ZENTRUM FÜR ENTWICKLUNGSFORSCHUNG (ZEF)

Economic and non-economic impacts of weather shocks in Ecuador
Unequal effects on vulnerable populations

DISSERTATION

zur

Erlangung des Grades

Doktorin der Agrarwissenschaften (Dr. agr.)

der

Agrar-, Ernährungs-, und Ingenieurwissenschaftlichen Fakultät

der Rheinischen Friedrich-Wilhelms-Universität Bonn

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Quito, Ecuador

Bonn, 2025

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Tag der Promotion: 28. Mai 2025

Angefertigt mit Genehmigung der Agrar-, Ernährungs-, und Ingenieurwissenschaftlichen Fakultät der Universität Bonn.

Printed with the German Academic Exchange Service (DAAD) support.

Abstract

Climate change threatens development. The more frequent and severe weather extremes already have economic and non-economic consequences that deepen social inequalities and disproportionately affect disadvantaged populations. This doctoral thesis examines the impacts of weather extremes on income distribution, poverty, and allocation of labor time, focusing on Ecuador, a highly vulnerable country to climate shocks. More generally, Latin America has received little attention in the literature on climate change impacts. We estimate the impact of weather shocks in rural and urban Ecuador resulting from people's reliance on climate-sensitive activities. We also analyze how weather shocks impact non-economic aspects such as time allocation. The study uses 25 annual panel datasets with statistical representation at the national, urban, and rural levels, enabling analyses based on over 100,000 observations with econometric models. The thesis consists of three essays.

In the first essay, the impacts of recurrent rainfall shocks on rural areas are explored. Weather extremes can damage productive assets and sources of income. Households already weakened by an initial shock become even more vulnerable to subsequent ones, especially if they have not fully recovered from the initial shock. Our findings reveal that a single shock reduces per capita income by 9%, and a second subsequent shock by 13%. The poorest are disproportionately affected, especially from the second shock that slashes their income by more than half, leaving them significantly more vulnerable and impoverished.

In the second essay, in addition to household and weather data, we incorporate geographic information, such as the risk of drought, landslides, and flooding, and analyze the social distributional effects of extreme weather events in urban areas. We find that women are more adversely impacted than men, and those living in high-risk areas suffer more than those in non-risky areas. However, the poorest of the poor endure the worst consequences. Rainfall shocks push the 10th percentile of households further away from the poverty line by -9.8 percentage points, expanding their poverty gap by 62%. We contribute to the urgent need to explore the effects of climate shocks in urban contexts and reveal how rainfall shocks exacerbate the socioeconomic conditions of disadvantaged urban populations, pushing them further into poverty and worsening social inequality.

The first two essays address economic aspects, providing new insights into the impacts of repeated weather shocks and geographic information. The third essay goes beyond economic impacts and explores how weather shocks affect labor allocation through time spent on household activities. We quantify how excessive and insufficient rainfall shocks increase the time spent on unpaid housework, especially among already disadvantaged groups such as women, poor households, rural communities, and the intersection of being a woman and poor. These analyses address a significant gap in the literature on climate change, gender, and labor allocation. The results show that rainfall shocks add two hours per week to domestic unpaid work. Disadvantaged populations suffer much worse consequences than the relatively better-off. The most affected group is poor women.

This thesis highlights that weather extremes have major economic and non-economic impacts. Poor households, women, and people living in high-risk areas are particularly vulnerable, implying that weather extremes are further widening disparities in economic and non-economic dimensions. The findings of this thesis emphasize the need for targeted strategies and policies, such as social safety nets, that mitigate the adverse impacts of climate change and promote equity and social inclusion.

Wirtschaftliche und nicht-wirtschaftliche Auswirkungen von Wetterextremen in Ecuador: Ungleiche Effekte auf vulnerable Bevölkerungsgruppen

Zusammenfassung

Die zunehmende Häufigkeit und Intensität extremer Wetterereignisse hat bereits sowohl wirtschaftliche als auch nicht-wirtschaftliche Folgen, die soziale Ungleichheiten vertiefen und benachteiligte Bevölkerungsgruppen überproportional treffen. Diese Doktorarbeit untersucht die Auswirkungen extremer Wetterereignisse auf die Einkommensverteilung, Armut und Arbeitszeitallokation, mit einem besonderen Fokus auf Ecuador, ein hochgradig anfälliges Land für Klimaschocks. Generell wurde Lateinamerika in der Literatur zu den Auswirkungen des Klimawandels bisher wenig berücksichtigt. In dieser Arbeit teilen wir eine Einschätzung zu den Auswirkungen von Wetterextremen auf ländliche und städtische Gebiete Ecuadors, insbesondere mit Hinblick auf die Abhängigkeit der Bevölkerung von klimaanfälligen wirtschaftlichen Tätigkeiten. Darüber hinaus analysieren wir, wie sich Wetterextreme auf nicht-wirtschaftliche Aspekte wie die Zeitnutzung auswirken. Die Studie basiert auf 25 jährlich erhobenen Panel-Datensätzen mit statistischer Repräsentativität auf nationaler, städtischer und ländlicher Ebene. Dies macht die Analyse von mehr als 100.000 Beobachtungen anhand ökonometrischer Modelle möglich. Die Dissertation besteht aus drei Aufsätzen.

Im ersten Aufsatz werden die Auswirkungen wiederkehrender Niederschlagsschocks auf ländliche Gebiete untersucht. Extreme Wetterereignisse können produktive Ressourcen und Einkommensquellen schädigen. Haushalte, die bereits durch einen ersten Schock geschwächt wurden, werden noch anfälliger für nachfolgende Schocks, insbesondere wenn sie sich nicht vollständig vom ersten erholt haben. Unsere Ergebnisse zeigen, dass ein einzelner Schock das Pro-Kopf-Einkommen um 9 % reduziert, während ein zweiter aufeinanderfolgender Schock es um 13 % senkt. Die ärmsten Haushalte sind überproportional betroffen, insbesondere durch den zweiten Schock, der ihr Einkommen um mehr als die Hälfte reduziert und sie erheblich verletzlicher und verarmter zurücklässt.

Im zweiten Aufsatz werden zusätzlich zu Haushalts- und Wetterdaten geographische Informationen wie das Risiko von Dürren, Erdrutschen und Überschwemmungen berücksichtigt. Es werden die sozialen Verteilungseffekte extremer Wetterereignisse in städtischen Gebieten analysiert. Unsere Ergebnisse zeigen, dass Frauen stärker betroffen sind als Männer und Haushalte in Hochrisikogebieten stärker betroffen sind als jene in weniger gefährdeten Gebieten. Besonders gravierend sind die Auswirkungen jedoch für die ärmsten Bevölkerungsgruppen. Niederschlagsschocks bringen das das ärmste 10. Perzentil der Haushalte um -9,8 Prozentpunkte weiter von der Armutsgrenze weg und vergrößern ihre Armutslücke um 62 %. Diese Studie leistet einen Beitrag zur dringend notwendigen Expansion der Forschungslandschaft bezüglich der Auswirkungen von Klimaschocks im städtischen Kontext, und zeigt auf, wie Niederschlagsschocks die sozioökonomischen Bedingungen benachteiligter städtischer Bevölkerungsgruppen verschlechtern, diesie tiefer in die Armut drängen und soziale Ungleichheiten verstärken.

Während sich die ersten beiden Aufsätze auf wirtschaftliche Aspekte konzentrieren und neue Erkenntnisse über wiederkehrende Klimaschocks und geographische Informationen liefern, geht der dritte Aufsatz über ökonomische Effekte hinaus und untersucht, wie Wetterextreme die Arbeitsallokation in Haushalten beeinflussen. Wir quantifizieren, wie übermäßige und unzureichende

Niederschläge die Zeit, die für unbezahlte Hausarbeit aufgewendet wird, erhöhen – insbesondere für bereits benachteiligte Gruppen wie Frauen, arme Haushalte, ländliche Gebiete und die doppelte Belastung von Frauen in Armut. Diese Analysen schließen eine bedeutende Forschungslücke im Zusammenhang mit dem Klimawandel, Geschlechterungleichheit und Arbeitsverteilung. Die Ergebnisse zeigen, dass Niederschlagsschocks zu einer wöchentlichen Mehrbelastung von zwei Stunden an unbezahlter Hausarbeit führen. Besonders stark betroffen sind sozial benachteiligte Bevölkerungsgruppen, wobei arme Frauen am stärksten unter den Folgen leiden.

Diese Dissertation zeigt, dass extreme Wetterereignisse erhebliche wirtschaftliche und nicht-wirtschaftliche Auswirkungen haben. Arme Haushalte, Frauen und Menschen in Hochrisikogebieten sind besonders gefährdet. Dies verdeutlicht, dass Klimaschocks bestehende Ungleichheiten in wirtschaftlichen und nicht-wirtschaftlichen Dimensionen weiter verschärfen. Die Ergebnisse dieser Arbeit unterstreichen die Notwendigkeit gezielter Strategien und politischer Maßnahmen – etwa sozialer Sicherungssysteme –, um die negativen Folgen des Klimawandels abzumildern und soziale Gerechtigkeit sowie soziale Teilhabe zu fördern.

Acknowledgments

I am finishing this beautiful stage of my life. But I have achieved this thanks to the people who were with me.

I want to thank my supervisors immensely. I am deeply grateful to Prof. Dr. Matin Qaim for his continuous support, dedication, attention to detail, and significant contributions to the thesis despite having an unimaginable workload. Thank you for all the time you spent reading my long emails, commenting on my ZEF presentations and the thesis, and always responding in record time. Thanks for being a role model. I also want to profoundly thank PD Dr. Alisher Mirzabaev, for his excellent guidance on the thesis, always with excellent recommendations for papers, but also guidance and advice for my pathway during and after the Ph.D. Thank you for the opportunity to visit IRRI, learn about the excellent work being carried out there, and meet outstanding people. An experience full of knowledge and good memories. Special thanks to Prof. Dr. Jan Börner for reviewing this thesis and Prof. Dr. Ina Danquah for agreeing to chair the Dissertation Committee.

Thanks to Max Voit, who always, with a smile or a joke, helped me when I did not know how to schedule an appointment or fill out forms. Thank you for your nice energy and willingness to help us. I appreciate Dr. Silke Tönsjost's commitment to fostering a supportive academic setting. Special thanks to the German Academic Exchange Service (DAAD) for funding this exciting journey of knowledge and to Parisa Asemi and Mirjam Fehler for their help.

Thanks to my family, who have always been my pillar of support. To my sister Angie, for always taking care of me. Thank you for the calls, the encouragement, and all the support you gave me. Thanks to my mom for being present throughout this journey with her words of support and time. Thank you to my dad for always watching over me. Thanks to my brother Freddy for his time, guidance, technical help, and advice on the thesis. To my brother Cesar for his unexpected calls asking how I am. To my niece and nephews, who are and always will be my favorite people, whom I love and who brighten my day just by seeing them. Thank you for your innocence and your joy. To Maxito, my godson, whose presence lights up my world. Thanks to my brother-in-law and sisters-in-law for their support and friendship.

My doctoral friends were always unconditional companions, turning this path into an adventure with unforgettable moments. Thanks to Wendy, Anni, Micely, Maru, David, Subash, Altynay, and June for sharing the academic life, but also life outside the Ph.D. I will always remember all the adventures we had together, the birthdays, carnivals, lakes, and the Christmas markets together. Many memories that I will always cherish. Thanks to my batchmates Jeremy, Frida, Hendrik, Kevin, Sohel, Arnold, and Mengistu, with whom we shared knowledge, but also many fun lunches, coffee times, laughter, ZEF seminars, and support whenever we needed it.

Thanks to me, for my dedication, effort, perseverance, and continued belief in myself.
Thank you all!

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List of abbreviations

CHIRPS	Climate Hazards InfraRed Precipitation with Station
CHIRTS	Climate Hazards InfraRed Temperature with Station
CNN	Cable News Network
ENEMDU	National Survey of Employment, Unemployment and Underemployment
FGT	Foster–Greer–Thorbecke indices
GGP	Geoinformation Generation Project for Territorial Management
IIE	Ecuadorian Space Institute
MAATE	Ministry of Environment, Water and Ecological Transition
TAM	Threat Analysis Against Mass Movements in Ecuador
UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention on Climate Change
UNHCR	United Nations High Commissioner for Refugees
USD	United States Dollar
ZEF	Center for Development Research

1. Introduction and motivation

1.1. Problem statement and framing the research

Climate change and extreme weather events adversely affect human and natural systems. In human systems, these impacts intersect with societal challenges such as inequality, poverty, and lack of infrastructure, among others (Ara Begum et al., 2022).

As shown in Figure 1.1, climate change, manifested through sea level rise, ocean acidification, glacier retreat, more frequent heatwaves, droughts, and extreme weather events, directly affects societies by reducing agricultural productivity, harming health, and damaging infrastructure and labor productivity. These societal impacts subsequently influence rural and urban households by creating economic pressures that reduce income and exacerbate poverty and inequality. Additionally, non-economic effects include increased unpaid household work. Climate change particularly impacts poor households that are less equipped to manage these challenges.

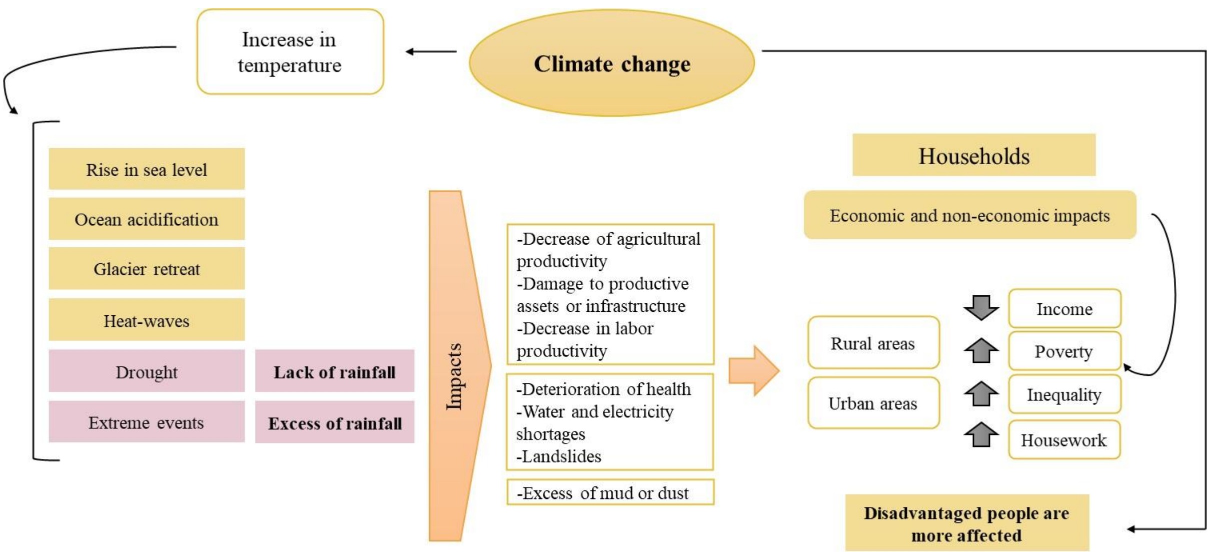


Figure 1.1 Climate change impacts on households

Source: Framework developed by the author

Specifically, extreme weather events severely affect rural areas due to their high dependence on weather-sensitive activities (Winsemius et al., 2018; Skoufias et al., 2011). Households in these areas are often poorer and have less access to information, technology, infrastructure, and social protection (Dasgupta et al., 2014; Nguyen et al., 2020). Climate shocks impact incomes and poverty levels in rural settings (Mendelsohn et al., 2007; Hallegatte et al., 2017).

In sub-Saharan Africa, heatwaves, floods, and droughts reduced income and increased poverty (Amare & Balana, 2023; Azzarri & Signorelli, 2020; Baez et al., 2020). In Vietnam, these events reduced per capita income, and poorer households were more affected (Arouri et al., 2015; Narloch, 2016). The increasing frequency of extreme weather events establishes challenging cycles that provide insufficient recovery time before the next shock strikes, exacerbating the impacts of recurrent shocks. These cycles hinder recovery in rural areas where such events directly disrupt livelihoods and productive assets (Pleninger, 2022). Recurrent weather extremes drive vulnerable households into temporary and chronic poverty traps, with economically disadvantaged families facing harsher income reductions than their wealthier counterparts (Bangalore et al., 2017; Boansi et al., 2021).

Globally, there has been a rapid expansion of urban areas and a growing concentration of the population in cities. According to Dodman et al. (2022), the risks posed by climate-related hazards have increased across urban settlements. These impacts are unevenly distributed within urban communities, disproportionately affecting the most economically and socially marginalized groups. Women, especially those living in poverty, are particularly vulnerable and face greater impacts due to lower educational levels, limited access to credit, and low incomes typically associated with informal employment (Chen & Carré, 2020; Dodman et al., 2023). In addition, residents in high-risk urban settings (e.g., slums and informal settlings) are more vulnerable. These households lack legal land ownership, adequate housing, and basic infrastructure, which makes them more susceptible to natural disasters. Low-income families are often more exposed to extreme weather events as unaffordable urban housing markets force them into these risky areas (Hardoy & Pandiella, 2009; Narloch and Bangalore, 2016; Hallegatte et al., 2020).

Extreme weather can exacerbate urban poverty. In countries such as Mexico, Bolivia, and Peru, floods, droughts, and other natural disasters have increased household and territorial poverty (Rodriguez-Oreggia et al., 2013; Hallegatte et al., 2018). Poor urban households that live in risk areas are more exposed to weather extremes, reducing their chances of escaping poverty (Hallegatte et al., 2020).

Climate change has severe economic consequences. Besides its impacts on income distribution, or poverty (Acevedo et al., 2020; Gray et al., 2022; Hallegatte et al., 2018), extreme events also disrupt household labor allocations. Rainfall shocks increase the time spent on unpaid domestic work, burdening disadvantaged groups.

For instance, weather events aggravate diseases (Allouche, 2011; Orimoloye et al., 2022). When these health issues affect household members, extra support is required, increasing the time spent on caregiving. However, the additional workload is experienced differently among household members and social groups (Jiao et al., 2020; UNFCCC Secretariat, 2022). Women, constrained by traditional gender roles, low-income households with limited resources, and rural areas with poor infrastructure face greater difficulties. These groups typically endure more severe consequences due to systemic barriers and social expectations, which exacerbate the disparities they experience. Qualitative or descriptive studies have found that women are more affected by weather extremes than men. And within women, poor women face a greater burden (Ajibade et al., 2013).

South America is highly exposed and vulnerable to climate change and is experiencing strong impacts. Studies show a rise in extreme weather events, which are becoming more intense (Dereczynski et al., 2020; Dunn et al., 2020). Climate impacts are increasing and exacerbating economic and non-economic gaps, affecting disadvantaged individuals, exacerbating existing vulnerabilities, and worsening living conditions (Castellanos et al., 2022).

Those already suffering are losing their development opportunities. Therefore, it is important to improve understanding of the differential impacts of climate change on people of different social statuses, sex, and other attributes (Ara Begum et al., 2022).

Many studies have focused on investigating the impacts of climate change and variability. However, the literature on the effects of *consecutive weather extremes* is scarce. In addition, more *studies in urban areas* need to consider geographic information and vulnerable groups. Studies on *labor allocations with quantitative approaches* -related to weather extremes- are also limited. According to Castellanos et al. (2022), research on the interactions between climate change and socioeconomic processes is markedly insufficient in Central and South America, particularly concerning vulnerable groups and urban regions. This limits people's understanding of climate change's consequences and can lead to underestimating its impacts (Sietsma et al., 2021). More research is urgently needed to understand better how poor and vulnerable communities are affected.

This thesis aims to contribute to addressing these gaps in the current literature. The thesis studies weather shocks' economic and non-economic impacts, highlighting heterogeneous effects on disadvantaged groups. Initially, the research explores the impacts of consecutive rainfall shocks in rural settings, considering the expected increase in frequency and severity of weather extremes. Subsequently, it focuses on the effects of weather shocks in urban areas, including geographic characteristics and vulnerable groups. The study also delves into how excess, and scarcity of rainfall affect time spent on unpaid domestic work and remunerated employment, contributing to the literature on gender and labor allocations. The research provides information that can guide decision-makers in understanding the impacts of weather shocks and proposes better and more targeted policies, especially in Latin America and the Caribbean.

1.2. Research area context

The research is conducted in Ecuador, located in the northwest of South America, and spanning an area of 248.513 km^2. The Andes Mountains traverse the country. The mountain chains divide the territory into three regions: Coast, Sierra, and Amazon, each with distinct climate characteristics, soils, landscapes, and biodiversity (World Bank, 2021).

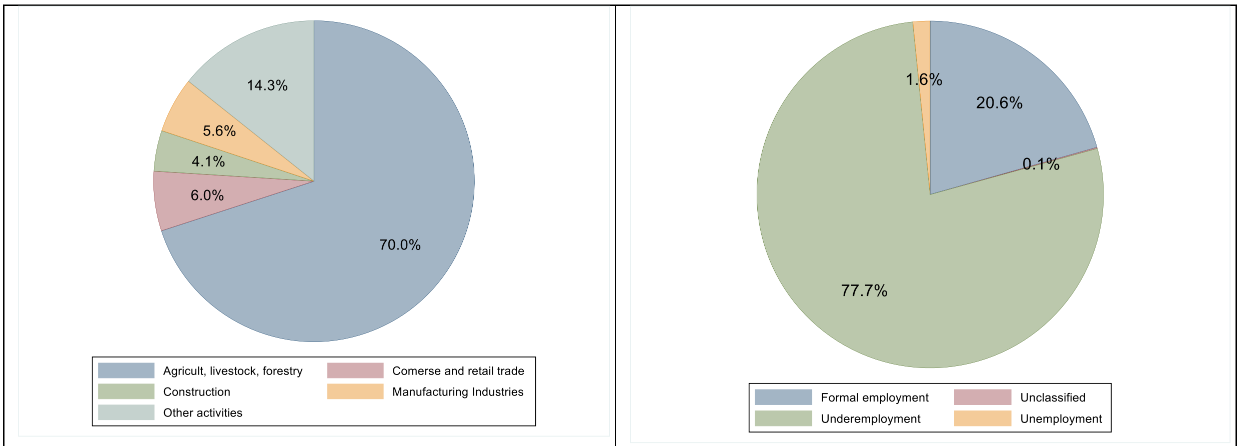
Due to its geographical, geological, oceanographic, and demographic conditions, Ecuador is highly vulnerable to extreme events, especially flooding. It has recently experienced a growing number of natural hazards, such as floods, landslides, storms, earthquakes, and droughts, resulting in significant loss of life and economic damages (World Bank Group, 2021; World Bank, 2021).

For instance, the first quarter of 2024 witnessed heavy rains causing floods and landslides. Homes, roads, bridges, and crops were damaged or destroyed due to the rapid rise in water levels. This also increased the incidence of insect- and water-borne diseases (Flood in Ecuador - Activations - International Disasters Charter, 2023; Blašković, 2024). Meanwhile, the last quarter of 2024 was characterized by severe droughts, which drained rivers and reservoirs, leading to wildfires and power outages of up to 14 hours per day, causing massive losses in productivity and sales (Turkewitz & Leon, 2024).

Ecuador is facing severe consequences from climate-induced hazards, which are expected to impact the economy and people, potentially reducing four percentage points of the GDP per capita by 2050 (World Bank, 2024). The effects are differentiated, but both rural and urban sectors are affected.

Agriculture is a major driver of Ecuador's economy, contributing nearly 10% to GDP and accounting for 32% of employment. This sector is particularly crucial in rural areas where households largely depend on it (World Bank, 2024).

In rural Ecuador, as shown in Figure 1.2, 70% of households rely on agriculture for their livelihoods, followed by commerce (6.0%), manufacturing industry (5.6%), and construction (4.1%). Only 20.6% of the population has formal employment, and around 80% are underemployed. This means their income does not reach the minimum wage, they work less than 40 hours a week, or they do not have social security. Almost half (41.8%) of the population is poor and 18.7% are in extreme poverty (ENEMDU-INEC, 2019Q4). Households in rural areas have worse socioeconomic conditions, making them more vulnerable to climate variations (Hallegatte, 2015).



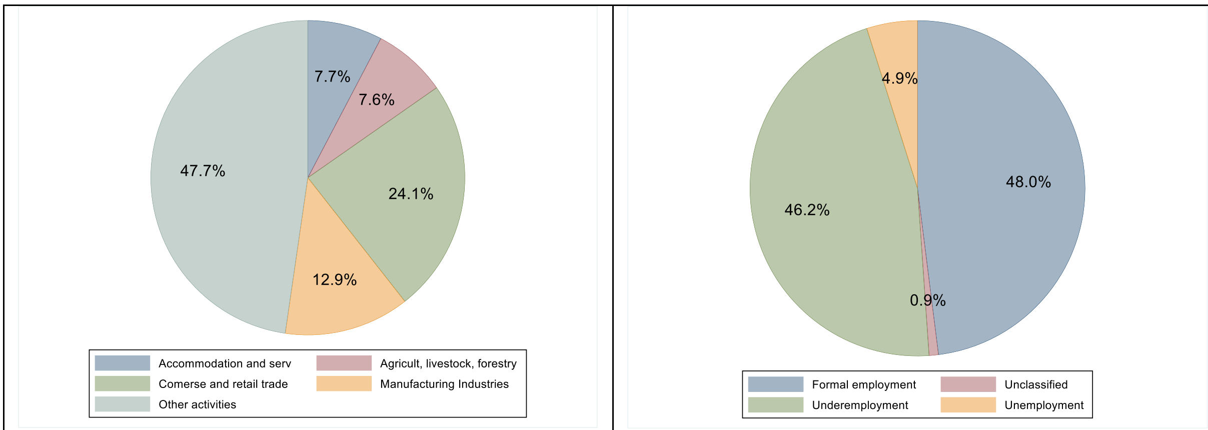
Panel A: Economic activities distribution

Panel B: Employment categories

Figure 1.2 Rural characteristics

Source: ENEMDU-INEC, 2019Q4

Urban areas comprise 65% of Ecuador's population (World Bank Group, 2023). The rapid urban expansion increases vulnerability and exposure to climate risks (Dodman et al., 2022). The main economic activities are commerce, accounting for 24.1%, followed by industry (12.9%) and services (7.7%). Agriculture makes up 7.6% (Figure 1.3). Although there is a higher employment rate (48%), a large percentage of the population (46.2%) remains underemployed.



Panel A: Economic activities distribution

Panel B: Employment categories

Figure 1.3 Urban characteristics

Source: ENEMDU-INEC, 2019Q4

There are vulnerable groups in cities. Women and people living in high-risk areas are more exposed to risks. The poor experience even harsher conditions within these groups and are particularly vulnerable (Birkmann et al., 2022).

According to the ENEMDU (2019Q4), Ecuador's average monthly per capita income is USD 221. Poor families in urban areas earn approximately USD 60 monthly, nearly one-third of the national average. The majority (65.5%) of these families are employed in the informal sector, with commerce (24.9%) and agriculture (15.5%) being the predominant economic activities. Additionally, 68.8% of the urban population has only basic education. Generally, the poor lack access to credit and social security, face relocation constraints and are engaged in activities that are highly sensitive to weather shocks, making them more vulnerable (Birkmann et al., 2022).

Besides economic disparities, there are significant differences in unpaid domestic work, which climate shocks can exacerbate. Women are especially impacted, but the poor and those in rural areas also face challenges. On average, unpaid domestic work amounts to 18.1 hours per week. However, as seen in Figure 1.4, women spend 27.8 hours while men spend only 7.6 hours. Poor households allocate 20.6 hours to such tasks, compared to 17.4 hours in non-poor households. In rural areas, people dedicate an average of 19.1 hours instead of 17.6 hours in urban settings. The most affected group is poor women, who spend 31.6 hours on unpaid housework, nearly twice the national average and four times more than the average man (ENEMDU Panels, 2014-2017). These disparities could worsen with climate shocks.

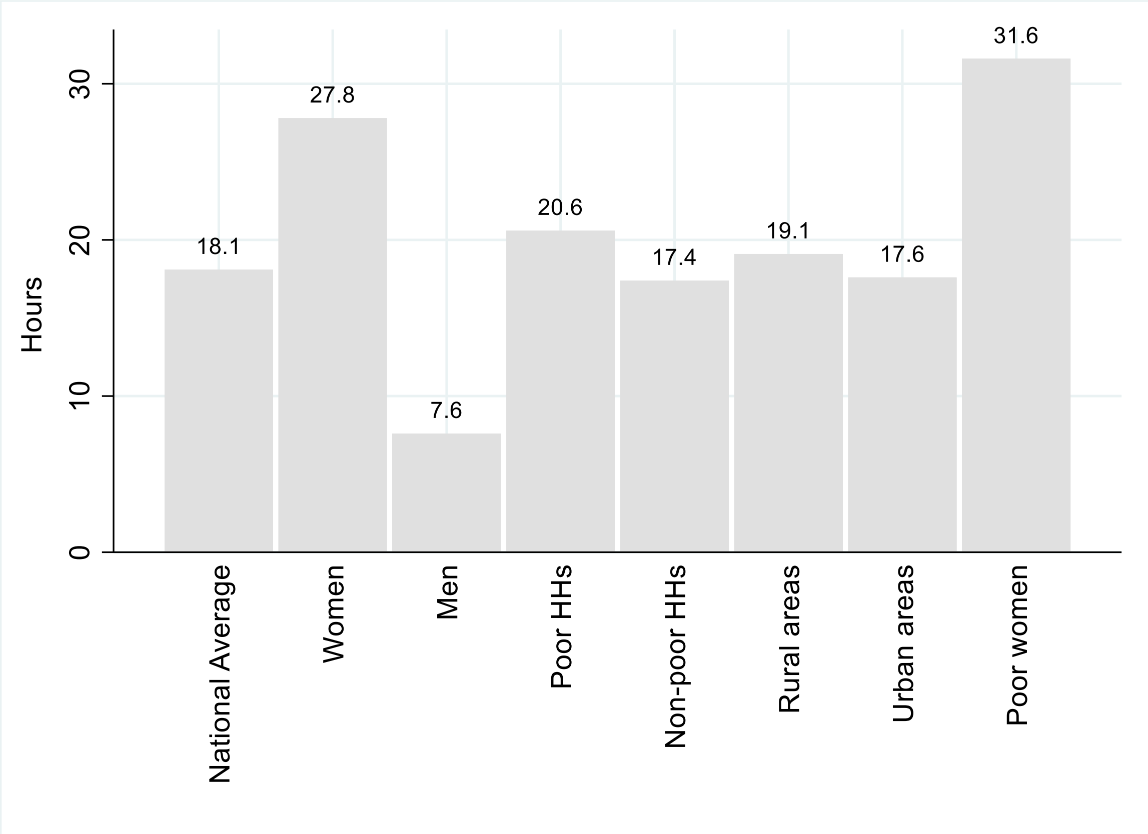


Figure 1.4 Total hours of unpaid domestic work by groups

Source: ENEMDU Panels, 2014-2017

1.3. Research questions and objectives

This thesis aims to explore the impacts of consecutive rainfall shocks on income distribution and poverty in rural areas. In urban settings, it combines weather and geographic information with household surveys to identify the effects of weather extremes on the distance to the poverty line. Finally, the thesis evaluates the additional burden of unpaid housework due to rainfall shocks. The specific research questions are:

- **What is the differentiated impact of consecutive rainfall shocks on income distribution and poverty in rural areas in Ecuador?**

Estimate the impact of *consecutive weather shocks on income distribution and poverty in rural areas* in Ecuador, focusing on the heterogeneous effects experienced by poor and nonpoor households.

