# A Drop of Love? Rainfall Shocks and Spousal Abuse: Evidence from Rural Peru

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# Rainfall Shocks and Spousal Abuse: Evidence from Rural Peru

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**Abstract**

We investigate whether the exposure to rainfall shocks affects the experience of physical intimate partner violence by women in rural areas of the Peruvian Andes. Using data from the Demographic and Health Surveys over the period 2005-2014, we track changes in women's experience of physical IPV following the exposure to rainfall shocks during the cropping season in the municipality. Our results indicate that the prevalence of physical intimate partner violence increases by 65 percent after the occurrence of events of drought, but not flood, during the cropping season. We argue, based on further results, that this effect is mediated by increased poverty-related stress and reduced female empowerment caused by rainfall shocks.

JEL Codes: D10, D13, I10, I15, O13.

Keywords: Health, Violence Against Women, Developing Countries.

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# 1 Introduction

At its 52nd. meeting in the year 2008, the UN Commission on the Status of Women called for greater attention on the gender impacts of climate change (Hemmati 2008). More than ten years have passed and there is still little understanding of these impacts. In particular, "[l]imited case examples and research have analy[z]ed and highlighted the links between gender norms, roles, relations, and health impacts of climate change" (WHO 2014, p. 6).

In an effort to meet these demands, social scientists have recently put forward the debate on the role climate change has in intensifying pre-existing gender inequalities (Rao et al. 2019). Intimate partner violence (IPV), the most common form of violence against women (VAW), is both a cause and a consequence of these inequalities.[1] Consequently, determining whether and how climate variability can impact IPV is essential for understanding how climate change may accentuate prevailing gender disparities. Research on this area, however, is scant and far less is known about the mechanisms that may cause this link.

In this paper, we aim at bridging this gap in research by examining the link between rainfall shocks and physical IPV in rural areas of the Peruvian Andes. Using spatial data on historical rainfalls from the University of Delaware's Terrestrial Precipitation project in combination with women's records on IPV from annual cross-sections of the Peruvian Demographic and Health Surveys over the period 2005-2014, we track changes in physical IPV following the exposure to rainfall shocks during the cropping season. We distinguish between the exposure to droughts and floods that we define as monthly rainfalls falling below the 5th. and above the 95th. percentiles in the distribution of long-term (1950-2010) local monthly rainfalls of this season, respectively.

Our focus on rural Peru is motivated by four facts. First, the prevalence rates of lifetime and recent physical IPV, of 61 and 25 percent respectively, were among the highest the world around at the beginning of our study period (Garcia-Moreno et al. 2006). Second, with

[1] IPV is defined as "any behavior within an intimate relationship that causes physical, psychological or sexual harm to those in the relationship" (WHO 2013). Research reveals that, circa 2010, an appalling 30 percent of women worldwide have suffered some form of physical or sexual IPV in their lifetimes (Devries et al. 2013). Women victims of IPV, and their children, may experience physical and psychological damages which encompass a severe health problem (ICRW 2009; Garcia-Moreno and Watts 2011).

roughly 80 percent of employment in agriculture and 75 percent of rainfed crop production, living conditions are intrinsically tied to weather realizations (Ponce et al. 2020). Third, limited access to credit markets prevents households from diversifying risk when dealing with adverse income shocks (Trivelli 2000). Fourth, the lack of adaptation and mitigation strategies make this region particularly vulnerable to climate variability (De la O Campos et al. 2018).[2]

In our empirical design, we compare the experience of physical IPV between woman exposed and not to rainfall shocks during the cropping season in a municipality. Specifically, we identify our effects of interest by harnessing temporary, local variation in rainfalls. The wealth of data at our disposal also permits us to explore different regression specifications by further conditioning on socio-demographic characteristics, other crop yield determinants, year and month (season) fixed effects, and local linear trends in the regressions.

We find that, relative to years of regular rainfalls, women's experience of physical IPV increases by 65 percent following the exposure to an event of drought, but not flood, during the cropping season. This estimate is statistically strong and robust to a variety of tests. Amongst other checks, we provide transparent, graphical depictions in support of our identifying assumption by showing that our results are neither explained by *ex-temp* or *ex-situ* rainfall shocks nor by temporal or spatial simulated noise. We also show that our results are not sensitive to the definition of the cropping season, the thresholds and metric used for defining rainfall shocks, and the data source used for retrieving monthly rainfalls.

When we further dig into the details of the aggression, we find that changes in moderate, but not severe, instances of physical IPV are behind our result. In particular, we find an increase of 60 percent in women's experience of violent acts such as being pushed/shook, slapped, punched, or kicked/dragged – actions that are not perpetrated to cause injury to the victim (Bott et al. 2012). Still, we find a 75 percent increase in women's report of sequels from the abuse in the form of bruises and lesions on their bodies.

[2]The importance of focusing in rural areas is well summarized in a comprehensive review of climate change issues: "(...) it is clear that shifting or erratic precipitation patterns have the potential to destabilize livelihoods in rural areas, contribute to serious declines in agricultural production, and erode food security" (USAID 2009).

Building on the literature of IPV, we identify two mechanisms linking rainfall shocks to IPV. On the one hand, the "family stress model" (Conger et al. 1990) predicts that economic strain can lead to marital conflict that can escalate into violence either because of emotional distress (Conger and Elder 1994; Johnson 2010; Card and Dahl 2011) or because of disputes over the use of money (Rabbani et al. 2008; Vives-Cases et al. 2009; Fehringer and Hindin 2014). On the other hand, household bargaining models (Farmer and Tiefenthaler 1997) that allow for men's reactions to changes in their power position in the relationship predict that violence arises because of a change in men's valuation of their partners (Anderberg and Rainer 2013; Anderberg et al. 2016). Alternatively, sociological theories of "male backlash" predict that violence may arise when men's authority and gender role in the family are questioned, particularly when men feel threats to their identity as the breadwinner or the family provider (Faludi 1992; Macmillan and Gartner 1999).

Consistent with our main result, we find that only the exposure to events of drought during the cropping season induces changes in the mediating factors. At the aggregate level, we find declines of 20 and 15 percent in household income and consumption per capita, respectively. At the individual level, we find a 20 and a 50 percent decline in women's employment and control over household income, respectively, as well as a 30 and a 60 percent increase in men's marital control and alcohol-related aggression, respectively. Our findings are indicative that physical IPV may result from an interplay between increased poverty-related stress that leads to undesired behaviors by men and reduced female empowerment.

We complement this analysis by incorporating the most up-to-date rainfall projections for the period 2025-2034 from the National Center for Atmospheric Research to obtain back-of-the-envelope calculations of the expected impact on physical IPV. Monthly rainfalls during the cropping season in the Peruvian Andes are projected to decline by 20 percent relative to the period 2005-2014. All in all, we project an increase in the prevalence of physical IPV of at least 25-30 percent for the next few years in this region, as nearly 50 percent more women are expected to be exposed to dry rainfall shocks under rather optimistic scenarios.

We make several contributions to the literature in economics. Most saliently, our study contributes to the nascent research on climatic shocks and VAW. While at its earliest this literature focused on femicides (Sekhri and Storeygard 2014), recent developments have turned their attention to the study of less fatal yet systematic forms of VAW that can ultimately lead to femicide, such as IPV (Abiona and Foureaux-Koppensteiner 2018; Cools et. al 2020; Epstein et al. 2020). A common caveat among these studies, all of them based in Africa, is the use of cross-sectional variation for identification which fails to account for spatial correlation across climatic shocks (Dell et al. 2014; Hsiang 2016). We advance these studies in several ways. First, our study takes place in a Latin American developing country where both gender norms and climate variability can largely differ from those observed in Africa. Second, our data structure allows us to estimate parameters net of any time and spatial correlation across rainfall shocks. Third, we explore a comprehensive range of pathways and can shed light on the mechanisms linking the exposure to rainfall shocks to IPV. Last, we project the effect of changing future weather conditions on physical IPV, which is particularly important for policymaking in the face of climate change.

Our study also adds substantially to the literature on income and IPV. We highlight the importance of income risk and emotional wellbeing in the family in determining IPV, reinforcing the notion that improvements in household economic security and reductions in poverty-related stress can reduce IPV (Fox et al. 2002; Schneider et al. 2016). Relatedly, we document increases in men's marital control, alcohol intake, and alcohol-related aggression that may link to the loss of financial control, stress, and anticipatory anxiety from reduced income and increased economic uncertainty.[3] We also emphasize the role female empowerment, as captured by women's financial autonomy and economic opportunities, in determining IPV, in line with previous empirical work supporting the idea that increased women's bargaining power or increased men's valuation of women can reduce IPV (Aizer

[3] A new batch of studies assessing public transfers programs has strengthened the claim that IPV results, to some extent, from reduced emotional wellbeing in the household (Buller et al. 2018). Experimental studies in developing countries have shown that treated households score higher in psychometric tests measuring emotional/psychological wellbeing relative to their untreated counterparts (Haushofer and Shapiro 2016; Roy et al. 2019; Haushofer et al. 2019; Heath et al. 2020). There is also evidence that these programs reduce men's alcohol consumption and alcohol-related aggression (Angelucci 2008; Díaz and Saldarriaga *forthcoming*).

2010; Anderberg et al. 2016; Krupoff et al. 2017; Ramos 2018; Tur-Prats 2019). Our results, however, contrast those from previous work showing that IPV could result from men's retaliation to a lost authority or gender identity as the "family provider" (Chin 2012; García-Ramos 2017; Guarnieri and Rainer 2018).

Our study also has implications for the literature assessing the lifetime effects of the exposure to climatic shocks in developing countries. Although evidence on the short- (Hoddinott and Kinsey 2001; Alderman et al. 2006; Maccini and Yang 2009; Rocha and Soares 2015; Rosales-Rueda 2018) and long-term (Pathania 2007; Stanke et al. 2013; Dinkelman 2017; Shah and Steinberg 2017; Joshi 2019) repercussions of the exposure to climatic shocks during critical developmental stages of life on the human capital of individuals abounds, its causes are not yet wholly understood.[4] We stress the importance of the family environment, in general, and IPV, in particular, as a transmission channel from early-in-life exposure to climatic shocks to later-in-life developmental outcomes (Currie and Vogl 2013; Doyle and Aizer 2018).[5]

Finally, our study also contributes to the climate-conflict literature. For the most part, studies focus on the conflict between unrelated individuals and are unable to provide hints on the causes of conflict outbreak as there is no history of interactions among disputing parties (Hsiang et al. 2013; Burke et al. 2015).[6] By focusing on intrafamily violence, we are able to inspect individual and relationship dynamics that can reveal details on the likely causes igniting conflict. While income risk plays a central role, other factors may also coact in prompting intrafamily violence. In this regard, we emphasize the importance of the loss of control of individual emotions when confronting climatic shocks, consistent with recent advances in this area (Burke et al. 2018; Mullins and White 2019; Baylis 2020).

[4]Typical explanations center around the inability of households to insure consumption when confronting with income shocks (Wolpin 1982; Paxson 1992; Jacoby and Skoufias 1998; Porter 2012)

[5]Earlier work in psychology has highlighted the role of childhood exposure to IPV in shaping individual outcomes (Edleson 1999; Fantuzzo and Mohr 1999). This idea has gained interest among economists analyzing human capital formation (Aizer and Currie 2014), but the empirical work is still limited: some explorations include the educational externalities of children's exposure to IPV (Carrell and Hoekstra 2010) and the effects of IPV during pregnancy on newborns health (Aizer 2011).

[6]Referred mechanisms are ill-defined and include expressions such as difficult economic conditions, weak government institutions, migration, and "grievances."

We organize the remainder of the paper as follows. In the following section, we describe the data sources and discuss the definition of the variables utilized in the empirical analysis. Next, we present our empirical approach for estimating the effect of the exposure to rainfall shocks on physical IPV. We then present our main results and additional analyses, including robustness checks, back-of-the-envelope projections of the effect of changing future weather conditions on the prevalence of physical IPV, and impacts on other forms of IPV. We next turn to the exploration of potential mechanisms. We continue with a general discussion and balance of our results. Finally, we render our conclusions.

# 2 Data and Measures

In this section, we describe the construction of our sample and the measures we utilize in our empirical analysis. We enclose herewith a Supplemental Web Data Appendix where we provide further details on our data assembling process.

## 2.1 Data Sources

### 2.1.1 Intimate Partner Violence

Information on IPV comes from repeated annual cross-sections of the Peruvian Demographic and Health Surveys (DHS) over the period 2005-2014. The DHS is conducted on an annual basis by the Peruvian National Bureau of Statistics (INEI for its Spanish acronym) and comprises information on health outcomes and socio-demographic characteristics of women of reproductive age (15-49 years). The experience of IPV is recorded in the module specific to spousal abuse – a shortened and modified version of the Conflict Tactic Scales (CTS) elaborated by Straus (1979, 1990) – targeted at women who have ever been in a relationship.[7]

The DHS protocol for the application of the module specific to spousal abuse aims at

[7]One empirical advantage of the Peruvian DHS is that it collects information on recent (i.e., during the past 12 months) instances of IPV experienced by women. This is important for determining whether the experience of IPV is recent or from the past and constitutes an improvement relative to other surveys that only record information on a lifetime experience of IPV.

reducing information disclosure and indicates that only one woman per household should be randomly selected to respond to this module under strict privacy conditions. Once the woman is selected and privacy is ensured, the experience of IPV is detected by directly asking women whether in their current (if married or cohabiting) or most recent relationship (if separated, divorced or widowed) their partners ever perpetrated a series of behaviorally specific acts pertaining physical, emotional/psychological or sexual IPV. Response rates are high, with less than 2 percent of women refusing to respond to this module each year.

#### 2.1.2 Historical Rainfalls

We retrieve information on monthly rainfalls from the University of Delaware's (UDel) Terrestrial Precipitation: Gridded Monthly Time Series V 5.01. This dataset provides georeferenced information on global monthly rainfalls over the period 1900-2017 for each node at a spatial resolution of 0.5×0.5 degrees (a 0.5 degree corresponds to approximately 56 kilometers at the equator). Monthly rainfalls for each node are calculated based on reanalysis techniques using records from several nearby weather stations.[8]

We utilize this information to compute municipality monthly rainfalls based on a weighted average of the monthly rainfalls of the nodes overlapping the municipality's boundary, where weights correspond to the fraction of the municipality's surface that is covered by the node.[9] In what follows, we refer to the set of nodes overlapping the municipality's boundary as its grid.[10] The resulting dataset is at the municipality-by-month level. We link these data with individual-level data from the DHS based on the municipality's identifier and the survey date (month and year).

[8]In the interest of performing an additional sensitivity analysis, we also utilize information on rainfalls from the University of East Anglia's (UEA) Climatic Research Unit Gridded Precipitation Time Series V 4.03. This dataset provides information on global monthly rainfalls over the period 1901-2018 for each node at a spatial resolution of 0.5×0.5 degrees.

[9]The Peruvian territory is politically divided into three administrative units: regions, provinces, and municipalities. Municipalities are the smallest administrative unit in Peru and correspond to the NUTS-3 (Nomenclature of Territorial Units for Statistics) administrative subdivision of the country. There are 1,834 municipalities across the Peruvian territory.

[10]We have also confirmed that our estimates remain unchanged when computing municipality monthly rainfalls by using the inverse of the Euclidean distance between the municipality's centroid and the nodes' centroids as weights.

### 2.1.3 Other Weather and Soil Characteristics

We also utilize information on the air temperature, the soil temperature, and the soil moisture. We obtain information on the air temperature from the UDel's Terrestrial Air Temperature: Gridded Monthly Time Series V 5.01 and obtain information on the soil temperature and moisture from the ERA-Interim Archive on Global Atmospheric Reanalysis.[11] We assemble a municipality-by-month-level dataset containing information on the air temperature and soil characteristics and link this dataset with individual-level data from the DHS based on the municipality's identifier and the survey date.

### 2.1.4 Ancillary Data on Household Income and Consumption

We appeal to an ancillary source for information on household income and consumption. We obtain these data from repeated annual cross-sections of the Peruvian National Household Survey (ENAHO for its Spanish acronym) over the period 2005-2014. Like the DHS, the ENAHO is conducted on an annual basis by the INEI. We match municipality-level data on monthly rainfalls with household-level information from the ENAHO based on the municipality's identifier and the survey date and configure the resulting dataset to match the sample characteristics of the DHS.

### 2.1.5 Future Rainfalls

We obtain projections on monthly rainfalls for the period 2025-2034 from the National Center for Atmospheric Research's (NCAR) Representative Concentration Pathways (RCP) database for the analysis of future impacts on the prevalence of IPV. Specifically, we utilize projections from the RCP-2.6 and RCP-4.5 models, which are the most *optimistic* in terms of future trajectories of greenhouse gas emissions. Data from the NCAR's RCP has served

[11] The UDel's Terrestrial Air Temperature: Gridded Monthly Time Series V 5.01 provides information on global monthly air temperature over the period 1900-2017 for each node at a resolution of $0.5\times0.5$ degrees. The ERA-Interim Archive on Global Atmospheric Reanalysis provides information on global monthly soil temperature and moisture over the period 2004-2014 at a resolution of $0.75\times0.75$ degrees (a 0.75 degree corresponds to approximately 80 kilometers at the equator).

as an input for the development of future climatic scenarios documented in the IPCC's Fifth Assessment Report (IPCC 2014).[12]

### 2.2 Sample Selection

We focus on rural areas of the Peruvian Andes as our context of the study, where roughly 80 percent of employment concentrates around agricultural activities, and 75 percent of the land used for agriculture relies on rainfed irrigation for cultivation.[13] To ensure that the livelihoods of households in our sample largely depend on agriculture, we only keep municipalities located above 1,000 meters over the sea level. Also, for empirical purposes, we only keep municipalities that we observe for more than one year over the period 2005-2014.

At the individual level, we focus on women who are the female household heads, who are married/cohabiting and living together with their partners, and who live in the municipality for at least one year. We do not focus on divorced/separated women as IPV is a common cause for relationship break-ups (Kishor and Johnson 2004). Also, the one-year residential window ensures that women in our sample are not temporary migrants to the municipality.[14] Our resulting sample comprises information from 15,110 women in 495 rural municipalities (314 grids) located in the Peruvian Andes.[15]

[12]The NCAR's RCP database is provided at a resolution of (approximately) 1.25×0.47 degrees. We perform a spatial interpolation based on a cubic polynomial to recover information on future monthly rainfalls at a resolution of 0.5×0.5 degrees.

[13]The Peruvian Andes is located above 500 meters over the sea level. Pulgar-Vidal (2014) characterizes this region as having a rugged and steep terrain, with varying temperatures depending on the altitude, and with rainy seasons showing between October and May (this season corresponds to the spring/summer time in the southern hemisphere). This region can extend until above 6,500 meters over the sea level. However, agriculture likely stops at an altitude of 4,000 meters (Aragón et al. *forthcoming*).

[14]In our sample of rural municipalities, 6 percent of women are divorced/separated, and 0.5 percent are widowed. Moreover, roughly 70 percent of women are married/cohabiting, and 96 percent of these women live together with their partners.

