Fast Tracking poverty reduction and prosperity for all

*Dominican Republic Poverty Assessment 2023*

Background Note on Poverty and Climate Change

Central America and the Dominican Republic Country Management Unit
Latin America and the Caribbean Region

April 2023
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4 Poverty and climate change

This chapter explores the nexus between welfare and climate change and variability (including climatic shocks) in the Dominican Republic. Welfare comprises monetary indicators (for example, income poverty) and non-monetary indicators (health, education). The evidence we examine includes both historical data and projections of future welfare measures under different climate forecasts.

The chapter is organized as follows. Section 1 provides an organizing framework to understand the nexus between climate and poverty. It delves into how individuals manage climatic risk to protect their welfare. Their capacity to manage risk is mediated by their exposure to hazards, as well as the endowments and preventive and coping mechanisms they have at hand. Section 2 characterizes the main climatic hazards that affect the Dominican Republic and how these are expected to change over time due to climate change. It then examines the extent to which people and assets are exposed to climatic risks, and how these are expected to change in the future. Section 3 summarizes the main strategies that households use to mitigate climate risks and cope with their impact, people, including the role of insurance and government assistance. Section 4 looks at the effects of past climatic hazards on welfare.

While climate change might bring some benefits—for instance, higher temperatures can increase productivity—these are few and far in between. As such, this chapter concentrates on the downsides of climate change. It starts with a discussion on the distribution of damages and deaths by type of climatic hazard in the Dominican Republic. It then lays out a new means of calculating the poverty impacts of climate hazards. This chapter will rely on the following sources of information:

**EM-DAT, compiled by The Center for Research on the Epidemiology of Disasters (CRED).** Since 1988, CRED has been collecting data on disasters by country going back to 1900. Drawing on news accounts and other sources, CRED compiles information on deaths, injuries, and damage for hurricanes, floods, and other natural disasters that killed 10 or more people, affected at least 100, or resulted in a state of emergency or a call for international assistance. CRED’s data (EM-DAT) form the only publicly available global disaster database. Trends related to these records are analyzed in this chapter for the past 20 years between 2000 and 2022. For presentational purposes, the chapter focuses on floods (which include wet landslides caused by rain), storms (including cyclones) and wildfires.

**The Dominican Republic Flood Risk Assessment Household Survey (DR-FIAS).** This multi-topic survey of 2,057 households was conducted between April and May 2021, collecting information on the impact of flooding, preventive behaviors and response mechanisms for the period between April 2019 and April 2021. The survey was stratified by level of exposure to flood risk (high risk vs low risk) and urban/rural location. These unique features make it possible to produce and disaggregate key indicators on flood prevention, coping and impacts by wealth.
status) and level of risk exposure. We therefore use this survey to better understand the relationship between flood risk and poverty in the Dominican Republic (see Annex 1).

The National Labor Force Survey (ENFT). The analysis for the impacts on poverty will draw primarily from the years 2000 to 2016 from the ENFT, a household survey started in 1991 that is the official source of national labor market statistics and poverty in the Dominican Republic. The ENFT questionnaire generates a detailed characterization of individual and household information. The sampling is representative of the Dominican population and covers the mainland and surrounding islands.

4.1 AN ORGANIZING FRAMEWORK

The Dominican Republic is highly exposed and vulnerable to a large range of climatic hazards. Exposed implies that, if the country were hit by a hazard, a large proportion of its population, assets, and economic activity would be affected. This high exposure is due to the DR’s small territory and population, and the concentration of economic activity and exports in a few sectors, including tourism, agriculture and services. Vulnerable means that, when hit by a hazard, the exposed people, assets, and sectors incur significant losses—that is, a large portion of consumption or assets are destroyed, and many jobs disappear. Vulnerability is determined by the mix of preventive and reactive measures that people, communities (given their levels of deprivation) and government can undertake to prepare for shocks.

Preventive measures reduce vulnerability and thereby contain deaths and damages. Prevention can take many forms, like heeding early warnings or protecting physical infrastructure. However, not all the impacts of hazards can be prevented, and impacts depend on how individuals and governments react to the risk of disasters and cope with their impact. As part of these responsive or coping measures, individuals can self-insure, benefit from community support, buy commercial insurance, or receive aid from government. The DR’s high sovereign debt levels reduce fiscal space for undertaking the costly investments required to resist or cope with shocks, while relatively high poverty levels also contribute to high vulnerability, by limiting people’s ability to invest in their own protection. The welfare trajectories of households are thus determined by the interaction of their exposure to shocks and by the preventive and reactive measures taken to confront them. Hazards turn into deaths and losses when households and assets are both exposed and vulnerable to them.

Combined with exposure and vulnerability, the likelihood of being hit by a climatic shock allows a risk to be quantified. In practice, however, while it is possible to quantify the likelihood of hurricanes with some confidence based on catastrophe modeling and historical data, it is very difficult to quantify the likelihood of the resulting economic shock. Climate change is also altering the probability of hydrometeorological events—such as hurricanes, floods, and storms—making

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1 Due to the lack of information on income gathered by the DR-FIAS survey, a wealth index is constructed using a Principal Component Analysis (PCA) from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values of the wealth index.
it more difficult to quantify future disaster risk. In this chapter, the word risk refers to the combination of exposure and vulnerability to some shocks, knowing that these shocks will happen in the future but with no reliable quantifiable information on the annual probability of occurrence. The diagram below lays out the framework for this section (Figure 1).

**Figure 1. Climate, climate actions and welfare outcomes: a conceptual framework**

4.2 **A HIGHLY EXPOSED COUNTRY**

4.2.1 **Characterization of climatic hazards and climate change**

**Climatic hazards and climate-related events are pervasive in the Dominican Republic due to its geographical location.** Lying within the North Atlantic Basin hurricane belt, the island is subject to frequent hurricanes and intense storms that can lead to extensive damage due to strong winds, storm surges, and extreme precipitation. Cyclones and hurricanes make landfall every two years on average, but can occur as often as twice per year or as rarely as every five to ten years. Additionally, river flooding is fairly frequent in general across the country, while the northeastern region is also vulnerable to flash floods and mudslides from severe storms. In contrast, rising temperatures in arid parts of the northwest have led to more severe drought, reducing crop yields and the supply of drinking water.

The DR was ranked the world’s 12th most-affected country by climatic hazards over 1998-2017 in the 2019 Global Climate Risk Index, with hurricanes and tropical storms recurrently causing

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2 The Global Climate Risk index, calculated by Germanwatch, analyses to what extent countries and regions have been affected by weather-related loss events (tropical storms, winter storms, severe weather, hail, tornados, local storms; hydrological events such as storm surges, river floods, flash floods, landslides; climatological events such as snow and ice, wildfires, and droughts) in terms
high human and economic losses. According to EM-DAT, The Dominican Republic was the second-most-affected country in the Caribbean by natural disasters during the last two decades (with 54 recorded disasters), preceded only by its neighbor Haiti (83 recorded disasters). The most frequent disasters are storms and floods (Figure 2). There is a clear need to study the most effective ways to reduce the costs of tropical storms, floods, cyclones and other related natural disasters, which especially affect poorest households.

The unique challenge facing the DR (albeit common to other Caribbean countries and small island states) is that almost 100 percent of its territory is exposed to natural hazards. Using data from ThinkHazard, the team identified areas that are relatively more exposed to multiple hazards. Figure 3 details their findings for the Dominican Republic. Red and orange shading indicates areas where high levels of intensity for multiple hazards intersect; these are generally along rivers and coastlines due to the combined risk of flooding, landslides, and other hazards. Blue shading indicates low exposure to all hazards.

The DR’s obvious vulnerability to climate hazards raises the question: how will climate change alter the country’s exposure to these risks in the future? Climate change manifests in many ways. As the IPCC has concluded, human beings are exposed to climate change through changing weather patterns (for example, more rainfall or more intense and frequent natural hazards) and of fatalities and economic losses based on data from Munich Re’s NatCatSERVICE: https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html.

3 A study from MEPyD & World Bank (2015) finds that the annual losses from natural disasters in the Dominican Republic from 1961 to 2014 averaged USD 420 million, the equivalent of 0.69 percent of 2015 GDP. Moreover, Ishizawa, Miranda, & Strobl (2019) measure light emissions to find that tropical storms in the DR affected local economic activity up to 15 months after the event, with an average fall of 2.1 percent in nighttime brightness.

4 A reclassification scheme was used to assign levels of intensity for each hazard (0-5, with “0” being no risk or unknown risk, “1” being very low risk and “5” being extremely high risk). Specifically included in the multi-hazard model mapping are hurricanes, fluvial flooding, pluvial flooding, coastal surges, landslides, and seismic risks.
indirectly through changes to water, air, ecosystems, agriculture, and the economy. Weather patterns can include climate-induced natural hazards and the slow onset effects of climate change (like sea level rise, increasing temperatures, and ocean acidification).

Climate change is measurably affecting many parts of the world already, including the DR. A long-term increase in temperature and rainfall precipitation has accelerated in the past four decades. In the DR, the temperature increased on average by 0.8 degrees Celsius between 1901 and 1980, before rising by another 0.6 degrees from 1981 to 2021 alone (Figure 4). Volatility in precipitation has also increased since the 1960s, with the highest peaks on observed annual precipitation recorded since 1980 (Figure 5).

While a number of studies have investigated how the Caribbean’s climate is likely to change in the long-run (Centella et al., 2008; Taylor, et., a. 2013; Karmalkar, et. al, 2013), only a few have specifically or partially focused on the DR. For example, Campbell et al. (2021) divide the Caribbean into six zones, showing that the DR’s zone is likely to experience an increase in temperature ranging on average from 1 to 2 degrees under scenarios that predict a global rise in temperature ranging between 1.5 and 2.5 degrees by 2050. However, regardless of the scenario employed, their results suggest no increase in rainfall, even as the DR’s annual precipitation has risen since the 1960s (see Figure 5). Nevertheless, Stennet-Brown et al (2019) find that the DR is the most vulnerable to climate change up until 2030 out of a group of seven other Caribbean countries (Jamaica, Guyana, Belize, Cuba, Trinidad and Tobago, Barbados, the Bahamas).