- **To what extent do rainfall shocks affect the distance to the poverty line in urban settings, considering geographic characteristics and disadvantaged populations?**

Estimate the impact of *rainfall shocks in urban settings on the distance to the poverty line, incorporating geographic information* such as susceptibility to floods, droughts, and landslides and considering the analysis of *disadvantaged groups*.

- **How does the excess and scarcity of rainfall impact labor time allocation, especially time spent on unpaid domestic work and paid employment across different demographics?**

Estimate the impact of the excess and scarcity rainfall on time spent on unpaid domestic work and paid work, exploring how these impacts vary among different demographics, including sex, economic status, geographical location, and the intersectionality of being poor and woman.

1.4. Research methodology

1.4.1. Data

We primarily use two sources of data. The first are the annual survey panels from the National Survey of Employment, Unemployment, and Underemployment (ENEMDU) conducted by Ecuador's National Institute of Statistics and Censuses (INEC). The second source is daily precipitation from the Climate Hazards Center at the University of California, Santa Barbara (CHIRPS). In addition, for the second essay (chapter three), we also use geographic information on land's risk or susceptibility to floods, droughts, and landslides from several institutions of the Ecuadorian government.

Household data

Household data comes from the ENEMDU. From 2007 to 2019, the survey took place quarterly nationwide (INEC, 2022). The annual panels enable analysis of the same units in different annual cohorts. For example, in the first quarter of 2016 and the first quarter of 2017 (INEC, 2017). Considering the objective of this research, 25 annual panels corresponding to different quarters from 2007 to 2019 were harmonized and stacked. For the first essay (chapter 2), the panels from 2013 to 2019, statistically representative of rural areas, were used. For the second essay (chapter three), we utilized data from 2007 to 2019, with statistical representation for urban settings. The third essay (chapter four) focuses on cohorts from 2014 to 2017, which contain information on individual labor allocations and are statistically representative at both urban and rural levels. In the ENEMDU, households are georeferenced at the census sector level, which allows us to determine their spatial location in the annual panels.

Weather data

Weather data comes from the Climate Hazards Center at the University of California, Santa Barbara, with a spatial resolution of approximately 5 km^2 (University of California, 2023).

We obtained the centroid for each census sector and gathered daily precipitation information for each centroid starting in 1981. We estimated the quarterly z-score for accumulated precipitation within each census sector. Based on the z-score values, we created different dummy variables, depending on the essays, to identify specific extreme weather shocks.

Ecuador has two seasons: the rainy season and the dry season. The rainy season is extended from November/December to April/May, and the remaining months correspond to the dry season. During the rainy season, the rainfall is abundant and can be very intense, and there is also high humidity. During the dry season, rainfall decreases dramatically, creating a cool and dry climate, characterized by sunny days and cold nights. On average, the first quarter of the year records the highest amount of precipitation (610mm); meanwhile, the third quarter (dry season) records the lowest amount (180mm) (CHIRPS, 2023).

Regarding temperature, Ecuador is characterized by warm and tropical climates in the coastal areas and temperate to cold climates in the highlands. Average temperatures in the Coast and Amazon range from 25°C to 34°C throughout the year. The Sierra region experiences a cooler climate, as temperatures decrease with elevation, typically fluctuating between 7°C and 21°C (UNHCR, 2023).

Geographic information

In the second essay (third chapter), we incorporate geographic information. The maps cartographically identify areas susceptible to floods, droughts, and landslides. They classify the territory according to its risk of these events: high risk, medium, low, and no risk. For floods, high susceptibility represents the territories where cyclic floods occur every year in the rainy season (IIE et al., 2015a). For droughts, high risk is defined when the probability of a drought occurring is greater than 45% (IIE et al., 2015b). For mass movements (landslides), territories with very high risk or susceptibility have steep slopes, with the presence of fractured rocks, without vegetation cover, and eroded soils that are not cohesive and compact (Undersecretary of Information Management and Risk Analysis, 2019).

With this information, we identify risky and non-risky territories. For each parish, we calculate the percentage of land with a high or very high risk of floods, drought, or landslides. For example, Rioverde has 19% of its territory at high risk of landslides, 6% at high risk of flooding, and 0.1% at high risk of drought. San Joaquin has 58% at high risk of landslides, 2% at high risk of flooding, and 0% at high risk of drought. We define a risky area if the parish has a high or very high risk of drought, flood, or landslide in at least 50% of its territory. In our example, Rioverde is a non-risky area, and San Joaquin is considered risky.

1.4.2. Methods

Given our use of panel data, we applied the fixed-effects model. This model controls for the effect of unobserved heterogeneity, eliminating potential biases in estimates that could arise from omitting time-invariant variables. The model is run at the household level in essays one and two, as shown in Table 1.1.

Table 1.1 Methods

Research question	**Data**	**Method**
What is the differentiated impact of consecutive rainfall shocks on income distribution and poverty in rural areas in Ecuador?	Rainfall data Temperature data Households surveys	Panel fixed effects at the household level
To what extent do rainfall shocks affect the distance to the poverty line in urban settings, considering geographic characteristics and disadvantaged populations?	Rainfall data Geographic characteristics Households surveys	Panel fixed effects at the household level
How does the excess and scarcity of rainfall impact labor time allocation, especially time spent on unpaid domestic work and paid employment across different demographics?	Rainfall data Households and individual surveys	Panel fixed effects at the individual level

The dependent variables include per capita income, poverty, poverty gap, severity, and the distance to the poverty line. In essay three (chapter four), the model is applied at the individual level for those aged over 15 years. The dependent variables are time spent on unpaid domestic work and remunerated work.

1.5. Limitations of the study

In the first essay (chapter two), we can identify only two consecutive rainfall shocks since we work with annual panels. The results indicate that the second shock has more severe consequences, highlighting the importance of analyzing the effects of multiple consecutive rainfall shocks, not limited to just two.

The second essay (chapter three) incorporates information on the risks of floods, droughts, and landslides. However, the households' exact location is confidential and unavailable, particularly because the ENEMDU collects income data. The variable for geographic characteristics considers the percentage of the parish at high risk, and we match it with the parish where the household is located. Within these territories, households in high-risk parishes may not reside at the exact risky point because we do not know the exact household location. Nonetheless, it would be important to incorporate geographic risk information at the exact point where households live for a more accurate estimation.

1.6. Organization of the thesis

This dissertation is organized into five chapters, each designed to address distinct aspects of the impacts of rainfall shocks on poverty, income distribution, and unpaid domestic work in Ecuador. Chapter one introduces the core research problems, the existing literature, and the gap this doctoral thesis covers. This section also explains Ecuador's context and outlines the study's overarching questions and objectives. Finally, it summarizes the data and methodologies employed. In chapter two (essay one), the focus shifts to the rural settings of Ecuador, where the recurrent nature of rainfall shocks is analyzed in relation to their effects on poverty levels and income distribution. Chapter three (essay two) extends the analysis to urban areas, specifically examining how rainfall shocks influence economic stability and push urban populations toward or further from the poverty line. Chapter four (essay three) deepens the exploration by studying the intersection of rainfall shocks with social inequalities, mainly through the lens of unpaid domestic work. It highlights how these shocks disproportionately intensify labor burdens in women, poor households, and rural areas, exacerbating existing inequalities. Chapter five, the overall conclusion, synthesizes the findings from the empirical essays, discusses their implications for policy and practice, and outlines high potential areas for future research.

Essay one

2. Effects of recurrent rainfall shocks on poverty and income distribution in rural Ecuador[1]

Abstract

Climate change is associated with an increasing frequency of extreme weather events, which can severely reduce people's welfare, especially in the Global South. Here, we analyze rainfall shocks' impacts–including lack and excessive rains – on economic and social outcomes, using micro-level panel data from rural Ecuador. We employ high-resolution climate data and georeferenced household survey data covering 2013 to 2019 to examine how single and repeated rainfall shocks affect income, poverty, and income distribution. Panel data regression models with household fixed effects show that rainfall shocks reduce per capita income by 9%. The income losses are larger for poor than for non-poor households. Two consecutive rainfall shocks have stronger negative income effects, especially among the poor, who have limited resilience capacity and lack the resources to recover quickly. Our estimates suggest that a second consecutive rainfall shock reduces the income among the poor by more than 50%. Recurrent rainfall shocks also increase the poverty rate, the poverty gap, and poverty severity. These results highlight the need to consider the social heterogeneity of climate change impacts in research and policymaking to understand and enhance people's climate resilience.

Keywords: rainfall shocks, income, poverty, agriculture, Ecuador

JEL Classification: D31, I32, Q54

2.1. Introduction

Climate change is increasing global land and sea surface temperatures and the frequency and severity of extreme weather events, such as heavy rains, floods, droughts, and heat waves (MAATE, 2022; Yesuph et al., 2023). These trends will likely intensify in the coming years

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[1] This study was published in the University of Bonn's institutional repository, bonndoc (https://doi.org/10.48565/bonndoc-507). It is a joint paper with Alisher Mirzabaev and Matin Qaim. M.C.L.P. was responsible for all parts of the research with support and advice from the co-authors.

and decades (Seneviratne et al., 2021). Low- and middle-income countries in tropical and subtropical regions are particularly affected (De Cian et al., 2016; Mendelsohn et al., 2006) and will also experience the largest damage due to their high reliance on agriculture and their lower adaptive capacities in comparison to high-income countries (Mendelsohn et al., 2006; Chuang, 2019). International attention is often paid to Africa and Asia, but many Latin American countries are also highly vulnerable and adversely affected by extreme weather events (Castellanos et al., 2022).

Weather extremes can negatively impact numerous economic activities. The most exposed are those related to agriculture, fisheries, and forestry because temperature and precipitation directly contribute to these production activities (Herrera et al., 2018). However, other sectors may be affected due to decreased labour productivity, deterioration of human health, increased unemployment, and destruction of infrastructure (Acevedo et al., 2020; Pleninger, 2022; Nguyen et al., 2020). Rural areas are more vulnerable than urban settings, not only because rural households tend to be more reliant on weather-sensitive sectors but also because they are often poorer and have less access to information, technology, infrastructure, financial intermediation, and social protection (Dasgupta et al., 2014; Lohmann & Lechtenfeld, 2015; Nguyen et al., 2020). In other words, climate change is a poverty amplifier: it increases the poverty headcount and makes poor people poorer, thus representing a significant obstacle to achieving the Sustainable Development Goal of poverty eradication (Hallegatte et al., 2016 & 2018; Hallegatte & Rozenberg, 2017; Winsemius et al., 2018).

Several studies examine the relationship between weather shocks and income or poverty. Mendelsohn et al. (2007) and Lokonon et al. (2015) point out that the income of rural and farm households is strongly affected by extreme weather events. Arouri et al. (2015) and Narloch (2016) find that severe rainfall and floods decrease per capita income and that poorer households are generally more vulnerable. In sub-Saharan Africa, heatwaves, floods, and droughts are associated with income losses and a rise in poverty (Amare & Balana, 2023; Azzarri & Signorelli, 2020; Baez et al., 2020; Salvucci & Santos, 2020). The loss in welfare pushes vulnerable households into short and long-term poverty traps, and poor families face stronger negative income effects than non-poor families (Bangalore et al., 2017; Boansi et al., 2021; Dasgupta, 2007).

However, most previous research focuses on the effects of a *single* weather shock or extreme event. Climate change manifests in an increase in the frequency of extreme events, which may create challenging cycles where people do not have enough time to recover before already facing the next shock. Such cycles would impede households' assets and human capital accumulation and aggravate the impacts of recurring shocks, especially among the most vulnerable population groups. For example, Pleninger (2022) finds that multiple natural disasters increase poverty more when they occur more frequently, as recurrent shocks do not allow for sufficient time to recover. Although few studies have analyzed the impact of multiple types of single shocks (such as earthquakes, severe storms, or fires), the literature on the effects of *recurrent weather shocks* on income distribution and poverty is very scarce. Also, most existing studies on the links between climate change and poverty relate to Africa and Asia or use global modelling approaches. Very little micro-level applied research focuses on Latin America (Castellanos et al., 2022; Cardoso Silva et al., 2024).

Here, we address these research gaps by analyzing the effects of recurrent rainfall shocks (including insufficient or excessive rain) during the same period across two consecutive years on household income and poverty in rural Ecuador. We consider up to two recurrent rainfall shocks. The study combines nationally representative and geo-referenced panel survey data with high-resolution climate data to evaluate the heterogeneous effects of rainfall shocks. We also estimate their effects on the poverty gap and poverty severity. Household-level data is crucial, as it captures income distribution effects that aggregate data often dissimulates, because of the poor's relatively small share of the total economy (Hallegatte et al., 2018).

The rest of this article is structured as follows. Section 2.2 presents the conceptual framework, discussing potential mechanisms of the effects of rainfall shocks on income and poverty, and why facing another recurrent shock could have greater consequences. Section 2.3 explains the data and econometric estimation approaches. Section 2.4 presents the results, whereas Section 2.5 discusses some broader implications and concludes.

2.2. Conceptual framework

A fundamental element of climate change is the increase in global temperatures and changes in rainfall patterns. These alterations raise sea levels, lead to glacier retreat, acidify the oceans, and increase the frequency and intensity of extreme weather events such as heavy rains or droughts (MAATE, 2022). In this study, we focus on the impacts of recurrent rainfall shocks, including too much rain as well as lack of rain, on household welfare in rural areas.

Climate change and weather shocks can affect households and their income through different mechanisms (Figure 2.1). Many rural households are involved in agriculture as farmers or laborers, and agricultural productivity has declined due to climate change (Cui & Tang, 2024), especially in tropical and subtropical regions. However, there are also other mechanisms through which adverse income effects can occur. According to the literature, extreme rainfall and droughts affect people mainly through food prices, labor productivity, health, and damage to infrastructure or assets (Hallegatte & Rozenberg, 2017).

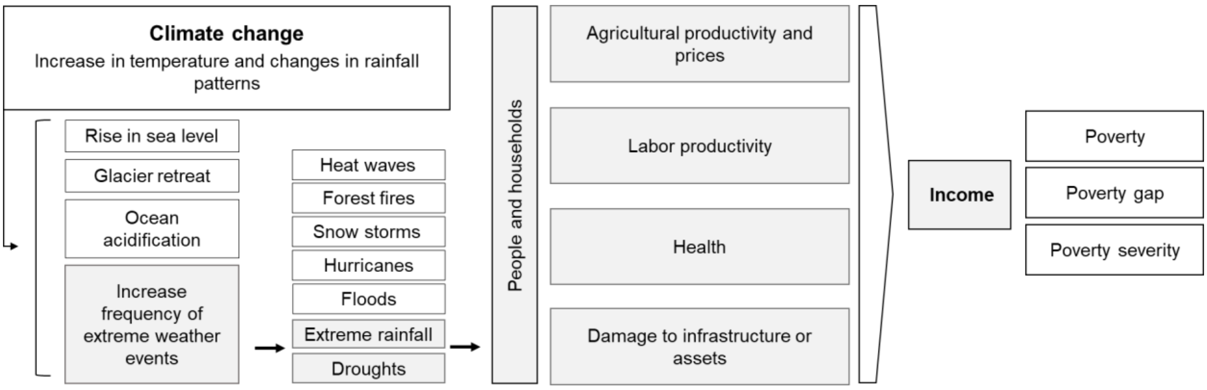


Figure 2.1 The link between climate change, income, and poverty

Changes in temperature, precipitation, and the frequency and severity of weather extremes result in lower agricultural productivity or sometimes complete crop losses (Cui & Tang, 2024). Reduced agricultural output contributes to food supply and demand imbalances, raising prices (Rao et al., 2017). Rising food prices negatively affect net food-buying households, reducing their real income. Food producers with net food selling positions may potentially benefit from rising prices. However, if the price effects do not offset the crop losses, income reductions are also likely for net food sellers (Olper et al., 2021; Nébié et al., 2021).

Extreme rains can cause flooding, which complicates access to workplaces, especially in rural areas where the transport infrastructure is often less developed. In order to deal with the consequences of flooding, more time and resources may be needed. Lower labor productivity and a potential decrease in work time due to extreme events will likely result in lower household incomes.

A related mechanism is human health. Climate change and weather extremes can cause diseases or aggravate negative health conditions, mainly affecting poor people with low access to health services and who live in more hazard-exposed locations and conditions (Hales et al., 2014; Caminade et al., 2014). For instance, changes in temperature and rainfall patterns can increase exposure to infectious diseases, such as diarrhea, malaria, or dengue (Brouwer et al., 2007). In addition, lower access to food and essential nutrients weakens people's immune systems and makes them more vulnerable to disease. When household members fall sick, they might be unable to work and/or require special care, resulting in income losses (Hallegatte et al., 2018).

Finally, extreme weather events can directly cause loss of income and decrease employment opportunities by affecting the public infrastructure and the asset base of businesses and households (Carter et al., 2007; Rao et al., 2017; Winsemius et al., 2018).

Our study focuses on the net impact of rainfall shocks on rural household incomes related to these mechanisms and possibly others. We also evaluate the impact on income poverty, the poverty gap, and poverty severity. Based on the literature (Birkmann et al., 2022; Herrera et al., 2018; Günther & Harttgen, 2009; Islam & Winkel, 2017), we hypothesize that weather extremes, in general, and rainfall shocks, in particular, negatively affect the poorest population segments the most, thus increasing poverty and inequality. We also posit that repeated rainfall shocks have more severe consequences than isolated shocks due to accumulating losses and reduced coping capacity.

According to Cui & Tang (2024), households can mitigate the impact of weather shocks on consumption with savings or crop stocks. However, most rural households in Ecuador are poor, with a monthly average per capita income of only USD 110, according to ENEMDU Panels (2013-2019). This amount is significantly below the cost of the monthly consumer basket, which is USD 715 (ENEMDU, 2019). This financial shortfall significantly reduces the likelihood of having savings. Therefore, the first shock affects their consumption and spending capacity. When facing a second shock, resources are already insufficient, increasing their vulnerability and worsening their economic situation.

The second shock usually has more severe effects since households have exhausted or reduced their assets. According to Aragón et al. (2021), weather shocks force families to sell livestock or other goods. If, during the first shock, they had to sell these assets, in the second event, they have fewer resources to face adversity, which leaves them more vulnerable and with fewer options to recover. Moreover, these shocks lead farmers to increase the area planted (Aragón et al., 2021), which reduces the capacity of the soil to restore and decreases productivity in future harvests. If this coincides with a new shock, losses may be even greater.

On the other hand, Jagnani et al. (2020) point out that households with limited resources tend to increase the use of pesticides and reduce the use of fertilizers after an extreme event. Although this strategy may be effective in the short term, a second shock could exhaust farmers' financial capacity to acquire inputs, leaving soils less fertile and reducing future yields. This imbalance, coupled with limited investment capacity, aggravates economic losses and hinders recovery in the medium and long term. That is, facing recurrent rainfall shocks have greater negative consequences for rural households.

2.3. Materials and method

We run regression models with households as the observation unit, relating different welfare indicators to extreme rainfall events experienced locally and accounting for other relevant factors. The dependent variables are per capita household income, poverty, poverty gap, and poverty severity. The main explanatory variables are indicators of recurrent rainfall shocks in each locality, controlling for confounding factors. The data on rural households are taken from Ecuador’s National Survey of Employment, Unemployment, and Underemployment (ENEMDU), conducted by the National Institute of Statistics and Censuses (INEC). Daily rainfall data are extracted from the Climate Hazards Center at the University of California, Santa Barbara (CHIRPS). The household and rainfall data are linked through the census sector code. Details of the data and the statistical approaches used are provided below.

2.3.1. Household data

The household data used comes from Ecuador's nations survey ENEMDU. ENEMDU is among the country's most important surveys for studying income and employment and the official source for calculating household living standards and poverty in Ecuador. The data are collected every quarter, and its sample design facilitates the construction of annual panels with specific subsamples (INEC, 2017). We use the surveys covering the period from 2013 to 2019, which provide data representative of rural areas (INEC, 2022).

This structure allows the analysis of the same households in two annual cohorts, for example, in the first quarter of 2016 (2016Q1) and the first quarter of 2017 (2017Q1). For the study, we stack 13 annual panels corresponding to the different quarters from 2013 to 2019. This results in 59,969 households, each observed over two periods (119,938 observations), as shown in Table 2.1.

Table 2.1 Annual panels (number of observations at the household level)

Panel	**Period**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Total**
Panel 1	Q4 (2013-2014)	3,942	3,942						**7,884**
Panel 2	Q1 (2014-2015)		3,352	3,352					**6,704**
Panel 3	Q2 (2014-2015)		8,900	8,900					**17,800**
Panel 4	Q3 (2014-2015)		1,206	1,206					**2,412**
Panel 5	Q3 (2015-2016)			2,067	2,067				**4,134**
Panel 6	Q4 (2015-2016)			9,353	9,353				**18,706**
Panel 7	Q1 (2016-2017)				4,285	4,285			**8,570**
Panel 8	Q2 (2016-2017)				4,336	4,336			**8,672**
Panel 9	Q3 (2016-2017)				1,655	1,655			**3,310**
Panel 10	Q1 (2018-2019)						4,912	4,912	**9,824**
Panel 11	Q2 (2018-2019)						5,254	5,254	**10,508**
Panel 12	Q3 (2018-2019)						5,350	5,350	**10,700**
Panel 13	Q4 (2018-2019)						5,357	5,357	**10,714**
Total		**3,942**	**17,400**	**24,878**	**21,696**	**10,276**	**20,873**	**20,873**	**119,938**

Source: ENEMDU Panels, 2013-2019

Ecuador has 40,558 census sectors. Census sectors represent a group of city blocks or settlements. Specifically, in rural areas, a census sector is a delimited area consisting of one or more settlements and, on average, includes 80 to 110 households (INEC, 2020). In the surveys, the sample households are georeferenced at the census sector level, allowing us to identify their geographic locations.

2.3.2. Weather data

Rainfall shocks cause the biggest weather-related losses in rural Ecuador (Ministry of Environment, 2012). The lack of rain mainly affects the agricultural sector, the principal economic activity in rural areas. Excess rain affects agriculture but also other sectors of the economy. The Ministry of Environment (2019 & 2021) indicates that from 2010 to 2020, homes, educational institutions, roads, bridges, and crops were affected and partly destroyed by extreme precipitation events, hampering all economic and social activities.

To capture the effect of weather, we work with daily rainfall data and construct suitable rainfall shock variables. The daily precipitation data were extracted from the Climate Hazards Center at the University of California, Santa Barbara. The "CHIRPS-daily" information provides data to a spatial resolution of approximately 5 km^2 (0.05° x 0.05°). It is estimated through satellite observations using infrared radiation and calibrated with ground-based weather stations worldwide (University of California, 2023).

For each area within the census sectors, we identify its centroid's geographical coordinates (latitude and longitude) and obtain the daily rainfall information of each centroid since 1981. To capture extreme weather shocks specific for each quarter, we first estimate the quarter accumulated rainfall for each census sector in the mentioned years. Then, we use this information to calculate the quarterly z-score for accumulated rainfall as follows:

$$z - score_{it} = \frac{Acp_{it} - \overline{Acp_i}}{Acp_i^{SD}} \qquad \text{(Equation 2.1)}$$

Where Acp_{it} is the accumulated rainfall of census sector i in quarter t. $\overline{Acp_i}$ is the historical average (for the corresponding quarter) of accumulated rainfall in census sector i, and Acp_i^{SD} is the standard deviation of the accumulated rainfall (for the corresponding quarter) in census sector i.

We identify an extreme event when the analyzed value Acp_{it} is significantly higher or lower than the historical average for the same quarter and territory, as done in previous studies (Boansi et al., 2021; Skoufias & Vinha, 2013; Amare et al., 2018). Using z-scores and recognizing that not all deviations from the long-term mean qualify as shocks, we measure rainfall shocks with dummy variables designed to capture extreme events as follows.

Considering the z-scores from Equation 2.1, the dummy takes the value of 1 if in a particular census sector z>2 (excess rain) or z<-2 (lack of rain), and 0 otherwise, since both excess and lack of rain have negative consequences for households in terms of income and poverty. For each household j, located in census sector i, we then count the number of shocks the household faced. Since we observe each household in two periods, the count variable can take 0, 1, or 2 values. Using this count, we construct two additional dummies: D_1pr_{jit} which takes the value of 1 if the household j in census sector i faced one rainfall shock, and 0 otherwise, and D_2pr_{jit} which takes the value of 1 if the household faced two consecutive rainfall shocks, and 0 otherwise. These two dummies characterize recurrent rainfall shocks in our regression models with zero shocks as the reference. Details of the regression models are explained below.

2.3.3. Regression models

To estimate the effects of rainfall shocks on income and poverty indicators, we use panel data regression models with household fixed effects of the following type:

$$Y_{jit} = \beta_o + \beta_1 D_1 pr_{jit} + \beta_2 D_2 pr_{jit} + \gamma \boldsymbol{X_{jit}} + \delta \boldsymbol{D_t} + \boldsymbol{\theta_j} + \varepsilon_{jit} \qquad \text{(Equation 2.2)}$$

Where Y_{jit} is the outcome variable for household j in census sector i and period t, and D_1pr_{jit} and D_2pr_{jit} are the two dummy variables representing one and two rainfall shocks, respectively, as explained in the previous subsection. $\boldsymbol{X_{jit}}$ is a vector of control variables that may also influence income or poverty, such as household size, education, and age of the household head, and whether or not the household receives conditional cash transfers under the Ecuador's Human Development Bonus program, among others. $\boldsymbol{D_t}$ is a vector of time dummies for the different quarters from 2013 to 2019, $\boldsymbol{\theta_j}$ is a vector of household fixed effects, controlling for unobserved time-invariant heterogeneity, and ε_{jit} is a random error term.

In these models in Equation 2.2, we are particularly interested in the coefficients β_1 and β_2. With household income as the dependent variable, a negative and significant β_1 would indicate that one rainfall shock has a negative effect on income. A negative and significant β_2 would indicate that two consecutive rainfall shocks have a negative effect on income. We are also interested in how the size of the two coefficients compare, hypothesizing that $|\beta_2| > |\beta_1|$.

In our estimates, we use deflated per capita income expressed in logarithmic terms as dependent variables, meaning that the coefficients β_1 and β_2 can be interpreted as percentage effects. We use robust standard errors to account for possible heteroskedasticity and employ survey sampling weights such that the estimates are representative (Azzarri & Signorelli, 2020) for rural Ecuador.

We start by estimating Equation 2.2 with the entire rural household sample. Subsequently, we re-estimate the same model with two subsamples, namely poor and non-poor households, to gain further insights into effect heterogeneity. We hypothesize that the negative income effects of rainfall shocks are more pronounced for poor than non-poor households.

Finally, we estimate Equation 2.2 with different poverty indicators as dependent variables. The indicators we use belong to the Foster-Greer-Thorbecke (FGT) class of poverty indices. The FGT index for a population is calculated using Equation 2.3, which allows for varying the weight (α) applied to the index level being analyzed (International Labour Organization, 2005).

$$FGT_\alpha = \frac{1}{n}\sum_{j=1}^{q}\left(\frac{p-y_j}{p}\right)^\alpha \qquad \text{(Equation 2.3)}$$

where n is the population size, q the number of households whose per capita income y is below the poverty line p, and α is a sensitivity parameter that can take values of 0, 1, or 2.

If $\alpha = 0$, the FGT_0 is the "headcount index", meaning the proportion of the population below the poverty line (International Labour Organization, 2005). We use the official poverty line for Ecuador established for 2006 (INEC, 2008), which we update using the official consumer price index. Expressed in current US dollars, the poverty line is equivalent to a monthly per capita income of 56.64 USD, which we use to differentiate between poor and non-poor households and to calculate the headcount index. In addition, we calculate a headcount index for the extreme poverty line of 31.92 USD. For estimating Equation 2.2, we create a poverty dummy as the dependent variable, which takes the value 1 if per capita income is below the poverty line and 0 otherwise.

If $\alpha = 1$, the FGT_1 is the "poverty gap", quantifying how far poor households are from the poverty line (International Labour Organization, 2005). We calculate the poverty gap for each household in the sample, which can take any value between 0 and 1. For non-poor households, the poverty gap is 0. Finally, if $\alpha = 2$, the FGT_2 is the "squared poverty gap", which is also known as the "poverty severity" (International Labour Organization, 2005). We use each household's poverty gap and poverty severity as dependent variables in the regression models explained in Equation 2.2. Note that for the poverty models, we expect positive estimates for β_1 and β_2, meaning that rainfall shocks are hypothesized to lead to rising poverty rates as well as rising poverty gaps and poverty severity.

We perform several tests to establish the validity of our estimation approaches. The test results are shown in Table A1 in the Appendix. The null hypothesis of homoskedasticity of the error terms is rejected in all models, meaning that our approach of using robust standard errors is appropriate. Likewise, the test results suggest that including time-fixed effects, as we do, is preferred. Finally, the Hausman test results suggest that the null hypothesis of no unobserved heterogeneity is rejected, meaning that our fixed effects estimator is preferred over the alternative random effects estimator.

