CHAPTER 4

Vulnerability to shocks and climate change

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KEY MESSAGES

VULNERABILITY TO SHOCKS AND CLIMATE CHANGE

- Because of its location and topography, Peru is highly vulnerable to natural disasters. However, not all households are equally exposed to the same shocks: low-income and rural households are more exposed to natural disasters, while the more well off experience more idiosyncratic economic shocks. Coping mechanisms vary by socioeconomic level. Households in the highest quintile of the expenditure distribution rely on savings, while the poorest depend on informal safety nets, such as family members, and on reducing food intake.

- Negative income shocks pose a challenge in the effort to reduce poverty because they decrease the incomes of poor households and increase the probability that nonpoor households will become poor. Nonpoor households experiencing shocks have a high probability of falling into poverty. Among nonpoor households, the probability of becoming poor in the subsequent year almost doubles if these households experience a natural disaster.

- Vulnerable households include households that are currently poor, as well as those nonpoor that are at risk of falling into poverty. Shielding the gains in poverty reduction requires an understanding of the dynamic dimension of poverty. Between 2017 and 2021, total vulnerability in Peru rose from 28.2 percent to 37.4 percent, with large spatial variation across districts and departments (departmentos or regions).

- Access to basic services varies by level of poverty and risk-induced vulnerability. Districts with the highest levels of poverty-induced vulnerability (the chronically poor) exhibit less access to government services. A group of districts may combine low poverty and high vulnerability rates. Despite having levels of access to services similar to the levels experienced in chronically poor districts, their economies are able to generate higher income levels, though they show high variability and substantial risk of falling into poverty.

- In a context of high exposure to risk and vulnerability, the economic impacts of climate change pose a challenge to efforts to reduce poverty and increase shared prosperity. Evidence on the effects of previous climate shocks may not provide a complete picture of the effects of climate change because accounting for adaptation is difficult.

- Climate inequality means that environmental stressors are not distributed equally. Low-income households have been more exposed to past extreme weather-related events because of spatial dynamics: these households tend to be in higher risk areas. Not all regions will be exposed to the same changes in weather patterns and risk. The poor and vulnerable will face the greatest weather variations, thereby increasing climate inequality.

- The specific impacts of climate change depend on the effects on the income-generating capacity of households and on the implementation of public and private adaptation initiatives. While government institutions play a key role in helping poor people manage the uncertain risks of climate change, the participation of local governments is limited.

During the last decade, Peru has been successful in reducing poverty and improving shared prosperity. However, because of the high frequency of shocks, sustaining these gains has proven difficult. The incidence and prevalence of shocks is expected to increase because of climate change, creating additional pressure on the capacity of households to respond, cope, and adapt to shocks. To continue the trend toward a reduction in poverty, adapting to this new environment is important.

This chapter contains five sections. The first uses information from the National Household Survey (Encuesta Nacional de Hogares, ENAHO) as evidence on the extent of the shocks affecting households, their role in increasing poverty, and the mechanisms households possess to cope with risks. The second section explores vulnerability, understood both as low income (poverty-induced vulnerability) and the risk of falling into poverty (risk-induced vulnerability). Leveraging the latest poverty mapping techniques estimates are produced of district-level vulnerability rates in 2017 and 2021. The third section shows how vulnerability correlates with access to basic services and the capacity to generate income. The fourth section deals with the impacts of climate change by examining the current state of climate inequality, whereby not all households experience weather shocks and the consequences of climate variability equally. Thus, low-income households now experience greater exposure to risks. This exposure is likely to increase in the future. The final section proposes recommendations.

4.1 Shocks and coping strategies

Because of its location and topography, Peru is highly vulnerable to natural disasters, and households are at a high risk of a variety of negative shocks. The country is located over the Nazca tectonic plate and surrounded by the Pacific Ring of Fire, a highly seismic region in which more than 80 percent of the world's earthquakes occur. The country is also exposed to the Humboldt Current, which provides the country with rich fishing waters, but also exposes it to periodic episodes of El Niño.[1] Experiences in the past two decades illustrate the extent to which these risks translate into negative shocks with large economic consequences. For example, the Pisco earthquake in 2007 caused damage valued at more than US$2 billion, while the 2017 El Niño episode affected 1.3 million Peruvians and caused losses estimated at US$3.1 billion.[2,3] The combination of geographical factors means that Peru is affected by seven of the nine possible characteristics that, accordingly to the United Nations Framework Convention on Climate Change, make a country vulnerable to natural disasters.[4]

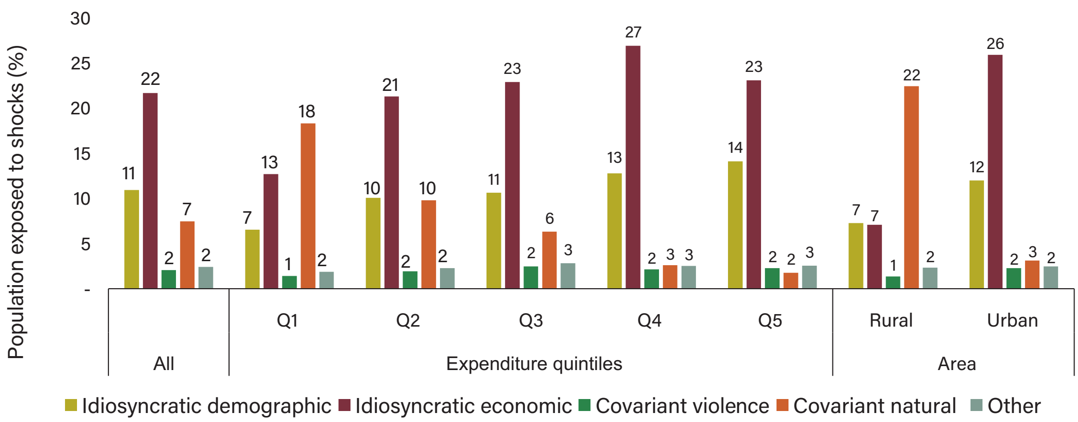
Shocks limit poverty reduction by lowering the income of poor households and increasing the risk that nonpoor households will fall back into poverty. Designing policies that help mitigate risk exposure requires understanding the frequency and intensity of a shock, as well as which households are more likely to be affected and their available coping mechanisms. Exposure to some of these shocks is captured by the ENAHO, which provide some information on the households affected by shocks. The National Statistics and Informatics institute (INEI) of Peru,

1. El Niño is a phenomenon that occurs when the surface of the Pacific Ocean becomes unusually warm, causing extreme events of rain and drastic climate variation (ECLAC 2014).**3.** MEF, 2019.
2. Tolmos (2011).
3. Molina et al. (2021).
4. These are earthquakes, low-lying coastal areas, arid and semiarid areas, areas exposed to flood, drought, and desertification, fragile mountain ecosystems, areas prone to disasters, areas with high urban air pollution, and economies largely dependent on income generated through the production and use of fossil fuels.

through ENAHO, measures self-reported exposure to shocks, whether these shocks impact income or assets, and the mechanisms adopted by households to cope with the shocks. Specifically, the survey considers the following shocks: natural events or natural disasters, the occurrence of criminal acts, abandonment by the head of household, serious illness or accident involving any member of the household, bankruptcy of a family business, and loss of employment by any household member. These shocks can be classified as aggregate or idiosyncratic shocks.[5]

In 2021, close to 40 percent of Peruvian households reported that they had experienced at least one negative shock. The most common shocks reported were idiosyncratic (29.4 percent). Among these, economic shocks were the most common (21.7 percent), such as losing employment or living with someone who lost their employment or bankruptcy of the family business during the previous 12 months. Demographic idiosyncratic shocks were the second most common type of shock (10.9 percent), such as living in a household in which a member had an accident or became ill during the previous 12 months. Covariant shocks were less common, but, among these, natural covariant shocks were experienced by 7.5 percent of the population. Other covariant shocks and other shocks in general were reported to a lesser extent (Figure 1).

Figure 1. Reported shocks, by per capita expenditure quintile and location, 2021



Source: INEI: ENAHO 2021.

Not all households are exposed to the same shocks. Low-income and rural households are more likely to be exposed to natural disasters, while urban and more well off households experience more idiosyncratic economic shocks. Socioeconomic level and place of residence change the amount of reporting on idiosyncratic and covariant shocks. Poorer and rural households mainly report that they suffer from natural disasters. Results show that 18.3 percent of households in the lowest per capita expenditure quintile and 22.4 percent of those in rural areas reported that they experienced a natural covariant shock in 2021. In contrast, urban and more well off households are more likely to report that they experienced economic idiosyncratic shocks. For

5. Shocks identified in ENAHO are classified as follows: (a) Idiosyncratic demographic shocks include abandonment by the household head and the sickness or involvement in an accident of a household member; (b) idiosyncratic economic shocks include the loss of employment and bankruptcy of a family business; (c) covariant violence shocks include criminal activity experienced by households; and (d) covariant natural shocks, that is, natural disasters.

example, 23.1 percent of households in the fifth quintile and 25.9 percent of urban households reported on economic idiosyncratic shocks, such as losing employment. This is above the rate reported by the poorest quintile (12.7 percent) or the rural population (17.1 percent). The difference in exposure between the poor and nonpoor is partly driven by geographic location and lower investment in mechanisms that improve resilience and reduce exposure. Moreover, in the search for better economic opportunities, land and housing market dynamics tend to push poorer households into areas with higher risk.[6] Poor and vulnerable households are also more widely exposed because of their economic conditions, such as low unemployment rates in rural area, and because poorer households rely more on self-employment and the informal sector.

The degree of exposure to each shock does not vary greatly across years unless there is a considerable event, such as an economic downturn or a large natural disaster. Self-reported shocks involve a combination of both exposure to risk and the actual damage that induces household to report the shock in the survey. The occurrence of objective shocks in Peru in the last couple of years reveals that the share of households that report they have been affected by shocks is fairly constant across years and that the rate of people reporting shocks is associated with observable negative events. Between 2018 and 2021, exposure to natural disasters remained constant. About 7.0 percent of people reported that they had been exposed to a shock. However, in 2017, the year in which the El Niño episode occurred in Peru, the share of the population that reported that they had experienced a natural disaster rose to 11.4 percent. A similar trend occurred with the appearance of COVID-19. While, in a normal year, 7.5 percent of the population reported an illness or accident at home, the share rose in 2021 to 10.0 percent nationwide, and, in areas such as the urban coast and the Lima Metropolitan Area, up to 12 percent of the population reported an illness, a trend that is consistent with areas more widely affected by COVID-19.

Although less common, some families experience more than one shock per year, while others display continuous exposure over the years, specially to natural disasters. In 2021, around 15 percent of the population that experienced a shock reported that they had been affected by more than one disaster. During that year, the most common combination of shocks involved illness and losing employment among the reporting population or household members. Before the pandemic, the most common combination of shocks involved a natural disaster and illness among the reporting population or household members. Reliance on a panel component of ENAHO allows an exploration of the exposure of households to shocks over time. Natural disasters display the greatest persistence over time. One-quarter to one-third of the population exposed to a natural disaster experiences another disaster the following year.[7] Sickness also shows persistence across years. About 18 percent of households reported that they had experienced a sickness or accident during two consecutive years. The repeated incidence of job loss and bankruptcy is less common. Only 9 percent (7 percent) of households experienced job loss (bankruptcy) across years.

