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Impact of Natural Disasters on Household Health and Education Expenditure: Evidence from El Niño Phenomenon in Peru

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Abstract

This study examines the impact of the 2017 El Niño phenomenon on per capita expenditures on health and education among rural households in the northern coastal region of Peru. We use household-level panel data from 2015 to 2019, along with district-level precipitation data. A difference-in-differences (DiD) model is proposed to compare households affected by the phenomenon with those that were not affected. The results show that the 2017 El Niño phenomenon had a negative effect on per capita expenditures on health and education for the affected rural households, possibly driven by a negative shock to agricultural income. Consequently, the findings suggest that individuals in affected households have reduced access to the benefits of acquiring health and education services, increasing their vulnerability to health risks and cognitive skill development challenges.

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1. Introduction

In recent years, extreme weather events have become increasingly frequent, raising concerns about their negative consequences for a nation's development (Guha-Sapir et al., 2013). In 2017, Peru experienced the devastating effects of the El Niño phenomenon, which affected over 2 million individuals and resulted in estimated losses exceeding 3.1 billion dollars, equivalent to 1.6 % of the Gross Domestic Product (Macroconsult, 2017). Given their high frequency of occurrence, it is crucial to quantify their impact on household expenditures.

The El Niño phenomenon is an extreme weather event that triggers natural disasters such as floods and landslides (Smith and Ubilava, 2017), primarily affecting the crops of rural households (Trinh et al., 2021). This impact is interpreted as a *shock* to the income of rural households, specifically to agricultural income, which is defined as *"the value generated by agricultural production activities"* (MAPA, 2021). In this context, it influences households' payment capacity, altering expenditure behavior on essential aspects such as health and education (Karim, 2018). Based on this, the research question is as follows: *What is the impact of the El Niño phenomenon on per capita expenditures on health and education among rural households?*

Economic theory posits that household vulnerability is a critical factor in measuring the intensity of impact (Cutter, 1996). Therefore, it is essential to consider households' response capacity, with a particular emphasis on consumption behavior (Wisner, 2004). Specifically, out-of-pocket expenditure is significant for households due to its connection with the poverty trap and its role as a complement to public spending (Guerrero-Ojeda, 2020).

On the other hand, empirical literature has shown that the impact of natural disasters on per capita expenditures on health and education among rural households does not have a clear direction. Evidence indicates a reduction in per capita expenditures on health and education (Anttila-Hughes and Hsiang, 2013), with floods and droughts having the most significant negative impact on rural households (Arouri et al., 2015). However, there is also evidence of an increase on per capita expenditures on both education (Garbero and Muttarak, 2013) and health (Lohmann and Lechtenfeld, 2015).

In order to solve the question posed, the proposed methodology is a difference-in-differences (DiD) model. The intervention is the El Niño phenomenon of 2017, being the treatment group the rural households that were affected by this phenomenon. Regarding the data, the National Household Survey (ENAHO) panel from the 2015-2019 period is used to identify per capita expenditures on health and education at the individual level, which is consolidated at the household level and exclusively selected for rural households. As well, a dataset on precipitation levels by district is constructed based on meteorological information provided by *the Power Project NASA*. Additionally, the inclusion of the control variables is important to account for household vulnerability (Cutter et al., 2003).

The research hypothesis suggests that the impact of the El Niño phenomenon has a negative relationship with per capita expenditure of rural households in Peru, as there is existing evidence of a reduction in household consumption (expenditure) in Peru in response to a natural disaster (Zegarra and Alarcón, 2014). Specifically, it is expected that households will reduce their expenditures on health and education, given that the percentage change in average monthly real per capita expenditure[1] for the period 2016-2017 was -3.4 % for education and -1 % for health, respectively (INEI, 2018).

In that sense, this study is expected to contribute to the literature by linking the El Niño phenomenon with per capita expenditures on health and education among households. Specifically, it focuses on the short-term consequences of natural disasters, which has not been evaluated for Peru. Furthermore, the research is valuable because it focuses on rural households, which have characteristics distinct from urban households. While there is extensive literature on the impact of natural disasters on rural households, this issue has not yet been addressed in the context of Peru. Additionally, the study focuses on households in the northern coastal region of Peru, a delimitation not covered in other studies.

The rest of the document is organized as follows: Section 2 presents the literature review. Section 3 outlines the conceptual framework. Section 5 details the datasets used, and Section 4 describes the methodology. Section 6 presents the results. Finally, Section 7 presents the conclusions.

2. Literature Review

The literature raises serious concerns about the impact of negative shocks on households financial stability as financial crisis (Thomas et al., 2004), macroeconomic disturbances (Duryea et al., 2007) and health shocks (He and Zhou, 2022) affects its consumption behavior. Household consumption is also affected by natural disasters (Bui et al., 2014), leading to an increase in poverty (Lopez-Calva and Juarez, 2009) and shifts in household vulnerability (Willroth et al., 2011).

Moreover, numerous studies investigate how natural disasters disrupt household expenditure. First, Karim (2018) examines the short-term economic impacts of recurrent floods on households in Bangladesh, focusing on income, expenditure, and assets. The results revealed a decrease in agricultural income and a negative response in household expenditure on crops and agricultural inputs. On the other hand, Wahdat and Gunderson (2021) assess the relationship between income lost due to a natural disaster and the subsequent consumption expenditure of agricultural households in Indiana, identifying a negative association between income variation and food expenditure. It is worth noting that in the studies mentioned, the effect on expenditure for health and education was found to be non-significant.

However, various studies report a significant relationship between the impact of natural disasters and expenditure on health and education. For example, Mottaleb et al. (2013) analyze the impact of Tropical Cyclone *Aila* on the income and expenditure of agricultural households in Bangladesh. The estimation showed that affected households had higher expenditure on health-related items and reduced spending on their children's school enrollment fees. On average, a household in the district affected by the cyclone spent 1,410 BDT [2] less on education and 1,290 BDT more on health. Similarly, Anttila-Hughes and Hsiang (2013) explore the effect of typhoons

[1] In constant soles (base = 2017).

