.427	0.426	0.196	0.217	0.462	0.598
S.E. regression	82.917	82.833	0.146	0.146	0.089	0.088	0.146	0.126

Source: Own database. Data sources can be found in Table A.1.
*Significance levels indicated by: * p < .01, ** p< .001, *** p < .0001*

Regarding the alternatives to *disaster10*, *disaster5* and *cc_vul* are not robust, since their sign and significance do not match the ones of *disaster10*. Thus, my initial variable *disaster10* shows to be better fit for my models. Further, as already mentioned, *agri_land* does not prove to be significant in the analysis, implying that my initial variable *agri_gdp* is more accurate to measure agricultural dependency in my model.

5. CONCLUSION

The specific impact of climate change on gender inequality is undeniable. Women's heightened vulnerability to climate-related challenges, as presented throughout this study, renders them disproportionately affected compared to men. The hypotheses that guided this research presented that countries experiencing greater climate change effects would exhibit higher levels of gender inequality, and that these impacts would be greater with time. Moreover, Africa's unique susceptibility to climate change motivated the focus of this study on the continent. To explore this nexus, a multiple regression cross-country model was constructed with an OLS approach.

After testing both the core and augmented models, significant results emerged. These link the frequency of natural disasters (with a 10-year accumulation) to the average years of schooling gap, indicating a counterintuitive narrowing of the gap, and partially to the reproductive health index, showing a deterioration. Other interesting findings highlight the significance of agricultural dependency (measured as *agri_gdp*) in almost all cases. Additionally, the dependency ratio emerges as influential in explaining variations in the reproductive health index and the average years of schooling gap. Moreover, GDP per capita and extreme poverty appear significant in accounting for differences in the labor participation gap, while civil wars are notable in their significance for the school enrollment gap. Despite the apparent validity of the climate change-gender inequality nexus, my preferred climate change variable (*disaster10)* is robust only when accounting for *g_school*. The alternative climate change variables are not robust. This may well reflect that the alternatives are less suitable to capture the impact of climate change. This calls for refinement to ensure the reliability of the model and enhance its external validity. Thus, while the hypotheses hold valid, further studies are needed to deepen the understanding of these complex relationships. Furthermore, future research should develop more nuanced models for these and other time frames and dimensions of gender inequality, such as those arising from income.

Regarding the limitations of this work, the scarcity of empirical studies posed a significant challenge, forcing this one to rely heavily on just theoretical literature for its foundation. Additionally, quantifying the multifaceted issues of gender inequality and climate change presents some obstacles. Capturing these abstract concepts and addressing all potential explanatory factors are challenging tasks, as well as data quality and historical data constraints. Additionally, while the study addresses women collectively, it is vital to recognize their diverse experiences and backgrounds. Thus, future intersectional investigations are encouraged. Despite these limitations, efforts have been made to construct accurate models and conduct a comprehensive analysis of the studied nexus.

Finally, it is imperative to continue exploring the nuanced impacts of climate change through a gendered lens, as this is essential for fostering equitable, resilient, and sustainable policy frameworks. By delving deeper into the gender-specific ramifications of climate change, policymakers can develop strategies that not only mitigate adverse effects but also empower marginalized communities, particularly women, in the face of environmental challenges.

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7. ANNEX I

Table A.1. Overview of indicators and their specifications

	Indicator	Name of variable	Description	Source
Dependent variables	Reproductive health index	health	Compounded index created from the *adolescent fertility rate* and the *maternal mortality rate*	World Bank Gender Data Portal
	Average years of schooling gap	g_school	Female/male ratio in terms of the average number of years of schooling	UNDP Human Development Reports (for 2010 and 2019)
	Enrollment ratio gap	g_enroll	Female/male ratio in terms of primary school enrollment, primary (as a % of net students, which excludes overage and underage students)	World Bank Data
	Labor force participation gap	g_labor	Female/male ratio in terms of the labor force participation rate (as a % of the total labor force)	World Development Indicators database
Independent variables	Disaster frequency	disaster10	Number of climate-related natural disasters. It encompasses various types of natural disasters, such as droughts, floods, storms, landslides and wildfires. It is built as the accumulated over a 10-year period (2000 to 2010 and 2010 and 2019), due to the likely presence of lingering and cumulative effects and the fact that most measures of the dependent variables are *circa* values.	IMF Climate Change Indicators
	GDP per capita	gdp_pc	Sum of gross value added by all resident producers in the economy plus any product taxes (less subsidies) not included in the valuation of output, divided by mid-year population	World Bank Data
	Agricultural dependency	agri_gdp and agri_land	agri_gdp: % agricultural contribution to GDP over total GDP agri_land: % of agricultural land over the total land area	World Bank Data
	Age dependency	dependency	Number of dependents aged zero to 14 and over the age of 65, as a % of the total population aged 15 to 64. It uses a 5-year lag to avoid reverse causation issues with	World Bank Data