5. Shocks identified in ENAHO are classified as follows: (a) Idiosyncratic demographic shocks include abandonment by the household head and the sickness or involvement in an accident of a household member; (b) idiosyncratic economic shocks include the loss of employment and bankruptcy of a family business; (c) covariant violence shocks include criminal activity experienced by households; and (d) covariant natural shocks, that is, natural disasters.

6. Hallegatte at al. (2019).

7. The range of 25 percent–33 percent depends on the year of the survey (2017–19).

Climate change is expected to increase the intensity and frequency of natural disasters. Poor households consistently experience the highest incidence of disasters caused by natural events. In the period analyzed (2017–21), the population in the lowest expenditure quintile repeatedly reported more exposure to natural disasters than the population in the highest expenditure quintile, 19 percent and 2 percent, respectively. The incidence of exposure is consistent with the finding that rural residents are more exposed to these shocks, while also showing lower income levels.

There are large regional differences in the characteristics of those who suffer natural disasters; thus, droughts, floods, and storms are more widely reported in rural areas in the Amazon and the Andes.[8] Between 2017 and 2021, an average of 27.4 percent of the population in the rural Andes reported that they had been exposed to natural disaster, while an average of 13.0 percent in rural Amazon reported a natural disaster during the same period. These rates are higher than the incidence in the rural coast, where on average 8.6 percent of the population reported an experience of a natural disaster. In contrast, urban areas across the country tend to report a lower incidence of natural disasters (about 3.8 percent), except in the case of the El Niño episode in 2017 that affected urban coastal areas. In 2017, about 13 percent of the population in urban coastal areas reported a natural disaster, while, during a normal year, less than 1 percent reports a disaster there. Although fewer natural disasters are a consistent trend in urban areas over the years, the incidence of large urban landslides (huaicos) that occur during episodes of intense rainfall are becoming more common in some urban areas in the Andes, such as Arequipa, Ayacucho, and Cusco. In 2021, close to 100 huaicos occurred in these regions. Thus, the share of the population in urban areas of the Andes that reported a natural disaster rose from 7 percent in 2017 to 10 percent in 2021.

Most households lack effective coping mechanisms and must rely on other family members to manage the effects of shocks. Government assistance does not appear to come into play during large shocks, pointing to the need for a more dynamic social protection system. In a normal year, 4.3 percent of households reported that they had received government support in managing the impact of a natural disaster. In years of large natural disasters, such as 2017, only 5.5 percent of households in urban areas of the coast, where the El Niño phenomenon occurred, reported that they had received government aid. This suggests that the government does not respond to large events or, at least, that the flow of government aid is not perceived then in greater proportion than in normal years. Meanwhile, the aid of other family members, savings, and reductions in consumption are more common coping mechanisms in the face of a natural disaster. In 2021, 55.2 percent of the population that had experienced a shock related to natural disasters received some type of family aid as a coping mechanism; 17.0 percent used savings; and 13.3 percent made adjustments in consumption in the face of the shock. Less common mechanisms were government support (7.2 percent), finding another job (6.0 percent), and obtaining a loan (4.0 percent).

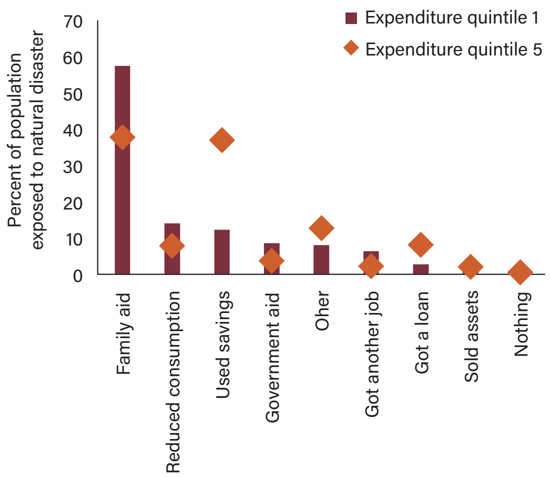
The type of coping mechanisms applied varies by socioeconomic status. Poor households depend on informal safety nets and reductions in

8. The Peruvian territory can be divided according to climate and vegetation into three large natural areas that cut across the country from south to north: the coast, the Andes, and the Amazon. These areas can also be classified as urban or rural.

food intake, while the more well off are more likely to be able to rely on savings. Reliance on informal coping mechanisms decreases with income. For example, in 2021, 57 percent of the population in the poorest quintile exposed to a natural disaster relied on family assistance to offset the negative impacts of the shock, while the share was only 38 percent among individuals in the richest quintile. Reducing consumption is the second most common coping mechanism among the poorest households (14.0 percent), while it is rarely a mechanism among the richest quintile (7.9 percent). The opposite is true in the case of using savings as a strategy to cope with a natural disaster. While 36.9 percent of households in the fifth quintile used savings, only 12.3 percent in the lowest quintile did so (Figure 2). The perception across the population that one is able to cope with the effect of a shock changes according to coping mechanism. Among those people who reported that they used their savings, 16.5 percent said they had been able to deal with the effects of the shock. In contrast, only 3.0 percent of those who reported that they had resorted to aid from family members said they had been able to cope.

Figure 2. Responses to natural disaster shocks, by per capita expenditure quintile, 2021

Population exposed to natural disaster, %



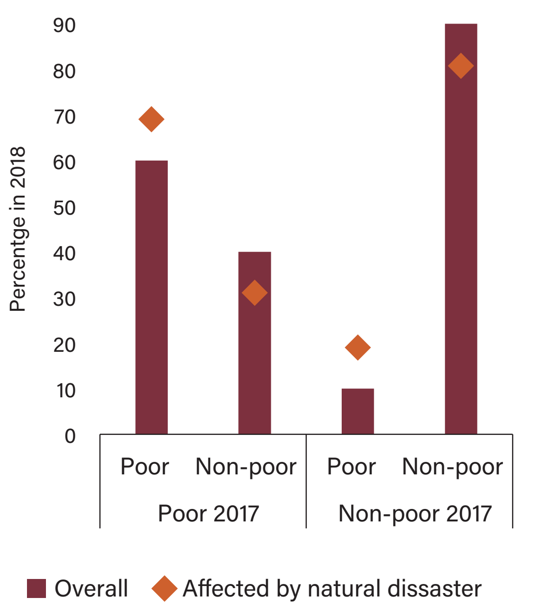
Source: INEI-Enaho 2021.
Note: Expenditure quintiles are constructed based on annualized per capita household expenditure.

The perception of helplessness in the face of natural disasters accounts for the highest share of individuals reporting on shocks in the household survey, revealing the deep economic impacts of the shocks and the vulnerability of the people affected. When asked when they estimate they will recover completely from the loss of income or assets suffered during a shock, 54 percent of the survey respondents who had affected by a natural disaster stated that they did not think they would ever recover the income or assets. Although such a sense of helpless is also associated with other shocks, it occurs at a much lower rate. Only 20 percent of the population affected by other shocks considering their situations helpless. Moreover, the perception that no complete recovery from the damage caused by a natural disaster is possible rose with time in 2017–21, suggesting that the destructiveness of natural disasters may be increasing.

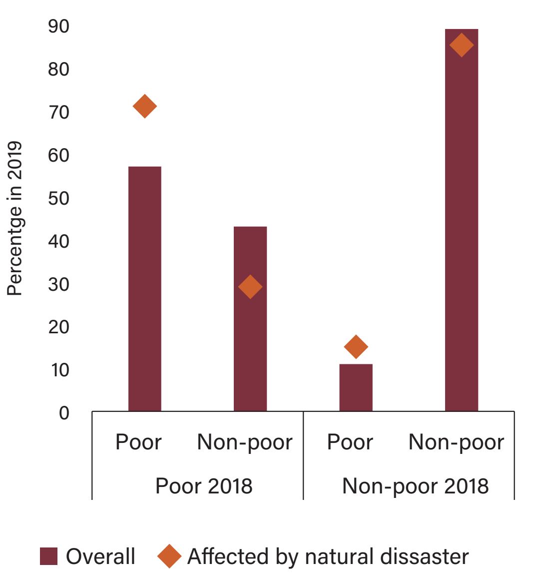
Exposure to a natural disaster increases the probability of becoming poor and limits the movement out of poverty. Nonpoor households experiencing shocks displayed a high probability of falling back into poverty. Evidence from the panel component of the ENAHO shows that, on average, 40 percent of poor households in 2017 were not poor in 2018. However, among those households that experienced a natural disaster, only 30 percent escaped poverty (Figure 3, panel a). A similar share is observed among the population that escaped poverty between 2018 and 2019, that is, the share of transitions out of poverty among those suffering a natural disaster was low (43 percent versus 29 percent) (Figure 3, panel b). In the case of nonpoor households in 2017, the probability of being poor in 2018 almost doubled, from 10 percent among the general population to 19 percent among those reporting a natural disaster. This showcases the importance of reducing the incidence of shocks to allow more rapid poverty reduction by raising the transition out of poverty and lowering the chance that nonpoor households fall back into poverty.

Figure 3. Transitions in and out of poverty and the impact of natural disasters, 2017–19

a. Transitions, 2017–18



b. Transitions, 2018–19



Source: INEI: ENAHO Panel, 2018–19.
Note: Transitions in 2019–20 and 2020–21 are not included because not all questions were applied in the survey during the pandemic.

4.2 Identifying vulnerable households

Shielding the gains in poverty reduction requires an understanding of the dynamic dimensions of poverty because nonpoor households still face high welfare volatility that puts them at risk of becoming poor. Sustained economic growth and social assistance through targeted transfers have contributed to the reduction of poverty and inequality. By combining income growth with support for low-income households, poverty was successfully reduced by about 40 percentage points between 2004 to 2019. As the COVID-19 pandemic showcased, poverty gains can be reversed in the presence of sustained shocks. To be effective, the response of social assistance programs needs to be based on an awareness not only of which households are currently poor, but also of which nonpoor households face the greatest risk of falling into poverty.

Vulnerable households include both those that are currently poor and those nonpoor households that are at risk of falling into poverty. Vulnerability is often defined as "the risk of households falling into or remaining in poverty because of either idiosyncratic hazards (due to characteristics of the individual household) or covariate/aggregate hazards (external to the household)".[9] Following the methodological approach of Gunther and Harttgen (2009) and Skoufias, Vinha, and Beyene (2021), it is possible to use cross-sectional data to estimate the probability that a household falls into poverty.

9. Naudé, Santos-Paulino, and McGillivray (2012, 2).

Box 1 provides methodological details on how to produce vulnerability estimates by combining the Gunther and Harttgen (2009) approach with small area estimation techniques from the poverty mapping literature. Vulnerable households include households that are currently poor (poverty-induced vulnerability) and households at risk of falling into poverty (risk-induced vulnerability). A household is identified as vulnerable if it has a predicted probability above 29 percent of falling into poverty from one year to another. Two poverty and vulnerability maps are constructed using the 2017 national census and the information available in the 2017 and 2021 ENAHO surveys.

Box 1. Quantifying Vulnerability to Poverty

Following Gunther and Harttgen's (2009) methodology allows estimates to be obtained of vulnerability rates, which are understood as the share of individuals who are vulnerable because of either poverty (experiencing current deprivations) or risk (a high probability of falling into poverty). However, in the description originally presented by the authors, the estimates are only representative at the smaller area characterized by statistical representativity in the household survey. It is possible to adapt their model into an empirical best (EB) approach that follows Molina and Rao (2010).