[2] Bangladesh currency (Bangladeshi Taka).

on household expenditure in the Philippines. In summary, it was found that households tend to reduce spending more on items resembling investments in human capital, such as medicines (-14.3 percentage points) and education (-13.3 percentage points). In contrast, expenditure on pure consumption goods, such as recreation, alcohol, and tobacco, decreased much less.

Regarding multiple shocks, Nguyen et al. (2020) assess the impact of floods and droughts on the consumption response of rural households in Cambodia. The results revealed a positive relationship between expenditure on education and flooding, while the effect of droughts was not significant. Likewise, the findings indicate a negative relationship between food expenditure and flooding.. In the same vein, Garbero and Muttarak (2013) investigate the impacts of droughts and floods on the consumption behavior of rural households in Thailand. A positive relationship was found between expenditure on education and both floods and droughts, with the particularity that expenditure on education increased as the average education level in the villages rose.

The literature also indicates that depending on the type of natural disaster, the impact on expenditure can vary. For example, Arouri et al. (2015) examine the effect of storms, floods, and droughts on the expenditure of rural households in Vietnam. The results showed that per capita expenditure in affected households decreased by approximately 2 to 5 percentage points due to storms, floods, and droughts. Specifically, it was found that floods and droughts had a more significant negative impact compared to storms. However, according to Lohmann and Lechtenfeld (2015), the short-term impact of a drought had a positive effect on health expenditure in rural households in Vietnam. Specifically, it was found that the drought imposed a financial burden on households, resulting in an increase on health expenditure by 9 to 17 percentage points of total consumption.

In Latin America, Skoufias et al. (2011) study the impact of climate *shocks* on the expenditure of rural households in Mexico, focusing on non-essential items and food expenditure. Based on the results, it was found that following a positive *shock* in the annual precipitation level, food expenditure increases, while expenditure on non-essential items, such as education, decreases. On the other hand, in Peru, the literature on natural disasters and their relationship with household expenditure is limited. However, there is a research paper by Zegarra and Alarcón (2014), which focuses on measuring the economic cost to Peruvian households arising from the loss of assets or income due to a natural disaster. The estimation showed that affected households lost, on average, 14.4 percentage points of their consumption expenditure compared to households that were not affected.

Regarding the El Niño phenomenon in particular, Corcuera García (2017) and Rosales-Rueda (2018) explore the impacts of this extreme natural event on health and education; however, their focus is from a human capital perspective. This is because they concentrate on the impact when the individual is in the womb, in other words, they assess the long-term effects. In contrast, this research aims to contribute to the literature by providing empirical evidence on the short-term impact of the El Niño phenomenon on per capita expenditures on health and education in rural households in Peru, thus addressing the gap that exists in the literature.

3. Conceptual Framework

The relationship between natural disasters and the economic characteristics of households is explained through the *Hazards of place model of vulnerability* developed by Cutter (1996), which links the geographical context and the communitys response capacity to a natural disaster. In summary, the model concludes that biophysical and social vulnerabilities are the primary determinants of a place's overall vulnerability, stemming from conditions such as household poverty (Cutter et al., 2003).

In this context, the intensity of the impact of natural disasters on society depends on a range of factors. As illustrated in Figure 4 of Annex A.1, demographic and economic characteristics are crucial in determining disaster risk, with floods and household consumption being among the key factors (Wisner, 2004). According to Wisner (2004), the risk of a natural disaster is determined by the following equation:

$$R = f(D, E, V) \tag{1}$$

Where R refers to the risk of a natural disaster, determined by the predetermined geophysical and climatic characteristics (D), the household's/individual's exposure to the natural disaster (E), and vulnerability (V), which pertains to the capacities of the exposed population to withstand socio-economic impacts. Ultimately, households living in poverty or situated in unsafe locations face a higher risk of experiencing the effects of natural disasters, leading to a more significant impact on their socio-economic indicators and altering their consumption behavior (Karim, 2018).

Concerning household consumption (expenditure) decisions, from a theoretical perspective, the occurrence of a natural disaster represents a potential negative *shock* to household income and assets (Strömberg, 2007). In this context, the negative impact on income leads to a reduction in the household's available resources, which is reflected in a contraction of the budget constraint [3]. This constraint refers to the set of goods that the household can afford (Jappelli and Pistaferri, 2010). This is illustrated in Figure 5 of Annex A.1, where a decrease in income results in an adjustment to household expenditure, signifying a shift in utility, as indicated by Equation 2 (Jappelli and Pistaferri, 2010).

$$\triangle U = U_1 - U_0 \tag{2}$$

Where $\triangle U$ represents the change in utility, determined by the difference between the post-disaster utility level (U_1) and the pre-disaster utility level (U_0). While a rational individual would allocate their post-disaster income to cover basic needs and maximize utility (Grampp, 1948), individual behavior does not always align with rational theory, leaving the final effect uncertain. Therefore, the literature has faced the challenge of quantifying the impact of natural disasters on households. Based on the models most commonly used in specialized literature, Cavallo and Noy (2009) present a short-term effects model that links the impact of natural disasters to an economic variable of interest at the household level.

[3] It is assumed that relative prices remain unchanged.

$$y_{it} = \alpha + \gamma DIS_{it} + \beta z_{it} + \epsilon \tag{3}$$

Where y represents the household's economic variable of interest, and DIS is a measure of the natural disaster impact in country i at time t. Typically, this measure is formulated as a binary indicator of the occurrence of the disaster, using criteria such as wind speed or precipitation levels. Additionally, a vector of control variables (z) is included.