ratio		gender inequality	
Urbanization rate[15]	urban	% of people living in urban areas of the total population	World Bank Data
Extreme poverty rate	poverty	Poverty headcount ratio at $2.15 a day (2017 PPP) as a % of total population	World Bank Development Indicators Database
Civil war	c_war	Dummy variable. According to the UCDP, 1000 battle-related fatalities is the threshold for civil wars. This variable takes the value of 1 if the country has suffered a civil war in the two previous years (2009 and 2010, or 2018 and 2019). This time frame is used given the persistent and cumulative effects of these conflicts.	Uppsala Conflict Data Program (UCDP)
Climate change vulnerability	cc_vul	Vulnerability measures a country's exposure, sensitivity and ability to adapt to the negative impact of climate change. ND-GAIN measures the overall vulnerability by considering vulnerability in six life-supporting sectors – food, water, health, ecosystem service, human habitat and infrastructure. It ranges from 0 to 1 (most vulnerable).	Notre Dame Global Adaptation Initiative (ND-GAIN)
Landlocked	landlock	Dummy variable. It takes the value of 1 if the country is landlocked, and 0 if it is not.	Casa África
Mobility rate	mobility	Female/male ratio measuring constraints on freedom of movement, including whether women can independently decide where to go, travel or live. It ranges from 0% to 100% (total mobility).	World Bank – Women, Business and the Law Department
Access to water	water	% of households over total households with the availability of at least 20 liters of water per person per day from a source within 1 kilometer of walking distance	WHO/UNICEF Joint Monitoring Programme (JMP) for Water Supply, Sanitation and Hygiene (WASH)
Female political empowerment	politics	The extent to which women enjoy civil liberties, can participate in civil society, and are represented in politics. It ranges from 0 to 1 (most empowered).	V-Dem

[15] Due to the lack of available data, the urbanization rate indicator uses as a proxy the percentage of urban population.

Table A.2. Summary statistics (for 2010 variables)

Variable	Mean	Median	S.D.	Min	Max
health_10	296.	299.	163.	25.5	744.
g_school_10	0.690	0.719	0.216	0.270	1.17
g_enroll_10	0.942	0.989	0.103	0.611	1.06
g_labor_10	0.746	0.799	0.202	0.206	1.01
disaster10_10	8.40	6.50	5.65	0.00	26.0
gdp_pc_10	0.0704	0.0273	0.162	0.00804	1.10
agri_gdp_10	0.221	0.195	0.151	0.0180	0.623
depend_05	0.836	0.880	0.156	0.450	1.10
urban_10	0.419	0.400	0.176	0.110	0.860
poverty_10	0.372	0.351	0.225	0.00410	0.801
c_war_10	0.167	0.00	0.377	0.00	1.00
disaster5_10	7.31	6.00	4.70	0.00	22.0
cc_vul_10	0.524	0.527	0.0748	0.367	0.687
agri_land_10	0.452	0.452	0.214	0.0370	0.799
mobility_10	0.781	0.750	0.228	0.00	1.00
water_10	0.556	0.512	0.189	0.249	0.997
politics_10	0.672	0.720	0.173	0.210	0.890

Source: Own database. Data sources can be found in Table A.1.