The basic idea behind poverty mapping techniques is to produce welfare indicators at administrative levels on which household surveys lack statistical representativity. Census data provide the statistical representativity for smaller administrative areas, but lack a welfare measure to estimate poverty (Elbers et al. 2007). The estimation here uses the welfare indicator from the 2017 and 2021 ENAHO household surveys. Formally, y_{ch} denotes consumption per capita for each household h in the district c. The model fit is improved through several steps, including estimating a separate regression for each region of the country, dropping high-leverage observations, and, to avoid overfitting, limiting the set of right-hand side variables using a Lasso regression. The prediction of household per capita expenditure uses a nested-error model that provides estimates of the variance in the predicted income that are caused by unobserved location and idiosyncratic effects, according to the following model:

$$y_{ch} = x_{ch}\beta + \eta_c + e_{ch}, \qquad h = 1, \dots, N_c, c = 1, \dots, C. \text{(B. 1.1)}$$

where η_c and e_{ch} are, respectively, location- and household-specific idiosyncratic errors, assumed to be independent of each other, satisfying the following:

$$\eta_c \overset{\text{iid}}{\sim} N(0, \sigma_\eta^2), \quad e_{ch} \overset{\text{iid}}{\sim} N(0, \sigma_e^2), \text{(B. 1.2)}$$

Where the variances σ_η^2 and σ_e^2 are unknown. Here, C is the number of locations in which the population is divided, and N_c is the number of households in location c, for c =1,..., C. Finally, β is the K×1 vector of coefficients.

A poverty map uses the welfare variable from the household survey and estimates a model that best predicts the expenditure distribution, with the model coefficients then used to predict the expenditure level (and poverty status) for each household in the 2017 National Census. Note that using the regression coefficients on the census variables means that only the variables present in both the household survey and the census can be used in equation B.1.1. The variables selected to predict household-level expenditure rates can be grouped into four broad categories: dwelling conditions (for example, the roofing and wall materials), access to public services (for instance, type of sewerage available, cooking fuel), household head characteristics (for example, education levels, employment status), and durable goods ownership (such as automobiles, washing machines, refrigerator).

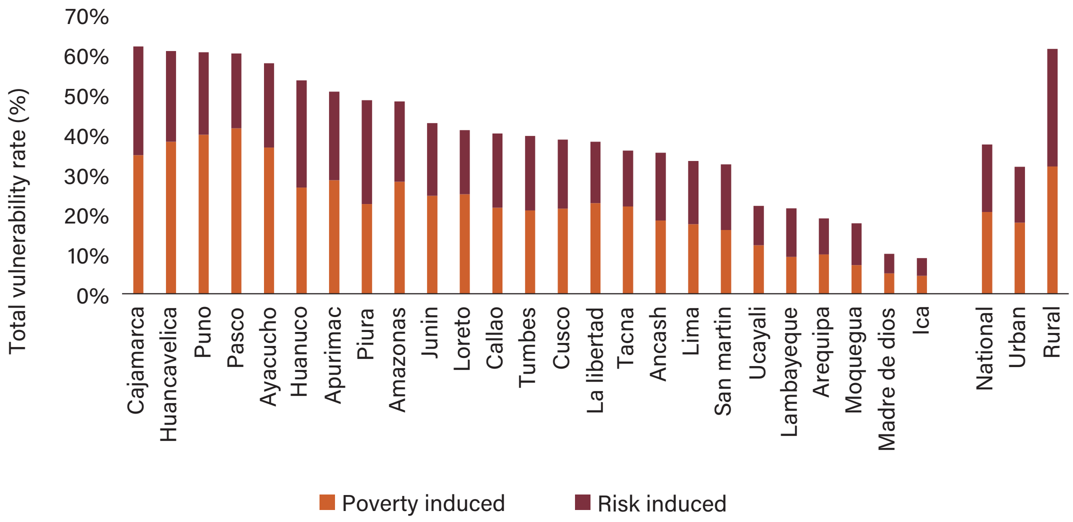
As part of the model calibration, the official poverty line that is defined at the [domain + urban/rural area + region] level (z) is used to test that the predicted poverty rates in the census sample for each region closely match the observed regional poverty rates in the household survey. Finally, the estimated variances for the location and idiosyncratic errors are recovered. This information provides estimates of the probability of falling into poverty following:

$$\hat{v}_{ch} = P(ln\hat{y}_{ch} < lnz|X,Z) = \phi\left(\frac{lnz - ln\hat{y}_{ch}}{\sqrt{\sigma^2_{u_c + e_{ch}}}}\right) \qquad \text{(B.1.3)}$$

Note that households are classified as vulnerable if their probability of becoming poor is above 29 percent.

In 2021, total vulnerability in Peru was 37.4 percent, with large levels of spatial variation across departments and urban and rural areas. The vulnerability rates were higher among households in rural areas than among urban households, 61.3 percent, and 31.8 percent, respectively. The higher rates in rural areas relative to urban areas were caused by higher levels of poverty-induced vulnerability (31.9 percent versus 17.8 percent) and higher risk-induced vulnerability (29.5 percent versus 14.0 percent). In addition, there was a wide dispersion of vulnerability rates across departments, ranging from 9 percent to 62 percent of the total population. Departments with low levels of aggregate vulnerability included Ica (8.9 percent), Madre de Dios (10.0 percent), Moquegua (17.6 percent), and Arequipa (18.8 percent), departments that are mostly located in the coast or the Amazon regions. In contrast, departments that have the highest levels of vulnerability tend to be located in the Andes, including Cajamarca (61.9 percent), Huancavelica (60.8 percent), Puno (60.5 percent), Pasco (60.2 percent), Ayacucho (57.8 percent), Huánuco (53.4 percent), and Apurímac (50.6 percent) (Figure 4).

Figure 4. Small area estimation: poverty incidence and vulnerability rate, by residence and region



Source: World Bank calculations based on ENAHO 2017 and 2021 and the 2017 National Census.
Note: A household is considered vulnerable if the probability that it will fall into poverty is more than 29 percent in one year or 50 percent in two years.

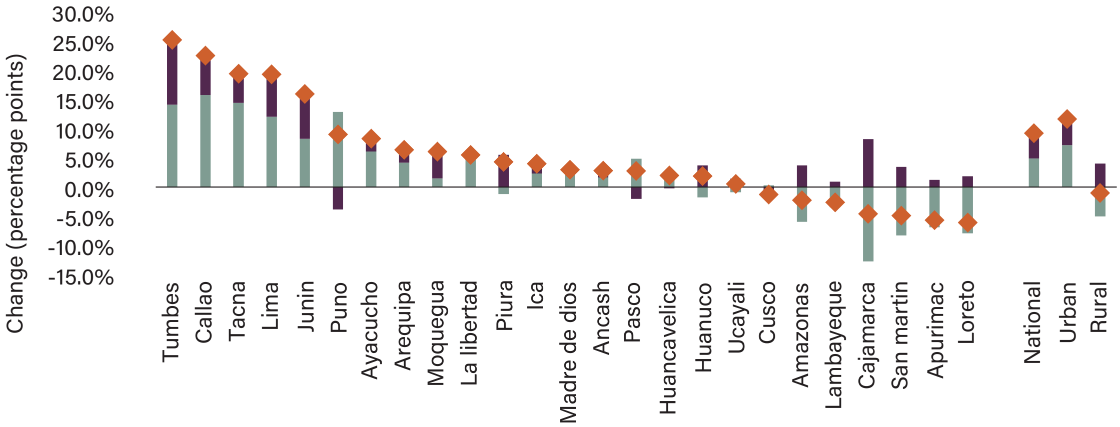
Spatial differences in the shares of poverty- and risk-induced vulnerability by area and department showcase that the geographic targeting of social programs based on poverty alone misses many households that are not poor, but that are vulnerable. At the national level, the ratio of poverty- to risk-induced vulnerability is 1.21, reflecting the fact that more households are vulnerable because they are already poor rather than because they risk becoming poor. This ratio is similar in urban areas (1.27), but slightly lower and more balanced in rural areas (1.08). Some departments with similar vulnerability rates may display a different composition in poverty and risk-induced vulnerability. For example, Ancash and Tacna have almost the same aggregate vulnerability rate (35.3 percent versus 35.8 percent), but, while, in the former, the ratio of poverty to risk-induced vulnerability is 1.08, it is 1.56 in the latter. Relatively high ratios of poverty to risk-induced vulnerability are also present in Pasco (2.2), Puno (1.93), Ayacucho (1.73), Huancavelica (1.68), Tacna (1.56), Loreto (1.55), La Libertad (1.47), Amazonas (1.39), and Junín (1.35). Few departments have more risk-induced vulnerable households than poverty-induced vulnerable households, including Huánuco (0.98), San Martín (0.96), Piura (0.86), Lambayeque (0.75), and Moquegua (0.68).

Between 2017 and 2021, total vulnerability in Peru rose from 28.2 percent to 37.4 percent. There was a similar increase in both poverty- and risk-induced vulnerability, at around 4.5 percentage points.[10] The highest increases in vulnerability rates were observed in the departments of Tumbes (25.1 percentage points), Callao (22.5 percentage points), Lima (19.2 percentage points), Tacna (19.3 percentage points), and Junín (15.9 percentage points) (Figure 5). Such expansions in vulnerability are

10. This general trend is in line with the trends in the official poverty rates. Nonetheless, poverty-induced vulnerability rates differ from official poverty estimates because they are the result of a survey-to-survey imputation methodology (Elbers et al. 2007). Moreover, because poverty-induced vulnerability is the result of a household income production function, it shares features with the concept of structural poverty (Günther and Harttgen 2009).

usually caused by increases in the rates of both poverty and risk-induced vulnerability; however, this is not always the case. For example, in the department of Puno, there was an overall increase in the rate of poverty-induced vulnerability of 12.9 percentage points that was partially offset by a decline by 3.8 percentage points in the risk-induced vulnerability rate between 2017 and 2021. Cajamarca represents a more extrema case. While poverty-induced vulnerability fell by 12.8 percentage points in line with observed changes in the poverty rate in the department, vulnerability only declined by 4.6 percentage points because there was a large rise in the risk-induced vulnerability rate of 8.2 percentage points. Only Cusco (1.3 percentage points) Amazonas (2.3 percentage points), Lambayeque (2.6 percentage points), Cajamarca (4.6 percentage points), San Martín (4.8 percentage points), Apurímac (5.6 percentage points), and Loreto (6.0 percentage points showed a reduction in aggregate vulnerability, mostly caused by large decreases in poverty.

Figure 5. Changes in total vulnerability rates, 2017–21



Source: World Bank calculations based on ENAHO 2017 and 2021 and the 2017 national census.
Note: A household is considered vulnerable if the probability that it will fall into poverty is more than 29 percent in one year or 50 percent in two years.

Based on the latest poverty mapping techniques, it is possible to report estimates of vulnerability rates for each of the 1,874 districts in Peru. Poverty and vulnerability rates among smaller administrative units are key to understanding welfare dynamics in the context of the new social challenges deriving from climate change. There is ample evidence on the importance of properly targeting antipoverty programs in the context of limited resources.[11] In the case of Peru, the ENAHO survey can only produce statistically representative estimates down to the department level. This level of spatial resolution might be too coarse, particularly in contexts where social assistance programs require the cross-referencing of more detailed information from administrative data and remote-sensed sources to understand the challenges in the access to services and natural-disaster–related hazards faced by households. Poverty mapping techniques allow estimates of the share of households below the poverty line in smaller administrative units on which direct measures are usually not available. By extending

11. See Alatas et al. (2012); Coady, Grosh, and Hoddinott, (2004); Brown, Ravallion, and van de Walle (2016), for example.

poverty mapping techniques to derive estimates of the share of households at risk of becoming poor, it is possible to generate valuable information about the areas in which households need additional assistance.