In addition, it is important to highlight that rural households possess different characteristics compared to urban households. According to Gardner (2005), agriculture is the primary driver of economic development in rural households, as investment in crops yields a positive return in income. In fact, 81.7 % of individuals living in rural areas rely on agricultural income for survival (Urrutia and Trivelli, 2019). From this perspective, natural disasters present a significant problem for rural households, as they often destroy crops and affect livestock (Trinh et al., 2021). In the same vein, accordingly to Gutiérrez et al. (2019), a key transmission mechanism in the relation between heavy rains and farmers is the reduction of income that farmers suffer.

Table 1 shows the crop composition measured by Production Value for 2023 (January-May), illustrating the agricultural dependence of the northern coastal regions. Specifically, La Libertad and Lambayeque exceed the 50 % threshold in terms of basic crops such as rice, blueberries, potatoes, and grapes. Aside from Lima Provinces, rice emerges as a principal crop of productive value, which could be affected by a natural disaster (Gutiérrez et al., 2019).

Table 1
Descriptive Statistics - Crop Composition 2023 (%)

	Rice	Blueberry	Potato	Grape	Total
Tumbes	20.7	0.01	0.01	0.01	20.7
Piura	15.6	1.2	0.6	17.9	35.3
La Libertad	23.1	14.6	13.4	3.0	54.1
Lambayeque	37.3	13.3	0.1	2.9	53.6
Ancash	15.8	9.7	16.3	1.2	43.0
Lima Provinces	0.01	2.4	3.8	13.3	19.5

Note: Crop composition measured by Production Value.
Source: *MIDAGRI*

Moreover, out-of-pocket expenditure[4] is an important factor for rural households in their goal of avoiding falling into the poverty trap. According to Guerrero-Ojeda (2020), out-of-pocket health expenditure is often high in these households, which increases the likelihood of impoverishment. However, it is emphasized that out-of-pocket expenditure on health and other sectors such as education is relevant to cover the limitations of insurance and monetary transfers from the public sector (Guerrero-Ojeda, 2020).

[4]Direct payment made by individuals who use the service and are not financed by the state.

Overall, the impact of the El Niño phenomenon is interpreted as a *shock* to agricultural income, which affects household spending behavior. Based on this, the research hypothesis suggests that the impact of the El Niño phenomenon should reduce per capita expenditures on health and education in rural households. We focus on these two factors due to their relevance in promoting comprehensive development, preventing diseases, and contributing to economic growth.

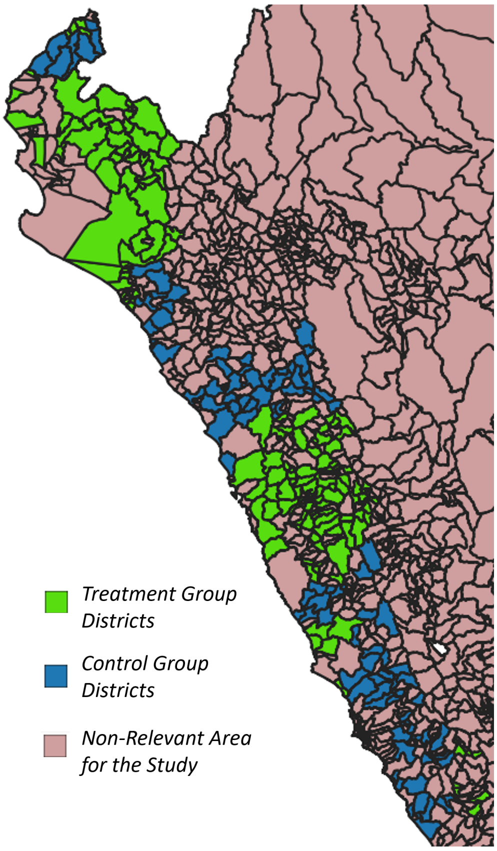
4. Methodology

Given that the objective of this research is to quantify the impact of the El Niño phenomenon on per capita household expenditures on health and education in rural areas, the difference-in-differences (DiD) model is the most appropriate. This approach measures the effect of an intervention on a treatment group relative to a comparison group that does not experience the intervention, across time (Bertrand et al., 2004). This model is particularly suitable for assessing the impact of a natural disaster, as such events create two distinct periods (pre-disaster and post-disaster), allowing for the analysis of changes over time (Roth et al., 2023).

In this research, the El Niño phenomenon serves as the intervention, which occurred in 2017. Regarding the treatment and control groups, these consist of rural households affected and unaffected by the El Niño phenomenon, respectively. To assess the impact on households, the level of precipitation in the district to which they belong was considered. Specifically, a household is classified as affected if the average precipitation during the months of January to May 2017 exceeds one standard deviation above the precipitation recorded during the same months in the period 2012–2016. This criterion is supported by Randell and Gray (2016), who also use the standard deviation as a threshold.

One of the major challenges of the research is selecting an appropriate control group to ensure the robustness of the results obtained. To address this, the geographical area under evaluation has been limited, as natural disasters tend to have greater intensity in specific regions (Botzen et al., 2019). In other words, the El Niño phenomenon does not affect all departments of Peru with the same intensity. Consequently, information was collected from rural households located exclusively in the northern coastal region, specifically from five departments: Tumbes, Piura, La Libertad, Lambayeque, and Ancash. Additionally, rural households from Lima Provinces, which share similar characteristics with the previously mentioned departments, were included in the sample. The treated and control districts are depicted in Figure 1.

Figure 1. Treated and Control Districts in the Northern Coastal Region of Peru



Source: *The Power Project Nasa*

Therefore, a difference-in-differences (DiD) model is employed, which is based on the specification of Cavallo and Noy (2009):

$$ln(y)_{hdt} = \beta_0 + \beta_1 Trat_d \times Post_t + \beta_2 z_{hdt} + \lambda_d + \mu_t + \epsilon_{hdt} \tag{4}$$

Where y represents our variable of interest, which denotes the per capita household expenditure on education or health for household h in district d in year t. Moreover, $Trat_d$ is a binary variable that takes the value of 1 if the household has been affected by the El Niño phenomenon, and $Post_t$ is a binary variable that takes the value of 1 if the year is subsequent to or coincides with the El Niño event. Additionally, z is a vector of control variables, fixed effects at the district (λ) and year (μ) levels are included, and ϵ is the error term. Based on Section 3, β_1 is expected to have a negative sign in Equation 4.

