A Drop of Love?

Rainfall Shocks and Spousal Abuse: Evidence from Rural Peru

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Abstract

Do women suffer more abuse from their partners during times of economic hardship? We address this inquiry by exploring whether and how exposure to rainfall shocks affects violence against women in rural Peru, where agriculture constitutes the main economic activity and crop yields largely depend on weather realizations. We find sizable impacts: exposure to an event of drought (but not flood) during the last rainy season increases the prevalence of physical violence perpetrated by male partners against women by 65 percent. Moreover, we find that women are 60 percent more likely to suffer physical trauma from the abuse – a result that is caused by the experience of more frequent, but not more severe, violent acts. These results may be explained by two underlying mechanisms: a decline in the time couples spend together that results from changes in spouses' employment patterns and that increases suspicion towards women and an increase in stress levels that leads to undesired behaviors such as alcohol disorders and alcohol-related aggressions from men.

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1 Introduction

Worldwide, over 30 percent of women have experienced some form of violence from their partners (WHO 2013). This form of violence, also known as intimate partner violence (hencerforth IPV), is both a cause and a consequence of gender inequality and experts agree that IPV against women arises from gender disparities at structural, society, communal, and relationship levels (WHO 2012). These disparities are related to patriarchal social norms and lower status of women in societies, low levels of women's empowerment, lack of family, social and legal support for women, amid other factors.

Importantly, poverty and low income levels have been regarded as major risk factors associated with IPV against women at all of its levels: individual, relationship, societal, and communal (Heise and García-Moreno 2002; WHO 2012). Thus far, the bulk of economics literature on IPV against women has focused on how low relative income levels among partners – that is, low income level of one partner relative to that of the other – affect IPV against women. Yet, the question of whether and how absolute low income levels and economic stress in the household affect spousal abuse has been addressed to a lesser extent.

Responding to this question is important for several reasons. First, the question of how economic hardship affects marital conflict and quality has long prevailed in the social sciences and its origin can be traced back to the Great Depression (Komarovsky 1940; Bakke 1940). Up to date, there is inconclusive evidence on whether IPV against women tends to increase with economic hardship: while some studies have documented a positive effect (Van der Berg and Tertilt 2013; Schneider et al. 2016) others have found no effect of economic stress on IPV against women (Iyengar 2009; Aizer 2010).[1] Second, in many societies, families have traditionally relied on only one source of income for subsistence (Dercon 2002). This is especially the case in developing countries where traditional gender norms together with highly concentrated markets around a single activity have led to a low participation of women

[1]Several explanations have been provided to explain why economic stress can lead to increases spousal abuse, including the elevated costs of separating from a partner during times of economic stress (Stevenson and Wolfers 2006), emotional cues arising from economic hardship or income loss (Card and Dahl 2011), and the increased time women spend with their potential victimizers due to increased unemployment (Dugan et al. 1999).

in the labor force (Alesina et al. 2013).[2] Finally, and from a policy perspective, responding to this question is important for the design and implementation of social policies aiming at preventing violence against women especially during times of economic adversity, such as recessions or natural disasters, when the social costs generated by increased IPV against women can be particularly high (WHO-LSHTM 2010).[3]

In this paper, we address this question and investigate whether and how income shocks – in the form of exposure to rainfall shocks - affect physical IPV against women in rural Peru. The choice of focusing on rural Peru is motivated by three considerations. First, the prevalence of lifetime IPV against women there is one of the highest the world around. According to a cross-country study, nearly 60 percent of women in rural Peru ever experienced some form of abuse from their partners (WHO 2005).[4] Second, income-generating activities there are highly concentrated around agriculture and households have limited access to credit markets (Trivelli 2000). This makes households incapable of diversifying risk by working in different activities or to smooth consumption through credit when faced with negative income shocks. Finally, the lack of irrigation infrastructure makes that agricultural yields largely depend on weather realizations there (Ponce et al. 2015).

Two other recent studies have analyzed whether IPV against women is affected by exposure to rainfall shocks. In a cross-country study in Sub-Saharan Africa, Cools et al. (2017) find that exposure to rainfall shocks increase violence against women but not women's overall risk of being abused for the first time in their marriages. Using data from Tanzania, Abiona and Foureaux-Koppensteiner (2017) find that exposure to dry rainfall shocks increase the

[2]Perhaps related to this observation is the fact that the prevalence of IPV against women is the highest in developing countries (WHO 2005).

[3]Economic loses for society include reparation costs, medical treatment, and lost productivity. Recent estimates indicate that IPV againt women represents nearly 3.3 percent of lost GDP for the U.S., with costs levying disproportionately in low- and middle-income countries (CDC 2003; WHO 2005). Estimates for developing countries suggest that the costs against women vary between 1.5 and 4 percent of GDP (Morrison and Orlando 1999; Ribero and Sanchez 2005). These costs are mostly related to lost productivity, in the form of reductions in earnings or forgone labor income that arise after instances of abuse experienced by women. There is also evidence of other unobserved impacts that are not usually taken into consideration when calculating the costs of IPV against women, such as health problems women victims of IPV and their children experience over time (Morrison and Orlando 2005).

[4]Recent estimates indicate that the lifetime prevalence of IPV against women there can be as high as 65 percent (INEI 2018).

incidence of violence against women. We go beyond these studies in a number of ways. In this regard, we are the first study that explores the effect of exposure to rainfall shocks on IPV against women in a Latin American developing country where gender norms can differ from those in Africa. We also advance in the literature by obtaining estimates of the effect of exposure to rainfall shocks on IPV against women that are net of the spacial correlation in weather events that has been documented previously (Cools et al. 2017). In fact, we show that only exposure to temporal, local rainfall shocks drive our main results. Lastly, we explore a range of potential mechanisms through which exposure to rainfall shocks can impact IPV against women. To our knowledge, ours is the first study analyzing this relationship in such a comprehensive way.

We bring together historical data on rainfall levels and information on instances of abuse experienced by women in the hands of their partners and find that physical IPV against women increases by 65 percent when households are exposed to droughts, but not floods, during the last rainy season in rural settings of the Peruvian Andean region. We also find an increase of about 60 percent in the probability a woman suffers physical trauma from the abuse following exposure to an event of drought. The increase in physical sequelae from the abuse is driven by more frequent but not more severe violent acts inflicted by male partners. Moreover, we find that the increase in domestic violence following exposure to events of drought in the municipality does not extend to other members of the household (such as children) but is only directed towards women.

In a complementary analysis, we find that household income per capita declines by 20 percent and household consumption per capita declines by 15 percent following exposure to an event of drought. Despite the decrease in family income, we do not find changes in relative income between partners. This indicates that the equilibrium in terms of the distribution of power across partners is not altered – a result that is also corroborated by no significant impact on indicators for woman's autonomy in household decision-making.

By contrast, we do find changes in employment patterns that differ across men and women. In particular, we find an increase in the probability men work as dependent, instead of independent, agricultural workers and a decline in female employment following exposure to events of drought. This finding suggests that men spend more time away from home since they have to work in farming activities in lands that are presumably farther away from the municipality of residence whereas women spend more time at home. We argue that time constraints arising from changes in employment patterns originate a lower interaction between partners in the relationship leading to marital instability and thereby subsequent violence exerted against women. In fact, we show that men are more likely to adopt controlling behaviors that are related with suspicion towards women. Yet, our results may also be explained by undesired behaviors such as alcohol-use disorders from men that can arise because of economic stress and can led to spousal abuse. In line with this argument, we find an increase in alcohol-related aggressions from male partners following exposure to an event of drought, as reported by women.

Our results do not support the conventional wisdoms that IPV against women is mainly affected by relative changes in spouses' income that can alter women's outside options or by a relative increase in female employment that could lead to the so-called "male backlash" effect during times of economic stress. Instead, our results are more aligned with the less explored "family stress model," whereby economic hardship lead to economic stress and economic strain that deteriorates the marital quality and opens space to conflict between partners (Conger et al. 1980). We regard this finding as our main contribution to the literature analyzing the relationship between income and violence against women.[5]

The rest of the paper is organized as follows. In section 2, we revise the related literature on income and violence against women. In section 3, we describe the data we use for the empirical analysis. In section 4, we describe the regression framework that will be used to uncover the effects of exposure to rainfall shocks on IPV against women. The results are presented in section 5. In section 6, we present the results for the channels of impact. In section 7, we present the conclusions of the study.

[5]Our work also contributes to the large body of research on climate on interpersonal conflict by providing a clear mechanism through which changes in climatic patterns may increase the risk of conflict (Burke et al. 2015).

2 Related Literature

Seminal papers in the economics literature addressing intimate partner violence against women propose that improvements in out-of-marriage options for women translate into higher empowerment and bargaining power, which in turn, translates into lower levels of intimate partner violence (Tauchen et al. 1991; Farmer and Tiefenthaler 1996). Subsequently, empirical evidence from developed countries suggests that improved aspects of women's empowerment indeed translate into lower intimate partner violence. These aspects related to women empowerment include income and labor market participation (Aizer 2010; Van der Berg and Terlit 2012), education (Erten and Keskin 2018), as well as changes in laws regulating divorce (Stevenson and Wolfers 2006) and changes in mandatory versus recommended arrest laws in cases of domestic abuse (Iyengar 2009).

A related explanation for a reduction in intimate partner violence as a consequence of women empowerment comes from criminology. This explanation proposes that female employment reduces exposure to risk as women spend less time together with their abusive partners (Dugger et al. 1999). Empirical evidence is mixed on this regard, it is rejected using data from a developed country such as the U.S. (Aizer 2010) but it is a potential channel in a developing country such as India (Chin 2011).

However, it is possible that women empowerment translates into higher intimate partner violence. Under an instrumental use of violence, one probable explanation for this result is that women empowerment intensifies the partner's incentives to use violence or threats of violence to reinstate a dominant position in the relationship. In particular, an intimate partner may use violence, or threats of violence, in order to control their wives behavior or resources under her control (Bloch and Rao 2002; Eswaran and Malhotra 2011; Bobonis, Gonzalez-Brenes and Castro 2013; Hidrobo et al. 2016).

The possibility that intimate partner violence increases with women empowerment is also proposed by the theory of male backlash from the sociological literature (Faludi 1992; Macmillan and Gartner 1999). This theory proposes that women empowerment threatens culturally established gender norms, which in turn, triggers men violence against women as an instrument to reinstate male dominance and female dependence. Empirical evidence is also mixed on this regard, some studies reject this explanation (Aizer 2010; Chin 2011; Field et al. 2016) while others find it plausible (Erten and Keskin 2018; Guarnieri and Rainer 2018). From within economics, the theory of identity (Akerlof and Kranton 2000) proposes that social categories, gender norms, and ideals condition decisions. When actions conform to norms and ideals, utility increases, when they do not, utility decreases. The theory of identity can accommodate the male backlash implication of empowerment and intimate partner violence (Tur-Prats 2017).

The expansion of cash and in kind transfers over the last two decades provides the opportunity to test some of these predictions in less developed country contexts. Evidence of the effects of conditional cash transfer programs (CCTs) on violence against women is mixed and largely depends on the form of violence. Most of the existing evidence comes from Latin American countries given the rapid expansion of CCTs therein. In a recent study, Bobonis et al. (2013) find that the Mexican *Oportunidades* program reduced physical violence against women by 40 percent. However, beneficiary women were also more likely to be victims of threats of physical violence, with no associated physical abuse. Also evaluating *Oportunidades*, Angelucci (2008) finds that small transfers reduced partner's aggressive behaviors by 37 percent, but large transfers increased spousal abuse.[6]

Other mechanisms related to intimate partner violence are stress, economic hardship and day-to-day conflict over financial resources that might escalate into aggression and batter. Evidence from a food assistance program in Ecuador suggests that as financial constraints loosen up, day-to-day conflict declines and this in turn reduces intimate partner violence (Buller et al 2016). There is also evidence from the U.S. that supports the stress channel as a probable explanation of intimate partner violence, in particular emotional cues that induces loss of male self-control and triggers violence (Card and Dahl 2011).

Several recent empirical studies explore the relationship between women's empowerment and intimate partner violence using historical events or cultural and custom heritage as

[6]The effects of *Oportunidades* on IPV against women, however, have been found to be short- rather than long-lasting (Bobonis and Castro 2010; Bobonis et al. 2015).

sources of exogenous variation for the identification of causal effects. These include the heritage from stem families in Spain (Tur-Prats 2015, 2017), cultural traditions in ancient agricultural societies that determine gender roles (Alesina et al. 2016), and the Anglo-French colonial division of Cameroon after World War I (Guarnieri and Rainer 2018).

Our paper relates directly to another relatively new strand in the literature of spousal abuse exploring the relationship of weather shocks and IPV against women. As far as we are aware, only a handful of studies address this relationship. Rainfall shocks are arguably random unexpected events from nature that provide a setting to explore the effects of income and labor supply on domestic violence. Sekhri and Stooreygard (2014) use district-level data from official crime records in India to show that rainfall shocks translate into a higher number of dowry killings and domestic abuse. Two other papers address directly the relationship between exposure to rainfall shocks and intimate partner violence using data from household surveys following the WHO recommended standards for recording violence data. Cools et al. (2017) use data from the Demographic and Health Surveys from several Sub-Saharan countries and find that exposure to rainfall shocks increase IPV against women but not the overall risk of suffering abuse for the first time in a marriage. Abiona and Foureaux-Koppensteiner (2017) use data from Tanzania and find that exposure to rainfall shocks increase the prevalence of intimate partner violence, in particular of physical abuse. They use household survey data that employ conflict tactic scale like questions to measure violence against women inflicted by her current partner. Further evidence suggests that women empowerment (being the household head or having access to inheritance rights) mitigates the negative effect of exposure to rainfall shocks on spousal abuse.

These three studies find that the lack of rainfall, as opposed to the excess of rainfall, is behind the increase of violence against women. This likely relates to the way dry shocks affect household income and in particular husbands and wives specific sources of incomes as well as their allocation of time between home and market production. Unfortunately, none of these studies provides evidence on how these rainfall shocks affect household or individual income and labor supply.

Only one study addresses the potential link between rainfall shocks and intimate partner violence through their impact on income and labor supply. Chin (2011) use data from the National Family Health Survey from India combined with data on rainfall variation over time and across Indian states classified as either wheat-growing or rice-growing states. In contrast to the cultivation of wheat that requires the use of the plough, rice cultivation rests on weeding and transplanting favoring the utilization of female labor. Since rice cultivation requires large amounts of water, state-level rainfall above its historical average in rice-growing regions generates a positive shock on the demand for female employment. She finds that rainfall shocks reduce intimate partner violence and increase women's employment in rice-growing regions. According to her results, the reduction in violence seems to respond to a decrease in exposure risk as women spend more time outside of the household and away from their partners.

In a related study, Krupoff et al. (2017) address the way weather shocks affect male-specific earnings and how this may translate into changes in IPV against women in Indonesia. Using ocean temperature data, they find that negative shocks on fishing conditions reduce men income borne on fishing activities, a traditional male-specific source of income in Indonesian coastal villages. These negative shocks also translate into lower acceptance of IPV by wives. A likely explanation for these findings is that as the income of husbands shrinks the relative income of wives increases, increasing their bargaining power, which, in turn, reduces wives' acceptance of violence. However, how a lower acceptance of violence translates into a reduction of actual instances of IPV against women is open to further investigation.

In the rest of the paper, we look into the relationship between exposure to rainfall shocks and IPV against women in rural settings ofnthe Peruvian Andean region and assess probable channels of transmission including changes in male-female relative income and labor supply, interpersonal traits and living arrangements, and male alcohol consumption.

3 Data and Measures

3.1 Data Sources

Motivated by the question of whether and how exposure to rainfall shocks affect IPV against women, in our principal empirical analysis we bring together data on monthly rainfall levels and instances of abuse experienced by women in rural Peru, in addition to socio-demographic characteristics of these women and of their partners. Information on rainfall levels is retrieved from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01) and information on instances of abuse experienced by women come from repeated annual cross-sections of the Peruvian Demographic and Health Surveys (DHS) over the period 2005-2014.

The Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01) provides global geo-referenced information of the air temperature and rainfall levels on a monthly basis for the period between 1900 and 2014. Rainfall levels are provided for each node in a two-dimensional layer of the world's map, and each node covers a spatial resolution of 0.5×0.5 degrees (a 0.5 degree corresponds to approximately 56 kilometers at the equator). Monthly average rainfall levels of each node are calculated using information from 20 nearby weather stations.