The evidence is mixed as to whether climate change will lead to a greater frequency or more intense storms and hurricanes in the North Atlantic basin (Knutson et al., 2020). However, most agree that rising sea levels induced by climate change will lead to greater storm surges when

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5 To control for the year-to-year volatility and avoid biased comparisons, the calculations of temperature and precipitation variations over time uses five-year averages. As an example, the 1961 point is estimated using the average (1961-1965) and the 1901 point using the average (1901-1905).
hurricanes approach the DR. Moreover, rainfall rates during tropical storms are also likely to increase in the basin due to climate change. Vosper et al (2020) find that the number of stalling hurricanes (the primary driver for extreme precipitation during storms) will increase under various future scenarios, and hence rainfall is in fact likely to increase for the DR.

To add to existing evidence in terms of how a changing climate is likely to affect the DR specifically, the team drew on data generated by the Climate Change Knowledge Portal (CCKP). The CCKP estimates temperature, rainfall, and sea level rise for a total of six climate models which assume various levels of adaptation challenges and mitigation, combined with five different greenhouses concentration scenarios.

Climate change is expected to increase average temperatures, decrease precipitation, and increase sea-level rise. The CCKP’s climate models find that projected mean temperature in the DR will increase by 2050 under all scenarios, by little less than a half to slightly over one degree Celsius. By the end of the century, temperatures will only remain relatively stable in the more optimistic scenario; otherwise, there is likely to be a further increase from 24.5°C to 25.9°C. The most pessimistic context predicts a temperature increase of nearly three degrees from its 2020 median value. By the end of the century, average temperatures are expected to increase by 2.5 to 5°C under the CCKP’s high-emissions scenario. To put this in context, since the 1960s, the mean annual temperature in the DR has increased by approximately 0.45°C, an average rate of 0.1°C per decade (Figure 6).

Sea level rise is expected to increase dramatically. Figure 7 shows the median prediction across models in terms of sea level rise in the DR. The sea level is forecast to increase by between 16 and 19 cm by 2050 versus current levels. At the end of the century, sea levels are predicted to further rise by between 23 and 48 cm. Overall, this constitutes increases ranging between 23 and 51 per cent of current sea levels within the next 80 years.

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6 https://climateknowledgeportal.worldbank.org/
7 The models represent five different climate scenarios, namely: low challenges to mitigation and adaption (SSP1), medium challenges to mitigation and adaptation (SSP2), high challenges to mitigation and adaptation (SSP3), low challenges to mitigation and high challenges to adaptation (SSP4), and high challenges to mitigation and low challenges to adaptation (SSP6). These are applied under five different greenhouse gas concentrations, i.e., 1.9, 2.6, 4.5, 7, and 8.5 W/m2.
The number of days of extreme heat is expected to increase noticeably by 2050. Extreme heat days (above 35 degrees Celsius) will become significantly more common in all but the most optimistic scenario. By 2040-2059, the average annual number of days surpassing the heat index would be around 9.34, compared to 1.36 in the 2020-2039. By the end of the century, in a considerable bad-case scenario there could be almost 42 days per year in the national average above 35 degrees, and some areas as the Distrito Nacional could reach up to 80 days.

The impact of climate change on aridity is ambiguous. Scenarios for precipitation range from rainfall remaining stable to it falling considerably (Figure 8). However, in terms of droughts, except for in the two most optimistic scenarios, considerably drier conditions are predicted from about 2030, with the median prognosis being a fall of 1.39 standard deviations (Figure 9).

Extreme precipitation events (defined as days with more than 20mm of rainfall) have not become more common in recent years. However, warmer temperatures in the near future means that days with extreme rainfall will occur more frequently.

**Figure 8.** Projected annual precipitation change under different climate scenarios (c.2000-2100)

**Figure 9.** Projected annual SPEI index under different climate scenarios (c.2000-2100)

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8 The heat Index is a measure of apparent temperature that includes the influence of atmospheric moisture. High temperatures with high moisture lead to high Heat Index. This presents the number of days where the Heat Index surpasses 35°C over the data aggregation period. Heat Index gives insight into seasonal heat risks and changing seasonal heat risks over time.

9 This simulation considers the shared socioeconomic pathway (SSP)3-7.0 for the September-November season (the warmest season in the country).
In sum, temperature rises have already been accelerating for decades. Climate change forecasts expect average temperatures and sea levels to continue to rise more sharply, along with drops in rainfall. The risk of extreme events like floods and droughts may also increase, exacerbating the country’s vulnerability to climate-related shocks.

4.2.2 People and assets are highly exposed to climatic risk

The DR is highly exposed to weather-related shocks and climate-related events. As noted before, the country is prone to various climatic hazards due to its geographical position and island status.

An innovative way to assess exposure is to stratify risk exposure into a household survey with national coverage by geographic domains and then assess the population in high-risk areas. This is precisely what the recently conducted (2021) household flood risk survey DR-FIAS did. According to the survey, 2.8 million people, equivalent to 27 percent of the DR’s population, live in areas at a high risk of flooding (Figure 10).

Some economic sectors are more exposed than others. 76 percent of workers in the DR are in the service sector, followed by 16 percent in manufacturing and construction, and 8 percent in agriculture. Leaving aside tourism services, the last two sectors are the most prone to be affected by climatic events, as their production is directly subject to the weather. As section 4 shows (Figure 13), most reported lost workdays due to flooding are in agriculture and construction. The poor are particularly vulnerable as they tend to be overrepresented in agriculture.
Another way to assess exposure is by overlaying asset maps with modeled hazard maps for different events with different probabilities. In addition to the probability of being hit by a hurricane or being affected by coastal floods, it is important for decision-making to know the geographical location of hazards. This makes possible to assess exposure—that is, the number of people and quantity and value of physical assets that would be affected by a hazard if it occurred.

Some key assets in harm’s way in the DR include energy generation, transmission, and distribution infrastructure. Furthermore, 35 percent of the transport network is vulnerable to extreme weather events. Other vulnerability assessments estimate that 13 provinces (some 40% of the total) have high to very high vulnerability levels. Santo Domingo is particularly vulnerable to weather-related disasters and climate-related events (CCDR Concept Note).

Urban areas are particularly exposed to climatic risks. The DR is highly urbanized. In 2020, 9.1 million people (82 percent of the total population) lived in urban areas, and the country continues to urbanize at a fast pace. Close to a third (28 percent) of the urban population (2.4 million people) lives in areas highly prone to flooding. Moreover, 85 percent of the population living in high-risk areas for floods reside in urban areas. By 2050, 12.2 million people (92 percent of the projected population) will be living in urban areas, mainly in small and medium cities across the country. Large metropolitan areas (Santo Domingo and Santiago) will continue to grow, though most of the new urbanization will be absorbed in cities with fewer than 300,000 inhabitants, which are expected to grow 6 percent annually on average.

Similarly, one third of dwellings in the Dominican Republic are considered structurally vulnerable to climate hazards and climate-related events. In highly urban areas, the percentage of informal and vulnerable housing is even higher. For example, in Greater Santo Domingo and Puerto Plata, approximately 43 and 70 percent of the population live in informal settlements, respectively (CCCDR concept note). The FIAS survey indicates that floods or excess rainfall have different effects on households across regions in the DR. Between 2019 and 2021, the share of households that reported losing goods due to these shocks were mainly concentrated in the south and southwestern parts of the country (figure 11).

Figure 10. Proportion of individuals at risk of flooding by area in the DR (2021)  
Figure 11. Share of households that lost goods due to floods or rainfall (2019-2021)

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12 Oficina Nacional de Estadística (ONE). *Estimaciones y proyecciones de la población urbana por año calendario, según sexo y grupos quinquenales de edad, 2000-2030.* Urban population is defined by the Dominican government as the people who live in municipal capitals or municipal districts; the rest of the population that does not reside in these areas is considered to be rural.

13 For the last two decades, the DR has had a higher urbanization rate than the LAC regional average, with the country following a similar urbanization trend to Central American countries. Urban growth was 1.9 percent in 2019 (compared to 1 percent for LAC). In the Caribbean, only Haiti (2.8 percent) surpasses the DR’s urban growth rates.

The probability of different hazards occurring, and the exposure of assets are not enough to assess the potential damage that could occur due to these hazards. Rather, one needs to take account of the exposure of assets in terms of their characteristics (see Box 1 for the case of housing) and combine these with potential events and their impact on these assets, to ultimately generate vulnerability curves that show the risk of asset loss.

Box 1. Impacts of climatic risks on housing in the Dominican Republic

**Housing is a particularly sensitive asset to hurricanes, floods, and tropical storms.** The team combined hazard and exposure data with assumptions on housing vulnerability to propose a measure of risk across the country. The resulting high risk measure reflects a combination of higher exposure relative to the size of the country and higher vulnerability of assets.

To assess the potential damage from tropical storm activity under climate change, a set of synthetically generated hypothetical hurricanes under current and future climate conditions was linked to the distribution of household building characteristics among the DR population as of 2018, drawing on the ESH data from SIUBEN. More specifically, for each hypothetical storm, the maximum wind exposure of each household’s building was translated into the likely subsequent damage ration using damage functions which take into account the fragilities of individual components of buildings and how their effects may compound. 100,000 simulations using the probability of each storm were then undertaken to calculate the average percentage building damage across the DR for typical N-return period hurricanes for four different climate models.