In relation to the vector of control variables, relevant factors that could affect the estimation are included. First, the education level of the household head, measured in years, is incorporated, as higher education leads to more prudent decision-making regarding expenditures (Garbero and Muttarak, 2013). On the other hand, housing characteristics, specifically the construction materials, are relevant because households built with better materials have lower exposure and are less vulnerable to natural disasters (Karim, 2018). Accordingly, the construction materials of the floor, walls, and roof of the household are included. Complementarily, the variable *subsidies*, referring to whether the household has participated in a social assistance program, is added (Skoufias et al., 2011). This approach addresses potential bias from omitted variables.

Furthermore, a limitation of the research is migration, which refers to the displacement of families to a new place of residence (Skoufias et al., 2011). This presents a challenge for the study as it would hinder the accurate identification of the impact on affected households. To address this issue, it was validated that households in the sample maintained a stable geographic location code (*ubigeo*) throughout the five years (2015–2019).

Additionally, to reduce the effect of potentially spurious outliers, the *winsorization* technique was applied. This method replaces the smallest and largest observations with values closest to them. To limit the influence of outliers on per capita health and education expenditures, the top 5 % of the data were replaced with the 95th percentile, and the bottom 5 % were replaced with the 5th percentile.

In this research, the application of this process was crucial due to the identification of several households with atypical per capita expenditures. For instance, in the case of health, there were observations reporting zero per capita health expenditure, as well as cases where it exceeded 982 soles, which is deemed excessive (Ginocchio, 2017). Regarding education, there were observations reporting zero per capita education expenditure, as well as cases where it exceeded 536 soles. Following the application of the technique, Figure 7 and 8 of Annex A.3 presents the distributions of per capita health expenditure and per capita education expenditure after outlier replacement, with the maximum values set at 982 soles for health and 536 soles for education.

5. Data

5.1 Precipitation Data

In this research, precipitation data is obtained from *The Power Project Nasa*. This portal provides satellite datasets on a global scale regarding climate, aimed at supporting renewable energy and agricultural needs. These data are supported by *NASA's Earth Science Division Applied Sciences Program* and cover various variables, such as solar radiation, precipitation levels, wind speed, temperature, humidity, among others.

It is worth highlighting that the average daily values from the meteorological database are presented in a time-series format. It has been shown that these satellite and model-based products are accurate enough to provide reliable data on meteorological resources in regions where surface measurements are limited or non-existent. These products offer two unique features: the data is global and is typically maintained continuously over time (Okamoto et al., 2008).

In particular, the model uses data on average monthly precipitation measured in 50km by 50km quadrants. To obtain precipitation data at the district level, a geolocation map was employed that links the geographic coordinates of each district. This allows for the precise assignment of precipitation data to each corresponding geographic location, providing more detailed and accurate information for the analysis. Given this, the merging of databases occurs at the district level. This process enables the identification of the affected districts and, consequently, the households impacted by the El Niño phenomenon.

Table 2 presents the precipitation level by year and region. Over the years, the average precipitation has exhibited an upward trend, with the exception of 2016, where a slight decline was recorded. It shows that the highest level of precipitation was recorded in 2017, coinciding with the onset of the El Niño phenomenon. Meanwhile, regional statistics reveal that Tumbes registers the highest average precipitation, whereas the provinces of Lima exhibit the lowest average precipitation.

Table 2

Descriptive Statistics - Precipitation Level

	Mean	Minimum	Maximum	St. Dev.
By Year				
2012	20.1	0.0	184.6	29.7
2013	21.7	0.0	168.8	29.2
2014	27.6	0.0	242.6	36.8
2015	43.5	0.0	432.4	49.8
2016	42.1	0.0	342.8	57.9
2017	69.1	0.0	532.6	81.2
By Region				
Tumbes	76.9	0.0	532.6	90.4
Piura	40.6	0.0	458.8	59.6
La Libertad	32.9	0.0	152.9	30.3
Lambayeque	16.9	0.0	242.6	34.3
Ancash	59.0	0.0	342.8	59.4
Lima Provinces	5.6	0.0	121.3	14.5
Observations	250	250	250	250

Note: Precipitation measured in millimeters (mm).
Source: *The Power Project Nasa*

Additionally, Figure 6 of Annex A.2 shows the average precipitation level for 2017 (January-May) in the provinces of the northern coastal region that have at least one district relevant to our research. The highest precipitation is observed in the eastern part of Áncash, followed by the department of Tumbes.

5.2 Household's Data

Another source utilized is data from the National Household Survey of Peru (ENAHO), provided by the National Institute of Statistics and Informatics (INEI). Specifically, the ENAHO panel dataset for 2015–2019 is employed, which includes data from the same households over the specified years. The purpose of ENAHO is to provide information for monitoring indicators related to living conditions. In this sense, its primary objective is to generate indicators that enable an understanding of the evolution of poverty and the living conditions of households (INEI, 2020).

The data include information related to health, education, income, and expenditures at both the household and individual levels. For this research, the unit of analysis is rural households, with a household being classified as rural if it belongs to an area with 1,999 or fewer inhabitants (Castillo, 2019). From this survey, it's possible to calculate the per capita expenditures on health and education for each evaluated household. This variable is constructed by dividing the household's expenditures on health or education by the number of household members.

Specifically, educational expenditure encompasses costs such as school uniform, school footwear, books, school supplies, enrollment, parents' association, tuiton, transportation, among others. It's relevant to highlight that educational expenditure also includes the purchase of technological devices such as televisions and computers, as Marshall (2002) states that these technologies expand the user's knowledge by providing access to new information, which empowers them to make better decisions. Meanwhile, health expenditure includes costs related to medical consultations, medicines, medical analysis, medical services, vaccines, contraceptives, glasses, hospitalization, surgical intervention and other similar expenses.