2.4. Results

2.4.1. Descriptive statistics

The primary economic activity that rural households in Ecuador are engaged in is agriculture, accounting for 65% of the sample, followed by commerce (8%), manufacturing (7%), and construction (5%). Only 24% of the rural population has formal employment (Table 2.2). About 74% are either working on their own farm or are informally employed, meaning they do not have social security protection. These patterns suggest that most households in rural Ecuador are quite vulnerable to climate shocks.

Table 2.2 Employment - rural Ecuador

Category	Percentage
Formal employment	23.77%
Informal employment	74.25%
Unemployment	1.98%

Source: ENEMDU Panels, 2013-2019

Table 2.3 summarizes the variables we use in our regression models. Panel A shows the dependent variables. The average monthly per capita income is around 110 USD. More than one-third of the population (35%) is affected by poverty, and 13% suffer from extreme poverty. The poverty gap and the poverty severity are 0.13 and 0.07, respectively. The lower part of Table 2.3 (Panel B) shows the control variables of the regression models. The average household head is 51 years old and has 6.8 years of education. The average household size is 4.0.

Table 2.3 Summary statistics of household characteristics

	N	Mean	SD	Min	Max
Panel A: *Main outcome variables*					
Per capita monthly income (deflated USD)	118,948	109.92	146.51	0.12	23,155.47
Poverty (dummy)	118,948	0.35	0.48	0.00	1.00
Extreme poverty (dummy)	118,948	0.13	0.34	0.00	1.00
Poverty gap (0-1)	118,948	0.13	0.23	0.00	1.00
Poverty severity	118,948	0.07	0.16	0.00	1.00
Panel B: *Household controls*					
Education head of household	119,938	6.82	4.16	0.00	22.00
Age head of household head	119,929	51.05	16.26	13.00	98.00
Number of people in the household	119,938	4.00	2.08	1.00	28.00
Number of children under 5 years old	119,938	0.44	0.71	0.00	8.00
Number of older adults (65 or older)	119,938	0.34	0.63	0.00	5.00
BDH beneficiary household	119,936	0.41	0.49	0.00	1.00

Source: ENEMDU Panels, 2013-2019

Regarding rainfall patterns, Ecuador has two seasons: the rainy and dry seasons. The rainy season extends from November/December to April/May, the remaining months correspond to the dry season (Ministry of Environment, 2021). During the rainy season, the rainfall is typically abundant and can be very intense, and there is also high humidity. In the dry season, low rainfall creates a cool and dry climate. Usually, the first quarter of the year records the highest amount of rainfall, whereas the third quarter records the lowest (Figure 2.2). In this sense, our study compares similar periods in terms of expected rain (for example, the first quarter of 2015 vs. the first quarter of 2016), and we refer to consecutive shocks considering these seasonality cycles.

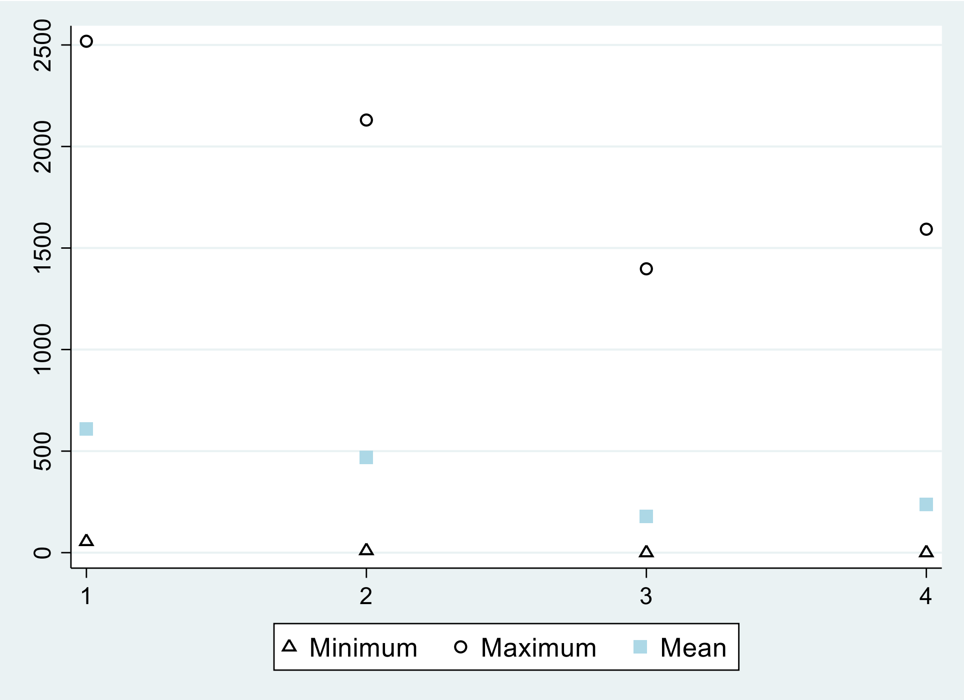


Figure 2.2 Quarterly accumulated precipitation (in mm for the period 1981-2020)

Source: CHIRPS (2023)

2.4.2. Econometric method

Income effects of rainfall shocks

Table 2.4 shows the estimated effects of rainfall shocks on per capita income, using fixed effects regression models as explained in Equation 2.2. Column (1) of Table 2.4 shows estimates of a model with only the rainfall shocks and no control variables included. Column (2) shows results with control variables included (full model results are shown in Table A2 in the Appendix). We mainly interpret the estimates of the model with control variables (column 2), as these are considered more reliable.

Table 2.4 Effects of recurrent rainfall shocks on per capita income

	(1)	(2)
One rainfall shock	-0.0879***	-0.0894***
	(0.0207)	(0.0206)
Two rainfall shocks	-0.165**	-0.133*
	(0.0687)	(0.0692)
Control variables	No	Yes
Time dummies	Yes	Yes
Observations	118,948	118,937
Number of id	59,922	59,919
R-squared	0.0060	0.0210

The dependent variable, per capita income, is expressed in logarithmic terms.
*Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

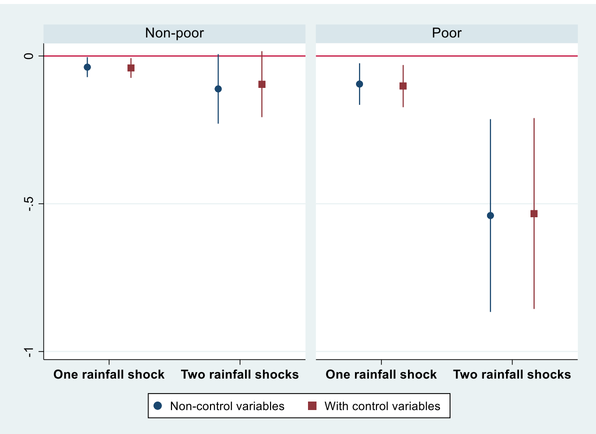
The estimate of -0.089 in column (2) of Table 2.4 implies that experiencing one rainfall shock reduces per capita income by approximately 9% after controlling for confounding factors. Two rainfall shocks lead to even larger income losses of 13%. The amplified magnitude suggests that the negative effects of rainfall shocks accumulate and may further worsen household welfare due to the reduced ability to recover between repeated shock events. That is, the first shock may leave households in a more vulnerable position and with fewer resources to face a subsequent second shock. Since CHIRTS (temperature) data are only available up to 2016 and not until 2019, the results of the regressions controlling for average temperature are presented in Table A2.1 in the Appendix. The results indicate the same pattern: negative effects of the first shock and more adverse impacts of the second. The temperature has no effect.

We estimate the same models with subsamples of poor and non-poor households to identify heterogeneous effects, using the official poverty line for separation. The results are presented in Table 2.5. As can be seen, rainfall shocks negatively affect the income of both poor and non-poor households. However, poor households suffer from larger income losses than non-poor households. One rainfall shock leads to an income loss of 4% among the non-poor and 10% among the poor. Two consecutive shocks reduce the income of non-poor households by 9.5%, yet the losses mount up to 53% for poor households. Rainfall shocks also tend to change the income distribution among the poor, as shown in Figure 2.3, Panel B. There is a higher proportion of households -that have not faced rainfall shocks- with higher incomes (black line). When facing rainfall shocks, the income distribution shifts to the left, indicating a higher concentration of households with lower income values (red line).

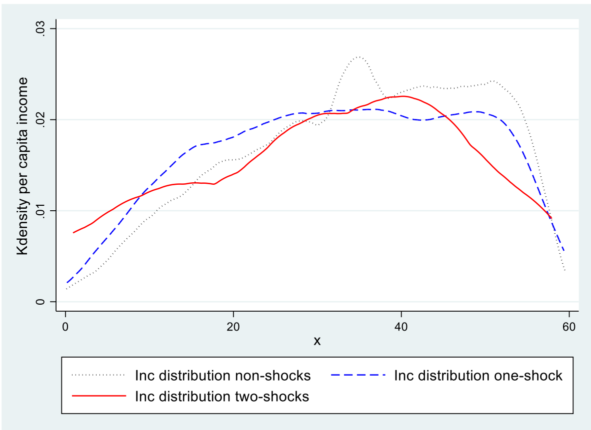
Table 2.5 Effects of recurrent rainfall shocks on per capita income (poor and non-poor households)

	Non-poor		**Poor**	
	(1)	**(2)**	**(3)**	**(4)**
One rainfall shock	-0.0377**	-0.0407**	-0.0949***	-0.102***
	(0.0172)	(0.017)	(0.0359)	(0.0364)
Two rainfall shocks	-0.111*	-0.0954*	-0.540***	-0.533***
	(0.06)	(0.057)	(0.166)	(0.165)
Control Variables	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	77,203	77,194	41,745	41,743
Number of id	47,180	47,175	29,353	29,352
R-squared	0.0130	0.0310	0.0060	0.0170

*Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*
Full model results are shown in Table A3 in the Appendix.



Panel A: Confidence intervals



Panel B: Income distribution among the poor

Figure 2.3 Effects of recurrent rainfall shocks on income distribution

Poverty effects of rainfall shocks

Table 2.6 shows the results of our regression models with the different poverty indicators as dependent variables. One rainfall shock increases the poverty headcount index by 3.7 percentage points (column 2) and the extreme poverty headcount by 2.9 percentage points (column 4). The effect of two rainfall shocks on poverty is not statistically significant, but on extreme poverty, it is significant: two consecutive rainfall shocks increase the prevalence of extreme poverty by 7 percentage points.

Table 2.6 Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity

	Poverty (dummy)		**Extreme poverty (dummy)**		**Poverty gap (0-1)**		**Poverty severity**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
One rainfall	0.0366***	0.0371***	0.0282***	0.0287***	0.0231***	0.0234***	0.0174***	0.0177***
shock	(0.0125)	(0.0125)	(0.00987)	(0.00985)	(0.00629)	(0.00629)	(0.00473)	(0.00474)
Two rainfall	0.0192	0.00483	0.0803***	0.0709***	0.0405**	0.0330*	0.0369***	0.0319***
shocks	(0.0494)	(0.0501)	(0.0231)	(0.0235)	(0.0182)	(0.0188)	(0.0107)	(0.0111)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,948	118,937	118,948	118,937	118,948	118,937	118,948	118,937
Number of id	59,922	59,919	59,922	59,919	59,922	59,919	59,922	59,919
R-squared	0.003	0.009	0.001	0.006	0.002	0.01	0.002	0.009

Robust standard errors are shown in parentheses.
**** p<0.01, ** p<0.05, * p<0.1. Full model results are shown in Table A4 in the Appendix.*

Finally, one rainfall shock significantly increases the poverty gap and severity. These effects further intensify after two consecutive shocks. The results suggest that rainfall shocks push rural households into poverty and deteriorate their economic conditions, moving them further from the poverty line. Tables A4.1 and A4.2 in the Appendix show the impacts, including temperature (2013-2016). The results show similar patterns: an increase in poverty measures, with more adverse consequences of the second shock. The temperature has no effect.

2.5. Conclusion and discussion

Climate change with rising temperatures and more frequent weather extremes has local consequences that differ between regions, countries, and population groups within countries. This study estimated the effects of rainfall shocks – including droughts and excessive rains – on income and poverty in rural Ecuador. Rural households in Ecuador are particularly vulnerable to rainfall shocks and other extreme weather events since they are exposed to floods and droughts, have a low adaptive capacity, and economically depend on agriculture and other activities sensitive to climate variations.

Our results show that one rainfall shock reduces the per capita income of rural households in Ecuador by 9% on average. Even though the magnitude of the effects differs, the general findings are consistent with earlier studies analyzing the effects in other geographic regions, including various countries in Africa and Asia (Amare & Balana, 2023; Arouri et al., 2015; Chuang, 2019; Hallegatte et al., 2018; Lokonon et al., 2015; Pleninger, 2022).

In rural Ecuador, we find that the income losses are more pronounced for poor than for non-poor households, which is also consistent with earlier research in other geographic settings (Boansi et al., 2021; Brouwer et al., 2007; Salvucci & Santos, 2020). What has not been analyzed much previously is how repeated weather shocks can further aggravate economic hardships and income distribution. Our results show that a second consecutive rainfall shock amplifies the income losses dramatically, especially for poor households: a second shock reduces per capita income by 13% on average and 53% for households below the poverty line. This very large negative effect on poor households is likely related to their low resilience and recovery capacity, given their insufficient access to savings, financial services, and social protection.

We also find that rainfall shocks increase poverty rates in rural Ecuador. One rainfall shock increases poverty by 3.7 pp and extreme poverty by 2.8 pp. A second rainfall shock increases extreme poverty by even 7.0 pp. Furthermore, the estimates show that rainfall shocks significantly increase the poverty gap and severity, with larger effects associated with repeated events. That climate change and extreme weather events can increase poverty rates considerably was also shown in different countries of Africa and Asia (Azzarri & Signorelli, 2020; Baez et al., 2020; Salvucci & Santos, 2020; Skoufias et al., 2011).

Overall, our study adds to the literature on the impacts of climate change and recurrent weather shocks on income distribution and poverty in the Global South. The findings show that severe negative consequences are observed not only in Africa and Asia but also in Latin America. The estimates with representative data from rural Ecuador underline that recurrent rainfall shocks have significant adverse income effects and hurt poor population groups over-proportionally. Although our study is limited to two consecutive shocks, showing that the second has a significantly greater impact, it paves the way for future research to investigate the effects of experiencing several consecutive, cascading, and/or compounding shocks on welfare outcomes, especially as climate change is expected to increase the frequency of these extreme events.

The results have important implications for further research and policymaking. Against the backdrop of ongoing climate change, not only mitigation but also effective adaptation strategies need to be urgently developed and implemented.

The resilience and recovery capacities of poor and vulnerable households must be strengthened, and these should include climate risk insurance and safety net programs that can help low-income families recover more quickly after facing an extreme weather event. The government can implement climate risk insurances, which provide immediate financial support to households in the wake of extreme weather events, enabling them to rebuild their livelihoods without falling deeper into poverty. Moreover, safety net programs, including conditional and unconditional cash transfers, can provide immediate relief to affected families. For instance, the Human Development Bonus (BDH), a conditional cash transfer program in Ecuador, could implement an emergency cash transfer to households affected by extreme events in addition to its regular cash transfers. For vulnerable households not covered by conditional cash transfers, delivering emergency relief funds or vouchers in anticipation of an event or immediately after its occurrence can accelerate recovery.

Given that many poor households depend on agriculture for their livelihoods, technical and institutional innovations to increase and stabilize yields are also important areas that need more policy attention. For instance, policies could promote climate-resilient crop varieties, improved irrigation systems, and sustainable land management practices. These could reduce yield variability under erratic weather conditions. At an institutional level, fostering access to agricultural extension services, training on adaptive farming techniques, and strengthening farmer cooperatives can enhance the adaptive capacity of rural communities. The data on particularly vulnerable regions and population segments are gradually improving, but more work is needed to understand the heterogeneity and design and target suitable interventions effectively. For example, poor agricultural households in the paramos. Enhanced data collection efforts are critical, especially for specific vulnerable groups.

Essay two

3. Rainfall shocks exacerbate urban poverty: Evidence from Ecuador[2]

Abstract

This study provides insights into the effects of weather shocks on disadvantaged urban populations in low and middle-income countries. Despite the significant growing impacts of climate change on urban areas and rapidly expanding urbanization across the developing world, little research has focused on climate change and weather shocks' impacts on urban populations. Therefore, this study aims to contribute to filling this critical gap. We use annual panels of household surveys from 2007 to 2019, weather information, and geographical characteristics of the territories in Ecuador to examine how rainfall shocks affect households' poverty levels. By applying fixed effects models, we identify that rainfall shocks, including excess and lack of rain, significantly exacerbate socioeconomic conditions, pushing poor urban households further down into poverty. These events disproportionately affect households living in risky areas and women more negatively. Families in the lowest income percentiles are most severely affected, underscoring their limited resilience and adaptive capacity. The study emphasizes the need for targeted interventions and resilience-building strategies to mitigate these adverse effects, particularly for vulnerable urban populations.

Keywords: rainfall shocks, poverty, urban area, Ecuador

JEL Classification: J16, I32, Q54

3.1. Introduction

Climate change is projected to intensify the recurrence and severity of extreme weather events, such as heavy rainfall, floods, droughts, and heat waves (Revi et al., 2014; MAATE, 2022; Yesuph et al., 2023). These events will increasingly affect larger populations, exacerbating poverty by pushing vulnerable groups deeper into poverty and reducing their capacity to recover (Hallegatte et al., 2018). This study examines the extent to which rainfall

[2] This study was published by the International Journal of Disaster Risk Reduction (https://doi.org/10.1016/j.ijdrr.2025.105539) and it is a joint paper with Alisher Mirzabaev. M.C.L.P. was responsible for all parts of the research with support and advice from the co-author.

shocks deteriorate the economic conditions of urban populations, with a particular focus on disadvantaged groups.

Weather shocks impact people and the economy through various pathways. The most direct effects occur in climate-sensitive activities, predominantly in rural areas, which have been widely studied (Acevedo et al., 2020; Birkmann et al., 2022). However, the highest concentration of urban population and the accelerated growth of cities have made urban communities more vulnerable to climate hazards (Dodman et al., 2022). Recent extreme rainfall events in southern Brazil, New Delhi or Valencia have had devastating consequences (CNN, 2024, May 10; CNN, 2024, July 1; CNN, 2024, October 31), highlighting the need for more research in urban settings. Women and people living in informal settlements are particularly affected, making it essential to assess the extent of these impacts on such vulnerable groups.

In informal settlements, residents lack legal ownership or security over their land or homes (United Nations Human Settlements Programme, 2015). These communities are often disconnected from basic infrastructure and services, and their housing typically does not comply with planning or building regulations. In cities, where land is scarce and expensive, housing markets frequently push low-income households toward informal settlements, where land is cheaper but more vulnerable to weather hazards (Hallegatte et al., 2020). This expansion often occurs in high-risk areas like floodplains, mountain slopes, or coastal zones (Hardoy & Pandiella, 2009). As a result, poor households in risky areas are more frequently impacted by natural disasters (Narloch and Bangalore, 2016; Hallegatte et al., 2020).

Women generally have less access to resources than men, including land, credit, decision-making structures, and technology. Additionally, they often have lower levels of education and training (Chen & Carré, 2020; Dodman et al., 2023). These disparities force many women into precarious, informal employment characterized by low and unstable incomes. Such economic instability increases their vulnerability to extreme weather events, as their livelihoods are more easily disrupted, limiting their capacity to diversify income sources or enhance resilience against climate-related shocks (Reckien et al., 2017). Consequently, the intersection of gender and poverty significantly amplifies their susceptibility to climate and weather shocks.

In urban areas, people living in high-risk zones, such as informal settlements, and vulnerable women are often below the poverty line (Bartlett et al., 2009; Narloch and Bangalore, 2018; Dodman et al., 2023). Poor households are disproportionately affected by climate shocks compared to wealthier residents due to their higher exposure to hazards, limited adaptive and coping capacities, and restricted access to financial resources, infrastructure, or insurance. They also face greater difficulty in relocating to safer areas. Any impact on their assets, income, or consumption deepens their vulnerability, making it harder to escape poverty (Hallegatte et al., 2014, 2017, 2018, 2020; Kaijser & Kronsell, 2014; Revi et al., 2014; Birkmann et al., 2022; Nakamura et al., 2023).

The literature has predominantly focused on the effects of climate shocks in rural areas, with limited attention given to urban settings (Plänitz, 2019). As urban areas expand and vulnerable groups increasingly face climate extremes, more research on urban impacts is urgently needed (Haque, 2020; Birkmann et al., 2022). Extreme weather events are worsening the economic conditions of disadvantaged populations, often pushing them into poverty. However, the extent to which rainfall shocks exacerbate these conditions in urban areas remains understudied. This research addresses this gap by assessing how rainfall shocks drive households further down the poverty line, considering vulnerable urban groups and differentiated effects across income percentiles.

The study uses annual panels from 2007 to 2019 at the household level, which allows us to control for unobservable factors and to identify the effects in vulnerable groups, which represent a small share of the national wealth and thus, their impacts would be almost imperceptible using regional or national data sources (macro-economic aggregates) (Hallegatte et al., 2018). This information is combined with rainfall data and geographical characteristics of the land, such as risk of flooding, landslides, and drought. It is one of the few studies that combine three sources of information: households, weather, and geographic data. The findings provide valuable insights for public policy by pinpointing who is most affected and the hotspots where the impacts are most severe.

The rest of the document is structured as follows. The conceptual framework (Section 3.2) details the pathways by which weather shocks affect household income and, therefore, push people further from the poverty line, worsening their economic condition. Section 3.3, Material and Methods, presents the data and methods used, followed by Section 3.4, which shows our findings. The paper concludes in Section 3.5.

3.2. Conceptual framework

Climate change is expected to increase the intensity and frequency of several risks, including a rise in temperature and heat waves, sea level, drought, precipitation, and extreme rainfall (Gran Castro & Ramos de Robles, 2019; Revi et al., 2014), as shown in Figure 3.1. This section analyzes how rainfall shocks affect people and worsen their economic conditions.

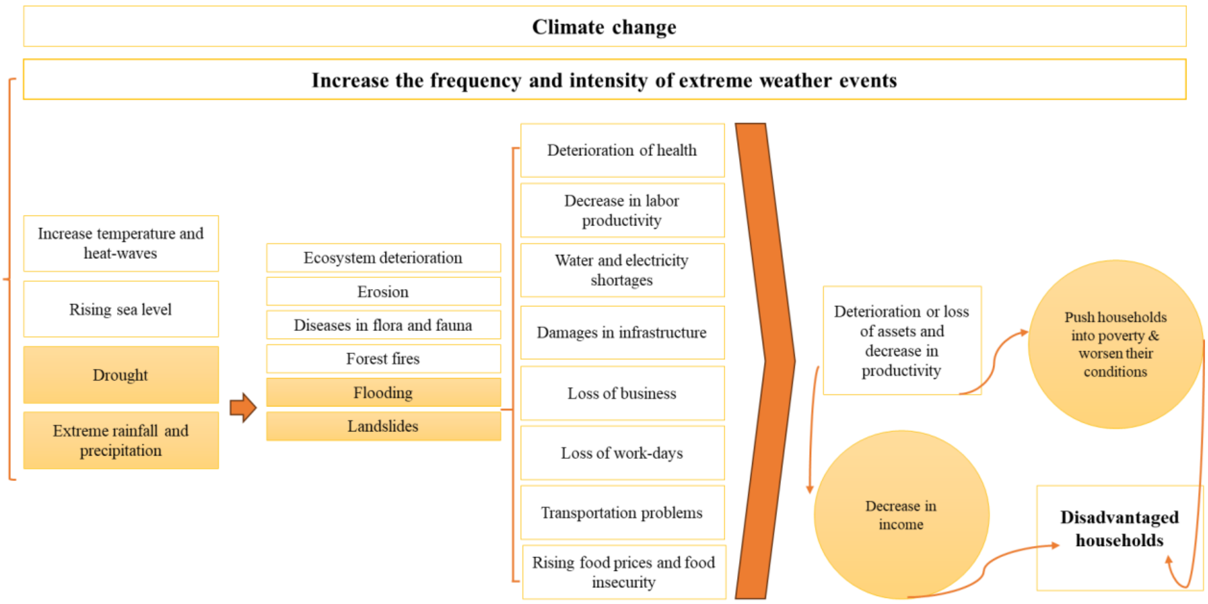


Figure 3.1 Climate change and socioeconomic impacts

Although there are some climatic risks, the most significant to urban areas arises from the increasing frequency and intensity of extreme rainfall events, including heavy rainstorms, cyclones, and hurricanes, which exacerbate hazards such as flooding and landslides (Satterthwaite et al., 2007; Gran Castro and Ramos de Robles, 2019; Dodman et al., 2022). Lack of rainfall also carries severe consequences, as evidenced in Ecuador, which has led to power outages from 8 to 14 hours per day (Associated Press, 2024, October 25). This study focuses on the impacts of rainfall shocks, including both excess and lack of rain.

The absence of rainfall can increase forest fires, erosion, and biodiversity loss. It negatively affects people due to rising electricity shortages (hydropower), which decrease business production and employment, deteriorate health due to contaminated water-related diseases, and increase the price of agricultural products linked to reduced supplies (Bartlett et al., 2009; Revi et al., 2014; Dodman et al., 2022; Amondo et al., 2022; Amondo et al., 2023).

On the other hand, extreme rainfall, usually related to floods and landslides, often damages or destroys the physical infrastructure, causes loss of business and livelihood options, and increases water-borne and water-related diseases, like malaria, typhoid, dengue, cholera, skin diseases, and infections. Flooding can contaminate water sources, disrupt power supply, and impede transportation, affecting food and fuel availability. Likewise, landslides are associated with the loss of infrastructure and detrimental effects on housing or businesses (Satterthwaite et al., 2007; Dodman et al., 2022). Floods and landslides damage or destroy homes and businesses and have economic implications because they affect households by reducing work hours, which implies a loss of income and, sometimes, jobs (Bartlett et al., 2009; Revi et al., 2014; Hallegatte et al., 2020).

Overall, climate shocks affect people's income, mainly through asset and productivity channels. The asset channel is associated with the loss of assets (financial, physical, human, and natural capital) due to damage caused by storms, floods, and landslides or the liquidation of assets forced by compromised livelihoods. The productivity channel is associated with the alteration in productivity caused by climate shocks, which may translate into reduced incomes. Infrastructure damage leads to disruption of livelihoods associated with losing business or workdays. The interruption in transportation does not allow people to travel to their workplaces, and water and electricity outages do not allow businesses to function correctly. Health issues reduce the ability of households to earn an income, as they become ill or must care for a family member and cannot work, or it also depletes their financial assets because of health expenditures (Hallegatte et al., 2014).

In the urban context, low-income households, poor women, and families residing in risky areas are often the most affected, mainly because they are more exposed to risk and are socioeconomically more vulnerable: greater exposure to hazards (living on flood plains or slopes), lack of risk-reducing housing and infrastructure (poor quality housing, lack of drainage systems), less adaptive capacity (lacking income or assets that allow them a move to non-risk areas), less state provision for assistance, and less legal and financial protection (lack of legal tenure of housing, or lack of insurance) (Bartlett et al., 2009; Winsemius et al., 2018; Gran Castro & Ramos de Robles, 2019). Extreme weather events reduce household income, destroy houses or productive capital, and become crucial in pushing disadvantaged households into poverty and keeping them poor (Hallegatte et al., 2014; Birkmann et al., 2022).

3.3. Materials and method

The study uses panel-fixed effects to analyze how weather shocks impact households in urban Ecuador. The dependent variable is the distance to the poverty line. The independent variables are rainfall shocks and household characteristics. The data is linked using territorial codes, resulting in a comprehensive database that includes household socioeconomic characteristics, rainfall shocks, and geographic information on landslide, flood, and drought risks within the territories.

3.3.1. Data

Household

Household data comes from the National Survey on Employment, Unemployment and Underemployment (ENEMDU). The survey is the official source for examining income distribution, poverty levels, employment conditions, and job market characteristics. The ENEMDU is conducted quarterly nationwide, ensuring national and urban representation (INEC, 2022). Between 2007 and 2019, the survey was developed using a conglomerate[3] panel approach. This approach helps create annual panels from a subsample and allows the examination of the same observation units across different annual cohorts. For example, we can observe the same households in two distinct periods: the first quarter of 2016 and the first quarter of 2017.

In this study, we focus on urban households, for which we harmonize and pool 25 annual panels corresponding to different quarters from 2007 to 2019. This resulted in 142,739 households observed over two periods (285,478 observations), as shown in Table B1 in the Appendix.

[3] Group of homes that belong to the same district.

The survey geo-references households at the census sector level, allowing us to identify households' geographic locations. In the urban area, a census sector encompasses a contiguous area that may include one or more city blocks, typically comprising around 150 households on average (INEC, 2020).

Weather

To capture the effect of extreme weather events, we estimate rainfall shocks, as done in previous studies (Skoufias and Vinha, 2013; Amare et al., 2018; Boansi et al., 2021). The daily rainfall data is obtained from the Climate Hazards Center at the University of California, Santa Barbara. The "CHIRPS-daily" dataset offers information to a spatial resolution of approximately 5 km^2 (0.05° x 0.05°), utilizing a combination of satellite observations with infrared data, and observations from weather stations across the globe (University of California, 2023).

We identify the centroid's geographical coordinates (longitude and latitude) within each census sector and gather the daily precipitation data since 1981. To capture the shocks for the corresponding quarter in every location, we estimate the quarter accumulated rainfall for each census sector Acp_{it}. Then, we calculate the quarterly z-score for accumulated rainfall, as shown in Equation 3.1.

$$z - score_{it} = \frac{Acp_{it} - \overline{Acp_{\iota t}}}{Acp_{it}^{SD}} \qquad \text{(Equation 3.1)}$$

Where Acp_{it} is the accumulated rainfall in census sector *i*, in quarter *t*. $\overline{Acp_{\iota}}$ is the historical average of accumulated rainfall in census sector i, for quarter t, and Acp_{i}^{SD} is the standard deviation of the accumulated rainfall in census sector *i* for the corresponding quarter.

Based on the z-score values and recognizing that not all deviations from the long-term mean qualify as shocks, we measure rainfall shocks with a dummy that takes the value of 1 if the z-score of the census sector *i* in quarter *t* is higher than 2 (too much rain) or lower than -2 (too little rain) and 0 otherwise. This means we consider the total effects of excess or scarce rain.