We superpose the rainfall nodes over the Peruvian map layer and extract those nodes that overlap the Peruvian boundary. A total of 483 rainfall nodes are required to cover the extent of the Peruvian layer entirely. The total surface of the Peruvian territory is 1.285 million squared kilometers and the surface coverage of roughly 3,100 squared kilometers by a rainfall node (recall that a 0.5 degree corresponds to approximately 56 kilometers) is consistent with the fact that over 400 rainfall nodes are needed in order to cover the whole extension of the Peruvian territory.

Next, we calculate monthly rainfalls at the municipality level.[7] This procedure is ex-

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

plained with further detail in Appendix A. In short, we proceed by first extracting the nodes that overlap each municipality boundary (in what follows, we refer to the set of nodes covering the municipality boundary as its grid) and then calculate municipality-level rainfalls based on a weighted average of the rainfall levels of each of its nodes, where the weights correspond to the fraction of the municipality's polygon that is covered by the node.[8] The resulting dataset is at the municipality-by-year-by-month level.

The Peruvian DHS are publicly available and collect individual-level information on a range of health indicators and socio-demographic characteristics of women of reproductive age (15-49 years). Important for this study, the DHS include a module specific to spousal abuse, comprising information about episodes of violence experienced by women.

The module specific to spousal abuse consists of a shortened and modified version of the Conflict Tactic Scales (CTS) elaborated by Strauss (1970, 1990). This module contains information about lifetime and recent events of spousal abuse and controlling behaviors exerted by the woman's partner and is directed to women who have ever been in a relationship. This information is complemented with a detailed description of the relationship (including the marital status and the duration of the relationship in years) and a socio-demographic profile of the partner.

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 partner ever perpetrated a series of behaviorally specific acts, including physical, psychological, and sexual abuse. One empirical advantage of the Peruvian DHS is that they collect information about recent violent events experienced by women. Specifically, women are asked about instances of abuse perpetrated by their partners during the 12 months prior to the survey date. This is important for determining whether the experience of abuse is recent or from the past and constitutes an improvement relative to other surveys that only record information about lifetime experience of violent events.

municipalities across the Peruvian territory.

[8]The average surface in our sample of municipalities that belong to the sampling frame of the DHS is 466 squared kilometers. This is consistent with the fact that the boundary of the average municipality is contained within 2.13 rainfall nodes and each node covers approximately 41 percent of its surface.

The DHS protocol for the application of the module specific to spousal abuse is intended to maximize the respondent's safety and confidentiality. This module is applied to only one women per household and is not applied if privacy is not ensured. These requirements aim at reducing information disclosure and, because of this, response rates are relatively high, with less than 2 percent of women refusing to respond the questionnaire.

Besides providing information on measures of IPV and marital control exerted by the male partner, the DHS also enquire women about living arrangements and attitudes that are specific to the relationship. Specifically, information about women's participation in household decision-making and tolerance of violence as well as partner's attitudes towards woman's rights/freedom of movement and emotional support towards his partner – as reported by the woman – is also recorded. The DHS, however, do not collect information on individual income nor on family income and consumption. For this reason, we appeal to an external data source in order to determine how income and consumption is affected by exposure to rainfall shocks.

Individual-level information obtained from the DHS is then matched with monthly data on rainfall levels based on the municipality identifier and the survey date (month and year). We complement this data with municipality-level monthly information on the air temperature, soil temperature, and soil moisture (volumetric soil water content). Information on air temperature levels is obtained from the same data source as that used for retrieving monthly rainfall levels and information on soil characteristics is obtained from the ERA-Interim 2004-2014 Archive on Global Atmospheric Reanalysis (Berrisford et al. 2011) produced by the European Centre for Medium-Range Weather Forecasts (ECMWF).[9]

Finally, our external data on income come from the Peruvian National Household Survey (ENAHO for its Spanish acronym) produced by the Instituto Nacional de Estadística e Informática. Alike the DHS, we match individual- and family-level information from the ENAHO with monthly data on rainfall levels using the municipality identifier and survey

[9]The ERA-Interim provides global geo-referenced information for a number weather parameters. This information is publicly available and is provided on a daily and monthly basis at a detail of 0.75×0.75 degrees. For additional details visit: https://www.ecmwf.int/en/forecasts/datasets/archive-datasets/reanalysis-datasets/era-interim.

date. In the next sub-section we explain how we configure both datasets – the DHS and the ENAHO – to match the sample characteristics from one another. It should be clarified, however, that our principal empirical analysis utilizes data from the DHS.

3.2 Sample Selection

The criteria followed to select our sample responds to our empirical objectives. In this line, we are interested in estimating how IPV against women responds to exposure to rainfall shocks in areas where agriculture constitutes the main economic activity and largely depends on weather realizations. Moreover, as the DHS do not contain information on income but this information is gathered from the ENAHO, we configure our sample in such a way to make it comparable across the two surveys. A detailed description of our filtering criteria along with information on the number of observations that we retain in each step of the sample selection procedure is provided in Appendix B.

We begin by selecting our area of study. According to the 1994 Agricultural Census (the latest agricultural census available in Peru before the initial year of our study time frame), 46 percent of the total surface used for agricultural activities in Peru is located in the Andean region (highlands), 36 percent in the Amazonian region, and 18 percent in the Coastal region. Around 74 percent of the land used for agricultural activities in the Andean region relies on rainfed irrigation for cultivation whereas the corresponding figures are 90 percent and 51 percent in the Amazonian and Coastal regions respectively.[10] In terms of agricultural producers, 69 percent of total producers are located in the Andean region as opposed to 17 and 14 percent located in the Amazonian and Coastal regions respectively.[11] As for the labor force, the 1993 Population and Housing Census reveals that 55 percent of all agricultural workers in Peru live in the Andean region (the corresponding figures are 24

[10]The Amazonian region is a tropical rainforest characterized for its humid climate, high precipitation, and dense vegetation.

[11]These figures are similar to the ones obtained from the 2012 Agricultural Census, revealing that 46 percent of the total surface used for agriculture in the country is located in the Andean region, where 70 percent of the agricultural land is rainfed. Also, 64 percent of total producers are located in the highlands whereas 20 and 16 percent were located in the Amazonian and Coastal regions respectively.

percent in the Amazonian region and 21 percent in the Coastal region) and 74 percent of all agricultural workers in the highlands live in rural settings.[12] Based on these figures, we focus on rural areas of the Andean region as our geographical context of study.

In terms of geography, our sample is composed of rural municipalities that are located above 1,000 meters over the sea level. The altitude threshold was chosen to match the definition of the Peruvian highlands.[13] Moreover, since we are interested in municipalities where agriculture is the main economic activity, we drop from our sample all municipalities that are province capitals as these municipalities likely have a lower concentration of the workforce around agricultural activities and are more connected with urban settings, thus allowing for a higher occupational mobility especially during times of adverse weather realizations. Lastly, and for empirical purposes, we retain in our sample all municipalities where we observe women surveyed in two different years over the period of study.[14] Appendix Table B.1 provides details on our geographical filtering/data cleaning procedure.

Appendix Table B.2 provides descriptive statistics at the municipality level. Municipalities in our sample are located between 1,008 and 4,465 meters over the sea level. According to the 1994 Agricultural Census, 7.8 percent of the average municipality's surface is used for agricultural activities and 71 of the cultivated land is rainfed. On average, there are 1,312 agricultural producers in each municipality and each of these producers holds around 0.02 squared kilometers (approximately 2 hectares) of land.[15] Employment in these municipali-

[12]According to the 2007 Population and Housing Census, 50 percent of all agricultural workers in Peru live in the Andean region whereas 28 percent live in the Amazonian region and 22 percent live in the Coastal region. Also, 77 percent of all agricultural workers in the Andean region live in rural settings.

[13]The mountainous region of Peru is located above the 500 meters over the sea level. Pulgar-Vidal (1938) characterizes this region (also known as the highlands) as having a rugged and steep terrain, with varied temperature levels 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). The highlands in Peru can extend until above the 6,500 meters over the sea level.

[14]This last filter responds to our estimation strategy that exploits variation in rainfall levels over time within the municipality. Our results are not sensitive to the inclusion of this filter to select our sample though.

[15]Figures from the 2012 Agricultural Census are not that different: on average, 9 percent of the municipality's surface is used for agricultural activities and nearly 70 percent of total cultivated land is rainfed. Remote sensing data from the Harmonized World Soil Database (HWSD) confirms that the share of the municipality's surface that is used for agricultural activities is nearly 7.5 percent. Rainfed land in the HWSD, however, represents approximately 61 percent of the total cultivated land. The discrepancy between these two figures may be explained by self-reporting in the census. Also, there are 1,670 agricultural producers

ties is mostly concentrated around agricultural activities. According to the 1993 Population and Housing Census, 77 percent of the rural population that is employed in these municipalities report agriculture as the main industry/sector, with 58 percent of all agricultural workers being producers and the rest providing labor to land holders.[16] As for weather and soil conditions, remote sensing information over the period 2004-2014 reveals that average rainfall and air temperature levels during a typical month in the cropping/rainy season are 102 millimeters and 13 degree Celsius respectively. Also during a typical month in the cropping/rainy season, average soil temperature is 15.8 degree Celsius while soil moisture is roughly 38 percent.

These figures reveal that a great deal of the workforce is concentrated around agricultural activities in our sample of municipalities. Moreover, agricultural production in these municipalities mostly depend on weather realizations as evidenced by the fact that crop cultivation heavily relies on rainfall as one of the main production inputs. Lastly, it is important to emphasize that production capacity in these localities is rather low given the small amount of land that the average agricultural producer holds.

We next select individual observations. We focus on women who responded the questionnaire on spousal abuse, who are the female household heads, and who are married or cohabiting and living with their partners in the same dwelling.[17] These filters are applied for several reasons. First, by definition, IPV can only happen if a woman is currently in a sentimental or sexual relationship. Second, given that IPV is a common reason for divorce/separation (Kishor and Johnson 2004), we do not focus on divorcees or recently separated women as experience of IPV for these women can be disproportionately high. Third, given that we are interested in *recent* events of IPV, the report of these events is less likely to happen among widowed women, which is the reason why we exclude them from our sam-

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and each producers holds, on average, 0.025 squared kilometers (2.5 hectares) of land based on the 2012 Agricultural Census.

[16]According to the 2007 Population and Housing Census 77 percent of the rural population that is employed in these municipalities work in agricultural activities and nearly 69 percent of all agricultural workers work in their own land.

[17]Roughly 70 percent of women of reproductive age in rural Peru are married or cohabiting and, of these women, 96 percent live with their partners.

ple.[18] Finally, these filters ensure that the DHS sample of women is similar to that from the ENAHO, since the partner's characteristics in the ENAHO (as opposed to the DHS) are only recorded if the partner is present at home.[19] Our last individual filtering criterion consists of excluding from our sample women who have been living in the municipality for less than one year or do not live in the municipality permanently (visitors). This restriction ensures that all women observed in our sample are not temporary migrants and that they have been living in the municipality during the last cropping/rainy season. Our final sample from the DHS comprises information from 15,110 women living in 495 rural municipalities located in the Peruvian highlands (314 grids). Appendix Table B.3 provides details on individual filtering/data cleaning procedure of the DHS sample.

As for our ancillary data from the ENAHO, our sample is composed of all women of reproductive age, who are the female household heads, who are married or cohabiting and who live with their partners in the same dwelling. Also, we keep in our sample women living in rural areas of the country, but we do not apply any filter for migration status since the ENAHO does not provide any information on the time the person has been living in the municipality where she was surveyed.[20] Finally, and in order to maintain the same geographical context, we retain in our sample from the ENAHO all women living in municipalities that match our DHS sample. The ancillary sample from the ENAHO contains information from 12,146 women living in 351 municipalities (237 grids). Appendix Table B.4 provides details on individual filtering/data cleaning procedure of the ENAHO sample.

3.3 Outcomes

In the empirical analysis we focus primarily on physical IPV. The reason why we focus on physical IPV is that the DHS record information on specific behaviors that do not require

[18]Also, it should be noticed that 6 percent of women in our selected municipalities are divorced or separated and only 0.5 percent of women are widowed.

[19]In our sample of married/cohabiting women, the prevalence of current (last 12 months) IPV among those living with their partners is 13 percent whereas that same figure for those not living with their partners is 8 percent.

[20]In our sample of municipalities from the DHS, 5.4 percent of women reports living in the municipality for less than a year or being visitors.

the respondent to identify as abusive in order to report them. By the contrary, detecting emotional/psychological violence requires that the respondent recognizes a behavior as violence in order to report it and, as such, the report may be subtle to subjective interpretation (Ellsberg and Heise 2005).[21]

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 committed by the male partner to construct different measures of physical abuse experienced by women.

Based on this definition, we construct an indicator that takes the value of 1 if the woman reported that, during the last 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. Our choice of physical IPV occurring during the last 12 months rather than lifetime experience of physical IPV as our principal outcome rests on the fact that we are interested in capturing temporary variations in this indicator that might result from exposure to recently observed rainfall shocks.[22]

We further delve on the characteristics of the abuse and construct an indicator for physical injuries/sequelae from the abuse. This indicator takes the value of 1 if the woman reported that, as a result of the physical abuse inflicted by her partner, she had bruises or lesions, sprains or broken bones/teeth, or needed medical assistance. 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).

[21] We do not focus on sexual violence because of its low prevalence. However, the effect of exposure to rainfall shocks on this and other measures of IPV, including emotional/psychological IPV, are analyzed in section 5.4.

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

It is important to emphasize that both measures of physical IPV against women are constructed from the woman's report and, because of this, some studies have pointed out that they may be subject to reporting error (Kishor 2005; Aizer 2010). In spite of these observations, there is limited evidence on the magnitude and/or direction of this bias and only recently have experts become interested in obtaining accurate measures of instances of IPV. In this line, a recent study based on an experimental design for elucidating the prevalence of different forms of IPV against women in urban Peru documents that underreport is more common among college-educated women but not among the less educated (Agüero and Frisancho 2017). This finding is important for our study since women in rural Peru tend to achieve low educational levels, which supports the fact that the prevalence of physical IPV that is measured based on self-reports by women living in rural settings is accurately estimated.

Given the lack of alternative methods for elucidating accurate figures of violence against women, self-reported measures of IPV are currently being 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). It has also been posited that self-assessed reporting based on a series of questions about specific acts of violence convey more information when compared to a single, generic question such as "ever experiencing some form of violence/abuse" because of the disassociation in the interpretation of the experience of an 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 specific violent act (Kishor and Johnson 2004).

3.4 Measuring Rainfall Shocks

Our interest is to measure exposure to rainfall shocks occurring during the cropping/rainy season. Yet, this season may differ across municipalities given the vast heterogeneity in terms of climate zones across the Peruvian territory. Therefore, we begin by determining the cropping/rainy season of each municipality.

Our methodology for defining the cropping/rainy season of each municipality builds on a simplified version of the Jönsson and Eklundh (2004) program for analyzing time-series of satellite sensor data. Also, given that our main explanatory variable is based on rainfall levels, we refrain from using alternative indicators such as vegetation growth in order to determine the cropping/rainy season of each municipality. Additional details as well as the validation of this methodology are provided in Appendix C.[23]

The determination of the cropping/rainy season of each municipality consist of five steps. First, with previous knowledge that the rainy/cropping season usually lies between the ending and beginning months of two consecutive years, we arrange the data in such a way that the first and last months of the year are anchored in July and June respectively. Second, with information on rainfall levels for each municipality in different months and years over the period 2000-2014 (a time length of 15 years that includes the period of our empirical analysis), we calculate the 25th percentile thresholds in the distribution of municipality rainfall levels of each year and keep the median of those values as our threshold level. Third, we construct indicators for each month when rainfall levels lie above that threshold. Fourth, we retain the months for whom we observe at least 13 years (or at least 85 percent of the total number of years that we observe each municipality-month data point) above that threshold. Finally, we select the earliest and latest month fulfilling the aforementioned condition and define the cropping/rainy season as the continuum of months that lie in between these two months inclusive.

Panel A of Figure 1 shows the starting months and the average duration (symbolized by the color and size of the circles respectively) of the cropping/rainy season across rural municipalities in the Peruvian highlands. In our sample, the cropping/rainy season usually starts between September and October each year and ends between April and May of the following year. The average duration varies between 7 to 8 months, with a minimum of 4 and a maximum of 9 months. Panel B of Figure 1 depicts the average monthly precipitation

[23]In Appendix D we show that our estimates remain unchanged when using vegetation growth to calculate the timing and length of the cropping/rainy season of each municipality.

for each season (cropping/rainy and dry) in each year over the period 1950-2010. Average monthly precipitation is around 90 millimeters during the cropping/rainy season and around 20 millimeters during the dry season.