Additionally, the survey enables the extraction of control variables, such as the educational level of the household head or specific characteristics of the dwelling. Likewise, an advantage of this survey is that it provides the geographic location code (*ubigeo*) of the household for each year, which is crucial for identifying whether the household has relocated to another district.

Table 3 presents the characteristics of households in 2016 and 2017, corresponding to the year prior to the treatment and the intervention year. In 2016, the average annual per capita expenditures on health and education is slightly lower for the treatment group, consistent with their slightly lower annual per capita income. In contrast, in year 2017, the treatment group shows a greater reduction in average annual per capita expenditures on health and education compared to the control group. On the other hand, access to basic services is similar for both groups.

Table 3

Descriptive Statistics - Household Characteristics

	Type	2016				2017			
		Unaffected households (D=0)		Affected households (D=1)		Unaffected households (D=0)		Affected households (D=1)	
		Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Male Head (%)	Binary	81.6	0.4	81.1	0.4	78.3	0.4	81.1	0.4
Head's Age	Discrete	53.1	16.7	52.7	16.1	54.4	16.9	53.7	15.8
Head's level of Education	Ordinal	4.3	1.8	3.9	1.8	4.3	1.8	3.9	1.9
N° of household members	Discrete	3.5	1.9	4.0	2.2	3.5	1.9	3.8	2.1
N° of household income earners	Discrete	2.0	0.9	2.2	1.1	2.0	1.0	2.2	1.1
Household income	Continuous	8.5	0.8	8.3	0.7	8.5	0.8	8.3	0.7
Household expenditure	Continuous	8.0	0.8	7.7	0.8	7.9	0.9	7.7	0.8
Household food expenditure	Continuous	7.7	0.7	7.6	0.6	7.7	0.6	7.7	0.6
Household education expenditure	Continuous	3.8	2.0	3.6	2.0	3.8	1.9	3.4	2.1
Household health expenditure	Continuous	3.7	2.0	3.5	1.8	3.8	1.8	3.4	1.9
Household with sewage (%)	Binary	36.7	0.5	39.4	0.5	42.1	0.5	38.6	0.5
Household with electricity (%)	Binary	89.4	0.3	87.8	0.3	90.0	0.3	89.0	0.3
Household with internet (%)	Binary	4.6	0.2	1.7	0.1	5.7	0.2	3.2	0.2
Subsidies (Extra Income)	Continuous	2.8	2.0	2.5	1.9	3.0	2.2	2.6	1.9
Observations		1,043	1,043	1,585	1,585	1,069	1,069	1,549	1,549

Notes: 1. Income and Expenditure expressed in logarithm at the annual per capita level. 2. Head´s level of education expressed in categories: 1: None, 2-4: Primary, 5-6: Secondary, 7-10: University/Institute, 11: Postgraduate.

Source: (INEI, 2020)

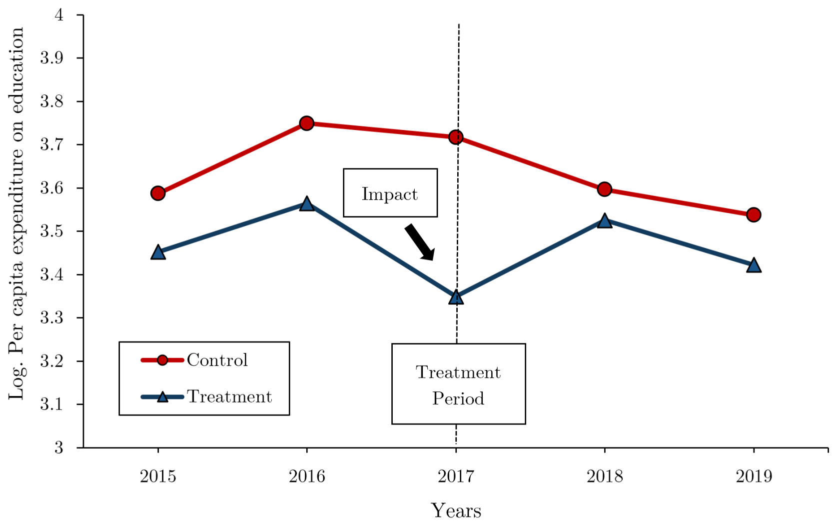
6. Results

6.1 Parallel trends assumption

In the difference-in-differences (DiD) model, the parallel trends assumption is a necessary condition. This assumption stipulates that, in the absence of the treatment, the treatment and control groups should evolve similarly over time (Barkowski, 2021). However, with the implementation of the treatment, a change in the trends of the groups is expected.

Figure 2 illustrates the trends of the logarithm of per capita expenditure on education for the control and treatment groups over the evaluated period. During 2015 and 2016, which represent the pre-treatment period, a similar rising trend is observed in both the control and treatment groups. However, following the intervention in 2017, a significant shift in the trend is evident for the treatment group.

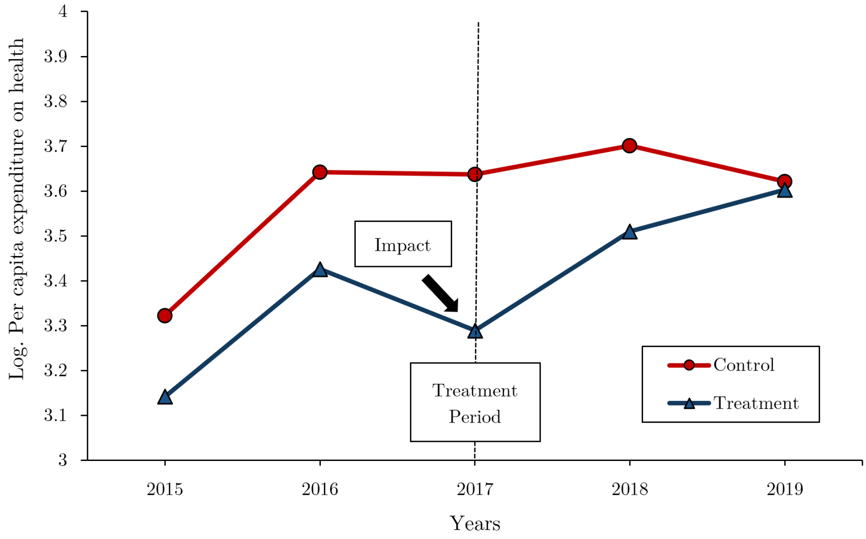
Figure 2. Logarithm of Per Capita Expenditure on Education