[15]We apply the following filters to the sample from the ENAHO: women of reproductive age, who are the household head or spouse of the household head, who are married/cohabiting and living together with their partners, and who live in municipalities that are also part of our DHS sample. We end up with information from 11,095 women in 341 municipalities (231 grids).

## 2.3 Outcomes

In our analysis, we focus primarily on physical IPV. The rationale behind this is that the DHS records information on specific, physically violent behaviors that do not require women to identify as abusive in order to report them. By contrast, detecting sexual or emotional/psychological IPV requires that women recognize the behavior as violence to report it, opening the possibility of subjective interpretation (Ellsberg and Heise 2005). Still, in a complementary analysis, we explore effects on other forms of IPV.

Physical IPV takes place if "[the] woman has been slapped, or had something thrown at her; pushed, shoved, or had her hair pulled; hit with a fist or something else that could hurt; choked or burnt; threatened with or had a weapon used against her" (WHO 2013). We utilize information provided by the DHS about a series of physically violent acts exerted by the male partner in order to construct different measures of physical IPV experienced by women.

Our principal outcome is an indicator for a woman's experience of physical IPV that takes the value of 1 if the woman reported that, in the past 12 months, her partner perpetrated any of the following violent acts: (i) pushed, shook, or thrown something at her; (ii) slapped her or twisted her arm; (iii) punched her with his fist or hit her with something that could hurt her; (iv) kicked her or dragged her; (v) tried to choke or burn her; (vi) threatened her with a knife or other weapon; or (vii) attacked her with a knife or other weapon.[16] Our choice of physical IPV occurring in the past 12 months as our principal outcome rests on the fact that we are interested in capturing temporary variations in this measure that might result from the exposure to recent rainfall shocks.[17]

We also examine the consequences of physical abuse on women's physical integrity. To that end, we construct an indicator for the experience of physical sequels that takes the value of 1 if the woman reported that she had bruises or lesions, sprains or broken bones/teeth,

[16]While the first four acts correspond to moderate physical IPV, the last three correspond to severe physical IPV (Garcia-Moreno et al. 2005; Bott et al. 2012).

[17]The WHO defines the self-reported experiences of IPV occurring in the past 12 months as "current intimate partner violence" (WHO 2013).

or needed medical assistance as a consequence of the physical abuse exerted by her partner. This indicator aims at capturing physical trauma that can ultimately result in death for women either directly through physiological causes or indirectly through mental health-related problems and subsequent suicide (WHO 2013).

In our analysis of other forms of IPV, we analyze changes in sexual and emotional/psychological IPV. Our outcome for sexual IPV is an indicator that takes the value of 1 if the woman reported that her partner committed any of the following acts in the past 12 months: (i) physically forced her to have sexual intercourse with him even when she did not want to; or (ii) forced her to perform any sexual act that she did not approve. Our outcome for emotional/psychological IPV is an indicator that takes the value of 1 if the woman reported that her partner committed any of the following acts in the past 12 months: (i) said or did something to humiliate her in front of others; (ii) threatened to hurt or harm her or someone she cares about; or (iii) threatened to leave home, take away her children, or take away economic/financial aid.

It is important to clarify that all our measures of IPV come from women's self-reports and may be subtle to bias from reporting error.[18] Yet, self-reported measures of IPV are widely used among scholars as "[g]old standard methods to estimate the prevalence of any form of violence are obtained by asking respondents direct questions about their experience of specific acts of violence over a defined period of time (...)" (WHO 2013). Experts agree that self-assessed reporting based on a series of questions about the experience of specific acts of violence convey more information when compared to a subjective, generic question such as "ever experiencing some form of violence/abuse" because of the disassociation in the interpretation of the experience of a specific violent act and the experience of violence itself and also because of the multiple opportunities a respondent has to disclose the experience of a violent act (Kishor and Johnson 2004).

[18]Although there is limited evidence on the magnitude and direction of this bias, a recent study based on the application of list experiments for identifying victims of different forms of IPV in urban Peru finds no significant differences in reporting of IPV across indirect (list) and direct (DHS-style) methods for elucidation (Agüero and Frisancho 2017). Another study, also in Peru, documents substantial underreporting from community-based targeting methods relative to self-reporting (Agüero et al. 2020).

## 2.4 Exposure to Rainfall Shocks during the Cropping Season

We define the cropping season as the continuum of months that we observe rainfalls falling above the 25th. percentile in the distribution of monthly rainfalls in the municipality over the period 2005-2014.[19] In Figure 1, we depict the starting month and the average duration (symbolized by the color and size of the circles respectively) of the cropping season of each municipality in the Peruvian Andes (Panel A) and the average monthly rainfalls observed in the cropping and harvesting seasons over the period 1950-2010. In our sample, the cropping season usually starts between September and October each year and ends between April and May of the following year, with an average duration of between 7 and 8 months. Average monthly rainfalls are about 90 millimeters during the cropping season and about 20 millimeters during the harvesting season.

Because our outcomes cover a recall period of 12 months, it may be the case that some violent events occurred in between the last two cropping seasons.[20] With that in mind, we follow Kudamatsu et al. (2016) and compute monthly rainfalls of the last cropping season as a weighted average of rainfalls observed in the cropping seasons of two consecutive years. Let $\mathrm{R}_{j1}$ and $\mathrm{R}_{j2}$ be the monthly rainfalls observed in the municipality in the last and second-to-last cropping seasons, respectively. Then, we compute monthly rainfalls of the last cropping season for a woman $i$ who lives in municipality $j$ and who is surveyed at date (month of year) $d$ as follows:

$$\mathrm{R}_{ijd} = \omega_{ij1} \cdot \mathrm{R}_{j1} + (1 - \omega_{ij1}) \cdot \mathrm{R}_{j2} \ ,$$

where $\omega_{ij1}$ is the weight ascribed to $\mathrm{R}_{j1}$. We define $\omega_{ij1}$ as the fraction of a year that elapsed between survey month, $m_i$, and the month corresponding to the end of the last harvesting

[19] Given that the official definition of the cropping season is based on rainfalls (FAO 1978), we refrain from using alternative indicators to define this season. We have confirmed though that our estimates remain unchanged when using an index of vegetation growth to calculate the timing and length of the cropping season of each municipality. The 25th. percentile threshold follows from a simplified version of the Jönsson and Eklundh (2004) program for analyzing time-series of satellite sensor data.

[20] For instance, it may be the case that the cropping season of a given municipality lies between the months of November and April of two consecutive years. If a woman in that municipality is surveyed in January of year 2010, then it may be the case that the relevant cropping season affecting her experience of physical IPV during the past 12 months is not the one from the period 2009-2010 but the one from the period 2008-2009.

season, $h_{j1}$: $\omega_{ij1} = (m_i - h_{j1})/12$.

Let $\mathrm{R}_j^p$ denote the p-th. percentile in the distribution of monthly rainfalls observed in the cropping season of municipality $j$ over the period 1950-2010. We construct indicators for the exposure to rainfall shocks, in the form of droughts or floods, during the last cropping season as follows:

$$\text{Rainfall Shock}_{ijd} = \begin{cases} \text{Drought}_{ijd} & = \mathbb{1}\left\{\mathrm{R}_{ijd} < \mathrm{R}_j^{05}\right\} \\ \text{Flood}_{ijd} & = \mathbb{1}\left\{\mathrm{R}_{ijd} > \mathrm{R}_j^{95}\right\} \end{cases},$$

where $\mathbb{1}\{.\}$ is the indicator function. In words, our indicators for the exposure to an event of drought or flood during the last cropping season take the value of 1 if average monthly rainfalls fall below the 5th. or above the 95th. percentiles in the distribution monthly rainfalls observed in that season in the municipality over the period 1950-2010, respectively.[21]

In our sample, the average 5th. and 95th. percentiles in the distribution of monthly rainfalls observed in the cropping season over the period 1950-2010 are 74 and 131 millimiters, respectively. Also, the average long-term (1950-2010) monthly rainfalls observed in the cropping season is 101 millimiters, and one standard deviation from this average is about 18.5 millimeters. This implies that the 5th. and 95th. percentiles are about $\pm 1.5$ standard deviations from the long-term monthly rainfalls observed in the cropping season.

In Figure 2, we show the distribution of rainfall shocks across the Peruvian Andes (Panel A) and the fraction of municipalities where an event of drought or flood is observed over the period 2005-2014 (Panel B). There are 140 rainfall shocks in our sample: 50 events of drought and 90 events of flood. From the 495 rural municipalities in our sample, 95 had at least one rainfall shock over the period 2005-2014: 26 had an event of drought, 63 had an event of flood, and 6 had both events. We observe rainfall shocks in almost all years, and these are scattered throughout the territory.

[21]Other studies have used the Standardized Precipitation Index (SPI) to define events of drought or flood (Rocha and Soares 2015; Andalón et al. 2016; Dinkelman 2017). In a sensitivity analysis, we show that our main results hold when we redefine the exposure to rainfall shocks based on thresholds derived from the SPI ($\pm 1.5$ standard deviations from the mean).

## 2.5 Descriptive Statistics

In Table 1, we present descriptive statistics of women in our sample. In column 2, we present descriptives for all women. The average woman in our sample is 34.5 years old and has attained almost 5.5 years of education, which corresponds to the incomplete primary educational level. Also, 62 percent of women respond that Spanish is their mother tongue. As for their partners, they are on average 38 years old and have completed 7 years of education, corresponding to the incomplete secondary educational level. Most of the couples in our sample are long-term relationships, with the average couple being together for around 15 years. However, less than half of these couples (49 percent) report formal marriage as their living arrangement.

In columns 3 through 5, we break the descriptives according to the exposure to different rainfall shocks: regular rainfalls, drought, and flood, respectively. In our sample, 421 women were exposed to an event of drought, 640 women were exposed to an event of flood, and the rest (14,049 women) were exposed to regular rainfalls during the last cropping season. We obtain adjusted differences of sample means between women exposed and not to rainfall shocks by regressing each characteristic on the indicator for the exposure to an event of drought or the indicator for the exposure to an event of flood during the last cropping season and including month, year, and municipality fixed effects as conditioning variables in the regressions. In columns 6 and 7, we present adjusted differences in means for the sub-sample of women exposed to an event of drought or regular rainfalls and the sub-sample of women exposed to an event of flood or regular rainfalls during the last cropping season, respectively. None of the resulting adjusted differences is statistically significant at conventional levels which speaks to the balance in the distribution of observed characteristics of women exposed to different rainfall shocks.

# 3 Empirical Methodology

We identify our effects of interest by comparing, in a given municipality, the experience of physical IPV between women who were exposed and not to rainfall shocks during the last cropping season. Formally, we perform linear regressions of the form:

$$\begin{aligned} \text{P-IPV}_{ijd} \quad &= \quad \alpha + \beta^{\mathrm{D}} \cdot \text{Drought}_{ijd} + \beta^{\mathrm{F}} \cdot \text{Flood}_{ijd} + X'_{ijd}\,\gamma + Z'_{jd}\,\psi \\ &\quad + \delta\,\theta_{gt} + \mu_j\,\mathbb{1}_j + \mu_m\,\mathbb{1}_m + \mu_y\,\mathbb{1}_y + \varepsilon_{ijd}\,, \end{aligned} \tag{1}$$

where $\text{P-IPV}_{ijd}$ is the indicator for the experience of physical IPV of woman $i$ who resides in municipality $j$ and who is surveyed at date (month $m$ of year $y$) $d$, $\text{Drought}_{ijd}$ and $\text{Flood}_{ijd}$ are the indicators for the exposure to an event of drought or an event of flood during the last cropping season respectively, $X'_{ijd}$ is a vector of woman, partner, and relationship characteristics, $Z'_{jd}$ is a vector of municipality characteristics observed during the last cropping season, $\theta_{gt}$ is a vector of grid-specific linear trends, $\mathbb{1}_j$, $\mathbb{1}_m$, and $\mathbb{1}_y$ are municipality, month and year fixed effects respectively, and $\varepsilon_{ijd}$ is an idiosyncratic error term.

In our most parsimonious specification, we include municipality, month, and year fixed effects in the regressions. These sets of fixed effects account for local-specific characteristics that are invariant over time (such as average weather conditions or social norms pertaining the status of women in the society) as well as seasonal and year-specific factors that are common to all municipalities (such as changes in weather patterns that describe a particular period of the year or nationwide factors that may evolve nonlinearly).[22] All these factors can potentially determine the prevalence of physical IPV differently across geography and over time.

In additional specifications, we include woman, partner, and relationship characteristics.

[22] One of such aggregate shocks affecting all municipalities in a given year is the *El Niño* Southern Oscillation (ENSO). This phenomenon is a climate pattern, usually observed every 4 to 5 years, that describes the warming of surface waters in the Eastern equatorial Pacific Ocean. The cooling phase of ENSO is usually referred to as *La Niña*. ENSO is known to cause unusually high-intensity rains in the Peruvian Andean region that lead to agricultural loses (most of them caused by landslides and soil erosion). In the period of study, this phenomenon was observed in years 2005-06 and 2009-10 according to the Peruvian National Service for Meteorology and Hydrology (SENAMHI for its Spanish acronym).

Specifically, we include indicators for the woman's age, educational attainment, and ethnicity (whether her mother tongue is Spanish); indicators for her partner's age and educational attainment; an indicator for being married, and indicators for the duration of the union in the regressions. These variables render control for individual- as well as couple-specific characteristics that can determine IPV (WHO 2012). We also include other municipality-specific weather and soil characteristics observed during the last cropping season that could affect agricultural production. In particular, we include indicators for the air temperature, the soil temperature, and the soil moisture in the regressions. The inclusion of these variables serves to partial out the effect of other potential crop yield determinants that may covary with rainfalls (van Ittersum and Rabbinge 1997; Nearing et al. 2004).

In our most comprehensive specification, we include grid-specific linear trends in the regressions. This array of controls is intended to rule out local differences that evolve linearly over time and also to adjust for potential deviations in the local weather from common-year effects. Grid-specific linear trends are common to all municipalities whose boundaries lie within the same grid and are observed in the same years.[23]

We are interested in estimating $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$, the coefficients on the indicators for the exposure to an event of drought and an event of flood during the last cropping season respectively. These coefficients measure the effect of the exposure to each of these rainfall shocks on the probability a woman experiences physical IPV. If estimates of $\beta^{\mathrm{D}}$ and/or $\beta^{\mathrm{F}}$ are positive and statistically significant, then this would imply that the exposure to rainfall shocks increases women's experience of physical IPV. In estimating these coefficients, we exploit year-to-year deviations from the municipality's historical trend in rainfalls observed during the cropping season.

The interpretation of these estimates as consistent, causal effects of the exposure to different rainfall shocks on women's experience of physical IPV relies on the assumption that temporary, local rainfall shocks (conditional on the set of observed characteristics) are uncorrelated with any underlying determinant of physical IPV. Although this assumption

[23]Our results are also robust to the inclusion of province- rather than grid-specific linear trends in the regression. There are 134 provinces in our sample of DHS municipalities.

is inherently untestable in the data, we provide some indirect tests to support that this is indeed the case. Specifically, we conduct a robustness analysis that shows that neither rainfall shocks observed in past or future years nor rainfall shocks observed in neighboring (bordering) municipalities affect the current experience of physical IPV among women residing in a given municipality.

Finally, in all regressions, we compute standard errors allowing for the error terms $\varepsilon_{ijd}$ in equation (1) to be correlated within each municipality by clustering at the municipality level. We have confirmed that our standard errors change little when estimated by clustering at the grid rather than at the municipality level.

# 4 Main Results

In this section we present our main results of the effect of the exposure to rainfall shocks on physical IPV from different regression specifications based on equation (1).

## 4.1 Graphical Analysis

We begin the presentation of our results by graphically analyzing the effect of the exposure to different intensities of rainfall shocks on physical IPV. To that end, we construct indicators for the exposure to mild, moderate, and severe dry/wet rainfall shocks that take the value of 1 if monthly rainfalls observed during the cropping season fall between the 10th.-15th./85th.-90th. percentiles, 5th.-10th./90th.-95th. percentiles, and 0th.-5th./95th.-100th. percentiles in the distribution of long-term municipality monthly rainfalls observed in this season, respectively. We plot estimates of the effect of the exposure to each of these rainfall shocks in Figure 3.

Our results indicate that women's experience of physical IPV increases following the exposure to dry rainfall shocks. However, we do not find that the exposure to wet rainfall shocks, in any of its intensities, affects women's experience of physical IPV. We find that the experience of physical IPV increases by between 5 to 8 percentage points following the exposure to extremely dry rainfall shocks, a result that translates into an increase of between 40 and 60 percent in the prevalence of physical IPV relative to periods of regular rainfalls.

## 4.2 Effect of the Exposure to Rainfall Shocks on Physical IPV

In Table 2, we present our baseline estimates of the effect of the exposure to rainfall shocks on women's experience of physical IPV. In Panel A, we present estimates when utilizing DHS sampling weights in the regressions and, in Panel B, we present estimates when equally weighting individual observations. For concreteness, we focus on the most comprehensive results that utilize sampling weights in the regressions when commenting on our results.

In column 1, we present the results from our most parsimonious specification that includes municipality, year, and month fixed effects as control variables in the regression. In columns 2 through 4 we include additional conditioning variables – specifically, we include woman characteristics (column 2), partner and relationship characteristics (column 3), and other crop yield determinants (column 4). Lastly, in column 5, we further adjust for secular trends in local weather characteristics by including grid-specific linear trends as additional control variables in the regressions.

Our estimate of $\beta^{\mathrm{F}}$, the coefficient associated with the exposure to an event of flood during the cropping season, is negative yet statistically insignificant. By contrast, our estimate of $\beta^{\mathrm{D}}$, the coefficient associated with the exposure to an event of drought during the cropping season, is positive and statistically significant at conventional levels across our different regression specifications. These results indicate that the probability a woman experiences physical IPV is affected by the exposure to an event of drought, but not flood, during the cropping season. On average, we find that this probability increased by 8.5 percentage points when the woman was exposed to an event of drought, implying a 65 percent increase in the prevalence of physical IPV relative to periods of regular rainfalls.

In Appendix Tables 1 through 5, we test for the sensitivity of our estimates to a change in the periodicity of the cropping season based on vegetation growth, a change in the definition of rainfall shocks based on the SPI, changes in the thresholds for defining rainfall shocks based on the 10th/90th percentiles in the distribution of historical rainfalls, a change in the metric of monthly rainfalls based on a 3-months moving average, and a change in the data source used for constructing monthly rainfalls, respectively. Qualitatively, our main result holds across our different sensitivity checks. Estimates of $\beta^{\mathrm{D}}$ range from 4 to 9.5 percentage points, implying an increase of between 35-75 percent in physical IPV following the exposure to an event of drought during the cropping season relative periods of regular rainfalls.

In Appendix Tables 6 and 7, we further delve in the characteristics of the abuse and analyze changes in separate acts of moderate and severe physical IPV, respectively. We find that the increase in physical IPV following the exposure to an event of drought during the cropping season is mainly characterized by moderate violent acts such as being pushed/shook or slapped. Overall, we find an increase of 8 percentage points, or roughly 65 percent, in the experience of moderate physical IPV relative to periods of regular rainfalls.