Once we have determined the cropping/rainy season of each municipality, we can compute the historical rainfall levels observed during this season for each year included in our dataset. However, as our measure for physical IPV is defined over the last 12 months, we need to take this into consideration when determining whether a woman was exposed or not to a rainfall shock in the past year.[24] We follow Kudamatsu et al. (2016) and compute a synthetic measure of the rainfall level observed during the last rainy season based on a weighted average of the rainfall levels observed in the municipality in the year the woman was surveyed and the previous year.

Let R_{j1} and R_{j2} be the rainfall levels observed in the municipality in the current and previous years respectively. Then, the synthetic rainfall level observed during the last rainy season for a woman who was surveyed in municipality j in date (month of year) d is computed as follows:

$$R_{jd} = \omega_{j1} \cdot (R_{j1}) + (1 - \omega_{j1}) \cdot (R_{j2}) \ ,$$

where ω_{j1} is the weight ascribed to R_{j1}. Weights are calculated based on the time difference (in months) between the survey month and the month corresponding to the end of the last harvesting season h_{j1} (or, equivalently, the month prior to the beginning of the most recent cropping/rainy season). Formally, we compute weights as follows: $\omega_{j1} = (m - h_{j1})/12$, where m indexes the survey month. For ease of exposition, we refer to this measure as the rainfall level observed during the last rainy season from this point forward.

Once the rainfall level observed during the last rainy season has been computed, we construct indicators for exposure to rainfall shocks based on the distribution of municipality-specific rainfall levels during the cropping/rainy season over the period 1950-2010. We define

[24] For instance, it can be the case that the cropping/rainy season of a given municipality lies between the months of November and April of two consecutive years. If a woman who is living in that municipality was surveyed in January of year 2010, then it may be the case that the relevant cropping/rainy 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.

exposure to episodes of drought and flood in the following way. Exposure to an episode of drought, denoted by $Drought_{jd}$, takes place when the rainfall level observed during the last rainy season falls below the 5th percentile of the local distribution of rainfalls. Similarly, exposure to an episode of flood, denoted by $Flood_{jd}$, takes place when the rainfall level observed during the last rainy season falls above the 95th percentile of the local distribution of rainfalls.[25]

In our sample of municipalities, the average 5th and 95th percentiles in the distribution of municipality-specific rainfall levels over the period 1950-2010 are 74 and 131 millimiters respectively. Also, a one standard deviation relative to the long-term (1950-2010) local rainfall mean is about 18.5 millimeters. This implies that the 5th and 95th percentiles are, on average, 1.5 standard deviations below and 1.6 standard deviations above the long-term local rainfall mean respectively.

Panel A of Figure 2 shows the distribution of rainfall shocks across the Peruvian territory. In total, there are 140 rainfall shocks in our sample: 50 events of drought and 90 events of flood. From the 495 rural municipalities in the Peruvian highlands, 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. Panel B of Figure 2 shows the fraction of municipalities for whom we observe an event of drought or flood over the period 2005-2014. We observe rainfall shocks in almost all the years of our study time frame.

3.5 Descriptive Statistics

In Panel A of Table 1 we present descriptive statistics of individual-level characteristics from our main sample according to exposure to rainfall shocks during the last rainy season. In column 2, we present descriptives for the whole sample. The average woman in our sample is 34.5 years old and has attained almost 5.5 years of education, which corresponds to the

[25]Other studies have used standardized precipitation to measure exposure to droughts or floods during the cropping/rainy season (Rocha and Soares 2015; Andalón et al. 2016). In Appendix D we test for the robustness of our estimates when re-defining exposure to events of drought and flood based on standardized precipitation.

incomplete primary educational level. This figure speaks of the low educational levels of women living in rural areas. Also, 62 percent of women in our sample 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 incomplete secondary educational level. Most of the couples in the 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.[26]

Columns 3 through 5 present descriptives according to exposure to different rainfall shocks: regular rainfalls, droughts, and floods respectively. In terms of individual observations, 421 women (around 2.8 percent of individual observations in our sample) were exposed to an event of drought, 640 women (around 4.2 percent of individual observations in our sample) were exposed to an event of flood, and the rest (14,049 women) were exposed to regular rainfall levels during the last rainy season. Except for ethnicity in the case of both women exposed to droughts and floods and formal marriage as the living arrangement of women exposed to droughts, there appears to be balance between the characteristics of women exposed to either droughts or floods and the characteristics of women who were exposed to regular rainfall levels during the last rainy season.

Adjusted differences between sample means of women exposed and not to rainfall shocks are obtained by regressing each characteristic on the indicator for exposure to an event of drought or the indicator for exposure to an event of flood during the last rainy season and including survey-month, survey-year, and municipality fixed effects as conditioning variables in the regressions. In column 6 we present the adjusted differences that result when restricting the sample to include women exposed to an event of drought or regular rainfall levels during the last rainy season. Column 7 repeats the same exercise but alternating with exposure to an event of flood or regular rainfall levels during the last rainy season. None of the resulting adjusted differences are statistically significant.

[26]According to the official reports from the 2007 Population and Housing Census, 52 percent households reported cohabitation. This figure is higher than that from the 1993 Population and Housing Census, where 40 percent households reported living together but not being formally married.

In Panel B of Table 1 we present descriptive statistics of municipality-level characteristics, where we have previously collapsed the data to obtain observations at the municipality-by-month-by-year level. All descriptives are computed for the last cropping/rainy season. Average monthly rainfall level is 104 millimeters and the air temperature during a typical month in this season is around 12.8 degree Celsius. Soil temperature is around 3 degrees higher than the air temperature and roughly 34 percent of the soil volume is liquid during the cropping/rainy season. Adjusted differences show that average rainfall levels are nearly 30 millimeters lower and 30 millimeters higher during droughts and floods respectively when compared to periods of regular rainfalls. Interestingly, the air temperature is higher during droughts and lower during floods relative to periods of regular rainfalls. There is no difference in terms of soil temperature and, despite the fact that it is statistically significant in periods of drought, the difference between soil moisture across different rainfall shocks is virtually zero.

In Table 2 we present descriptive statistics on individual income and family income and consumption from the ancillary sample from the ENAHO. In our ancillary sample from the ENAHO, 312 women (around 2.6 percent) were exposed to an event of drought, 560 women (around 4.6 percent)) were exposed to an event of flood, and the rest (11,247 women) were exposed to regular rainfall levels during the last rainy season. Relative to the DHS sample, women (and their partners) in the ENAHO sample are older and have slightly lower years of education.[27] Woman's and partner's ethnicity shows a similar pattern than that from the DHS sample, although we find a lower share of women responding being formally married relative to the DHS sample. Adjusted differences show balance across the majority of individual characteristics in the ENAHO sample.

[27]This may partly be a result of the oversampling of women of reproductive age in the DHS which creates that the average age of surveyed women centers around 35 years. Because younger cohorts tend to achieve higher educational levels in Peru, this may also explain why the average years of education of women in the DHS is higher than that from women in the ENAHO.

4 Regression Framework

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

$$P\text{-}IPV_{ijd} = \alpha + \beta^D \cdot Drought_{jd} + \beta^F \cdot Flood_{jd} + X'_{ijd}\,\gamma + Z'_{jd}\,\delta + I_j + I_m + I_t + \varepsilon_{ijd}\ , \quad (1)$$

where $P\text{-}IPV_{ijmt}$ is the outcome for physical IPV experienced by woman i living in municipality j who was surveyed in date (month of year) d, $Drought_{jd}$ and $Flood_{jd}$ are the indicators for exposure to an event of drought and exposure to an event of flood during the last rainy season respectively, X'_{ijd} is an array of woman, partner, and relationship characteristics, Z'_{jd} comprises municipality characteristics of the last rainy season and that can potentially determine agricultural yields, I_j, I_m, and I_t are municipality, survey-month, and survey-year fixed effects respectively, and ε_{ijmt} is an error term.

In the most parsimonious specification, we include municipality fixed effects to account for locality-specific weather characteristics as well as local characteristics that are invariant over time but can potentially determine the prevalence of physical IPV against women such as social norms, societal/community structure, status of women in the society, amid others. We also include survey-month fixed effects to control for seasonal changes in the weather within the year that are general to all municipalities. Finally, we include survey-year fixed effects to capture aggregate shocks impacting all rural municipalities in a given year.[28]

Additional specifications include woman, partner, and relationship characteristics. Specifically, we include indicators for the woman's age, educational attainment, and ethnicity

[28] One of such aggregate shocks impacting all municipalities in a specified period of time is the so-called El Niño Phenomenon. 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 Niña, as opposed to El Niño, is the climatic pattern that describes a cooling phase of the surface waters. El Niño phenomenon is known to cause unusually high-intensity rainfalls in the Peruvian highlands that lead to agricultural loses. In the time span of our study, this phenomenon was observed in the period 2005-2006 and 2009-2010 according to the Peruvian National Service for Meteorology and Hydrology (SENAMHI for its Spanish acronym).

(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. These additional controls may remove individual- as well as couple-specific characteristics that have been found to determine IPV against women (WHO 2012) and whose failure to control for may confound the effects of exposure to rainfall shocks on physical IPV against women.

In our most comprehensive specification we include, on top of the aforementioned controls, other weather and soil characteristics observed during the last rainy season that could potentially determine agricultural yields. In particular, we include the air temperature (in degree Celsius), soil temperature(in degree Celsius), and soil moisture (percent of soil volume that is water) as conditioning variables in the regressions. As shown by the descriptive statistics, changes in these variables are closely related with changes in rainfall levels and all of these are regarded as factors determining agricultural yields (Van Ittersum and Rabbinge 1997; Van Ittersum et al. 2003; Nearing et al. 2004). Thus, the inclusion of these variables as additional controls in the regressions serve to partial out the effects of other potential crop yield determinants that may covary with rainfall levels and whose failure to control for may result in bias estimates of the effects of interest.[29] These variables are calculated for the last rainy season, in a similar manner that we calculate the (synthetic) rainfall level during the last rainy season.

We are interested in estimating β^D and β^F, the coefficients on the indicators of exposure to events of drought and exposure to events of flood respectively. These coefficients measure the effect of exposure to each of these rainfall shocks during the last rainy season on measures of physical IPV experienced by women. In estimating these coefficients, we rely on the assumption that temporary, local rainfall shocks – conditional on the set of observed characteristics – are uncorrelated with any latent determinant of physical IPV against

[29] In fact, the negative correlation observed between rainfall and air temperature may constitute a potential caveat in our empirical analysis as increased temperature levels (that are observed together with reduced rainfall levels) have been shown to affect interpersonal conflict (Burke et al. 2015). Moreover, it has been long posited by the psychological literature that individuals tend to behave more aggressively towards one another in contexts of high temperature levels (Vrij et al. 1994).

women. Although this assumption cannot be directly tested in the data, we perform a series of falsification or placebo tests to support this assumption. We return to this discussion in section 5.3.

Standard errors in all the regressions are estimated by clustering at the municipality level. This way we allow for an arbitrary correlation between the error terms of different observations within the same municipality. As an additional sensitivity check, in Appendix D we present the main results when estimating standard errors by clustering at the grid level.

5 Results

5.1 Effect of Rainfall Shocks on Income and Consumption

We begin the discussion of our results by presenting estimates of the effect of exposure to rainfall shocks on income and consumption. In Table 3 we present estimates of the effects of rainfall shocks on household income per capita (columns 1 and 2), as well as woman's (columns 3 and 4) and partner's (columns 5 and 6) total (cash plus in-kind) and cash income. For concreteness, we focus on cash income when commenting the results.

We find that exposure to an event of drought during the last rainy season reduces household income per capita by almost PER$ 25. This corresponds to a decrease of nearly 20 percent in household income per capita from a benchmark of PER$ 133 observed during times of regular rainfall levels. Individual income is also affected by exposure to rainfall shocks during the last rainy season. We find that being exposed to an event of drought during the last rainy decreases women's earned income by PER$ 30 or roughly 45 percent. However, exposure to an event of flood during the last rainy season increases women's earned income by PER$ 25 or about 37 percent. Although less precisely estimated, we also find a decrease of PER$ 31, or nearly 6.5 percent, in men's earned income following events of drought during the last rainy season. We do not find, however, that men's earned income is affected by exposure to events of flood during the last rainy season.

The effects of exposure to rainfall shocks during the last rainy season on household consumption per capita are shown in Table 4. We find a decrease in total consumption per capita by PER$ 20, or around 13 percent, following exposure to an event of drought during the last rainy season. This effect is very similar to the one found on household income per capita, suggesting that the decrease in household income per capita following exposure to an event of drought during the last rainy season translates almost one for one into household total consumption per capita. This implies that rural households in the Peruvian highlands cannot smooth consumption through savings, credit, or other type of insurance during times of economic hardship originated by negative rainfall shocks.

We also find decreases in almost all dimensions of household consumption following an event of drought during the last rainy season, with food consumption being the most affected dimension. On average, we find that exposure to an event of drought reduces food consumption per capita by PER$ 12 or nearly 14 percent. In terms of magnitude, the decrease in food consumption per capita is almost the same as the decrease in total consumption per capita, implying that decreases in household consumption during times of economics hardship leads to immediate downward adjustments in food consumption in the household. The reason why this may be the case is because food consumption represents over 50 percent of total household consumption in our sample.

In sum, our results indicate that household income and consumption are negatively affected when the household is exposed to an event of drought during the last rainy season. We do not find, however, that exposure to events of drought affect household income or consumption. In terms of individual income, woman's earned income decreases when exposed to an event of drought and increases when exposed to an event of flood during the last rainy season. Man's earned income is only responsive to exposure to an event of drought during the last rainy season, although the negative effect that is found is not precisely estimated. We next turn to discuss how exposure to rainfall shocks affect physical IPV against women.

5.2 Effect of Rainfall Shocks on Physical IPV Against Women

Figure 3 plots estimates of the effect of exposure to different intensities of dry and wet rainfall shocks during the last rainy season on the probability that a woman experienced physical IPV in the last 12 months (Panel A) and the probability that a woman was physically injured from the abuse (Panel B). These estimates arise from augmented specifications based on equation (1) where, on top of the indicators for exposure to events of drought and flood, we have included indicators for exposure to events of mild and moderate dry and wet rainfall shocks during the last rainy season. The indicators for exposure to moderate dry/wet rainfall shocks take the value of 1 if the rainfall level during the last rainy season lay within the 5th-10th/90th-95th percentile brackets whereas the indicators for exposure to mild dry/wet rainfall shocks take the value of 1 if the rainfall level during the last rainy season lay within the 10th-15th/85th-90th percentile brackets of the distribution of local rainfall levels observed during the cropping/rainy season over 1950-2010. Interestingly, we find that physical IPV against women is only affected by exposure to events of drought during the last rainy season. The effects of exposure to all the remaining wet or dry rainfall shocks are statistically insignificant.

The effects of exposure to events of drought or flood during the last rainy season on physical IPV against women are outlined in Table 5. In columns 1 through 4 we present estimates from different regression specifications based on equation (1) when the dependent variable is the indicator for woman's experience of physical IPV in the last 12 months. In columns 5 through 8 we present analogous estimates when the dependent variable is the indicator for whether the woman was physically injured from the abuse. In Panel A, we present estimates when weighting individual observations by the DHS sampling weights whereas in Panel B we present estimates when equally weighting individual observations. For concreteness, we focus on the most comprehensive results that uses sampling weights in the regressions when commenting our results.[30]

[30] In Appendix D we present the results from a series of sensitivity checks. In particular, we present the results when clustering standard errors at the grid level (Appendix Table D.1), when defining the cropping/rainy season based on measures of vegetation growth (Appendix Table D.2), and when constructing the

We find that exposure to events of drought, but not flood, during the last rainy season affect physical IPV against women. On average, we find that exposure to an event of drought during the last rainy season increases the probability a woman experiences physical IPV by 8.5 percentage points and increases the probability a woman has physical sequelae from the abuse by 6.5 percentage points. The point estimates for both measures of physical IPV against women remain fairly stable when we progressively add covariates in the regressions.

Qualitatively, our results can be linked to the way rainfall shocks affect family income and consumption. In fact, the absence of effects of events of flood on family income and consumption may explain why we do not observe that the experience of physical IPV against women is affected by exposure to an event of flood during the last rainy season. This result is consistent with the one from Abiona and Foureaux-Koppensteiner (2017) who documented that domestic violence is mainly affected by dry rather than wet shocks observed during the rainy season and may be linked with the idea that relationship factors such as economic stress can trigger IPV against women (WHO 2012).

