Weather Shocks and Violence Against Women in Sub-Saharan Africa

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Abstract

We use variation in rainfall to study how income shocks affect intimate partner violence in Sub-Saharan Africa. The analysis proves the presence of and corrects for spatial autocorrelation in weather shocks. We find no evidence supporting our theory that unusually low levels of rainfall would increase intimate partner violence. This holds both for the probability of experiencing violence in a given year, and for the risk of experiencing violence for the first time during the course of a marriage. We speculate that the collective nature and slow onset of droughts trigger less aggression and more adherence to social norms than other income shocks that might increase violence against women in Sub-Saharan Africa and elsewhere.

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1 Introduction

Sub-Saharan Africa has one of the highest levels of violence against women among the regions of the world (World Health Organization, 2013). Why that is the case is an intriguing question, and the region has been plagued with other factors that are commonly thought to affect violence, such as conflicts and poor institutional quality. As Sub-Saharan Africa is also the world's poorest region, a plausible hypothesis is that violence is so widespread there because households are poor (Cools and Kotsadam, 2014). We seek to contribute to this understanding by using one of the most common sources of income variation in the developing world, namely variation in rainfall (e.g., Burke, Gong, and Jones (2015); Harari and La Ferrara (2013)).

The strategy of using rainfall variation as a proxy for income shocks has several potential advantages, mainly in terms of identification. As poor areas are different from rich areas on many dimensions, such as having poor institutions and poor schools, it is hard to disentangle the causal effects of contextual poverty from the effects of these other factors. Similarly, at the individual level it is hard to distinguish the effects of poverty on violence from factors that may cause both poverty and violence such as low impulse control or self-esteem. By using deviations in rainfall relative to what is normally observed in each location, we are exploiting an exogenous source of variation in income. Whether a rainfall shock occurs in one year or the next at a particular location is random, and we are able to exploit this random variation using a fixed effects framework.

Rainfall is relevant for African households due to the largely agrarian structure of the economies (Burke, Gong, and Jones, 2015) and low levels of irrigation (Miguel, Satyanath, and Sergenti, 2004). Another advantage of using rainfall shocks is in terms of availability at the local level. Even if economic growth at the local level would have been random, there is no systematic collection of any income data at such a fine level. A major disadvantage relates to being able to interpret the effects as stemming solely from income shocks. While there is no question that rainfall affects income, it may also affect other things such as conflicts or the mood of people directly. We are open to the possibility that other channels may also partly explain the relationship between rainfall shocks and violence and our reduced form results do not allow for a distinction of different mechanisms. Nonetheless, the reduced form effects of rainfall variability on domestic violence are interesting on their own, as mean rainfall will likely decrease in dry regions and extreme precipitation events are very likely to become more intense and frequent due to global climate change in large parts of Africa (IPCC, 2014).

The idea of using rainfall to identify the effects of income shocks on violence against women is not without precedence. Miguel (2005) uses local rainfall variation to identify the effects of income shocks on witch killings of elderly women in a district in rural Tanzania. He finds that there are twice as many murders of this kind in the years following weather shocks as compared to normal years. Sekhri and Storeygard (2013) analyze the effects of rainfall in India and find a positive effect of droughts on both domestic violence and murder of spouses, but no statistically significant effect of floods. Our study contributes to the literature by analyzing the effects of weather shocks in a large sample of African countries with different climates and cultures.

We combine data on precipitation from the ERA-Interim project with the best available data on domestic violence, namely the Demographic and Health Surveys (DHS). In recent years, the DHS surveys include questions on domestic violence, and they also contain GPS coordinates at the level of the primary sampling unit. This enables us to connect experiences of abuse to rainfall shocks. Our complete sample consists of 149,000 women in 17 countries. Despite being the best available large scale data set on domestic violence, DHS is still limited in time as the respondents exposed to the domestic violence module are surveyed between 2003-2013. Furthermore, we have repeated observations on domestic violence for nine countries only. We therefore analyze the data using several different empirical strategies, with their respective advantages and disadvantages.

Our main variable of interest is whether the women have experienced violence during the last year before the survey. We believe that this measure is the most accurate as it is easiest recalled, and that year-to-year changes in violence against women would be the most responsive to climatic variation. However, we also investigate two measures of violence on the extensive margin, i.e., reflecting whether climatic shocks create more victims of intimate partner violence. These are the probability of having ever experienced violence in a relationship, and the probability of experiencing violence for the first time in a marriage or cohabiting union in a given year.