Source: (INEI, 2020)

Similar to the case of education, Figure 3 displays the trends of the logarithm of per capita expenditure on health. The control and treatment groups reveal a pattern similar to the trend observed in education during 2015 and 2016; however, this trend has a steeper slope. Subsequently, following the intervention in 2017, a drastic shift in the trend is once again observed in the treatment group. Thus, the parallel trends assumption is satisfied for both health and education categories.

Figure 3. Logarithm of Per Capita Expenditure on Health



Source: (INEI, 2020)

6.2 Results and Discussion

With respect to the potential causal relationship, Table 4 presents the regression coefficients estimating the impact of the El Niño phenomenon on per capita expenditures on health and education. The first two columns show the effect on health expenditure, while the last two columns display education expenditure, with the second and fourth columns incorporating control variables to provide a more robust estimation.

The coefficients in Table 4 are found to be negative and significant across all categories. For example, interpreting the coefficient in the second column, the occurrence of the El Niño phenomenon led to a 18.6 percentage-point reduction on per capita health expenditures among affected households compared to unaffected households. The effect for health weakens slightly when control variables are excluded, dropping to 18.0 percentage points. Conversely, when control variables are included for education, a reduction of 17.4 percentage points is observed, whereas excluding control variables reveals a reduction of 16.0 percentage points. Therefore, the negative effect varies between 16 and 19 percentage points, which is slightly higher than the estimates reported by Anttila-Hughes and Hsiang (2013) and Zegarra and Alarcón (2014).

This negative effect can be considered detrimental because individuals from affected households will have reduced access to the benefits of obtaining health and education services. Ultimately, a lower expenditure on health leads to a reduced number of medical appointments, less available medicine, and fewer preventive check-ups. On the other hand, a lower expenditure on education leads to less access to educational sessions, lower teaching quality, and fewer academic research resources. Thus, individuals are more vulnerable to the risk of illnesses and to the development of their cognitive skills.

Table 4
Effect of the El Niño Phenomenon on Per Capita Expenditures on Health and Education.

	(1)	(2)	(3)	(4)
	ln(Per cap. exp. on health)		ln(Per cap. exp. on education)	
Affected Household	-0.180**	-0.186**	-0.160*	-0.174**
	(0.024)	(0.019)	(0.068)	(0.046)
Head education		0.069***		0.062***
		(0.000)		(0.000)
Walls		0.359***		0.364***
		(0.000)		(0.000)
Floor		0.531***		0.529***
		(0.000)		(0.000)
Roof		0.231**		0.187*
		(0.028)		(0.091)
Subsidies		0.00005***		-0.0001***
		(0.000)		(0.000)
Constant	3.589***	3.326***	3.600***	3.448***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13,366	13,306	13,366	13,306
R^2	0.178	0.191	0.138	0.148

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

Likewise, the reduction in education and health expenditures can be interpreted as a household mitigation strategy to increase savings and safeguard their crops in anticipation of future natural disasters. Several factors shape this mitigation decision, such as access to credit, past disaster experiences and the household head's degree of risk aversion. This last factor is a key determinant as a risk-loving household head may invest less in crop protection in order to have greater savings; while a risk-averse household head would allocate a larger sum of money for protection, affecting their short-term financial capacity (Bakkensen and Conte, 2022).

Furthermore, in Table 5, each column presents the regression coefficient of the El Niño phenomenon's effect on per capita expenditures on health and education, with a specific focus on their subcategories. For health, two effects are evaluated: expenditure on medicines/medical procedures and medical services[5]. Similarly, for education, two effects are analyzed: expenditure on Uniforms/Books and Logistics[6] . The findings indicate that the effects are also negative and significant, ranging from 15 to 29 percentage points. Thus, the hypothesis outlined in Section 3 is confirmed.

[5]Medical services include Consultation, Tomography, Dental Service, Ophthalmology Service, Health Check-up and Other services.

[6]Logistics include Fees, Enrollment, Parents' Association and Transportation.

Table 5
Effect of the El Niño Phenomenon on Subcategories of Per Capita Expenditures on Health and Education.

	(1) Medicines/ Procedures	(2) Medical Services	(3) Uniform/ Books	(4) Logistics
Affected Household	-0.293***	-0.247***	-0.232***	-0.151**
	(0.000)	(0.000)	(0.001)	(0.013)
Head education	0.048***	0.040***	0.012	0.044***
	(0.000)	(0.000)	(0.103)	(0.000)
Walls	0.327***	0.261***	0.181***	0.138**
	(0.000)	(0.000)	(0.004)	(0.032)
Floor	0.508***	0.706***	0.164	0.361***
	(0.000)	(0.000)	(0.174)	(0.009)
Roof	0.160	0.179*	0.014	0.287***
	(0.138)	(0.082)	(0.886)	(0.008)
Subsidies	0.00003***	0.00004***	-0.00003***	-0.00004***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.901***	2.320***	2.211***	1.325***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13,306	13,306	13,306	13,306
R^2	0.172	0.165	0.137	0.203

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

In contrast to the reviewed literature, results from Table 5 are significantly overestimated, especially in the subcategory of medicines and medical procedures. Compared to other countries, this greater reduction in expenditure from Peruvian rural households can be attributed to their heightened vulnerability. Specifically, the structural weakness of housing materials elevates the risk of incurring additional expenses due to damage from natural disasters (Zegarra and Alarcón, 2014), which constrains household financial resources. To offset these unforeseen costs, individuals are compelled to make more substantial reductions in higher-value goods and services, in this case, medicines and medical procedures (Proaño and Bernabé, 2018).