Geographic
We obtain geographic information on land's risk or susceptibility to floods, droughts, and landslides from the Geoinformation generation project for territorial management GGP and Threat analysis against mass movements in Ecuador TAM in collaboration with the Ecuadorian Space Institute; the Ministry of Agriculture, Livestock, Aquaculture, and Fisheries; the General Coordination of the National Information System; and the National Risk and Emergency Management Service.

The Geoinformation generation project generated information to identify susceptible areas to droughts and floods, while the National risk and emergency management service provided information on landslides. The maps cartographically identify areas susceptible to floods, droughts, and landslides nationally. They classify the territory according to its risk of these events: high risk, medium, low, and no risk.

For floods, the GGP analyzed the soil and climate or weather characteristics: topography (relief and slopes), lithology, geomorphology, pedology, soil forms (valleys, slopes), and frequency and location of precipitation. This analysis classified Ecuadorian territory into high, medium, low, and non-susceptible flood zones. High susceptibility represents the territories where cyclic floods occur every year in the rainy season, and areas without susceptibility are not prone to flooding (IIE et al., 2015a).

For droughts, the GGP studied the precipitation patterns, temperature, evapotranspiration, humidity, and the shapes and relief of the soil (valleys, slopes). According to the analysis, the project classified the territory as high risk, medium, low, or no drought risk. High risk is defined when the probability of a drought occurring is greater than 45%, and a no threat is determined when there is no probability of occurrence (IIE et al., 2015b).

To establish the level of risk or susceptibility of mass movements (landslides), the TAM studied the variables of structural density (geological faults, structural lineaments), slope and texture of the soil, geology (lithology), precipitation, effective depth, and stability. According to the analysis, the Risk service classified the territory as a very high risk, high, medium, low, and no landslide risk. Territories with very high risk or susceptibility of landslides have steep slopes, with the presence of fractured rocks, without vegetation cover, and eroded soils that are not very cohesive and compact. No risk corresponds to stable territories with no probability of mass movements occurring, with flat to gentle terrain slopes, no greater than 5% (Subsecretaria de Gestión de la Información y Análisis de Riesgos, 2019).

With this information, we identify risky and non-risky territories. For each parish, we calculate the percentage of land with a high or very high risk of floods, drought, or landslides. For example, Rioverde in the province of Esmeraldas has 19% of its territory at very high or high risk of landslides, 6% at high risk of flooding, and 0.1% at high risk of drought. San Joaquin, in Cuenca, has 58% of its territory at high risk of landslides, 2% at high risk of flooding, and 0% at high risk of drought. Then, we identify risky territories if the parish has a high or very high risk of drought, flood, or landslide in at least 50% of its territory. In our example, Rioverde is a non-risky area, and San Joaquin is considered risky.

3.3.2. Econometric method

We employ fixed effects to estimate whether rainfall shocks worsen households' economic conditions (Equation 3.2). This approach eliminates the effect of time-invariant unobserved heterogeneity among households and isolates the impact of rainfall shocks on the household's location.

$$Y_{jit} = \beta_o + \beta_1 Dpr_{jit} + \gamma X_{jit} + \delta D_t + \theta_j + \varepsilon_{jit} \qquad \text{(Equation 3.2)}$$

Where Y_{jit} corresponds to the distance to the poverty line for household j (located in the census sector i) in the quarter t. Dpr_{jit} is the dummy representing facing a rainfall shock (excess or lack of rain), and X_{jit} is the vector of independent variables for household j in the period t. We include household characteristics such as the education and age of the household head, number of household members, number of elderly (older than 65), and number of children (younger than 5). We also incorporate temporal dummies for each quarter: Dt.

We calculate the distance to the poverty line as the ratio $\left(\frac{y_{ji}-z}{z}\right)$, which corresponds to the difference between the household per capita income y_{ji} and the threshold (poverty line z), divided by the poverty line z. The ratio represents the percentage of how close (or far) families are to the poverty line. Values nearing -1 indicate that households are significantly below the poverty line (poorer), while those approaching 0 signify being nearly at the poverty line (less poor). Wealthier households have positive values. This metric offers deeper insight into how far people are from reaching the income threshold, assessing the depth of their poverty.

We adopt Ecuador's official poverty line. Since June 2006, the consumption poverty line from the Living Conditions Survey (ECV-5) has been updated using the Consumer Price Index (INEC, 2008). The ECV-5 sets the poverty line at 56.64 USD. Our approach employs data from household surveys and their sampling weight to estimate the model, ensuring the representativeness and statistical validity of the estimates (Azzarri & Signorelli, 2020).

To evaluate differentiated or heterogeneous effects of rainfall shocks on the urban population, we first identify the vulnerable groups mentioned in the literature: people living in risky areas and women. Second, to assess whether the most disadvantaged are more affected, we analyze subsamples considering the percentiles 10, 25, 50, and 75 and apply the abovementioned model (Equation 3.2). Note that we have stacked 25 bases. Therefore, the amount of data allows us to perform these subsamples.

We conducted several tests to validate our estimation method. The results are presented in Table B2 of the Appendix. We use robust standard errors because we reject the null hypothesis of homoscedastic error terms across all models. Additionally, the test outcomes favour the inclusion of time-fixed effects, which we have incorporated into our analysis. Finally, the Hausman test led us to reject the null hypothesis of no unobserved heterogeneity, indicating a preference for our fixed-effects estimator over the random-effects alternative.

3.4. Results

3.4.1. Descriptive statistics

To estimate how much rainfall shocks affect households in urban Ecuador, we consider the variables described in Table 3.1. Panel A shows the dependent variable, distance to the poverty line, and panel B shows the control variables: rainfall shocks, the education and age of the head of household, the number of people in the household, the number of children younger than five years, and the number of adults older than 65.

The distance to the poverty line, on average, is 2.55. That is, household per capita income is, on average, 2.55 times higher than the poverty line. According to the merged household and weather data, around 4% of households face rainfall shocks. Families are more impacted by excessive rainfall than by its scarcity, with 2017 experiencing the highest number of these weather extremes (Figure 3.2). From 2007-2019, the average education level of the head of the household was 10.45 years, and the age of 50.85 years. The average household size is 3.81 individuals with 0.37 children under five years old. Considering households with at least one child under five, the average is 1.28.

Table 3.1 Summary statistics - household characteristics

	N	**Mean**	**SD**	**Min**	**Max**
Panel A: Outcome variable					
Distance to the poverty line	285,478	2.55	4.58	- 1.00	736.19
Panel B: Household controls					
Rainfall shock	*288,568*	*0.042*	*0.20*	-	*1.00*
Education head of household	288,568	10.45	4.89	-	23.00
Age head of household	288,534	50.85	15.32	14.00	98.00
Number of people in the household	288,568	3.81	1.91	1.00	26.00
Number of children under 5 years old	288,568	0.37	0.65	-	7.00
Number of older adults (65 or older)	288,568	0.28	0.57	-	5.00

Source: ENEMDU Panels 2007-2019

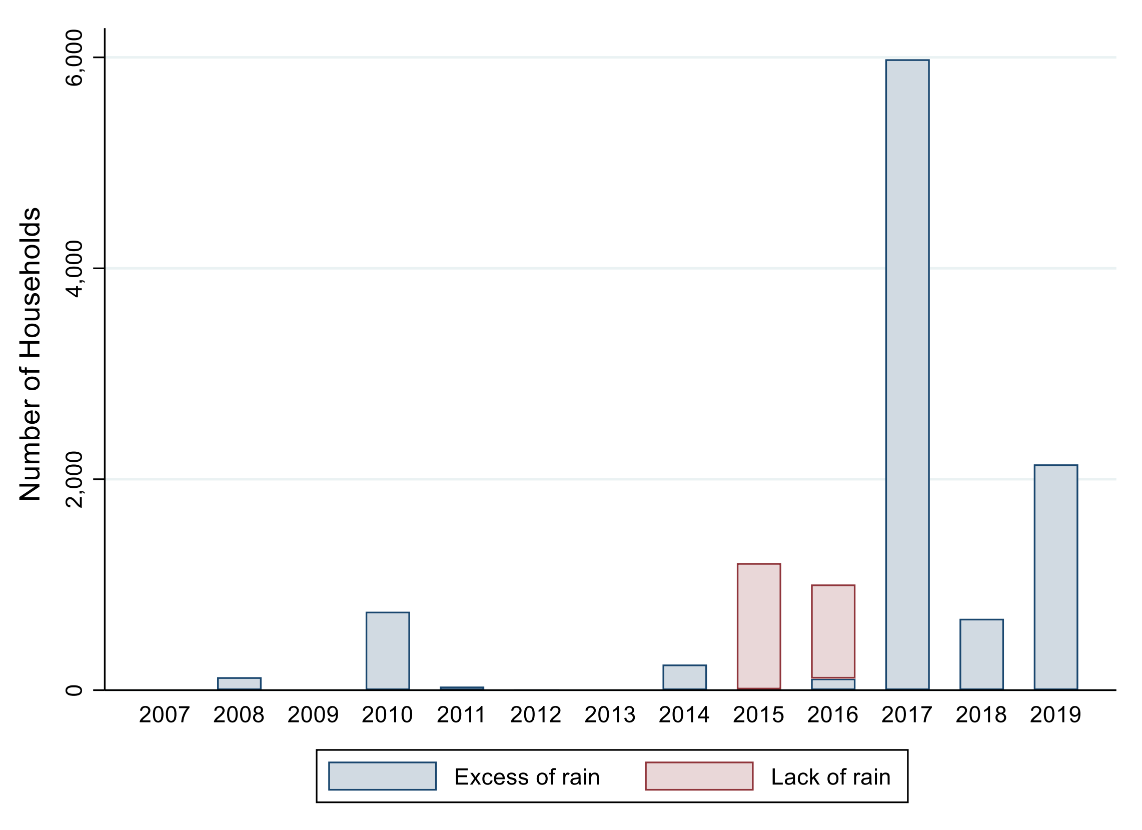


Figure 3.2 Households facing rainfall shocks per year

Source: ENEMDU Panels 2007-2019 and CHIRTS data

In addition, to understand the context of the urban area, the main economic activities are commerce (22.18%), manufacture (13.35%), transportation and storage (9.41%), construction (9.18%), and agriculture (8.74%), which together contribute 62.86% (ENEMDU Panels, 2007-2019). Regarding employment, 58.51% of the population benefits from formal employment. However, underemployment affects 38.57% of workers, implying that a considerable segment of the population may face inadequate or insufficient working conditions despite employment. The unemployment rate is 2.92%. Urban poverty reaches 13.74%, and 3.74% of the population is extremely poor.

Lower-income households experience more adverse working conditions. The average per capita income in the poor population is 38.96 USD, and the distance to the poverty line is -0.31; on average, poor people are 31% far from the poverty line. Only 14.95% have formal employment, and 78.76% are underemployed. The unemployment rate in this segment is 6.3%. In the case of poor women, 87.42% are underemployed, 8.35% are unemployed, and only 4.23% are formally employed. In general, the income of people in risky areas is lower than those in non-risk areas.

3.4.2. Econometric method

Table 3.2 presents the results of the econometric model (Equation 3.2). The first five columns do not include control variables: column one (1) shows the impact on the total urban area, and columns 2 to 5 on the different percentiles: 10, 25, 50, and 75. Columns 6 to 10 represent the results, including control variables, for the total urban area and the different percentiles.

Table 3.2 Effect of rainfall shocks on the distance to the poverty line

	Urban Area (1)	**Per10 (2)**	**Per25 (3)**	**Per50 (4)**	**Per75 (5)**	**Urban Area (6)**	**Per10 (7)**	**Per25 (8)**	**Per50 (9)**	**Per75 (10)**
Rainfall shock	**0.0769**	**-0.0953 *****	**-0.0705 *****	**-0.0385 ****	**-0.029**	**0.084**	**-0.0980 *****	**-0.0725 *****	**-0.0376 ****	**-0.03**
	(1.19)	(-3.19)	(-3.58)	(-2.19)	(-1.61)	(1.3)	(-3.34)	(-3.69)	(-2.14)	(-1.57)
Control Variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285478	16968	50866	118134	196525	285446	16964	50856	118115	196501
Adjusted R-squared	0.001	0.036	0.01	0.006	0.004	0.008	0.04	0.013	0.012	0.019

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

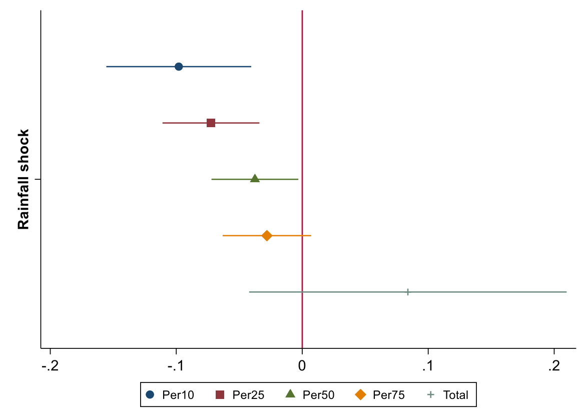
The complete table with the results of the control variables is found in Table B3 in the Appendix.

The analysis reveals a significant negative impact of rainfall shocks (excess or lack of rain) on the distance to the poverty line as we move toward the lowest income percentiles, consistent under various specifications of the model (with and without control variables).

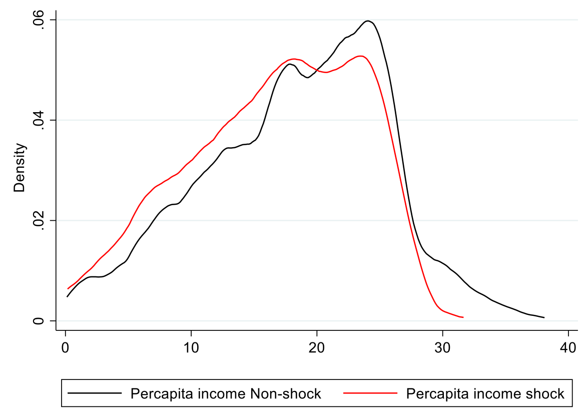
Weather extremes have heterogeneous effects across population segments. While we observe a non-significant effect in the urban area in general (column 6), the results show an inverse and significant relationship in the lowest income percentiles. Rainfall shocks increase the distance from the poverty line for households in the 10th, 25th, and 50th percentiles. The gap widens by -9.8 percentage points for the 10th percentile (column 7), -7.2 percentage points for the 25th percentile (column 8), and -3.8 percentage points for the 50th percentile (column 9).

As shown in Figure 3.3, Panel A, lower-income households are disproportionately affected. They are more vulnerable to these climatic events, resulting in income distribution changes for those facing a rainfall shock (Figure 3.3, Panel B). As illustrated in Figure 3.3, Panel C, the 10th percentile is, on average, -52% below the poverty line. However, when exposed to a rainfall shock, their position shifts further to -62% below the poverty line, highlighting the disproportionate impact experienced by this income group compared to other percentiles.

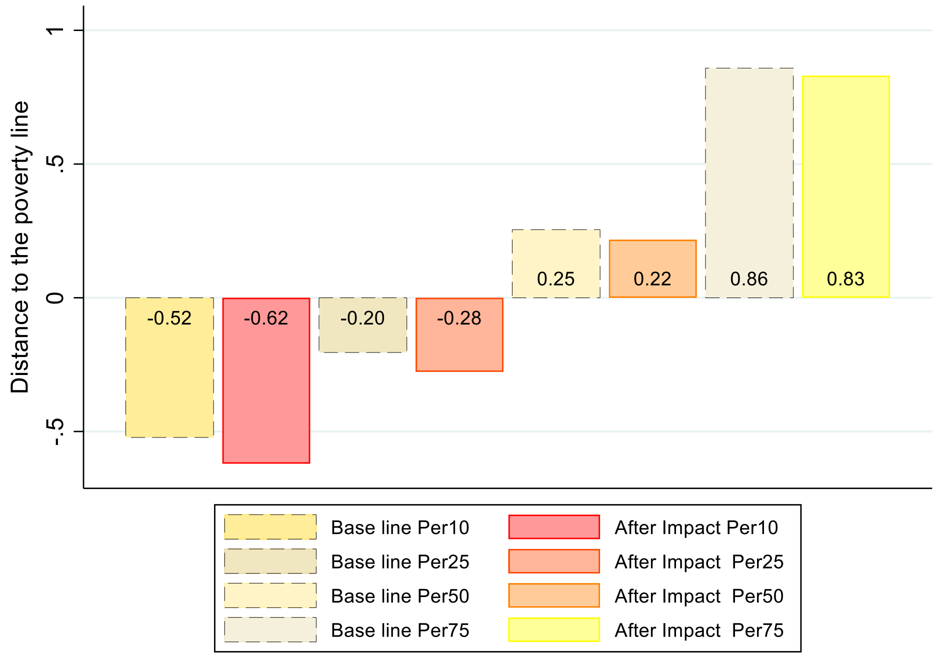
Low-income households often depend on climate-sensitive livelihoods, such as informal labor or agriculture, which makes them prone to income loss from reduced work opportunities, damaged infrastructure, or crop losses. Limited access to savings, insurance, or alternative income streams restricts their ability to mitigate these effects. They also lack the resources to invest in protective measures like flood barriers, resilient housing, or electric generators during power outages, amplifying the impact of rainfall shocks on their daily lives (Bartlett et al., 2009; Winsemius et al., 2018; Gran Castro & Ramos de Robles, 2019).



Panel A: Distance to the poverty line



Panel B: Income distribution



Panel C: Distance to the poverty line: Baseline and total effect

Figure 3.3 Effect of rainfall shocks on the distance to the poverty line and income distribution

To identify heterogeneous effects, we use the model of Equation 3.2 and analyze different subsamples. The results in the different income percentiles are presented in Table 3.3 and Table 3.4. Table 3.3 shows the impact on Risky (columns 1-5) and non-risky areas (columns 6-10), and Table 3.4 on Women (columns 1-5) and Men (columns 6-10).

Table 3.3 Effect of rainfall shocks on the distance to the poverty line: Risky and non-risky areas

	Risky areas	**Per10**	**Per25**	**Per50**	**Per75**	**Non-risky areas**	**Per10**	**Per25**	**Per50**	**Per75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Rainfall shock	**0.0046**	**-0.153*****	**-0.130*****	**-0.0761*****	**-0.0806*****	**0.144**	**-0.0617**	**-0.0219**	**0.0171**	**0.026**
	(0.07)	(-3.51)	(-3.94)	(-2.85)	(-3.01)	(1.07)	(-1.51)	(-0.90)	(0.66)	(0.95)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152609	8182	26731	64449	107438	130052	8262	22916	51686	86592
Adjusted R-squared	0.01	0.062	0.023	0.016	0.021	0.007	0.075	0.014	0.011	0.018

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*
The complete table with the control variables' results is found in Tables B4 and B5 in the Appendix.

In risky areas, rainfall shocks negatively and significantly affect the distance to the poverty line across all the percentiles but have a more pronounced effect in the lowest ones. For instance, households in the 10th percentile that face a shock move away from the poverty line by -15 percentage points (column 2). And, at the 75th percentile, the distance to the poverty line moves by -8 percentage points (column 5). These results highlight the vulnerability of all households in risky territories, where rain-related events not only directly threaten physical security but also exacerbate poverty conditions, disproportionately impacting the poorest.

Conversely, in areas without inherent risks (columns 6-10), the impact of rainfall shocks on the distance to the poverty line is negligible or insignificant. However, it is worth noting that the coefficient value shows a bigger negative effect for the lower percentiles (Table 3.3 and Figure 3.4, Panel A).

Low-income families in high-risk areas often lack infrastructure, with poor drainage systems, unpaved roads, and homes or businesses built with low-quality materials. Such conditions, along with their economic limitations, amplify their vulnerability to weather extremes (Bartlett et al., 2009; Winsemius et al., 2018; Gran Castro and Ramos de Robles, 2019).

These insights underscore the need to factor in location and geographic environment when formulating adaptation and mitigation strategies against climate change. They highlight the necessity of prioritizing high-risk areas where the most vulnerable households are concentrated.

Table 3.4 Effect of rainfall shocks on the distance to the poverty line: Women and men

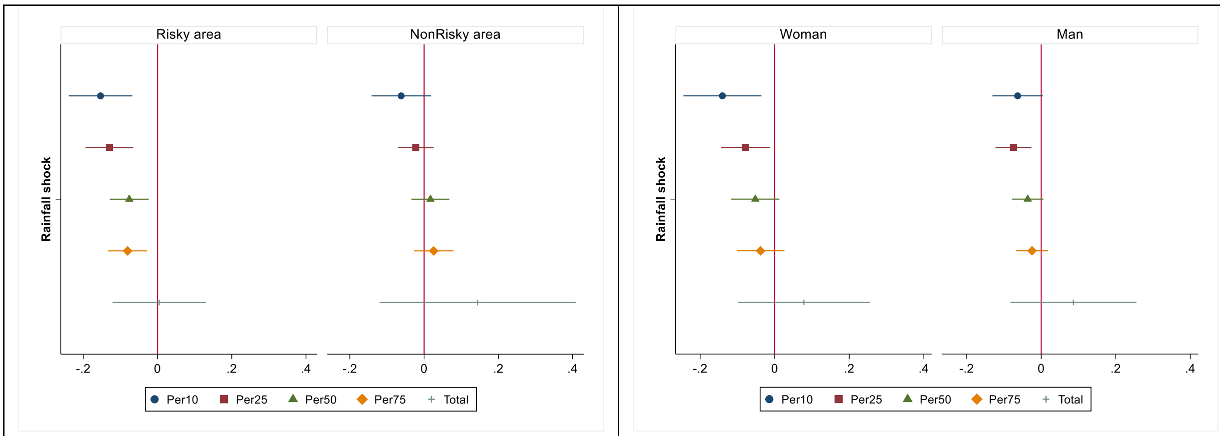
	Women	**Per10**	**Per25**	**Per50**	**Per75**	**Men**	**Per10**	**Per25**	**Per50**	**Per75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Rainfall shock	**0.0783**	**-0.140*****	**-0.0783****	**-0.052**	**-0.0379**	**0.0865**	**-0.0631***	**-0.0745*****	**-0.036***	**-0.0246**
	(0.87)	(-2.63)	(-2.36)	(-1.58)	(-1.16)	(1.00)	(-1.83)	(-3.03)	(-1.69)	(-1.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83048	5747	16209	36453	59394	202398	11217	34647	81662	137107
Adjusted R-squared	0.012	0.104	0.03	0.016	0.021	0.007	0.034	0.015	0.012	0.02

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

The complete table with the control variables' results is found in Tables B6 and B7 in the Appendix.

The "Women and Men" analysis concludes that women in the lowest percentiles experience a severe impact. Rainfall shocks move women in the 10th percentile from the poverty line by approximately -14 percentage points (column 2). This contrasts with the non-significant effect from 50 and 75 percentiles (columns 4 and 5). Men in the lowest percentile are also affected by -6 percentage points (column 7), but less severely than women. However, these men experience greater consequences than women from high percentiles (column 5). The results can be seen graphically in Figure 3.4, Panel B.

The average distance to the poverty line for women in the 10th percentile is -52%. Rainfall shocks increase this value by -14 percentage points, placing them at -66% after a shock, meaning they are in a worse condition. Low-income women typically have lower levels of education and primarily engage in informal work (ENEMDU Panels 2007-2019), an economic activity particularly vulnerable to climate shocks in urban areas (Dodman et al., 2023). Furthermore, they lack access to financial resources such as savings, insurance, or credit, which could help mitigate the impacts of these shocks (Chen & Carré, 2020; Dodman et al., 2023).



Panel A: Risky and non-risky areas

Panel B: Women and men

Figure 3.4 Effect of rainfall shocks on the distance to the poverty line: subsample analysis

3.5. Conclusion and discussion

Despite increasing urbanization rates, the urban impacts of climate and weather shocks remain understudied compared to those of rural areas (Plänitz, 2019). This study estimates the effect of rainfall shocks in urban Ecuador, considering vulnerable groups, such as women and households in risky areas, in their different income percentiles.

The results show rainfall shocks significantly aggravate economic disparities, increasing the distance to the poverty line, especially in the lowest percentiles. In general, women are more affected than men, and people who live in risky areas are more affected than those who live in safer areas. Rainfall shocks exacerbate poverty distribution within populations but also existing inequalities based on sex, especially in the lower percentiles. In the 10th percentile, people living in risky areas (-15.3 percentage points) and women (-14.0 percentage points) are the most affected. In the high percentiles, people living in risky areas also show harmful effects of rainfall shocks.

Current literature has not focused on evaluating how climate change and shocks move people away from the poverty line. However, some studies show that these events increase poverty or decrease income. In this sense, our results are consistent with studies on the relationship between urban poverty and climate change. In Mexico, Bolivia, and Peru, floods, droughts, or natural disasters have increased household and territorial poverty (Rodriguez-Oreggia et al., 2013; Hallegatte et al., 2018). Poor urban households are usually more exposed to floods than the average urban population. Extreme events lower the chance of poverty escape (Hallegatte et al., 2020; Nakamura et al., 2023).

The disproportionate exposure of disadvantaged groups to environmental risks makes them more vulnerable, thus exacerbating already existing poverty traps (Narloch and Bangalore, 2018). This disparity in impact reflects differences in the capacity to adapt and mitigate extreme climate events (attributed to limited access to infrastructure, credit, safety nets, etc.), underscoring the urgency of addressing inequalities in vulnerability and capacity to respond to climate changes.

In this sense, our analysis contributes to understanding the interactions between extreme weather events and vulnerable groups in urban areas and highlights the importance of considering the dimensions of sex, poverty, and geographical environment (risky areas) when evaluating the socioeconomic impacts of climatic events and developing policies, adaptation, and mitigation strategies against climate change.

Most governments in developing countries give little attention to the urban poor in their policies and investments, especially regarding climate change and natural disasters (Dodman et al., 2023). This underscores the need for inclusive public policies and climate change adaptation strategies targeted at these groups.

It is important to cross-reference poverty maps with geographic information such as landslide, flood, or drought risk maps. This can help identify where and who is most affected, emphasizing how women are impacted. With this information, risk management policies (land-use regulations) can be integrated with infrastructure improvement programs and poverty reduction strategies. For example, in risk areas with informal settlements, governments can implement regulations that prevent the construction of homes/businesses, assess the possibility of relocation, or mitigate the impacts of extreme weather events by creating specific adaptation plans. These plans should promote climate-resistant infrastructure, including the construction or enhancement of drainage systems, flood barriers, or the reinforcement of slopes and building retaining walls to stabilize areas prone to landslides. Relocation programs should consider affordable housing in lower-risk areas, ensuring these regions have essential services and employment opportunities.

Social protection schemes incorporating disadvantaged groups could also be strengthened. For example, the government can map households benefiting from the Human Development Bonus, a conditional cash transfer program in Ecuador, and identify those living in high-risk areas. For residents in risky zones, immediate access to emergency cash transfers or low-interest credits should be facilitated to aid recovery in extreme weather events. Furthermore, these social protection schemes could be extended, ensuring that poor households residing in high-risk areas are included.

Government aid must be quick and effective since a one-time drop in income may force households to sell assets in a rush (often at a low price) with long-term consequences, structurally affecting their poverty level. These policies will help these households navigate and recover from the negative impacts of rainfall shocks.

Essay three

4. Rainfall shocks intensify unpaid domestic work and increase social inequalities: Evidence from Ecuador[4]

Abstract

Weather extremes exacerbate existing social inequalities. This paper explores the impact of rainfall shocks on labour time allocation, using panel household survey data from 2014 to 2017 and rainfall information. Applying fixed effects, we find that rainfall shocks increase the time spent on unpaid housework, adding two hours per week. This increased burden falls disproportionately on already disadvantaged population groups: women, poor households, and rural residents. Rainfall shocks also decrease the time allocated to paid work among women. The intersectional impact on poor women is yet more severe, with an increase of five hours in unpaid domestic work. Rainfall shocks widen and deepen gender and social gaps by increasing hours spent on unpaid housework and potentially reducing time for income-generating activities or rest. The study highlights the broader socio-economic implications of rainfall shocks, suggesting the need for policies to alleviate the unpaid domestic workload and support the most vulnerable groups.

Keywords: rainfall shocks, labour allocation, unpaid housework, heterogeneous effects

JEL Classification: Q54, J16, I32, D13

4.1. Introduction

Climate change and weather variability have major impacts on natural and human systems. In people, extreme weather events decrease household income and labor productivity, increase poverty and unemployment, or deteriorate health (Acevedo et al., 2020; Gray et al., 2022; Hallegatte et al., 2018; Rocque et al., 2021). In addition to causing economic losses, the increased frequency and intensity of extreme events also disrupt daily routines and time management at home or work.

[4] This is a joint paper with Alisher Mirzabaev. M.C.L.P. was responsible for all parts of the research with support and advice from the co-author.

Weather phenomena, such as rainfall shocks, encompass periods of intense rainfall or extended dry spells. These extreme conditions impact housework. For instance, excess rain can introduce mud and water into homes, while lack of rain can lead to dust accumulation, increasing cleaning time.

The consequences of rainfall shocks over unpaid household chores are experienced differently among household members and social groups, influenced by gender, socioeconomic status, or area (Jiao et al., 2020; UNFCCC Secretariat, 2022). Women, due to traditional gender roles, low-income households constrained by limited resources, and rural areas hindered by inadequate infrastructure experience more significant repercussions compared to men, high-income households, or people living in urban areas.

Gender, a social construct, assigns differing roles and expectations to women and men based on societal norms (Alston, 2013). Despite men's increasing participation in household responsibilities, women still predominantly manage domestic duties and caregiving (Apps, 2004; Ferrant et al., 2014). Globally, women dedicate at least 2.5 times more hours to unpaid housework than men (International Labour Organization, 2016; Rubiano-Matulevich & Viollaz, 2019). Both men's and women's workloads may increase during extreme events, though in different ways and amounts. Men often engage in cleaning activities like draining water using buckets. Meanwhile, women tend to focus more on mopping, sweeping, cooking, or ensuring the family's well-being (Ajibade et al., 2013). Given women's role in household chores, weather shocks can increase domestic unpaid work burden and deepen the gender gap. Furthermore, considering that time is a limited resource, an increase in household chores may decrease the number of hours in income-generating activities or leisure time.