We next inspect the extent to which the increase in physical abuse can cause harm to women. In Table 3, we present estimates of the effect of the exposure to rainfall shocks on the probability of experiencing physical sequels from the abuse. We find an increase of between 6.5 and 8 percentage points, or 60-75 percent, in the report of suffering physical sequels from the abuse following the exposure to an event of drought during the cropping season. These sequels manifest mainly in the form of bruises or lesions on women's bodies (see Appendix Table 8).

In sum, we find that the exposure to an event of drought, but not flood, during the cropping season increases women's experience of physical IPV by 65 percent. This result is characterized by an increase in the experience of moderate acts of physical IPV that, although less severe, can still cause injuries to women victims of abuse. In terms of magnitudes, our estimates are somewhat larger than those reported in previous studies. Effect sizes reported by Epstein et al. (2020) for sub-Sahara African countries imply a 15 percent increase in physical IPV while those reported by Abiona and Foureaux-Koppensteiner (2018) for Tanzania imply a 50 percent increase in physical IPV after the occurrence of events of drought during the cropping season.[24] We argue that this difference in magnitudes owes to the existence of spatial correlation across rainfall shocks that introduce a downward bias in the estimates reported by previous studies.[25]

### 4.3 Robustness Analysis

A key assumption of our empirical design is that changes in the experience of physical IPV are only caused by temporary, local variations in rainfalls. We present evidence in support of this assumption by showing that neither *ex-temp* nor *ex-situ* rainfall shocks affect women's experience of physical IPV. We also show that neither temporal nor spatial correlation across rainfall shocks drive our results.

We begin our robustness analysis by performing an augmented regression of the form of equation (1) where our main explanatory variables consist of a set of indicators for the exposure to rainfall shocks in the second-to-last, last, and future cropping seasons in the municipality where the woman resides an in any neighboring municipality. We depict the results from this augmented regression specification in Figure 4. Consistent with our main result, we find that only the exposure to an event of drought during the last cropping season in the municipality where the woman resides increases the experience of physical IPV by roughly 8 percentage points. Based on two different F-tests, we cannot reject the null hypotheses that the estimated coefficients on the indicators for the exposure to *ex-temp* or *ex-situ* rainfall shocks are jointly equal to zero. These results provide support for our assumption that our estimates obtain from variation in temporary, local rainfalls only.

Next, we show that our main estimate is not contaminated by temporal or spatial simulated noise by performing two different permutation tests (1,000 permutations each) that

[24] Abiona and Foureaux-Koppenstainer (2018) report effects of rainfall deviations from long-term means on physical IPV and indicate that a -1 standard deviation rainfall shock corresponds to a 15 percent decrease in rainfall relative to the long-run mean. We use this equivalence and the estimates they report in Panel A of Table 4 to approximate the impact of the exposure to a rainfall shock of -1.5 standard deviations on physical IPV to be around 50 percent. Sekhri and Storeygard (2014) report an effect size similar in magnitude for India: from their estimates, we compute that a rainfall shock of -1.5 standard deviations increases reports on domestic violence by around 40 percent.

[25] In particular, the existence of spatial correlation across rainfall shocks could make those women who are classified as not exposed to rainfall shocks also suffer from physical IPV though less severely.

randomly reassign rainfall shocks by (i) changing the date when the rainfall shocked occurred in the municipality (permutations within municipalities) or (ii) changing the municipality where the rainfall shocked occurred but maintaining its date (permutations across municipalities).[26] We depict the resulting density distributions of estimates of $\beta^{\mathrm{D}}$ (left) and $\beta^{\mathrm{F}}$ (right) from the permutation tests in Figure 5. As expected, the density distributions are centered around zero, which implies that neither temporal nor spatial simulated rainfall shocks affect the experience of physical IPV. Notably, our estimate of $\beta^{\mathrm{D}}$ (but not that of $\beta^{\mathrm{F}}$) lies outside the confidence intervals constructed from the implied distribution moments. These results further support the fact that our estimates are not driven by temporal or spatial correlation across rainfall shocks.

In Appendix Tables 9 through 11, we present the results from additional robustness analyses. We show that our main results maintain even after controlling for women's history of IPV that can determine the current experience of physical IPV (see Appendix Table 9). We also underline the importance of rainfalls as a factor of production by showing that the experience of physical IPV is not affected by rainfall shocks that occurred during the harvesting season in our sample of rural municipalities or in urban areas of the Peruvian Andes where employment is less concentrated around agriculture (see Appendix Tables 10 and 11, respectively).

## 4.4 Projected Change in Physical IPV

We next explore how changing future weather conditions may affect physical IPV in the Peruvian Andes. To that end, we obtain back-of-the-envelope calculations of the expected change in the prevalence of physical IPV from rainfall projections over the period 2025-2034. In calculating these effects, we assume both a constant population across time and space and a constant relationship between the exposure to rainfall shocks and physical IPV.

Projected rainfalls over the period 2025-2034 will reach around 80 millimeters a month during the cropping season. This represents a decline of nearly 20 percent in rainfalls relative

[26] We perform permutations across municipalities within the same region.

to those from the period 2005-2014. Even more, roughly 45 percent of women who were not exposed to rainfall shocks will be exposed to at least one event of drought during this period.[27]

To calculate the effects of changing future weather conditions on physical IPV, let $\Delta^{\mathrm{D}}_{j,t}$ be the projected net change in the probability that women in municipality $j$ will be exposed to an event of drought in the cropping season of year $t$ relative to the average over the period 2005-2014, $s_j$ be the share of women who live in municipality $j$, and $\hat{\beta}^{\mathrm{D}}$ be the estimated effect of the exposure to an event of drought during the cropping season on physical IPV. We compute the projected effect on physical IPV over the period $\tau$, spanning the years $t$ and $T$, as follows:

$$\mathbb{E}\left[\hat{\beta}^{\mathrm{D}}_{\tau}\right] = \left(\frac{1}{\tau}\sum_{t}^{T}\sum_{j}^{J} s_j\,\Delta^{\mathrm{D}}_{j,t}\right)\hat{\beta}^{\mathrm{D}},$$

where $\mathbb{E}$ is the expectations operator.

We present the results from these projections in Table 4. We calculate an increase of between 3.5 and 4 percentage points in physical IPV resulting from higher exposure to future events of drought. These results translate into a projected increase of 25-30 percent in the prevalence of physical IPV in the Peruvian Andes for the period 2025-2034.

## 4.5 Other Forms of IPV

We close this section by analyzing the effect of the exposure to rainfall shocks on other forms of IPV. We present estimates of the effect of the exposure to rainfall shocks on sexual (column 1 through 5) and emotional/psychological (columns 6 through 10) IPV in Table 5. Our results indicate that only the experience of sexual IPV is affected by the exposure to rainfall shocks during the cropping season.[28] In particular, we find an increase of about

[27]Interestingly, we also find a substantial increase in the variance of projected rainfalls which speaks to the higher uncertainty inhabitants of the Peruvian Andes will face with regards to rainfalls in the future. Whether and how this increase in the "unpredictability" of future rainfalls will affect women's experience of physical IPV remains an open question.

[28]We do find, however, positive effects of the exposure to an event of drought during the last cropping season on acts of emotional/psychological IPV related to intimidation. It is worth mentioning that DHS questions involving emotional/psychological IPV include a degree of subjectivity that makes its measurement and interpretation difficult (Ellsberg and Heise 2005). For instance, these questions are worded as if the woman has been "insulted/humiliated," which can be subtle to individual interpretation because of three

3 percentage points (although imprecisely estimated) in sexual IPV, mainly in the form of forced/unwanted sex (see Appendix Table 12), following the exposure to an event of drought during the cropping season.

Our results on sexual IPV, though qualitatively similar, differ in magnitude with those reported by Abiona and Foureaux-Koppensteiner (2018) and Epstein et al. (2020). While the first study reports a rather modest effect, the second study reports a 20-30 percent increase following the exposure to dry rainfall shocks. As for emotional/psychological IPV, our results are consistent with those from Epstein et al. (2020) who find no effects on this form of IPV after the occurrence of dry rainfall shocks.

# 5 Mechanisms

In this section, we review the potential mechanisms leading from the exposure to rainfall shocks during the cropping season to physical IPV. For concreteness, we present estimates from our most comprehensive specification of equation (1).

## 5.1 Household Income and Consumption

We leverage information from our ancillary ENAHO dataset to explore the effects of the exposure to rainfall shocks on household income and consumption. Because in-kind transfers account for a significant share of household income, we analyze these effects on both total and cash income and consumption per capita.[29] We present the results in Table 5.

Our results indicate that the exposure to an event of drought reduces household total and cash income per capita by PER$ 30 and PER$ 27, respectively. These effects correspond to a decline of nearly 15 and 20 percent in household total and cash income per capita relative

reasons: (i) by not asking the woman whether her partner committed a specific act; (ii) by making the woman recognize a specific behavior as violent; and (iii) by adding terms whose interpretation may vary across different contexts (Kishor and Johnson 2004; MacQuarrie et al. 2014).

[29] We construct total income and consumption by adding up cash and in-kind transfers. In our empirical sample, in-kind transfers represent 30 and 35 percent of the total income and consumption per capita respectively.

to periods of regular rainfalls, respectively. We also find that household total and cash consumption per capita decline by PER$ 22 and PER$ 23, which correspond to a decline of around 10 and 15 percent relative to periods of regular rainfalls, respectively.

Interestingly, the decline in household income per capita following the exposure to an event of drought translates almost one-for-one into household consumption per capita. This implies that rural households in the Peruvian Andes are unable to cope with dry rainfall shocks that reduce agricultural output and thereby household income. In this regard, our results are consistent with previous studies documenting limited access to credit and low saving rates for rural households in Peru that prevent them from smoothing consumption through savings, credit, transfers, or other types of insurance in times of economic hardship (Trivelli 2000; Alvarado et al. 2001).

The lack of an effect on household income and consumption may explain why we do not find impacts on women's experience of physical IPV when households are exposed to wet rainfall shocks, insofar as household income indeed mediates this effect. A handful of factors that make farmers in the Peruvian Andes cope better with excessive rainfalls, including ancient water storage practices and water flow management (Sanabria et al. 2014; Cruz et al. 2017), terrain slope and ruggedness (Pulgar-Vidal 2014), crop mix and other adaptation strategies (Ponce 2020), and intensiveness in the use of agricultural inputs (Aragón et al. *forthcoming*), may explain this lack of an effect. Besides, the Peruvian Andes are characterized by having steep, rocky hills that produce rapid surface runoff and prevents the water from penetrate the soil which may explain why, unlike in other regions in the world, excessive rainfalls may not necessarily create flooding.[30]

## 5.2 Employment

We next analyze how employment changes following the exposure to rainfall shocks. We explore changes in overall employment and agricultural employment and present our results

[30] These terrain features, however, may create other types of natural disasters such as landslides, mudflows, and increased river flows, that can damage agricultural land (CENEPRED 2018).

in Table 6. To capture different patterns among partners, we inspect changes in employment for women (columns 1 and 2) and men (columns 3 and 4) separately.

We find that female employment declines by 13.1 percentage points (23 percent) after the exposure to an event of drought relative to periods of regular rainfalls. Although the point estimate on female agricultural employment is negative, suggesting that women are less likely to work in agricultural activities after being exposed to an event of drought, this is imprecisely estimated. Our results do not point to changes in male overall and agricultural employment patterns following the exposure to rainfall shocks. This result comes with no surprise, given the high concentration of male work around agricultural activities in the Peruvian Andes.

## 5.3 Women's Financial Independence and Control Over Income

In Table 7, we report estimates of the effects of the exposure to rainfall shocks along four margins of women's financial independence and control over household finances: working for pay (column 1), earning more than their partners (column 2), having exclusive control over their income (column 2), having exclusive control over their partners' income (column 3). While the first two indicators capture women's ability to generate their income and how their income compares to that of their partners, the last two indicators capture women's control over household resources.

We find that women exposed to an event of drought are 12 percentage points (35 percent) less likely to work for pay and 7.5 percentage points (80 percent) less likely to earn more than their partners relative to periods of regular rainfalls. Turning to women's control over household finances, we find a decline of 7.7 percentage points (50 percent) in the probability that women exhibit exclusive control over their income, but no effect on the probability of women controlling their partners' income, after being exposed to an event of drought relative to periods of regular rainfalls.[31] Altogether, these findings are consistent with our previous

[31] We have revised that our estimates of the effect of the exposure to rainfall shocks on control over own income hold even when we focus on employed women only.

result indicating that women have a lower probability of being employed after being exposed to an event of drought during the cropping season.

## 5.4 Intrahousehold Dynamics

In Table 8, we report estimates of the effects of the exposure to rainfall shocks on indicators for intrahousehold dynamics, principally capturing living arrangements and interpersonal traits among partners. In columns 1 and 2 we examine changes in women's justification of wife-beatings and decision-making autonomy, respectively, whereas in columns 3 and 4 we examine changes in men's emotional support towards women and marital control, respectively.

We do not find statistically significant effects of the exposure to rainfall shocks on women's justification of wife-beatings nor in women's decision-making autonomy. These results imply, in principle, that women's tolerance to physical IPV and their power position and agency within the relationship do not change after being exposed to an event of drought relative to periods of regular rainfalls. Turning to men behaviors, although we do not find changes in emotional support towards women, we do find an increase in marital control following the exposure to an event of drought. In particular, we find that men's marital control increases by 12 percentage points (32 percent) relative to periods of regular rainfalls.[32]

## 5.5 Men's Alcohol Consumption and Violent Behavior

In Table 9, we present estimates of the effects of the exposure to rainfall shocks on outcomes aimed at capturing men's misconducts that may originate from financial distress and economic uncertainty. These outcomes consist of indicators for alcohol consumption (column 1), frequent alcohol consumption (column 2), and alcohol-related aggression (column 3).[33]

[32]Further analysis based on women's report (not shown) indicates that the increase in men's marital controlling issues is driven by both the isolation (coercive behaviors related to social and financial seclusion) and suspicion (coercive behaviors related to jealousy) domains of marital control.

[33]The phrasing of the question on alcohol-related aggression also includes intoxication by hard drugs. Yet, the most recent study about drug consumption in Peru indicates that only 0.7 percent of the rural population in the 12-65 age range has ever tried illegal drugs, which suggests that intoxication in rural areas

We construct these indicators based on women's reports.

We find an increase of 11 percentage points (15 percent) in the probability that men drink alcohol but no effect in the frequency with which they drink alcohol after being exposed to an event of drought. Remarkably, we find an increase of 5 percentage points (60 percent) in men's alcohol-related aggression following the exposure to an event of drought relative to periods of regular rainfalls. This result constitutes an important finding given that roughly 20 percent of recent episodes of physical IPV experienced by women where committed when their partners were intoxicated by alcohol (INEI 2015).

# 6 Discussion

We now turn to discuss the factors mapping the exposure to rainfall shocks during the cropping season to women's experience of physical IPV. Our discussion is based on, but not limited to, the pathways we could examine from our data. In particular, our results point to reductions in two mediating factors: (i) emotional wellbeing, from a decline in household income, and (ii) female empowerment, from a decline in economic opportunities for women.

The decline in household income following the exposure to an event of drought during the cropping season may prompt physical IPV through three different yet intertwined pathways. First, economic hardships generate economic pressure which may lead to poverty-related stress. This manifests mainly in daily-basis strains and hassles that economic uncertainty creates, deteriorating the emotional wellbeing of individuals and inducing relational problems that could increase the risk of IPV, as implied by the "family stress model" (Conger et al. 1990). Second, a decline in the availability of cash or in-kind resources required to meet daily needs may lead to an increase in marital conflict (Johnson 2009; Vives-Cases et al. 2009). In particular, the lack of financial means could increase the risk of IPV by increasing the frequency of arguments about how to spend household resources and that could escalate into verbal and physical aggression (Johnson 2009; Rabbani et al. 2008; Vives-Cases et al.

is mostly the result of excessive alcohol consumption (DEVIDA 2012).

2009; Fehringer and Hindin 2014). Third, an increase in stress and anxiety from economic uncertainty may lead to substance abuse, alcohol in particular, which could also increase the risk of IPV (Klosterman and Fals-Stewart 2006). In turn, alcohol intake is one of the principal contributors to IPV as it is "(...) thought to reduce inhibitions, cloud judgement, and impair inability to interpret social cues" (Jewkes 2002).

A handful of reasons can explain why men inflict physical violence against their partners during times of economic hardship. On the one hand, the pathway of poverty-related stress is consistent with the hypothesis of the expressive use of violence whereby men derive direct utility (for instance, by releasing tension) from inflicting physical violence (Eswaran and Malhotra 2011). On the other hand, the pathway of disputes over the use of money can accommodate the hypothesis of the instrumental use of violence whereby men could use physical violence as an instrument to align household resources with their preferences (Anderberg and Rainer 2013; Ramos 2018; Haushofer et al. 2019). On the third hand, the pathway of alcohol abuse is consistent with the behavioral "cue-triggered" theory whereby men "lose control" in response to some negative cues (Card and Dahl 2011). Our results, we argue, could accommodate all these three hypotheses.

Another important result is that men and women are affected differently from the exposure to an event of drought during the cropping season. In particular, while men do not see changes in their work prospects, women do experience a decline in employment. This leads to a higher degree of women's economic dependence on their partners which may induce changes in the power position between partners to the detriment of women. As stated by theories of household bargaining (Tauchen et al. 1991; Farmer and Tiefenthaler 1997; Aizer 2010), this may increase the risk of IPV by reducing women's ability to separate or to threaten their partners to separate credibly. This may be exacerbated by the fact that uncertainty about future economic options could make women even more reluctant to leave an abusive relationship in times of economic hardship (Schneider et al. 2016).

While we do not find changes in markers of female empowerment, such as women's justification of wife-beatings or decision-making autonomy, suggesting, in principle, that women's power position and agency within the relationship do not change, this result could accommodate the fact that women may divert more time to household activities after being exposed to an event of drought during the cropping season.[34] This may result from both a decrease in women's work prospects and an increase in marital control from their partners which is consistent with studies pointing to changes in men's valuation of women in response to female economic opportunities (Anderberg and Rainer 2013; Anderberg et al. 2016) and also with those arguing that the loss of economic control can create an urge for men to exert control over other spheres, such as their partners' affairs, in times of economic hardship (Melzer 2002; Stark 2007).[35] Our results, however, do not point to an increase in IPV due to a "male backlash" generated by changes in gender roles or identities within the family (Faludi 1992; Macmillan and Gartner 1999).

# 7 Conclusion

We obtain causal estimates of the effect of the exposure to rainfall shocks on the experience of physical IPV by women in rural areas of the Peruvian Andes. Our main result is that the prevalence of physical IPV increases by 65 percent following the exposure to an event of drought, but not flood, during the cropping season. Though mainly characterized by moderate acts of physical IPV, we still find a 75 percent increase in sequels from the abuse in the form of bruises and lesions on women's bodies.