Table A.3. Summary statistics (for 2019 variables)

Variable	Mean	Median	S.D.	Min	Max
health_19	226.	201.	136.	23.5	612.
g_school_19	0.760	0.804	0.193	0.352	1.17
g_enroll_19	0.969	1.00	0.0989	0.611	1.13
g_labor_19	0.750	0.798	0.199	0.235	1.01
disaster10_19	9.60	8.00	6.59	1.00	23.0
gdp_pc_19	0.0734	0.0287	0.169	0.00730	1.16
agri_gdp_19	0.196	0.184	0.137	0.0160	0.627
depend_14	0.807	0.855	0.167	0.410	1.06
urban_19	0.481	0.465	0.180	0.140	0.910
poverty_19	0.341	0.312	0.223	0.00	0.744
c_war_19	0.292	0.00	0.459	0.00	1.00
disaster5_19	5.88	4.00	4.60	0.00	16.0
cc_vul_19	0.514	0.516	0.0739	0.376	0.679

agri_land_19	0.465	0.457	0.216	0.0390	0.801
mobility_19	0.818	0.875	0.223	0.00	1.00
water_19	0.604	0.573	0.197	0.244	1.00
politics_19	0.700	0.750	0.144	0.360	0.860

Source: Own database. Data sources can be found in Table A.1.

Table A.4. Countries included in this study

Algeria	Madagascar
Angola	Malawi
Benin	Mali
Botswana	Mauritania
Burkina Faso	Mauritius
Burundi	Morocco
Cape Verde	Mozambique
Cameroon	Namibia
Central African Republic	Niger
Chad	Nigeria
Côte d'Ivoire	Republic of Congo
Democratic Republic of Congo	Rwanda
Egypt	Sao Tome and Principe
Eswatini	Senegal
Ethiopia	Sierra Leone
Gabon	Somalia
Gambia	South Africa
Ghana	Sudan
Guinea	Tanzania
Guinea-Bissau	Togo
Kenya	Tunisia
Lesotho	Uganda
Liberia	Zambia
Libya	Zimbabwe

Figure A.1. Correlation matrix for 2010 (core model variables)

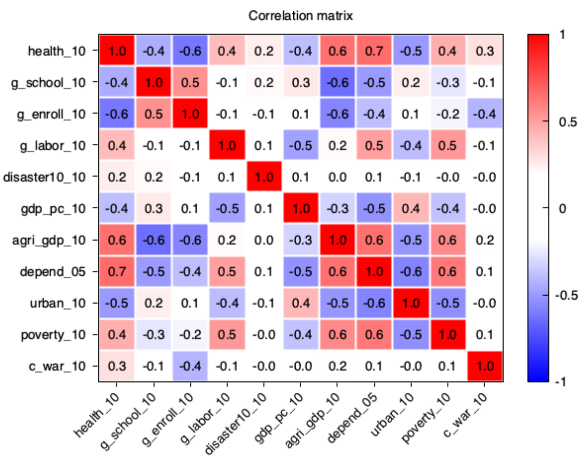


Figure 1.2. Correlation matrix for 2019 (core model variables)

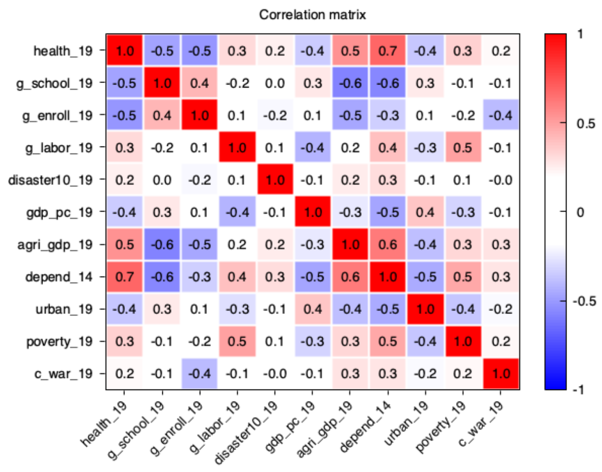


Figure A.3. Correlation matrix for 2010 (independent variables, core and augmented models)