We start by using variation in weather shocks in the total cross-sectional sample, and analyze whether rainfall shocks are correlated with the risk of having been abused last year. This strategy uses a large sample but has serious drawbacks in terms of internal validity. Since rainfall is determined by large weather systems, places that are close to each other are likely to be affected by shocks at the same time. As places close in space are likely to share many characteristics, including culture and institutions, areas that experience a shock are likely to differ from areas that do not. We prove that this indeed causes the residuals to be spatially autocorrelated, and add spatial polynomials to correct for this.

As it is not possible to control for area fixed effects in the pooled cross-sectional analysis, we proceed to use two other strategies that enable us to control for grid level fixed effects. The second strategy consists of using a limited sample from nine countries for which we have repeated surveys. Even though the surveys are not longitudinal in the sense that each household is followed over time, it is a repeated cross section whereby we have observations from two time periods at the grid level. Aggregating the data to the grid level and measuring the effects of droughts and floods on the change in the probability of women experiencing violence essentially controls for all time invariant confounders. Using this model, we cannot reject spatial independence of residuals in our most elaborate specification. We can also verify that droughts increase the likelihood of observing a level of household wealth within the two lowest quintiles of the wealth distribution. This strategy is thereby stronger in terms of identification, but the drawbacks are a limited sample size and that the two samples in the same areas might differ in the different years.

The third strategy instead exploits the fact that women who have experienced partner violence are also asked how many years passed after marriage before they were abused for the first time. Since we also know how long each woman has been married, we can combine our weather data with the timing of first abuse and see whether weather shocks affect the risk of being abused for the first time. We deem this strategy to be strongest in terms of internal validity as we are exploiting a 10-year time series within the same sample. This analysis identifies climatic determinants of the extensive margin of abuse, i.e., factors that contribute to husbands crossing the important boundary it is to start becoming abusive towards their wives. However, it does not capture the intensity or the likelihood of re-occurrence of violence within a relationship.

Using the cross-sectional and first differencing strategies, we do not find any indication that droughts or floods increase the likelihood of experiencing violence during the preceding year in the models where spatial independence is plausible. On the contrary, estimates are fairly close to 0 and we can reject that droughts raise violence levels by more than 4 percentage points in the cross-sectional model and more than 10 percentage points in the first differenced model. Our duration model mimics these findings as we find that droughts either reduce the risk of experiencing violence for the first time in a marriage, or do not affect the risk at all. These findings cause for a re-thinking of the income-violence relationship as perhaps being mitigated by important tertiary factors, such as isolation or feelings of unfairness.

2 Theories on the effect of weather on violence

This section reviews the literature with respect to the possible links between weather-induced income shocks and violence. The effect going from droughts and floods to violence may, however, also work through other channels. In particular, bad weather has been linked directly to frustration and aggression as well as to eco-migration. The second part of this section reviews the literature with respect to these other mechanisms.

2.1 Income and violence

Empirical studies document a strong, negative correlation between economic development and domestic violence at the country level (Duflo, 2012; Doepke and Tertilt, 2009). Poorer women within countries are generally more exposed to violence than are women with higher incomes (Benton and Craib, 2011; Jewkes, 2002; True, 2012). The positive association between poverty and crime is one of the most robust findings in criminology (Benson et al., 2003). The relationship is also found with respect to domestic violence. For instance, Schneider, Harknett, and McLanahan (2016) found that the Great Recession in the United States led to an increase in intimate partner violence in households experiencing economic hardship, and to more controlling behaviour by men towards their partners in communities where unemployment levels increased.

A few studies have investigated the relationship between rainfall and crime. Mehlum, Miguel, and Torvik (2006) find that low rainfall in 19th century Germany increased crime and they show that the effect runs via increased grain prices that lower real wages. Two previous papers have analyzed the effects of rainfall on violence against women directly. Both interpret the findings as going through income. Sekhri and Storeygard (2013) analyze the effects of rainfall in India and find a positive effect of droughts on both domestic violence and dowry deaths but no statistically significant effect of floods. They interpret the findings using a theory where men exert violence on their wives in order to extract resources from in-laws. Dowry killings further enable the man to re-marry and receive dowry payments from a new family. They document that dowry killings in India lead to more dowry payments. Miguel (2005) uses local rainfall variation to identify the effects of income shocks on murder of "witches" in a district in rural Tanzania. He finds twice as many witch murders in years following droughts or floods. He further shows that extremes at each end of the rainfall distribution leads to large income drops at the local level, with somewhat larger effects of floods, and interprets the results as negative income shocks leading to the murdering of old women.