Damage due to hurricanes is likely to increase in the future. Current predictions anticipate stronger and potentially more frequent storms, which may then also lead to greater housing vulnerability, depending where these storms strike. For the DR the vulnerability exercise predicted large differences across climate models, indicating the inherent uncertainty involved in tracking hurricanes and predicting intensity. Storms of a magnitude that recur every 20 years, under current climate conditions, are predicted to cause up to 6.5 percent of damage, depending on the model. For three of the models, their predicted damage will increase by the end of the century by up to 14 percent. 50-year return period storms under the current climate are expected to produce average damages of between 0.05 and 10.7 percent. For four of the climate models, this damage will increase by between 1.8 percent and 23.4 per cent. Storms returning on average every century are characterized by a further noticeable damage increase (3.2 to 24.2 percent). By the end of the century are likely to increase for three models, and could be as high as 42.9 per cent. Finally, the very storms that recur only once every 500 years are predicted to cause increased damage for three of five of the models. Overall, the simulations imply that damage due to intensive storms is likely to rise, particularly for the rarer and more damaging storms.

Source: FIAS-2021.
Note: The survey is not representative for regions or provinces; therefore estimates are subject to measurement error.
4.2.3 The poor are disproportionately exposed to floods and storms

The poor and vulnerable are more exposed to heavy rainfall and tropical storms in at least two ways. First, they tend to settle in hazard-prone areas where they can more easily afford to live. Poor households are typically pushed onto steep land or into informal settlements where land ownership is easier to come by and rents cheaper, but which are also more susceptible to damage by floods or landslides. Almost half (46 percent) of the population that live in highly flood prone areas are poor (belong to the bottom 40 percent of the wealth index).

Wealthier households are less likely to live in areas at a high risk of flooding.

**The poor are the most vulnerable to flooding.** Among the bottom two quintiles of the wealth distribution, one in every four households are at high risk of flood. In rural areas, the share of the poor population living in high-risk areas is around 29 percent, falling to 25 percent in urban centers. The incidence of high flood risk among better-off households (the top quintile of the wealth distribution) is around 14 percent in urban areas and 10 percent in rural areas (Figure 12).

![Figure 12. Proportion of households in high-risk areas by wealth quintiles and rural/urban areas (2021)](image)

**Poverty is also linked to practices that magnify exposure to climatic variability.** For instance, the use of cheap, poor-quality housing materials, or and engaging in activities that are less resilient to climate change, such as rain-fed agriculture. More than three-quarters of the poorest households have zinc roofs, which are liable to be lost or damaged during hurricanes; only 19 percent use concrete. By contrast, almost nine in ten of the wealthiest households reinforce their roofs with concrete. This exposure is compounded by the fact that the poor tend to live in more flood-prone areas. 76 percent of the poor population in high-risk areas have zinc roofs, compared to 63 percent of the poor population in low-risk areas. Other studies confirm that a large share of Dominicans does not have access to adequate housing, and more than a third of the population lives in houses that could be considered structurally vulnerable to adverse climatic shocks.

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15 Status of poverty is defined as individuals that belong to the bottom 40 percent of the wealth distribution index.
In addition, more poor households earn their livelihoods in risk-prone sectors. Close to 40 percent of the poorest Dominican workers are engaged in agriculture and construction. By contrast, 87 percent of the wealthiest individuals work in the service sector, which is theoretically much less affected by climatic events.

The overexposure of the poor to climatic risks due to their use of less resilient housing materials, living in areas with limited infrastructure, and engaging in production activities which are typically unsafe or less resilient to hazards, can be partially mitigated by the adoption of preventive and reactive measures.

4.3 PREVENTION AND COPING

Given their exposure to risk, people decide how much risk to bear and how to reduce it given the choices they have (World Bank, 2010). A person (or family) can take prevention measures that reduce the loss from a hazard (living on an upper floor or raised building to avoid losses from a flood), or buy insurance that compensates for losses when they occur. But not all shocks can be prevented, and impacts depend on how individuals and governments react and cope. There is also a distinction between self-insurance (when the person hopes to be able to absorb a loss by previously putting aside some of their own money or in-kind savings) and market insurance (which pays out a specified sum when the event occurs).

This section seeks to glean insights from the FIAS household survey to understand better how Dominicans prevent, insure, and cope when faced with climate hazards as individuals and through government relief.
4.3.1. Household flood preparedness

Preparedness to face climate shocks is among the most critical ways to prevent human losses and physical damage and mitigate negative shocks. This section describes some of the preventive actions that Dominican households take when faced with the risk of floods subject to their resources, knowledge, and access to information.

Households living in areas at a high risk of flooding correctly perceive themselves as more vulnerable to floods, but are only marginally more likely to take steps to mitigate it. Over half of the households with high exposure to flood risk live in dwellings with inadequate wall, roof and flooring materials. And yet, households at high risk of flooding adopt preventive measures (like cleaning drains or placing sandbags) against floods in similar numbers to those living in low-risk areas (Figure 15). Very few households fail to see the need for taking any preventive measures at all, but some of them lie in high-risk flood areas.\textsuperscript{16}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure15.png}
\caption{Preparedness to face climate shocks by risk status (2021)}
\end{figure}


\textit{Note}: A wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

\textbf{Poorer households perceive themselves as more likely to be affected by floods or rainfall within the next year than wealthier households.} Acknowledging the risks of floods should increase, at least in theory, the preventive and mitigation measures that poor households can implement. Yet as the previous paragraph noted in practice this does not seems to happen. The dwelling

\textsuperscript{16} Less than 5 percent of households (111 out of 2,057) reported not taking any preventive actions against floods or storms between April 2019 and April 2021, of which close to one-quarter lived in high flood-risk areas.
materials used in poorer homes and type of economic activity performed by their members leave them more vulnerable to climate shocks.

Figure 16. Households that perceive themselves likely to be affected by floods in the next year (2021)

![Figure 16](image_url)

**Source:** FIAS, 2021.

**Note:** A wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

**Poorer households are more likely to undertake simple preventive measures to protect their dwellings from floods.** Two-thirds of households in the DR perform cleaning work as a preventive action against floods. Preventive measures related to cleaning the house or drainage channels are taken similarly across different quintiles of wealth. However, digging a ditch, building a wall and putting sandbags around the house are more often done by the poorest households (Table 1).

<table>
<thead>
<tr>
<th>Measure</th>
<th>Quintiles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poorest</td>
</tr>
<tr>
<td>Cleaning dwelling surroundings</td>
<td>65.9</td>
</tr>
<tr>
<td>Cleaning drainage channels to prevent clogging</td>
<td>49.1</td>
</tr>
<tr>
<td>Participating in flood prevention activities</td>
<td>21.9</td>
</tr>
<tr>
<td>Digging a ditch around dwelling</td>
<td>38.5</td>
</tr>
<tr>
<td>Building a wall around dwelling</td>
<td>23.6</td>
</tr>
<tr>
<td>Putting sandbags around dwelling</td>
<td>15.2</td>
</tr>
</tbody>
</table>


**Note:** The wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.
Paradoxically, poorer households tend to search less for weather information or receive flood warnings. Receiving insufficient flood alerts or not looking for information on weather forecasts can reduce awareness of flooding and hinder readiness to face potential shocks. But among the poorest households, only 39 percent monitor weather forecasts compared to 72 percent among the richest households (Figure 15). The main channel used to search for weather information also varies across wealth levels: poorest households rely more on TV while wealthier households tend to scan social media or check web pages. But only two thirds of poor houses have a TV, and only 9 percent have a computer or tablet with which to access web pages. As such, improving access to weather information could increase the level of awareness during flooding events and bring huge dividends to the poor. Finally, only the wealthiest households can afford insurance against floods.

Figure 17. Preventive actions against floods by wealth quintile

Note: A wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

Better educated households are more active in searching for weather information, attending flooding information seminars, and taking out insurance. Households headed by someone with tertiary education are better informed on weather conditions: 74 percent of them actively look for weather information, relative to 55 percent of those with secondary education and 45 percent with those with primary education or less. A similar association is observed with the reception of flood warnings: 63 percent of household heads with tertiary education received them, compared to 35 percent of household heads with no or only primary education. Concerning participation in courses related to floods, the share is low in all households, albeit slightly higher in better-educated ones. Finally, having insurance for flood damage is more prevalent among those with tertiary education (8.6 percent).

Figure 18. Measures of prevention for floods by education of household head (2021)
Behavioral biases may prevent households from undertaking more preventive actions. Households in high- and low-risk prone areas check weather information, dig a ditch, clean drainage channels, and build flood-containing walls in similar proportions. At the same time, high-risk households do perceive themselves more vulnerable. So, a loss-aversion bias may be at work: people care more about the costs of undertaking some action (like retrofitting a dwelling, buying a TV, computer or tablet with which to check the forecast, or buying insurance) than about its gains, even if these are equal-sized.

Households that lost goods due to floods in 2019-21 are more aware of floods than non-affected households: they search more for weather information (65 percent versus 53 percent) and participate in more flood seminars (7 percent versus 2 percent) (Figure 17). This likely reflects the fact that people tend to underestimate the risks they have not experienced and overestimate those that they have. So people take more precautions after experiencing a shock as their perceptions of risk rise. As only half of affected households received warnings about floods, there is a clear need to increase the warning messages across the country. On the other hand, households that did not lose goods to flooding have a slightly higher proportion of insurance against floods, 3.7 percent compared to 2 percent in affected households.

Figure 19. Flood prevention/mitigation measures by households that lost goods due to floods (2021)

Note: A wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

But there are also more prosaic explanations for why people may take fewer prevention measures than might be expected. First, people without security of ownership or tenancy will be reluctant to incur the expense of prevention—even if they know the benefits—because they would not benefit if evicted. On average, household owners carry out more specific prevention measures to floods, like building a wall or digging a ditch around the house to divert the water, than households that rent or do not own their property. Second, people may not be able to afford preventive measures. Only the richest households in urban areas have insurance against floods; and incidentally these tend to be low-risk areas. In rural areas, the proportion of households with insurance against floods is close to zero.