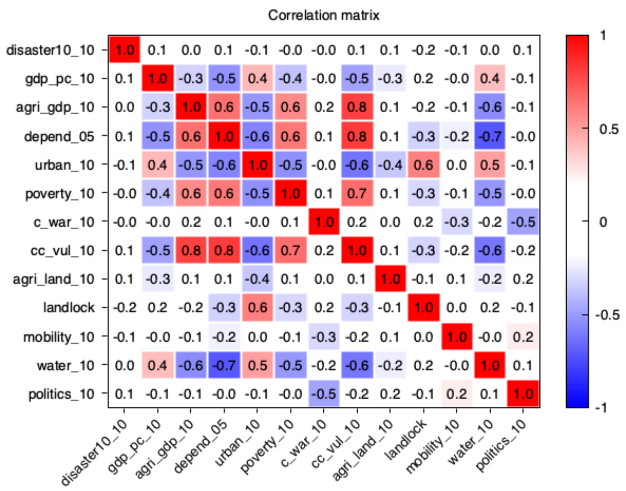
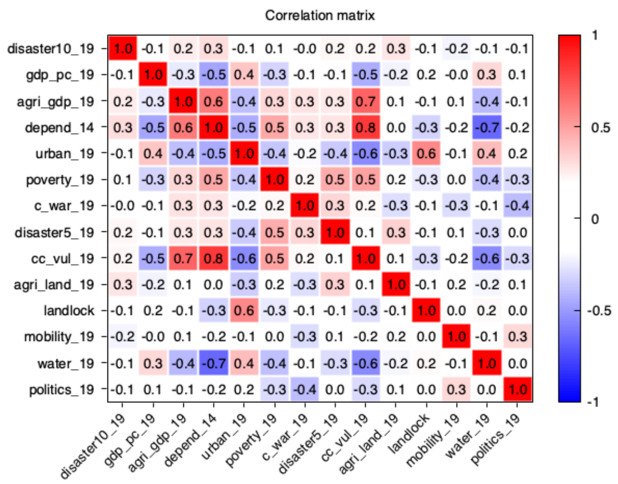


Figure A.4. Correlation matrix for 2019 (independent variables, core and augmented models)



8. ANNEX II

Core models for 2010:

Model 2: OLS, using observations 1-48
Dependent variable: g_school_10

	coefficient	std. error	t-ratio	p-value	
const	1.26775	0.165893	7.642	3.39e-09	***
disaster10_10	0.00774665	0.00332057	2.333	0.0250	**
gdp_pc_10	-0.0352673	0.135651	-0.2600	0.7963	
agri_gdp_10	-1.00831	0.165853	-6.080	4.43e-07	***
depend_05	-0.461319	0.189338	-2.436	0.0196	**
urban_10	-0.240848	0.135742	-1.774	0.0840	*
poverty_10	0.153249	0.110375	1.388	0.1731	
c_war_10	0.0518076	0.0487834	1.062	0.2949	
d_19	-0.376007	0.129441	-2.905	0.0061	***
d_27	0.550549	0.125370	4.391	8.70e-05	***

Mean dependent var	0.690382	S.D. dependent var	0.216054
Sum squared resid	0.564386	S.E. of regression	0.121870
R-squared	0.742751	Adjusted R-squared	0.681823
F(9, 38)	12.19073	P-value(F)	8.91e-09
Log-likelihood	38.52818	Akaike criterion	-57.05636
Schwarz criterion	-38.34435	Hannan-Quinn	-49.98507
rho	0.036059	Durbin-Watson	1.912728

Model 1: OLS, using observations 1-48
Dependent variable: health_10

	coefficient	std. error	t-ratio	p-value	
const	-31.5115	151.510	-0.2080	0.8363	
disaster10_10	5.79629	3.02581	1.916	0.0626	*
gdp_pc_10	-123.295	124.759	-0.9883	0.3290	
agri_gdp_10	373.801	151.299	2.471	0.0178	**
depend_05	298.018	168.639	1.767	0.0848	*
urban_10	-105.564	124.383	-0.8487	0.4011	
poverty_10	-35.3798	99.7525	-0.3547	0.7247	
c_war_10	80.5381	44.6422	1.804	0.0788	*

Mean dependent var	296.3125	S.D. dependent var	163.2244
Sum squared resid	504058.0	S.E. of regression	112.2562
R-squared	0.597457	Adjusted R-squared	0.527012
F(7, 40)	8.481183	P-value(F)	2.48e-06
Log-likelihood	-290.3309	Akaike criterion	596.6619
Schwarz criterion	611.6315	Hannan-Quinn	602.3189
rho	0.103732	Durbin-Watson	1.765237