District-level vulnerability rates in 2017 and 2021 show substantial spatial variation. Map 1 illustrate district-level vulnerability rates in Peru during these two years. The panels indicate that the districts on the coast have lower shares of vulnerable households relative to the Amazon and the Andes. Additionally, the panels reaffirm the lack of a one-to-one relationship between vulnerability due to poverty and vulnerability due to risk. Even within the regions with high poverty headcount ratios, it is possible to find districts with relatively low levels of poverty. Appendix B contains maps disaggregated by poverty-induced and risk-induced vulnerability.

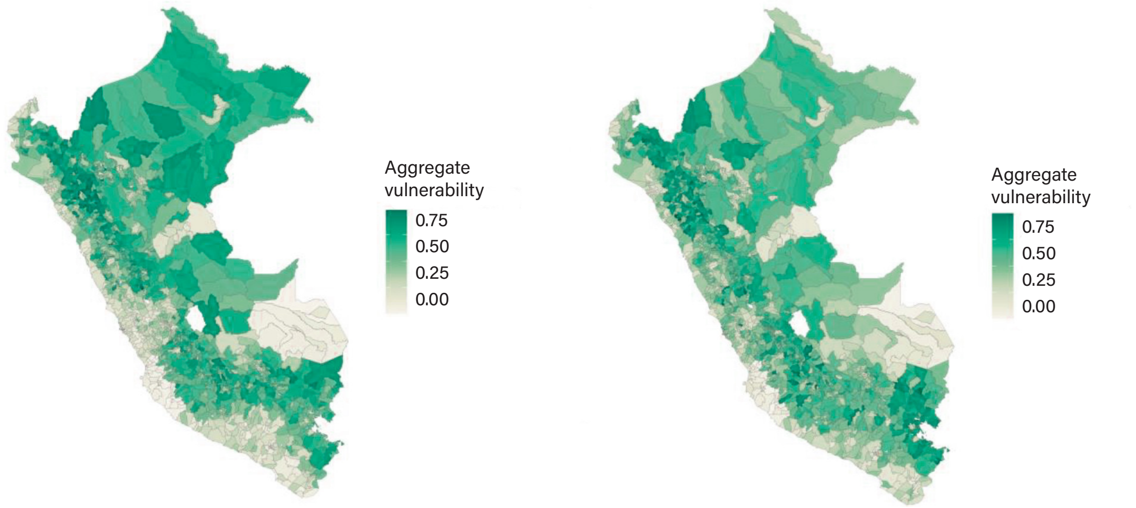
Map 1. Total vulnerability rates

District aggregate vulnerability 2017 household survey model

District aggregate vulnerability 2021 household survey model

a. 2017

b. 2021

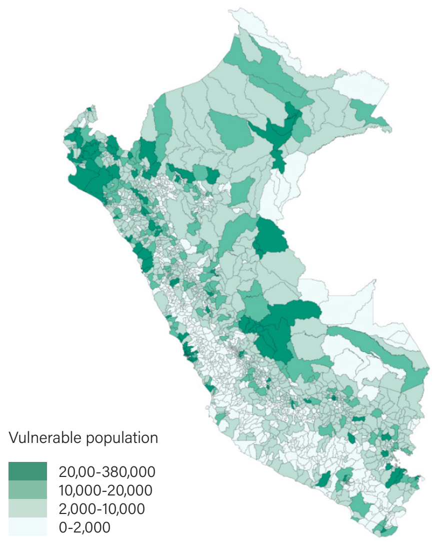


Source: World Bank calculations based on ENAHO 2017 and 2021 and the 2017 National Census.
Note: A household is considered vulnerable if the probability that it will fall into poverty is more than 29 percent in one year or 50 percent in two years.

Pockets of vulnerability are found in districts throughout all three major parts of Peru, particularly in the northern and central coast, the central Andes highlands, and the Amazon rainforest (Map 2). The biggest pockets of vulnerability are in Lima, that is, in the districts of Ate, Comas, San Juan de Lurigancho, and San Martin de Porres. These four districts account for 1.2 million vulnerable people at risk of falling below the poverty line. They also represent a significant pocket of the poverty-induced vulnerable, with over 500,000 poor. On average, 61 percent of the population in these districts is either at risk of falling into poverty or of remaining poor. These four districts account for 10.4 percent of all the vulnerable in the country and 9.6 percent of the country's total population. Other districts in Lima are characterized by an even clearer overrepresentation of the poor and vulnerable. In Carabyllo, for example, half the population is at risk of falling below the poverty line, and 25 percent is already poor and risks remaining under the poverty line. Thus, the total vulnerability in the district is 75 percent. The district represents 3.5 percent of Lima's population, but 5.0 percent of the vulnerable in Lima. Pockets of vulnerability outside Lima are on the northern coast (the district of El Porvenir, in Trujillo, with close to 150,000 vulnerable), in the northern Andes (the district of Cajamarca, in Cajamarca, with over 100,000 vulnerable), in the central Andes (the Amarilis district, in Huánuco, with close to 50,000 vulnerable), and in the northern Amazon (the district of San Juan Bautista, in Loreto, with 55,000 vulnerable).

Like poverty, vulnerability is more highly concentrated in urban areas. Of the 10 million Peruvians identified as vulnerable in 2021, that is, at risk of falling below the poverty line, 72.6 percent were living in urban areas. Only 17.5 percent were in rural areas, and the remaining 9.8 percent were in semiurban areas.[12] Rural areas are characterized by higher vulnerability rates relative to urban areas, at 61.3 percent and 31.8 percent, respectively. The higher rate in rural areas is caused by higher levels of poverty-induced vulnerability (31.9 percent versus 17.8 percent) and risk-induced vulnerability (29.5 percent versus 14.0 percent). However, urban areas have a larger share of the vulnerable because they account for more people.

Map 2. Total vulnerable population, 2021

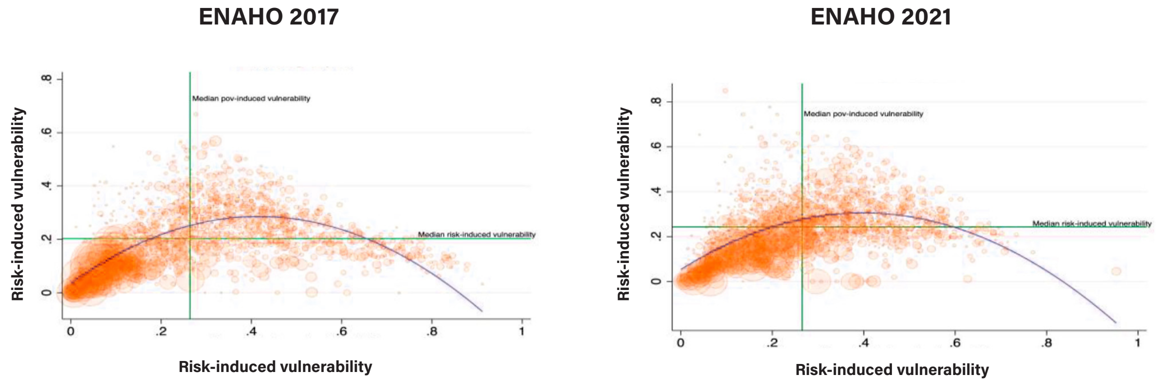


Source: World Bank calculations using National Household Survey data and the 2017 census.

Based on their vulnerability rate, districts can be sorted into three groups: low-vulnerability, high-vulnerability, and the chronically poor districts.[13] Figure 6 shows the distribution of poverty- and risk-induced vulnerability across the districts of Peru. Districts in the low-vulnerability groups have not only levels of poverty-induced vulnerability below the national median, but also few households at risk of poverty (lower left quadrant). In contrast, districts in the high-vulnerability group (upper left quadrant), despite relatively low poverty rates, present high levels of income volatility. Finally, chronically poor districts (the two right quadrants) have high poverty rates that leave, by construction, few households at risk of poverty. Figure 6 shows that most districts in the low-vulnerability groups tend to have larger populations, meaning they are considered urban, while small rural districts represent almost all the households in the chronically poor group. Despite the changes in poverty and vulnerability between 2017 and 2021, the general trends described above held in both years.

12. Urban, semiurban, and rural areas are identified following the relevant district typology of the National Institute of Statistics and Informatics.
13. Regions (departments) are sorted using the median, unweighted values of poverty- and risk-induce vulnerability across districts).
Low-vulnerability districts have low levels of poverty and low levels of vulnerability. High-vulnerability districts have low poverty rates, but high risk-induced vulnerability. Chronically poor districts have high poverty-induced vulnerability.

Figure 6. Poverty- and risk-induced vulnerability



Marker size: District population 2017

Marker size: District population 2017

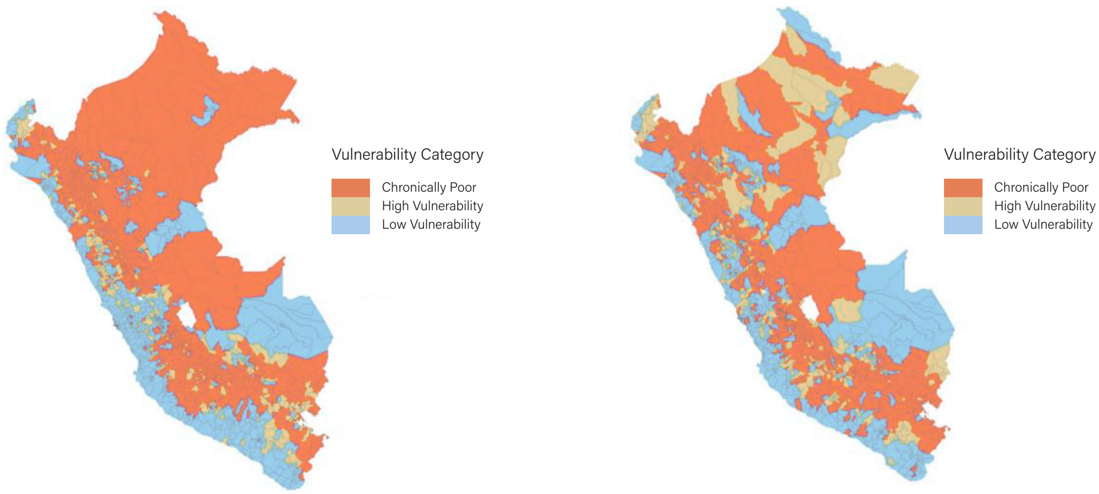
Source: World Bank calculations based on ENAHO 2017 and 2021 and the 2017 National Census.
Note: A household is considered vulnerable if the probability that it will fall into poverty is more than 29 percent in one year or 50 percent in two years. Regions are sorted using the median, unweighted values of poverty- and risk-induced vulnerability across districts. Low-poverty districts have low levels of poverty and low levels of vulnerability. High-vulnerability districts have low poverty rates. but high levels of risk-induced vulnerability. Chronically poor districts have high levels of poverty-induced vulnerability. The marker size shows the district population. Small marker size represents rural districts using the official definition of ENAHO.

Between 2017 and 2021, districts in northern Peru shifted from the chronically poor to the high-vulnerability category. Map 3 shows the geographical distribution of districts in each category, reaffirming that they are spread across all regions of the country. The transition from chronically poor to high vulnerability in northern Peru meant that several of the districts rose out of the chronically poor category. However, these districts still contain households with a high probability of falling back into poverty. The transition from chronically poor to high vulnerability has mainly taken place in the northern Amazon area. Among policy makers, this should be a priority area in efforts to expand social insurance to prevent the vulnerable from slipping back into poverty.