Frustration

Poverty leads to frustration which gives rise to mental processes related to escape or aggression. The frustration-aggression hypothesis is the most common psychological theory explaining the link between poverty and aggression (Barlett and Anderson, 2013). Having insufficient income to meet the needs of one's family is also stressful, and stress is thought to influence the degree of domestic violence (Jewkes, 2002).[1] In addition, anxiety lowers the ability of people to exert self-control. Mani et al. (2013) find that

[1] As poverty also leads to stress, Barlett and Anderson (2013) argue that The General Aggression Model (GAM) is a better psychological framework for understanding the effects. GAM argues for an interaction between personality and situational input variables that affect internal emotional state that then lead to either aggressive or non-aggressive behavior. As we are primarily

poverty reduces cognitive capacity in a laboratory study as well as in a field study. Poverty also requires demanding mental processes as the poor must face harder tradeoffs and try to keep expenses down. As the human cognitive system is limited these poverty induced mental processes compete with other necessary processes for attention. In the field study they exploit that Indian sugarcane farmers experience cycles of poverty whereby they are poorest just before harvest and richest just after. They find that the same farmer has lower cognitive ability when poor as compared to when being relatively richer. As cognitive capacities such as self-control are consistently argued to be important in the psychology of violence (e.g., DeWall, Anderson, and Bushman (2011)) there is a plausible link between income shocks and violence against women at the individual level. Negative shocks also trigger frustration. Frustration arises when reality turns out to be worse than expected (Munyo and Rossi, 2013). An unanticipated negative drop in household income thereby leads to frustration and frustration in turn is thought to lead to aggression. Similar predictions are found in the so called negative affect theory proposed by Berkowitz (1983) which stipulates that aversive events increases aggression. Experiments with animals show that unexpected negative shocks cause frustration leading to aggressive behavior (see Munyo and Rossi (2013) for an overview). Consistent with such a framework, Card and Dahl (2011) find that upset losses in American football, i.e., losses where the team was expected to win, lead to more violence against women. Similarly, Munyo and Rossi (2013) use soccer games as natural experiments and combine this with property crime data from Montevideo, Uruguay. They find that frustration leads to a spike in violent crime (robbery) one hour after the game.

Power and dominance

Droughts may cause reductions in income which are not necessarily evenly distributed between men and women. One of the most popular sociological theories of domestic violence, the resource theory, suggests that men with few other resources may use violence to maintain dominance within the family (Goode, 1971; Vyas and Watts, 2009). Similarly, according to the backlash theory, men may use violence to counteract any reduction in their relative power to reinstate their dominance (e.g., Eswaran and Malhotra (2011)). In status inconsistency theories where atypical roles threaten male identity (Hornung, McCullough, and Sugimoto, 1981), male loss of income or employment could lead to increased violence. Changes to the power relation between spouses is also important in economic bargaining theories of domestic violence. These models focus on women's outside options, which is usually considered to be the utility level in case of divorce (e.g., Lundberg and Pollak (1996); Pollak (2005); Eswaran and Malhotra (2011)). Worsened outside options through reduced female income should then increase violence within marriage – all else equal (Farmer and Tiefenthaler, 1997). In bargaining models where violence is instrumental or extractive, reduced income flows to the husband may lead to more violence if there are resources to extract from women or their relatives (e.g., Bloch and Rao (2002); Sekhri and Storeygard (2013)).

Communal factors

In addition to the effects of individual level poverty, there is an argument to be made that lack of protective social norms and low social control cause more violence. Benson et al. (2003) argue that there is more violence

interested in the reduced form effects of weather on violence, without specifying whether the internal mechanism is via, e.g., frustration or stress, we remain agnostic about what psychological theory best explain the relationship and we are content with showing that there are many possibilities via which income may be psychologically related to violence.

in poor communities for cultural and institutional reasons. They build on social disorganization theory which predicts poor areas to have weaker social bonds between individuals leading to less social control and more social isolation. Hence, even if the acceptance of violence is not higher in such areas, people are less likely to intervene and the levels of abuse are argued to be higher. The husbands thereby gain a type of impunity, which is even higher if acceptance rates are also higher in poorer areas. Indeed, Benson et al. (2003) argue that poor areas also have higher acceptance rates.[2] Poverty at the contextual level also reduces the quality of social institutions such as the local police, which may further aggravate problems of violence (Uthman, Moradi, and Lawoko, 2009).