Regarding socioeconomic status, poor households face greater negative impacts on the time dedicated to unpaid domestic work due to their limited resources to cope with the effects of weather extremes (Goh, 2012). Ajibade et al. (2013) found that high-income households did not experience significant impacts during flooding compared to low-income households. This disparity is primarily because wealthier families have the financial resources to hire guards, drivers, or maids who assist with cleaning and ensuring children's safety. They also tend to have access to appliances like vacuum cleaners, washing machines, and dishwashers that help reduce the time needed for household chores, as well as living in areas with full access to drainage systems or essential services. In contrast, poor households must allocate more personal time and effort to manage the additional workload brought on by weather shocks, as they lack the means to outsource these tasks (Ajibade et al., 2013) or purchase household appliances. In addition, they usually live in marginal areas with limited or non-existent drainage systems (Hallegatte et al., 2020).

Rural areas in developing countries are characterized by infrastructural deficiencies, which make them particularly vulnerable during rainfall shocks. These include poor road conditions, limited access to markets or supermarkets, inadequate health and education services, and unreliable transportation (International Fund for Agricultural Development, 2010). Additionally, houses are often constructed with low-quality materials and lack access to essential utilities (International Fund for Agricultural Development, 2010). Poor road infrastructure can become impassable during heavy rain, isolating communities and making it challenging to obtain necessary supplies. Limited market access means families cannot easily purchase food and other essentials, increasing the time spent sourcing these items. Inadequate health services exacerbate the impact of weather-related illnesses, requiring more household care time. Moreover, low-quality housing materials are less resistant to weather extremes, increasing the time and effort spent on repairs and maintenance.

Finally, gender inequalities combined with structural conditions intensify the vulnerability to extreme climate events. Women in poverty face multiple disadvantages: First, they are expected to contribute more to housework. Second, they have limited access to credit, healthcare, and education. Many work in the informal labor market, where incomes are low and unstable, and live in precarious settlements without proper access to water or sanitation (FAO, 2011; Moser, 1996; Sweetman, 1996; Enarson & Morrow, 1998). The "intersectionality" of poverty and sex exposes these women to additional burdens, increasing the time dedicated to unpaid housework and affecting the time spent in remunerated work, rest, or leisure.

Several studies have explored the impact of weather shocks on various aspects of household life, including income, poverty, health, or employment (Acevedo et al., 2020; Gray et al., 2022; Hallegatte et al., 2018; Rocque et al., 2021). Some studies have studied the relationship between extreme events and household chores qualitatively or descriptively. However, there is a significant gap in the literature addressing the extent to which extreme weather events affect the time spent on unpaid housework. This study contributes to the limited body of quantitative research examining the impact of rainfall shocks- both excess and scarce rain- on unpaid housework and remunerated work. We focus on different vulnerable groups: women, poor households, and rural areas, and we also explore the intersectionality of being a poor woman, sparsely explored in the literature. By filling this gap, our research aims to understand better how these weather events exacerbate existing inequalities, thereby informing climate policies to better address the needs of those most affected.

The document is structured as follows: Section 4.2 presents the conceptual framework, analyzing how extreme weather events influence household chores. Section 4.3 details the data sources utilized in the study, including weather and household information, as well as the methodological approach employed to quantify the impact of rainfall shocks. In section 4.4, we present the findings derived from the fixed-effects model. Finally, section 4.5 concludes the chapter by summarizing the key findings and discussing their policy implications.

4.2. Conceptual framework

Climate change is expected to increase the intensity and frequency of several risks, including a rise in temperature and heat waves, sea level rise, drought, and changes in rainfall patterns (Gran Castro & Ramos de Robles, 2019; Revi et al., 2014). Large-scale weather shocks increase the house workload, which requires household members to spend more time on unpaid domestic chores (Fruttero et al., 2023; Jabeen, 2014). This section analyzes how rainfall, including excess or lack thereof, affects total unpaid housework time, and the time spent cleaning, cooking, caring for children, the elderly, and the sick, doing laundry, and shopping in markets or supermarkets (Figure 4.1).

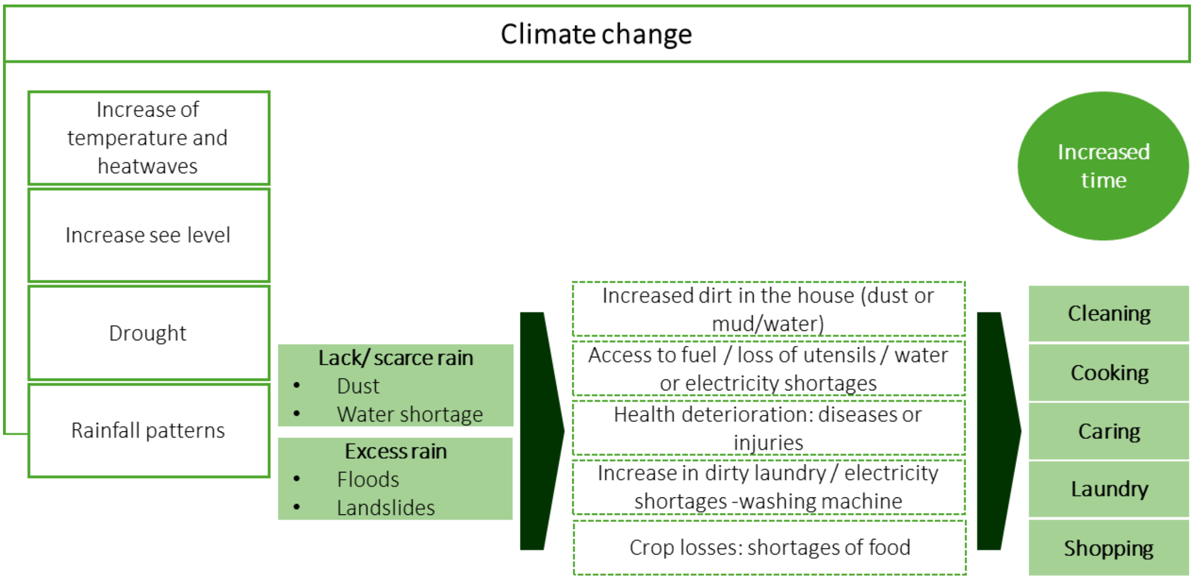


Figure 4.1 The link between climate change and unpaid household chores

Prolonged periods of insufficient rain can lead to increased dust levels in the environment and water or electricity shortages, which impact household chores. The first occurs because the lack of moisture allows soil and other particulate matter to dry out and become loose. As a result, even slight disturbances such as wind or human activities can easily lift these dry particles into the air, leading to higher dust concentrations (Yang et al., 2019). When there is a high dust level, it easily infiltrates homes through windows, doors, and even small cracks, settling on furniture, floors, and other surfaces. Therefore, family members may need to clean more frequently to maintain a dust- and germ-free home environment. Water or electricity shortages occur because a lack of rain affects water bodies such as rivers, lakes, and reservoirs, which are critical household water sources. Water shortage affects domestic activities such as washing, cooking, cleaning, hygiene, childcare, and food processing (Abid et al., 2018). Electricity shortages disrupt the operation of essential appliances like washing machines, dryers, vacuum cleaners, microwaves, and electric stoves, increasing the burden of domestic chores as many tasks must be completed manually.

High dust accumulation in the environment or water shortages can also exacerbate health conditions (Allouche, 2011). Prolonged exposure to airborne dust particles has been linked to respiratory issues or allergies (Orimoloye et al., 2022) and water shortages or drought to diarrhea or cholera, mainly if individuals rely on unsafe water sources (Jung et al., 2023).

These health problems may necessitate additional support when household members are affected, increasing caregiving duties and time.

Rainfall scarcity also reduces crop yields or causes harvest losses, diminishing food availability in local markets in the short term (Allouche, 2011; Annecke, 2010). The short supply of food items can lead to increased grocery shopping time. Families are often forced to travel greater distances or visit multiple stores to find the necessary goods, which increases the time burden and adds financial and physical strain, particularly on those with limited transportation options.

On the other hand, extreme or excessive rainfalls exacerbate hazards such as flooding and landslides (Dodman et al., 2022; Gran Castro & Ramos de Robles, 2019; Satterthwaite et al., 2007), which often affect physical infrastructure (Bartlett et al., 2009; Hallegatte et al., 2020; Revi et al., 2014), aggravate health, and cause problems with transport or services (store closures).

Intense rainfall may result in household disruptions, especially when water or mud seeps into homes, usually combined with inadequate or blocked drainage facilities and lower plinth levels (Jabeen, 2014). This intrusion increases the time required for cleaning: clearing the water, scrubbing floors, or sanitizing surfaces. Extreme rainfall can also impact fuel sources for cooking. Wet wood or charcoal can prolong cooking times, as they are harder to ignite and maintain. According to Ajibade et al. (2013), such weather events can lead to the loss or damage of cooking utensils, further limiting cooking activities. In households where members usually eat outside, rainfall shocks can restrict mobility, forcing them to eat at home. Excessive rainfall increases the likelihood of clothes getting wet or dirty, adding extra time to laundry tasks.

These extreme weather phenomena, associated with excessive rainfall, also increase water-related diseases, including malaria, typhoid, dengue, cholera, and skin diseases. Landslides can result in physical injuries due to falling debris or individuals trapped under displaced earth (Abid et al., 2018; Rusmadi et al., 2018). During such events, the risk of illness rises, requiring additional care and support from household members, further increasing caregiving responsibilities and placing additional strain on families.

Like droughts, extreme rainfall can lead to agricultural losses (Annecke, 2010; Habtezion, 2016), reducing the accessibility and availability of farm products in local markets (United Nations Women, 2009). Furthermore, extreme rainfall can damage roads, disrupt transportation, or close stores due to flooded or damaged infrastructure (Mason & Agan, 2015). These issues force households to spend more time grocery shopping.

Since time is a limited resource, increased household responsibilities can impact other aspects of daily life. When these tasks demand more time, it often can reduce available hours for paid work, potentially affecting income-earning employment (Crépon & Kramarz, 2002). Similarly, reducing leisure or rest time can diminish overall well-being and have negative impacts on health. This forced reallocation of individual labor can lower the quality of life by limiting opportunities for recreation and reducing income-generating capacity.

Usually, the impacts are differentiated between women and men, low and high-income households, and rural and urban areas. For example, the increase in family members' diseases amplifies women's caregiving role (Fonjong & Zama, 2023). Poorer households might spend more time cleaning because they cannot afford to hire people to carry out these tasks, and the absence of infrastructure, observed in rural areas, makes it more difficult for people to complete household chores during extreme events (Jabeen, 2014). In this sense, we want to estimate to what extent extreme or lack of rainfall affects people's time in unpaid household duties, considering the heterogeneous effects within social groups.

4.3. Materials and method

We employ panel fixed effects modeling to investigate the effect of weather shocks on unpaid household work and remunerated work in Ecuador. Our dependent variables are the total hours spent on housework, such as cleaning, shopping, caring for children, the elderly or the sick, cooking, doing laundry, helping kids with schoolwork, and the remunerated working hours. Independent variables include rainfall shocks, and we control with individual and household characteristics. Rainfall data was extracted from the Climate Hazards Center at the University of California, Santa Barbara (CHIRPS), and the information on households was gathered from the ENEMDU survey. We connected household data with rainfall information using the specific census sector codes.

4.3.1. Data

Household

Household data come from the National Employment, Unemployment, and Underemployment Survey (ENEMDU). The survey utilizes a conglomerate[5] panel approach to establish annual panels from selected subsamples and allows tracking of the same observational units over different years. For example, we can compare the same individuals in the second quarter of 2014 and 2015. Conducted quarterly, the ENEMDU provides national coverage and is statistically representative at national, urban, and rural levels (INEC, 2022).

We use the "Participation in housework" module, which includes questions about the number of hours per week that people dedicate to household chores (in general) and considers specific activities such as cleaning the house (sweeping, mopping, making beds, cleaning), shopping in markets and supermarkets, laundry (washing, ironing, sewing, folding clothes), cooking (preparing breakfast, lunch, and dinner), caring for children, the elderly or the sick, and helping children with schoolwork. We also use the number of hours working (paid work).

Our research analyzes the differences between women and men, poor and non-poor households, rural and urban areas, and intersectionality, such as that of poor women. For this, we harmonize and pool two annual panels corresponding to the second semester from 2014 to 2017 (first panel: 2014Q2 and 2015Q2 & second panel: 2016Q2 and 2017Q1). This resulted in 83,384 individuals over 15 years of age, observed over two comparable periods (166,768 observations).

Households in the survey are georeferenced at census sector levels. In the urban area, the census sector is a continuous delimited area consisting of one or more city blocks and comprises an average of 150 households. The rural area has an average of 80 to 110 households and can consist of one or more settlements (INEC, 2020).

[5] Group of homes that belong to the same district.

Weather

We extract daily precipitation data from the Climate Hazards Center at the University of California, Santa Barbara. The "CHIRPS-daily" information provides data to a spatial resolution of approximately 5 km^2 (University of California, 2023). For each census sector, we identify its centroid's geographic coordinates—latitude and longitude. We then use these coordinates to obtain daily precipitation data since 1981.

To capture the rainfall shocks for each quarter in every location, we estimate the quarter's accumulated rainfall for all the census sectors Acp_{it}. Then, we calculate the quarterly z-score for accumulated rainfall for every territory (Equation 4.1).

$$z - score_{it} = \frac{Acp_{it} - \overline{Acp_{it}}}{Acp_{it}^{SD}} \quad \text{(Equation 4.1)}$$

Where Acp_{it} represents the accumulated rainfall in census sector i during quarter t. $\overline{Acp_{it}}$ refers to the historical average of accumulated rainfall for census sector i in quarter t, while Acp_{it}^{SD} is the standard deviation of the accumulated rainfall for the same sector and quarter.

Using z-scores, we create a dummy variable $Drainfall_{jit}$: 1 indicates a positive ($z - score_{it}$ > 2) or negative rainfall shock ($z - score_{it}$ < -2), and 0 otherwise. The dummy allows us to capture the impacts of both excessive (z-score above 2) and scarce (z-score below -2) rainfall within each census sector during specific quarters. This approach follows previous studies, as not all deviations from the long-term mean constitute a shock (Skoufias & Vinha, 2013; Amare et al., 2018; Boansi et al., 2021). Additionally, to provide a more detailed analysis, we separately examine the effects of the excess rainfall dummy (z-score above 2) and the lack of rainfall dummy (z-score below -2). The results of both analyses are presented in Section 4.4.

4.3.2. Econometric method

We employ panel fixed effects to control unobserved heterogeneity among individuals. Our dependent variables refer to the number of hours per week that people dedicate to household chores and paid work, and we control for the characteristics of individuals and households.

$$Y_{jit} = \beta_o + \beta_1 Drainfall_{jit} + \gamma X_{jit} + \delta D_t + \theta_j + \varepsilon_{jit} \quad \text{(Equation 4.2)}$$

In Equation 4.2, j is the individual, i is the census sector, and t is time. Y_{jit} corresponds to the number of hours spent per week on housework activities, including cleaning, cooking, caring, doing laundry, shopping, and helping children with schoolwork; and the total hours of paid work performed by individual j in census sector i in quarter t. $Drainfall_{jit}$ is the rainfall shock dummy (including scarcity and excess rainfall) for each individual in the corresponding census sector and quarter. X_{jit} is the vector of controls at the individual and household levels: the years of education, age, marital status, and number of working hours of each individual, the education and age of the household head, the number of household members, the number of children (younger than 5), the number of elderly (older than 65), and the per capita income. We also add temporal dummies for each quarter: Dt.

$$Y_{jit} = \beta_2 + \beta_3 Dscarce_{jit} + \beta_4 Dexcess_{jit} + \gamma X_{jit} + \delta D_t + \theta_j + \varepsilon_{jit} \quad \text{(Equation 4.3)}$$

In Equation 4.3, we analyze the effect of the scarcity and excess rainfall dummies separately, where $Dscarce_{jit}$ and $Dexcess_{jit}$ correspond to the lack and excess rainfall shocks each person faces in the corresponding census sector and quarter. The other elements of the equation are those named above in Equation 4.2.

In these models (Equations 4.2 and 4.3), we are particularly interested in the coefficients β_1 (Equation 4.2) and β_3 and β_4 (Equation 4.3). With housework hours as the dependent variable, a positive and significant β_1, β_3, and β_4 would indicate that rainfall shock increases time spent on household chores.

The study also focuses on the differentiated effects of rainfall shocks on specific groups: women & men, poor[6] & non-poor households, and rural & urban areas, to gain further insights into effect heterogeneity. We run the model in Equations 4.2 and 4.3 for each of these subsamples of the survey and employ their expansion factor (sampling weight) to estimate the model, ensuring the representativeness and statistical validity of the estimates (Azzarri &

[6] To identify poor households, we adopt Ecuador's official poverty line.

Signorelli, 2020). We hypothesize that the impact will be greater on women, low-income households, and rural areas compared to men, wealthier households, and urban areas.

Finally, we employed clustered standard errors and conducted two tests to validate our estimation method. The test results are presented in Table C1 of the Appendix and support the inclusion of time-fixed effects, which we have integrated into our model, and the preference for the fixed-effects estimator over the random-effects alternative.

4.4. Results

4.4.1. Descriptive statistics

To estimate our models, we consider the variables described in Table 4.1. Panel A shows the dependent variables, and panel B the control variables at the individual and household levels.

According to the survey, people dedicate 18.06 hours per week to household chores. On average, 2.75 hours cleaning the house, 7.23 hours cooking, 2.66 hours caring for children, the elderly, or the sick, 2.49 doing laundry, 1.63 shopping, and 1.30 helping children with schoolwork. People also spend 38.19 hours per week working (paid employment). In general, cooking, cleaning, caring for a household member, and doing laundry are among the most demanding activities in housework.

Regarding the independent variables, around 8% of the individuals face a rainfall shock in the studied period. At the individual level, the average education is 10.15 years, and the age is 40.67 years old. Most are married or in a common-law relationship (58%). At the household level, the average education of the head of the household is 9.34 years, and the age is 50.56. The average number of people in the household is 4.40, and the monthly per capita income reaches 165.80 USD.

Table 4.1 Summary statistics

	N	Mean	Std. dev.	Min	Max
Panel A: Dependent variables (total hours)					
Total household chores	166,768	18.06	17.02	0	128
Cleaning	166,768	2.75	3.11	0	49
Cooking	166,768	7.23	7.84	0	40
Caring	166,768	2.66	5.67	0	84
Laundry	166,768	2.49	3.08	0	43
Shopping	166,768	1.63	1.67	0	20
Schoolwork	166,768	1.30	2.97	0	49
Paid work	107,378	38.19	14.78	1	129
Panel B: Independent variables					
Rainfall shock (shock=1)	***166,768***	***0.08***	***0.28***	***0***	***1***
Education person (years)	166,768	10.15	4.70	0	22
Age person (years)	166,765	40.67	17.96	15	98
Marital status (married=1)	166,768	0.58	0.49	0	1
Education head of household (years)	166,768	9.34	4.88	0	22
Age head of household (years)	166,749	50.56	14.78	15	98
Number of people in the household	166,768	4.40	2.05	1	24
Number of children under 5 years old	166,768	0.44	0.72	0	8
Number of older adults (over 65)	166,768	0.29	0.60	0	5
Per capita income (USD)	165,550	165.80	232.12	0.14	42,925

Source: ENEMDU Panels (2014-2017)

In most societies, women -in addition to the role of income earners- are primarily responsible for household chores (Jiao et al., 2020). According to the ENEMDU Panels (2014-2017), women spend 3.6 times as much on unpaid housework as men. Women in Ecuador dedicate 27.80 hours per week to unpaid domestic duties, 20 hours more than men, who dedicate an average of 7.56 hours. As shown in Figure 4.2, Panel A, women focus on cooking, laundry, caring, and cleaning, while men spend some time on cooking, cleaning, and shopping.

On average, poor households spend 20.64 hours per week on domestic chores, and non-poor 17.44 hours. Poor families primarily concentrate on cooking and caring for household members, whereas non-poor emphasize cooking and cleaning tasks (Figure 4.2, Panel B). In rural areas, people dedicate an average of 19.13 hours to household chores, compared to 17.56 hours in urban areas. In both settings, cooking and cleaning are the primary activities.

Women in poor households tend to spend more time on household chores. Figure 4.2, Panel D shows that poor women work 31.65 hours on unpaid housework, almost twice the national average and four times more than the average man. The main activities are cooking, caring for household members, doing laundry, and cleaning. Poor and non-poor men spend similar amounts of time on household chores.

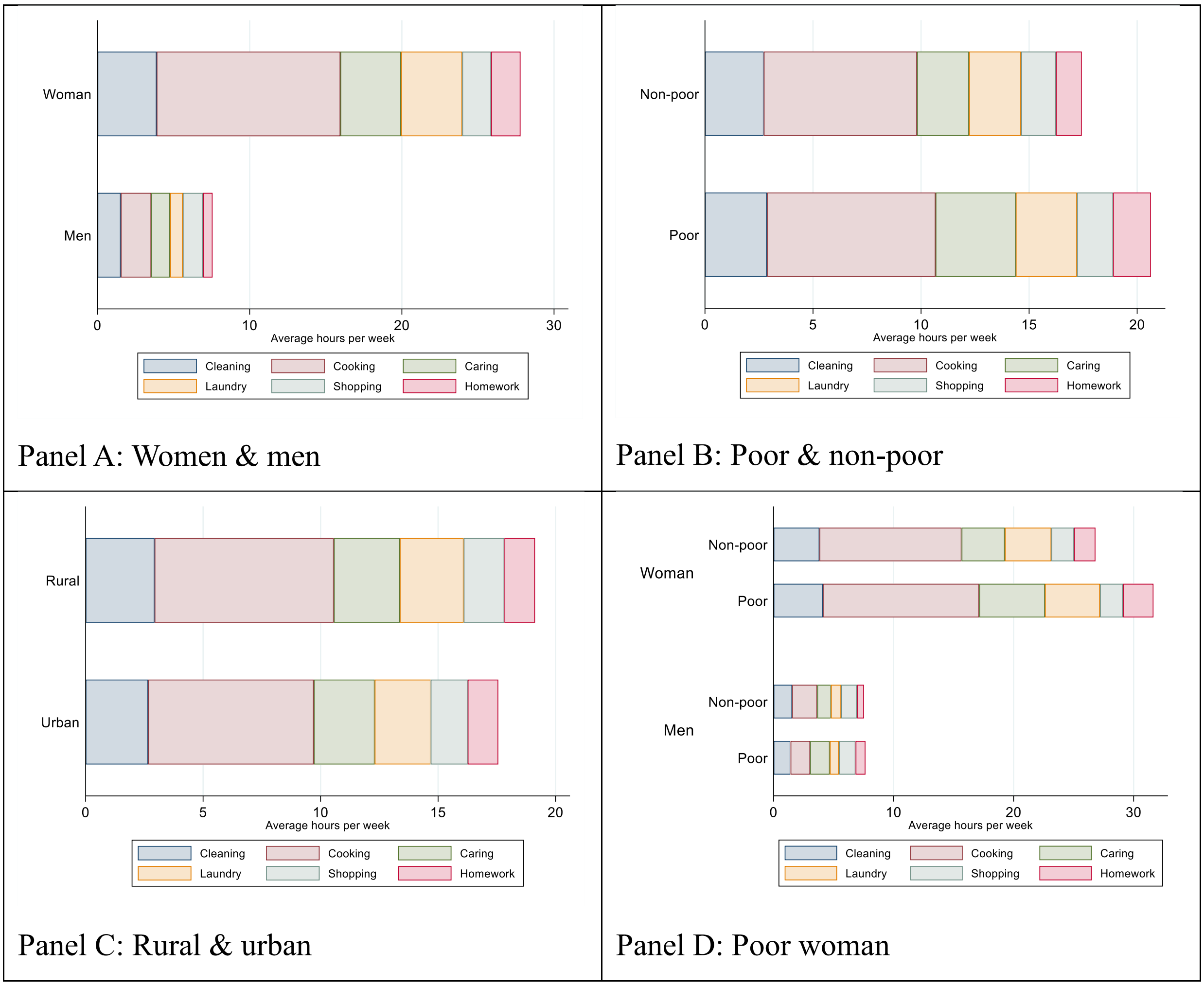


Figure 4.2 Average hours per week in household chores

4.4.2. Econometric method

We estimate Equation 4.2. The findings, including control variables, are presented in Table 4.2 and illustrated in Figure 4.3, Panel A. Panel B of Figure 4.3 depicts the analysis, considering the dummies for excess and lack of rainfall (Equation 4.3) separately.

Table 4.2 Effect of rainfall shocks on time spent on household chores and work

	Total housework	Cleaning	Cooking	Caring	Laundry	Shopping	Schoolwork	Paid work
Rainfall shock	**2.170*** (5.61)**	**0.516*** (4.64)**	**0.682*** (4.26)**	**0.363** (2.58)**	**0.337*** (3.53)**	**0.199*** (3.52)**	**0.0726 (0.94)**	**-0.773* (-1.87)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165529	165529	165529	165529	165529	165529	165529	107369
Adjusted R-squared	0.032	0.01	0.021	0.029	0.009	0.003	0.006	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Table C2 in the Appendix presents results without control variables, while Table C3 provides details of the control variables.*

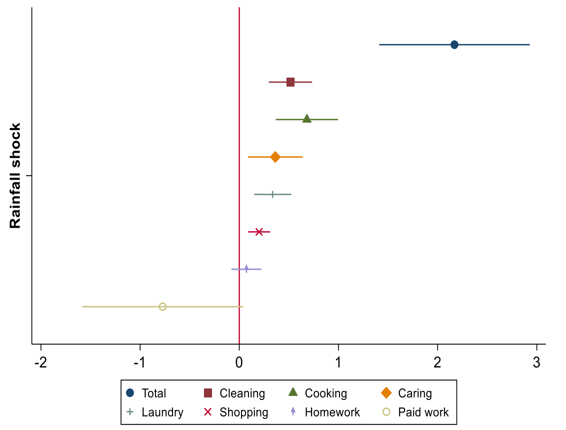
The results show a significant impact of rainfall shocks on unpaid housework. These shocks increase total hours spent on household chores by 2.17 hours per week, which represents a rise of 19% in the workload.

Cleaning time increases by 0.51 hours. Figure 4.3, Panel B shows that both scarce and excessive rainfall have an impact, with scarce rainfall having a slightly greater effect. Dust appears to create a heavier workload compared to the effects of excessive rainfall. Cooking time increases by 0.68 hours. While the lack of rainfall shows no significant effect, heavy rain can wet fuel or damage utensils, extending cooking time (Figure 4.3, Panel B).

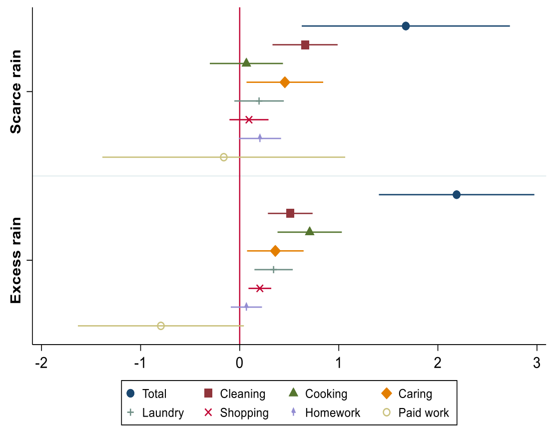
Health deterioration caused by weather events is related to an increase of 0.36 hours spent caring for children, the elderly, or the sick. Both excessive and scarce rainfall have a similar impact (Figure 4.3, Panel B). Rain shocks also add 0.33 hours to laundry time, with excess rainfall having a greater and significant effect (Figure 4.3, Panel B), likely due to increased clothes soiling. Shopping in supermarkets or markets takes 0.19 hours longer, mainly due to excessive rainfall, which likely makes it more difficult to transport and acquire food supplies.

Rainfall shocks do not impact the time people dedicate to helping children with schoolwork. However, unlike all other impacts, the effect on paid work is negative, reducing it by approximately one hour per week.

Figure 4.3, Panel C shows that the distribution of total hours spent on housework moves slightly to the right in households that faced a rainfall shock compared to those that did not. The results indicate a significant increase in unpaid housework. Cleaning, cooking, and caring are the most affected activities. Time is a limited resource. If unpaid housework increases, paid work hours decrease (Samtleben & Müller, 2022) and likely leisure/sleep time (defined as the remaining time by Wales and Woodland, 1977). Reducing paid work hours may be related to employment losses (Crépon & Kramarz, 2002), and insufficient sleep to anxiety and depression (Chapman et al., 2013). The increased domestic burden generated by rainfall shocks may have economic and mental health repercussions at the household level.

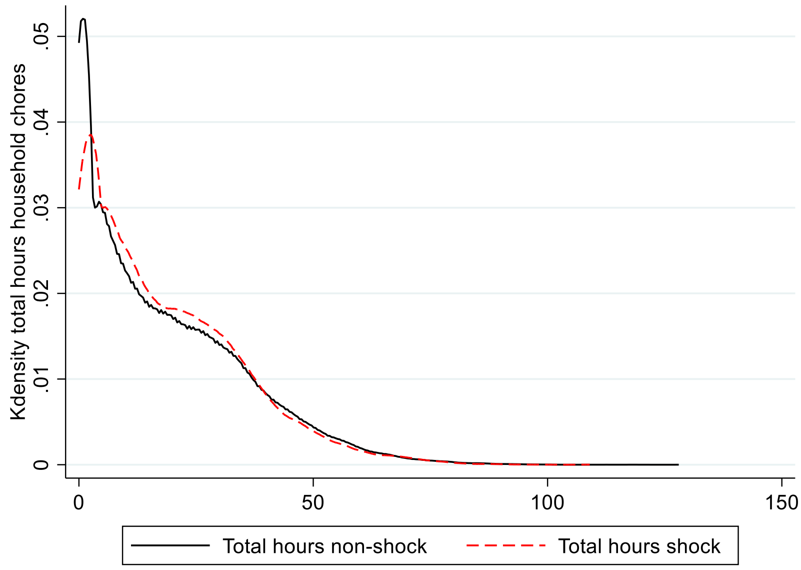


Panel A: Confidence intervals -rainfall shock



Panel B: Confidence intervals -Scarce & Excess

Table C4 in the Appendix presents the results



Panel C: Total hours distribution

Figure 4.3 Effect of rainfall shocks

We analyze different subsamples (using Equation 4.2) to identify heterogeneous effects: men and women, poor and non-poor households, and rural and urban populations. Table 4.3 presents the results for women and men, including control variables, alongside Figure 4.4, Panel A. Panel B provides the findings, separately examining the dummies for excess and lack of rainfall (Equation 4.3).