Following this line, the subcategory of educational logistics aligns with the findings of the reviewed literature, as it does not represent a significant expense for Peruvian rural households. Contrary to medical expenses, there is a broader range of pricing options available for school fees and transportation (Balarin and Saavedra, 2021). On certain occasions, households may face minimal or no expenses if they choose a low-cost school and students can reach it on foot. Therefore, in response to the El Niño phenomenon, these expenses exhibit the least negative change.

Regarding the hypothesized mechanism mentioned in Section 2, observed patterns from crop composition (Table 1) and results align closely with this hypothesis. In particular, the high percentage of dependence on a limited range of crops underscores the vulnerability of agricultural businesses to natural shocks (Gutiérrez et al., 2019). In addition, the results show that the effect on out-of-pocket expenditures remains negative when evaluating different components (education/health), suggesting that the negative impact originates from the income source, tightening the household's budget constraint (Jappelli and Pistaferri, 2010).

6.3 Robustness checks

To assess the robustness of the results , the regressions were re-estimated using a restricted time frame that includes one year before and one year after the intervention year (2016, 2017 and 2018). The findings, presented in Table 6 of Annex A.4, confirm the negative impact of the El Niño phenomenon on per capita expenditure on health including control variables, while the coefficients left were not significant.

Additionally, a multicollinearity analysis was conducted to determine whether the independent and control variables are strongly associated. High correlation among these variables could lead to issues, reducing the results precision. Table 7 of Annex A.4 presents the correlation matrix of the independent and control variables, with the highest correlation coefficient being 0.5, which corresponds to the relationship between roof and wall. Consequently, no multicollinearity issues were detected.

7. Conclusion and Policy Implications

This research examines the impact of the 2017 El Niño phenomenon on per capita expenditures on health and education for rural households in the northern coastal region of Peru. A robust negative impact of the El Niño phenomenon was found on per capita expenditures on health and education for affected rural households. Specifically, the negative impact ranged between 16 and 19 percentage points, expanding to a range of 15 to 29 percentage points when analyzing the subcategories of health and education. The negative impact is possibly attributed to the negative *shock* to agricultural income, given that rural households are the most dependent on this source of income.

Based on this, the results suggest that individuals from affected households will have reduced access to the benefits of obtaining health and education services. Consequently, individuals become more vulnerable to health risks and cognitive skill development challenges. In addition, Peruvian rural households face greater expenditures reductions due to their heightened vulnerability, particularly in medicines and medical procedures, while educational logistics exhibit the least negative change.

Given that this research focuses on the out-of-pocket expenditure of rural households, future research lines could include state spending on health and education to provide conclusions from a governmental perspective. From this, the analysis could be expanded to include state investment in infrastructure in these districts, such as the construction of better hospitals and schools, which impacts the well-being of households. Furthermore, the analysis would be enriched by including state spending on roads, pavements, and structures adjacent to households.

In conclusion, it was observed that the negative impact of the El Niño phenomenon on essential household expenditures such as health and education goes beyond a mere budget adjustment to mitigate the adverse effects. In response, policymakers are recommended to implement measures to counteract the negative impact, thereby potentially increasing the out-of-pocket expenditure that rural households have reduced.

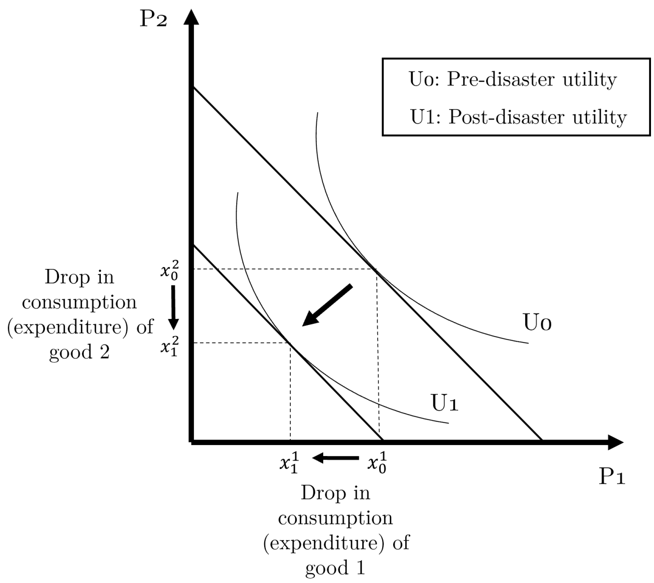
1. Appendix

A.1 Natural Disasters Theory

Figure 4. Determinants of Disaster Risk

Source: (Wisner, 2004)

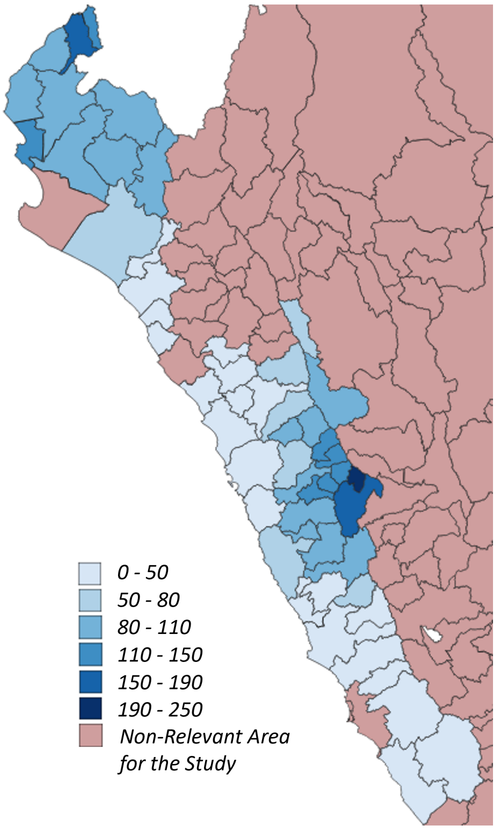
Figure 5. Decline in Household Welfare due to a Natural Disaster