Map 3. Spatial distribution of vulnerability categories, by district

a. 2017

b. 2021



Source: World Bank calculations based on ENAHO 2017 and 2021 and the 2017 National Census.
Note: Chronically poor districts show rates of poverty-induced vulnerability above the district unweighted median. Low- (high-) vulnerability districts present rates of poverty-induced vulnerability below the district median, but show risk-induced vulnerability rates below (above) the district unweighted median. A household is considered vulnerable if the probability that it will fall into poverty is above 29 percent.

4.3 Correlates of vulnerability

Poverty- and risk-induced vulnerability highlight different economic challenges: deprivation versus variations in welfare. From a public policy perspective, it is important to understand how overlapping factors contribute (or limit) the capacity of households to increase income and improve the resilience to adverse shocks. In this sense, exploring the correlation of vulnerability and the characteristics of districts is key to understanding major issues in promoting income creation, intergenerational mobility, and the possibility of reducing variations in income. In particular, if structural poverty is the main concern, cash transfer programs or programs that enhance the delivery of basic services and facilitate investment in physical and human capital are likely to be the most appropriate. In contrast, if vulnerability is primarily risk induced (such as severe income fluctuations among the uninsured), then an insurance program may be needed to raise resilience.[14]

The amount of access to basic services distinguishes districts at different levels of poverty- and risk-induced vulnerability. Poverty-induced vulnerability is associated with the capacity to produce income, while risk-induced vulnerability is associated with the possibility of sustaining, over time, a level of expenditure above the poverty line. Correlates of access to basic services across different levels of poverty- and risk-induced vulnerability show that districts with high poverty rates exhibit lower educational attainment and less access to health care and internet access, as well as a higher share of labor in the primary sectors.

Chronically poor districts are characterized by less access to government services, limiting the opportunity to produce income. Access to government services is key to improving the capacity of households to generate income.[15] Figure shows systematic differences in the access to government services in chronically poor districts. In particular, the access to markets in these districts is limited by the lack of paved roads: only 16.8 percent are paved (4.6 percentage points less than the share in low vulnerability districts). Households in these districts are mostly rural (79.4 percent), highlighting that the labor force is more highly concentrated in the primary sector (68.0 percent versus 41.4 percent in low-vulnerability districts). The greater dependance on the primary sector and the poor connectivity to markets underlines that the opportunities for generating stable income in these districts may be limited. Moreover, the available information shows that government services are limited and low in quality. Only 15 percent of public schools are considered to be in a good condition (7 percentage points less than in low-vulnerability districts), and only one-quarter have access to basic services (24 percentage points less than low-vulnerability districts).[16] Access to health services is limited by the lower number of doctors per capita, which translates into worse performance in health indicators, such as lower vaccination rates, and higher rates of child undernourishment and anemia.

High-vulnerability districts exhibit levels of service access similar to those in chronically poor districts, but at much lower poverty rates. Households in high-vulnerability districts, though not poor, show high income variability. High-vulnerability districts show higher shares of rural households and jobs in the primary sector relative to chronically poor districts (87.2 percent

14. Skoufias et al. (2021).

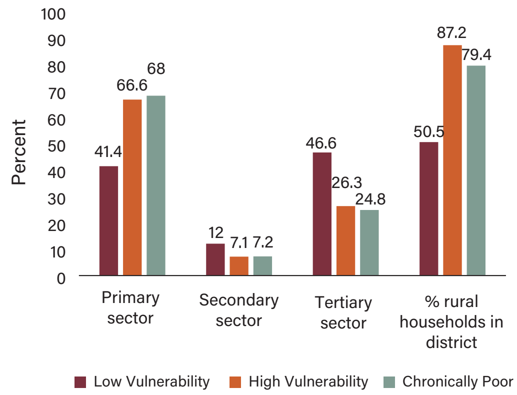
15. The main results are the outcome of the use of the 2021 poverty and vulnerability mapping. Some correlates based on the 2017 map are available in the appendixes.

16. Schools are in good condition if they are constructed of safe, good-quality materials. Schools with access to basic services have piped water, sewerage, and electricity.

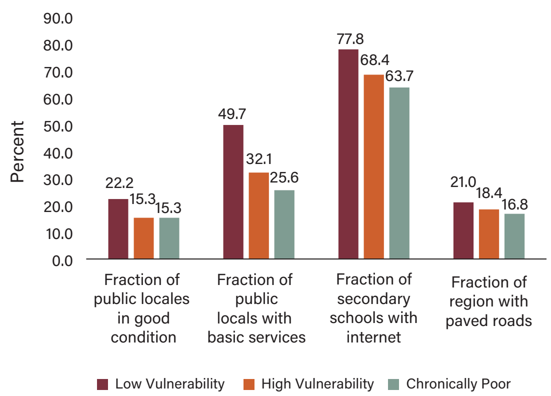
versus 79.4 percent). Access rates to services are lower than in districts with low vulnerability and closer to the rates observed in chronically poor districts. This gap also exists in the quality of services, revealed in the lower number of doctors per capita, the poorer quality of public education facilities, and the smaller share of paved roads.

Figure 7. Service access, by district type

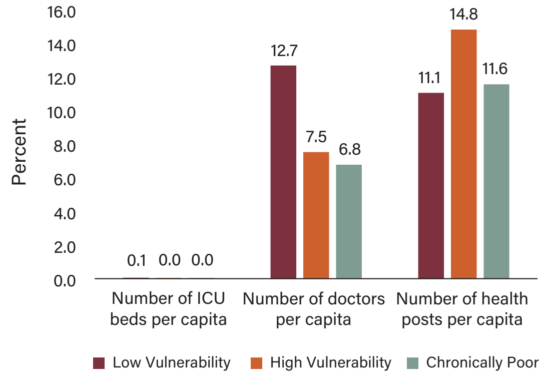
a. Percent of workers by sector and area



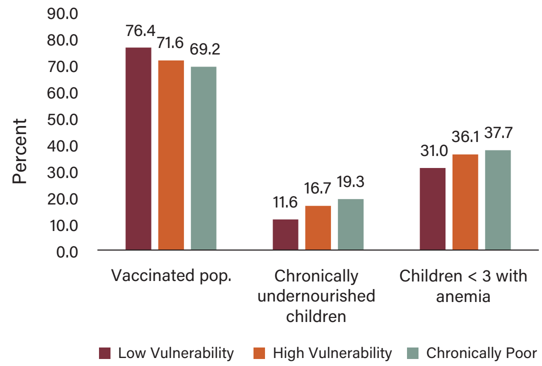
b. Infrastructure access and quality



c. Health-related infrastructure



d. Health indicators



Source: World Bank calculations based on 2017 and 2021 ENAHO data, the 2017 National Census, and Fathom remote-sensing data.
Note: Chronically poor districts show rates of poverty-induced vulnerability above the district unweighted median. Low- (high-) vulnerability districts present rates of poverty-induced vulnerability below the district median, but show risk-induced vulnerability rates below (above) the district unweighted median. A household is considered vulnerable if the probability that it will fall into poverty is above 29 percent.

4.4. The distributional effects of climate change[17]

In a context of substantial exposure to risk and vulnerability, the economic impacts of climate change pose a challenge in the effort to reduce poverty and increase shared prosperity. The impacts of climate change represent a growing threat to economic development because they influence the production capacity in most economic sectors, which translates into large welfare losses among the population, especially the poor and individuals with less capacity to adapt. The impacts are already visible. For example, the country has lost 43 percent of surface glacial area since 1970, a key source of water for the 10 million Peruvians in the Lima Metropolitan Area. These impacts are expected to become more pronounced as the frequency and intensity of shocks rises and as climate variations become more extreme across the country.

By 2050, changes in climate are expected to have affected the country's economic growth and development trajectory, with annualized losses in gross domestic product (GDP) of up to 1 percent and higher poverty rates. The "Peru: Country Climate and Development Report" (World Bank 2022) provides a general model for estimating the impacts of climate change on the economy by accounting for (1) more intense and frequent flood events, (2) the impact of heat on general productivity, and (3) the impact of climate change on agricultural and fishery yields. The results show that GDP would drop by 0.8 percent by 2050 if no mitigation measures are implemented.[18] Even under scenarios in which mitigation measures are implemented, GDP losses will still be 0.2 percent per year.[19] As a result of these losses, poverty would increase by 0.22 percentage points.[20] If additional effects through higher food price increases and lower agricultural earnings are included, the model predicts an additional 1 percent of the population will fall into poverty by 2030.[21] Hsiang et al. (2007) provide a framework to identify the six main channels through which the negative effects of climate change are exacerbated, including agriculture, labor supply, the incidence of disease, and the higher incidence of natural disasters. Box 2 provides details on the impacts of climate change in the primary sector, labor supply, and the higher incidence of disasters.

17. This section is based on the analysis in World Bank (2022), "Peru: Country Climate and Development Report," November, Latin America and Caribbean Region, World Bank, Washington, DC.

18. This is known as the business as usual (BaU) scenario, the RCP 8.5, or the warming scenario. The scenario assumes no concentrated efforts to cut back on greenhouse gas emissions. See SENAMHI (2021) for more information on the scenario.

19. The GDP loss estimates are based on a general equilibrium macroeconomic model of Peru augmented by core climate change variables from World Bank (2022). The losses in GDP through selected climate change impacts would result in higher poverty by 2050. Under the BaU scenario, estimates yield the following losses by sector: 4.3 percent in agriculture, 20.7 percent in fisheries, 0.2 percent in mining, 0.6 percent in industry, and 0.3 percent in services.

20. The increase in poverty occurs under the BAU scenario (RCP 8.5), whereby GDP losses are 0.8 percent. Poverty rates are estimated using a poverty projection model based on GDP-to-employment elasticities and productivity-to-income elasticities. GDP growth by sector is taken from the World Bank Macro-Fiscal Model (MFMod), which estimates changes in GDP through estimates on agriculture, fishing, mining, industry, and the service sectors (Burns et al. 2019).

21. The World Bank (2022) includes a scenario showing the effects of increased food prices and agricultural earnings of 2 percent–5 percent.

Agricultural, fisheries, and livestock production

Extreme temperatures will reduce agricultural yields. The greater frequency of drought, floods, frost, and cold waves will impact the agriculture sector, especially in rain-fed systems, which represent 64 percent of the land currently cultivated in Peru.[a] More extreme fluctuations in climate will cause a decline in yields in key agricultural products in Peru, such as potatoes, lima beans, green peas, barley, soft corn, wheat, and beans.[b] The agricultural sector could face losses of 23.9 percent–33.1 percent in the sector's GDP during 2010–2100.[c] Moreover, higher temperatures and climate variation could incentivize a transition toward low-value crops, reducing the income-generating capacity of rural households.[d]

Changes in water temperatures, the flows of currents, and acidification will impact the productivity of fisheries and livestock. The impact of climate change on the productivity of the ocean is expected to produce, by the end of the century, cumulative losses of around 30 times the size of the sector's current GDP. As the temperature in tropical and subtropical areas rises, livestock production will be hindered by higher animal stress, which constrains weight gain and raises mortality rates, and by a greater prevalence of disease. The economic impact generated by climate change could lead to a loss of up to 90 percent of livestock GDP by 2100 relative to 2011 levels.[e]

Labor supply

Extreme temperatures limit the person-hours available for the production of goods and services, especially in work performed outdoors. Mining and agriculture are exposed to outdoor temperatures and, in 2021, employed 30 percent of the labor force. Over 90 percent and close to 20 percent of the workers in agriculture and mining, respectively, are active in the informal sector, limiting the options available for adapting to higher temperatures.