Table 2. Adoption of flood preventive measures by status of home ownership (2021)

<table>
<thead>
<tr>
<th>Panel A: Physical preventive measures</th>
<th>Non-owners</th>
<th>Owners</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cleaning dwelling surroundings</td>
<td>65.7</td>
<td>67.2</td>
</tr>
<tr>
<td>Cleaning drainage channels to prevent clogging</td>
<td>49.7</td>
<td>55.6</td>
</tr>
<tr>
<td>Participating in flood prevention courses</td>
<td>12.0</td>
<td>23.7</td>
</tr>
<tr>
<td>Digging a ditch around dwelling</td>
<td>17.9</td>
<td>29.2</td>
</tr>
<tr>
<td>Building a wall around dwelling</td>
<td>13.4</td>
<td>17.7</td>
</tr>
<tr>
<td>Putting sandbags around dwelling</td>
<td>8.4</td>
<td>10.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Soft preventive measures</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Search for weather information</td>
<td>55.9</td>
<td>51.7</td>
</tr>
<tr>
<td>Received warning about risks of floods or rain</td>
<td>45.8</td>
<td>42.5</td>
</tr>
<tr>
<td>Has insurance for flood damage</td>
<td>4.7</td>
<td>2.5</td>
</tr>
</tbody>
</table>


Note: House ownership can occur in many ways (purchased, donated, constructed or gifted)

These various factors (flood risk, dwelling materials, education, wealth, experience of flooding, property ownership etc.) are, of course, correlated. Nonetheless, when running a multivariate regression (controlling for all of them simultaneously) on the probability of adopting preventing measures, most of these factors remain statistically significant, and in the expected direction. For instance, those households located in areas at higher risk of floods or affected by recent hurricanes are more prone to adopting preventive measures. And those households that own
their property are more likely to engage in preventive actions. The results of this regression are presented in Annex 2.

Mitigating climatic shocks thus imply undertaking measures that reduce exposure and vulnerability to contain deaths and damages. Ultimately, not all shocks can be prevented. As we have observed, many households do not undertake preventive actions; this chapter proposed two limited but plausible explanations.

Extreme weather events that cannot be prevented or insured against must be endured. To make this easier, a variety of coping mechanisms (“informal insurance,” as distinct from market insurance) exist, many rooted in tradition and custom. The next section explores some of the coping strategies devised by Dominicans in the wake of floods.

4.4.2. Coping with floods

People protect against the vagaries of weather in many ways. In rural areas, people save grain or livestock to sell in order to raise emergency funds; people in towns and cities do the same with jewelry and durables, and they also borrow from friends and neighbours after a climatic shock. However, these informal strategies (otherwise known as co-insurance) almost never provide full protection against risk.

The poor, by definition, have lower physical and human capital endowments with which to protect themselves. Climatic hazards often affect entire communities, limiting the ability of their members to lend peers money or other forms of support and thereby making co-insurance less effective. Combined with the lower physical and human capital endowments characteristic of poor households, this makes them badly situated to handle risk-related losses.

The lack of assets to protect against or recover from aggregate shocks can lead poor households to cope inadequately. An inspection of coping strategies in the Dominican Republic between 2019 and 2021 in the wake of floods and tropical storms found that savings were more readily available to wealthier families. Poorer families worked more hours and borrowed more money (given limited access to formal credit and insurance) to counter the effects of climatic shocks on consumption (Table 3). This asymmetry could have longer-term impacts on the poorest households, as they face liquidity constraints. For some in the DR, especially those near subsistence consumption, the inability to smooth consumption requires cutting back on health care, food and education. Cutting back on food consumption to smooth consumption can lead to persistent negative effects on human capital (Banerjee, Breza, Duflo, & Kinnan, 2019).

Table 3. Principal reaction of households affected by floods to cover the costs of floods by quintiles of wealth (%

<table>
<thead>
<tr>
<th>Reaction</th>
<th>Poorest</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Richest</th>
</tr>
</thead>
<tbody>
<tr>
<td>No costs</td>
<td>54.6</td>
<td>58.8</td>
<td>54.6</td>
<td>71.6</td>
<td>60.8</td>
</tr>
<tr>
<td>Use savings</td>
<td>17.6</td>
<td>21.2</td>
<td>21.3</td>
<td>18.3</td>
<td>26.1</td>
</tr>
</tbody>
</table>
Use assets | 1.0 | 0.8 | 0.5 | 0.0 | 0.0
Use loans | 15.4 | 12.1 | 13.1 | 9.1 | 9.6
Other | 2.3 | 2.1 | 0.9 | 0.0 | 1.0
Reduction of expenditure or consumption | 2.9 | 0.5 | 2.3 | 0.0 | 0.0
Employment responses* | 4.8 | 1.1 | 1.9 | 1.0 | 1.4
Migration responses* | 1.3 | 3.5 | 5.4 | 0.0 | 1.0
Households (thousands) | 377 | 395 | 335 | 403 | 250


Notes: The wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index. *Employment responses refer to members of the household without work that went to work, or working members that worked overtime or looked for additional work. **Migration responses refer to members of household migrating, or other relatives that came to live to the house to help.

Of course, people do not wait for help to begin repairing their homes and rebuilding their lives. But the poor with nothing to fall back on or at the risk of resorting to harmful coping behaviors like eating less, may require help. In these contexts, the DR government often provides transfers in cash and kind.

**Assistance and type of assistance for households affected by floods**

If immediate remedial action is taken by governments, drops in consumption and income losses can be smoothed. Well-targeted, sufficient and timely food aid or cash transfers can stabilize consumption or avoid welfare impacts in the wake of climate shocks. But this is not always the case in the Dominican Republic.

**While assistance is higher among households that lost goods due to floods, overall assistance is negligible.** During floods, 4 percent of households that lose goods receive assistance compared to 1.3 percent of those that do not lose any. After floods, the share is 7.7 percent and 1.8 percent, respectively (Figure 18). Similarly, poorer households tend to receive higher shares of assistance than wealthier households (4 percent versus 1 percent), but very few of those affected receive any support at all (Figure 19).

**Figure 20. Assistance for households affected by floods or rainfall (2019-2021)**

**Figure 21. Share of households receiving assistance after flooding events by wealth quantile (2019-21)**

Note: A wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

**Food assistance from government is the main form of support.** Most of the time, help comes from the government, followed by friends and neighbors. Of all the households that received assistance, 58.8 percent reported that the help came from the national and/or municipal government. The type of assistance is mainly food and in kind (excluding food), reaching 63.3 percent of all households that received assistance (Figure 20).

**Figure 22. Who provides assistance, and what type of assistance households receive, after flooding events (2019-2021)**

<table>
<thead>
<tr>
<th>a. Who assisted</th>
<th>b. Type of assistance</th>
</tr>
</thead>
<tbody>
<tr>
<td>National government</td>
<td>35.8</td>
</tr>
<tr>
<td>Friends and neighbors</td>
<td>23.8</td>
</tr>
<tr>
<td>Municipal government</td>
<td>23</td>
</tr>
<tr>
<td>Friends and neighbors and others</td>
<td>6.3</td>
</tr>
<tr>
<td>Religious org and friends</td>
<td>3</td>
</tr>
<tr>
<td>Other</td>
<td>2.2</td>
</tr>
<tr>
<td>Religious organization</td>
<td>2.2</td>
</tr>
<tr>
<td>Municipal government and friends</td>
<td>1.8</td>
</tr>
<tr>
<td>NGO</td>
<td>1.5</td>
</tr>
<tr>
<td>Community organisation</td>
<td>0.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Food</th>
<th>In kind (excluding food)</th>
<th>Other</th>
<th>Cash, in kind and labour</th>
<th>Cash and food</th>
<th>In kind and other</th>
<th>Cash</th>
<th>Labour</th>
<th>In kind and labor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage</td>
<td>49.6</td>
<td>13.7</td>
<td>12.3</td>
<td>8.8</td>
<td>6.8</td>
<td>4.7</td>
<td>2.1</td>
<td>1.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Source: FIAS, 2021. Note: The sample is restricted to households that are affected by floods and that receive assistance after floods. Some answers combine two different responses and therefore appear more than once.

Note: A wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

The DR is moving towards an adaptive social protection system (ASP) with an emergency cash transfer, a social registry with national coverage, and a flexible payment system. If well-targeted and delivered on time, these measures could have a profound impact in assisting poor households in dealing with climate shocks.

**In sum, unfortunately not all disasters can be prevented. As such, their impacts will often depend on how individuals and governments react and cope.** Climatic shocks often affect entire communities, making co-insurance less effective, which combined with the lower physical and human capital endowments characteristic of poor households make them badly situated to cope with losses. They have few assets to mitigate the impact of a disaster, and public assistance is minimal or doesn’t come at all; in such conditions negative impacts on welfare are all but inevitable. The next section explores serious direct impacts like death, as well as indirect impacts through drops in consumption or human capital losses.
4.4 IMPACTS ON WELFARE

How can we assess the impacts of climate change on welfare over time? Climate change is demonstrably taking place already in many parts of the world, including the Dominican Republic. As such, the welfare impacts of climate change can be assessed looking back at recent historical data. This section presents an original assessment of the historic impact of climatic shocks on observed welfare outputs like labor income and monetary poverty in the DR. Trends in temperature and rainfall variability are expected to continue. Climate science and economic theory can therefore be combined to forecast welfare impacts using climate projections.

4.4.1. Past Impacts, Immediate Effects - Deaths and Distress from Disasters

Few people die from disasters, but more are being affected (injured, homeless, and in need of immediate assistance). Among the most visible and direct impacts of climate change is more and stronger natural hazards, which can often kill. In the DR, more than 1,300 people died from such shocks between 2001 and 2022. Figure 21, drawing on EM-DAT data, nevertheless shows that deaths dropped considerably over the past decades: a few years with many deaths punctuate most years with few deaths. The number of people affected in the last decade seems to be dropping as well, but numbers are still in the thousands.