Further analysis reveals that economic security is central in explaining this relationship as we find that the rise in physical IPV coincides with declines in per capita household income and consumption expenditures. However, two other important factors may also

[34] However, we take these results with caution as the DHS questions related to women's decision-making autonomy are generic and not tied to specific events, let alone the fact that they are not framed within a specific recall period. Because of this, we cannot link these results directly to the reference period spanning the 12 months before the survey date.

[35] In fact, another potential pathway through which physical IPV may arise relates to the hypothesis of declining domesticity from work (Dugan et al. 1999; Dugan et al. 2003). It seems that the decline in women's employment following the exposure to an event of drought may lead to an increase in physical IPV by making women spend more time with an abusive partner in the household. The lack of information on time use in our dataset, however, does not allow us to test for such hypothesis.

coact in prompting physical IPV: on the one hand, reduced emotional wellbeing that leads to undesired behaviors from men, such as alcohol-related aggression and marital control, and, on the other hand, reduced female empowerment from lower economic opportunities for women and a higher financial dependency on men.

From a public policy standpoint, our study highlights the importance of deepening the debate over the design of policies focusing on gender equality in the face of climate change. Even though research on this area is still incipient, there is an urge to understand how climatic variability will affect the wellbeing of women in rural areas of the developing world, mainly through its impacts on pre-existing gender disparities. Policies aimed at mitigating income risk and fostering rural development after the occurrence of climatic shocks, we believe, should be coupled with strategies to protect women from abuse and promote economic opportunities targeted at them.

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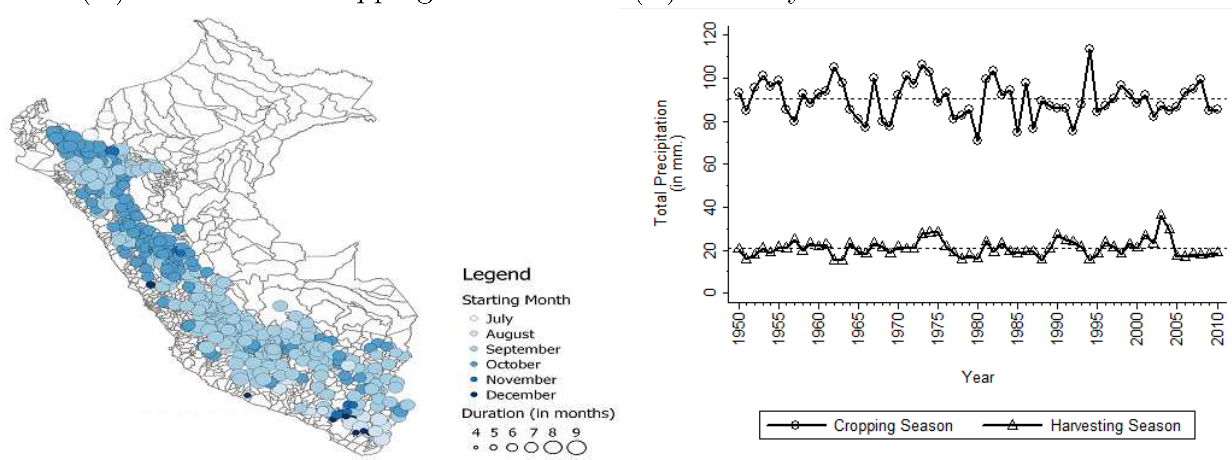
**Figure 1: Cropping Season in the Peruvian Andean Region**

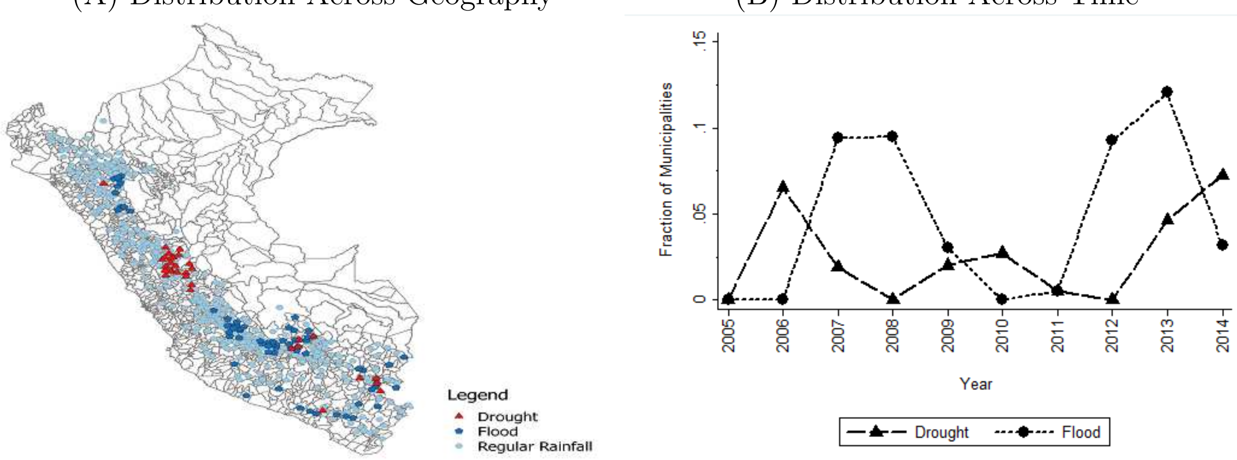
(A) Duration of Cropping Season (B) Monthly Rainfall Levels Across Seasons




Notes: The figure shows the starting month and duration of the rainy season (Panel A) and the total rainfall level (total precipitation) by season over the period 1950-2010 (Panel B) for rural municipalities in the Peruvian Andean region. The starting month of the cropping season is symbolized by the color and the duration by the size of the circles. Seasonal rainfall levels are calculated by averaging across municipalities in each season of the year.
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

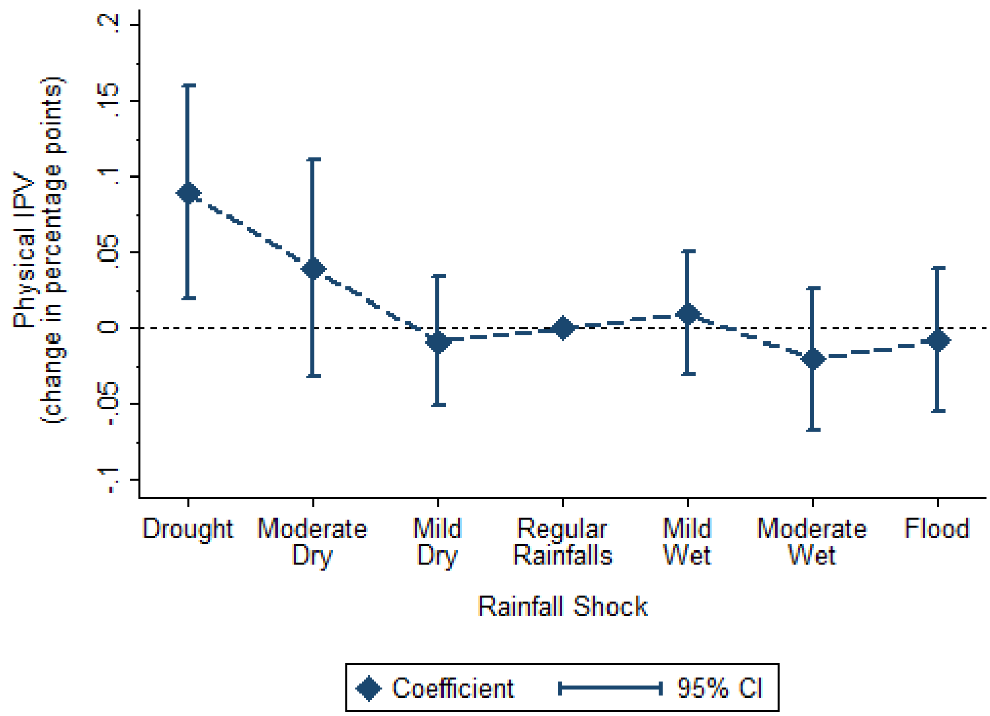
**Figure 2: Distribution of Rainfall Shocks Across Geography and Time**

(A) Distribution Across Geography (B) Distribution Across Time



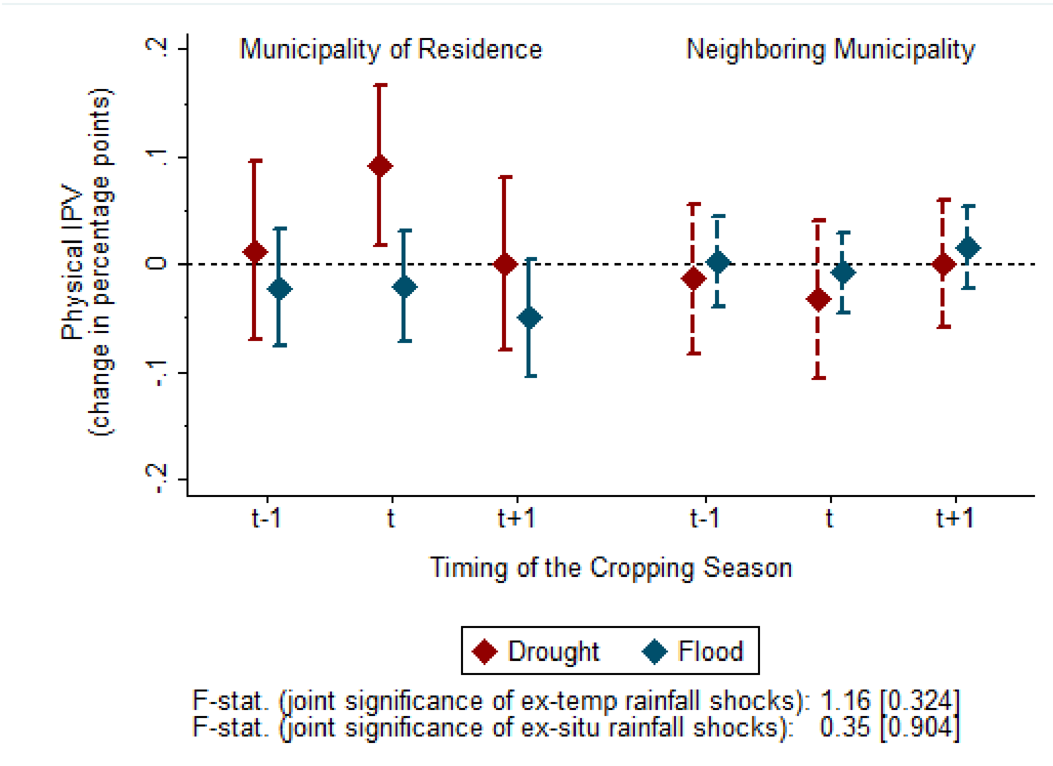

Notes: The figure shows the geographical distribution of rainfall shocks for rural municipalities in the Peruvian Andean region that are observed in the DHS sampling frame (Panel A) and the fraction of municipalities with rainfall shocks (Panel B) over the period 2005-2014.
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series (V 5.01).

**Figure 3: Exposure to Rainfall Shocks and Physical IPV**




Notes: The figure shows estimates, along with their 95% confidence intervals, of the effect of exposure to different intensities of rainfall shocks on women's experience of physical IPV. Estimates are obtained from an augmented regression of the form of equation (1), where the dependent variable is an indicator for a woman's experience of physical IPV during the past 12 months and the main explanatory variables are indicators for exposure to mild, moderate, and severe events of drought and flood. Mild, moderate, and severe events of drought are defined as rainfall levels observed during the last cropping season lying between the 10th-15th percentiles, between the 5th-10th percentiles, and between the 0th-5th percentiles respectively. Mild, moderate, and severe events of flood are defined as rainfall levels observed during the last cropping season lying between the 85th-90th percentiles, between the 90th-95th percentiles, and between the 95th-100th percentiles respectively. The regression includes woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as control variables. DHS sampling weights are used in the regression.
Source: Authors' calculations based on the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

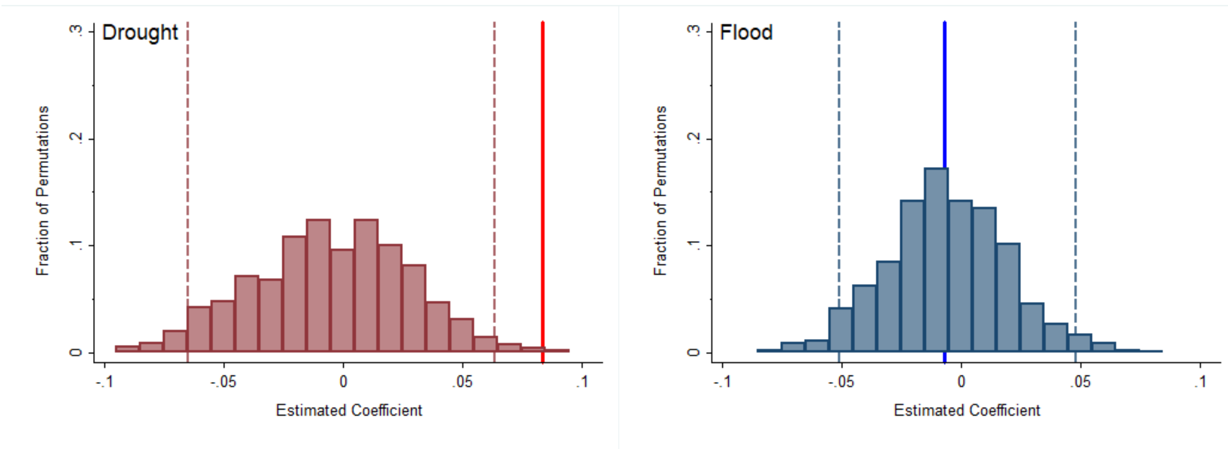
**Figure 4: Testing for Local and Transitory Effects**



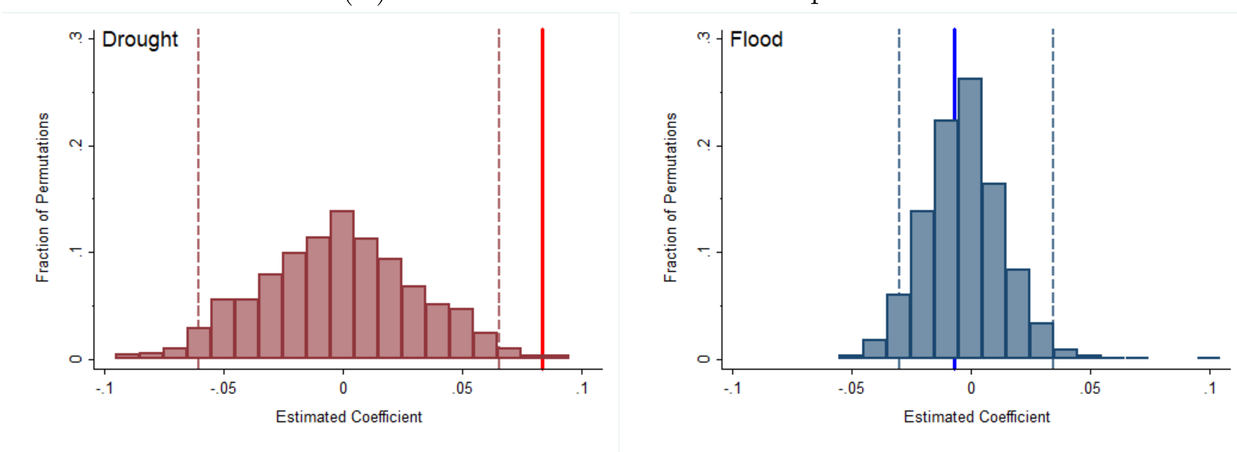

Notes: The figure shows estimates, along with their 95% confidence intervals, of the effect of the exposure to rainfall shocks on women's experience of physical IPV. Estimates are obtained from an augmented regression of the form of equation (1), where the dependent variable is an indicator for a woman's experience of physical IPV during the past 12 months and the main explanatory variables are indicators for the exposure to rainfall shocks in the woman's municipality of residence and in any neighboring municipality during the past (t-1), last (t), and future (t+1) cropping seasons. The regression includes woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as control variables. DHS sampling weights are used in the regression. F-statistics of joint significance tests of *ex-temp* rainfall shocks ($H_0 : \hat{\beta}^{\mathrm{D}_{t-1}} = \hat{\beta}^{\mathrm{F}_{t-1}} = \hat{\beta}^{\mathrm{D}_{t+1}} = \hat{\beta}^{\mathrm{F}_{t+1}} = 0$) and *ex-situ* rainfall shocks ($H_0 : \hat{\beta}^{\mathrm{D}^N_{t-1}} = \hat{\beta}^{\mathrm{F}^N_{t-1}} = \hat{\beta}^{\mathrm{D}^N_t} = \hat{\beta}^{\mathrm{F}^N_t} = \hat{\beta}^{\mathrm{D}^N_{t+1}} = \hat{\beta}^{\mathrm{F}^N_{t+1}} = 0$), along with their corresponding p-values (in brackets), are reported at the bottom of the graph.
Source: Authors' calculations based on the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Figure 5: Density Distributions from Permutation Tests**