Climate change can transform the economic landscape, incentivizing migration in the search for economic opportunity and access to dwindling natural resources. It is expected that changes in economic geography will incentivize higher internal migration from rural to urban areas. Past extreme weather events have also been linked with out-migration, a stylized fact that is reinforced because rising temperatures and extreme weather events been more closely associated with districts that are already net migrant senders in Peru.[f] This raises concerns about the capacity of urban areas to absorb climate-driven migration in a context of dwindling resources. For example, water scarcity will increase as glacial melt and changes in precipitation will significantly impact the timing and availability of water for agriculture, drinking, and energy production, and constitute the main source of drinking water in Lima.[g] Moreover, lower water access will also impact electricity production, which, in Peru, relies on hydroelectric power for two-thirds of the capacity.[h]

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a. World Bank (2017), "Gaining Momentum in Peruvian Agriculture: Opportunities to Increase Productivity and Enhance Competitiveness".
b. FAO (2015), "Modelling System for Agricultural Impacts of Climate Change (MOSAICC)".
c. ECLAC (2014), "Climate Change in Peru." Economic Commission for Latin America and the Caribbean.
d. Aragon et al. (2021).
e. IFPRI (2019), "Climate Change, Agriculture, and Adaptation Options for Peru".
f. In contrast, the more populated areas (which tend to attract internal migrants) experienced an increase in temperature that was smaller than in the average district. In 2008–17, more than 674,339 people were internally displaced because of extreme temperatures, floods, earthquakes, storms, wet mass movements. See IDMC (Internal Displacement Monitoring Centre) 2019, Peru country information (as of December 31, 2018), https://www.internal-displacement.org/countries/peru.
g. The Potable Water and Sewerage Service of Lima (SEDAPAL) is already struggling to confront regular water shortages, which will only become more severe as the population grows and the demand for water increases.
h. Recent research suggests that most Peruvian hydropower stations will experience slight increases in capacity, albeit with greater variability, out to 2100 (Caceres et al. 2021).

Higher incidence of disasters

Extreme temperature and changes in water levels will amplify the frequency and intensity of natural disasters. At current temperatures, Peru already has a high frequency of hazards (mostly earthquakes, floods, landslides, and drought). The country lies in the Pacific Ring of Fire, a highly seismic region in which about 80 percent of the world's earthquakes occur. It is also one of the countries most affected by the climatic phenomenon known as El Niño, which is associated with a greater incidence of floods (along the coast) and drought (in the highlands).[i] Increased glacial melt and changes in precipitation will significantly impact the frequency and intensity of floods, landslides, and drought. The severe episodes of El Niño in 1982–83 and 1997–98 caused estimated losses of US$6.8 billion. The recent episode in 2017 damaged roads, residences, bridges, farming areas, educational institutions, irrigation canals, and health care facilities, with estimated losses of 1.6 percent of GDP.[j] The amount of damage reaches 3.4 percent–6.4 percent of GDP if waterborne diseases are considered.[k] In addition, 18 percent of the road network was destroyed during the recent episode, and half was damaged.

Previous evidence on the effects of climate shocks may not provide a full picture of the effects of climate change because accounting for adaptation is difficult. Negative impacts on economic activity and poverty occur through a variety of mechanisms. Empirical studies rely on specific climate-related shocks that do not reflect permanent changes in the temperature and rainfall means over long periods.[22] In contrast, climate change is a gradual process that provides opportunities for adaptation, which means that the experience of large climatic shocks may not be useful in inferring impacts. In the presence of gradual change, multiple adaptation strategies are possible across households and by government, such as changes in income-generating activities, migration, and infrastructure projects.[23]

The information available showcases the large variation in exposure to floods, landslides, heat waves, and variations in precipitation in Peru. Because of its geographical extension, topography, and location, Peru has a variety of environmental conditions that lead to a wide range of risk. Map 4 shows how these risks are distributed across the districts of the country and that regions are exposed to different combinations of environmental risk. For example, while the risk of landslide is high on the central coast and in the Andes (Map 4, panel a), these same areas, because of environmental conditions, tend to be less prone to heat waves (Map 4, panel c). As expected, the coast and the Andes are also susceptible to precipitation anomalies (Map 4, panel d). In contrast, the northern coast and northern Amazon are more prone to heat waves.

i. World Bank (2016).

j. Macroconsult, "El Niño costero: Daños ya suman US$ 3,124 millones según Macroconsult," https://rpp.pe/economia/economia/el-nino-costero-danos-ya-suman-s--noticia-1039319.

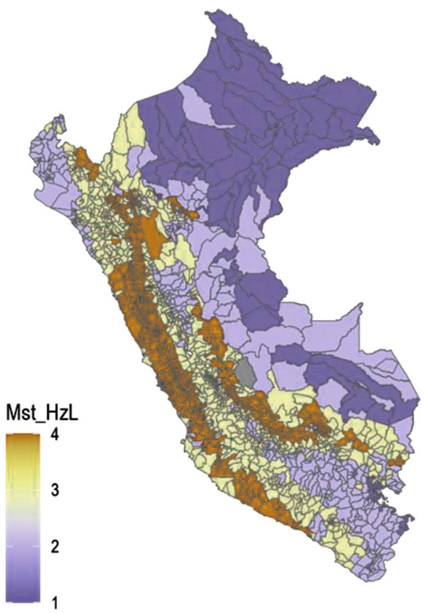
k. World Bank (2022), "Lines in the Water: Peru Water Security Diagnostic," Draft.

22. Jedwab et al. (2022).

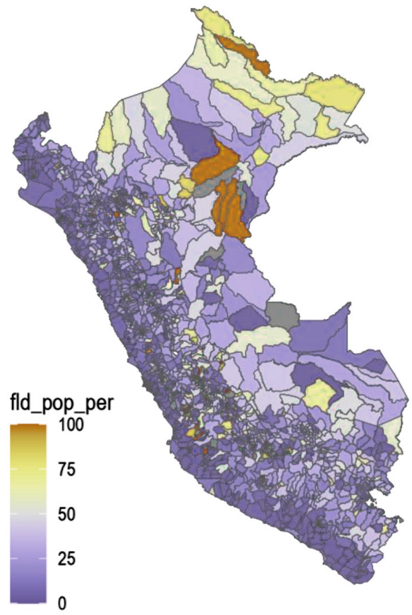
23. Some adaptation and mitigation investments are detailed by the World Bank (2022). Specifically, investments are proposed in the transport, forestry, agriculture, water, fishing, and energy sectors. For example, in transport, decarbonization measures through the development of trucking centers, the expansion of scrapping programs, electrification, and changes in habits are proposed. In agriculture, measures such as pest management, diversification in crops and livestock, soil erosion management and control technologies, and soil fertilization practices are proposed.

Map 4. Distribution of risk, Peru

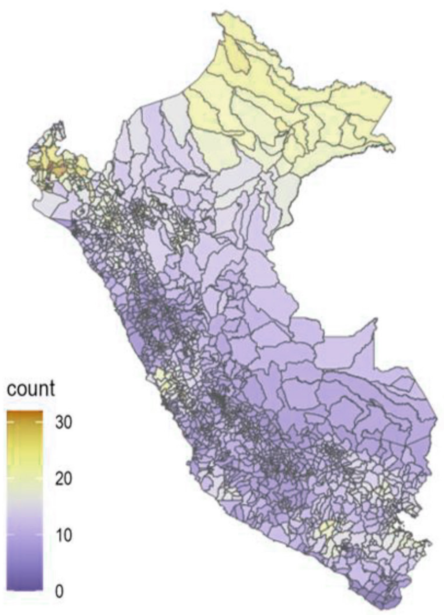
a. Landslide hazard map (hazard index)



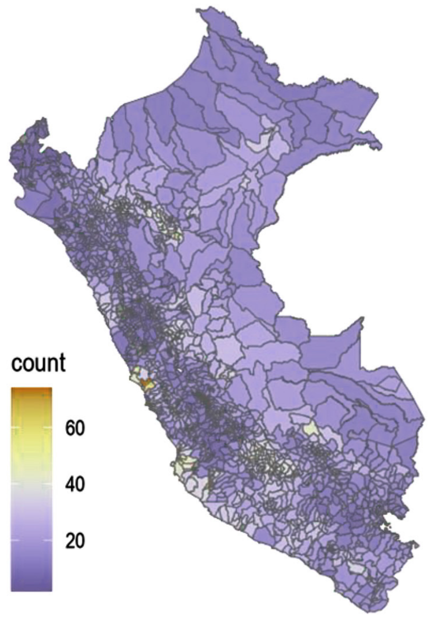
b. Population exposed to flooding



c. Exposure to heat waves, 2000–20



d. Exposure to precipitation anomalies, 2000–20

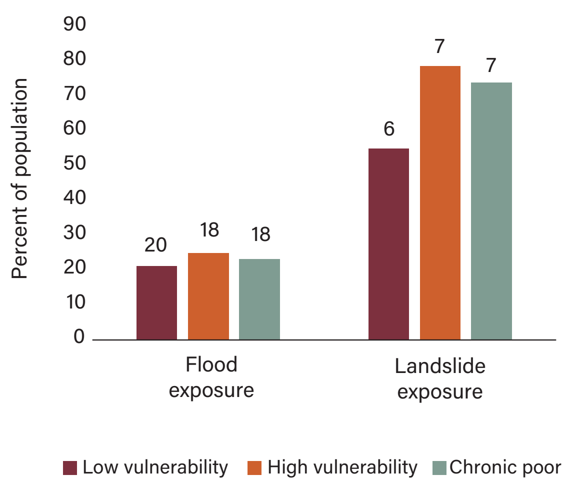


Source: Elaboration based on Fathom, SENAMHI, NASA, World Bank, and WorldPop data.
Note: Exposure to floods is measured as the share of the population exposed to a flooding event that could occur once every 100 years using Fathom data for floods and WorldPop data for population. Exposure to landslide is measured as the share of the population that is susceptible based on historic events of landslide from NASA and WorldPop data. Exposure to heat waves is measured as the number of months in 2000–20 in which temperatures were 2 standard deviations above the national average in 1981–99, using SENAMHI climate data. Exposure to precipitation anomalies is measured as the number of months in 2000–20 during which precipitation was 2 standard deviations above the national average in 1981–99, using SENAMHI climate data.

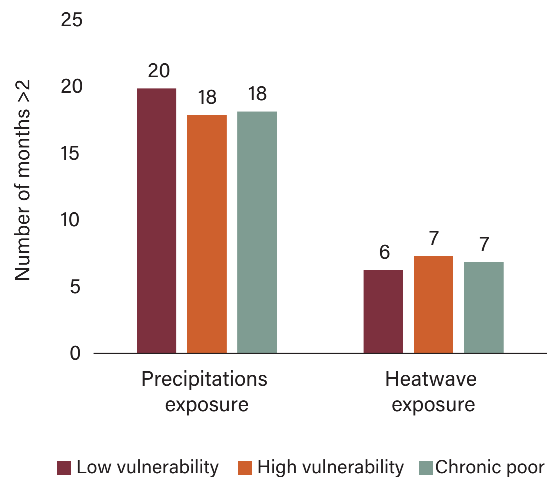
Climate inequality means that low-income households have been more highly exposed to extreme weather-related events because of spatial dynamics that place them in areas of higher risk. The exposure to specific natural hazards is a combination of meteorological, geographic, and institutional factors. In the case of Peru, 4.3 million people are exposed to floods, and 7.3 million are highly or moderately exposed to landslides. By combining the results from the poverty and vulnerability maps with additional risk indicators, one may infer that districts with higher poverty-driven vulnerability (the chronically poor in Figure a) experience greater exposure to landslides relative to districts with low vulnerability. In particular, 74 percent of the population in chronically poor districts are at a moderate or high risk of exposure to landslides, in contrast with 57 percent of the people living in low-vulnerability districts. The results do not show that important differences in the exposure to floods by vulnerability level among the populations in these districts, 23 percent versus 21 percent, indicating that shocks are location specific (Figure a). Similarly, exposure to heat waves and to precipitation anomalies is homogeneous across vulnerability levels (Figure).