We further delve on the characteristics of the abuse and explore the effects of exposure to rainfall shocks on the intensity of physical IPV experienced by women along two dimensions: severity and frequency of the violent acts. Exploring these effects is important for determining whether the observed increase in physically injured women following events of drought results from women being more frequently battered, from women experiencing harsher physical abuse, or a combination of both. Moreover, exploring the effects of rainfall shocks on the degree of severity of physical violent acts is important in and of itself, as severe violent acts perpetrated by male partners are considered one of the main factors increasing the risk

indicators for exposure to events of drought and flood based on standardized precipitation (Appendix Table D.3). The results remain unchanged when clustering standard errors at the grid level. When re-defining the cropping/rainy season based on the vegetation growth index (EVI-2), we find an increase of 6 percentage points and a decrease of 4 percentage points in the probability a woman experiences physical IPV after being exposed to events of drought and flood during the last rainy season respectively. Also, we find that the probability a woman has physical sequelae from the abuse increases by 6.5 percentage points after being exposed to an event of drought during the last rainy season. Lastly, when re-defining exposure to rainfall shocks based on standardized precipitation, we find that exposure to an event of drought during the last rainy season increases the probability a woman experiences physical IPV by 6.5 percentage points and increases the probability a woman a woman has physical sequelae from the abuse by 4 percentage points.

of femicide (WHO 2012).

We follow García-Moreno et al. (2005) and Bott et. al (2012) and construct two measures for severity of physical IPV. The first is an indicator for the experience of moderate acts of physical IPV against women that takes the value of 1 if the woman has been pushed/shook, slapped, punched or kicked/dragged by her male partner. The second is an indicator for the experience of severe acts of physical IPV against women that takes the value of 1 if the woman has been chocked/burnt, threatened with a gun or attacked with a gun.

Next, we utilize information on how frequent each component of moderate and severe violent acts were perpetrated (the categories are: frequently, sometimes, and never) to construct z-scores that are intended to capture the frequency of experience of violent acts within each of these two dimensions. We proceed by first calculating a raw score capturing a combination between the frequency and the number of different violent acts experienced by the woman. The raw score ranges from 0 to 8 in the case of moderate physical IPV and form 0 to 6 in the case of severe physical IPV. We then utilize the means and standard deviations of these scores observed for women who were exposed to regular rainfall levels during the last rainy season to construct the z-scores, with higher values indicating more frequent and/or more varied physical aggressions experienced by the women.

In Table 6, we present the effects of rainfall shocks on each component – along with the aggregate indicator and the z-score – of moderate physical IPV experienced by women. The corresponding results for severe physical IPV experienced by women are presented in Table 7. We find that the increase in woman's experience of physical IPV following events of drought during the last rainy season is mostly driven by moderate acts of physical IPV such as being pushed/shook, slapped, or punched. The results indicate that the experience of moderate physical IPV increases by 8.4 percentage points, or about 66 percent, for women exposed to an event of drought relative to their counterparts exposed to regular rainfall levels during the last rainy season. The point estimate is of the same magnitude as that capturing the effect of exposure to an event of drought on overall physical IPV experienced by women and that is reported in Table 5. By contrast, we do not find impacts of exposure to events of drought nor to exposure to events of flood during the last rainy season on woman's experience of severe physical IPV.

The results also indicate an increase in the z-score for the frequency of moderate physical IPV experienced by the woman after being exposed to an event of drought during the last rainy season. The frequency/variety of moderate violent acts perpetrated by the male partner increases by a 0.19 standard deviation when woman are exposed to an event of drought relative to women exposed to regular rainfall levels during the last rainy season. Yet, there is no associated change in the frequency/variety of severe violent acts perpetrated by male partners following exposure to an event of drought during the last rainy season.

All in all, we find that exposure to negative rainfall shocks in the form of droughts during the last rainy season increases women's experience of physical IPV. This effect is sizable, representing a 65 percent increase in the prevalence of physical IPV against woman relative to periods of regular rainfall levels. The increase in physical IPV against women is mainly driven by moderate acts of physical abuse. But despite the fact that these events do not directly attempt against women's life, they do have physical sequelae on their bodies: our results indicate that women exposed to an event of drought are 64 percent more likely to suffer physical trauma from the abuse inflicted by their partners relative to women exposed to regular rainfall levels during the last rainy season.

5.3 Robustness Checks

A key assumption in our analysis is that changes in measures of physical IPV against women are only caused by temporary variations in rainfall levels that are observed in the municipality where the woman resides. In this section, we present evidence in support of this assumption. We first show that neither exposure to past nor future rainfall shocks impact current events of physical IPV against women. Next, we show that rainfall shocks observed in neighboring municipalities have no effect on physical IPV experienced by women. Finally, and to discard the possibility that our estimates are driven by a specific sub-group of women that are more prone to suffer abuse in the hands of their partners or whose families are more attached to agricultural activities, we also show that our estimates remain stable even when we control for past history of abuse and for land and livestock ownership in the regressions.

In Table 8 we present the results from regressions exploring the effects of exposure to past and future rainfall shocks – events of drought and flood that were observed in the municipality in the preceding and succeeding years – on current physical IPV experienced by women. In columns 1 and 4, we replace the indicators for exposure to events of drought and flood during the last rainy season by the same indicators constructed with information on rainfall levels from the previous rainy season. In columns 2 and 5, we perform the same exercise but with the indicators for exposure to future events of drought or flood – rainfall shocks that were observed in the municipality in the year after the woman was surveyed. In columns 3 and 6, we present the results when including indicators for exposure to current, past, and future rainfall shocks in the regressions.

Results indicate that exposure to past rainfall shocks do not affect the probability a woman experiences physical IPV or results physically injured from the abuse in the year when she was surveyed. Estimates of the effect of exposure to rainfall shocks during the last rainy season on both outcomes remain unchanged when adding indicators for exposure to past and future rainfall shocks in the regressions. Moreover, F-tests for joint significance between the coefficients on exposure to events of past and future droughts are not rejected. This implies that the effect of exposure to these events on current physical IPV experienced by women are jointly insignificant, providing evidence that only temporary rainfall shocks are driving our main results.

We next test for whether changes in physical IPV against women are only driven by local (municipality-specific) ranfall shocks. To that end, we first construct indicators for exposure to events of drought or flood in any neighboring municipality to where the woman resides and then perform regressions using these indicators as our main explanatory variables. Under the null hypothesis that only rainfall shocks are driving our main results, we should expect no effects of exposure to rainfall shocks in neighboring municipalities on women's experience of physical IPV.

We present the results in Table 9. We find no effects of exposure to events of drought or flood during the last rainy season in neighboring municipalities on physical IPV experienced by women (column 1) nor on the probability of having physical sequelae from the abyse (column 3). In columns 2 and 4 we add the indicators for exposure to events of drought and flood during the last rainy season in the municipality where the woman resides and only find statistically significant effects for exposure to events of drought during the last rainy season observed in the municipality of residence. The F-tests for equality of effects of exposure to events of drought during the last rainy season in the municipality where the woman resides and a neighboring municipality is rejected at conventional levels. We interpret these results as evidence that only locality-specific rainfall shocks cause changes in women's experience of physical IPV.

We also discard the possibility that our estimates are driven by the sub-group of women that may be more prone to suffer physical IPV. To that end, we control for past history of physical abuse in the regressions. We construct two indicators capturing past history of abuse for women: an indicator that takes the value of 1 if the woman reported that she witnessed interparental violence during childhood (exposure to violence between parents) and an indicator for whether the woman reported that she has suffered physical IPV in the hands of a previous sentimental partner (past history of abusing partners). These factors have been associated with increased IPV experienced by women (WHO 2012). The results are presented in Appendix Table E.1. We find that witnessing interparental violence and having a history of physical abuse in the hands of an ex-partner are both positively associated with physical IPV against women. Our estimates on the effect of exposure to rainfall shocks on physical IPV against women remains unchanged when adding these covariates in the regressions.

Finally, we also discard the possibility that our estimates are driven by the sub-group of women whose families are more involved in agricultural activities. We do so by including in the regressions indicators for land size and indicators for whether the households owns livestock (herds or farm animals).[31] The results are presented in Appendix Table E.2. We find that holding 10 or more hectares of land is positively associated with physical IPV against women. However, we find no association between owning livestock and physical IPV against women. Our main results on the effect of exposure to rainfall shocks on physical IPV against women remain unchanged when adding these covariates in the regressions.

5.4 Other Forms of IPV Against Women

We next explore whether exposure to rainfall shocks during the last rainy season affect other forms of IPV against women. Specifically, we explore whether emotional/psychological and sexual violence as well as overall IPV are affected by exposure to events of drought or flood during the last rainy season. The indicator for overall IPV is constructed based on the definition of the WHO and takes the value of 1 if the woman experienced any form of violence (that is: physical, emotional/psychological, or sexual violence) in the hands of her partner in the last 12 months (WHO 2013).

The results are presented in Table 10. Each column in the table shows an estimate of the effects of exposure to events of droughts and floods on physical IPV (column 1), emotional/psychological IPV (column 2), sexual IPV (column 3), and overall IPV (column 4). Although imprecisely estimated, we find an increase of 3 percentage points in the probability a woman experiences emotional/psychological IPV when exposed to an event of drought during the last rainy season. We also find an increase of 4 percentage points in the probability a woman experiences sexual violence after being exposed to an event of drought during the last rainy season. Overall IPV increases by 7.7 percentage points, or by 40 percent, following events of drought from a benchmark of 20 percent observed in periods of regular rainfall levels during the last rainy season.

[31] Including indicators for land size in the regressions is also a form of controlling for production capacity of the household.

5.5 Is Violence only Targeted to Women in the Household?

We close this section by analyzing for whether other forms of domestic violence arise after exposure to rainfall shocks during the last rainy season. We begin by exploring for the possibility that a woman inflicts physical violence against her partner (that is, physical IPV against men) after being exposed to a rainfall shock during the last rainy season. Next, we explore for whether children in the household are also victims of physical violence by analyzing for the possibility of observing corporal punishment against children following exposure to rainfall shocks during the last rainy season.[32] The results of these analyses will help revealing whether increases in instances of abuse following events of drought during the last rainy season results from exclusively targeting women as victims or from an overall increase in inter-personal conflict within the household.

The results are presented in Table 11. In column 1 we present the effects of exposure to rainfall shocks on the indicator for physical IPV against men. We find a decrease of 2.4 percentage points in the probability a woman inflicts physical violence on her partner after being exposed to an event of drought during the last rainy season. We do not find effects of exposure to events of flood during the last rainy season on physical IPV against men. In columns 2 through 4 we present the effects of exposure to rainfall shocks on indicators for corporal punishment against children in the household, inflicted by the man (column 2), by the woman (column 3), and by any parent (column 4). We do not find any statistically significant effect of exposure to rainfall shocks during the last rainy season on corporal punishment inflicted against children.

These results are indicative that the increase in domestic violence following events of drought during the last rainy season is exclusively driven by physical IPV against women. We now turn to examine the potential channels through which exposure to rainfall shocks may affect physical IPV against women.

[32]The Centers for Disease Control and Prevention (CDC) defines corporal punishment (physical abuse) as "(...) the use of physical force, such as hitting, kicking, shaking, burning, or other shows of force against a child" (Fortson et al. 2016). Our indicator for corporal punishment against children includes slaps, hitting with closed fist or with an object, and/or throwing water to their bodies. This variable is only available from DHS of year 2010 onwards.

6 Channels of Impact

6.1 Employment

We begin the analysis on channels of impact by exploring whether exposure to rainfall shocks during the last rainy season led to changes in employment status among couples. As reviewed in section 2, changes in employment following exposure to rainfall shocks can mediate physical IPV against women in a number of ways, the two most prominent being exposure reduction and male backlash.

In Table 12 we present estimates of the effects of exposure to rainfall shocks on employment, employment in agricultural and non-agricultural activities, and categories of employment (independent or dependent worker) for agricultural and non-agricultural activities both for women (Panel A) and men (Panel B) in our sample from the ENAHO. Before describing the results, it is worth revising the employment patterns among women and men in our sample of municipalities. In our sample, roughly 30 percent of women are employed, and employed women work mostly in independent non-agricultural activities. By contrast, almost all men in these municipalities work and male work is mostly concentrated agricultural activities with nearly 90 percent of males being employed as independent workers in agricultural activities – that is, working their own lands.

Turning to the results, we find that female (but not male) employment declines with the exposure to an event of drought during the last rainy season, although this effect is not precisely estimated.[33] For women, we find that employment in activities other than agriculture are more responsive to exposure to rainfall shocks during the last rainy season. In particular, we find that the probability of being employed as a dependent worker in non-agricultural activities decrease by 2 percentage points following exposure to events of drought during the last rainy season. For men, we find an increase in employment in agricultural activities and a decline in employment in non-agricultural activities. Specifically, we find an

[33] A similar result emerges when analyzing the effects of exposure to rainfall shocks on indicators for employment constructed from DHS data. Information from the DHS, however, does not allow us to examine the effects of exposure to rainfall shocks on different categories of employment.

increase in the probability of being employed as a dependent worker in agricultural activities of 4 percentage points and a decrease in the probability of being employed as a dependent worker in non-agricultural activities of 6 percentage points.

These results describe two clear patterns: a decrease in employment for women and a substitution from dependent work in non-agricultural activities to dependent work in agricultural activities for men. These two patterns rule out the two principal mechanisms trough which employment can affect IPV against women. On the one hand, *absolute* male employment does not decrease following exposure to events of drought during the last rainy season; a result that indicates no reduction in the time women spend with their aggressors. On the other hand, *relative* male employment increases; a result that implies that men do not lose their power position nor do they degrade their "gender role" within the household.

The results on female and male employment, however, open another potential channel: suspicion and isolation from the man towards his partner that could ultimately escalate into violence against the woman. If the substitution in male employment towards dependent agricultural activities implies being more time away from home at the same time that the woman stays longer at home since she is not working anymore, then this could lead to a lower interaction among partners as well as increased jealousy behaviors and increased marital control from the man.[34] Although this idea contrasts with what the "exposure reduction" theory claims, some studies in the sociology literature have posited that time constraints can lead to marital instability, especially if the time devoted to the requirements of work makes it difficult to fulfill the requirements of the marriage (Burgess 1981; Greenhaus and Beutell 1985).[35] We return to this discussion in section 6.3.

[34] An increase in the time men spend away from home can occur if they have to work for agricultural producers in neighboring municipalities that have not experienced an event of drought during the last rainy season which would increase commuting times mainly.

[35] Increased time away from home can also decrease marital satisfaction and thus increase conflict among partners (Huber and Spitze 1980; Booth and White 1980).

6.2 Relative Income

We next explore whether exposure to rainfall shocks during the last rainy season affects woman's income relative to that of their partner. We construct three measures of relative income based on information from the ENAHO: an indicator for whether the woman earns more than her partner, the woman's income as a share of total household income, and the woman's income as a share of the couple's (her and her partner's) income. We present the results in Table 13.

We do not find changes in the probability that a woman earns more than her partner not in woman's income as a share of household nor couple's total income following exposure to an event of drought during the last rainy season.[36] However, we do find an increase in the probability that a woman earns more than her partner as well as increases in woman's income as a share of household and couple's total income after being exposed to an event of flood during the last rainy season. We interpret these results as if changes in woman's relative income in the relationship may not explain increases in women's experience of physical IPV following events of drought during the last rainy season.

6.3 Interpersonal Traits and Living Arrangements

We further explore whether exposure to rainfall shocks affects interpersonal traits and living arrangements in the relationship such as woman's justification of violence (tolerance of violence), woman's autonomy in household decision-making, partner's emotional support towards the woman, and partner's marital control. Woman's acceptance of violence and low autonomy in household decision-making are regarded as some of the main determinants of IPV against women (WHO 2012). Low emotional support towards women and increased marital control by male partners are examples of ideologies of male dominance, as these behaviors mirror a degradation of women in the relationship which is associated with increased IPV against women (Jewkes 2002; MacQuarrie et al. 2014).

[36]Similar results are obtained from a regression where the dependent variable is an indicator for whether the woman earns more than her partner as reported in the DHS.

In Table 14 we show the results of the effect of exposure to rainfall shocks on measures of interpersonal traits and living arrangements in the relationship. Regarding female behaviors, we do not find statistically significant effects in justification of wife beating nor in autonomy in household decision-making. The last result is consistent with the fact that the woman's power position does not change given the lower income she has – and thus, the lower resources she controls – after being exposed to an event of drought during the last rainy season.