Table 4.3 Effect of rainfall shocks on time spent on household chores and work: women & men

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Rainfall shock	**3.083***** **(5.28)**	**1.164***** **(3.82)**	**0.734***** **(4.29)**	**0.281***** **(3.46)**	**1.106***** **(4.09)**	**0.226*** **(1.88)**	**0.508**** **(2.37)**	**0.188*** **(1.68)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85740	79789	85740	79789	85740	79789	85740	79789
Adjusted R-squared	0.047	0.02	0.013	0.01	0.033	0.016	0.042	0.016

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.*

Continuation of Table 4.3

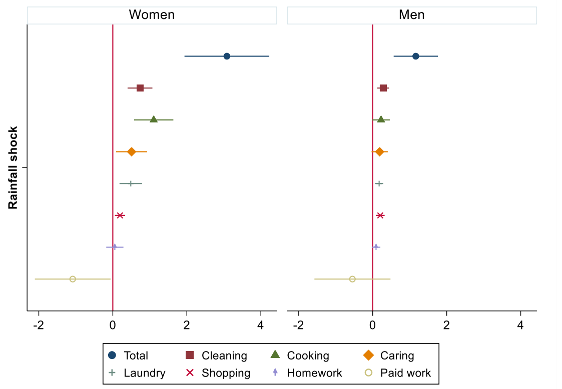
	Laundry	Laundry	Shopping	Shopping	Schoolwork	Schoolwork	Paid work	Paid work
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Rainfall shock	**0.486*****	**0.174*****	**0.195*****	**0.204*****	**0.0548**	**0.0907**	**-1.083****	**-0.548**
	(3.13)	**(3.09)**	**(2.76)**	**(3.39)**	**(0.46)**	**(1.53)**	**(-2.08)**	**(-1.04)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85740	79789	85740	79789	85740	79789	45025	62344
Adjusted R-squared	0.013	0.007	0.004	0.006	0.008	0.004	0.003	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Table C5 in the Appendix presents results without control variables, while Table C6 provides details of the control variables.*

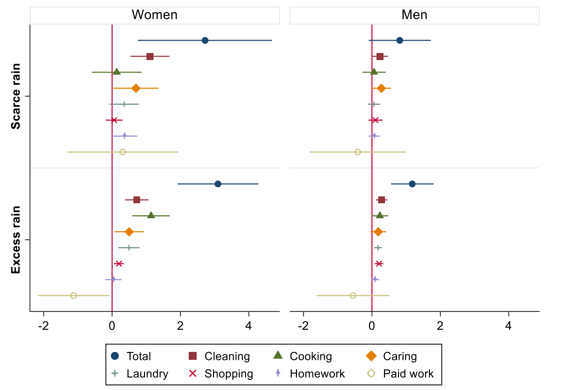
When analyzing the results by sex, even though women already have the greatest domestic burden compared to men, rainfall shocks exacerbated these differences, increasing women's time spent on unpaid housework. A rainfall shock adds 3 hours per week to women's unpaid housework time, which is 2.6 times higher than the 1.16 hours for men. As shown in Figure 4.4, Panel B, excessive rainfall has a slightly greater impact than scarcity.

Weather shocks extend cleaning time for women to more than double that of men, with weekly increases of 0.73, compared to 0.28 hours for men. Men face similar impacts from both excessive and scarce rainfall, while women are more affected by lack of rainfall (Figure 4.4, Panel B). Rainfall shocks increase cooking time, mainly for women, by 1 hour, driven primarily by excessive rainfall. According to Figure 4.4, Panel B, excess and lack of rain have a negligible effect on men. These shocks also affect women's caregiving time twice as much as men's, with weekly shifts of 0.50 and 0.18 hours, respectively. Extreme and scarce rainfall have a similar impact (Figure 4.4, Panel B).

Laundry time rises for both men and women, with the effect being 2.7 times greater for women. Rainfall shocks also lead to more time spent shopping for both sexes, and based on Figure 4.4, Panel B, it is primarily driven by excessive rainfall. Rainfall shocks do not impact the time spent helping children with schoolwork. However, they reduce 1 hour of paid work for women, especially during periods of excessive rainfall. Extreme weather events increase unpaid domestic work, particularly for women, while reducing paid work hours, worsening gender gaps. This impact limits their ability to participate fully in the labor market (Samtleben & Müller, 2022) and can even minimize the time for rest or recreational activities (Clifford Astbury et al., 2020).



Panel A: Confidence intervals -rainfall shock



Panel B: Confidence intervals - Scarce & Excess

Table C7 in the Appendix presents the results

Figure 4.4 Effect of rainfall shocks: Women & men

Regarding the effect on poor and non-poor households, Table 4.4 and Figure 4.5 (Panel A) display the results, including control variables for Equation 4.2. Panel B represents the findings using separate dummies for excess and lack of rainfall (Equation 4.3).

Table 4.4 Effect of rainfall shocks on time spent on household chores and work: poor & non-poor households

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Rainfall shock	**3.476*****	**1.876*****	**0.990*****	**0.387*****	**1.050*****	**0.647*****	**0.583***	**0.359****
	(4.71)	**(4.59)**	**(5.15)**	**(3.08)**	**(3.23)**	**(3.88)**	**(1.79)**	**(2.30)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37855	127674	37855	127674	37855	127674	37855	127674
Adjusted R-squared	0.032	0.031	0.02	0.008	0.019	0.022	0.031	0.034

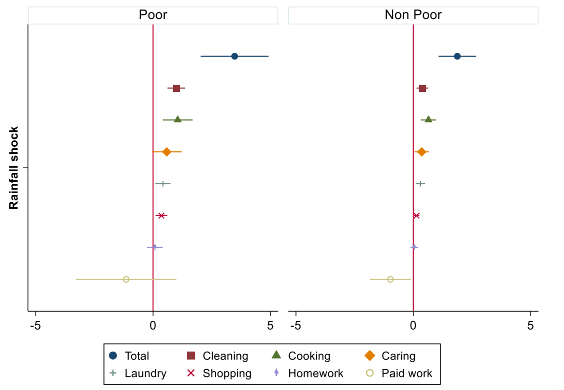
Continuation of Table 4.4

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Schoolwork**	**Schoolwork**	**Paid work**	**Paid work**
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Rainfall shock	**0.419****	**0.304*****	**0.355*****	**0.137****	**0.0791**	**0.0403**	**-1.148**	**-0.972****
	(2.53)	**(2.96)**	**(2.82)**	**(2.31)**	**(0.46)**	**(0.48)**	**(-1.05)**	**(-2.19)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37855	127674	37855	127674	37855	127674	23017	83697
Adjusted R-squared	0.01	0.008	0.005	0.003	0.008	0.006	0.007	0.002

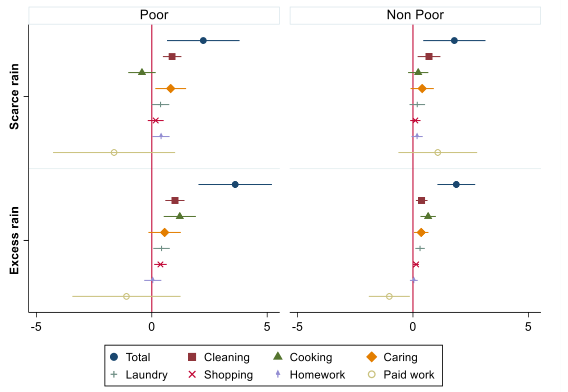
*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Table C8 in the Appendix presents results without control variables, while Table C9 provides details of the control variables.*

The analysis reveals a stronger impact on poor households, with rainfall shocks raising housework by 3.47 hours per week, nearly double the 1.87 hours in high-income households.

A similar pattern is observed in the time spent cleaning, cooking, caring, and shopping. In cleaning, poor households spend 0.99 hours more, while non-poor households spend 0.38. As shown in Figure 4.5, Panel B, excessive and lack of rainfall have similar impacts. Rainfall shocks add 1.05 hours of cooking time in poor households and 0.64 hours in non-poor, with excessive rain being the primary driver. Caregiving time increases in both groups, with rain scarcity showing a pronounced effect on poor households (Figure 4.5, Panel B). Time spent on laundry and shopping also rises more in low-income households than in high-income ones, with excessive rain as the main factor. Time spent helping with schoolwork remains unaffected, while paid work hours decrease for both groups but are significant only for non-poor households.



Panel A: Confidence intervals - rainfall shock



Panel B: Confidence intervals - Scarce & Excess

Table C10 in the Appendix presents the results

Figure 4.5 Effect of rainfall shocks: poor & non-poor households

Table 4.5 and Figure 4.6 (Panel A) show the effects on rural and urban households (Equation 4.2). Panel B presents the results using distinct dummies for excess and scarce rainfall from Equation 4.3.

Table 4.5 Effect of rainfall shocks on time spent on household chores and work: rural & urban area

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Rainfall shock	**3.003*****	**1.604*****	**0.794*****	**0.326****	**1.069*****	**0.323**	**0.576*****	**0.311**
	(5.00)	**(3.04)**	**(4.60)**	**(2.19)**	**(4.26)**	**(1.57)**	**(2.81)**	**(1.57)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63926	101603	63926	101603	63926	101603	63926	101603
Adjusted R-squared	0.026	0.037	0.014	0.011	0.019	0.025	0.029	0.03

Continuation of Table 4.5

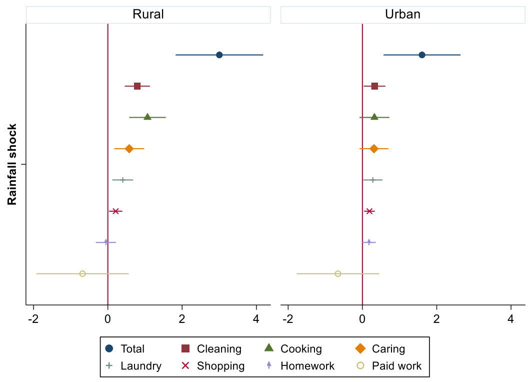
	Laundry	**Laundry**	**Shopping**	**Shopping**	**Schoolwork**	**Schoolwork**	**Paid work**	**Paid work**
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Rainfall shock	**0.402******	**0.279****	**0.212****	**0.189****	**-0.0502**	**0.178***	**-0.681**	**-0.659**
	(2.80)	**(2.12)**	**(2.35)**	**(2.57)**	**(-0.36)**	**(1.91)**	**(-1.08)**	**(-1.16)**
Education	0.00524	-0.023	-0.00239	-0.00488	0.0303	-0.00458	0.226*	0.0697
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63926	101603	63926	101603	63926	101603	45322	62047
Adjusted R-squared	0.007	0.011	0.002	0.005	0.005	0.007	0.002	0.002

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Table C11 in the Appendix presents results without control variables, while Table C12 provides details of the control variables.*

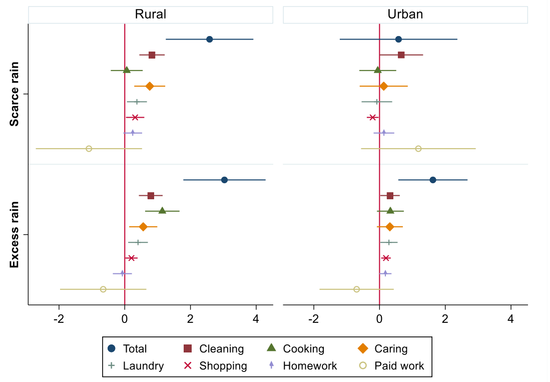
Rainfall shocks add 3 hours of housework per week in rural areas, nearly double the 1.60 hours in urban ones. Figure 4.6, Panel B shows that scarce and excessive rainfall strongly affects rural areas, while excessive rain mainly impacts urban areas.

In rural households, cleaning time increases by 0.79 hours compared to 0.32 hours in urban settings. Based on Figure 4.6, Panel B, lack of rain has slightly more implications than excess rain. Additionally, cooking time is impacted by 1.06 extra hours in rural households, primarily driven by excessive rainfall. The urban area experiences a non-significant effect on cooking time. Meanwhile, rural areas are mainly impacted by excess rain.

The impact on caregiving and laundry is more pronounced in rural areas. Caregiving time increases by 0.57 hours in rural households, with no significant effect in urban settings. Rainfall shocks also add 0.40 hours to laundry time in rural areas and 0.27 hours in urban ones. In rural households, both excessive and scarce rainfall contribute to the additional time spent on caregiving and laundry. In contrast, in urban households, the effect is primarily driven by excessive rainfall (Figure 4.6, Panel B). Although paid work time shows a negative sign, it is not statistically significant.



Panel A: Confidence intervals -rainfall shock



Panel B: Confidence intervals - Scarce & Excess

Table C13 in the Appendix presents the results

Figure 4.6 Effect of rainfall shocks: rural & urban area

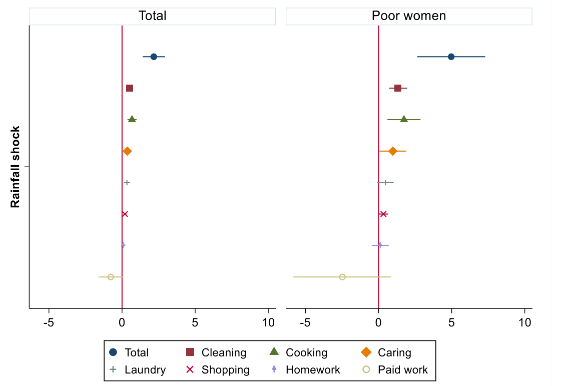
Finally, Table 4.6 and Figure 4.7 (Panel A) present the effects of rainfall shocks on household chores and paid work among poor women. We examine whether the intersectionality of being a woman and living below the poverty line is associated with more pronounced weather effects. Panel B represents the findings using separate dummies for excess and lack of rainfall.

Table 4.6 Effect of rainfall shocks on time spent on household chores and work: Poor women

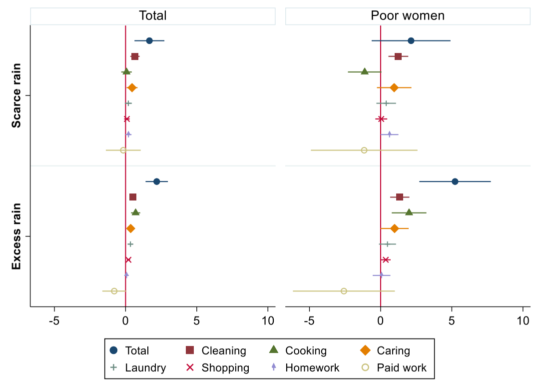
	Total housework	**Cleaning**	**Cooking**	**Caring**	**Laundry**	**Shopping**	**Schoolwork**	**Paid work**
Rainfall shock	**4.969*****	**1.336*****	**1.736*****	**0.977****	**0.474***	**0.334****	**0.112**	**-2.476**
	(4.19)	**(4.20)**	**(3.01)**	**(2.10)**	**(1.67)**	**(2.06)**	**(0.38)**	**(-1.45)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20189	20189	20189	20189	20189	20189	20189	9604
Adjusted R-squared	0.046	0.027	0.036	0.04	0.014	0.01	0.009	0.012

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Table C14 in the Appendix presents results without control variables, while Table C15 provides details of the control variables.*

Poor women experience more adverse impacts from rainfall shocks on housework. Weather extremes add five extra hours per week to unpaid domestic workload, primarily due to increased time on cooking (1.73 hours), cleaning (1.33 hours), and caregiving (0.97 hours). Based on Figure 4.7, Panel B, both excessive and scarce rainfall have similar effects on cleaning and caregiving. However, cooking time is more affected by excessive rain. Although paid work hours do not have a statistically significant effect, the estimated impact is -2.47 hours, suggesting potential negative consequences for paid employment. Rainfall shocks intensify the unpaid domestic burden for poor women, limiting paid employment and rest, and potentially deteriorating mental health (Crépon & Kramarz, 2002; Chapman et al., 2013; Clifford Astbury et al., 2020; Samtleben & Müller, 2022).



Panel A: Confidence intervals -rainfall shock



Panel B: Confidence intervals -Scarce & Excess

Table C16 in the Appendix presents the results

Figure 4.7 Effect of rainfall shocks: Poor women

4.5. Conclusion and discussion

As many researchers have studied, extreme weather events affect the household economy, but they also influence individual labor time allocations. This study examines the extent to which rainfall shocks impact time spent on unpaid domestic work, focusing on heterogeneous effects among vulnerable groups: women, poor households, rural populations, and the intersectionality of being both poor and a woman.

The results show that rainfall shocks increase the time spent on unpaid housework. The overall effect is around two hours per week, which represents a rise of 19%. However, women, low-income families, and the rural area are more impacted. The most affected group is poor women, with an additional five hours. Time in remunerated work decreases for women.

In many countries, women already bear the greatest domestic burden, and rainfall shocks reinforce these differences, increasing the gap between men and women. In our analysis, women experience more than double the increase in unpaid housework time compared to men, adding three (3) hours per week. The same pattern is found in poor and rural families, twice as affected as non-poor households and urban areas. High-income households usually have resources to hire people or access appliances for housework, and urban settings have better infrastructure or access to essential services. Rural areas suffer negative consequences from both excess and insufficient rainfall, while urban areas primarily from excessive rain. Cleaning, cooking, and caring are the most affected activities. Cleaning time increases more with scarce rainfall, likely due to dust, while cooking, laundry, and shopping are more impacted by excessive rainfall. Increasing unpaid housework reduces the time available for paid work, particularly for women.

Current literature has focused little on quantitatively evaluating the effect of weather shocks on unpaid housework, especially considering different socioeconomic groups, territories, or intersectionality. However, some studies show that women are more affected, which is consistent with our results. Specifically, extreme events increase the time spent on housework and childcare for women compared to men, and for poor women compared to non-poor women (Ajibade et al., 2013). Even though married men also increase their time in housework, a significant gap persists between women and men (Ajibade et al., 2013; Jiao et al., 2020).

Extreme events, which are expected to be more intense and frequent due to climate change, increase the time spent on unpaid domestic work for groups that are already disadvantaged: women, low-income families, and rural households. The additional burden on household chores limits paid employment and reduces time to sleep, which may lead to mental health deterioration (Samtleben & Müller, 2022; Chapman et al., 2013; Clifford Astbury et al., 2020). It also restricts time to participate in decision-making at the public level resulting in climate change policies that do not consider their conditions or necessities (Jiao et al., 2020; Rusmadi et al., 2018; UNDP, 2023; Hannan, 2011). Those who perform these tasks often have insufficient social protection, as they are not formally recognized as part of the labor economy. This phenomenon not only compromises their well-being but can also diminish government tax revenues.

As we design policies to address this challenge, we need a better understanding of how climate change affects different groups, which our study contributes to. Climate change will reinforce the gender division in household chores and exacerbate the pre-existing inequalities of vulnerable groups who already suffer negative consequences of climate change on their income or health (Ajibade et al., 2013; Jiao et al., 2020; UNDP, 2023).

Policies and strategies must consider sex, socioeconomic status, and location when assessing the impacts of climate shocks. Our findings highlight the need to develop interventions to alleviate or prevent the additional burdens imposed by weather events.

Governments must promote adequate infrastructure or essential services in low-income neighborhoods or rural areas. For example, improving or constructing drainage systems should be prioritized to help prevent damage during heavy rains. Likewise, basic services such as potable water, access to electricity, or gas for cooking without depending on weather conditions must be ensured. For poor households, the Ministry of Housing can offer grants or loans with low interest rates to improve housing quality, especially in areas prone to climate risks. For rural areas, access to health services and childcare or care for the elderly must be ensured to help alleviate this additional burden on vulnerable households.

Regarding gender roles, it is important to encourage men's participation in household chores through formal and informal education. For instance, campaigns that raise awareness about the equitable distribution of household responsibilities. This can be accompanied by labor reforms such as paternity leave for men, which currently grants 12 weeks to women and 10 to 15 days for men in Ecuador.

Given the reduction in paid work, particularly among women, policies should prioritize the provision of subsidies or economic support for female household heads to soften the loss of income and maintain household welfare. Public policies must recognize and value unpaid domestic work by providing social protection systems that support individuals involved in these activities. Finally, women, poor households, and rural families must be included in public policy decision-making processes in order to understand their needs and be able to meet them.

5. Conclusions, policy recommendations, and scope for further research

The thesis explores the economic and non-economic impacts of rainfall shocks in Ecuador, highlighting how these extreme events disproportionately affect disadvantaged populations in rural and urban settings. Additionally, they alter the distribution of individual labor allocations to unpaid household work and remunerated employment. The findings suggest that weather extremes have negative implications for poverty, income, poverty gaps, and daily household labor allocations, exacerbating pre-existing social inequalities and the vulnerability of specific groups.

The first essay (second chapter) estimated the effects of rainfall shocks – including excess and lack of rain – on income distribution and poverty in rural Ecuador. In rural areas, where productive assets are more sensitive, weather extremes can damage them, and consecutive rainfall shocks can have severe consequences on people's well-being. A single rainfall shock reduces the per capita income of rural households by 9%, and the poorest households are the most affected. This finding is consistent with previous studies (Amare & Balana, 2023; Hallegatte et al., 2018; Pleninger, 2022; Boansi et al., 2021; Salvucci & Santos, 2020). However, the second consecutive rainfall shock dramatically amplifies income losses, especially for poor households, by -53%. Furthermore, the estimates show that rainfall shocks substantially widen the poverty gap and severity, with larger effects associated with repeated events. A single shock leaves households vulnerable, and if they do not have time or resources to recover, the second shock has more drastic consequences. Considering that climate change will increase the frequency and severity of extreme events, our analysis contributes to a better understanding of the dynamics of consecutive shocks and their more severe impacts on households, especially the poorest ones.

Despite increasing urbanization rates, extreme weather events' impacts in urban areas remain understudied compared to rural areas (Plänitz, 2019). Chapter three demonstrates that rainfall shocks exacerbate economic disparities in urban settings, aligning with previous studies (Rodriguez-Oreggia et al., 2013; Hallegatte et al., 2020; Nakamura et al., 2023), and increase the distance from the poverty line. Women are more affected than men, and people living in risky areas suffer more than those in safer regions. Among these disadvantaged groups, the poorest are the hardest hit. In the 10th percentile, those living in risky areas experience a significant reduction in their economic level by -15.3 percentage points, and women from the lowest percentile are also greatly impacted by -14.0 percentage points. Rainfall shocks not only worsen the distribution of poverty but also intensify existing inequalities based on sex, particularly affecting those in the lower percentiles. Our analysis contributes to understanding the interactions between extreme weather events and vulnerable groups in urban areas. It highlights the importance of considering sex, socioeconomic status, and geographic characteristics (floods, landslides, or drought risk) when evaluating the socioeconomic impacts of climatic events and developing policies against climate change.

As many researchers have studied, extreme weather events affect the household economy, but they also influence time allocation for unpaid and paid work. Essay three (chapter four) analyzes the relationship between excess and lack of rainfall and the time spent on unpaid domestic chores, focusing on different impacts between men and women, low and high-income households, and rural and urban areas. The results show that weather extremes add two hours per week to housework, particularly impacting women, low-income families, and rural areas. The most affected group is poor women, experiencing an increase of five hours. In general, excess rain has greater consequences than lack of rain. The increase in domestic workload not only reinforces existing gender inequalities but also limits the time available for paid work and rest, especially among women.

Some studies show that women are more affected, which is consistent with our results (Ajibade et al., 2013; Jiao et al., 2020). Current literature has focused little on quantitatively evaluating the effect of weather shocks on unpaid housework, especially considering different socioeconomic groups, territories, or intersectionality. Our study contributes to a better understanding of the heterogeneous effects of weather shocks on labor time allocation.

Governments have limited resources, especially in low—and middle-income countries. Therefore, first, it is important to identify where and who the most affected groups are. In rural areas, poor farmers are disproportionately impacted. In urban settings, pinpointing risk zones is crucial, as not only are the poor affected, but particularly poor households living in risk areas. After rainfall shocks, women suffer from reduced incomes and increased time spent on unpaid housework.

Given the economic and non-economic impacts mentioned before, policies should be designed considering sex, socioeconomic status, geographic location, and geographic characteristics (landslide, flood, and drought risk).

The effects of consecutive rainfall shocks are more severe. Therefore, urgent and rapid policies should be developed to assist affected households, especially the poor. Economic support programs, such as climate risk insurance, safety nets, and relief funds, should be implemented to assist low-income families in rapidly recovering after an extreme event. Climate risk insurance must be accessible and affordable, particularly for low-income households disproportionately vulnerable to the devastating impacts of consecutive climate events. For instance, weather index insurances are also positively associated with the use of improved seeds and the increase in crop yield, benefiting these populations (Sibiko & Qaim, 2020). Safety net programs like cash transfer schemes could integrate emergency transfers targeted at beneficiary households affected by extreme events. For vulnerable households not covered by these programs, providing emergency relief funds—either in anticipation of or immediately following an event—can significantly accelerate recovery. These social protection programs may include grants for home repairs, support for the revival of local businesses, and assistance in the agricultural sector, ensuring that communities can reestablish their livelihoods as quickly as possible. Furthermore, given the high dependence on agriculture, it is essential to strengthen technical and institutional innovations to increase and stabilize yields. This can be achieved through the promotion of climate-resilient crop varieties, the adoption of climate-smart agricultural practices, and the implementation of efficient irrigation systems. These efforts should be accompanied by training in adaptive farming techniques, which can enhance the adaptive capacity of rural communities. Finally, improving data collection—especially data focused on specific vulnerable groups -is crucial for designing and implementing more effective and targeted interventions.

Governments in developing countries have paid little attention to the urban poor (Dodman et al., 2023). It is essential to cross-reference poverty maps with risk maps for landslides or floods to identify the most vulnerable urban populations accurately. Risk management policies, infrastructure improvement programs, and poverty reduction strategies could be developed based on this analysis. In high-risk areas with informal settlements, it is important to implement regulations that prevent the expansion and construction of housing or businesses in risky areas or evaluate the feasibility of relocating affected populations. Additionally, the impacts of extreme weather events can be mitigated by promoting climate-resilient infrastructure, such as improving drainage systems, constructing flood barriers, or reinforcing slopes. Similarly, collaboration with social protection programs is necessary. These programs could be expanded to include poor households residing in high-risk areas. As mentioned, it is essential to consider providing emergency cash transfers or low-interest credits to beneficiaries in risk zones facing extreme events.

Rainfall shocks affect labor time allocation, increasing time spent on unpaid household chores and decreasing paid work, especially for women. Our findings underscore the need for interventions to mitigate or prevent the extra burdens imposed by these events. Governments must promote adequate road infrastructure, essential services, child/elder care centers, and health services, especially in low-income and rural neighborhoods. Ministries can offer grants or loans with low interest rates to improve housing quality, mainly in areas prone to climate risks. Promoting male participation in household chores through formal and informal education, as well as labor reforms, such as paternity leave, is also crucial. Given the reduction in paid work, particularly among women, policies should prioritize providing relief funds or economic support for urban female household heads. Public policies should acknowledge and value unpaid domestic work by establishing social protection systems that support those involved in these tasks.

In general, it is important to include vulnerable groups, such as women, poor households, and rural families, in public policy decision-making processes to know and cover their needs. Also, government aid must be quick and effective since a one-time drop in income may force households to sell assets in a rush (often at a low price), which has long-term consequences and structurally affects their poverty level. Finally, public institutions should collaborate with researchers and local communities to monitor and evaluate the effectiveness of policies and adapt them as needed. This guarantees that adaptation and mitigation strategies are not only effective but also promote social equity and economic resilience. Moreover, they must be sustainable over the long term and adaptable to the population's evolving needs in a constantly changing climate.

The research analyzes the heterogeneous impacts of rainfall shocks in Ecuador but also emphasizes the need for future studies that delve deeper into understanding these dynamics and adaptation and mitigation measures for disadvantaged populations.

The research has contributed significantly to literature by situating the results at the forefront of knowledge on climate change and its societal impacts. The initial analysis in the first essay (second chapter), though limited to two consecutive shocks, reveals that the subsequent shocks have increasingly severe effects. This finding underscores the need for future research to delve into the repercussions of *multiple consecutive weather shocks* on welfare outcomes, especially as climate change is anticipated to heighten the frequency of these extreme events. By highlighting these critical areas, the study not only advances our understanding but also paves the way for future investigative pathways that could further elucidate the complex dynamics of climate impacts on society.

As observed in the second essay (third chapter), in urban areas, the lowest percentiles of women and people living in high-risk areas are the most affected. We believe it is important to continue developing studies that consider intersectionality, such as poor women in hazardous areas, and to examine the economic activities most affected in urban settings. This will help understand the transmission channels of the effects of weather extremes in urban areas. The analysis should integrate poverty maps, geographic data, as well as socioeconomic and demographic household information.

Considering the findings from the third essay (chapter four), future research could explore the psychological impacts of increased domestic burdens that arise from weather extremes, with a particular focus on mental health outcomes such as stress and anxiety. This study should pay special attention to the experiences of women, poor families, and rural areas who are disproportionately affected. Additionally, investigating community-based adaptation strategies could offer practical solutions to reduce the individual burden. Such research could examine the effectiveness of community-led initiatives like shared childcare during extreme weather events or collective resources for managing household tasks, especially in the most vulnerable communities. By integrating these approaches, future research can provide a comprehensive understanding of the challenges and develop more robust strategies to address the needs of those most impacted by climate variability.

In general, once we understand the impacts, we must explore strategies that allow people to adapt, enhance their resilience, and mitigate these effects effectively. There is a significant gap in understanding how the poor respond to climate change, the support they require, and the interconnections among development policies, poverty reduction, and climate change actions (Ryan & Bustos, 2019; Satterthwaite et al., 2020). This knowledge will help create effective strategies to meet the immediate and long-term needs of disadvantaged populations already identified. For instance, researching the development of mobile applications that provide adaptive advice shows how technology can play a significant role. However, it is also necessary to understand the limitations of adopting these technologies, particularly in poor households with low levels of education or in rural homes with limited connectivity.