Source: (Jappelli and Pistaferri, 2010)

A.2 Level of precipitation

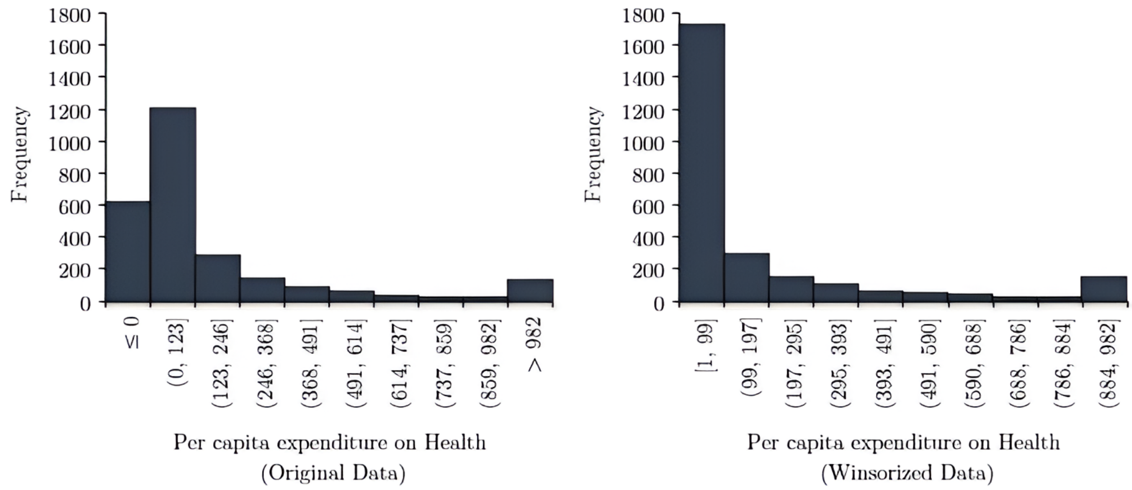
Figure 6. Average Precipitation (mm) from January to May 2017 in the Northern Coastal Region of Peru



Source: *The Power Project Nasa*

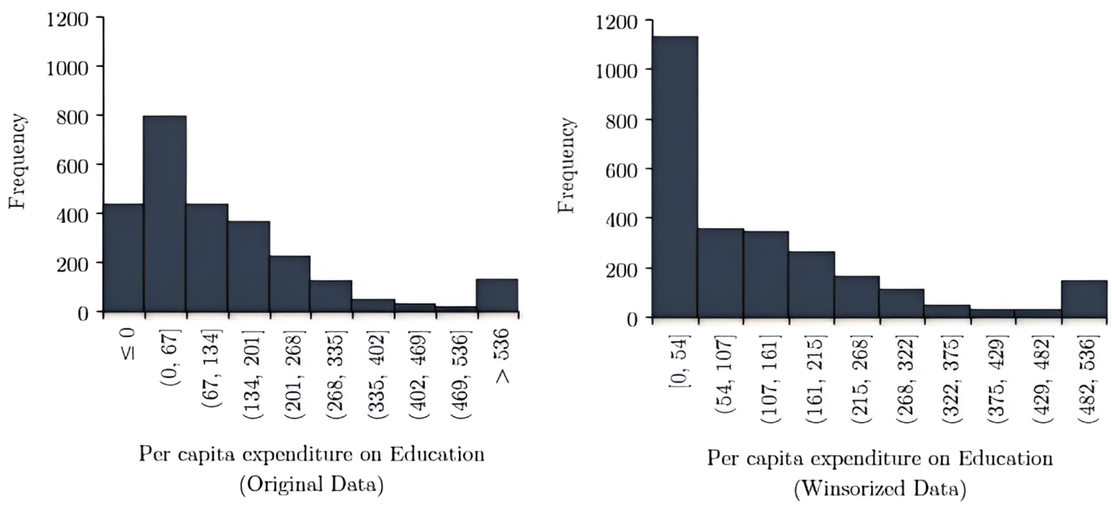
A.3 Winsorization

Figure 7. Per capita expenditure on Health (Original Data vs Winsorized Data)



Source: (INEI, 2020)

Figure 8. Per capita expenditure on Education (Original Data vs Winsorized Data)



Source: (INEI, 2020)

A.4 Robustness checks

Table 6

Effect of the El Niño Phenomenon on Per Capita Expenditures on Health and Education (2016–2018)

	(1)	(2)	(3)	(4)
	ln(Per cap. exp. on health)		ln(Per cap. exp. on education)	
Affected Household	-0.140	-0.147*	-0.131	-0.152
	(0.109)	(0.091)	(0.173)	(0.113)
Head education		0.052***		0.068***
		(0.000)		(0.000)
Walls		0.293***		0.393***
		(0.002)		(0.000)
Floor		0.522***		0.648***
		(0.003)		(0.000)
Roof		0.398***		-0.019
		(0.005)		(0.897)
Subsidies		0.0001***		-0.00004***
		(0.000)		(0.000)
Constant	-3.630***	3.402***	3.636***	3.470***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,208	8,171	8,208	8,171
R^2	0.204	0.216	0.164	0.175

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7

Correlation Matrix of Independent and Control Variables

	Affected Households	Head Education	Wall	Floor	Roof	Subsidies
Affected Households	1.0					
Head education	-0.1	1.0				
Wall	-0.1	0.1	1.0			
Floor	-0.1	0.1	0.3	1.0		
Roof	-0.1	0.1	0.5	0.3	1.0	
Subsidies	0.03	-0.03	-0.02	0.005	-0.008	1.0

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