(A) Permutations Within Municipalities




(B) Permutations Between Municipalities




Notes: The figure shows the density distribution of estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different permutation tests (1,000 permutations), where the indicators for the exposure to events of drought or flood are randomly assigned by changing the date of occurrence within the same municipality (Panel A) or by changing the municipality where the events occurred (within a given region) and preserving the date of occurrence (Panel B). The red and blue solid vertical lines correspond to our point estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from column 5 of Panel A in Table 2, respectively. The dashed vertical lines correspond to the 95% confidence intervals constructed from the first and second moments of the distribution of estimates across the permutations. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as control variables. DHS sampling weights are used in all regressions.
Source: Authors' calculations based on the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 1: Descriptive Statistics**

| Variable | (1) Range [min.-max.] | (2) Whole Sample (mean) | (3) Regular Rainfall (mean) | (4) Drought (mean) | (5) Flood (mean) | (6) Adj. Diff. (4)-(3) | (7) Adj. Diff. (5)-(3) |
|---|---|---|---|---|---|---|---|
| Woman's age | [15 - 49] | 34.46 | 34.45 | 34.24 | 34.63 | 0.42 | -0.49 |
| Woman's schooling | [0 - 17] | 5.44 | 5.44 | 5.46 | 5.42 | 0.20 | -0.16 |
| Woman's ethnicity | [0 - 1] | 0.62 | 0.62 | 0.81 | 0.50 | -0.01 | -0.02 |
| Partner's age | [18 - 92] | 38.30 | 38.30 | 38.15 | 38.34 | 0.86 | -0.39 |
| Partner's schooling | [0 - 17] | 7.22 | 7.23 | 7.00 | 7.10 | -0.06 | -0.19 |
| Years of union | [0 - 38] | 14.91 | 14.93 | 14.26 | 14.90 | -0.06 | -0.68 |
| Formally married | [0 - 1] | 0.49 | 0.50 | 0.38 | 0.51 | -0.01 | -0.02 |
| $N$ | | 15,110 | 14,049 | 421 | 640 | 14,470 | 14,689 |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows descriptive statistics for women's characteristics. The range of each variable is shown in column 1. Sample means for the whole sample of women, the sub-sample of women exposed to regular rainfalls, the sub-sample of women exposed to an event of drought, and the sub-sample of women exposed to an event of flood during the last cropping season are reported in columns 2 through 5, respectively. Adjusted differences are obtained by regressing each variable on an indicator for the exposure to an event of drought (column 6) or an indicator for the exposure to an event of flood (column 7) during the last cropping season and controlling for month, year, and municipality fixed effects. The sub-sample used for calculating adjusted differences in column 6 includes women exposed to regular rainfalls or to an event of drought during the last cropping season. The sub-sample used for calculating adjusted differences in column 7 includes women exposed to regular rainfalls or to an event of flood during the last cropping season. The total sample is composed of women of reproductive age (15-49 years), who live in rural municipalities in the Peruvian Andes, who respond the DHS module specific to spousal abuse, who are the household heads or spouses of the household head, who are married/cohabiting and living with their partners, and who live in the municipality at least for one year. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 2: Effect of Rainfall Shocks on Physical IPV**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.128) | | | | |
| | Panel A: Using DHS Sampling Weights | | | | |
| Drought | 0.085*** | 0.087*** | 0.083*** | 0.084*** | 0.084** |
| | (0.030) | (0.030) | (0.029) | (0.029) | (0.034) |
| Flood | -0.027 | -0.028 | -0.028 | -0.025 | -0.007 |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.025) |
| | Panel B: Unweighted Regressions | | | | |
| Drought | 0.054** | 0.055** | 0.053** | 0.052** | 0.064** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.025) |
| Flood | -0.015 | -0.015 | -0.015 | -0.014 | -0.006 |
| | (0.021) | (0.022) | (0.021) | (0.021) | (0.025) |
| *N* | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different specifications based on equation (1) in section 3, by using DHS sampling weights (Panel A) or by equally weighting individual observations (Panel B) in the regressions. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. The vector of woman characteristics includes indicators for age (20-24; 25-29; 30-34; 35-39; 40-44; 45-49; base: 19 or younger), indicators for educational attainment (incomplete primary, complete primary, incomplete secondary, high school degree or more education; base: no education), and an indicator for ethnicity (mother tongue is Spanish). The vector of partner and relationship characteristics includes indicators for partner's age (20-24; 25-29; 30-34; 35-39; 40-44; 45-or more; base: 19 or younger), indicators for partner's educational attainment (incomplete primary, complete primary, incomplete secondary, high school degree or more education; base: no education), indicators for the duration of the union (2-5 years; 6-9 years; 10 years or more; base: 1 year or less), and an indicator for being formally married. The vector of other crop yield determinants observed during the last cropping season includes indicators for average monthly air temperature (10°C-15°C; 15°C-20°C; 20°C or more; base: less than 10°C), indicators for average monthly soil temperature (10°C-15°C; 15°C-20°C; 20°C or more; base: less than 10°C), and indicators for average monthly soil moisture (25%-30%; 30%-35%; 35% or more; base: less than 25%). All regressions include municipality, month, and year fixed effects. Further details of each specification are described within the table. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 3: Physical Sequels from the Abuse**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Had Physical Sequels from the Abuse (Mean: 0.103) | | | | |
| Drought | 0.067** | 0.068*** | 0.066** | 0.066** | 0.078** |
| | (0.027) | (0.026) | (0.026) | (0.026) | (0.031) |
| Flood | -0.022 | -0.023 | -0.022 | -0.021 | -0.005 |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.024) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. DHS sampling weights are used in all regressions. See the notes on the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 4: Projected Change in the Prevalence of Physical IPV**

| | Projected Net Change in the Exposure to Events of Drought | | | Projected Change in the Prevalence of Physical IPV | | |
|---|---|---|---|---|---|---|
| | 2025-2029 | 2030-2034 | 2025-2034 | 2025-2029 | 2030-2034 | 2025-2034 |
| RCP-2.6 | 0.468 | 0.455 | 0.461 | 0.040 | 0.039 | 0.039 |
| | | | | [0.009;0.071] | [0.008;0.069] | [0.008;0.071] |
| RCP-4.5 | 0.451 | 0.437 | 0.444 | 0.037 | 0.036 | 0.037 |
| | | | | [0.008;0.068] | [0.008;0.066] | [0.008;0.067] |

Notes: The table shows the projected net change in the fraction of women exposed to events of drought and the projected change in the prevalence of physical IPV, along with their 95% confidence intervals (in brackets), in the Peruvian Andes for the period 2025-2034. The data used for calculations come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the NCAR's RCP database.

**Table 5: Other Forms of IPV**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Sexual IPV (Mean: 0.041) | | | | | Woman Experienced Emotional IPV (Mean: 0.148) | | | | |
| Drought | 0.045** | 0.045* | 0.045* | 0.044* | 0.028 | 0.037 | 0.038 | 0.034 | 0.032 | 0.033 |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.019) | (0.030) | (0.030) | (0.030) | (0.029) | (0.032) |
| Flood | 0.007 | 0.008 | 0.008 | 0.010 | 0.017 | -0.014 | -0.012 | -0.012 | -0.013 | -0.004 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.016) | (0.025) | (0.025) | (0.025) | (0.025) | (0.030) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 6: Household Income and Consumption Per Capita**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | Income Per Capita | | Consumption Per Capita | |
| | Total | Cash | Total | Cash |
| Drought | -35.914** | -31.935** | -23.274** | -19.188** |
| | (15.039) | (12.916) | (11.646) | (8.763) |
| Flood | -2.285 | -4.114 | 2.524 | 0.298 |
| | (8.305) | (7.169) | (7.106) | (6.035) |
| $N$ | 11,095 | 11,095 | 11,095 | 11,095 |
| Number of clusters | 341 | 341 | 341 | 341 |
| Dependent variable mean | 171.880 | 121.970 | 151.940 | 95.540 |
| Woman characteristics | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | Yes | Yes | Yes | Yes |
| Other crop yield determinants | Yes | Yes | Yes | Yes |
| Grid-specific linear trends | Yes | Yes | Yes | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. ENAHO sampling weights are used in all regressions. See the notes on the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian ENAHO, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 7: Female and Male Employment**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Women | | Men | |
| Dependent Variable: | Employed | Agricultural Worker | Employed | Agricultural Worker |
| Drought | -0.131** | -0.085 | 0.004 | 0.006 |
| | (0.054) | (0.057) | (0.004) | (0.040) |
| Flood | 0.066* | 0.059* | 0.004 | 0.053 |
| | (0.036) | (0.034) | (0.004) | (0.033) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.576 | 0.373 | 0.994 | 0.595 |
| Woman characteristics | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | Yes | Yes | Yes | Yes |
| Other crop yield determinants | Yes | Yes | Yes | Yes |
| Grid-specific linear trends | Yes | Yes | Yes | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 8: Women's Financial Independence and Control Over Income**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | Paid Work | Earns More t./ Partner | Controls Own Income | Controls Partner's Income |
| Drought | -0.121*** | -0.075*** | -0.077** | -0.036 |
| | (0.037) | (0.025) | (0.034) | (0.032) |
| Flood | 0.000 | 0.028 | -0.058** | 0.002 |
| | (0.034) | (0.027) | (0.026) | (0.028) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.327 | 0.091 | 0.157 | 0.155 |
| Woman characteristics | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | Yes | Yes | Yes | Yes |
| Other crop yield determinants | Yes | Yes | Yes | Yes |
| Grid-specific linear trends | Yes | Yes | Yes | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 9: Intrahousehold Dynamics**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Women | | Men | |
| Dependent Variable: | Justifies Wife Beatings | Decision Making Autonomy | Emotional Support | Marital Control |
| Drought | -0.019 | -0.021 | 0.003 | 0.119*** |
| | (0.013) | (0.030) | (0.010) | (0.037) |
| Flood | -0.004 | -0.001 | -0.009 | 0.022 |
| | (0.014) | (0.020) | (0.009) | (0.033 |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.080 | 0.917 | 0.978 | 0.372 |
| Woman characteristics | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | Yes | Yes | Yes | Yes |
| Other crop yield determinants | Yes | Yes | Yes | Yes |
| Grid-specific linear trends | Yes | Yes | Yes | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Table 10: Men's Alcohol Consumption and Violent Behavior**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable: | Drinks Alcohol | Drinks Alcohol Frequently | Alcohol-related Aggression |
| Drought | 0.107** | 0.018 | 0.047** |
| | (0.052) | (0.025) | (0.024) |
| Flood | -0.007 | 0.016 | 0.016 |
| | (0.032) | (0.016) | (0.024) |
| $N$ | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 |
| Dependent variable mean | 0.714 | 0.055 | 0.076 |
| Woman characteristics | Yes | Yes | Yes |
| Partner and relationship characteristics | Yes | Yes | Yes |
| Other crop yield determinants | Yes | Yes | Yes |
| Grid-specific linear trends | Yes | Yes | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Each column shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different regressions based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each regression are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

# Appendix Tables

**Appendix Table 1: Sensitivity Analysis**
**(Re-defining the Cropping Season based on Vegetation Growth)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.127) | | | | |
| Drought | 0.079*** | 0.078*** | 0.074*** | 0.074*** | 0.082** |
| | (0.028) | (0.028) | (0.027) | (0.027) | (0.036) |
| Flood | -0.016 | -0.016 | -0.017 | -0.014 | 0.026 |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.024) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different specifications based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. The timing of the cropping season in each municipality is calculated based on the Enhanced Vegetation Index 2 (EVI-2) over the period 2005-2014. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each specification are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis, and the NASA's MEaSUREs repository.

**Appendix Table 2: Sensitivity Analysis**
**(Re-defining Rainfall Shocks based on the Standardized Precipitation Index)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.127) | | | | |
| Drought | 0.073** | 0.072** | 0.068** | 0.066** | 0.094** |
| | (0.030) | (0.029) | (0.028) | (0.029) | (0.046) |
| Flood | -0.003 | -0.004 | -0.004 | -0.002 | -0.001 |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.022) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different specifications based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. The indicators for the exposure to events of drought and flood are constructed from the Standardized Precipitation Index (SPI) and defined based on $\pm 1.5$ standard deviations from the municipality's long-term (1950-2010) average monthly rainfalls of the cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each specification are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 3: Sensitivity Analysis**
**(Re-defining Rainfall Shocks based on the 10th./90th. Percentiles)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.127) | | | | |
| Drought | 0.059** | 0.060** | 0.057** | 0.056** | 0.070* |
| | (0.026) | (0.025) | (0.025) | (0.025) | (0.037) |
| Flood | -0.004 | -0.004 | -0.005 | -0.004 | -0.011 |
| | (0.016) | (0.015) | (0.016) | (0.016) | (0.018) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\text{D}}$ and $\beta^{\text{F}}$ from different specifications based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. The indicators for the exposure to events of drought and flood are re-defined based on the 10th./90th. percentiles in the distribution of long-term (1950-2010) municipality monthly rainfalls of the cropping season. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each specification are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 4: Sensitivity Analysis**
**(Smoothing Monthly Rainfalls based on a 3-months Moving Average)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.128) | | | | |
| Drought | 0.062** | 0.065** | 0.062** | 0.061** | 0.077* |
| | (0.029) | (0.028) | (0.027) | (0.027) | (0.043) |
| Flood | -0.022 | -0.022 | -0.024 | -0.022 | -0.001 |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.028) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\text{D}}$ and $\beta^{\text{F}}$ from different specifications based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. The time series of municipality's monthly rainfalls have been smoothed used a 3-months moving average. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each specification are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 5: Sensitivity Analysis (Using Precipitation Data from the UEA's CRU-TS)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.128) | | | | |
| Drought | 0.045* | 0.045* | 0.041* | 0.041* | 0.053 |
| | (0.026) | (0.025) | (0.024) | (0.024) | (0.040) |
| Flood | -0.034 | -0.035* | -0.034 | -0.031 | -0.004 |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.026) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different specifications based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. The time series of municipality's monthly rainfalls have been constructed based on the UEA's Climate Research Unit database. Clustered standard errors at the municipality level are shown in parentheses. All regressions include municipality, month, and year fixed effects. Further details of each specification are described within the table. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UEA's CRU Gridded Precipitation Time Series V 4.03, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 6: Effect of Rainfall Shocks on Moderate P-IPV**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Specific Acts of Moderate P-IPV | | | | |
| Dependent Variable: | Pushed/ Shook | Slapped | Punched | Kicked/ Dragged | Moderate P-IPV |
| Drought | 0.054** | 0.065*** | 0.032 | 0.018 | 0.081** |
| | (0.026) | (0.022) | (0.028) | (0.027) | (0.034) |
| Flood | -0.001 | 0.016 | 0.028 | 0.027 | -0.006 |
| | (0.023) | (0.020) | (0.023) | (0.020) | (0.024) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.099 | 0.076 | 0.079 | 0.057 | 0.126 |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as controls. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 7: Effect of Rainfall Shocks on Severe P-IPV**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Specific Acts of Severe P-IPV | | | |
| Dependent Variable: | Choked/ Burnt | Threatened w./ gun | Attacked w./ gun | Severe P-IPV |
| Drought | -0.009 | -0.001 | -0.001 | -0.006 |
| | (0.009) | (0.009) | (0.008) | (0.012) |
| Flood | 0.021* | 0.012 | 0.011 | 0.025 |
| | (0.011) | (0.011) | (0.009) | (0.022) |
| *N* | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.099 | 0.076 | 0.079 | 0.057 |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as controls. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 8: Effect of Rainfall Shocks on Physical Sequels from the Abuse**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Consequences of the Abuse | | | |
| Dependent Variable: | Bruises/ Lesions | Broken Bones/ Teeth | Required Medical Attention | Physical Sequels |
| Drought | 0.077** | 0.017 | 0.007 | 0.078** |
| | (0.031) | (0.013) | (0.022) | (0.031) |
| Flood | -0.004 | 0.023* | 0.016 | -0.005 |
| | (0.024) | (0.013) | (0.015) | (0.024) |
| *N* | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.102 | 0.024 | 0.027 | 0.103 |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as controls. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 9: Additional Robustness Analysis (Controlling for Women's History of IPV)**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.128) | | |
| Drought | 0.084** | 0.084** | 0.084** |
| | (0.034) | (0.034) | (0.034) |
| Flood | -0.006 | -0.007 | -0.007 |
| | (0.025) | (0.025) | (0.025) |
| Past experience of IPV (ex partner) | 0.028 | | 0.023 |
| | (0.032) | | (0.032) |
| Witnessed interparental violence | | 0.055*** | 0.055*** |
| | | (0.008) | (0.008) |
| $N$ | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from an augmented specification based on equation (1) in section 3 that also controls for the woman's history of IPV. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as controls. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 10: Additional Robustness Analysis (Rainfall Shocks Observed During the Harvesting Season)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.128) | | | | |
| Drought | 0.008 | 0.007 | 0.009 | 0.010 | -0.007 |
| | (0.029) | (0.029) | (0.029) | (0.030) | (0.030) |
| Flood | -0.005 | -0.006 | -0.003 | 0.000 | -0.028 |
| | (0.023) | (0.023) | (0.023) | (0.024) | (0.029) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| F-stat. ($H_0 : \hat{\beta}^{\mathrm{D}} = \hat{\beta}^{\mathrm{F}} = 0$) | 0.057 | 0.070 | 0.054 | 0.056 | 0.497 |
| p-value | [0.945] | [0.933] | [0.947] | [0.945] | [0.608] |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different specifications based on equation (1) in section 3. The indicators for drought and flood are constructed based on the distribution of rainfalls observed in the municipality during the harvesting season over the period 1950-2010. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last harvesting season. All regressions include municipality, month, and year fixed effects. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 11: Additional Robustness Analysis**
**(Rainfall Shocks in Urban Areas of the Peruvian Andean Region)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Woman Experienced Physical IPV (Mean = 0.157) | | | | |
| Drought | -0.008 | -0.009 | -0.008 | -0.008 | 0.001 |
| | (0.019) | (0.016) | (0.016) | (0.017) | (0.017) |
| Flood | -0.023 | -0.024 | -0.025 | -0.021 | -0.012 |
| | (0.020) | (0.019) | (0.019) | (0.019) | (0.020) |
| $N$ | 14,318 | 14,318 | 14,318 | 14,318 | 14,318 |
| Number of clusters | 346 | 346 | 346 | 346 | 346 |
| F-stat. ($H_0 : \hat{\beta}^{\mathrm{D}} = \hat{\beta}^{\mathrm{F}} = 0$) | 0.713 | 0.830 | 0.894 | 0.631 | 0.180 |
| p-value | [0.491] | [0.437] | [0.410] | [0.533] | [0.835] |
| Woman characteristics | No | Yes | Yes | Yes | Yes |
| Partner and relationship characteristics | No | No | Yes | Yes | Yes |
| Other crop yield determinants | No | No | No | Yes | Yes |
| Grid-specific linear trends | No | No | No | No | Yes |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{\mathrm{D}}$ and $\beta^{\mathrm{F}}$ from different specifications based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. All regressions include municipality, month, and year fixed effects. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

**Appendix Table 12: Effects of Rainfall Shocks on Components of Other Forms of IPV**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Sexual IPV | | Emotional/Psychological IPV | | |
| Dependent Variable: | Forced Sex | Unapproved Sexual Acts | Humiliation/ Insults | Threats w./ making harm | Threats w./ abandonment |
| Drought | 0.031* | 0.018 | 0.042 | 0.048* | 0.044** |
| | (0.019) | (0.016) | (0.027) | (0.028) | (0.021) |
| Flood | 0.023 | 0.010 | -0.017 | 0.028 | 0.018 |
| | (0.016) | (0.009) | (0.026) | (0.024) | (0.020) |
| $N$ | 15,110 | 15,110 | 15,110 | 15,110 | 15,110 |
| Number of clusters | 495 | 495 | 495 | 495 | 495 |
| Dependent variable mean | 0.037 | 0.021 | 0.106 | 0.059 | 0.079 |

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of $\beta^{D}$ and $\beta^{F}$ based on equation (1) in section 3. The dependent variable mean is calculated by averaging across the sub-group of women who were exposed to regular rainfalls during the last cropping season. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, grid-specific linear trends, and municipality, month and year fixed effects as controls. DHS sampling weights are used in all regressions. See the notes to Table 1 and the main text for information about the sample composition. The data used for the regressions come from the 2005-2014 Peruvian DHS, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

# Supplemental Data Appendix (Online Publication)

In this Supplemental Data Appendix, we describe our data sources and provide detailed information on our data cleaning and assembling procedures. We begin by describing our data sources. Next, we describe our data cleaning and sample filtering and selection procedures. Finally, we describe our variable construction procedure.

## S1. Data Sources

### S1.1. Principal Data Sources

In our empirical analysis, we bring together contemporaneous data on instances of IPV experienced by women in rural Peru and historical data on rainfalls. Data on instances of IPV experienced by women is obtained from annual cross-sections of the Peruvian Demographic and Health Survey (DHS) over the period 2005-2014. Data on rainfalls is obtained from the University of Delaware's (UDel) Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01 (TP-GMTS).