Model 3: OLS, using observations 1–48
Dependent variable: g_enroll_10

	coefficient	std. error	t-ratio	p-value	
const	1.19395	0.107662	11.09	9.00e-14	***
disaster10_10	−0.00146392	0.00215012	−0.6809	0.4999	
gdp_pc_10	−0.000497008	0.0886532	−0.005606	0.9956	
agri_gdp_10	−0.405308	0.107512	−3.770	0.0005	***
depend_05	−0.115209	0.119834	−0.9614	0.3421	
urban_10	−0.142336	0.0883858	−1.610	0.1152	
poverty_10	0.0529152	0.0708835	0.7465	0.4597	
c_war_10	−0.0853152	0.0317225	−2.689	0.0104	**

Mean dependent var	0.941677	S.D. dependent var	0.103450
Sum squared resid	0.254521	S.E. of regression	0.079769
R-squared	0.493985	Adjusted R-squared	0.405433
F(7, 40)	5.578438	P-value(F)	0.000156
Log-likelihood	57.64074	Akaike criterion	−99.28149
Schwarz criterion	−84.31188	Hannan–Quinn	−93.62445
rho	0.129027	Durbin–Watson	1.741716

Model 4: OLS, using observations 1–48
Dependent variable: g_labor_10

	coefficient	std. error	t-ratio	p-value	
const	0.458695	0.217979	2.104	0.0417	**
disaster10_10	0.00305746	0.00435327	0.7023	0.4865	
gdp_pc_10	−0.343872	0.179493	−1.916	0.0626	*
agri_gdp_10	−0.385232	0.217676	−1.770	0.0844	*
depend_05	0.346084	0.242623	1.426	0.1615	
urban_10	−0.0805908	0.178951	−0.4503	0.6549	
poverty_10	0.345107	0.143515	2.405	0.0209	**
c_war_10	−0.0789397	0.0642273	−1.229	0.2262	

Mean dependent var	0.746103	S.D. dependent var	0.202387
Sum squared resid	1.043345	S.E. of regression	0.161504
R-squared	0.458045	Adjusted R-squared	0.363203
F(7, 40)	4.829553	P-value(F)	0.000518
Log-likelihood	23.78140	Akaike criterion	−31.56281
Schwarz criterion	−16.59320	Hannan–Quinn	−25.90577
rho	−0.269445	Durbin–Watson	2.525894

Core models for 2019:

Model 5: OLS, using observations 1–48
Dependent variable: health_19

	coefficient	std. error	t-ratio	p-value	
const	−82.2172	90.8792	−0.9047	0.3713	
disaster10_19	0.159023	1.92893	0.08244	0.9347	
gdp_pc_19	−53.3342	80.8039	−0.6600	0.5132	
agri_gdp_19	246.093	111.080	2.215	0.0328	**
depend_14	308.016	107.670	2.861	0.0068	***
urban_19	−13.2297	78.0350	−0.1695	0.8663	
poverty_19	31.6447	60.8664	0.5199	0.6061	
c_war_19	−15.7557	28.2748	−0.5572	0.5806	
d_10	297.092	85.9658	3.456	0.0014	***
d_34	372.317	85.0293	4.379	9.04e-05	***

Mean dependent var	225.9479	S.D. dependent var	135.7574
Sum squared resid	241825.1	S.E. of regression	79.77354
R-squared	0.720825	Adjusted R-squared	0.654705
F(9, 38)	10.90170	P-value(F)	3.82e-08
Log-likelihood	−272.7035	Akaike criterion	565.4070
Schwarz criterion	584.1190	Hannan–Quinn	572.4783
rho	0.367591	Durbin–Watson	1.262331

Model 7: OLS, using observations 1-48
Dependent variable: g_school_19

	coefficient	std. error	t-ratio	p-value	
const	1.22435	0.165056	7.418	4.95e-09	***
disaster10_19	0.00831094	0.00342185	2.429	0.0197	**
gdp_pc_19	0.0230158	0.147033	0.1565	0.8764	
agri_gdp_19	−0.612943	0.201746	−3.038	0.0042	***
depend_14	−0.578975	0.191197	−3.028	0.0043	***
urban_19	−0.0423930	0.139592	−0.3037	0.7629	
poverty_19	0.149749	0.110819	1.351	0.1842	
c_war_19	0.0377310	0.0492445	0.7662	0.4481	