As for the male behaviors, we do not find effects of exposure to rainfall shocks on emotional support towards his partner. However, we do find a 10 percentage points increase in marital control from the partner following exposure to an event of drought during the last rainy season. In a complementary analysis (not shown but available from the authors) we further examined whether exposure to rainfall shocks during the last rainy season affected any of the two broad dimensions of marital control, suspicion and isolation (MacQuarrie et al. 2014), and find an a 7.5 percentage points (25 percent) increase in suspicion but not on isolation from the man towards his partner.[37] The decline in the time men and women spend together that arises from men working longer hours (and the potential increase in commuting times) and women staying longer at home that is jointly observed with increased suspicion from the man may partially explain the observed increase in physical IPV against women following exposure to an event of drought during the last rainy season.

6.4 Alcohol Consumption

We close the discussion on potential channels of impact by presenting estimates of the effects of exposure to rainfall shocks on alcohol consumption and alcohol-related aggressions by the male partner. Exploring the effects of exposure to rainfall shocks on alcohol consumption disorders and alcohol-related aggressions is particularly important because of its association with increased stress levels especially during times of economic hardship (Keyes et al. 2012).

[37]The indicator for suspicion takes the value of 1 if the woman reports that her partner behaves jealousy, accuses her of being unfaithful, or wants to know her location at all times. The indicator for isolation takes the value of 1 if the woman reports that her partner limits her contact with her friends, limits her contact with her family, or does not trust her with money.

Moreover, alcohol consumption by men is associated with IPV, as "[it] is thought to reduce inhibitions, cloud judgement, and impair the ability to interpret social cues" (Jewkes 2002).

In Table 15 we present estimates of the effect of exposure to rainfall shocks on alcohol consumption by the partner (column 1), whether the partner binge drinking (column 2), and whether the partner was intoxicated when the physical aggression against the woman occurred (column 3). All of these indicators are constructed based on the woman's report. We do not find statistically significant effects of exposure to rainfall shocks during the last rainy season on the probability that the partner drinks alcohol nor in the probability that the partner frequently binge drinking, as reported by the woman. However, we do find that exposure to an event of drought during the last rainy season increases the likelihood that the woman reports that the aggression occurred when the partner was intoxicated with alcohol by 0.04 percentage points, implying an increase of nearly 50 percent (from a benchmark of 8 percent) in alcohol-related aggressions.

Based on these results, occasional heavy drinking from men can partly explain why we observe increases in physical IPV against women following exposure to events of drought during the last rainy season. This result is supported by previous evidence from Latin American countries suggesting that instances of abuse against women were most of the time caused by partner's alcohol use (Bott et al. 2012). Whether alcohol use by men is triggered by increased stress levels resulting from economic hardship, however, remains an open question.

7 Discussion and Conclusion

A number of studies examining the effect of income on spousal abuse have focused on evaluating how relative changes in spouses' income alter the distribution of power within the household and thereby violence against women. The question remains how spousal abuse is affected by absolute, rather then relative, income shocks. In this paper, we addressed this question by exploring how income shocks – in the form of rainfall shocks – affect physical intimate partner violence against women in the context of rural Peru, where agriculture constitutes, to a large extent, the only income-generating activity of households and agricultural yields largely depend on weather realizations.

Exploiting variation in rainfall levels within municipalities over time, we find that exposure to an event of drought, but not flood, during the last rainy season increases physical abuse experienced by women in the hands of their partners. In particular, we found an 8.5 percentage points increase in the probability a women experiences physical violence from her partner and a 6.5 percentage points increase in the probability a woman suffers physical trauma from the abuse. The increase in physical sequelae experienced by women results from them being more frequently, but not more severely, battered by their partners. In terms of magnitude, our estimates are impressive. Relative to periods of regular rainfall levels, the prevalence of physical IPV against women in the same municipality increases by 65 percent and the likelihood of them suffering physical trauma from the abuse increases by around 60 percent.

Even though these effects may appear large, it should also be noted that this is an extremely adverse shock that severely affects household income and consumption, and may as well have repercussions on interpersonal traits among partners. Two pieces of evidence validate our main findings. On the one hand, we found that household income and consumption per capita decline by 20 and 15 percent respectively following exposure to events of drought during the last rainy season. On the other hand, our results are not that different from what it has been found in previous studies on the effect of income on spousal abuse. For instance, it has been documented that increasing household monthly income per capita by 12.5 percent in rural Peru through conditional cash transfers reduce spousal abuse by between 30 to 50 percent (Perova 2010; Ritter 2014; Diaz and Saldarriaga 2018).[38] Assuming linearity, this would imply that a decline of 20 percent in household income per capita would increase spousal abuse by at least 50 percent.

[38]Conditional Cash Transfer programs (CCTs) are social programs that provide households with a periodical stipend conditional on them meeting a series of education and health requirements. In other Latin American countries, it has been found that CCTs reduce physical intimate partner violence against women by between 30 to 40 percent (Angelucci 2008; Bobonis et al. 2013).

Although it is difficult to ascribe our results to a particular channel, further analysis of the data indicates that increases in physical intimate partner violence against women following exposure to events of drought may be driven by two underlying mechanisms. The first mechanism is related with changes in employment patterns of spouses that can increase marital control towards women and thereby opening the space for conflict. In this regard, we found that men spend longer hours working while women spend more time at home following a decline in female employment. This could limit the time couples spend together which may lead to a lower interaction among partners and increase controlling behaviors from men (Burgess 1981; Greenhaus and Beutell 1985). In fact, we find that marital control from men – in the form of suspicion towards women – increases after exposure to an event of drought during the last rainy season. The second mechanism is related with undesired behaviors that may arise during times of economic hardship; namely, alcohol-use disorders from men. In this line, we also found that our main results are partly explained by an increase in alcohol-related aggressions following exposure to an event of drought during the last rainy season. Life stressors such as low income levels have been found to increase alcohol disorders (Keyes et al. 2012) which have been also linked to spousal abuse (Jewkes 2002; Bott et al. 2012).

Our results have broader implications for societies whose income-generating activities are highly concentrated around agriculture in terms of violence against women and, more broadly, gender-based inequalities. Although events of rainfall shocks are rarely observed, these events have been occurring with increased frequency during the past two decades and different forecasts made by experts conclude that more frequent and increasingly severe droughts as well as lost of fertile land used for agriculture will be some of the many consequences of climate change in the future (IPCC 2014). Thus, it comes with no surprise that violence against women may constitute one of the main future health burdens in developing countries, where a large fraction of the population works in agricultural-related activities and strategies aiming at mitigating the effects of climate change on this economic activity – such as enhancing irrigation technologies – have not been implemented to a large scale.

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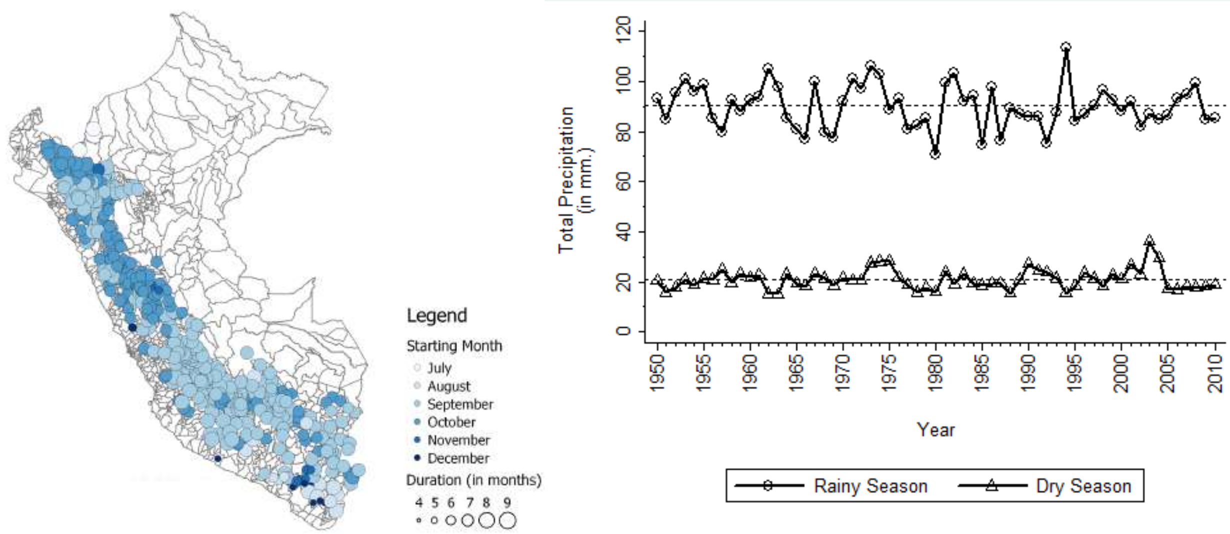
Figure 1: Rainy Season in the Peruvian Highlands

(A) Duration of the Rainy Season (B) Average Monthly Rainfall across Seasons

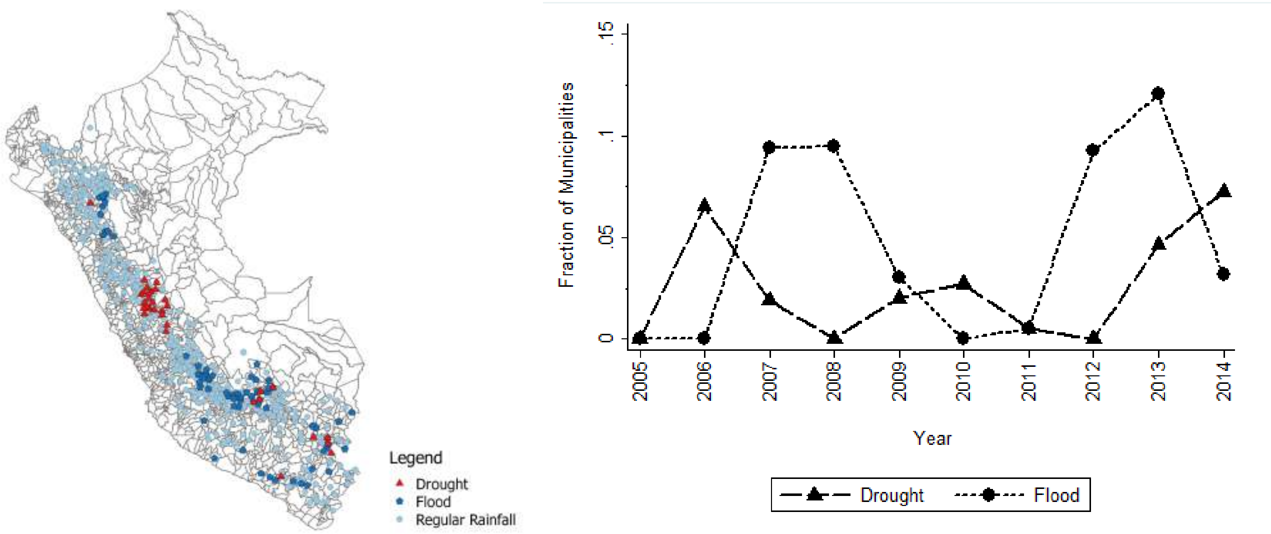


<u>Notes</u>: The figure shows the starting month and duration of the rainy season (Panel A) and the total rainfall level (total precipitation) by season over time (Panel B) for rural municipalities in the Peruvian highlands. The starting month is symbolized by the color and the duration by the size of the circles. Seasonal rainfalls are calculated by averaging total rainfall levels for each season across municipalities in each year.

Source: Author's own calculations based on the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (Version 4.01).

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

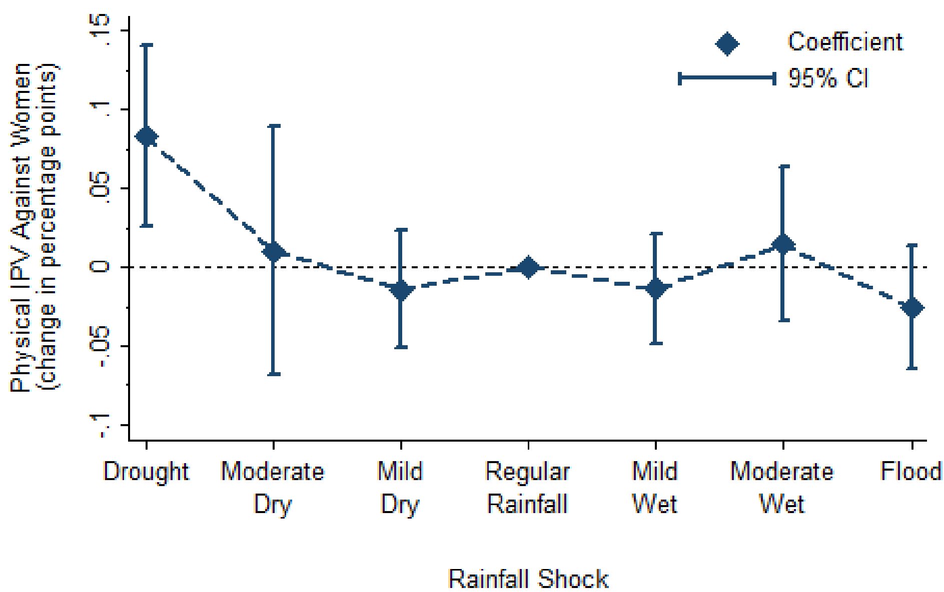
(A) Distribution Across Geography (B) Distribution Over Time



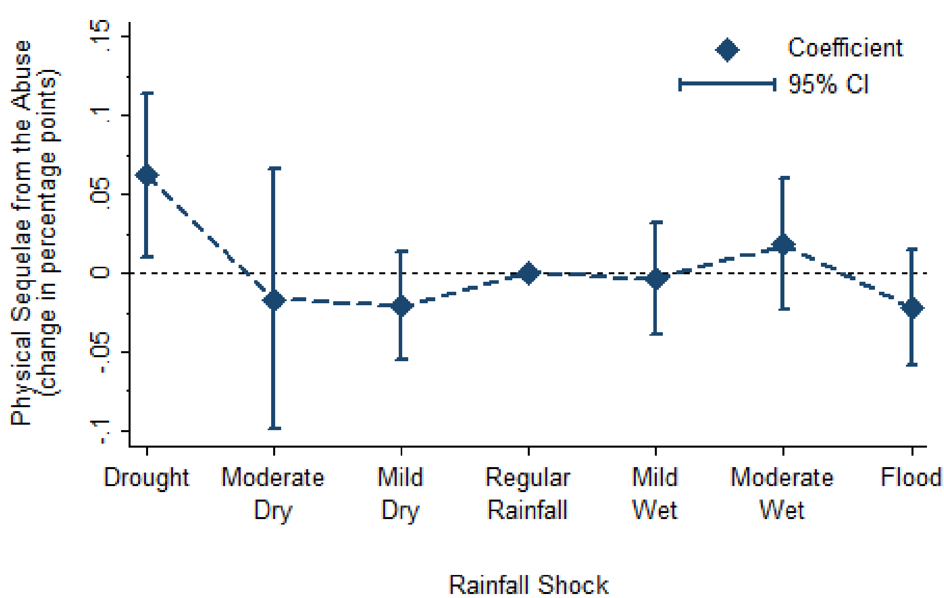
Notes: The figure shows the geographical distribution of rainfall shocks for rural municipalities in the Peruvian highlands that are observed in the DHS sampling frame (Panel A) and the fraction of municipalities with rainfall shocks (Panel B) over the period 2005-2014 .
Source: Author's own calculations based on the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01).