The DHS is a nationwide representative sample of households that is conducted by the Peruvian National Bureau of Statistics (INEI for its Spanish acronym) on an annual basis since the year 2004 (with a 4-year periodicity in previous years, starting in 1986). The DHS includes a module specific to spousal abuse – a shortened and modified version of the Conflict Tactics Scales elaborated by Straus (1979, 1990) that collects information on past and recent experiences of IPV among women of reproductive age (15-49 years) who have ever been in a relationship. We utilize this information to construct a sample of women.

The UDel's TP-GMTS provides georeferenced information on global monthly average rainfalls. Information on monthly rainfalls is first retrieved from 20 nearby weather stations and then interpolated at a resolution of $0.5^\circ \times 0.5^\circ$ (a $0.5^\circ$ equals approximately $56\text{km}^2$ at the equator). We also retrieve information on monthly rainfalls (at a resolution of $0.5^\circ \times 0.5^\circ$) from the University of East Anglia's (UEA) CRU Gridded Precipitation Time Series V 4.03 (CRU-TS), intending to perform additional sensitivity analyses. We utilize these data to construct municipality-by-month level rainfalls using specialized Geographic Information System (GIS) software.

We complement these data with information on other crop yield determinants including the air temperature, the soil temperature, and the soil moisture. Information on monthly temperatures is provided by the UDel's Terrestrial Air Temperature: 1900-2017 Gridded Monthly Time Series V 5.01 at a resolution of $0.5^\circ \times 0.5^\circ$. Information on monthly soil temperature and soil moisture (volumetric soil water content) are provided by the ERA-Interim 2004-2014 Archive on Global Atmospheric Reanalysis at a resolution of $0.75^\circ \times 0.75^\circ$. We process these data using GIS software to obtain information on these crop yield determinants at the municipality-by-month level.

## S1.2. Ancillary Data Sources

We use the Peruvian National Household Survey (ENAHO for its Spanish acronym) to obtain information on household income and consumption. Like the DHS, the ENAHO is conducted on an annual basis by the INEI. To make both samples compatible, we configure the household characteristics of our sample from the ENAHO to match those from the DHS.

# S2. Data Cleaning

## S2.1. Geographical Targeting

According to the 1994 Agricultural Census (the latest agricultural census available before the initial year of our study's period), 46% of the total surface used for agricultural activities in Peru is located in the Andes and around 74% of the land used for agricultural activities there relies on rainfed irrigation for cultivation. In terms of agricultural producers, 69% of total producers in Peru are located in the Andes and, according to the 1993 Population and Housing Census, 55% of all agricultural workers in Peru live in this region.[36]

Based on these figures, we focus on rural areas of the Peruvian Andes as our geographical context of the study. This region is located above 500 and can extend until 6,500 meters over the sea level. Pulgar-Vidal (2014) characterizes this region as having a rugged and steep terrain, with varying temperatures depending on the altitude, and with rainy seasons showing between October and May each year (this season corresponds to the spring/summertime in the southern hemisphere).

## S2.2. Selection of Municipalities

In Table S2.1, we show the number of municipalities, grids, and individual observations that we lose as we progressively restrict the data to match our geographical target. Our initial dataset (row A) consists of 1,297 municipalities (642 grids) with 172,380 observations across the Peruvian territory. Once we restrict the sample to keep rural municipalities only (row B), we are left with 1,074 municipalities contained in 593 grids and with a total of 59,014 observations. Next, we keep municipalities located above the 1,000 meters over the sea level (row C), which corresponds to the Peruvian Andes.[37] After this filter is applied, we retain 880 municipalities (473 grids) and 42,226 observations. Next, we exclude all municipalities that are province capitals (row D). These municipalities likely have a lower concentration of the workforce around agriculture and are more connected with urban settings, thus allowing for higher occupational mobility especially during times of adverse weather realizations. Once we exclude these municipalities, we are left with 769 municipalities (435 grids) and 35,047 observations. Our last filter consists of retaining municipalities that we observe in the DHS

[36] These figures are similar to the ones obtained from the 2012 Agricultural Census, revealing that 46% of the total surface used for agriculture in the country is located in the Andes, where 70% of the land used for agriculture is rainfed. Also, 64% of total producers are located in this region and, according to the 2007 Population and Housing Census, 50% of all agricultural workers in Peru live there.

[37] The threshold of the 1,000 meters over the sea level was chosen because agricultural activities become more important above this altitude.

sampling frame of two different years over the period 2005-2014 (row E). This filter permits us to exploit inter-temporal variation in rainfalls within a given municipality. We are finally left with 495 municipalities (314 grids) and 30,200 observations.

In Table S2.2, we show descriptive statistics for these municipalities. According to the 1994 Agricultural Census, 8% of the surface is destined to agricultural activities and 71% of the cultivated land is rainfed. In terms of employment, 76.7% of all employed individuals work in agricultural-related activities and 60.5% of all agricultural workers work their land, according to the 1993 Population and Housing Census.[38] Altogether, these figures imply that economic activity in our sample of DHS municipalities is highly concentrated around agriculture and agricultural productivity is tightly linked to weather realizations.

**Table S2.1: Geographical Filtering Procedure**

| Level: | Municipalities | | Grids | | Individuals | |
|---|---|---|---|---|---|---|
| Measure: | *N* | % | *N* | % | *N* | % |
| (A) Initial dataset | 1,297 | 100.00 | 642 | 100.00 | 172,380 | 100.00 |
| (B) Rural municipalities | 1,074 | 82.81 | 593 | 92.37 | 59,014 | 34.23 |
| (C) Altitude above 1,000 m.o.s.l. | 880 | 67.85 | 473 | 73.68 | 42,226 | 24.50 |
| (D) Excluding province capitals | 769 | 59.29 | 435 | 67.76 | 35,047 | 20.33 |
| (E) Panel municipalities | 495 | 38.16 | 314 | 48.91 | 30,200 | 17.52 |

Notes: The table provides details on the geographical filtering procedure for our sample from the DHS and quantifies the data loss as we progressively restrict our sample in order to keep rural municipalities in the Peruvian Andes (above 1,000 meters over the sea level), that are not province capitals, and that we observe in at least two different years of the DHS sampling frame over the period 2005-2014. In rows B through E we show the number and share of municipalities, grids and individual observations remaining after each of the implied cleaning step relative to the initial dataset described in row A.
Source: Authors' calculations using data from the 2005-2014 Peruvian DHS.

[38] These figures are similar to the ones obtained from the 2012 Agricultural Census, revealing that 9% of the municipality surface is used for agricultural activities and 70% of the agricultural land is rainfed. As for the workforce, the 2007 Population and Housing Census indicates that 77.4% of all employed individuals work in agricultural-related activities and 58.4% of all agricultural workers work their land.

**Table S2.2: Descriptive Statistics for Municipalities**

| Variable | Range [min. - max.] | Mean | Standard Deviation |
|---|---|---|---|
| Altitude (meters over the sea level) | [1,008 - 4,645] | 3,058.71 | 777.41 |
| Surface (km$^2$) | [8.40 - 21,900.60] | 466.33 | 1,108.48 |
| Cultivated land in 1994 (km$^2$) | [0.60 - 448.25] | 36.41 | 43.68 |
| Percentage of cultivated land that is rainfed in 1994 | [0.00 - 100.00] | 71.04 | 30.00 |
| Number of agricultural producers in 1994 | [113 - 8,368] | 1,312.66 | 1,088.87 |
| Size of land per agricultural producer in 1994 (km$^2$) | [0.00 - 0.34] | 0.03 | 0.02 |
| Cultivated land in 2012 (km$^2$) | [0.31 - 509.65] | 41.84 | 61.04 |
| Percentage of cultivated land that is rainfed in 2012 | [0.00 - 100.00] | 69.69 | 31.01 |
| Number of agricultural producers in 2012 | [106 - 13,270] | 1,670.60 | 1,655.12 |
| Size of land per agricultural producer in 2012 (km$^2$) | [0.00 - 0.51] | 0.03 | 0.04 |
| Cultivated land in 2000 (percentage/HWSD) | [0.00 - 45.69] | 7.51 | 6.98 |
| Percentage of cultivated land that is rainfed in 2000 (HWSD) | [0.00 - 100.00] | 60.48 | 32.90 |
| Agricultural employment in 1993 (percent of total employment) | [5.88 - 100.00] | 76.70 | 16.50 |
| Agricultural employment in 2007 (percent of total employment) | [3.36 - 100.00] | 77.41 | 16.17 |
| Long-term monthly rainfall level during cropping season (mm) | [6.21 - 390.69] | 101.01 | 39.33 |
| Monthly rainfall level during cropping season (mm) | [8.75 - 392.65] | 102.89 | 40.01 |
| Monthly air temperature during cropping season (°C) | [0.66 - 28.81] | 12.31 | 5.26 |
| Soil temperature during cropping season (°C) | [8.95 - 24.35] | 15.87 | 3.50 |
| Soil moisture during cropping season (%) | [2.09 - 37.30] | 33.79 | 3.60 |

Notes: The table shows descriptive statistics for the sample of DHS municipalities. There are 495 municipalities in the sample contained within 314 grids. Descriptive statistics for long-term monthly rainfalls observed during the cropping season are computed by averaging across time over the period 1950-2010. Descriptive statistics of monthly rainfalls, monthly air temperature, monthly soil temperature, and monthly soil moisture during the cropping season are obtained by averaging across time over the period 2005-2014. The data used for calculating descriptive statistics come from the 1994 and 2012 Agricultural Censuses, the 1993 and 2007 Population and Housing Censuses, the UDel's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01, and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

## S2.3. Selection of Individual Observations

In Table S2.3, we describe the individual filtering procedure for the DHS sample. From the 30,200 women living in rural municipalities in the Peruvian highlands (row A), 22,324 reported ever being in a relationship and thus are eligible to respond to the module on spousal abuse/domestic violence (row B). Since this module is applied to only one woman per household, we are left with 19,327 women (row C). From these women, 19,287 ended up responding to the questionnaire (row D). As can be inferred from these figures, non-response rates are small and the main reason for data loss is because privacy was not ensured. We further keep women who are the household heads or spouses of the household heads, which leaves us with 17,146 women in the sample. Moreover, since we focus on women currently in a relationship, we drop from the sample all women who are widowed, divorced, or not living together with their partners. We thus retain 15,403 currently married/cohabiting women who are living together with their partners (row F). Finally, to ensure that we are correctly assigning the rainfalls from the two previous completed cropping seasons in the municipality, we keep in our sample all women who live in the municipality for at least one year (row G). Our final sample comprises information from 15,110 women in 495 rural municipalities located in the Peruvian Andes.

We present descriptive statistics for our sample of women from the DHS in Table S2.4. The average woman in our sample is 35 years old and has attained 5.5 years of education (incomplete primary). Also, 62% of women in our sample have Spanish as their mother tongue. As for their partners, they are around 38 years old and have attained 7 years of education (incomplete secondary). Finally, 50% of couples in our sample are formally married and the average duration of the relationship is nearly 15 years.

**Table S2.3: Individual Filtering Procedure (DHS Sample)**

| Level: | Municipalities | | Grids | | Individuals | |
|---|---|---|---|---|---|---|
| Measure: | *N* | % | *N* | % | *N* | % |
| (A) Rural municipalities in the Peruvian Andean region | 495 | 100.00 | 314 | 100.00 | 30,200 | 100.00 |
| (B) Ever in a relationship | 495 | 100.00 | 314 | 100.00 | 22,324 | 73.92 |
| (C) Selected for responding the DV questionnaire | 495 | 100.00 | 314 | 100.00 | 19,327 | 64.00 |
| (D) Responded the DV questionnaire | 495 | 100.00 | 314 | 100.00 | 19,287 | 63.86 |
| (E) Household head or spouse of the household head | 495 | 100.00 | 314 | 100.00 | 17,146 | 56.77 |
| (F) Married/cohabiting and living with partner | 495 | 100.00 | 314 | 100.00 | 15,403 | 51.00 |
| (G) Living in the municipality for at least 1 year | 495 | 100.00 | 314 | 100.00 | 15,110 | 50.03 |

Notes: The table provides details on the individual filtering procedure for our sample from the DHS and quantifies the data loss as we progressively restrict our sample in order to keep women of reproductive ages (15-49 years), who responded the DHS module specific to spousal abuse, who are household heads or spouses of the household head, who are married/cohabiting and living with their partners, and who are living in the municipality for at least 1 year. In rows B through G we show the number and share of municipalities, grids and individual observations remaining after each of the implied cleaning step relative to the initial dataset described in row A.
Source: Authors' calculations using data from the 2005-2014 Peruvian DHS.

**Table S2.4: Descriptive Statistics of Women (DHS Sample)**

| Variable | Range [min. - max.] | Mean | Standard Deviation |
|---|---|---|---|
| Woman's age | [15 - 49] | 34.46 | 8.14 |
| Woman's schooling | [0 - 17] | 5.44 | 3.73 |
| Woman's ethnicity [a] | [0 - 1] | 0.62 | 0.49 |
| Partner's age | [18 - 92] | 38.30 | 9.30 |
| Partner's schooling | [0 - 17] | 7.22 | 3.69 |
| Formally married | [0 - 1] | 0.49 | 0.50 |
| Years of union | [0 - 38] | 14.91 | 8.15 |

Notes: The table provides descriptive statistics of individual characteristics for the sample of women from the DHS. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian DHS.
a/. Woman's mother tongue is Spanish.

## S2.4. Individual Filtering Procedure: ENAHO Sample

In Table S2.5, we describe the individual filtering procedure for the ENAHO sample. From the 32,939 women living in rural municipalities in the Peruvian Andes that belong to the DHS sampling frame (row A), 25,859 are of reproductive age (row B). From these women, 14,504 are the household heads or spouses of the household heads (row C). Finally, we retain in our sample women who are currently married/cohabiting and living together with their partners. Our final sample from the ENAHO comprises information from 11,095 women in 341 municipalities in the Peruvian Andes.

In Table S2.6, we present descriptive statistics for our sample of women from the ENAHO. Overall, we find a similar distribution in observed characteristics from our sample of women from the ENAHO when compared to those from our sample of women from the DHS.

**Table S2.5: Individual Filtering Procedure (ENAHO)**

| Level: | Municipalities | | Grids | | Individuals | |
|---|---|---|---|---|---|---|
| Measure: | $N$ | % | $N$ | % | $N$ | % |
| (A) DHS municipalities | 341 | 100.00 | 231 | 100.00 | 32,939 | 100.00 |
| (B) Reproductive age | 341 | 100.00 | 231 | 100.00 | 25,859 | 78.51 |
| (C) Household head or spouse of the household head | 341 | 100.00 | 231 | 100.00 | 14,504 | 44.03 |
| (D) Married/cohabiting and living with the partner | 341 | 100.00 | 231 | 100.00 | 11,095 | 33.68 |

Notes: The table provides details on the individual filtering procedure for our ancillary sample from the ENAHO and quantifies the data loss as we progressively restrict our sample in order to keep women of reproductive ages (15-49 years), who are household heads or spouses of the household head, who are married/cohabiting and living with their partners, and who live in rural municipalities of the Peruvian Andes that belong to the DHS sampling frame over the period 2005-2014. In rows B through D we show the number and share of municipalities, grids, and individual observations remaining after each of the implied cleaning step relative to the initial dataset described in row A.
Source: Authors' calculations using data from the 2005-2014 Peruvian ENAHO.

**Table S2.6: Descriptive Statistics of Women (ENAHO Sample)**

| Variable | Range [min. - max.] | Mean | Standard Deviation |
|---|---|---|---|
| Woman's age | [15 - 49] | 36.62 | 7.70 |
| Woman's schooling | [0 - 17] | 4.06 | 3.41 |
| Woman's ethnicity [a] | [0 - 1] | 0.63 | 0.48 |
| Partner's age | [17 - 88] | 40.44 | 9.06 |
| Partner's schooling | [0 - 18] | 5.79 | 3.96 |
| Formally married | [0 - 1] | 0.41 | 0.49 |

Notes: The table provides descriptive statistics of individual characteristics for the sample of women from the ENAHO. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian ENAHO.
a/. Woman's mother tongue is Spanish.

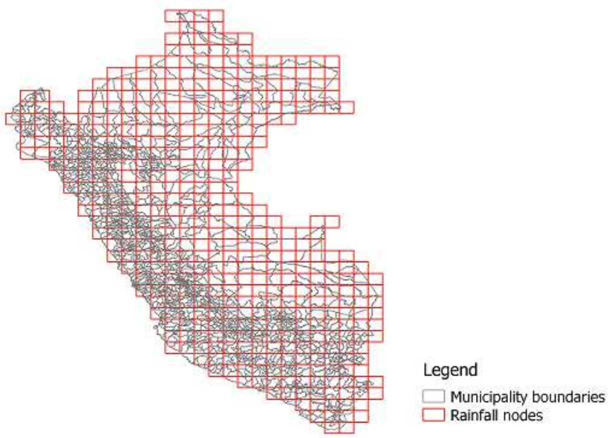
# S3. Municipality Monthly Rainfall Levels

## S3.1. Historical Rainfall Levels

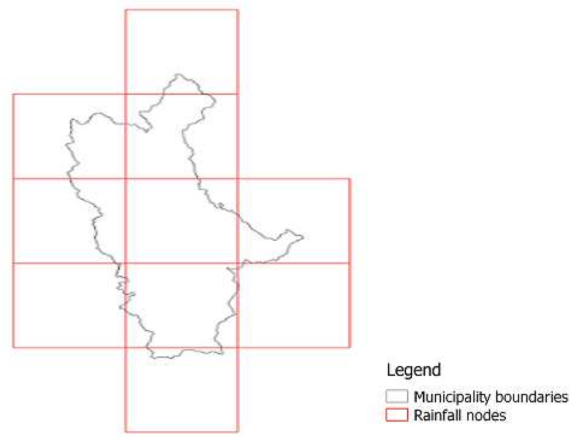
In Panel A of Figure S3.1, we depict the distribution of rainfall nodes across the Peruvian territory.[39] In Panels B and C, we show a municipality whose boundary is contained within multiple rainfall nodes and a group of municipalities (shaded in lines) whose boundaries are contained within a single rainfall node, respectively. We denote the set of rainfall nodes that overlap the municipality's boundary as its grid.

**Figure S3.1: Spatial Distribution of Rainfall Nodes**

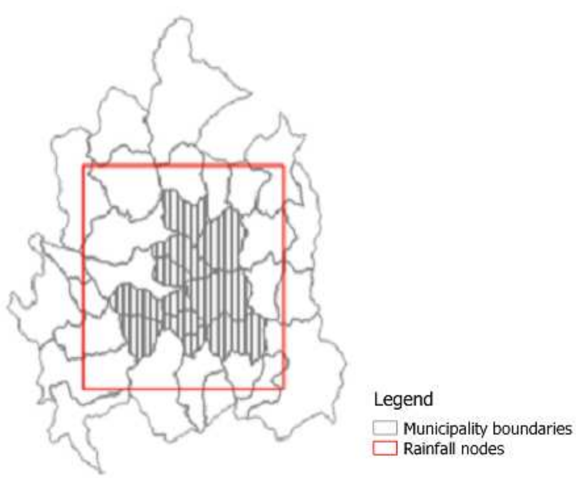
(A) Rainfall Nodes Across Peru




(B) Overlapped by Multiple Rainfall Nodes




(C) Overlapped by a Single Rainfall Node




Notes: The figure shows the distribution of rainfall nodes across the Peruvian territory (Panel A) and illustrations of a municipality whose boundary is contained within multiple rainfall nodes (Panel B) and of a group of municipalities whose boundaries are contained within a single rainfall node (Panel C).
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

[39] Administratively, the Peruvian territory is divided into regions, provinces, and municipalities. Municipalities are the smallest administrative unit in Peru and correspond to the NUTS-3 (Nomenclature of Territorial Units for Statistics) subdivision of the country.