In a paper also using DHS data on violence from Sub-Saharan Africa, Alesina, Brioschi, and Ferrara (2016) found that ancient socioeconomic conditions determine social norms about gender roles and intrafamily violence which persist even when the initial conditions change. In particular, they found that women whose ancestors lived in nomadic and isolated settlements, compared to those living in more compact settlements, were exposed to a higher probability of violence and were more prone to justify it. One of the explanations they provide for this is that the former settlements represent less developed communities.

Weather shocks are perfectly correlated within a community. Therefore our results show the combined effect of negative income shocks to the community as well as to the individual. The fact that they are shocks, as opposed to more stable characteristics, also potentially gives rise to additional mechanisms. Barlett and Anderson (2013) argue that aggregate economic downturns make people fearful, frustrated, stressed and hostile and they find that indicators of poor economic times in randomly assigned news clips cause aggression related emotions. This suggests that aggregate economic shifts influence aggression at the individual level, perhaps in addition to the effects of more constant levels of poverty. On the other hand, strong social norms against violence against women in a community and social control and cohesion may protect women also during economic crises. There may furthermore be aspects of the particular income shock from lack of rainfall which makes it more likely that such protective institutions will continue to be operating. Droughts cause collective income losses affecting entire communities, and may be seen as exogenous and perhaps coincidental by the affected men. In contrast, intimate partner violence following the Great Recession in the United States may be caused both by a feeling of individual unfairness for men who lose their employment, and a feeling of collective unfairness if a richer segment of society is seen as causing the crisis (Schneider, Harknett, and McLanahan, 2016). A shared and naturally occurring drought shock may be met by collective solutions and sentiments of belonging which may trigger less aggression among men and possibly even strengthen social norms and women's position. Furthermore, the crippling onset of droughts may give communities time to respond to the crisis in a manner which is in accordance with social norms. Frey, Savage, and Torgler (2011) make the argument that the slow sinking of the ship Titanic in 1912 contributed to high survival rates of women and children whereas there was less adherence to norms that protect vulnerable groups during the rapid sinking of Lusitania by a torpedo attack in 1915. They believe their findings can be extended to the study of modern natural disasters and argue that variation in time for co-ordinated responses is an important factor.

The relationship between rainfall and group conflict is consistently interpreted as going via income. Miguel, Satyanath, and Sergenti (2004) find that lower rainfall growth led to more conflict in SSA and also documents that economic growth is lower when rainfall growth is lower. Bohlken and Sergenti (2010) use a similar approach and show that negative rainfall shocks increase Muslim-Hindu riots in India. The mechanism leading rainfall shocks to conflict in the economics literature goes via income in the sense that

[2] Uthman, Moradi, and Lawoko (2009) find that individuals living in poorer areas have higher acceptance of domestic violence in a study of 17 African countries between 2003 and 2007.

lower incomes lower the opportunity cost of violence and reduces the state's capacity to defend itself (Dell, Jones, and Olken, 2013).

2.2 Other mechanisms

Weather shocks may also affect violence through other channels. The most commonly studied weather induced effect on violence links temperature directly to aggression. Ranson (2014) finds crime to be a function of temperature over 50 years in 300 U.S. counties. Jacob et al. (2007) find that higher temperature increases violent crimes and that increased rainfall reduces it. The authors interpret the results as weather having a direct and immediate effect on crime. High temperature is consistently associated with violence in the psychological literature, where the heat hypothesis states that hot temperature increases aggression by increasing hostility feelings and thoughts (Anderson, 2001). The simplest version of the theory is that people become cranky at uncomfortable temperatures. The result that heat leads to violence has been found in cross sectional and panel data studies, in experiments, and in historical analyzes (see Anderson and DeLisi (2011) for an overview).[3]

Floods and droughts may also cause both temporary and permanent migration, which may increase violence. Anderson and DeLisi (2011) review the effects of weather changes on violence via Eco-migration. When Hurricane Katrina hit the US in 2005, it flooded about 80 percent of New Orleans, causing over a million people to emigrate. Initially, Houston received most migrants and had a huge increase in homicides the following months.[4] Also cooling is related to violence. The little ice age between 1300 and 1850 was a period of much war and violence that Fagan (2000) attributes to the climate change via its effects on food shortages. Anderson and DeLisi (2011) argue that all types of rapid climate change in terms of cooling, heating, floods, and droughts, are likely to spur violence because it threatens human resources. As bad weather in terms of rainfall may also affect migration and people's mood directly, just as temperature, we keep the possibility of these causal pathways open.