Figure 8. Exposure to landslides, floods, heat waves, and precipitation anomalies, by vulnerability

a. Exposure to floods and landslides, by vulnerability level, 2017
% of population



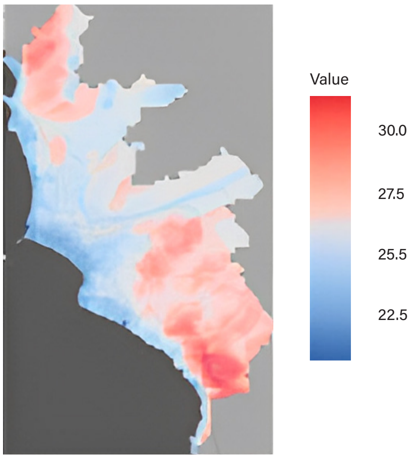
b. Exposure to heat waves and precipitation anomalies, by vulnerability level, 2000–20
Months, number



Source: Elaboration based on FATHOM, SENAMHI, NASA, World Bank, and WorldPop data on natural hazard exposure and, for vulnerability, World Bank calculations using 2017 ENAHO and the 2017 national census.
Note: Exposure to floods is measured as the share of the population exposed to a flooding event that could occur once every 100 years using Fathom data for floods and WorldPop data for population. Exposure to landslide is measured as the share of the population that is susceptible based on historic events of landslide from NASA and WorldPop data. Exposure to heat waves is measured as the number of months in 2000–20 in which temperatures were 2 standard deviations above the national average in 1981–99, using SENAMHI climate data. Exposure to precipitation anomalies is measured as the number of months in 2000–20 during which precipitation was 2 standard deviations above the national average in 1981–99, using SENAMHI climate data.

Environmental stressors are not distributed equally. Because of location-specific conditions, local studies must be implemented. Climate information is accessible at a resolution that is much higher than the resolution available in household surveys. Aggregating climate information at the level at which household surveys provide statistically representative numbers results in losing a large part of the information, which, in the case of certain shocks, such as heat waves, masks spatial inequalities in the ways households experience environmental stressors. Heat waves constitute a good example of an environmental stressor with a high degree of spatial variation that is unequally distributed even across relatively small geographical areas. Leveraging the poverty map for the Lima Metropolitan Area, Map 5 shows how, during a heat wave in late 2016, various parts of the metropolitan area consistently experienced higher temperatures, up to 15°C higher than the cooler parts of the city. By counting the number of heat waves each district experienced during 2000–20 and contrasting the result with the poverty map information, results show a consistent pattern: areas characterized by lower incomes experienced more heat anomalies (Figure panel a).[24] Furthermore, the role of heat as an environmental stressor is compounded by the fact that areas with a higher incidence of heat waves have, on average, less access to services and are characterized by dwellings that are inadequate for this type of shock. Figure , panel b shows, for example, that access to water correlates negatively with poverty, a trend that is reinforced by dwelling characteristics, such as poor types of roofs, floor materials, and sewerage.

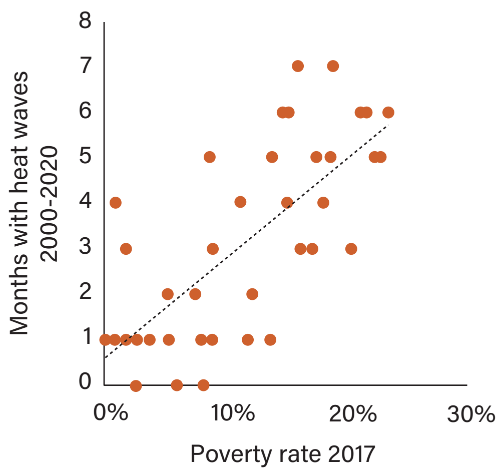
Map 5. Average daily maximum temperatures, Lima Metropolitan Area, October 2016



Source: National Service for Meteorology and Hydrology (SENAMHI).
Note: The map shows the average maximum temperatures in October 2016, a month which presented higher than average temperatures in the Lima Metropolitan Area.

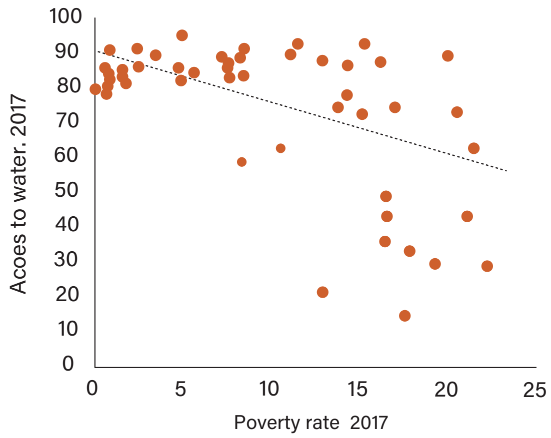
Figure 9. Heat waves, the poverty rate, and access to safe water, Lima Metropolitan Area

a. Heat waves (2000–20) and the poverty rate (2017)



24. The heat wave in the Lima Metropolitan Area refers to a month in which the average temperature was two standard deviations above the historical mean in 1980–2020. Similar results are found by Hsu, A., Sheriff, G., Chakraborty, T. et al. 2021, "Disproportionate Exposure to Urban Heat Island Intensity across Major US Cities," Nat Commun 12, 2721, https://doi.org/10.1038/s41467-021-22799-5 in US cities, where low-income households are located in areas and have infrastructure that reinforce heat waves.

b. Access to safe water, 2017, %



Source: World Bank calculations using 2017 ENAHO and the 2017 National Census. Heat information: National Service for Meteorology and Hydrology (SENAMHI).
Note: Panel a shows the number of times in 2000–20 that a district experienced a maximum temperature two standard deviations above the district-specific temperature in 1980–2000.

Not all the regions will be exposed to the same changes in weather patterns and in increases in the risk associated with climate change. Evidence suggests that the poor and vulnerable will be facing the highest levels of weather variations in the future, raising climate-inequality. Following a scenario of high emissions, the National Service of Meteorology and Hydrology of Peru (SENAMHI) estimates that, by 2050, precipitation will exhibit local variations that range from increases (reductions) of 45 percent (40 percent). The highest reductions in precipitation are expected to occur in the Amazon, while the most marked rises are expected on the coast, while regions in the Andes will suffer from both reductions and increases in precipitation. Drops in precipitation will be more common among highly vulnerable and chronically poor districts (49 percent and 48 percent, respectively) than among low-vulnerability districts (40 percent). Annual temperatures are expected to rise by between 1.7°C and 3.5°C nationwide. The Amazon is expected to display the biggest changes in temperature (from 2.8°C to 3.2°C), and the coast will experience the smallest, but still significant, increases (from 2.0°C to 2.4°C).[25] More than 75 percent of the districts in Peru are projected to display increases in temperature of more than 2.4°C in the next 30 years. Districts with projected temperature increases larger than 2.4°C are more likely to be among the chronically poor or highly vulnerable category. Around 85 percent of districts will be in these categories, compared with only 60 percent among the low-vulnerability districts (Figure 10).

Figure 10. Changes in temperature, by district category

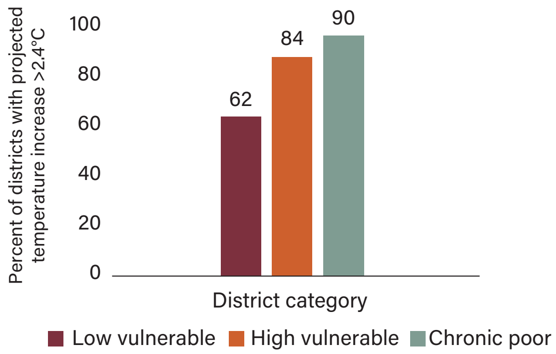
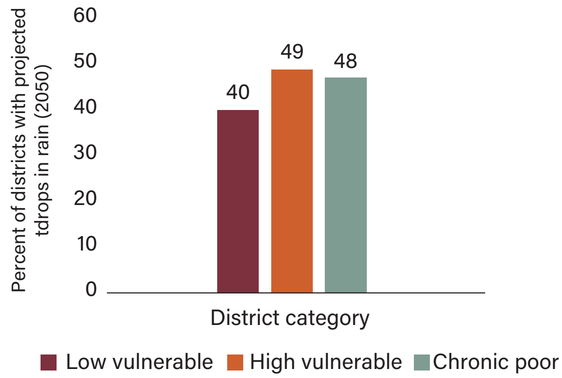


Figure 11. Expected drops in rainfall by 2050, by district category



Source: World Bank calculations using 2017 and 2021 ENAHO data and the 2017 national census. Climate changes by 2050 are taken from SENAMHI projections using the RCP8.5 scenario.
Note: A household is considered vulnerable if the probability that it will fall into poverty is above 29 percent.

25. The baseline considered is the period between 1980 and 2005, and the projections refer to the period 2036–65, centered on 2050. Changes in temperature and precipitation are estimated at a spatial resolution of 5 kilometers by 2050. This is the RCP8.5 or BaU scenario.

Specific impacts depend on the impacts on income-generating capacity and the level of public and private adaptation initiatives. Current inequalities in income and service access affect the exposure to climate hazards, the susceptibility of households to damage caused by climate hazards; and the ability of households to cope with and recover from the damage.[26] The extent to which a household is more or less exposed, susceptible to damage, and can cope and recover from climate-related shocks requires situation-specific studies that control for household characteristics, geographical conditions, and the type and intensity of shocks. Available data show that low-income households possess fewer resources for the management and recovery from negative shocks. This means they must rely on their own coping strategies, which often have detrimental effects on their long-term capacity to generate income and may become exhausted in the face of multiple shocks. Moreover, because poor people are mostly active in the informal sector (87 percent versus 65.6 percent among nonpoor households), they also have less access to formal health and labor insurance, which puts them at a disadvantage in building resilience.

Government institutions play a key role in helping poor people manage the uncertain risks of climate change. This includes promoting mitigation and adaptation actions and centralizing data. There are several measures that the various levels of government can implement to prepare the population for natural hazards, save lives, and reduce economic loss. These measures involve early warning, evacuation systems, and disaster risk prevention programs. Given the location of the country and the socioenvironmental conditions, Peruvians are highly exposed to natural disasters. Identifying the vulnerabilities to climate change, the potential economic and social impacts of shocks, and strategies to build resilience and the capacity to cope is the first step in developing and adopting mitigation and adaptation plans. That the districts that are currently poorer are projected to experience larger temperature increases suggests that climate change will worsen economic inequality across the country, signaling the need to target climate mitigation responses geographically. The implementation of such systems requires the centralization of data on the occurrence of natural events and the continuous monitoring of changes in climate (climate stations distributed across the country) and projections (from national and international models). However, there is no systematized index of climate change exposure for the entire country, though some independent efforts exist.[27]

In practice, the participation of local governments is limited. At the local level, municipalities are the highest authorities responsible for disaster risk management within their areas of competence. For instance, fewer than a quarter of the municipalities have developed risk maps, and the share is only 27 percent in districts with poverty rates higher than 50 percent. Furthermore, only 13 regions (52 percent of the total), 28 provinces (14 percent) and 39 districts (2 percent) have drafted disaster prevention plans. In practice, risk management has been undertaken mainly by central authorities.