Figure 23. Disasters are killing fewer Dominicans, but more are being affected

The number of affected people should not be lightly dismissed. While a drop in the number of people affected in recent years may reflect more comprehensive coverage of the databases or better government programs and responses due to the role of cell phones/social media in early warnings, the high number of affected people could still reflect greater exposure to hazards. Moreover, complacency might arise from keeping mortality under control, while ignoring that disasters also cause survivors lasting distress.
4.4.2. Damage and Losses can Increase Poverty

Even if they recover, victims are worse off for having experienced the climatic shock. The most visible and severe impact of many climatic shocks is death. But for survivors, climate shocks also bring indirect difficulties: socio-economic activities are disrupted and public infrastructure and physical and productive assets are damaged or destroyed. In urban areas, floods and hurricanes damage housing, which is often used to host a small business like a workshop or cafe, especially in the DR. Damage may also occur to infrastructure (water, sanitation, electricity) or social facilities (schools, health centers). In rural areas, climatic shocks may result in crop and livestock losses and destruction of housing and infrastructure as in urban areas.

The provision of public services for households is similarly impacted for all households across the wealth distribution. Floods similarly affect household water supply, sewerage and the electricity service irrespective of wealth quintile. The main service affected due to floods is electricity, with 24 to 30 percent of households reporting power cuts depending on the wealth quintile. These power outages could have negative impacts on households via losses on employment and productivity (Ali, 2016), as electricity is a crucial input for production at home (for example, in a small business or restaurants) or industry. The productivity loss can be explained by the reduction in the physical or cognitive ability of workers: for example, the reduction in labor efficiency when electricity outages coincide with high temperatures or low visibility (Ali, 2016). Importantly, these losses are more prevalent in developing countries, where many small businesses are run out of households.

Between 2019 and 2021, half a million Dominican households in high-risk areas were affected by floods or excessive rainfall in some way. Power cuts and water entering the dwelling are the most common impacts. Around one in four urban households living in high-risk areas reported flooding inside their houses. Impacts on the water supply are more prevalent among households living in high-risk areas (21 and 24 percent of households affected in high-risk urban and rural areas, respectively). The electricity supply was interrupted after flooding for between 22 and 27 percent of households regardless of their risk exposure (Figure 22).

Figure 24. Share of households affected by floods by type of effect and zone (% 2019-2021)
**Damage to and Losses of Physical and Human Capital Assets**

The poor and vulnerable are more susceptible to losses from heavy rainfall and tropical storms. Poorer households report water entering their dwellings or damaging their goods more often. The specific characteristics of more affluent households (for example, better drainage and sealed entrances) mitigate the risk of floodwater entering their home. One in four poor households report floodwater entering their houses between 2019 and 2021, compared to only 11 percent in the wealthiest households. Flooding inside dwellings is particularly problematic because it increases the probability of immediate health impacts such as injuries or insect bites that can lead to infected wounds or chronic diseases (Du, FitzGerald, Clark & Hou, 2010). Flooding is also related to an increased risk of hepatitis E, gastrointestinal diseases and bacterial diseases like leptospirosis, particularly in areas with poor hygiene (Alderman, Turner, & Tong, 2012). Relatedly, the proportion of households in the poorest quintile that report losing household goods due to floods is 12.5 percent, compared to 5.8 percent in the wealthiest quintile (Table 4).

**Table 4. Share of households affected by flooding by quintiles of wealth (%, 2019-2021)**

<table>
<thead>
<tr>
<th>Quintiles</th>
<th>Poorest</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Richest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water entered house</td>
<td>26.2</td>
<td>21.4</td>
<td>17.9</td>
<td>16.1</td>
<td>11.0</td>
</tr>
<tr>
<td>Lost household goods</td>
<td>12.5</td>
<td>7.8</td>
<td>6.2</td>
<td>4.3</td>
<td>5.8</td>
</tr>
<tr>
<td>Water source affected</td>
<td>17.5</td>
<td>17.5</td>
<td>18.3</td>
<td>16.9</td>
<td>14.4</td>
</tr>
<tr>
<td>Sanitary service affected</td>
<td>7.4</td>
<td>6.1</td>
<td>6.8</td>
<td>6.4</td>
<td>4.9</td>
</tr>
<tr>
<td>Electricity service affected</td>
<td>24.2</td>
<td>30.0</td>
<td>24.6</td>
<td>26.1</td>
<td>23.7</td>
</tr>
<tr>
<td>Households (thousands)</td>
<td>734</td>
<td>755</td>
<td>621</td>
<td>709</td>
<td>682</td>
</tr>
</tbody>
</table>


**Note:** The wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

A multivariate regression analysis confirms that wealth status is inversely correlated with reporting flood-related losses and water entering the house (see Annex 3). Living in high flood-risk areas during the major hurricanes Laura and Isaias (July-August 2020), which brought with them heavy rainfall, is also associated with higher chances of experiencing asset losses and water damage.

The poorest workers also miss more workdays due to floods. Around 18 percent of workers in the poorest households reported losing days of work between 2019 and 2021 after being affected by a flood. Only 4 percent of all workers in the wealthiest households reported the same (Figure 11). Each time flooding prevents workers from coming into work, it makes it more likely they will lose their job. And loss of employment is associated with a decrease in the current and long-term earnings of workers, even if they find a new job in a similar firm (Jacobson, LaLonde & Sullivan, 1993).
Workers in the agriculture and construction sector are the most affected in terms of missed workdays due to floods or rainfall. Both agriculture and construction represent less than 15 percent of total employment in the DR, but poor and affected households (proxied by lost workdays) are overrepresented in these sectors. In April 2019-2021, one quarter of agricultural workers reported missing work due to these phenomena (Figure 13). Some sectors like real estate, health services, and public administration were not affected by floods during that two-year period.
Households linked to small-scale agriculture or livestock rearing tend to be in the poorest households, many of whom lost half of their total production to floods. 17 percent of poor households grow crops or rear livestock, while only 6 percent of the wealthiest homes are engaged in these economic activities. A large portion of households linked to agricultural or livestock activities were affected by floods during this period, ranging from 30 percent to 41 percent depending on their wealth quintile (Table 5). Importantly, in the vast majority of those households their crops were affected. 91 percent of the poorest households reported losses of more than half of their crop production, compared to 33 percent in the wealthier households. This difference could imply long-term obstacles to the prosperity and wellbeing of poorer households: without access to insurance or credit, repeated production losses due to flooding could trap them in poverty.

Table 5. Share of flooding-affected agricultural households by wealth quintile, (2019-2021)

<table>
<thead>
<tr>
<th>Quintile</th>
<th>Poorest</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Richest</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHs with agricultural or livestock activities</td>
<td>16.9</td>
<td>10.8</td>
<td>13.3</td>
<td>9.4</td>
<td>6.3</td>
</tr>
<tr>
<td>Agricultural activities were affected by floods or rainfall</td>
<td>36.5</td>
<td>37.9</td>
<td>32.9</td>
<td>41.4</td>
<td>30.5</td>
</tr>
<tr>
<td>Crops were affected</td>
<td>76.5</td>
<td>85.0</td>
<td>92.5</td>
<td>100.0</td>
<td>76.5</td>
</tr>
<tr>
<td>More than half of crop production destroyed in last flood</td>
<td>91.3</td>
<td>56.3</td>
<td>77.7</td>
<td>74.1</td>
<td>32.8</td>
</tr>
</tbody>
</table>

Note: reference period is April 2019 to April 2021.
The wealth index is constructed using a PCA analysis from a range of goods that the household has along with certain characteristics of the households. Next, the first principal component is used to predict the values to create five quintiles of the wealth index.

Individuals whose households were flooded are significantly more affected in terms of labor, education and health outcomes (Table 6). In households where water enters their dwellings, individuals missed workdays more frequently relative to those in households that were affected by flooding but where water did not enter their home, or individuals from households that were not affected at all (23 percent versus 17 percent and 5 percent, respectively). They also show more job losses (95 percent could return to work by the time of the interview versus 98 percent and 99 percent, respectively). They missed school days more frequently (28 percent versus 18 percent and 7 percent) and had significantly more health problems due to floods (9 percent versus 1 percent and 0.8 percent).

Table 6. Outcomes for individuals ages 5-64 by effect of flooding, 2019-2021

<table>
<thead>
<tr>
<th>Household affected by floods, but water did not enter</th>
<th>Household not affected by floods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floodwater entered dwelling</td>
<td></td>
</tr>
<tr>
<td>Missed work due to issues with floods</td>
<td>22.7</td>
</tr>
<tr>
<td>Workdays lost due to the last flood</td>
<td>4.7</td>
</tr>
<tr>
<td>Could return to work after the last flood</td>
<td>94.6</td>
</tr>
<tr>
<td>Panel A: Labor outcomes for individuals between 25 and 64 years</td>
<td></td>
</tr>
</tbody>
</table>
Families in the DR employ different kinds of coping strategies to mitigate the impact of flooding on household production. Some miss workdays, pull children out of school to work at home, or send a member or the head of the household to a nearby city to look for work. These join potential strategies like selling durable assets, using savings, or selling livestock. It is difficult to establish which of these strategies are more or less effective or damaging for example, making children work could alleviate short-term difficulties but ultimately lead to them permanently dropping out of school, hampering their life chances. However, it is clear that the short-term consumption of poor households affected by floods tends to drop sharply, and that government support tends to arrive late or not at all.

**Box 2: Do floods affect women and men equally?**

This section explores the differentiated impacts that flooding has for women and men in Dominican Republic. The analysis is focused on the labor market as well as how preventive measures and household profiles could be linked to those asymmetrical impacts. No significant gender differences were observed in the impacts of flooding upon educational and health outcomes, but for labor outcomes there are differential effects.

**Men lose workdays more often due to floods, but permanent job losses are more likely among employed women.**

Men are overrepresented in construction and agriculture, both of which are vulnerable to the elements. As a result, more men reported missing workdays due to floods than women between 2019 and 2021 (16 percent vs 9 percent). Relatedly, men lost on average 4.5 days of work during the last flood experienced, while females lost on average 3.2 days. However, after a flooding event, 6 percent of women could not return to work by the time of the interview versus 2 percent for men. Thus, flood recovery is smoother for men. This situation mimics the trends observed during the COVID-19 pandemic, where more men recovered their pre-pandemic employment levels than women by 2021.