Mean dependent var	0.760175	S.D. dependent var	0.192818
Sum squared resid	0.849422	S.E. of regression	0.145724
R-squared	0.513892	Adjusted R-squared	0.428823
F(7, 40)	6.040898	P-value(F)	0.000076
Log-likelihood	28.71656	Akaike criterion	−41.43311
Schwarz criterion	−26.46351	Hannan-Quinn	−35.77608
rho	0.109705	Durbin-Watson	1.769026

Model 8: OLS, using observations 1-48
Dependent variable: g_enroll_19

	coefficient	std. error	t-ratio	p-value	
const	1.10180	0.0921229	11.96	1.27e-14	***
disaster10_19	−0.00264711	0.00193161	−1.370	0.1784	
gdp_pc_19	−0.0273650	0.0822545	−0.3327	0.7412	
agri_gdp_19	−0.287923	0.113007	−2.548	0.0149	**
depend_14	0.0259360	0.109545	0.2368	0.8141	
urban_19	−0.0796464	0.0790354	−1.008	0.3198	
poverty_19	−0.00811544	0.0618370	−0.1312	0.8963	
c_war_19	−0.0805285	0.0278394	−2.893	0.0062	***
d_10	−0.243837	0.0874633	−2.788	0.0082	***

Mean dependent var	0.969293	S.D. dependent var	0.098883
Sum squared resid	0.257245	S.E. of regression	0.081216
R-squared	0.440238	Adjusted R-squared	0.325416
F(8, 39)	3.834065	P-value(F)	0.002079
Log-likelihood	57.38522	Akaike criterion	−96.77045
Schwarz criterion	−79.92964	Hannan-Quinn	−90.40628
rho	0.105291	Durbin-Watson	1.783936

Model 10: OLS, using observations 1-48
Dependent variable: g_labor_19

	coefficient	std. error	t-ratio	p-value	
const	0.570951	0.167052	3.418	0.0015	***
disaster10_19	0.00258431	0.00336434	0.7681	0.4473	
gdp_pc_19	−0.346166	0.141615	−2.444	0.0194	**
agri_gdp_19	0.126198	0.215481	0.5857	0.5617	
depend_14	0.0993288	0.191293	0.5192	0.6067	
urban_19	0.0129494	0.138074	0.09379	0.9258	
poverty_19	0.334062	0.110087	3.035	0.0044	***
c_war_19	−0.0658411	0.0503005	−1.309	0.1986	
d_13	−0.365572	0.156091	−2.342	0.0247	**
d_28	−0.360772	0.142970	−2.523	0.0160	**
d_40	−0.515816	0.172111	−2.997	0.0048	***

Mean dependent var	0.750179	S.D. dependent var	0.198849
Sum squared resid	0.708258	S.E. of regression	0.138355
R-squared	0.618892	Adjusted R-squared	0.515890
F(10, 37)	6.008531	P-value(F)	0.000024
Log-likelihood	33.07851	Akaike criterion	−44.15701
Schwarz criterion	−23.57380	Hannan-Quinn	−36.37859
rho	−0.041059	Durbin-Watson	2.069012

Selected augmented models:

Model 11: OLS, using observations 1–48
Dependent variable: health_10

	coefficient	std. error	t-ratio	p-value	
const	217.781	210.381	1.035	0.3071	
disaster10_10	6.11332	3.01696	2.026	0.0498	**
gdp_pc_10	−138.648	123.512	−1.123	0.2687	
agri_gdp_10	379.278	153.171	2.476	0.0178	**
depend_05	131.626	191.601	0.6870	0.4963	
urban_10	−12.6041	146.147	−0.08624	0.9317	
poverty_10	−51.6709	98.7315	−0.5233	0.6038	
c_war_10	84.3255	45.1661	1.867	0.0696	*
landlock	−43.8875	46.0475	−0.9531	0.3466	
water_10	−209.180	128.599	−1.627	0.1121	

Mean dependent var	296.3125	S.D. dependent var	163.2244
Sum squared resid	464525.0	S.E. of regression	110.5637
R-squared	0.629028	Adjusted R-squared	0.541167
F(9, 38)	7.159297	P-value(F)	5.46e-06
Log-likelihood	−288.3707	Akaike criterion	596.7414
Schwarz criterion	615.4535	Hannan–Quinn	603.8127
rho	0.142509	Durbin–Watson	1.707414