26. Islam and Winkel (2017).
27. Independent efforts have been undertaken to systematize the information available at the province or regional level, such as the index of climate change risk used on Piura and Trujillo (CAF 2021), the map of disaster risks and vulnerability to climate change in Arequipa, Ayacucho, and Cusco (SINIA 2017), and the identification of disaster risk conditions and vulnerability to climate change in Ayacucho (SIGRID 2016). With the participation of local governments, these efforts could be systematized to create a nationwide measure of vulnerability to climate change.

4.5. Recommendations

Given Peru's vulnerability to natural hazards and the unequal distribution of the associated shocks across the country, a first step in preparing for the future would be to improve the identification of the areas and populations most exposed to climate shocks. Because georeferenced data are available in Peru (including data on the exposure to the risk of natural disasters, poverty incidence, and the quality of public services), these data should be integrated to guide policy makers in the establishment of initiatives to be prepared for future shocks. In Mexico, for example, the government has created an atlas of vulnerability to climate change across municipalities based on available data and on the expertise of local governments that became involved through a participatory process.[28]

A second step in preparing for the shocks of natural disasters would be to design adaptative social protection measures that include the vulnerable. This would involve increasing the coverage in urban areas because poverty is now an urban phenomenon in Peru. It would also involve institutionalizing flexibility arrangements that may be quickly expand if this is required, improving the interoperability of data systems, and boosting the coverage and flexibility of digital payment processes. Adaptation also implies aiming to reduce the share of informal work given that informal workers are more vulnerable than their formal counterparts.[29]

A third step would consist of improving coordination and accountability in climate and disaster risk management. Local and regional governments are currently responsible for implementing climate change policies, but the associated coordination and direction mechanisms to align these efforts with national objectives are limited, and few government authorities have the necessary implementation capacity. For instance, fewer than a quarter of the municipalities have developed risk maps. Local and regional government budgets are allocated at the beginning of the year. A complementary policy would involve conditioning the allocation of resources on the formulation and regular updating of risk management plans and improving the geographical targeting of resilient investments.

In a fourth step, the government could improve the access to resilient infrastructure and higher-quality public services. The distribution of infrastructure in Peru one of most unequal in the Latin America and Caribbean region. Poor connectivity greatly amplifies the cost of addressing external shocks. Entire communities are cut off from markets if the road network is damaged. This is especially relevant for small farmers in the Amazon and the Andes who see their production and, potentially, their incomes diminished because they are unable to reach consumers on the coast. Likewise, because climate change may overwhelm it, the health care system must be prepared to respond to surges in demand. In particular, the sector must increase the share of doctors and nurses to levels recommended by the World Health Organization and improve the spatial distribution of health services, which are currently only concentrated on the coast.

28. ANVCC (2018).
29. World Bank (2022).

In the fifth step, as countries increase their efforts to fight climate change, Peru must prepare to respond to a reduction in productivity from activities that are intensive in emissions. Only 1 percent of Peruvian exports would currently be subject to Europe's emission ban. However, if the ban were extended to minerals, estimates show that an additional 6 percent of exports might be affected.[30] Thus, the promotion of green jobs and green activities would serve as insurance against future changes in regulations among countries that import Peruvian products.

30. World Bank (2022).

Apendixes

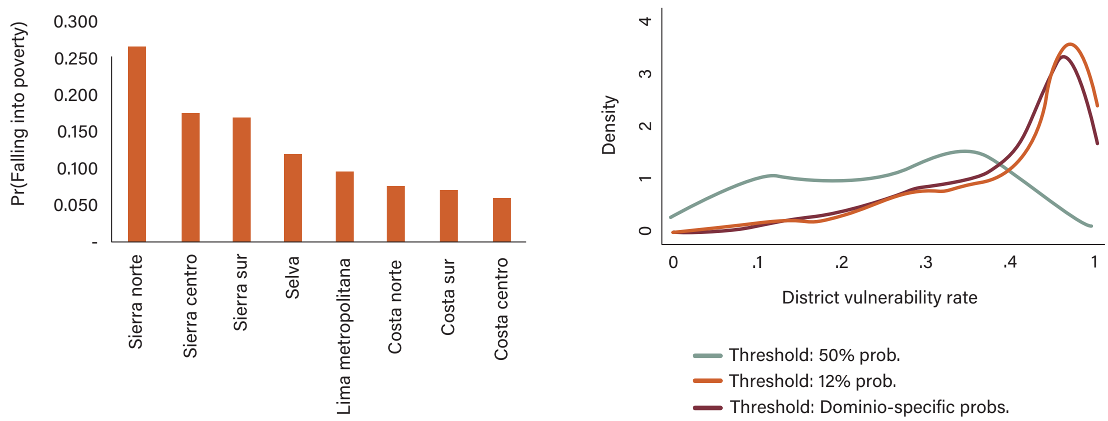
Appendix A. Vulnerability under different poverty probability thresholds

In the 2017–19 sample, 12 percent of the households that were poor in 2017 had incomes above the poverty line in 2019. Reflecting the more difficult economic environment in 2021, the probability of falling into poverty increased to around 14 percent in 2019–21. In line with this result, there was also a reduction in the incidence of transitions out of poverty. While about 46 percent of the households that had been poor stopped being poor during the earlier period, only 40 percent did so in 2019–21. There are large spatial variations in the probability of falling into poverty. One nonpoor household in every four in the Sierra Norte became poor between 2017 and 2019. This is almost five times greater than the average probability faced by a household in the central districts along the coast (Costa Centro) (Figure a).

Figure A.1. Vulnerability under various thresholds of the risk of falling into poverty

a. Probability of falling into poverty, by region, 2017–19

b. Distribution of district-level vulnerability rates, by threshold



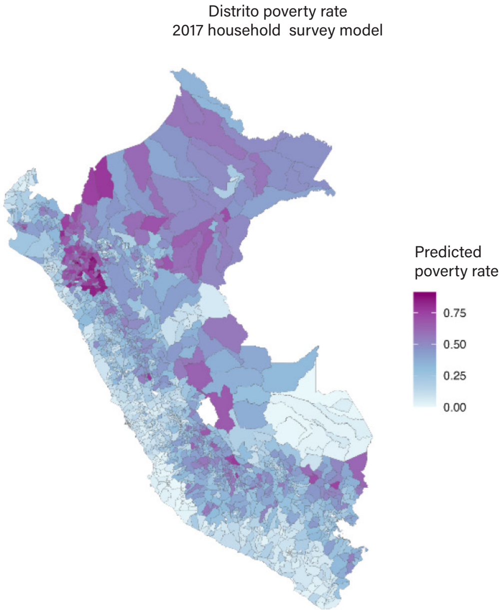
Source: World Bank calculations based on 2017 and 2021 data of ENAHO.

Vulnerability rates change according to the vulnerability threshold that is applied. Because poverty-induced vulnerability depends on projected incomes, the vulnerability rate remains unchanged across various vulnerability thresholds. Using the 29 percent threshold in the probability of falling into poverty (the threshold used to produce the main results of this chapter), 28.1 percent of households were vulnerable in 2017. Using, instead, a threshold of 12 percent as the average probability of falling into poverty, the vulnerability rate increases to 52.8 percent. Using domain-specific probabilities, total vulnerability is 45.3 percent. A similar trend occurs in the 2021 results. Figure A.1, panel b shows the distribution of the district vulnerability rates by each threshold.

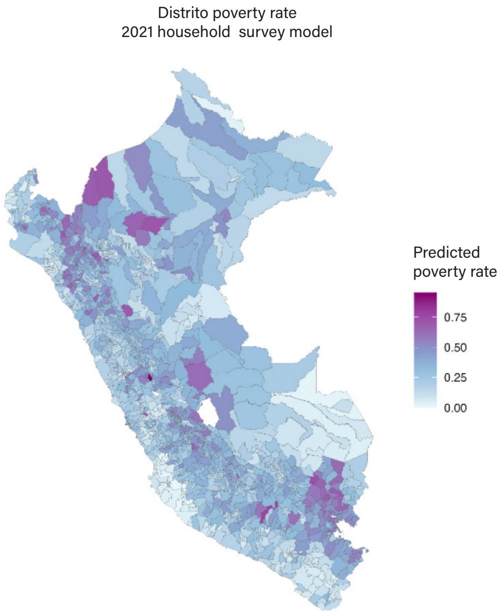
Appendix B. Vulnerability rate maps

Map B. Vulnerability rate maps, by poverty and risk-induced vulnerability

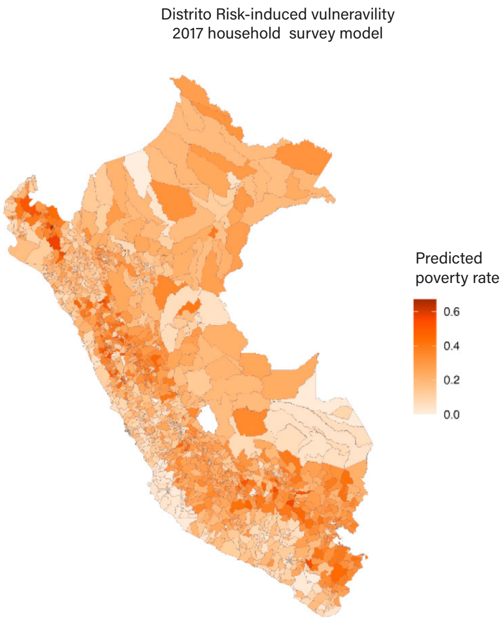
b.1. Poverty-induced vulnerability, 2017



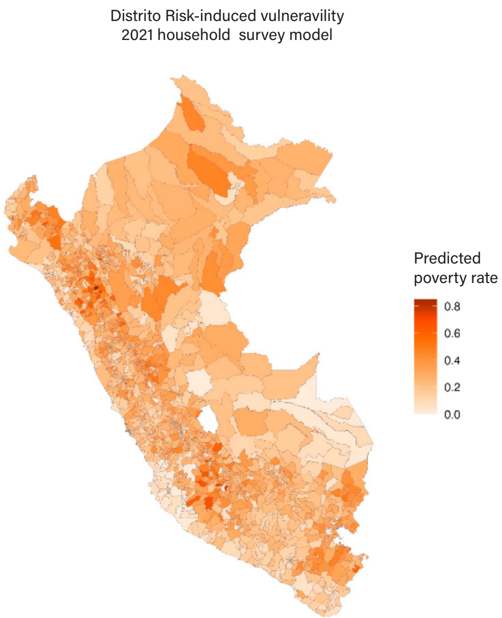
b.2. Poverty-induced vulnerability, 2021



b.3. Risk-induced vulnerability, 2017



b.4. Risk-induced vulnerability, 2021



Source: World Bank calculations based on 2017 and 2021 ENAHO data and the 2017 National Census.
Note: A household is considered vulnerable if the probability that it will fall into poverty is more than 29 percent in one year or 50 percent in two years.

Vulnerability to shocks and climate change

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