We calculate municipality monthly rainfalls as follows: (i) if the municipality's boundary lays within one rainfall node, then we ascribe to that municipality the corresponding monthly rainfalls of the rainfall node where it is contained, and (ii) if the municipality's boundary is intersected by several rainfall nodes, then we ascribe to that municipality the weighted average of the monthly rainfalls of all its associated rainfall nodes, where the weights correspond to the share of the municipality's territory that is contained within each rainfall node. The resulting dataset is at the municipality-by-month level.

## S3.2. Future Rainfall Levels

We also use information on future rainfall levels from the Representative Concentration Pathways (RCP) database assembled by the National Center for Atmospheric Research (NCAR). In short, the RCP obtains projections of different atmospheric and oceanic climate variables based on a series of *pathways* in terms of future greenhouse gas (GHG) emission and concentration up until the end of the 21st. century.

We retrieve monthly gridded data, at a resolution of (approximately) $1.25° \times 0.47°$, on rainfall projections over the period 2025-2034 from two RCP climatic scenarios: the RCP-2.6 and the RCP-4.5. These two scenarios correspond to the low and medium *pathways* of future GHG emission and concentration, respectively. We interpolate the original data based on a cubic polynomial to recover gridded information on monthly rainfalls at a resolution of $0.5° \times 0.5°$ and then calculate municipality monthly rainfalls the same manner we did with the historical data.

# S4. Rainfall Shocks During the Cropping Season

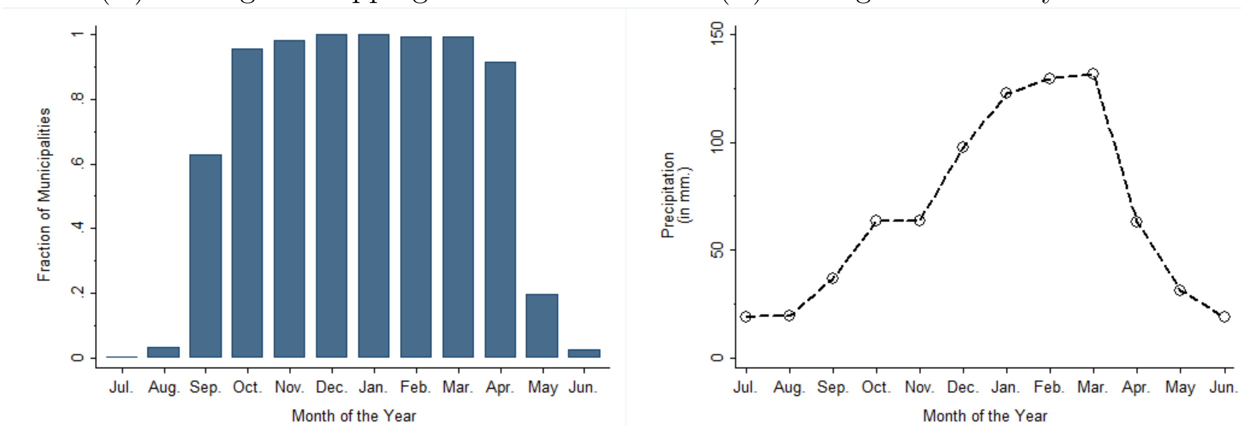
## S4.1. Determination of the Cropping Season

We determine the cropping season by analyzing the cyclicality of municipality rainfalls throughout the year. We use a simplified version of the Jönsson and Eklundh (2004) program for analyzing time-series of satellite sensor data and focus on the period 2005-2014, where each year is defined as the time span between July and June of two contiguous calendar years. With information at the municipality-by-month level, we first obtain, for each municipality-year data point, the 25th. percentile in the distribution of year-long rainfalls. We then use the median of the collection of these values as our thresholds and construct indicators for months whose rainfalls lie above these values. Next, we define a candidate month for the cropping season as that month with 10 years of rainfalls above the specified threshold. Finally, we define the cropping season of the municipality as the continuum of time between the earliest and latest candidate months.

In Figure S4.1, we show the fraction of municipalities in our sample whose cropping season falls within each month (Panel A) and the average rainfall in each month of the year (Panel B). On average, the cropping season has a duration of between 7.5 and 8 months, usually spanning the period between September and April of two consecutive years. Average rainfalls in a typical month during the cropping season reach around 103mm.

**Figure S4.1: Determination of the Cropping Season Based on Rainfalls**

(A) Timing of Cropping Season (B) Average Rainfalls by Month




Notes: The figure shows the fraction of municipalities whose cropping season falls within each month (Panel A) and the average rainfalls observed in each month of the year (Panel B). Both graphs are constructed based on municipality monthly rainfalls over the period 2005-2014.
Source: Authors' calculations based on the Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

## S4.2. Validation

We validate our procedure for determining the cropping season based on rainfalls by comparing it to an alternate procedure that is based on vegetation growth. To this end, we utilize monthly gridded information on the Enhanced Vegetation Index 2 (EVI-2) over the period 2005-2014 from the NASA's MEaSUREs data repository.[40] Information on EVI-2 is provided at a resolution of $0.05°\times0.05°$, which corresponds to a surface of approximately $5\text{km}^2$. We follow a similar procedure to the one used with rainfalls to determine the cropping season of each municipality based on vegetation growth.

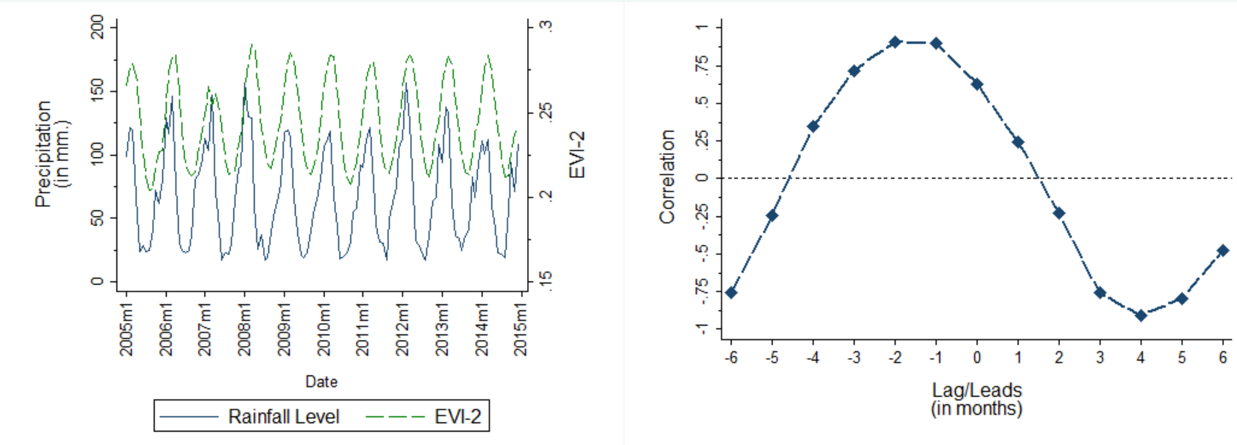
In Figure S4.2, we show the cross-correlation between rainfalls and vegetation growth. In Panel A we plot average monthly rainfalls (left axis) and vegetation growth (right axis) for municipalities in our sample over the period 2005-2014. The graph shows that rainfalls do a good job of tracking vegetation growth. In Panel B we depict the correlation between the monthly EVI-2 and the lags and leads of monthly rainfalls. The cross-correlation peaks at the second and first lags of monthly rainfalls, implying that vegetation growth lags rainfalls.

It follows from this analysis that a more accurate determination of the cropping season is given by defining this season based on rainfalls rather than relying on vegetation growth indexes. In fact, the FAO defines the cropping (growing/planting) season based on rainfalls. According to the official definition, the cropping season is "the period (in days) during a year when precipitation exceeds half of the potential evapotranspiration" (FAO 1978).

[40]The Enhanced Vegetation Index 2 (EVI-2) is an optimized vegetation index derived from remote sensing systems and designed to enhance the vegetation signal with improved sensitivity in high biomass regions. Relative to its predecessor, the Normalized Difference Vegetation Index (NDVI), the EVI-2 is not chlorophyll sensitive and is more responsive to canopy structural variations.

**Figure S4.2: Rainfalls and Vegetation Growth**

(A) Time Trends (B) Correlation



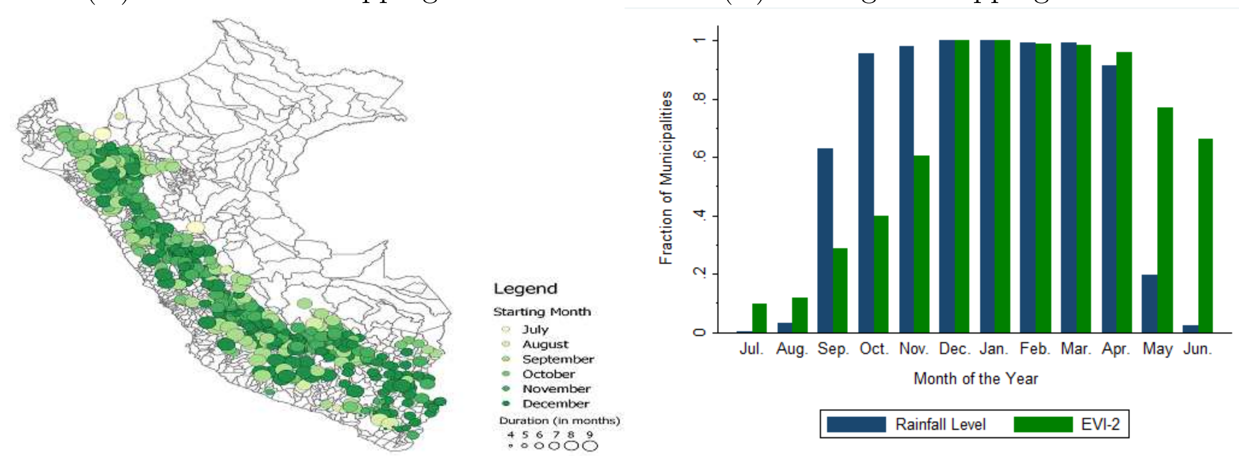

Notes: The figure shows the trend in monthly EVI and rainfalls over time (Panel A) and the cross-correlations between the EVI and the monthly lags and leads of rainfalls (Panel B). Monthly EVI and rainfalls shown in Panel A are obtained by averaging across municipalities. Both graphs are constructed based on monthly EVI and rainfalls over the period 2005-2014.
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01 and the NASA MEaSUREs Vegetation Index and Phenology (VIP): Vegetation Indices Monthly Global 0.05° CMG – EVI-2.

Next, we verify the consistency in the determination of the cropping season when following one procedure or the other. In Figure S4.3, we depict the starting month and duration of the cropping season based on vegetation growth (Panel A) and the fraction of municipalities whose cropping season falls within each month of the year when determining the cropping season based on rainfalls or vegetation growth (Panel B). If we re-define the cropping season based on vegetation growth, the average starting and ending months of this season are October and May respectively and the average duration of the cropping season is between 8 to 8.5 months. When comparing the cropping seasons according to its different determination procedures, we observe that this season begins (and ends) earlier when defined based on rainfalls. This observation is consistent with the fact that vegetation growth tends to lag rainfalls.

We take these comparisons as evidence that our procedure for determining the cropping season based on rainfalls is valid. We have shown that rainfalls are highly correlated with vegetation growth and have also pointed out that, consistent with the germination stage of plant growth, increases in rainfalls usually precede vegetation growth. Thus, a more accurate picture of the cropping season may be described by rainfalls rather than vegetation growth since *greenness* might only be observed after the germination stage of the planting cycle.

**Figure S4.3: Determination of the Cropping Season Based on Vegetation Growth**

(A) Duration of Cropping Season (B) Timing of Cropping Season



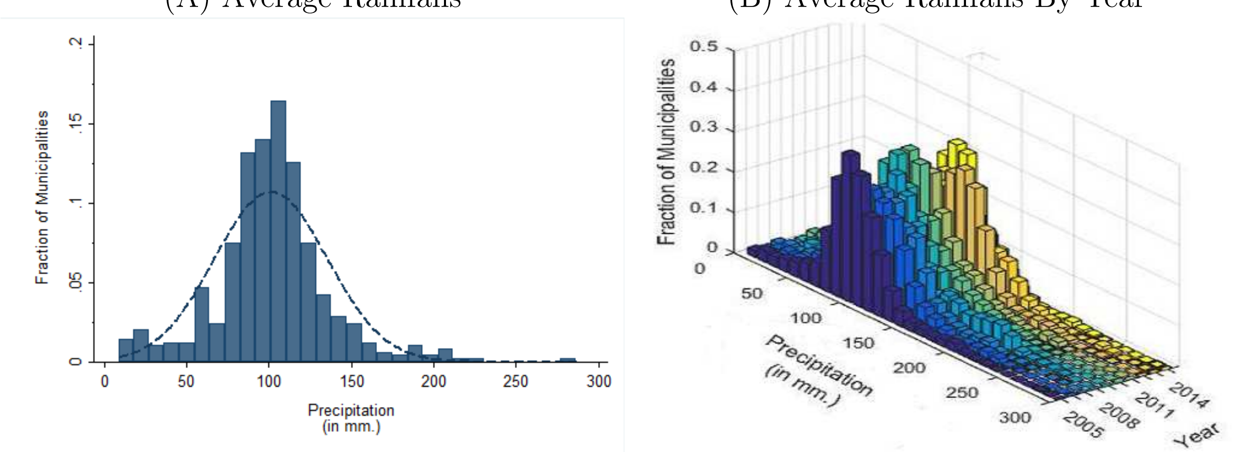

Notes: The figure shows the starting month (color of the circles) and duration of the cropping season (size of the circles) when this season is determined based on the EVI-2 (Panel A) and the fraction of municipalities whose corresponding cropping seasons fall within each month of the year (Panel B).
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01 and the NASA MEaSUREs Vegetation Index and Phenology (VIP): Vegetation Indices Monthly Global 0.05° CMG – EVI-2.

## S4.3. Rainfall Levels During the Cropping Season

In Figure S4.4, we present the distribution of average monthly rainfalls of the cropping season across municipalities over the period 2005-2014 (Panel A) and across municipalities for each year over the period 2005-2014 (Panel B).

**Figure S4.4: Average Monthly Rainfalls**

(A) Average Rainfalls (B) Average Rainfalls By Year

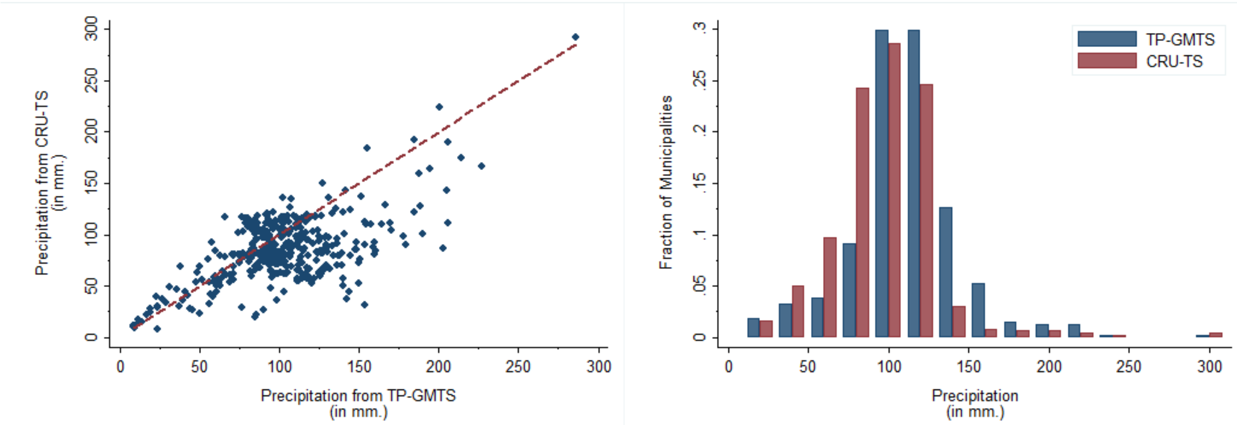



Notes: The figure shows the distribution of municipality average monthly rainfalls observed during the cropping season over the period 2005-2014 (Panel A) and the distribution of municipality monthly rainfalls observed during the cropping season for each year over the period 2005-2014 (Panel B).
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

In Figure S4.5, we present the cross-correlation between monthly rainfalls (Panel A) and the distributions of average monthly rainfalls observed during the cropping season (Panel B) calculated from each of our data sources. Although there is a strong positive correlation between monthly rainfalls derived from both data sources, rainfalls obtained from the CRU-TS dataset tend to be lower than those from the TP-GMTS.

**Figure S4.5: Monthly Rainfalls From Different Data Sources**

(A) Correlation (B) Distribution



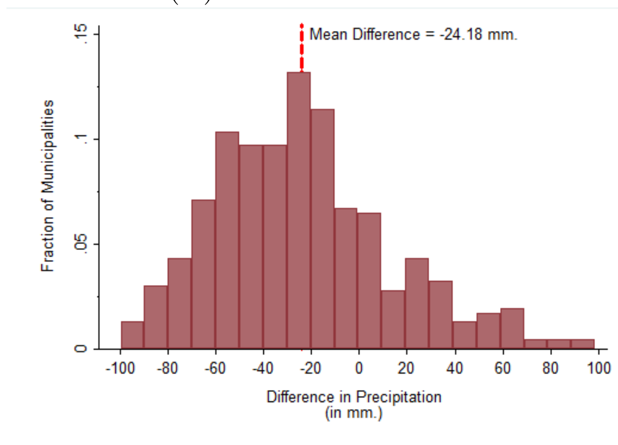

Notes: The figure shows the cross-correlation between monthly rainfalls observed during the cropping season (Panel A) and the distributions of municipality average monthly rainfalls observed during the cropping season (Panel B) constructed from the TP-GMTS and the CRU-TS datasets. The red line on the graph in Panel A corresponds to the 45° line.
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01 and the UEA's Climatic Research Unit Gridded Precipitation Time Series Dataset 1901-2018 V 4.03.