**Job losses for women are focused among poorer households. Floods might be producing additional barriers to the development of vulnerable Dominican women.**

The proportion of men that can return to their work after a flooding event is higher than among women, especially among poorer households. At most, 90 percent of women in the poorest households returned to work, compared to full recovery for those in the wealthiest households. Younger women also found it somewhat harder to return to work: 12 percent of female workers between 25 and 34 years old did not return to work after the last experienced flood, compared to 2 percent of females between 35 and 54 years old.

**Higher permanent job losses among young women might be explained by the presence of children within the household.**

The presence of children (aged 5 or below) in the household significantly changes the impact of flooding on labor market outcomes for women. 11 percent of women living in households with children did not return to work after a flooding event, compared to 1 percent of women living in child-free households. Social norms that cast women in the role of primary carers amplify the burden on women when they lose their job. Specific policies boosting childcare in the area could help mitigate the asymmetric impact of floods on females.
In the DR, female-headed households search less for weather information and are less likely to receive flooding warnings relative to male-headed households. The share of male-headed households receiving flood warnings is 47 percent, but this falls to only 40 percent for women-headed households. The proportion of households actively searching for weather information is 56 percent for those headed by men, and 50 percent for women-headed households. Female household heads have similar levels of education and access to radio, TV and mobile phones than male heads, but tend to be older, which may mean they are less likely to consult web pages or news channels for flood information.

Assets (physical and human capital) help to generate income, which in turn enables households to consume goods and services. Loss or interrupted access to income-generating assets (i.e., sewing machines, fridge, cooking equipment) occasioned by floods or other climatic events can cause income to plunge. And tighter budgets have the potential to lessen consumption. Indeed, poorer households are more likely to incur additional expenses when affected by floods. In the poorest quintile, the proportion that incurred further costs from floods is 45.4 percent relative to 39.2 percent in the wealthiest quintile.

The inability to smooth consumption after climatic shocks can push people into poverty. A comparative study of 15 countries from Africa, South and East Asia and Latin America found that experiencing shocks while receiving no social protection was among the main drivers of poverty. Among all types of shocks, natural disasters were the second-most common reason why people became poor, with health issues and mortality the most common reason (Narayan, Pritchett and Kapoor, 2009). As noted, some people, especially those near subsistence consumption, reduce their consumption to counter the effects of climatic shocks, which may explain why shocks cause many to fall into poverty.

Box 3: Poverty impacts of climatic risks in the Dominican Republic

Objective. This analysis by the World Bank focuses on understanding and quantifying the causal effects of tropical cyclones and flooding on households’ economic well-being in Dominican Republic (focusing on poverty and labor income outcomes). The empirical design exploits cross sectional variation in weather shocks across locations to estimate the causal effects of weather shocks on household-level outcomes.

Data. The database gathered for this study combines several datasets. To begin with, we use repeated cross-sections of geographically coded household-level data from the Labor Force Survey (ENFT) collected bi-annually between 2001 and 2016. Weather shocks combining meteorological variables (rainfall and wind speed) with technical vulnerability variables come from a variety of sources (see Annex 4). The wind data contains information on all tropical cyclones that have occurred within the Atlantic Ocean since 1949, including the position of the eye of the storm and its maximum wind speed at 6-hour intervals. Flood hazard data has complete coverage of the Dominican Republic and a spatial resolution of approximately 90m. The values describe the fluvial flood hazard (a river that exceeds its capacity because of excessive rainfall) and pluvial flood hazard (caused when heavy rainfall creates a flood event independent of an overflowing water body) expressed as the maximum expected water depth in meters at 10 different return periods for each type of flood. Rainfall information comes from the network of weather stations spread over the DR territory (grids) and runs from 1979 to 2016.

Methodology. The estimation strategy builds on the fact that cyclones and flooding are a source of exogenous variation that impacts geographical locations at different intensities over the course of the time sample. The empirical method takes advantage of the different intensities and types of weather shocks observed across locations between survey waves. Weather shocks at different locations generate changes in household outcomes that vary systematically across locations. We also exploit observable differences in vulnerability to cyclones and precipitation. We control for local characteristics and trends that affect household outcomes, aggregate shocks (at
different frequencies) not related to weather, and non-weather shocks that affect households differentially across locations. The model of the impact of weather shocks on household outcomes is as follows:

\[ Y_{int} = c + \beta H(s_{mt}, z_{mt}) + \rho F(r_{mt}, v_{mt}) + \delta X_{int} + f(m, t) + \epsilon_{int} \]

Where,

\[ Y \] is the relevant outcome variable (mainly income poverty, poverty gap and labor income) for household \( i \) in location \( m \) at time \( t \). \( H(.) \) is a measure of windstorm shocks at location \( m \) at time \( t \). \( F(.) \) is a measure of flood shocks in location \( m \) at time \( t \). \( X_{int} \) is a vector of constant and time varying household characteristics. \( f(m, t) \) is a deterministic component of poverty that varies over time and location, and \( \epsilon_{int} \) is an i.i.d random disturbance affecting household \( i \) at time \( t \). The \( H(.) \) shock is a function of raw measurement of cyclones wind speed \( s \), and cyclone specific vulnerability \( z \), while the \( F \) shock is assumed to be a function of precipitation \( r \) and flooding vulnerability \( v \). We assume that flooding shocks for location \( m \) and time \( t \) are given by the following functional form:

\[ F(r, v) = \begin{cases} 1 & \text{if } rv^\gamma \geq \gamma \\ 0 & \text{otherwise} \end{cases} \]

Where \( \alpha \) and \( \gamma \) are parameters, \( r \) is a measure of rainfall and \( v \) is a measure of vulnerability defined as the share of the population of location \( m \) in flood zones.\(^{17}\) A second assumption concerns the baseline definition of the \( H \) shock and consists of assuming \( z_{int} = 1 \) and that \( (s_{m,t}, z_{mt}) = I(\max_t(s_{mt}) \geq 96) \). That is, we assume that the wind shock is equal to 1 if the maximum wind observed in period \( t \) at location \( m \) is greater than 96 and zero otherwise.\(^{18}\) We confirm the quality of our assumption on \( z_{int} = 1 \) using auxiliary estimations where we include a vector of house quality and neighborhood characteristics as to proxy for \( z_{int} \). These variables are presumably related to cyclone (windstorms) vulnerability for a given household interacted with the cyclone shock. We also consider alternative definitions of \( H \).

It is assumed that the vector of household characteristics affects household outcomes linearly according to vector \( \gamma \). This vector captures household-level differences in outcomes within a period of time and a location that are not accounted by weather shocks. It is assumed that these variables contain enough richness that they can capture aggregate shocks that are not related to weather.\(^{19}\) It is also assumed that the aggregate secular component of household outcomes are composed of three elements. First, a “crisis” dummy that takes the value 1 in the years when the DR experienced a financial crisis (i.e. 2003-2004), an intercept that depends on location and a linear time trend that depends on location:

\[ f(m, t) = \phi \text{Crisis}_i + \mu(m) + t\theta(m) \]

In our estimations we assume that \( m \) and \( \theta \) are permanent fixed effects and linear trends that are allowed to vary across regions but are constant for all municipalities within a region.

**Results.** Our first set of regression investigates the impact of weather shocks measured over the six months prior to each survey wave. The rainfall variable that enters our flood shocks is measured as the maximum seven-day precipitation observed over the period. The flood vulnerability variable is measured as described in the previous section. The combination of rains and vulnerability determine the value (0 or 1) taken by the flood shock variable depending on the vulnerability in the region and the scale and threshold parameters in the measurement of the weather shock. The windstorm shock variable takes a value of 1 if there was at least one cyclone event, defined as

\(^{17}\) More precisely, our vulnerability indicator consists of the share of population in location \( m \) that resides in a sublocation of \( m \) for which the maximum flooding depth within the next 100 years equals at least 10 meters deep. The construction of these variables is described in our data section.

\(^{18}\) Based on the Saffir-Simpson scale that define hurricane categories. Sustained winds over 96mph are defined (at least) as a category two hurricane, which is conceptualized as extremely dangerous winds that will cause extensive damage.

\(^{19}\) However, in auxiliary regressions we include Hodrick Prescott filtered observations of semi-annual GDP, filtered at different frequencies. These filtered series allow us to purge our regression of aggregate shocks not related to weather.
a wind speed above 96KmH sustained over 10 minutes, within the period. In our basic estimations, the cyclone vulnerability variable is set to 1 for all locations and survey waves.

Our baseline estimation is presented in Table B3.1 and considers the effects of floods and cyclones on the basic set of household outcomes. All the coefficients for floods have the expected sign. Floods increase poverty and extreme poverty, lower all measures of income considered, increase poverty gaps, and decrease hours of work. Results suggest that heavy windstorms account for an increase of 2.4 percentage points in overall poverty and 0.8 percentage points in extreme poverty. Floods produce similar impact, increasing overall poverty by around 2.4 percentage points. The poverty impact is correlated with decreases in family income; in particular household labor income is reduced by around 4.7 percent by floods and 3.4 percent due to windstorm events. Note that the effect of both floods and cyclones is stronger in increasing poverty than in increasing extreme poverty, and both have the expected sign. The impact for the already-poor population is considerable: the poverty gap (the distance between family income and the poverty line) increases by 13 percent associated with flooding events and around 10 percent for heavy windstorms.

Results also indicate a clear case that the effects of weather shocks during the last six months come primarily from shocks experienced in the last month. This suggests that the impact on outcomes is usually short-lived. However, the results should be taken with caution, as the study is restricted to one-time effects of shocks in the last six months. The study is silent about the effect of continued exposure to weather shocks over protracted periods of time.