Finally, the importance of policies and strategies to combat climate change and weather shocks underscores the need to study how economic or political actors perceive climate change. These actors are crucial in shaping local, regional, and national policies. If they do not recognize climate change as a pressing issue, they will be unlikely to prioritize it. Their perceptions determine the urgency and allocation of resources for climate action. As the adage suggests, *"If the problem does not exist, there are no solutions"* (Castellanos et al., 2022).

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Appendix A to Essay one (chapter two)

Table A1 Model specification tests

	Joint F test - Time fixed effects		Wald test - Heteroskedasticity		Hausman test		
Model (dependent variable)	**F(13, 59918)**	**Prob > F**	**Chi2 (59919)**	**Prob > Chi2**	**Chi2 (*)**	**Chi2 (*)**	**Prob > Chi2**
Per capita income	9.58	0	7.50E+41	0	Chi2(20)	1942.51	0
Poverty	4.69	0	2.80E+41	0	Chi2(20)	2090.25	0
Extreme poverty	3.3	0	9.90E+41	0	Chi2(21)	1478.7	0
Poverty gap	5.52	0	1.80E+44	0	Chi2(21)	2376.77	0
Poverty severity	4.32	0	9.00E+41	0	Chi2(20)	4989.37	0

Table A2 Effects of recurrent rainfall shocks on per capita income

	(1)	**(2)**
One rainfall shock	**-0.0879*****	**-0.0894*****
	(0.0207)	(0.0206)
Two rainfall shocks	**-0.165****	**-0.133***
	(0.0687)	(0.0692)
Education head of household		**0.00780*****
		(0.00246)
Age head of household		**0.00198***
		(0.00103)
Number of people in the household		**-0.0562*****
		(0.00564)
Number of children under 5 years old		**-0.0705*****
		(0.0126)
Number of older adults (65 or older)		**-0.0366***
		(0.019)
BDH beneficiary household		**0.105*****
		(0.0157)
Time dummies	Yes	Yes
Observations	118,948	118,937
Number of id	59,922	59,919
R-squared	0.0060	0.0210

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

Table A2.1 Effects of recurrent rainfall shocks on per capita income (2013-2016) without and with temperature

	Without temperature		With temperature	
One rainfall shock	**-0.0843*** **	**-0.0851 *** **	**-0.0795*** **	**-0.0817*** **
	-0.0268	-0.0266	-0.0276	-0.0274
Two rainfall shocks	**-0.203***	**-0.154**	**-0.203***	**-0.154**
	-0.107	-0.104	-0.107	-0.104
Average temperature			**-0.0133**	**-0.0096**
			-0.018	-0.0178
Control variables	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	67,315	67,308	67,315	67,308
Number of id	38,973	38,971	38,973	38,971
R-squared	0.0120	0.0240	0.0120	0.0240

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

Table A3 Effects of recurrent rainfall shocks on income (poor and non-poor households)

	Non-poor		Poor	
	(1)	**(2)**	**(1)**	**(2)**
One rainfall shock	**-0.0377****	**-0.0407****	**-0.0949*** **	**-0.102*** **
	(0.0172)	(0.017)	(0.0359)	(0.0364)
Two rainfall shocks	**-0.111***	**-0.0954***	**-0.540*** **	**-0.533*** **
	(0.06)	(0.057)	(0.166)	(0.165)
Education head of household		**0.00840*** **		**0.000468**
		(0.00255)		(0.00483)
Age head of household		**0.000918**		**0.00113**
		(0.000946)		(0.00216)
Number of people in the household		**-0.0532*** **		**-0.0174***
		(0.00568)		(0.0105)
Number of children under 5 years old		**-0.0397*** **		**-0.0534****
		(0.0137)		(0.0216)
Number of older adults (65 or older)		**-0.0214**		**-0.0418**
		(0.0175)		(0.0446)
BDH beneficiary household		**-0.0236***		**0.162*** **
		(0.0143)		(0.0342)
Time dummies	Yes	Yes	Yes	Yes
Observations	77,203	77,194	41,745	41,743
Number of id	47,180	47,175	29,353	29,352
R-squared	0.0130	0.0310	0.0060	0.0170

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

Table A4 Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity

	Poverty (dummy)		**Extreme poverty (dummy)**		**Poverty gap (0-1)**		**Poverty severity**	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
One rainfall shock	**0.0366*** **	**0.0371*** **	**0.0282*** **	**0.0287*** **	**0.0231*** **	**0.0234*** **	**0.0174*** **	**0.0177*** **
	(0.0125)	(0.0125)	(0.00987)	(0.00985)	(0.00629)	(0.00629)	(0.00473)	(0.00474)
Two rainfall shocks	**0.0192**	**0.00483**	**0.0803*** **	**0.0709*** **	**0.0405** **	**0.0330* **	**0.0369*** **	**0.0319*** **
	(0.0494)	(0.0501)	(0.0231)	(0.0235)	(0.0182)	(0.0188)	(0.0107)	(0.0111)
Education head of household		**-0.0037** **		**-5.98E-05**		**-0.00086**		**-0.00013**
		(0.00162)		(0.00128)		(0.000735)		(0.000532)
Age head of household		**-0.00129* **		**-0.00086**		**-0.000554* **		**-0.00033**
		(0.000728)		(0.000568)		(0.000329)		(0.000225)
Number of people in the household		**0.0165*** **		**0.0102*** **		**0.00833*** **		**0.00549*** **
		(0.00359)		(0.00276)		(0.00171)		(0.00128)
Number of children under 5 years old		**0.0420*** **		**0.0303*** **		**0.0225*** **		**0.0149*** **
		(0.00855)		(0.0073)		(0.00434)		(0.00329)
Number of older adults (65 or older)		**0.015**		**0.00317**		**0.00104**		**0.000537**
		(0.012)		(0.00898)		(0.00583)		(0.00455)
BDH beneficiary Household		**-0.067*** **		**-0.0472*** **		**-0.0386*** **		**-0.0276*** **
		(0.0105)		(0.0085)		(0.00529)		(0.00417)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,948	118,937	118,948	118,937	118,948	118,937	118,948	118,937
Number of id	59,922	59,919	59,922	59,919	59,922	59,919	59,922	59,919
R-squared	0.003	0.009	0.001	0.006	0.002	0.01	0.002	0.009

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

Table A4.1 Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity (2013-2016) without temperature

	Poverty (dummy)		**Extreme poverty (dummy)**		**Poverty gap (0-1)**		**Poverty severity**	
One rainfall shock	**0.0401****	**0.0405****	**0.0393*****	**0.0399*****	**0.0292*****	**0.0296*****	**0.0204*****	**0.0207*****
	-0.016	-0.016	-0.0143	-0.0143	-0.00889	-0.00885	-0.00698	-0.00694
Two rainfall shocks	**0.0777**	**0.06**	**0.158*****	**0.147*****	**0.0922*****	**0.0830*****	**0.0738*****	**0.0679*****
	-0.0908	-0.0908	-0.0559	-0.0567	-0.0311	-0.0316	-0.0213	-0.0217
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,315	67,308	67,315	67,308	67,315	67,308	67,315	67,308
Number of id	38,973	38,971	38,973	38,971	38,973	38,971	38,973	38,971
R-squared	0.0040	0.0090	0.0010	0.0040	0.0030	0.0080	0.0020	0.0060

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

Table A4.2 Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity (2013-2016) with temperature

	Poverty (dummy)		**Extreme poverty (dummy)**		**Poverty gap (0-1)**		**Poverty severity**	
One rainfall shock	**0.0330****	**0.0340****	**0.0394*****	**0.0403*****	**0.0278*****	**0.0285*****	**0.0199*****	**0.0204*****
	-0.0167	-0.0167	-0.0146	-0.0146	-0.0091	-0.00907	-0.00709	-0.00706
Two rainfall shocks	**0.0784**	**0.0607**	**0.158*****	**0.147*****	**0.0923*****	**0.0832*****	**0.0739*****	**0.0680*****
	-0.0908	-0.0908	-0.0559	-0.0567	-0.0311	-0.0316	-0.0213	-0.0217
Average temperature	**0.0201***	**0.0184**	**-0.000294**	**-0.00123**	**0.00402**	**0.00325**	**0.00143**	**0.000942**
	-0.0116	-0.0115	-0.00945	-0.00944	-0.00944	-0.00552	-0.00425	-0.00423
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,315	67,308	67,315	67,308	67,315	67,308	67,315	67,308
Number of id	38,973	38,971	38,973	38,971	38,973	38,971	38,973	38,971
R-squared	0.0040	0.0100	0.0010	0.0040	0.0030	0.0080	0.0020	0.0070

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

Appendix B to Essay two (chapter three)

Table B1 Annual panels (number of observations at the household level), ENEMDU Panels 2007-2019

Panels	Period	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Panel 1	Q3 (2007-2008)	3,920	3,928	0	0	0	0	0	0	0	0	0	0	0	**7,848**
Panel 2	Q4 (2007-2008)	3,886	3,907	0	0	0	0	0	0	0	0	0	0	0	**7,793**
Panel 3	Q1 (2008-2009)	0	3,973	3,999	0	0	0	0	0	0	0	0	0	0	**7,972**
Panel 4	Q2 (2008-2009)	0	3,916	3,906	0	0	0	0	0	0	0	0	0	0	**7,822**
Panel 5	Q3 (2009-2010)	0	0	4,078	4,102	0	0	0	0	0	0	0	0	0	**8,180**
Panel 6	Q4 (2009-2010)	0	0	3,829	3,862	0	0	0	0	0	0	0	0	0	**7,691**
Panel 7	Q1 (2010-2011)	0	0	0	3,752	3,746	0	0	0	0	0	0	0	0	**7,498**
Panel 8	Q2 (2010-2011)	0	0	0	3,903	3,930	0	0	0	0	0	0	0	0	**7,833**
Panel 9	Q4 (2011-2012)	0	0	0	0	3,205	3,180	0	0	0	0	0	0	0	**6,385**
Panel 10	Q1 (2012-2013)	0	0	0	0	0	3,554	3,552	0	0	0	0	0	0	**7,106**
Panel 11	Q2 (2012-2013)	0	0	0	0	0	4,175	4,151	0	0	0	0	0	0	**8,326**
Panel 12	Q3 (2013-2014)	0	0	0	0	0	0	1,320	1,349	0	0	0	0	0	**2,669**
Panel 13	Q4 (2013-2014)	0	0	0	0	0	0	5,663	5,675	0	0	0	0	0	**11,338**
Panel 14	Q1 (2014-2015)	0	0	0	0	0	0	0	6,852	6,853	0	0	0	0	**13,705**
Panel 15	Q2 (2014-2015)	0	0	0	0	0	0	0	13,032	13,014	0	0	0	0	**26,046**
Panel 16	Q3 (2014-2015)	0	0	0	0	0	0	0	3,827	3,827	0	0	0	0	**7,654**
Panel 17	Q3 (2015-2016)	0	0	0	0	0	0	0	0	3,723	3,716	0	0	0	**7,439**
Panel 18	Q4 (2015-2016)	0	0	0	0	0	0	0	0	13,717	13,784	0	0	0	**27,501**
Panel 19	Q1 (2016-2017)	0	0	0	0	0	0	0	0	0	7,792	7,805	0	0	**15,597**
Panel 20	Q2 (2016-2017)	0	0	0	0	0	0	0	0	0	7,854	7,844	0	0	**15,698**
Panel 21	Q3 (2016-2017)	0	0	0	0	0	0	0	0	0	3,644	3,677	0	0	**7,321**
Panel 22	Q1 (2018-2019)	0	0	0	0	0	0	0	0	0	0	0	7,713	7,681	**15,394**
Panel 23	Q2 (2018-2019)	0	0	0	0	0	0	0	0	0	0	0	8,334	8,323	**16,657**
Panel 24	Q3 (2018-2019)	0	0	0	0	0	0	0	0	0	0	0	8,417	8,413	**16,830**
Panel 25	Q4 (2018-2019)	0	0	0	0	0	0	0	0	0	0	0	8,594	8,581	**17,175**
Total		**7,806**	**15,724**	**15,812**	**15,619**	**10,881**	**10,909**	**14,686**	**30,735**	**41,134**	**36,790**	**19,326**	**33,058**	**32,998**	**285,478**

Table B2 Robustness tests

Model	Joint F test - Time-fixed effects		Wald test – Heteroskedasticity		Hausman test	
	F (*)	**Prob > F**	**Chi2 (*)**	**Prob > Chi2**	**Chi2 (*)**	**Prob > Chi2**
Distance to the poverty line (total urban area)	3.32	0.0000	1.8E+43	0.0000	3858.99	0.0000
Women	2.35	0.0002	7.1E+43	0.0000	7136.71	0.0000
Men	2.29	0.0002	1.8E+42	0.0000	1759.58	0.0000
Risky territories	2.23	0.0004	1.0E+42	0.0000	1787.54	0.0000
Non-risky territories	2.96	0.0000	2.2E+42	0.0000	2006.64	0.0000

Table B3 Effect of rainfall shocks on the distance to the poverty line

	Urb Area (1)	**Per10 (2)**	**Per25 (3)**	**Per50 (4)**	**Per75 (5)**	**Urb Area (6)**	**Per10 (7)**	**Per25 (8)**	**Per50 (9)**	**Per75 (10)**
Rainfall shock	**0.077**	**-0.095*** **	**-0.0705*** **	**-0.0385** **	**-0.029**	**0.084**	**-0.0980*** **	**-0.0725*** **	**-0.0376** **	**-0.03**
	(1.19)	(-3.19)	(-3.58)	(-2.19)	(-1.61)	(1.3)	(-3.34)	(-3.69)	(-2.14)	(-1.57)
Education head of						0.0457***	0.00238	0.00315	0.00158	0.00783***
Household						-6.9	-0.93	-1.64	-0.88	-3.77
Age head of						0.00459*	0.00246	0.00107	0.0007	0.00141
Household						-1.88	-1.87	-1.25	-0.91	-1.6
Number of people in the						-0.231***	-0.0002	0.00949*	-0.0021	-0.0330***
Household						(-15.77)	(-0.04)	-2.44	(-0.58)	(-7.02)
Number of children						-0.191***	-0.0088	-0.0356***	-0.0749***	-0.152***
under 5 years						(-6.32)	(-0.76)	(-4.35)	(-9.01)	(-15.57)
Number of older adults						-0.254***	-0.0253	-0.0219	-0.0157	-0.0713***
(over 65)						(-6.03)	(-1.22)	(-1.30)	(-1.02)	(-4.07)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285478	16968	50866	118134	196525	285446	16964	50856	118115	196501
Adjusted R-squared	0.001	0.036	0.01	0.006	0.004	0.008	0.04	0.013	0.012	0.019

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table B4 Effect of rainfall shocks on the distance to the poverty line: Risky areas

	Risky areas (1)	**Per10 (2)**	**Per25 (3)**	**Per50 (4)**	**Per75 (5)**	**Risky areas (6)**	**Per10 (7)**	**Per25 (8)**	**Per50 (9)**	**Per75 (10)**
Rainfall shock	**0.00767**	**-0.144*****	**-0.126*****	**-0.0762*****	**-0.0791*****	**0.0046**	**-0.153*****	**-0.130*****	**-0.0761*****	**-0.0806*****
	(0.12)	(-3.20)	(-3.82)	(-2.86)	(-2.96)	(0.07)	(-3.51)	(-3.94)	(-2.85)	(-3.01)
Education head of household						0.0430***	0.00455	0.00302	0.00279	0.00681*
						-4.71	-1.26	-1.14	-1.16	-2.48
Age head of household						0.000988	0.00318	0.00165	0.000688	0.000342
						-0.31	-1.71	-1.31	-0.64	-0.29
Number of people in the household						-0.232***	0.00913	0.0118*	0.0000365	-0.0347***
						(-13.52)	-1.59	-2.21	-0.01	(-5.48)
Number of children under 5 years old						-0.172***	-0.0163	-0.0392***	-0.0788***	-0.151***
						(-4.83)	(-1.03)	(-3.63)	(-7.63)	(-12.02)
Number of older adults (over 65)						-0.269***	-0.03	-0.0365	-0.00819	-0.0637**
						(-4.47)	(-0.78)	(-1.41)	(-0.37)	(-2.67)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152627	8183	26737	64461	107452	152609	8182	26731	64449	107438
Adjusted R-squared	0.001	0.053	0.018	0.01	0.005	0.01	0.062	0.023	0.016	0.021

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table B5 Effect of rainfall shocks on the distance to the poverty line: Non-risky areas

	Non-risky areas	**Per10**	**Per25**	**Per50**	**Per75**	**Non-risky areas**	**Per10**	**Per25**	**Per50**	**Per75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Rainfall shock	**0.139**	**-0.063**	**-0.0221**	**0.0157**	**0.0266**	**0.144**	**-0.0617**	**-0.0219**	**0.0171**	**0.026**
	(1.03)	(-1.51)	(-0.90)	(0.6)	(0.96)	(1.07)	(-1.51)	(-0.90)	(0.66)	(0.95)
Education head of household						0.0504***	0.00228	0.00378	0.00102	0.0106**
						-5.05	-0.65	-1.33	-0.37	-3.21
Age head of household						0.00911*	0.00242	0.0012	0.00128	0.00352*
						-2.37	-1.28	-1.07	-1.11	-2.53
Number of people in the household						-0.238***	-0.0143*	0.0048	-0.00601	-0.0306***
						(-8.85)	(-2.22)	-0.82	(-1.04)	(-4.15)
Number of children under 5 years old						-0.230***	0.00971	-0.0289*	-0.0682***	-0.157***
						(-4.28)	-0.64	(-2.25)	(-4.72)	(-9.81)
Number of older adults (over 65)						-0.237***	-0.00256	-0.00919	-0.0257	-0.0808**
						(-3.96)	(-0.11)	(-0.42)	(-1.19)	(-3.06)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130066	8265	22920	51693	86602	130052	8262	22916	51686	86592
Adjusted R-squared	0.002	0.066	0.012	0.006	0.005	0.007	0.075	0.014	0.011	0.018

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table B6 Effect of rainfall shocks on the distance to the poverty line: Women

	Women	**Per10**	**Per25**	**Per50**	**Per75**	**Women**	**Per10**	**Per25**	**Per50**	**Per75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Rainfall shock	**0.0826**	**-0.138*** **	**-0.0743** **	**-0.052**	**-0.0379**	**0.0783**	**-0.140*** **	**-0.0783** **	**-0.052**	**-0.0379**
	(0.9)	(-2.60)	(-2.22)	(-1.58)	(-1.15)	(0.87)	(-2.63)	(-2.36)	(-1.58)	(-1.16)
Education head of household						0.0376***	0.00444	0.00187	0.00302	0.00852*
						-3.83	-0.92	-0.45	-0.86	-2.12
Age head of Household						0.000499	0.00241	0.00317	0.00308	0.00157
						-0.1	-1	-1.8	-1.84	-0.81
Number of people in the household						-0.173***	-0.00472	0.0125	-0.00134	-0.0218**
						(-7.88)	(-0.63)	-1.9	(-0.21)	(-2.61)
Number of children under 5 years old						-0.202***	-0.00842	-0.0413*	-0.0786***	-0.181***
						(-3.29)	(-0.45)	(-2.57)	(-5.18)	(-10.07)
Number of older adults (over 65)						-0.394***	-0.00033	-0.0414	-0.0203	-0.118***
						(-4.69)	(-0.01)	(-1.11)	(-0.62)	(-3.63)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83058	5748	16213	36460	59402	83048	5747	16209	36453	59394
Adjusted R-squared	0.002	0.099	0.024	0.009	0.004	0.012	0.104	0.03	0.016	0.021

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table B7 Effect of rainfall shocks on the distance to the poverty line: Men

	Men (1)	**Per10 (2)**	**Per25 (3)**	**Per50 (4)**	**Per75 (5)**	**Men (6)**	**Per10 (7)**	**Per25 (8)**	**Per50 (9)**	**Per75 (10)**
Rainfall shock	**0.0769**	**-0.064***	**-0.0730*****	**-0.0375***	**-0.0263**	**0.0865**	**-0.0631***	**-0.0745*****	**-0.036***	**-0.0246**
	(0.89)	(-1.84)	(-2.97)	(-1.75)	(-1.19)	(1.00)	(-1.83)	(-3.03)	(-1.69)	(-1.12)
Education head of household						0.0467***	0.00251	0.00202	0.00166	0.00650*
						-4.53	-0.78	-0.83	-0.72	-2.34
Age head of household						0.00753	0.000687	0.000227	-0.000243	0.000707
						-1.51	-0.25	-0.16	(-0.18)	-0.47
Number of people in the household						-0.270***	0.00112	0.00861	-0.00698	-0.0442***
						(-13.14)	-0.18	-1.71	(-1.47)	(-7.28)
Number of children under 5 years old						-0.181***	-0.00792	-0.0381***	-0.0670***	-0.133***
						(-4.85)	(-0.55)	(-3.87)	(-6.37)	(-11.08)
Number of older adults (over 65)						-0.230***	-0.0275	-0.0195	-0.0117	-0.0539*
						(-4.26)	(-1.02)	(-0.97)	(-0.63)	(-2.41)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202420	11220	34653	81674	137123	202398	11217	34647	81662	137107
Adjusted R-squared	0.001	0.032	0.012	0.007	0.005	0.007	0.034	0.015	0.012	0.02

*t statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Appendix C to Essay three (chapter four)

Table C1 Robustness tests

Model		Joint F test - Time-fixed effects		Hausman test	
		F (*)	Prob > F	Chi2 (*)	Prob > Chi2
Total population	*Household chores*	*52.72*	0.00000	3346.46	0.00000
	Cleaning	*8.23*	0.00030	774.52	0.00000
	Shopping	*21.6*	0.00000	374.96	0.00000
	Caring	*38.52*	0.00000	1009.23	0.00000

Table C2 Effect of rainfall shocks on time spent on household chores and work (without control variables)

	Total housework	Cleaning	Cooking	Caring	Laundry	Shopping	Schoolwork	Paid work
Rainfall shock	**2.220*** **	**0.533*** **	**0.712*** **	**0.363** **	**0.343*** **	**0.198*** **	**0.0711**	**-0.79* **
	(5.72)	**(4.85)**	**(4.42)**	**(2.45)**	**(3.59)**	**(3.52)**	**(0.92)**	**(-1.90)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	166768	166768	166768	166768	166768	166768	166768	107378
Adjusted R-squared	0.005	0.002	0.004	0.002	0.001	0.001	0.001	0

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C3 Effect of rainfall shocks on time spent on household chores and work (including control variables)

	Total housework	Cleaning	Cooking	Caring	Laundry	Shopping	Schoolwork	Paid work
Rainfall shock	**2.170*** **	**0.516*** **	**0.682*** **	**0.363** **	**0.337*** **	**0.199*** **	**0.0726**	**-0.773* **
	(5.61)	**(4.64)**	**(4.26)**	**(2.58)**	**(3.53)**	**(3.52)**	**(0.94)**	**(-1.87)**
Education	0.00397	0.00152	0.0224	-0.00889	-0.0139	-0.00406	0.00692	0.118
	(0.09)	(0.14)	(1.13)	(-0.44)	(-1.36)	(-0.70)	(0.66)	(1.72)
Age	0.0556	0.00653	0.0687***	0.00914	-0.0260*	0.000876	-0.00363	-0.0825
	(1.18)	(0.50)	(3.48)	(0.42)	(-2.02)	(0.11)	(-0.39)	(-1.10)
Marital status	1.018**	-0.0348	0.132	0.659***	0.211*	0.0994	-0.0479	-0.525
(married=1)	(2.62)	(-0.39)	(0.72)	(3.52)	(2.15)	(1.72)	(-0.53)	(-0.97)
Number of hours	-0.119***	-0.0174***	-0.0419***	-0.0270***	-0.0156***	-0.00422***	-0.0124***	
worked (occupation)	(-24.70)	(-14.40)	(-20.84)	(-12.85)	(-14.53)	(-6.46)	(-11.80)	
Education head	0.0328	-0.000746	0.00498	0.00544	0.00984	0.00925	0.00404	0.0233
of household	(0.77)	(-0.06)	(0.28)	(0.26)	(0.95)	(1.42)	(0.39)	(0.36)

Age head	0.0186	-0.00017	0.00136	-0.000686	0.0109*	0.00172	0.00553	0.0112
of household	(0.81)	(-0.04)	(0.16)	(-0.06)	(2.22)	(0.50)	(1.28)	(0.37)
Number of people	-0.723***	-0.157***	-0.420***	-0.104*	-0.0710**	-0.0489***	0.0788***	0.368*
in the household	(-7.36)	(-5.58)	(-10.67)	(-2.00)	(-3.09)	(-3.31)	(3.70)	(2.33)
Number of children	2.321***	0.139*	0.192*	1.935***	0.0908	0.0234	-0.0593	-0.542
under 5 years old	(10.18)	(2.38)	(2.30)	(15.36)	(1.94)	(0.72)	(-1.08)	(-1.80)
Number of older	0.443	0.145	-0.0226	0.616***	-0.133	-0.0693	-0.0933*	-0.415
adults (over 65)	(1.49)	(1.52)	(-0.17)	(3.97)	(-1.79)	(-1.30)	(-2.11)	(-0.73)
Per capita income	-0.000175	0.000111	-0.00017	-0.000127	-0.0000352	0.0000313	0.0000149	
	(-0.82)	(1.58)	(-1.72)	(-1.60)	(-0.73)	(0.85)	(0.33)	
Constant	18.57***	3.499***	6.750***	1.956*	3.604***	1.723***	1.043**	38.85***
	(9.49)	(6.00)	(7.59)	(2.35)	(6.53)	(5.29)	(2.74)	(11.60)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165529	165529	165529	165529	165529	165529	165529	107369
Adjusted R-squared	0.032	0.01	0.021	0.029	0.009	0.003	0.006	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C4 Effect of excessive and scarce rainfall shocks on time spent on household chores and work

	Total housework	**Cleaning**	**Cooking**	**Caring**	**Laundry**	**Shopping**	**Homework**	**Paid work**
Scarce rainfall	**1.676****	**0.660*****	**0.0675**	**0.456***	**0.196**	**0.0938**	**0.204**	**-0.161**
	(3.13)	**(3.94)**	**(0.36)**	**(2.31)**	**(1.54)**	**(0.93)**	**(1.88)**	**(-0.26)**
Excess rainfall	**2.189*****	**0.510*****	**0.706*****	**0.360***	**0.342*****	**0.204*****	**0.0675**	**-0.795**
	(5.47)	**(4.43)**	**(4.27)**	**(2.47)**	**(3.47)**	**(3.48)**	**(0.84)**	**(-1.86)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165529	165529	165529	165529	165529	165529	165529	107369
Adjusted R-squared	0.032	0.01	0.021	0.029	0.009	0.003	0.006	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C5 Effect of rainfall shocks on time spent on household chores and work: women & men (without control variables)

	Total housework	Total housework	Cleaning	Cleaning	Cooking	Cooking	Caring	Caring
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Rainfall shock	**3.200*****	**1.177*****	**0.764*****	**0.288*****	**1.150*****	**0.245****	**0.545****	**0.169**
	(5.40)	**(3.93)**	**(4.49)**	**(3.56)**	**(4.22)**	**(2.04)**	**(2.41)**	**(1.49)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86344	80424	86344	80424	86344	80424	86344	80424
Adjusted R-squared	0.006	0.007	0.004	0.003	0.005	0.003	0.002	0.003

Continuation of Table C5

	Laundry	Laundry	Shopping	Shopping	Schoolwork	Schoolwork	Paid work	Paid work
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Rainfall shock	**0.497*****	**0.180*****	**0.194*****	**0.202*****	**0.0515**	**0.0928**	**-1.121****	**-0.571**
	(3.16)	**(3.23)**	**(2.75)**	**(3.41)**	**(0.44)**	**(1.58)**	**(-2.15)**	**(-1.08)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86344	80424	86344	80424	86344	80424	45031	62347
Adjusted R-squared	0.002	0.001	0.002	0.005	0.001	0.001	0.001	0

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C6 Effect of rainfall shocks on time spent on household chores and work: women & men (including control variables)

	Total housework	Total housework	Cleaning	Cleaning	Cooking	Cooking	Caring	Caring
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Rainfall shock	**3.083*****	**1.164*****	**0.734*****	**0.281*****	**1.106*****	**0.226***	**0.508****	**0.188***
	(5.28)	**(3.82)**	**(4.29)**	**(3.46)**	**(4.09)**	**(1.88)**	**(2.37)**	**(1.68)**
Education	-0.00185	0.00499	0.00414	0.00134	0.0267	0.0083	-0.0308	0.0168
	(-0.03)	(0.11)	(0.22)	(0.10)	(0.88)	(0.42)	(-0.98)	(0.90)
Age	0.0937	0.019	0.0141	0.000199	0.0941**	0.0404*	0.0129	0.00416
	(1.31)	(0.33)	(0.69)	(0.01)	(2.71)	(2.01)	(0.42)	(0.15)
Marital status	2.576***	-1.384**	0.0172	-0.157	1.078***	-1.375***	0.939**	0.406**
(married=1)	(4.58)	(-2.98)	(0.13)	(-1.38)	(4.11)	(-6.19)	(3.17)	(2.70)
Number of hours	-0.170***	-0.0588***	-0.0231***	-0.0111***	-0.0656***	-0.0149***	-0.0356***	-0.0166***
worked	(-22.36)	(-12.05)	(-11.45)	(-9.37)	(-19.63)	(-7.52)	(-10.50)	(-8.31)