Figure 3: Effect of Rainfall Shocks on Physical IPV by Intensity of the Shock

(A) Woman Experienced Physical IPV



(B) Woman was Physically Injured from the Abuse



Notes: The figure shows estimates of exposure to different intensities of rainfall shocks on the probability a woman experiences physical IPV in the last 12 months (Panel A) and on the probability a woman was physically injured from the abuse (Panel B).
Source: Author's own calculations based on the 2005-2014 Peruvian Demographic and Health Surveys (DHS), the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 1: Descriptive Statistics from the Main Sample (DHS)

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)
			Panel A: Individual Level				
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
Observations		15,110	14,049	421	640	14,470	14,689
			Panel B: Municipality Level				
Rainfall level (mm)	[0.44 - 401.44]	104.34	103.49	86.1	131.11	-27.28***	30.61***
Air temperature (°C)	[0.58 - 29.2]	12.77	12.7	16.83	11.95	0.39***	-0.15*
Soil temperature (°C)	[8.9 - 24.45]	15.89	15.87	17.75	15.27	0.01	0.02
Soil moisture (%)	[2.03 - 37.92]	33.82	33.79	34.72	33.87	0.00***	0.00
Observations		1,896	1,756	50	90	1,806	1,846

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows descriptive statistics for individual level characteristics (Panel A) and municipality level characteristics (Panel B) from the main sample of women constructed from the DHS. Data is collapsed at the municipality-by-year-by-month level in order to obtain descriptive statistics at the municipality level. Municipality level characteristics are based on the last rainy season. The range (minimum and maximum levels) of each variable is shown in column 1. Sample means for the whole sample are reported in column 2. Sample means for the sub-samples exposed to regular rainfall levels, droughts, and floods are reported in columns 3, 4, and 5 respectively. Adjusted differences are obtained by regressing each variable on an indicator for exposure to a drought event (column 6) or an indicator for exposure to a flood event (column 7) and controlling for survey-month, survey-year, and municipality fixed effects. The sample for calculating adjusted differences in column 6 includes observations exposed to regular rainfall levels or events of drought during the last rainy season. The sample for calculating adjusted differences in column 7 includes observations exposed to regular rainfall levels or events of flood during the last rainy season. The total sample is composed of women of reproductive ages (15-49 years), who live in rural municipalities in the Peruvian highlands, who responded 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 are non-migrants. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 2: Descriptive Statistics from the Ancillary Sample (ENAHO)

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]	36.35	36.37	35.85	36.21	-0.82*	-0.49
Woman's schooling	[0 - 18]	4.40	4.38	4.26	4.77	-0.16	0.14
Woman's ethnicity	[0 - 1]	0.65	0.65	0.82	0.50	0.00	-0.02
Partner's age	[17 - 88]	40.17	40.18	40.07	39.93	-0.66	-0.44
Partner's schooling	[0 - 18]	6.13	6.11	5.97	6.68	0.03	0.44**
Partner's ethnicity	[0 - 1]	0.66	0.65	0.82	0.53	0.01	-0.01
Formally married	[0 - 1]	0.40	0.40	0.33	0.54	-0.03	-0.02
Observations		12,146	11,247	312	560	11,559	11,807

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows descriptive statistics for individual level characteristics from the ancillary sample of women and households constructed from the ENAHO. The range (minimum and maximum levels) of each variable is shown in column 1. Sample means for the whole sample are reported in column 2. Sample means for the sub-samples exposed to regular rainfall levels, droughts, and floods are reported in columns 3, 4, and 5 respectively. Adjusted differences are obtained by regressing each variable on an indicator for exposure to a drought event (column 6) or an indicator for exposure to a flood event (column 7) and controlling for survey-month, survey-year, and municipality fixed effects. The sample for calculating adjusted differences in column 6 includes observations exposed to regular rainfall levels or events of drought during the last rainy season. The sample for calculating adjusted differences in column 7 includes observations exposed to regular rainfall levels or events of flood during the last rainy season. The total sample is composed of women of reproductive ages (15-49 years), who live in rural municipalities in the Peruvian highlands belonging to the DHS sampling frame, who are the household heads or spouses of the household head, and who are married/cohabiting and living with their partners. The data used for calculating descriptive statistics come from the 2005-2014 Peruvian National Household Surveys (ENAHO), and from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01).

Table 3: Effect of Rainfall Shocks on Household and Individual Income

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Household Income (per capita)		Woman's Income		Partner's Income	
	Total	Cash	Total	Cash	Total	Cash
Drought	-26.255**	-24.900**	-30.157*	-30.332**	-32.039	-31.421
	(12.010)	(10.443)	(18.228)	(12.532)	(39.952)	(33.396)
Flood	2.074	0.361	31.967**	24.640**	3.125	-6.119
	(8.204)	(7.104)	(15.665)	(12.267)	(31.737)	(28.380)
N	12,146	12,146	12,146	12,146	12,146	12,146
Clusters	351	351	351	351	351	351
Dependent variable mean	183.2	133.2	98.65	67.87	669.6	479.9
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	No	No	No	No
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to household income per capita, woman's income, and partner's income. Clustered standard errors at the municipality level are shown in parentheses. ENAHO sampling weights are used in all regressions. The vector of individual characteristics in the regressions where the dependent variable is the woman's income includes indicators for woman's age (20-24; 25-29; 30-34; 35-39; 40-44; 45-49; base: 19 or less), indicators for woman's educational attainment (incomplete primary, complete primary, incomplete secondary, high school degree or more education; base: no education), and an indicator for woman's ethnicity (whether the mother tongue is Spanish). The vector of individual characteristics in the regressions where the dependent variable is the partner's income includes indicators for partner's age (20-24; 25-29; 30-34; 35-39; 40-44; 45-48; 50 or more; base: 19 or less), indicators for partner's educational attainment (incomplete primary, complete primary, incomplete secondary, high school degree or more education; base: no education), and an indicator for partner's ethnicity (whether the mother tongue is Spanish). The vector of household characteristics includes indicators for household size (3; 4; 5; 6 or more; base: 2 household members), an indicator for whether the household head is male, indicators for the household head's age (20-24; 25-29; 30-34; 35-39; 40-44; 45-48; 50 or more; base: 19 or less), and indicators for the household head's educational attainment (incomplete primary, complete primary, incomplete secondary, high school degree or more education; base: no education). The vector of other crop yield determinants includes indicators for average monthly air temperature (10-15; 15-20; 20 or more; base: less than 10 degree Celsius), indicators for average monthly soil temperature (10-15; 15-20; 20 or more; base: less than 10 degree Celsius), and indicators for average monthly soil moisture (25-30; 30-35; 35 or more; base: less than 25 percent), and all of these covariates correspond to the last rainy season. All regressions include survey-month, survey-year, and municipality fixed effects as conditioning variables. See the notes to Table 2 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian National Household Surveys (ENAHO), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 4: Effect of Rainfall Shocks on Household Consumption Per Capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Categories of consumption (per capita)							
Dependent Variable:	Food	Clothing	Housing/ Services	Health	Transport	Leisure	Other	Consumption (per capita)
Drought	-11.674***	-2.581*	-2.466***	1.006	-1.561	-0.990	-1.782	-20.219**
	(4.321)	(1.416)	(0.844)	(2.595)	(1.595)	(2.037)	(1.099)	(8.263)
Flood	3.279	0.293	2.335**	1.537	-1.312	0.593	0.180	7.010
	(3.291)	(1.252)	(1.004)	(1.331)	(1.334)	(1.370)	(0.870)	(6.011)
N	12,146	12,146	12,146	12,146	12,146	12,146	12,146	12,146
Clusters	351	351	351	351	351	351	351	351
Dependent variable mean	83.84	15.33	16.81	7.128	10.68	9.257	9.973	153.8
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to different types of household consumption per capita. Clustered standard errors at the municipality level are shown in parentheses. ENAHO sampling weights are used in all regressions. All regressions include household characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables. See the notes to Table 3 for details about the variables included in the vectors of household characteristics and other crop yield determinants. See the notes to Table 2 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian National Household Surveys (ENAHO), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 5: Effect of Rainfall Shocks on Physical IPV Against Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Woman Experienced Physical IPV (Mean = 0.128)				Woman was Physically Injured from the Abuse (Mean = 0.103)			
	Panel A: Using DHS Sampling Weights							
Drought	0.085***	0.087***	0.083***	0.084***	0.067**	0.068***	0.066**	0.066**
	(0.030)	(0.030)	(0.029)	(0.029)	(0.027)	(0.026)	(0.026)	(0.026)
Flood	-0.027	-0.028	-0.028	-0.025	-0.022	-0.023	-0.022	-0.021
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
N	15,110	15,110	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495	495	495
	Panel B: Unweighted Regressions							
Drought	0.054**	0.055**	0.053**	0.052**	0.051**	0.052**	0.051**	0.048**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)	(0.022)
Flood	-0.015	-0.015	-0.015	-0.014	-0.013	-0.012	-0.012	-0.012
	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
N	15,110	15,110	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495	495	495
Woman characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Partner and relationship characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Other crop yield determinants	No	No	No	Yes	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 β^D and β^F from different specifications based on equation (1) in section 4, by using DHS sampling weights (Panel A) or by equally weighting individual observations (Panel B) in the regressions. The dependent variables – along with their corresponding sample means – are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 4) and an indicator for whether the woman was physically injured from the abuse (columns 5 through 8). Dependent variable means correspond to that of the sub-group of women not exposed to rainfall shocks. 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 (whether the mother tongue is Spanish). The vector of partner and relationship characteristics includes the partner's age (20-24; 25-29; 30-34; 35-39; 40-44; 45-or more; base: 19 or younger), the 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 relationship (2-5 years; 6-9 years; 10 years or more; base: 1 year or less), and an indicator for being formally married. See the notes to Table 3 for details about the variables included in the vector of other crop yield determinants. All regressions include survey-month, survey-year, and municipality fixed effects. See the notes to Table 1 and the main text for information about the sample composition. Further details of each specification are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 6: Effect of Rainfall Shocks on Moderate Physical IPV Against Women

	(1)	(2)	(3)	(4)	(5)	(6)
	Components of Moderate P-IPV					
Dependent Variable:	Pushed/ Shook	Slapped	Punched	Kicked/ Dragged	Moderate P-IPV	Std. Score
Drought	0.054**	0.075***	0.047**	0.033	0.084***	0.191**
	(0.024)	(0.022)	(0.022)	(0.021)	(0.029)	(0.088)
Flood	-0.011	-0.003	-0.004	0.008	-0.025	0.037
	(0.018)	(0.018)	(0.022)	(0.017)	(0.021)	(0.087)
N	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495
Dependent variable mean	0.099	0.076	0.079	0.057	0.126	0.000
Woman characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for moderate acts of physical IPV experienced by the woman in the last 12 months. Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 7: Effect of Rainfall Shocks on Severe Physical IPV Against Women

	(1)	(2)	(3)	(4)	(5)
	Components of Severe P-IPV				
Dependent Variable:	Choked/ Burnt	Threatened w./ gun	Attacked w./gun	Severe P-IPV	Std. Score
Drought	-0.003	0.003	0.002	-0.002	0.033
	(0.008)	(0.008)	(0.007)	(0.010)	(0.097)
Flood	0.011	0.008	0.006	0.015	0.101
	(0.010)	(0.006)	(0.004)	(0.011)	(0.094)
N	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495
Dependent variable mean	0.013	0.009	0.005	0.019	0.000
Woman characteristics	Yes	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for severe acts of physical IPV experienced by the woman in the last 12 months. Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 8: Robustness Analysis (Testing for Temporal Shocks)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)			Women was Physically Injured from the Abuse (Mean = 0.103)		
Drought			0.085***			0.065**
			(0.029)			(0.026)
Flood			-0.031			-0.028
			(0.021)			(0.020)
Drought $(t-1)$	-0.001		0.001	-0.006		-0.006
	(0.033)		(0.033)	(0.037)		(0.039)
Flood $(t-1)$	-0.015		-0.019	-0.008		-0.009
	(0.025)		(0.025)	(0.024)		(0.024)
Drought $(t+1)$		0.022	0.027		0.021	0.025
		(0.027)	(0.026)		(0.025)	(0.025)
Flood $(t+1)$		-0.019	-0.020		-0.025	-0.027
		(0.019)	(0.018)		(0.017)	(0.017)
F-stat. (H_0: $\beta^{D_{t-1}} = \beta^{D_{t+1}} = 0$)			0.542			0.540
p-value			[0.582]			[0.583]
N	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495
Woman characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F as well as $\beta^{D_{t-1}}$, $\beta^{F_{t-1}}$, $\beta^{D_{t+1}}$, $\beta^{F_{t+1}}$, the coefficients on the indicators for exposure to events of drought and flood observed in the municipality during the preceding and succeeding rainy seasons respectively, from different specifications based on equation (1) in section 4. The dependent variables – along with their corresponding sample means – are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 3) and an indicator for whether the woman was physically injured from the abuse (columns 4 through 6). Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 9: Robustness Analysis (Testing for Local Shocks)

	(1)	(2)	(3)	(4)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)		Women was Physically Injured from the Abuse (Mean = 0.103)	
Drought		0.102***		0.084***
		(0.033)		(0.031)
Flood		-0.021		-0.020
		(0.020)		(0.019)
Drought in neighboring municipality	0.016	-0.036	0.009	-0.034
	(0.028)	(0.026)	(0.023)	(0.025)
Flood in neighboring municipality	-0.019	-0.013	-0.009	-0.003
	(0.015)	(0.015)	(0.013)	(0.018)3
F-stat. (H_0: $\beta^D = \beta^{D_{Neighbor}}$)		8.071		5.786
p-value		[0.005]		[0.017]
N	15,110	15,110	15,110	15,110
Clusters	495	495	495	495
Woman characteristics	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F as well as $\beta^{D_{Neighbor}}$ and $\beta^{F_{Neighbor}}$, the coefficients on the indicators for exposure to events of drought and flood observed during the last rainy season in neighboring municipalities respectively, from different specifications based on equation (1) in section 4. The dependent variables – along with their corresponding sample means – are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 and 2) and an indicator for whether the woman was physically injured from the abuse (columns 3 and 4). Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 10: Effect of Rainfall Shocks on Other Forms of IPV Against Women

	(1)	(2)	(3)	(4)
	Type of IPV			
Dependent Variable:	Physical	Emotional/ Psychological	Sexual	IPV
Drought	0.084***	0.032	0.044*	0.077**
	(0.029)	(0.029)	(0.023)	(0.030)
Flood	-0.025	-0.013	0.010	-0.024
	(0.020)	(0.025)	(0.012)	(0.025)
N	15,110	15,110	15,110	15,110
Clusters	495	495	495	495
Dependent variable mean	0.128	0.148	0.041	0.196
Woman characteristics	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for moderate acts of physical IPV experienced by the woman in the last 12 months. Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 11: Effect of Rainfall Shocks on Other Domestic Violence

	(1)	(2)	(3)	(4)
		Corporal Punishment Against Children		
Dependent Variable:	P-IPV Against Men	Partner	Woman	Any Parent
Drought	-0.024**	0.007	0.043	-0.032
	(0.010)	(0.050)	(0.037)	(0.048)
Flood	-0.005	0.021	0.024	0.016
	(0.007)	(0.038)	(0.036)	(0.043)
N	15,110	10,475	10,475	10,475
Clusters	495	481	481	481
R-squared	0.051	0.149	0.139	0.154
Dependent variable mean	0.015	0.365	0.406	0.510
Woman characteristics	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for physical IPV against men (column 1) and indicators for corporal punishment against children in the household (columns 2 through 4). Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. The number of observations in columns 2 through 4 is smaller than that from column 1 because information on disciplining methods was only collected in the DHS from year 2010 onwards. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 12: Channels of Impact (Employment)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Categories of Employment			
Dependent Variable:	Employed	Agric.	Other Activities	Indep. (Agric.)	Dep. (Agric.)	Indep. (Other)	Dep. (Other)
				Panel A: Women			
Drought	-0.067	-0.031	-0.045	-0.022	-0.010	-0.027	-0.021**
	(0.041)	(0.027)	(0.032)	(0.023)	(0.012)	(0.028)	(0.009)
Flood	-0.007	0.000	-0.002	0.007	-0.005	-0.012	0.012
	(0.027)	(0.018)	(0.021)	(0.017)	(0.010)	(0.020)	(0.008)
N	12,146	12,146	12,146	12,146	12,146	12,146	12,146
Clusters	351	351	351	351	351	351	351
Dependent variable mean	0.282	0.097	0.206	0.065	0.034	0.186	0.022
				Panel B: Men			
Drought	-0.006	0.046*	-0.069**	0.042	0.038*	-0.009	-0.060**
	(0.009)	(0.028)	(0.029)	(0.028)	(0.022)	(0.023)	(0.024)
Flood	-0.012	-0.023	0.054*	-0.011	-0.048***	0.024	0.028
	(0.010)	(0.016)	(0.031)	(0.017)	(0.016)	(0.019)	(0.025)
N	12,146	12,146	12,146	12,146	12,146	12,146	12,146
Clusters	351	351	351	351	351	351	351
Dependent variable mean	0.984	0.912	0.309	0.896	0.135	0.130	0.183
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for being employed and different categories of employment for women (Panel A) and men (Panel B). Clustered standard errors at the municipality level are shown in parentheses. ENAHO sampling weights are used in all regressions. All regressions include individual characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 3 for information about the variables included in the vectors of individual characteristics and the vector of other crop yield determinants). See the notes to Table 2 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian National Household Surveys (ENAHO), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 13: Channels of Impact (Relative Income)