Table B3.1. Baseline Regressions

<table>
<thead>
<tr>
<th></th>
<th>Poverty</th>
<th>Extreme poverty</th>
<th>Ln labor income</th>
<th>Ln hourly wage</th>
<th>Ln total income</th>
<th>Poverty gap</th>
<th>Extreme poverty gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flood</td>
<td>0.0244***</td>
<td>0.00902***</td>
<td>-0.0440***</td>
<td>-0.0472***</td>
<td>-0.0415***</td>
<td>0.0180***</td>
<td>0.0022***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0042)</td>
<td>(0.00606)</td>
<td>(0.00989)</td>
<td>(0.00720)</td>
<td>(0.00720)</td>
<td>(0.00396)</td>
<td>(0.00103)</td>
</tr>
<tr>
<td>Windstorm</td>
<td>0.0248***</td>
<td>0.00900***</td>
<td>-0.0403***</td>
<td>-0.0314***</td>
<td>-0.0470***</td>
<td>0.0177***</td>
<td>0.0016***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00263)</td>
<td>(0.00166)</td>
<td>(0.00956)</td>
<td>(0.00552)</td>
<td>(0.00552)</td>
<td>(0.00132)</td>
<td>(0.000792)</td>
</tr>
<tr>
<td>Crisis</td>
<td>0.0546***</td>
<td>0.0160***</td>
<td>-0.144***</td>
<td>-0.147***</td>
<td>-0.105***</td>
<td>0.0205***</td>
<td>0.00313***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00326)</td>
<td>(0.00206)</td>
<td>(0.00624)</td>
<td>(0.00682)</td>
<td>(0.00556)</td>
<td>(0.00151)</td>
<td>(0.000792)</td>
</tr>
<tr>
<td>Obs</td>
<td>168829</td>
<td>168830</td>
<td>145578</td>
<td>125655</td>
<td>168857</td>
<td>168829</td>
<td>168829</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.204</td>
<td>0.112</td>
<td>0.346</td>
<td>0.284</td>
<td>0.369</td>
<td>0.212</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Notes: Results from OLS regression controlling for age, sex, years of education, and marital status of household head, demographic dependency ratio and area of residence (urban/rural). All estimations include location-specific fixed effects, location-specific time trends. For income-related variables the number of observations drops because zero or negative observations is not defined: a robustness check adding 1 cent to every income category is available from the authors and yields similar results. Precipitation reference period: 1 month before the ENFT collection period using 5 days of accumulated precipitation to classify extreme events. Source: Calculations by the authors based on data from ENFT and flood and windstorms data.

A second set of regressions measures the impacts of floods and cyclones at different time horizons. The period of time aggregation for the weather shocks varies by only including the weather data from two or one months before the survey is deployed. This selects some shocks from the regression, in particular, shocks occurring earlier in the semester that runs between adjacent waves of the household survey. Selecting shocks at different horizons enables us to isolate the effect of shocks that occur closest to the survey wave. By comparing the magnitude of the restricted effects with the magnitude of the effects in the baseline regressions, we can investigate the time pattern of the impact of weather shocks on households. The comparison of coefficients reveals that the effect of windstorms on income-related variables does not vary substantially when only the cyclones in either the last 2 or 1 months before the survey are included.

In the case of floods, the impacts on income-related variables (columns 3-5) drop quite substantially when only shocks in the 2 months prior to the survey are kept, but do not fall as much when only shocks from the month before are kept. We interpret this pattern as reflecting some instability in the estimated coefficient, which, according to the probabilities of the t-statistics, is not measured very precisely. In summary, the impact of cyclones seems to be coming from cyclones within 1 month of the survey for all outcomes, while the effect of flooding seems less stable across specifications, reflecting lower precision.

Table B3.2. Percent Change with Respect to Baseline Coefficient
4.5 CONCLUSION

The Dominican Republic is highly vulnerable to climate change and variability, particularly floods and tropical storms. Climatic shocks cause death and destruction and can affect welfare, both in the short- and long-run. Survivors may find their incomes plunge, thus reducing consumption expenditures on food, health or education. The evidence demonstrates that income and consumption poverty, health and nutrition are measurably affected by climate change. Poor households bear the bulk of the impacts and use costly strategies to cope with the aftermath of a shock: they may migrate, sell their few available goods (including productive assets), take children out of school, or undermine their long-term health by eating less well, all of which can reduce lifetime earnings. Greater public support for poor and vulnerable households is warranted, as the evidence shows that government protection is meager and rarely reaches those who need it. Families adopt preventive measures against flood and storm risks, but cognitive biases, liquidity constraints, perverse land incentives and asymmetric information impair the wider adoption of these measures across the population.
REFERENCES


ANNEXES.

ANNEX 1. The Dominican Republic Flood Risk Assessment Household Survey (DR-FIAS)

Sample frame

The census frame of reference is based on the household count of the census segments contained in the segmentation used to carry out the IX Census of 2010, which were chosen as primary sampling units (UPM). The process of segmentation of this framework of geographical areas or conglomerates, was carried out taking as a geographical unit the municipal districts within the municipality and province, with their respective polygons, supervision area and segments. To this framework were added several variables segmented by high and low risks to floods according to the work carried out by the World Bank DRM team.

The database of geographical clusters was assessed and verified to select the UPMs as geographical conglomerates of the sampling frames to conduct the surveys, and includes the entire country containing the number private households of 25 to 200 per UPM. The reference framework has a total of 37,711 UPM or geographical clusters and 2,614,109 occupied private dwellings. Table A1 contains the distribution of conglomerates such as UPMs and occupied private dwellings of this reference census framework:

Selected sample

For the survey, a total of 2,560 households were selected in private dwellings in 128 geographic clusters or census segments as primary sampling units (PSUs), of which 1,280 households were selected in urban areas in 64 PSUs or census segments, and 1,280 households were also selected in rural areas in 64 PSUs or geographic clusters. However, during the survey in the field, some households were lost for various reasons, such as: refusal to give the interview, members temporarily absent, dwellings unoccupied or converted into businesses, etc. Table A2 shows the distribution of households with completed questionnaires in occupied private dwellings and the response rates (RR) obtained during the survey, by estimation domain.

Table A1. Total effective geographic clusters, selected households with complete interviews, according to estimation domain or stratum

<table>
<thead>
<tr>
<th>Geographical domain of estimation or stratum</th>
<th>Selected PSU (Response rate=100%)</th>
<th>Selected households</th>
<th>Effective households</th>
<th>Response rate % (RR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>128</td>
<td>2,560</td>
<td>2057</td>
<td>80.4</td>
</tr>
<tr>
<td>1. Urban areas at high risk of flooding</td>
<td>32</td>
<td>640</td>
<td>505</td>
<td>78.9</td>
</tr>
<tr>
<td>2. Urban areas at low risk of flooding</td>
<td>32</td>
<td>640</td>
<td>456</td>
<td>71.3</td>
</tr>
<tr>
<td>3. Rural areas at high risk of flooding</td>
<td>32</td>
<td>640</td>
<td>553</td>
<td>86.4</td>
</tr>
<tr>
<td>4. Rural areas at low risk of flooding</td>
<td>32</td>
<td>640</td>
<td>543</td>
<td>84.8</td>
</tr>
</tbody>
</table>

Figure A1. Spatial distribution of coordinates of the selected clusters
Data collection

The final sample is equally distributed into the four main strata: 1) urban areas at high risk of flooding, 2) urban areas at low risk of flooding, 3) rural areas at high risk of flooding, and 4) rural areas at low risk of flooding. The final design consisted of 32 conglomerates per strata and 20 households per conglomerate. The final number of surveys conducted during the fieldwork was 2,057 households with a response rate of 80.6 percent.
### ANNEX 2. Correlates of Preventive Measures against Floods (OLS regression)

<table>
<thead>
<tr>
<th></th>
<th>Perform soft prevention measures</th>
<th>Perform physical prevention measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>2nd wealth quintile</td>
<td>0.040</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>3rd wealth quintile</td>
<td>0.035</td>
<td>-0.080</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>4rd wealth quintile</td>
<td>0.075**</td>
<td>-0.046</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>5th wealth quintile</td>
<td>0.111***</td>
<td>-0.090*</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Own dwelling</td>
<td>0.040</td>
<td>0.060***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>High-risk areas</td>
<td>0.008</td>
<td>0.054**</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Urban</td>
<td>-0.006</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Rainfall/100 (Laura)</td>
<td>0.065***</td>
<td>0.130***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Rainfall/100 (Isaias)</td>
<td>0.064***</td>
<td>0.149**</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.332***</td>
<td>-0.169</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.283)</td>
</tr>
</tbody>
</table>

Households: 3,314,533

R-squared: 0.035

---

Cluster standard errors in parentheses

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

**Notes:**

(a) Control variables included in the regression are level of education, age, gender and marital status of household head. Also, the latitude and longitude of the household is included as control.

(b) Survey weights are used in the estimation of the linear probability model. All the coefficients should be interpreted as changes in the probability of the independent variable; hence they are multiplied by 100 and interpreted as percentage points change.