In Figure S4.6, we depict the distribution of projected differences in monthly rainfalls during the cropping season from the RCP-2.6 (Panels A and B) and RCP-4.5 (Panels C and D) models. The left panels show the overall distribution whereas the right panels show the distribution across space. The projections for the period 2025-2034 are similar across both models and imply a decrease of 20-25mm. (roughly 20%) in monthly rainfalls during the cropping season relative to the average over the period 2005-2014 in the Peruvian Andes.

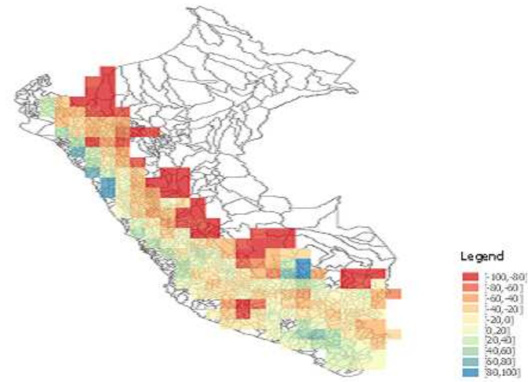
The figure also shows that not all municipalities will be equally affected by future climate variability. While average monthly rainfalls will likely decline in municipalities located close to the Amazonas, they will tend to increase in municipalities located close to the Coast. As a result, there will also be an increase in the variability of average monthly rainfalls during the cropping season both across and within municipalities.

**Figure S4.6: Distribution of Projected Differences in Monthly Rainfalls**

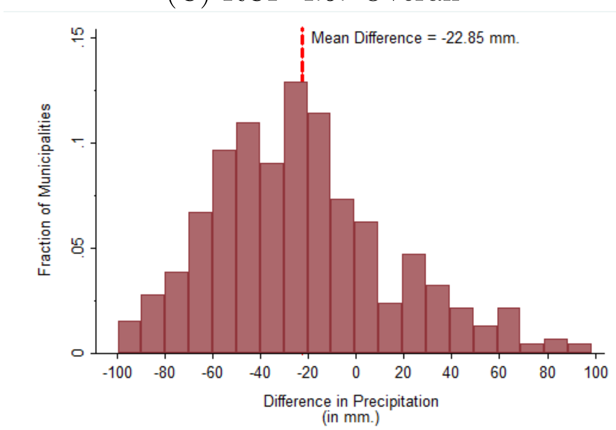
(A) RCP-2.6: Overall



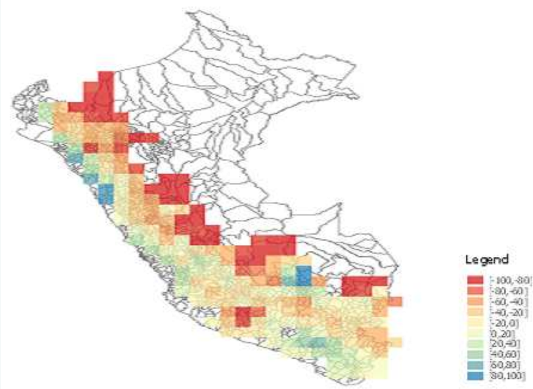

(B) RCP-2.6: Across Space




(C) RCP-4.5: Overall




(D) RCP-4.5: Across Space




Notes: The figure shows the distributions of projected overall (left panels) and spatial (right panels) differences in rainfalls observed during the cropping season in the Peruvian Andes. Projections are based on the RCP-2.6 (Panels A and B) and RCP-4.5 (Panels C and D) models.
Source: Authors' calculations based on the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01 and the NCAR's RCP database.

## S4.4. Exposure to Rainfall Shocks During the Cropping Season

We compute rainfalls observed during the last cropping season based on a weighted average of the rainfalls observed during the cropping seasons of the calendar year when the woman is surveyed and the previous calendar year. Let $\mathrm{R}_{j1}$ and $\mathrm{R}_{j2}$ be the rainfalls observed during the cropping seasons of the current (the year when the woman is surveyed by the DHS) and previous calendar years in municipality $j$, respectively. We calculate average monthly rainfalls to which a woman $i$ who lives in municipality $j$ and is surveyed at date (month of the year) $d$ was exposed during the last cropping season as follows:

$$\mathrm{R}_{ijd} = \omega_{ij1} \cdot \mathrm{R}_{j1} + (1 - \omega_{ij1}) \cdot \mathrm{R}_{j2} \ ,$$

where $\omega_{ij1}$ is the weight ascribed to $\mathrm{R}_{j1}$. We compute weights as follows: $\omega_{ij1} = (m_i - h_{j1})/12$, where $m_i$ is the survey month and $h_{j1}$ is the month corresponding to the end of the last harvesting season (or the month prior to the beginning of the most recent cropping season). This implies that $R_{ijd} = R_{j2}$ (or, equivalently, $\omega_{ij1} = 0$) if the woman is surveyed in the ending month of the most recent harvesting season.

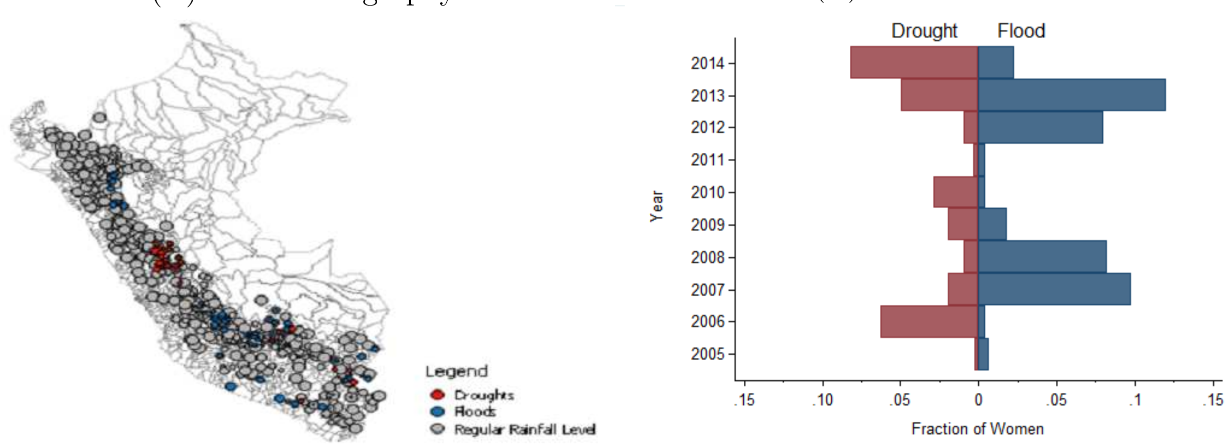
Let $R_j^p$ denote the p-th. percentile in the distribution of municipality's $j$ monthly rainfalls observed during the cropping season over the period 1950-2010. We construct indicators for the exposure to rainfall shocks – events of drought and flood – during the last cropping season as follows:

$$\text{Rainfall Shock}_{ijd} = \begin{cases} \text{Drought}_{ijd} & = \mathbb{1}\left\{R_{ijd} < R_j^{05}\right\} \\ \text{Flood}_{ijd} & = \mathbb{1}\left\{R_{ijd} > R_j^{95}\right\} \end{cases}$$

In Figure S4.7, we show the distribution of rainfall shocks in our sample across geography (Panel A) and across time (Panel B). The graph indicates that there is considerable variation in the exposure to rainfall shocks both across different municipalities and across different years in our sample.

**Figure S4.7: Distribution of Rainfall Shocks**

(A) Across Geography (B) Across Time




Notes: The figure shows the distribution of women exposed to rainfall shocks across geography (Panel A) and across time (Panel B) in our sample.
Source: Authors' calculations based on the 2005-2014 Peruvian DHS and the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

# S.5. Outcome Variables

## S5.1. The DHS Questionnaire on Domestic Violence

In Figure S5.1, we present the English version (own translation) of the Peruvian DHS questionnaire on spousal abuse/domestic violence (DV questionnaire). Question 1004 includes items on emotional/psychological IPV whereas question 1005 includes items on physical and sexual IPV. All questions are asked sequentially, beginning by ever experiencing some violent act and, conditional on a positive response, continuing with the frequency in the experience of such behavior during the past 12 months.

## Figure S5.1: The DHS Questionnaire on Domestic Violence

| QUEST. | QUESTIONS AND FILTERS | | CATEGORIES AND CODES | | GO TO |
|---|---|---|---|---|---|
| 1004 | Now, if you allow me, I need to ask you some questions about your couple's relationship with you (last) (husband/partner).<br>Did your (last) (husband/partner) ever: | | | | |
| A | say or do something to humiliate you in front of others? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| B | threaten to hurt or harm you or someone you care about? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| C | threaten to leave home, take away your children, or take away financial aid? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| 1005 | Did your (last) (husband/partner) ever: | | | | |
| A | push you, shake you, or throw something at you? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| B | slap you or twist your arm? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| C | punch you with his fist or with something that could hurt you? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| D | kick you or drag you? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| E | try to choke you or burn you? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| F | attack you with a knife, gun, or another weapon? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| G | threaten you with a knife, gun, or another weapon? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| H | physically force you to have sexual intercourse with him when you did not want to? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |
| I | force you to perform sexual acts you do not approve of? | YES 1<br>NO 2 | How often in the previous 12 months? | Very often........ 1<br>Sometimes........ 2<br>Never............... 3 | |

Note: The figure shows the English version of the questionnaire on domestic violence from the Peruvian Demographic and Health Surveys, constructed from the authors' own translation.
Source: Peruvian DHS.

## S5.2. Physical IPV

In our analysis, we mainly focus on physical IPV (P-IPV). Our principal outcome is an indicator for the experience of P-IPV that takes the value of 1 if, during the past 12 months, the woman's partner perpetrated any of the physically violent acts listed in parts (A) through (G) of question 1005 from the DV questionnaire.

We further characterize the experience of P-IPV according to its severity and construct three additional outcomes. The first one is an indicator for the experience of moderate P-IPV that takes the value of 1 if, during the past 12 months, the woman experienced physically violent acts (A) through (D). The second one is an indicator for the experience of severe P-IPV that takes the value of 1 if, during the past 12 months, the woman experienced physically violent acts (E) through (G). The third one is an indicator for the experience of physical sequels from the abuse that takes the value of 1 if the woman reports that, as a consequence of the physical abuse exerted by her partner, she had bruises or lesions, sprains or broken bones/teeth, or required medical assistance.

We present sample means of outcomes for P-IPV in Table S5.1.

**Table S5.1: Sample Means of Physical IPV**

| | Whole Sample | Regular Rainfalls | Drought | Flood |
|---|---|---|---|---|
| Any Physical IPV | 0.13 | 0.13 | 0.20 | 0.13 |
| Any moderate Physical IPV | 0.13 | 0.13 | 0.20 | 0.12 |
| Any severe Physical IPV | 0.02 | 0.02 | 0.03 | 0.03 |
| Pushed/shook | 0.10 | 0.10 | 0.15 | 0.11 |
| Slapped | 0.08 | 0.08 | 0.14 | 0.08 |
| Punched | 0.08 | 0.08 | 0.12 | 0.08 |
| Kicked/dragged | 0.06 | 0.06 | 0.10 | 0.06 |
| Chocked/burnt | 0.01 | 0.01 | 0.02 | 0.02 |
| Threatened with a gun | 0.01 | 0.01 | 0.01 | 0.01 |
| Attacked with a gun | 0.01 | 0.01 | 0.01 | 0.01 |
| Any Physical Sequel | 0.10 | 0.10 | 0.16 | 0.10 |
| Bruises/lesions | 0.10 | 0.10 | 0.16 | 0.10 |
| Broken bones/teeth | 0.02 | 0.02 | 0.03 | 0.03 |
| Required medical assistance | 0.03 | 0.03 | 0.05 | 0.04 |
| Observations | 15,110 | 14,049 | 421 | 640 |

Notes: The table provides sample means of outcomes for physical IPV. Sample means for the whole sample are presented in column 1. Sample means for the sub-samples exposed to regular rainfalls, droughts, and floods are reported in columns 2 through 4, respectively. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian DHS and the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

## S5.2. Other Forms of IPV

We construct two additional indicators that measure the occurrence of sexual and emotional/psychological IPV. Our outcome for sexual IPV is an indicator that takes the value of 1 if the woman reported that, during the past twelve months, her partner perpetrated any of the violent acts listed in parts (H) and (I) of question 1005 from the DV questionnaire. Our outcome for emotional/psychological IPV is an indicator that takes the value of 1 if the woman reported that, during the past twelve months, her partner perpetrated any of the violent acts listed in parts (A) through (C) of question 1004 from the DV questionnaire. We present sample means of other forms of IPV in Table S5.2.

**Table S5.2: Sample Means of Other Forms of IPV**

| | Whole Sample | Regular Rainfalls | Drought | Flood |
|---|---|---|---|---|
| Any sexual IPV | 0.04 | 0.04 | 0.08 | 0.05 |
| Forced sexual intercourse | 0.04 | 0.04 | 0.08 | 0.05 |
| Unapproved sexual acts | 0.02 | 0.02 | 0.03 | 0.03 |
| Any emotional/psychological IPV | 0.15 | 0.15 | 0.18 | 0.16 |
| Humiliated | 0.11 | 0.11 | 0.15 | 0.12 |
| Threatened with making harm | 0.06 | 0.06 | 0.09 | 0.07 |
| Threatened with abandonment | 0.08 | 0.08 | 0.10 | 0.09 |
| Observations | 15,110 | 14,049 | 421 | 640 |

Notes: The table provides sample means of outcomes for sexual IPV and emotional/psychological IPV. Sample means for the whole sample are presented in column 2. Sample means for the sub-samples exposed to regular rainfalls, droughts, and floods are reported in columns 3 through 5, respectively. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian DHS and the Udel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

## S5.3. Additional Outcomes: Channels of Impact

In our analysis, we explore the role of five different channels through which the exposure to rainfall shocks could have affected the experience of P-IPV: (i) household income and consumption; (ii) employment; (ii) women's financial independence and control over income; (iv) intrahousehold dynamics; and (v) men's alcohol consumption and violent behavior. Below, we describe in detail the construction of our outcomes for the study of mechanisms and present descriptive statistics of these outcomes.

### (i) Household Income and Consumption

- **Income per capita**: Value of household total income (cash and in-kind) divided by the number of household members (deflated; PER$ of year 2012).
- **Consumption per capita**: Value of household total consumption (cash and in-kind) divided by the number of household members (deflated; PER$ of year 2012).

**(ii) Employment**

- **Employed**: Indicator that takes the value of 1 if the woman/partner were employed at any point during the past twelve months.

- **Agricultural worker**: Indicator that takes the value of 1 if the woman/partner were employed in the agricultural sector (agricultural activities) at any point during the past twelve months.

**(iii) Women's Financial Independence and Control Over Income**

- **Paid work**: Indicator that takes the value of 1 if the woman was employed and received money for her work at any point during the past twelve months.

- **Earns more than partner**: Indicator that takes the value of 1 if the woman reported having equal or higher earnings than her partner during the past twelve months.

- **Controls own income**: Indicator that takes the value of 1 if the woman has full control over her income.

- **Controls partner's income**: Indicator that takes the value of 1 if the woman has full control over her partner's income.

**(iv) Intrahousehold Dynamics**

- **Decision-making autonomy**: Indicator that takes the value of 1 if the woman participates (alone or together with her partner/other people) in any household decision-making on: health care; making large household purchases; making daily household purchases; visits to family or relatives; or food to be cooked each day.

- **Justification of wife-beatings**: Indicator that takes the value of 1 if the woman agrees that wife-beating is justified in any of the following cases: if she goes out without telling her partner; if she neglects the children; if she argues with her partner; if she refuses to have sex with her partner; or if she burns the food that she is cooking.

- **Marital control**: Indicator that takes the value of 1 if the woman reports that her partner exhibits any of the following behaviors: gets jealous if she talks with another man; accuses her of being unfaithful; does not allow her to meet her friends; tries to limit her contact with her family/relatives; insists on knowing where she is at all times, or; does not trust her with money.

- **Emotional support**: Indicator that takes the value of 1 if the woman reports that her partner exhibits any of the following behaviors: is tender or lovely with her; spends free time with her; considers her opinions; respects her wishes; or respects her rights.

**(v) Men's Alcohol Consumption and Violent Behavior**

- **Drinks alcohol**: Indicator that takes the value of 1 if the woman reports that her partner drinks alcoholic beverages.

- **Drinks alcohol frequently**: Indicator that takes the value of 1 if the woman reports that her partner drinks alcoholic beverages frequently.
- **Alcohol-related aggression**: Indicator that takes the value of 1 if the woman reports that at least one act of P-IPV perpetrated by her partner during the past twelve months occurred when he had drunk alcohol before.

We present sample means of these outcomes in Table S5.3.

**Table S5.3: Sample Means of Other Forms of IPV**

| | Whole Sample | Regular Rainfalls | Drought | Flood |
|---|---|---|---|---|
| Household Income and Consumption | | | | |
| Household income per capita (total) | 172.93 | 171.88 | 170.01 | 200.18 |
| Household income per capita (cash) | 121.56 | 120.97 | 115.29 | 139.47 |
| Household consumption per capita (total) | 153.10 | 151.94 | 153.75 | 181.25 |
| Household consumption per capita (cash) | 96.23 | 95.54 | 93.49 | 114.70 |
| Employment | | | | |
| Woman is employed | 0.58 | 0.58 | 0.55 | 0.59 |
| Woman is an agricultural worker | 0.37 | 0.37 | 0.44 | 0.35 |
| Partner is employed | 0.99 | 0.99 | 1.00 | 0.99 |
| Partner is an agricultural worker | 0.59 | 0.59 | 0.78 | 0.46 |
| Women's Financial Independence and Control Over Income | | | | |
| Paid work | 0.03 | 0.03 | 0.02 | 0.04 |
| Earns more than partner | 0.09 | 0.09 | 0.04 | 0.12 |
| Controls own income | 0.16 | 0.16 | 0.09 | 0.16 |
| Controls partner's income | 0.16 | 0.15 | 0.14 | 0.23 |
| Intrahousehold Dynamics | | | | |
| Woman's decision-making autonomy | 0.08 | 0.08 | 0.06 | 0.07 |
| Woman's justification of wife-beatings | 0.92 | 0.92 | 0.88 | 0.92 |
| Men's emotional support | 0.98 | 0.98 | 0.97 | 0.96 |
| Men's marital control | 0.37 | 0.37 | 0.43 | 0.39 |
| Men's Alcohol Consumption and Violent Behavior | | | | |
| Drinks alcohol | 0.71 | 0.71 | 0.73 | 0.65 |
| Drinks alcohol frequently | 0.05 | 0.05 | 0.06 | 0.05 |
| Alcohol-related aggression | 0.08 | 0.08 | 0.12 | 0.07 |
| Observations (DHS) | 15,110 | 14,049 | 421 | 640 |
| Observations (ENAHO) | 11,095 | 10,308 | 274 | 513 |

Notes: The table provides sample means of outcomes used for the analysis of channels of impact. Sample means for the whole sample are presented in column 1. Sample means for the sub-samples exposed to regular rainfalls, droughts, and floods are reported in columns 2 through 4, respectively. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian DHS, the 2005-2014 Peruvian ENAHO, and the UDel's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series V 5.01.

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