	(1)	(2)	(3)
Dependent Variable:	Earns More	Income / HH Income	Income / Couple Income
Drought	-0.009	-0.014	-0.014
	(0.016)	(0.015)	(0.018)
Flood	0.031**	0.022*	0.024*
	(0.015)	(0.011)	(0.012)
N	12,146	12,146	12,146
Clusters	351	351	351
Dependent variable mean	0.065	0.086	0.096
Individual characteristics	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to measures of relative income in the household. Clustered standard errors at the municipality level are shown in parentheses. ENAHO sampling weights are used in all regressions. All regressions include individual characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 3 for information about the variables included in the vectors of individual characteristics and the vector of other crop yield determinants). See the notes to Table 2 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian National Household Surveys (ENAHO), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 14: Channels of Impact (Interpersonal Traits and Living Arrangements)

	(1)	(2)	(3)	(4)
	Female Behaviors		Male Behaviors	
Dependent Variable:	Justifies Wife Beating	Decision Making Autonomy	Emotional Support	Marital Control
Drought	-0.019	-0.021	0.003	0.102***
	(0.013)	(0.030)	(0.010)	(0.037)
Flood	-0.004	-0.001	-0.009	0.019
	(0.014)	(0.020)	(0.009)	(0.030)
N	15,110	15,110	15,110	15,110
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

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for interpersonal traits and living arrangements in the relationship. Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Table 15: Channels of Impact (Alcohol Consumption by the Partner)

	(1)	(2)	(3)
Dependent Variable:	Drinks Alcohol	Binge Drinking	Alcohol-related Aggression
Drought	0.023	-0.000	0.043**
	(0.041)	(0.018)	(0.019)
Flood	-0.029	0.001	0.003
	(0.030)	(0.013)	(0.018)
N	15,110	10,475	10,475
Clusters	495	481	481
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

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of each column and correspond to indicators for alcohol consumption and alcohol-related aggressions by the male partner. Clustered standard errors at the municipality level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Appendix Material

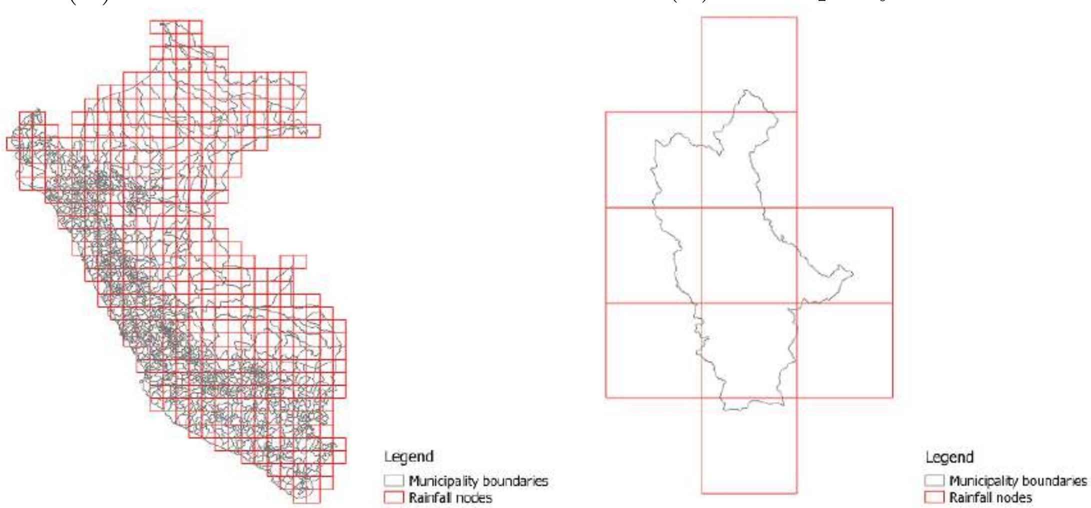
A. Interpolation of Rainfall Levels

Panel A of Appendix Figure A.1 depicts the distribution of rainfall nodes across the Peruvian territory. The underlying layer shows the municipality boundaries.[39] In order to explain how we proceed to interpolate municipality-level rainfalls, Panel B of Appendix Figure A.1 shows the intersection of different rainfall nodes and a municipality. We denote the set of rainfall nodes intersecting the municipality boundary as its grid.

We interpolate municipality-level rainfalls as follows: (i) in case that the municipality boundary lays within one rainfall node then we ascribe to that municipality the corresponding rainfall levels of the rainfall node where it is contained, and (ii) in case that the municipality boundary is intersected by several rainfall nodes – as it is the case in the example – then we ascribe to that municipality the weighted average of the rainfall levels of all of its associated rainfall nodes, where the weights correspond to the share of the municipality's territory that is contained within each rainfall node.

Appendix Figure A.1: Spatial Distribution of Rainfall Nodes

(A) Rainfall Nodes Across Peru (B) Municipality's Grid



Notes: The figure shows the spatial distribution of rainfall nodes along the Peruvian territory (Panel A) and an illustration of a municipality's grid (Panel B).
Source: Authors' own calculations based on the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (Version 4.01).

[39] Administratively, the Peruvian territory is divided into regions (*regiones/departamentos*), provinces within regions (*provincias*) and municipalities within provinces (*distrito/municipio*). Municipalities are the smallest administrative unit of Peru and corresponds to the NUTS-3 (Nomenclature of Territorial Units for Statistics) subdivision of the country.

B. Data Cleaning

We describe our process for filtering and cleaning the Peruvian 2005-2014 DHS data. We first describe our geographical filtering procedure and then explain our filters for keeping individual-level observations in our sample.

B.1. Geographical Filtering Procedure

In our study, we focus on municipalities where agriculture constitutes the principal economic activity. Appendix Table B.1 shows the number of municipalities, grids and individual observations that we loss 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 all over 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 women of reproductive age. Next we drop all municipalities with no observations above the 1000 meters over the sea level (row C). After this filter is applied, we retain 880 municipalities (473 grids) and 42,226 observations. We next exclude all municipalities that are province capitals (row D). These municipalities likely have a lower concentration of the workforce around agricultural activities and are more connected with urban settings, thus allowing for a 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 for whom we observe individuals surveyed in two different years over the period 2005-2014 (row E). As we observe individuals from a given municipality in different points in time, this filter permits us to exploit inter-temporal variation in rainfall levels within a given locality. We are left with 495 municipalities (314 grids) and 30,200 observations.

This final sample of municipalities represents around 60% of all rural municipalities located in the Peruvian highlands that belong to the DHS sampling frame of the period 2005-2014. We are left with roughly 72% of the total number of observations within these municipalities.

Appendix Table B.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) Elevation above 1000 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: This table provides details on the geographic filtering procedure and quantifies the data loss as we progressively restrict our sample in order to keep rural municipalities in the Peruvian highlands (above 1000 meters over the sea level), that are not province capitals and for whom we observe individuals surveyed in different years. 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' own calculations using data from the 2005-2014 Peruvian Demographic and Health Surveys (DHS).

Descriptive statistics for these municipalities are shown in Appendix Table B.2. According to the 1994 Agricultural Census, 8% of the municipality's surface is destined to agricultural activities and 71% cultivated land is rainfed. These figures are similar to the ones obtained from the 2012 Agricultural Census, revealing that 9% of the municipality's surface is used for agricultural activities and 70% of the agricultural land is rainfed. In terms of employment, 76.7% (77.4%) of all employed individuals work in agricultural-related activities and 60.5% (58.4%) of all agricultural workers work their own land, according to the 1993 (2007) Population and Housing Census. Altogether, these figures imply that economic activity in our sample of DHS municipalities is highly concentrated around agriculture and, importantly, crop yields mostly depend on weather realizations as a high share of the cultivated land therein is rainfed.

Appendix Table B.2: Descriptive Statistics of DHS Municipalities

Variable	(1) Range [min. - max.]	(2) Mean	(3) 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	[113.00 - 8,368.00]	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	[106.00 - 13,270.00]	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
Percentage independent agricultural employment in 1993	[0.00 - 100.00]	58.35	22.22
Agricultural employment in 2007 (percent of total employment)	[3.36 - 100.00]	77.41	16.17
Percentage independent agricultural employment in 2007	[0.00 - 100.00]	68.65	19.86
Monthly rainfall during the rainy season (mm)	[8.25 - 391.36]	102.14	39.78
Monthly air temperature during the rainy season (°C)	[0.73 - 28.86]	12.35	5.26
Soil temperature during the rainy season (°C)	[8.95 - 24.40]	15.86	3.51
Soil moisture during the rainy season (%)	[2.09 - 37.34]	33.78	3.61

Notes: The table shows descriptive statistics for the final sample of DHS municipalities. There are 495 municipalities in the sample. Information on rainfall, air temperature, soil temperature, and soil moisture during the rainy season is first averaged across time (over the period 2000-2014) for each municipality and then averaged across municipalities to obtain the descriptives. The data used for calculating descriptive statistics come from the 1994 and 2012 Agricultural Censuses, from the 1993 and 2007 Population and Housing Censuses, from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

B.2. Individual Filtering Procedure: DHS Sample

Appendix Table B.3 describes 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 specific to 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 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 possible. In order to make the sample of women surveyed by the DHS as similar as we can with that from the EHANO, we keep women who are the household heads or spouses of the household heads in the sample. This filter responds to the fact that, in the ENAHO, we can only know with certainty that a man and a woman form a couple if they are both the household heads. This 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 with their partners in the same dwelling (row F). Finally, to ensure that we are correctly assigning the rainfall levels from the two previous completed rainy seasons in the municipality of residence, we keep in our sample all women who report being living in the municipality for at least one year (row G).

Our final sample comprises information from 15,110 women living in 495 rural municipalities in the Peruvian highlands. This number of observations represents 88% of married/cohabiting women who are the female household heads and who responded the module specific to spousal abuse in our sample. This sample has been configured in a manner that it reflects the status of women of reproductive age who are currently in a relationship and who live in rural areas where agriculture largely depends on weather realizations and constitutes the principal economic activity. Any other additional filter applied over this sample is discussed in the main text.

Appendix Table B.3: Individual Filtering Procedure (DHS Sample)

Level:	Municipalities		Grids		Individuals	
Measure:	*N*	%	*N*	%	*N*	%
(A) Rural municipalities in the Peruvian highlands	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 her 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: This table provides details on the individual filtering procedure 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 non-migrants. 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' own calculations using data from the 2005-2014 Peruvian Demographic and Health Surveys (DHS).

B.3. Individual Filtering Procedure: ENAHO Sample

Appendix Table B.4 describes the individual filtering procedure for the ENAHO sample. From the 32,939 women living in rural municipalities in the Peruvian highlands 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 with their partners in the same dwelling. This leaves us with a final sample of 12,146 women who live in 351 municipalities (237 grids) and were surveyed by the ENAHO.

Appendix Table B.4: Individual Filtering Procedure (ENAHO Sample)

Level:	Municipalities		Grids		Individuals	
Measure:	N	%	N	%	N	%
(A) DHS municipalities	351	100.00	237	100.00	32,939	100.00
(B) Reproductive age	351	100.00	237	100.00	25,859	78.51
(C) Household head or spouse of the household head	351	100.00	237	100.00	14,504	44.03
(D) Married/cohabiting and living with the partner	351	100.00	237	100.00	12,146	36.87

Notes: This table provides details on the individual filtering procedure 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, and who are married/cohabiting and living with their partners. 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' own calculations using data from the 2005-2014 Peruvian National Household Surveys (ENAHO).

C. Determination of the Rainy Season

Agriculture in Peru heavily depends on the seasonal rains during the growing/cropping/rainy season. In this appendix we explain in detail the criteria we use to determine the cropping/rainy season of each municipality.

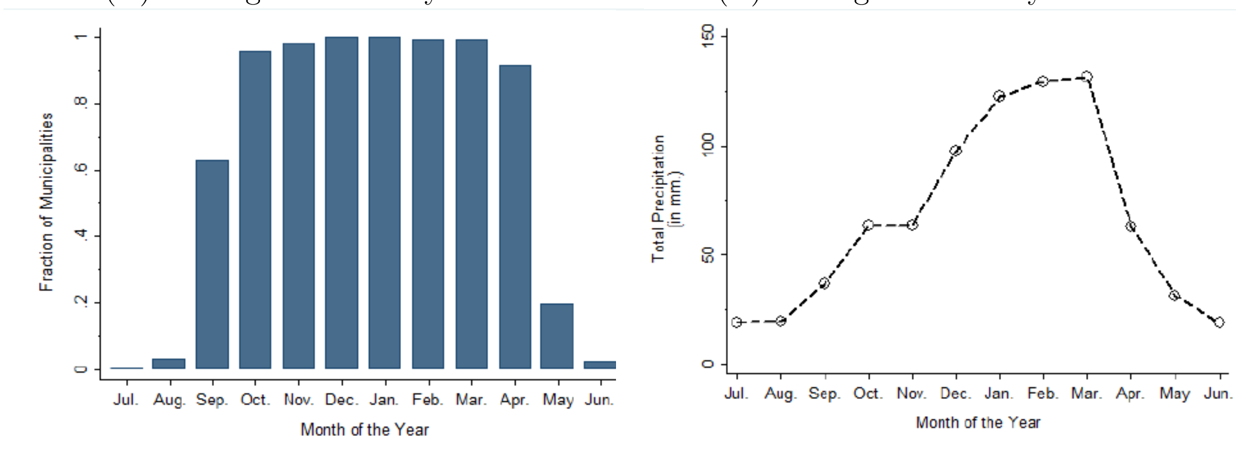
C.1. Computation

In order to determine the cropping/rainy season of each municipality, we analyze the cyclicality of location-specific rainfall levels 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 2000-2014. In our dataset, a year is defined as the time span between July and June of two contiguous years. With information at the municipality-by-year-by-month level, we first obtain, for each municipality-year data point, the 25th percentile of the distribution of year-long rainfall levels. We then keep the median of the collection of these values as our municipality-specific threshold level and construct indicators for months whose rainfall levels lie above this threshold. We next define a candidate month for the rainy season as that with at least 13 (out of 15) years of rainfall levels above the specified threshold. Finally, we define the cropping/rainy season of that municipality as the time span between the earliest and latest candidate months, inclusive.

Appendix Figure C.1 shows the fraction of municipalities in our sample whose cropping/rainy season lies within each month of the year (Panel A) and the average rainfall level in each month of the year (Panel B). On average, the cropping/rainy season has a duration of between 7.5 and 8 months, usually going from September to April of two consecutive years. The average rainfall level in a typical month during the cropping/rainy season is 95 mm.

Appendix Figure C.1: Rainy Season in DHS Municipalities

(A) Timing of the Rainy Season (B) Average Rainfall by Month



Notes: The figure shows the fraction of municipalities whose cropping/rainy season lies within each month of the year (Panel A) and the average rainfall level in each month of the year (Panel B). Both graphs are constructed based on municipality-level monthly information on rainfall levels over the period 2000-2014. Source: Authors' own calculations based on the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (Version 4.01).

C.2. Validation

We validate our computation of the rainy season based on rainfall levels by comparing it to an alternative definition based on vegetation growth. To this end, we utilize monthly gridded information on Enhanced Vegetation Index 2 (EVI-2) over the period 2000-2014 from the NASA's MEaSUREs data repository.[40] Information on EVI-2 is provided at a detail of 0.05×0.05 degrees, which corresponds to a surface of approximately 5 km^2. We follow a similar methodology to the one used with the rainfall levels to determine the cropping/rainy season of each municipality based on vegetation growth.[41]

[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. For further information about the EVI-2, visit: https://lpdaac.usgs.gov/dataset_discovery/measures/measures_products_table/vipphen_evi2_v004.