(occupation)								
Education head of household	0.0453	0.0342	0.00522	-0.00667	-0.0075	0.0302	0.0164	-0.00978
	(0.78)	(0.75)	(0.29)	(-0.53)	(-0.28)	(1.54)	(0.59)	(-0.54)
Age head of household	0.0338	-0.00189	0.00507	-0.00632	0.00632	-0.00631	-0.0078	0.00658
	(1.13)	(-0.07)	(0.70)	(-1.18)	(0.48)	(-0.59)	(-0.52)	(0.49)
Number of people in the household	-0.882***	-0.565***	-0.196***	-0.118***	-0.534***	-0.308***	-0.143	-0.0608
	(-6.05)	(-5.22)	(-4.66)	(-4.86)	(-8.37)	(-7.23)	(-1.91)	(-1.25)
Number of children under 5 years old	3.343***	1.214***	0.184*	0.0886	0.161	0.243**	2.931***	0.839***
	(9.73)	(5.42)	(2.14)	(1.64)	(1.13)	(3.08)	(15.06)	(8.57)
Number of older adults (over 65)	0.758	0.104	0.226	0.0588	0.0755	-0.123	0.811***	0.394**
	(1.72)	(0.29)	(1.50)	(0.71)	(0.35)	(-0.76)	(3.48)	(2.78)
Per capita income	-0.000765*	0.00023	0.000109	0.000115	-0.000521**	0.0000749	-0.000286*	-0.0000191
	(-2.16)	(1.03)	(1.00)	(1.87)	(-2.60)	(0.77)	(-1.97)	(-0.37)
Constant	25.33***	10.78***	4.083***	2.735***	10.48***	2.804**	3.021*	0.639
	(8.15)	(4.85)	(4.53)	(4.50)	(6.69)	(3.23)	(2.25)	(0.77)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85740	79789	85740	79789	85740	79789	85740	79789
Adjusted R-squared	0.047	0.02	0.013	0.01	0.033	0.016	0.042	0.016

Continuation of Table C6

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Schoolwork**	**Schoolwork**	**Paid work**	**Paid work**
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Rainfall shock	**0.486*** **	**0.174*** **	**0.195*** **	**0.204*** **	**0.0548**	**0.0907**	**-1.083*** **	**-0.548**
	(3.13)	**(3.09)**	**(2.76)**	**(3.39)**	**(0.46)**	**(1.53)**	**(-2.08)**	**(-1.04)**
Education	-0.0101	-0.0181	-0.00179	-0.00449	0.00998	0.00114	0.211*	0.113
	(-0.64)	(-1.85)	(-0.21)	(-0.43)	(0.62)	(0.11)	(2.12)	(1.05)
Age	-0.0323	-0.0158	0.00455	-0.00363	0.000314	-0.00637	-0.0965	-0.0643
	(-1.60)	(-1.17)	(0.46)	(-0.27)	(0.02)	(-0.54)	(-0.83)	(-0.71)
Marital status (married=1	0.546***	-0.324***	0.098	0.092	-0.102	-0.0251	-1.455*	0.318
	(3.59)	(-3.49)	(1.41)	(0.98)	(-0.71)	(-0.34)	(-2.00)	(0.43)

)								
Number of hours worked (occupation)	-0.0233***	-0.00660***	-0.00543***	-0.00283**	-0.0174***	-0.00685***		
	(-13.02)	(-7.11)	(-6.06)	(-3.22)	(-10.40)	(-6.99)		
Education head of household	0.0142	0.00793	0.0143	0.00329	0.00274	0.00926	0.151	-0.0808
	(0.86)	(0.80)	(1.85)	(0.31)	(0.19)	(0.93)	(1.84)	(-0.79)
Age head of household	0.0187*	0.000615	0.000291	0.0036	0.0113	-0.0000605	0.0489	-0.0124
	(2.24)	(0.16)	(0.08)	(0.61)	(1.75)	(-0.01)	(1.18)	(-0.30)
Number of people in the household	-0.0689	-0.0747**	-0.0542**	-0.0441*	0.114***	0.0408*	0.308	0.401*
	(-1.84)	(-3.20)	(-2.81)	(-2.46)	(3.34)	(2.03)	(1.40)	(2.29)
Number of children under 5 years old	0.146	0.0367	0.0355	0.0111	-0.115	-0.00455	-0.758	-0.449
	(1.87)	(0.85)	(0.86)	(0.26)	(-1.35)	(-0.09)	(-1.52)	(-1.23)
Number of older adults (over 65)	-0.153	-0.108	-0.0228	-0.117	-0.180**	-0.000546	0.134	-0.759
	(-1.28)	(-1.55)	(-0.37)	(-1.53)	(-2.66)	(-0.01)	(0.16)	(-1.32)
Per capita income	-0.0000969	-0.0000022	-4.75E-06	0.0000615	0.0000347	1.85E-07		
	(-1.07)	(-0.05)	(-0.10)	(1.33)	(0.44)	(0.01)		
Constant	4.753***	2.275***	1.877***	1.529**	1.117	0.798	32.06***	42.17***
	(5.24)	(4.08)	(4.36)	(3.10)	(1.72)	(1.85)	(5.93)	(11.15)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85740	79789	85740	79789	85740	79789	45025	62344
Adjusted R-squared	0.013	0.007	0.004	0.006	0.008	0.004	0.003	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C7 Effect of excessive and scarce rainfall shocks on time spent on household chores and work: women & men

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Scarce rainfall	**2.718****	**0.814**	**1.106*****	**0.240***	**0.136**	**0.0619**	**0.697***	**0.275**
	(2.72)	**(1.76)**	**(3.79)**	**(2.04)**	**(0.37)**	**(0.35)**	**(2.05)**	**(1.91)**
Excess rainfall	**3.096*****	**1.179*****	**0.721*****	**0.283*****	**1.140*****	**0.233**	**0.501***	**0.184**
	(5.14)	**(3.73)**	**(4.09)**	**(3.35)**	**(4.09)**	**(1.86)**	**(2.27)**	**(1.59)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85740	79789	85740	79789	85740	79789	85740	79789
Adjusted R-squared	0.047	0.02	0.014	0.01	0.033	0.016	0.042	0.016

Continuation of Table C7

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Homework**	**Homework**	**Paid work**	**Paid work**
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Scarce rainfall	**0.354**	**0.0613**	**0.0604**	**0.104**	**0.364**	**0.0709**	**0.311**	**-0.414**
	(1.61)	**(0.65)**	**(0.48)**	**(0.99)**	**(1.95)**	**(0.81)**	**(0.38)**	**(-0.58)**
Excess rainfall	**0.490****	**0.179****	**0.199****	**0.209*****	**0.0437**	**0.0915**	**-1.126***	**-0.553**
	(3.06)	**(3.06)**	**(2.74)**	**(3.34)**	**(0.36)**	**(1.49)**	**(-2.10)**	**(-1.02)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85740	79789	85740	79789	85740	79789	45025	62344
Adjusted R-squared	0.013	0.007	0.004	0.006	0.008	0.004	0.003	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C8 Effect of rainfall shocks on time spent on household chores and work: poor & non-poor households (without control variables)

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Rainfall shock	**3.489*****	**1.910*****	**1.006*****	**0.400*****	**1.081*****	**0.688*****	**0.562***	**0.331****
	(4.75)	**(4.68)**	**(5.18)**	**(3.23)**	**(3.37)**	**(4.11)**	**(1.65)**	**(2.03)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37857	127693	37857	127693	37857	127693	37857	127693
Adjusted R-squared	0.011	0.004	0.011	0.001	0.013	0.003	0.001	0.002

Continuation of Table C8

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Schoolwork**	**Schoolwork**	**Paid work**	**Paid work**
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Rainfall shock	**0.407****	**0.312*****	**0.353*****	**0.142****	**0.0794**	**0.0373**	**-1.05**	**-0.987****
	(2.42)	**(3.04)**	**(2.79)**	**(2.42)**	**(0.47)**	**(0.44)**	**(-0.95)**	**(-2.19)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37857	127693	37857	127693	37857	127693	23017	83706
Adjusted R-squared	0.002	0.001	0.004	0.001	0.004	0	0.004	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C9 Effect of rainfall shocks on time spent on household chores and work: poor & non-poor households (including control variables)

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Rainfall shock	**3.476*****	**1.876*****	**0.990*****	**0.387*****	**1.050*****	**0.647*****	**0.583***	**0.359****
	(4.71)	**(4.59)**	**(5.15)**	**(3.08)**	**(3.23)**	**(3.88)**	**(1.79)**	**(2.30)**
Education	-0.158	0.00364	-0.0980*	0.011	0.0263	0.0393	0.0284	-0.0385
	(-1.10)	(0.07)	(-2.06)	(0.75)	(0.42)	(1.69)	(0.55)	(-1.77)
Age	0.225	0.0635	0.0437	0.00734	0.0199	0.0737**	0.172**	-0.00111
	(1.39)	(1.22)	(1.19)	(0.50)	(0.33)	(3.04)	(2.79)	(-0.05)
Marital status	1.079	0.992*	0.0589	-0.0104	0.382	0.0708	-0.225	0.787***
(married=1)	(0.80)	(2.16)	(0.14)	(-0.10)	(0.56)	(0.34)	(-0.26)	(3.81)
Number of hours	-0.107***	-0.115***	-0.0148***	-0.0156***	-0.0258***	-0.0442***	-0.0379***	-0.0228***
worked	(-8.11)	(-20.16)	(-4.32)	(-9.98)	(-4.26)	(-17.74)	(-6.40)	(-10.30)

(occupation)								
Education head of household	0.0243	0.0582	0.000578	-0.000107	-0.0518	0.0121	-0.0457	0.0187
	(0.15)	(1.25)	(0.01)	(-0.01)	(-0.87)	(0.60)	(-0.72)	(0.80)
Age head of household	-0.0647	0.0322	-0.0115	0.00331	0.00254	0.0022	-0.0716**	0.00634
	(-1.03)	(1.17)	(-0.89)	(0.57)	(0.10)	(0.21)	(-2.62)	(0.46)
Number of people in the household	-0.637*	-0.598***	-0.180*	-0.147***	-0.279*	-0.409***	-0.123	-0.024
	(-2.14)	(-4.96)	(-2.53)	(-4.20)	(-2.55)	(-8.37)	(-0.63)	(-0.43)
Number of children under 5 years old	2.504***	2.573***	0.275	0.139*	0.225	0.168	1.781***	2.204***
	(5.04)	(9.17)	(1.79)	(2.19)	(1.25)	(1.60)	(6.33)	(13.32)
Number of older adults (over 65)	-0.0374	0.438	0.0216	0.154	0.199	-0.177	0.0279	0.726***
	(-0.04)	(1.19)	(0.10)	(1.23)	(0.59)	(-1.07)	(0.05)	(4.00)
Per capita income	0.0102	-0.000153	0.00368	0.000123	0.00576	-0.000162	-0.00127	-0.000124
	(0.68)	(-0.70)	(1.01)	(1.69)	(0.97)	(-1.59)	(-0.14)	(-1.60)
Constant	18.29*	15.99***	3.223*	2.984***	8.144**	6.080***	0.863	1.498
	(2.44)	(6.96)	(2.04)	(4.34)	(3.15)	(5.57)	(0.26)	(1.60)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37855	127674	37855	127674	37855	127674	37855	127674
Adjusted R-squared	0.032	0.031	0.02	0.008	0.019	0.022	0.031	0.034

Continuation of Table C9

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Schoolwork**	**Schoolwork**	**Paid work**	**Paid work**
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Rainfall shock	**0.419****	**0.304*****	**0.355*****	**0.137****	**0.0791**	**0.0403**	**-1.148**	**-0.972****
	(2.53)	**(2.96)**	**(2.82)**	**(2.31)**	**(0.46)**	**(0.48)**	**(-1.05)**	**(-2.19)**
Education	-0.0986**	-0.00402	-0.0214	-0.00255	0.00554	-0.00164	0.258	0.0966
	(-2.72)	(-0.34)	(-1.09)	(-0.35)	(0.14)	(-0.14)	(1.17)	(1.21)
Age	0.0113	-0.0189	-0.0253	0.00835	0.00362	-0.00583	-0.0601	-0.16
	(0.19)	(-1.38)	(-1.13)	(0.93)	(0.12)	(-0.58)	(-0.27)	(-1.85)
Marital status (married=1)	0.584	0.109	0.258	0.0547	0.021	-0.019	0.721	-0.494
	(1.67)	(0.99)	(1.88)	(0.79)	(0.06)	(-0.18)	(0.42)	(-0.86)
Number of hours	-0.0125**	-0.0153**	-0.00139	-0.00417*	-0.0149***	-0.0125***		

	*	*		**				
worked (occupation)	(-3.94)	(-12.52)	(-0.65)	(-5.61)	(-4.28)	(-10.18)		
Education head	0.0824*	0.0035	0.0186	0.0115	0.0202	0.0125	-0.478*	0.13
of household	(2.39)	(0.30)	(0.92)	(1.47)	(0.43)	(1.13)	(-2.42)	(1.72)
Age head	0.0218	0.00826	-0.00503	0.00318	-0.00094	0.00891	0.0328	0.0254
of household	(1.46)	(1.47)	(-0.60)	(0.73)	(-0.10)	(1.55)	(0.30)	(0.73)
Number of people	-0.0283	-0.0553	0.00386	-0.0510*	-0.0304	0.0887**	-0.404	0.461*
in the household	(-0.48)	(-1.96)	(0.11)	(-2.56)	(-0.58)	(3.22)	(-1.08)	(2.43)
Number of children	0.146	0.0879	-0.015	0.0629	0.0915	-0.0888	-0.0256	-0.29
under 5 years old	(1.19)	(1.50)	(-0.20)	(1.62)	(0.80)	(-1.34)	(-0.04)	(-0.75)
Number of older	-0.204	-0.135	0.0649	-0.0531	-0.147	-0.0766	-1.135	-0.199
adults (over 65)	(-1.20)	(-1.43)	(0.51)	(-0.77)	(-1.00)	(-1.37)	(-0.65)	(-0.28)
Per capita income	0.00579	-0.0000321	-0.00191	0.0000301	-0.00186	0.0000116		
	(1.31)	(-0.66)	(-0.86)	(0.80)	(-0.54)	(0.26)		
Constant	1.259	3.294***	2.832**	1.248**	1.974	0.889*	37.17***	40.82***
	(0.53)	(5.23)	(2.96)	(3.24)	(1.40)	(2.00)	(3.59)	(10.59)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37855	127674	37855	127674	37855	127674	23017	83697
Adjusted R-squared	0.01	0.008	0.005	0.003	0.008	0.006	0.007	0.002

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C10 Effect of excessive and scarce rainfall shocks on time spent on household chores and work: poor & non-poor households

	Total housework	Total housework	Cleaning	Cleaning	Cooking	Cooking	Caring	Caring
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Scarce rainfall	**2.232****	**1.793****	**0.882*****	**0.696****	**-0.425**	**0.227**	**0.820***	**0.4**
	(2.78)	**(2.61)**	**(4.32)**	**(2.77)**	**(-1.40)**	**(1.02)**	**(2.41)**	**(1.56)**
Excess rainfall	**3.614*****	**1.878*****	**1.002*****	**0.379****	**1.214*****	**0.658*****	**0.557**	**0.358***
	(4.45)	**(4.50)**	**(4.72)**	**(2.96)**	**(3.42)**	**(3.86)**	**(1.55)**	**(2.25)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37855	127674	37855	127674	37855	127674	37855	127674
Adjusted R-squared	0.032	0.031	0.02	0.008	0.02	0.022	0.031	0.034

Continuation of Table C10

	Laundry	Laundry	Shopping	Shopping	Homework	Homework	Paid work	Paid work
	Poor	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**
Scarce rainfall	**0.379**	**0.187**	**0.171**	**0.103**	**0.404***	**0.179**	**-1.633**	**1.075**
	(1.96)	**(1.09)**	**(0.97)**	**(0.90)**	**(2.16)**	**(1.43)**	**(-1.21)**	**(1.24)**
Excess rainfall	**0.423***	**0.307****	**0.376****	**0.138***	**0.0429**	**0.0368**	**-1.097**	**-1.024***
	(2.32)	**(2.93)**	**(2.71)**	**(2.28)**	**(0.23)**	**(0.43)**	**(-0.92)**	**(-2.26)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37855	127674	37855	127674	37855	127674	23017	83697
Adjusted R-squared	0.01	0.008	0.005	0.003	0.008	0.006	0.007	0.002

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C11 Effect of rainfall shocks on time spent on household chores and work: rural & urban areas (without control variables)

	Total housework	Total housework	Cleaning	Cleaning	Cooking	Cooking	Caring	Caring
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Rainfall shock	**3.033***** **(4.96)**	**1.671***** **(3.19)**	**0.815***** **(4.76)**	**0.341**** **(2.32)**	**1.098***** **(4.30)**	**0.35*** **(1.73)**	**0.551**** **(2.51)**	**0.329** **(1.61)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64376	102392	64376	102392	64376	102392	64376	102392
Adjusted R-squared	0.008	0.005	0.008	0.001	0.008	0.002	0.001	0.003

Continuation of Table C11

	Laundry	Laundry	Shopping	Shopping	Schoolwork	Schoolwork	Paid work	Paid work
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Rainfall shock	**0.420***** **(2.87)**	**0.279**** **(2.12)**	**0.206**** **(2.29)**	**0.191***** **(2.63)**	**-0.0575** **(-0.41)**	**0.181*** **(1.96)**	**-0.701** **(-1.11)**	**-0.69** **(-1.20)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64376	102392	64376	102392	64376	102392	45327	62051
Adjusted R-squared	0.002	0.001	0.002	0.003	0.001	0.002	0.001	0.001

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C12 Effect of rainfall shocks on time spent on household chores and work: rural & urban area (including control variables)

	Total housework	Total housework	Cleaning	Cleaning	Cooking	Cooking	Caring	Caring
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Rainfall shock	**3.003*****	**1.604*****	**0.794*****	**0.326****	**1.069*****	**0.323**	**0.576*****	**0.311**
	(5.00)	**(3.04)**	**(4.60)**	**(2.19)**	**(4.26)**	**(1.57)**	**(2.81)**	**(1.57)**
Education	0.0424	-0.015	0.0296	-0.0104	-0.0229	0.045	0.00251	-0.0171
	(0.56)	(-0.29)	(1.38)	(-0.80)	(-0.69)	(1.85)	(0.06)	(-0.74)
Age	-0.0766	0.131*	-0.0256	0.0243	0.015	0.0979***	-0.000594	0.0167
	(-0.98)	(2.23)	(-1.14)	(1.53)	(0.47)	(3.90)	(-0.02)	(0.60)
Marital status	1.24	0.92	-0.0372	-0.0343	0.0124	0.176	0.877**	0.571*
(married=1)	(1.86)	(1.94)	(-0.22)	(-0.33)	(0.04)	(0.77)	(3.27)	(2.37)
Number of hours	-0.0985***	-0.127***	-0.0151**	-0.0183**	-0.0287**	-0.0483**	-0.0292**	-0.0258**

			*	*	*	*	*	*
worked (occupation)	(-11.38)	(-22.08)	(-7.61)	(-12.05)	(-8.88)	(-19.27)	(-7.03)	(-10.82)
Education head	0.0639	0.0185	-0.0365	0.0138	0.0172	-0.00206	0.0575	-0.0153
of household	(0.80)	(0.37)	(-1.59)	(0.96)	(0.53)	(-0.10)	(1.45)	(-0.64)
Age head	0.0184	0.0186	-0.00116	0.000588	0.01	-0.00322	-0.00711	0.00232
of household	(0.45)	(0.67)	(-0.14)	(0.10)	(0.77)	(-0.29)	(-0.39)	(0.15)
Number of people	-0.781***	-0.691***	-0.147***	-0.161***	-0.476***	-0.394***	-0.109	-0.0999
in the household	(-5.39)	(-5.48)	(-3.79)	(-4.37)	(-8.64)	(-7.71)	(-1.49)	(-1.46)
Number of children	2.231***	2.381***	0.064	0.185*	0.233	0.178	1.915***	1.946***
under 5 years old	(7.10)	(7.72)	(0.69)	(2.49)	(1.71)	(1.66)	(11.72)	(11.22)
Number of older	-0.0796	0.684*	0.148	0.138	-0.0703	0.00128	0.289	0.773***
adults (over 65)	(-0.14)	(1.97)	(1.10)	(1.09)	(-0.26)	(0.01)	(1.05)	(4.21)
Per capita income	0.000318	-0.000198	0.000106	0.000113	0.000206	-0.000184	0.0000826	-0.000151
	(0.45)	(-0.88)	(0.44)	(1.55)	(0.60)	(-1.76)	(0.34)	(-1.74)
Constant	24.35***	15.33***	5.049***	2.576***	9.126***	5.373***	2.327	1.847
	(8.39)	(5.89)	(5.29)	(3.51)	(6.62)	(4.64)	(1.75)	(1.74)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63926	101603	63926	101603	63926	101603	63926	101603
Adjusted R-squared	0.026	0.037	0.014	0.011	0.019	0.025	0.029	0.03

Continuation of Table C12

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Schoolwork**	**Schoolwork**	**Paid work**	**Paid work**
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Rainfall shock	**0.402*** **	**0.279** **	**0.212** **	**0.189** **	**-0.0502**	**0.178***	**-0.681**	**-0.659**
	(2.80)	**(2.12)**	**(2.35)**	**(2.57)**	**(-0.36)**	**(1.91)**	**(-1.08)**	**(-1.16)**
Education	0.00524	-0.023	-0.00239	-0.00488	0.0303	-0.00458	0.226*	0.0697
	(0.28)	(-1.90)	(-0.24)	(-0.70)	(1.90)	(-0.34)	(2.15)	(0.77)
Age	-0.0455*	-0.0147	-0.00361	0.00397	-0.0163	0.0032	-0.07	-0.0934
	(-2.49)	(-0.85)	(-0.23)	(0.43)	(-0.97)	(0.29)	(-0.58)	(-0.99)
Marital status	0.122	0.245*	0.00535	0.143*	0.26	-0.18	0.551	-1.04
(married=1)	(0.77)	(2.02)	(0.06)	(2.02)	(1.93)	(-1.59)	(0.78)	(-1.46)

Number of hours worked (occupation)	-0.0119***	-0.0172***	-0.00294*	-0.00462***	-0.0107***	-0.0132***		
	(-5.63)	(-13.94)	(-2.28)	(-6.13)	(-7.28)	(-9.60)		
Education head of household	0.012	0.00885	0.0122	0.008	0.00144	0.00516	-0.221*	0.142
	(0.64)	(0.71)	(0.97)	(1.07)	(0.07)	(0.45)	(-2.22)	(1.73)
Age head of household	0.00729	0.0127*	0.00143	0.00179	0.00787	0.00447	0.00356	0.0181
	(0.90)	(2.07)	(0.21)	(0.47)	(1.07)	(0.84)	(0.08)	(0.46)
Number of people in the household	-0.105**	-0.0547*	-0.0177	-0.0626***	0.0758*	0.0808**	0.171	0.471*
	(-2.65)	(-1.97)	(-0.68)	(-3.50)	(2.47)	(2.89)	(0.80)	(2.23)
Number of children under 5 years old	0.1	0.0876	-0.0245	0.0498	-0.0569	-0.0649	-0.168	-0.798*
	(1.41)	(1.43)	(-0.41)	(1.30)	(-0.82)	(-0.85)	(-0.39)	(-1.97)
Number of older adults (over 65)	-0.195	-0.104	-0.121	-0.0468	-0.131	-0.077	-1.347*	0.163
	(-1.59)	(-1.12)	(-1.22)	(-0.74)	(-1.55)	(-1.52)	(-2.10)	(0.20)
Per capita income	-0.000239	-7.88E-06	-0.000014	0.0000345	0.000175	-3.07E-06		
	(-1.19)	(-0.16)	(-0.10)	(0.90)	(1.70)	(-0.06)		
Constant	4.802***	2.955***	1.962***	1.523***	1.086	1.056*	37.25***	39.48***
	(6.24)	(3.92)	(3.32)	(3.84)	(1.74)	(2.20)	(6.87)	(9.27)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63926	101603	63926	101603	63926	101603	45322	62047
Adjusted R-squared	0.007	0.011	0.002	0.005	0.005	0.007	0.002	0.002

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C13 Effect of excessive and scarce rainfall shocks on time spent on household chores and work: rural & urban area

	Total housework	**Total housework**	**Cleaning**	**Cleaning**	**Cooking**	**Cooking**	**Caring**	**Caring**
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Scarce rainfall	**2.582*** **	**0.579**	**0.830*** **	**0.66**	**0.0609**	**-0.0536**	**0.760** **	**0.128**
	(3.80)	**(0.63)**	**(4.22)**	**(1.95)**	**(0.25)**	**(-0.19)**	**(3.17)**	**(0.34)**
Excess rainfall	**3.035*** **	**1.625** **	**0.792*** **	**0.319***	**1.143*** **	**0.33**	**0.563** **	**0.314**
	(4.76)	**(3.02)**	**(4.30)**	**(2.11)**	**(4.28)**	**(1.58)**	**(2.58)**	**(1.56)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63926	101603	63926	101603	63926	101603	63926	101603
Adjusted R-squared	0.026	0.037	0.014	0.011	0.019	0.025	0.029	0.03

Continuation of Table C13

	Laundry	**Laundry**	**Shopping**	**Shopping**	**Homework**	**Homework**	**Paid work**	**Paid work**
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Scarce rainfall	**0.371***	**-0.081**	**0.317***	**-0.208***	**0.243**	**0.134**	**-1.09**	**1.183**
	(2.39)	**(-0.34)**	**(2.22)**	**(-2.28)**	**(1.67)**	**(0.84)**	**(-1.32)**	**(1.33)**
Excess rainfall	**0.404** **	**0.286***	**0.204***	**0.197** **	**-0.072**	**0.178**	**-0.655**	**-0.696**
	(2.64)	**(2.14)**	**(2.13)**	**(2.63)**	**(-0.49)**	**(1.89)**	**(-0.98)**	**(-1.21)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63926	101603	63926	101603	63926	101603	45322	62047
Adjusted R-squared	0.007	0.011	0.002	0.005	0.005	0.007	0.002	0.002

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C14 Effect of rainfall shocks on time spent on household chores and work: poor women (without control variables)

	Total housework	**Cleaning**	**Cooking**	**Caring**	**Laundry**	**Shopping**	**Schoolwork**	**Paid work**
Rainfall shock	**5.059*** **	**1.368*** **	**1.788*** **	**1.003***	**0.464**	**0.328** **	**0.108**	**-2.45**
	(4.15)	**(4.22)**	**(3.11)**	**(1.95)**	**(1.63)**	**(2.03)**	**(0.37)**	**(-1.43)**
Control variables	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20191	20191	20191	20191	20191	20191	20191	9604
Adjusted R-squared	0.017	0.015	0.026	0.002	0.003	0.008	0.005	0.008

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C15 Effect of rainfall shocks on time spent on household chores and work: Poor women (including control variables)

	Total housework	**Cleaning**	**Cooking**	**Caring**	**Laundry**	**Shopping**	**Schoolwork**	**Paid work**
Rainfall shock	**4.969*** **	**1.336*** **	**1.736*** **	**0.977** **	**0.474***	**0.334** **	**0.112**	**-2.476**
	(4.19)	**(4.20)**	**(3.01)**	**(2.10)**	**(1.67)**	**(2.06)**	**(0.38)**	**(-1.45)**
Education	-0.158	-0.135	0.0203	0.0614	-0.144*	-0.00859	0.0473	-0.0454
	(-0.72)	(-1.83)	(0.22)	(0.75)	(-2.57)	(-0.28)	(0.74)	(-0.15)
Age	0.367	0.0519	0.0163	0.256**	0.00506	-0.0108	0.0484	0.459
	(1.55)	(1.07)	(0.16)	(2.72)	(0.06)	(-0.38)	(1.06)	(1.26)
Marital status	3.056	0.133	1.475	-0.109	1.118*	0.215	0.225	-1.234
(married=1)	(1.74)	(0.23)	(1.72)	(-0.09)	(2.46)	(1.46)	(0.43)	(-0.48)
Number of hours	-0.140***	-0.0205***	-0.0375***	-0.0470***	-0.0160***	-0.00209	-0.0166**	
worked (occupation)	(-6.61)	(-3.62)	(-3.74)	(-4.56)	(-3.37)	(-0.78)	(-3.08)	
Education head	-0.0933	-0.0226	-0.1	-0.0882	0.084	0.0316	0.00231	-0.322
of household	(-0.45)	(-0.44)	(-1.11)	(-1.02)	(1.71)	(1.24)	(0.04)	(-1.19)
Age head	-0.0633	-0.0213	0.00801	-0.0746*	0.0299	-0.0061	0.000745	0.0514
of household	(-0.78)	(-1.14)	(0.23)	(-1.98)	(1.34)	(-0.68)	(0.07)	(0.36)
Number of people	-0.971*	-0.253*	-0.432*	-0.249	-0.0571	-0.00711	0.0269	0.0822
in the household	(-2.44)	(-2.41)	(-2.40)	(-1.13)	(-0.65)	(-0.16)	(0.37)	(0.15)
Number of children	3.612***	0.361	0.311	2.551***	0.232	0.0794	0.0768	-0.918
under 5 years old	(5.09)	(1.56)	(1.04)	(6.29)	(1.25)	(0.75)	(0.43)	(-0.81)

Number of older adults (over 65)	0.548	0.18	0.39	0.0746	-0.102	0.245	-0.241	-0.758
	(0.44)	(0.56)	(0.78)	(0.09)	(-0.37)	(1.70)	(-1.08)	(-0.41)
Per capita income	0.0201	0.00586	0.0111	-0.000848	0.00873	-0.00306	-0.00168	
	(0.98)	(1.05)	(1.12)	(-0.07)	(1.36)	(-0.99)	(-0.33)	
Constant	23.21*	5.134*	13.25**	-0.692	2.821	2.418	0.277	10.07
	(2.27)	(2.42)	(3.10)	(-0.16)	(0.80)	(1.94)	(0.14)	(0.61)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20189	20189	20189	20189	20189	20189	20189	9604
Adjusted R-squared	0.046	0.027	0.036	0.04	0.014	0.01	0.009	0.012

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table C16 Effect of excessive and scarce rainfall shocks on time spent on household chores and work: Poor women

	Total housework	**Cleaning**	**Cooking**	**Caring**	**Laundry**	**Shopping**	**Homework**	**Paid work**
Scarce rainfall	**2.14**	**1.244*** **	**-1.118**	**0.952**	**0.392**	**0.0448**	**0.626***	**-1.154**
	(1.51)	**(3.50)**	**(-1.86)**	**(1.54)**	**(1.11)**	**(0.21)**	**(1.97)**	**(-0.60)**
Excess rainfall	**5.230*** **	**1.344*** **	**1.999** **	**0.98**	**0.481**	**0.361***	**0.0645**	**-2.581**
	(4.08)	**(3.90)**	**(3.22)**	**(1.94)**	**(1.57)**	**(2.06)**	**(0.20)**	**(-1.41)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20189	20189	20189	20189	20189	20189	20189	9604
Adjusted R-squared	0.046	0.026	0.037	0.039	0.014	0.011	0.009	0.012

*t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01*