(c) The rainfall data for hurricanes Isaias (July 30, 2020) and Laura (August 22-23, 2020) was extracted from the GPM rainfall satellite mission, which provides half hourly observations at the 0.1 degree resolution. Rainfall for each storm was identified as rainfall that fell in DR during the lifetime of the storm when it was within 500km of the DR, and then summed to obtain a storm total. Each household was matched to the closest grid cell sum, as determined by the distance to the cell’s centroid, generating a household specific storm rainfall aggregate value.
ANNEX 3. Correlates of Flood Impacts (OLS regression)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Water entered dwelling</th>
<th>Household lost goods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical prevention measures</td>
<td>0.093***</td>
<td>0.055***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Soft prevention measures</td>
<td>0.059**</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>2nd wealth quintile</td>
<td>-0.071**</td>
<td>-0.064**</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>3rd wealth quintile</td>
<td>-0.109**</td>
<td>-0.069***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>4th wealth quintile</td>
<td>-0.113***</td>
<td>-0.088***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>5th wealth quintile</td>
<td>-0.182***</td>
<td>-0.077**</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Own dwelling</td>
<td>0.063**</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>High-risk areas</td>
<td>0.053*</td>
<td>0.045***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.019</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Rainfall/100 (Laura)</td>
<td>0.118***</td>
<td>0.051*</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Rainfall/100 (Isaias)</td>
<td>0.112**</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.603**</td>
<td>-0.187</td>
</tr>
<tr>
<td></td>
<td>(0.271)</td>
<td>(0.209)</td>
</tr>
</tbody>
</table>

| Households                                      | 3,314,533              | 3,314,533            |
| R-squared                                       | 0.067                  | 0.046                |

Cluster standard errors in parentheses

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

Notes:
(a) Control variables included in the regression are level of education, age, gender and marital status of household head. Also, the latitude and longitude of the household is included as control.
(b) Survey weights are used in the estimation of the linear probability model. All the coefficients should be interpreted as changes in the probability of the independent variable; hence they are multiplied by 100 and interpreted as percentage points change.
(c) The rainfall data for hurricanes Isaias (July 30, 2020) and Laura (August 22-23, 2020) was extracted from the GPM rainfall satellite mission, which provides half-hourly observations at the 0.1 degree resolution. Rainfall for each storm was identified as rainfall that fell in DR during the lifetime of the storm when it was within 500km of the DR, and then summed to obtain a storm total. Each household was matched to the closest grid cell sum, as determined by the distance to the cell's centroid, generating a household specific storm rainfall aggregate value.
ANNEX 4. Variable Information on Poverty Impacts of Climatic Shocks (OLS regression)

Household Survey Data

The Encuesta Nacional de Fuerza de Trabajo (ENFT) is a household survey started in 1991. The ENFT sampling is representative of the DR population, and covers the Dominican Republic’s territory and surrounding islands with an average response rate of 82 percent. The ENFT questionnaire covers a detailed characterization of individual, households, and housing information. The ENFT is the official source of national labor market statistics and poverty in Dominican Republic.

Several changes to the sampling design and periodicity of the ENFT were conducted over its first decade. We thus focus on the survey waves within the 2001-2016 period. In this period, the survey was deployed every six months during the first week of April and October. Between 2001 and 2002, the survey was based on 576 geographical Primary Sampling Units (PSU). These sampling areas were originally delineated by the 1996 Census. The PSU definitions were updated for survey waves conducted in 2003 and beyond by using the updated PSU from the 2002 Census, and the number of PSU was increased to about 980.

The household’s PSU is available in our dataset, but more granular geographical information is not provided by the ENFT to protect the anonymity of respondents. While it would be desirable to base our geographic granularity on the PSU definition, the random selection of PSUs for interviewing leave us with a heavily unbalanced panel. We thus focus on the “Municipio” geographical aggregation level. Since each Municipio contains many PSU and the sampling of PSU is stratified at the Municipio level, we guarantee the availability of a sample of households for each Municipio at every wave of the survey.

To exploit the geographical coding of the ENFT, we took two steps. First, we linked each one of the Municipio labels provided in each household entry of the survey waves to a geographical polygon coming from the relevant census delineation. For this purpose, we superimposed the census delineation over an administrative map obtained from Google Maps and then used the Municipio names from the survey to link the household survey observations to the physical census polygon.

In a second step we linked the Municipio polygons across waves. For waves that used the same census delineation this was trivial. For adjacent waves that employ different census delineations we found the best geographical matching polygons and linked them across survey waves. Also, we used the harmonized household weights provided by the ENFT to ensure the backward comparability of the 2001-2002 sampling with the 2003-2016 sampling.

Welfare Variables
We employ several ENFT variables at the household level to construct the indicators that we employ as dependent and independent variables in our regressions. All monetary values are expressed in constant Dominican Pesos of 2007 using the monthly CPI available provided by the Central Bank of DR at [https://www.bancentral.gov.do/a/d/2534-precios](https://www.bancentral.gov.do/a/d/2534-precios).

**Dependent Variables, Income:**

The ENFT provides comprehensive information about sources of income. Total labor income includes monetary and the self-assessed value of in-kind labor compensation. Monetary labor income includes salary, commission, tips, overtime, paid vacation, bonuses, occupational dividends, fringe benefits, business profits, secondary or contractor’s occupational income. In-kind labor income includes compensation for primary and secondary activities in terms of food, housing, transportation, fuel, cellphone and other goods and services. Monetary nonlabor income includes retirement, interest and dividends, rental, domestic transfers, divorce, bequest, government aid. In-kind nonlabor income includes in-kind transfers from family, school and government. Foreign income includes pension, interest and dividends, bequests and remittances. Household income corresponds to the sum of income across all members of the household classified as working during the previous week.

**Dependent Variables, Poverty:**

*Poor*: dummy variable takes the value 1 if the household is considered poor. The variable is constructed by comparing the household total income per person to the poverty line. The poverty line used corresponds to the cost of the minimum food and basic services bundle and is available from [https://www.one.gob.do/sociales/pobreza-asistencia-social-y-condiciones-de-vida/pobreza](https://www.one.gob.do/sociales/pobreza-asistencia-social-y-condiciones-de-vida/pobreza).

*Extreme*: dummy variable takes the value 1 if the household is considered extremely poor. The variable is constructed by comparing the household total income to the extreme poverty line. This poverty line corresponds to the cost of a minimum food bundle and is available from the link in the previous definition.

*Gap*: this variable measures the gap between the household and the poverty line. We calculate it as the ratio of the real per capita household income and the poverty line for extreme poverty minus one.

*GapExtreme*: this variable measures the percent gap. We calculate it as the ratio of the real per capita household income and the poverty line for extreme poverty minus one.

*Log_pc_y*: log of total family income.

*Log_pc_nonl_y*: Log of percapita nonlabor income.

*Pc_L_y*: Percapita labor income.

**Dependent Variables, Other:**
**Crowded**: This variable takes the value 1 if there is overcrowding in the household. We say that a household is overcrowded if the number of people divided by the number of dormitories in the living quarters is greater than 3.

**ChildLabor**: Dummy that takes the value 1 if there is at least one person under 15 years old registered as working.

**AssetIndex**: Consists of a principal components principal factor.

**NumAssets**: Counts the number of durable good classes that the household owns among the following set of classes: stove, refrigerator, car, motorcycle, D/C to A/C current inverter (used with batteries during power outages).

### Climatic Data

**Wind Data**

Our wind data comes from the HURDAT Best Track database available from the National Oceanic and Atmospheric Administration (NOAA). This data contains details on all tropical cyclones that have occurred within the Atlantic Ocean since 1949. The data contains information on all tropical cyclones in the North Atlantic Basin, including the position of the eye and the maximum wind speed of the storm at 6-hour intervals. We focus on observations of maximum sustained winds over a 10-minute period observed at 6-hour intervals over the entire life of each tropical cyclone in the data.

**Flood Hazard Data**

We employ proprietary flood hazard data from Fathom (previously SSBN). The data has complete coverage of the Dominican Republic and a spatial resolution of 3 arcsecond (approximately 90m). The values describe the fluvial flood hazard (a river that exceeds its capacity because of excessive rainfall) and pluvial flood hazard (caused when heavy rainfall creates a flood event independent of an overflowing water body) expressed as the maximum expected water depth in meters at 10 different return periods for each type of flood. We choose the depth values corresponding to a 1-in-100 year flood, that is, the water depth that is expected to be exceeded on average once every hundred years. More specifically, we consider that a cell of the grid is flood-prone if the water depth is expected to exceed 30 cm in a 1-in-100 year flood, either fluvial or pluvial.

The flood model consists of an empirical relationship that predicts flood incidences based on the accumulated normalized rainfall and exposed population:

\[ R_{m,p,d} = \begin{cases} 
1, & \text{if } A_{m,p,d} \cdot (E_m)^\beta \geq U \\
0, & \text{if } A_{m,p,d} \cdot (E_m)^\beta < U 
\end{cases} \]

where \( R \) is a flood incidence indicator variable for municipality \( m \) at day \( d \), \( A \) the normalized precipitation accumulated over the past \( p \) days, \( E \) is the share of exposed population, and \( U \) are the parameters to be estimated. To calibrate parameters \( \beta \) and \( U \), one needs data on daily

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20 Calibration results for \( p=5 \) and \( 30 \) are given in Table 1. Accordingly, for both accumulation windows the optimum value of \( \beta \) is 0.25. In contrast, using a shorter accumulation period suggests a substantially higher threshold value \( U \). The higher F1-score for \( p=30 \) than \( p=5 \) (25.8 vs. 18.1%)
accumulated rainfall and flood exposed population and indicators of known flood events at the municipality level. In that sense, we use the geo-localized inventory of DISINVENTAR of reported events over the period 2000-2012, while accumulated, alternatively over 5 or 30 days, daily rainfall was derived from the CHIRPS\textsuperscript{21} data, and flood exposed population was identified from the flood model described above. Since there was some concern that the probability of reporting a flood event in DISINVENTAR could be larger in municipalities where more of the population was affected, the municipality’s exposed population and the number of events captured in DESINVENTAR were compared. The correlation coefficient was found to be 0.84, supporting the likely underreporting of flood events in less populated areas. Thus, the validation exercise for the flood model was restricted to municipalities that had at least 50,000 inhabitants as of 2002, resulting in 25 regional units. Calibration is assessed using an F\textsubscript{1}-score.

\emph{Rainfall Data}

Rainfall information comes from the network of weather stations administered by National Weather Office (ONAMET) and the National Institute of Hydric Resources (INDRHI) and from satellite information of the Modern Era Retrospective-analysis for Research and Applications (MERRA). The station data runs from 1979 to 2016. This data was collected by a collection of stations spread over the DR territory (grids). After 2011 the number of installed grids is 114. The raw data for 1979 to 2011 comes from (at most) 126 stations and the data for 2012-2016 comes from (at most) 114 stations. Stations break down over time and there are other data issues that reduce the effective number of stations at a particular measurement day.

\textsuperscript{21} CHIRPS: Rainfall Estimates from Rain Gauge and Satellite Observations. University of California.