Model 13: OLS, using observations 1–48
Dependent variable: g_school_10

	coefficient	std. error	t-ratio	p-value	
const	1.17816	0.245215	4.805	2.73e-05	***
disaster10_10	0.00735048	0.00340194	2.161	0.0375	**
gdp_pc_10	−0.0440258	0.138660	−0.3175	0.7527	
agri_gdp_10	−0.965036	0.175174	−5.509	3.15e-06	***
depend_05	−0.416196	0.228233	−1.824	0.0765	*
urban_10	−0.180979	0.169182	−1.070	0.2919	
poverty_10	0.152977	0.112131	1.364	0.1810	
c_war_10	0.0613783	0.0508442	1.207	0.2352	
landlock	−0.0382216	0.0542900	−0.7040	0.4859	
water_10	0.0838221	0.149489	0.5607	0.5785	
d_19	−0.365049	0.136663	−2.671	0.0113	**
d_27	0.510610	0.134147	3.806	0.0005	***

Mean dependent var	0.690382	S.D. dependent var	0.216054
Sum squared resid	0.550638	S.E. of regression	0.123675
R-squared	0.749017	Adjusted R-squared	0.672328
F(11, 36)	9.766904	P-value(F)	7.38e-08
Log-likelihood	39.12003	Akaike criterion	−54.24005
Schwarz criterion	−31.78564	Hannan–Quinn	−45.75450
rho	0.014603	Durbin–Watson	1.956443

Model 15: OLS, using observations 1-48
Dependent variable: health_19

	coefficient	std. error	t-ratio	p-value	
const	43.4510	134.348	0.3234	0.7482	
disaster10_19	0.641253	1.95443	0.3281	0.7447	
gdp_pc_19	−56.5470	81.4955	−0.6939	0.4922	
agri_gdp_19	231.958	115.733	2.004	0.0526	*
depend_14	226.170	129.774	1.743	0.0899	*
urban_19	−12.4795	93.2388	−0.1338	0.8943	
poverty_19	23.2192	61.2818	0.3789	0.7070	
c_war_19	−6.23515	29.0815	−0.2144	0.8314	
landlock	12.2190	32.4970	0.3760	0.7091	
water_19	−115.520	84.5247	−1.367	0.1802	
d_10	309.933	86.3674	3.589	0.0010	***
d_34	350.837	86.1910	4.070	0.0002	***

Mean dependent var	225.9479	S.D. dependent var	135.7574
Sum squared resid	228131.4	S.E. of regression	79.60516
R-squared	0.736634	Adjusted R-squared	0.656161
F(11, 36)	9.153795	P-value(F)	1.64e-07
Log-likelihood	−271.3045	Akaike criterion	566.6089
Schwarz criterion	589.0634	Hannan-Quinn	575.0945
rho	0.371856	Durbin-Watson	1.255516

Model 17: OLS, using observations 1-48
Dependent variable: g_school_19

	coefficient	std. error	t-ratio	p-value	
const	1.19225	0.234681	5.080	1.10e-05	***
disaster10_19	0.00711509	0.00331340	2.147	0.0384	**
gdp_pc_19	−0.00202047	0.141940	−0.01423	0.9887	
agri_gdp_19	−0.582947	0.202491	−2.879	0.0066	***
depend_14	−0.519772	0.226027	−2.300	0.0272	**
urban_19	0.0341096	0.162385	0.2101	0.8348	
poverty_19	0.0949585	0.108866	0.8722	0.3887	
c_war_19	0.0273820	0.0483951	0.5658	0.5749	
landlock	−0.0563526	0.0570541	−0.9877	0.3297	
water_19	0.0369163	0.146042	0.2528	0.8018	
d_38	−0.330603	0.148096	−2.232	0.0317	**

Mean dependent var	0.760175	S.D. dependent var	0.192818
Sum squared resid	0.715912	S.E. of regression	0.139101
R-squared	0.590297	Adjusted R-squared	0.479567
F(10, 37)	5.330942	P-value(F)	0.000077
Log-likelihood	32.82053	Akaike criterion	−43.64106
Schwarz criterion	−23.05785	Hannan-Quinn	−35.86263
rho	0.172375	Durbin-Watson	1.649649