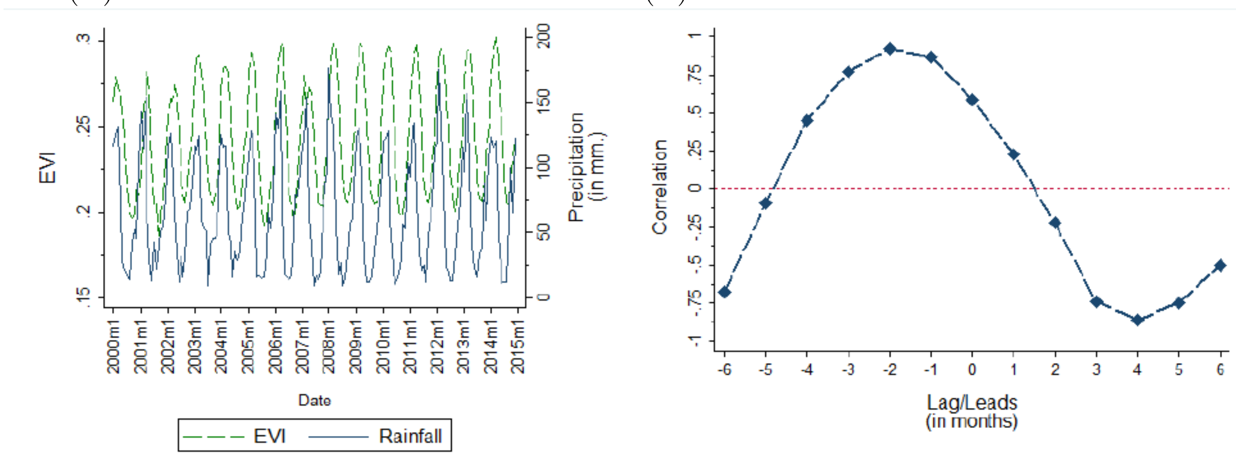
[41]Specifically, we begin by obtaining average monthly vegetation growth in each municipality. To that end, we average monthly EVI-2 across all nodes contained within the boundary of each municipality. Next, for each municipality-year data point we calculate the 25th percentile of the distribution of year-long vegetation growth and take the median of those values as the threshold level of each municipality. We then proceed to count the number of years the vegetation growth index of each month lies above the specified threshold and

In Appendix Figure C.2 we show the cross-correlation between rainfall levels and vegetation growth. In Panel A we plot the monthly vegetation growth (left axis) and monthly rainfall level (right axis) for the average municipality in our sample over the period 2000-2014. The graph shows that rainfall levels do a good job in tracking vegetation growth. Panel B depicts the correlation between the monthly EVI-2 and the lags and leads of rainfall levels. The cross-correlation peaks at the second and first lags of rainfall levels, implying that increased rainfall levels precede vegetation growth or, put simply, vegetation growth lags rainfall.

From this analysis, it follows that a more accurate description of the cropping/rainy season is given by defining this season based on the rainfall levels rather than relying on vegetation indices. In fact, the FAO defines the cropping/rainy season (growing season) based on rainfalls and not on vegetation growth. According to the official definition, the growing season "is the period (in days) during a year when precipitation exceeds half of the potential evapotranspiration" (FAO 1978).

Appendix Figure C.2: Rainfall Levels and Vegetation Growth

(A) Time Trends in EVI and Rainfall (B) Correlation between EVI and Rainfall



Notes: The figure shows the trend in monthly EVI and rainfall level over time (Panel A) and the cross-correlations between the EVI and the monthly lags and leads of rainfall levels (Panel B). Monthly EVI and rainfall level shown in Panel A are obtained by averaging monthly figures across municipalities. Both graphs are constructed based on municipality-level monthly information on EVI and rainfall levels over the period 2000-2014.
Source: Authors' own calculations based on the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (Version 4.01) and on the NASA MEaSUREs Vegentation Index and Phenology (VIP): Vegetation Indices Monthly Global 0.05° CMG – EVI-2.

We further verify the consistency in the definition of the cropping/rainy season when following one method or the other (that is, based on rainfall or vegetation growth). Appendix Figure C.3 depicts the starting month and duration of the cropping/rainy season based on

keep the months whose count at least 13 (out of 15) years. We keep the earliest and latest months (again, we have re-defined the data so that our earliest month is July of year $t-1$ and latest month is June of year t) that fulfil this condition and define the cropping/rainy season (based on vegetation growth) as the continuum of months within the earliest and latest months inclusive.

vegetation growth (Panel A) and the fraction of municipalities whose rainy season falls within each month of the year when defining the cropping/rainy season based on rainfall or vegetation growth (Panel B).

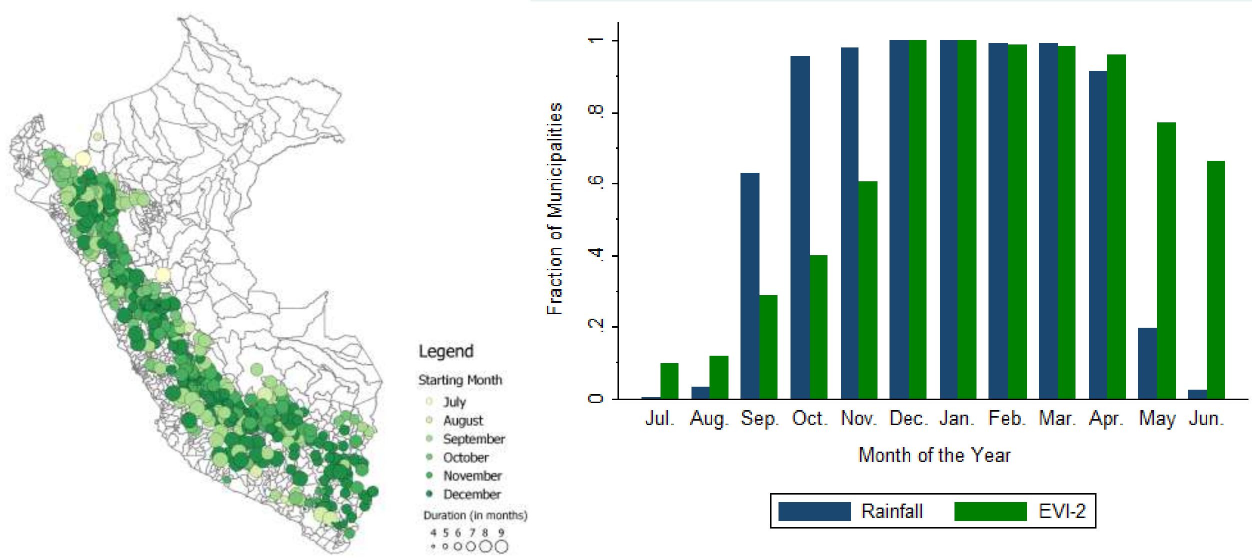
If we re-define the cropping/rainy season based on vegetation growth, the average starting and ending months of this season are October and May respectively and the average duration of the cropping/rainy season is between 8 to 8.5 months. When comparing the cropping/rainy season defined based on rainfall or vegetation growth, it can be observed that the rainy season begins (and ends) earlier when defined based on rainfall. This observation is consistent with the fact that rainfall tends to lag vegetation growth in our sample of municipalities.

We take these comparisons as evidence that our definition of the cropping/growing season based on rainfall levels is valid. We have shown that rainfall is highly correlated with vegetation growth in the municipalities in our sample. Yet, we have also pointed out that increases in rainfall levels usually precede vegetation growth, which is consistent with the germination stage of plant growth. Thus, a more accurate picture of the cropping period may be described by rainfall rather than vegetation growth since *greenness* (and thus, vegetation growth) might only be observed after the germination stage of the planting cycle.

Appendix Figure C.3: Rainy Season in the Peruvian Highlands (Alternative Definition)

(A) Duration of the Rainy Season

(B) Timing of the Rainy Season



Notes: The figure shows the starting month and duration of the rainy season when the cropping/rainy season is defined based on the EVI-2 (Panel A) and fraction of municipalities whose corresponding cropping/rainy season lies within each month of the year (Panel B). The starting month is symbolized by the color and the duration by the size of the circles. Both graphs are constructed based on municipality-level information on rainfall levels and vegetation growth index (EVI-2) over the period 2000-2014.
Source: Author's own calculations based on the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (Version 4.01) and on the NASA MEaSUREs Vegetation Index and Phenology (VIP): Vegetation Indices Monthly Global 0.05° CMG – EVI-2.

D. Sensitivity Checks

We consider three factors that may affect our results both quantitatively and qualitatively: (1) estimation of standard errors, (2) timing of the cropping/rainy season, and (3) definition of exposure to events of drought or flood.

Information on rainfall levels in our historical weather data is interpolated at the municipality level. However, given the structure of our data, it is possible that two or more municipalities have the same rainfall levels because they share the same rainfall nodes. Given that there is no variability in rainfall levels over time across these municipalities, a more conservative approach for estimating standard errors would be to cluster at the grid level. In Appendix Table D.1, we present our main estimates when clustering standard errors at the grid level in the regressions. Despite the fact that we find a slight increase in the estimated standard errors, this does not affect the statistical significance of our main results. All of our estimates preserve their statistical significance when compared to our main results presented in the main text.

Next, we discuss the results when re-defining the cropping/rainy season based on vegetation growth.[42] In Appendix Table D.2, we present the results when using the alternative cropping/rainy season derived from vegetation growth. We find that exposure to events of drought during the last rainy season increases the probability a woman experiences physical IPV by between 6 to 6.5 percentage points which is smaller than our main effects outlined in the main text.[43] The estimates of the effect of exposure to rainfall shocks on the probability a woman is physically hurt from the abuse are similar to the ones discussed in the main text and confirm that exposure to events of drought, but not flood, during the last rainy season increases the probability a woman has physical trauma from the abuse. Altogether, the evidence presented here is consistent with our main results and corroborates that exposure to events of drought during the last rainy season affects physical IPV against women, regardless of the method employed for defining the cropping/rainy season.

Finally, we check for whether constructing our indicators for exposure to rainfall shocks based on standardized precipitation affects our main results. We re-define exposure to events of droughts/flood if the rainfall level observed during the last rainy season falls below/above 1.5σ relative to the long-term (1950-2010) local rainfall mean observed during the cropping/rainy season. The results are presented in Appendix Table D.3 and indicate that exposure to an event of drought during the last rainy season increases the probability a woman experiences physical IPV by 6.5 percentage points and increases the probability a woman is physically injured from the abuse by 4 percentage points. Although the point estimates are smaller, they are qualitatively the same as those summarized in the main text.

[42] Re-defining the cropping/rainy season based on vegetation growth can alter our main estimates for two reasons. First, as described in Appendix C, the cropping/rainy season derived from vegetation growth tends to begin and end later than that derived from rainfall levels which implies that the indicators for exposure to rainfall shocks may be affected by the difference in rainfall levels between the months of no overlap across the two calculation methods. Second, the duration of the cropping/rainy season based on vegetation growth tends to be slightly longer which may in turn affect exposure to rainfall shocks.

[43] We also find that exposure to events of flood during the last rainy season reduces the probability a woman experiences physical IPV by between 3.5 to 4 percentage points.

Appendix Table D.1: Effects of Rainfall Shocks on Physical IPV Against Women
(Clustering Standard Errors at the Grid Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)				Women was Physically Injured from the Abuse (Mean = 0.103)			
Drought	0.085***	0.087***	0.083***	0.084***	0.067**	0.068**	0.066**	0.066**
	(0.029)	(0.029)	(0.028)	(0.028)	(0.027)	(0.027)	(0.026)	(0.026)
Flood	-0.027	-0.028	-0.028	-0.025	-0.022	-0.023	-0.022	-0.021
	(0.020)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
N	15,110	15,110	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	314	314	314	314	314	314	314	314
Woman characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Partner and relationship characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Other crop yield determinants	No	No	No	Yes	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 β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 4) and an indicator for whether the woman was physically injured from the abuse (columns 5 through 8). Clustered standard errors at the grid level are shown in parentheses. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Appendix Table D.2: Effects of Rainfall Shocks on Physical IPV Against Women
(Re-defining the Cropping/Rainy Season Based on Vegetation Growth)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)				Women was Physically Injured from the Abuse (Mean = 0.103)			
Drought	0.071**	0.068**	0.065**	0.059*	0.074***	0.073***	0.071***	0.064**
	(0.031)	(0.031)	(0.031)	(0.031)	(0.026)	(0.026)	(0.026)	(0.027)
Flood	-0.034*	-0.034*	-0.034*	-0.041**	-0.023	-0.024	-0.024	-0.032*
	(0.019)	(0.018)	(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
N	15,110	15,110	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495	495	495
Woman characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Partner and relationship characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Other crop yield determinants	No	No	No	Yes	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 β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 4) and an indicator for whether the woman was physically injured from the abuse (columns 5 through 8). Clustered standard errors at the municipality level are shown in parentheses. The indicators for exposure to events of drought or flood during the last rainy season are constructed by re-defining the rainy season of each municipality based on the cyclicality of vegetation growth (see Appendix C for further details). DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Appendix Table D.3: Effects of Rainfall Shocks on Physical IPV Against Women
(Using Standardized Precipitation to Define Exposure to Rainfall Shocks During the Last Rainy Season)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)				Women was Physically Injured from the Abuse (Mean = 0.103)			
Drought	0.073**	0.072**	0.068**	0.066**	0.046*	0.046*	0.043*	0.042
	(0.030)	(0.029)	(0.028)	(0.029)	(0.027)	(0.026)	(0.025)	(0.026)
Flood	-0.003	-0.004	-0.004	-0.002	0.000	-0.001	-0.001	0.001
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)
N	15,110	15,110	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495	495	495
Woman characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Partner and relationship characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Other crop yield determinants	No	No	No	Yes	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 β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 4) and an indicator for whether the woman was physically injured from the abuse (columns 5 through 8). Clustered standard errors at the municipality level are shown in parentheses. The indicators for exposure to events of drought or flood during the last rainy season are constructed based on standardized precipitation and take the value of 1 if the rainfall level during the last rainy season falls below/above 1.5 standard deviations from the long-term (1950-2010) local rainfall mean respectively. DHS sampling weights are used in all regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

E. Additional Robustness Analysis

Appendix Table E.1: Additional Robustness Analysis
(Controlling for Past History of Abuse)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)			Women was Physically Injured from the Abuse (Mean = 0.103)		
Drought	0.088***	0.083***	0.088***	0.070***	0.066**	0.069***
	(0.030)	(0.029)	(0.029)	(0.026)	(0.026)	(0.026)
Flood	-0.025	-0.024	-0.025	-0.021	-0.020	-0.021
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)
Witnessed interparental violence	0.057***		0.057***	0.046***		0.046***
	(0.008)		(0.008)	(0.007)		(0.007)
Experienced IPV with an ex-partner		0.038	0.034		0.014	0.010
		(0.031)	(0.031)		(0.025)	(0.025)
N	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495
Woman characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 3) and an indicator for whether the woman was physically injured from the abuse (columns 4 through 6). Clustered standard errors at the grid level are shown in parentheses. DHS sampling weights are used in all regressions. In columns 1 and 3 we include an indicator for whether the woman witnessed interparental violence as a conditioning variable in the regressions. In columns 2 and 5 we include an indicator for whether the woman experienced physical IPV in the hands of an ex-partner as a conditioning variable in the regressions. In columns 3 and 6 we include both indicators as conditioning variable in the regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.

Appendix Table E.2: Additional Robustness Analysis
(Controlling for Agricultural and Household Assets)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Women Experienced Physical IPV (Mean = 0.128)			Women was Physically Injured from the Abuse (Mean = 0.103)		
Drought	0.083***	0.083***	0.082***	0.065**	0.065**	0.064**
	(0.029)	(0.029)	(0.029)	(0.026)	(0.026)	(0.026)
Flood	-0.025	-0.024	-0.025	-0.021	-0.020	-0.021
	(0.020)	(0.020)	(0.020)	(0.018)	(0.019)	(0.018)
Land size: less than 5 hectares	-0.007		-0.008	0.001		-0.000
	(0.008)		(0.008)	(0.007)		(0.007)
Land size: between 5 and 10 hectares	-0.025*		-0.026*	-0.017		-0.019
	(0.014)		(0.014)	(0.013)		(0.013)
Land size: more than 10 hectares	0.042**		0.041**	0.052***		0.052***
	(0.019)		(0.019)	(0.019)		(0.019)
Household owns livestock		0.017	0.018		0.021	0.021
		(0.017)	(0.017)		(0.014)	(0.014)
N	15,110	15,110	15,110	15,110	15,110	15,110
Clusters	495	495	495	495	495	495
Woman characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Partner and relationship characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Other crop yield determinants	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively. The table shows estimates of β^D and β^F from different specifications based on equation (1) in section 4. The dependent variables are listed at the top of the table and correspond to an indicator for physical IPV experienced by the woman in the last 12 months (columns 1 through 3) and an indicator for whether the woman was physically injured from the abuse (columns 4 through 6). Clustered standard errors at the grid level are shown in parentheses. DHS sampling weights are used in all regressions. In columns 1 and 3 we include indicators for land size (less than 5 hectares; between 5 to 10 hectares; more than 10 hectares; base: household does not own land) as conditioning variables in the regressions. In columns 2 and 5 we include an indicator for whether the household owns livestock (hers or farm animals) as a conditioning variable in the regressions. In columns 3 and 6 we include both indicators as conditioning variable in the regressions. All regressions include woman characteristics, partner and relationship characteristics, other crop yield determinants, survey-month, survey-year, and municipality fixed effects as conditioning variables (see the notes to Table 2 for further details). See the notes to Table 1 and the main text for information about the sample composition. Further details of each regression are described within the table. The data used for the regressions come from the 2005-2014 Peruvian Demographic and Health Surveys (DHS), from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series (V 4.01), and from the ERA-Interim 2004-2014 Archive on Monthly Global Atmospheric Reanalysis.