3 Data

3.1 Survey data and dependent variables

We use data from the Demographic and Health Surveys (DHS), which provide standardized surveys across years and countries. DHS include GPS coordinates with a random error at the DHS cluster level, a cluster being one or several geographically close villages, or a neighborhood in an urban area.

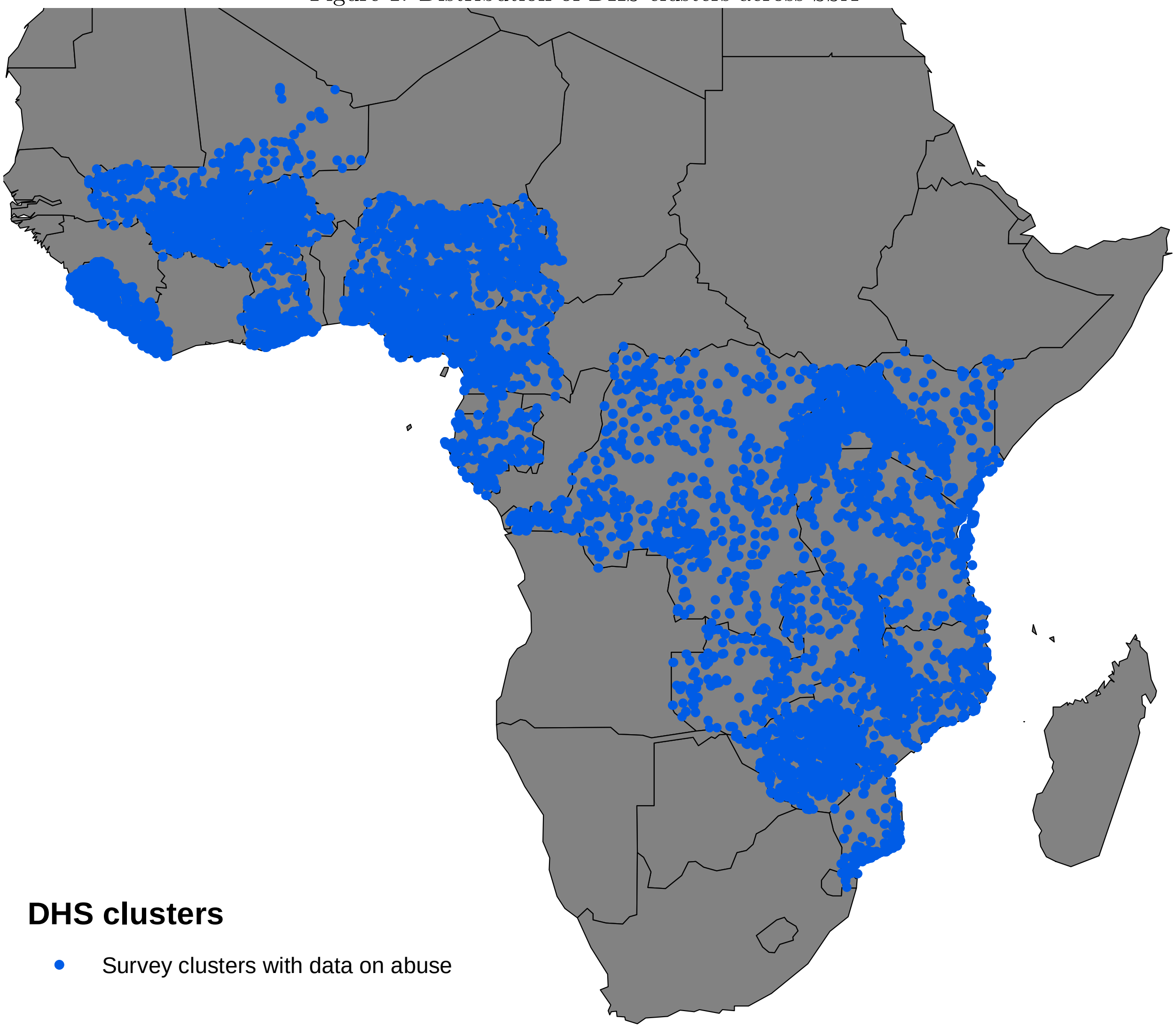
At the end of the 1990s, a standardized module was developed with questions about the respondents' experiences with domestic violence. We combine all surveys carried out in Sub-Saharan Africa (SSA) that

[3] There is some evidence that the relation between weather and violence is biological, at least regarding temperature (Dell, Jones, and Olken, 2013). Temperature affects serotonin neurotransmission in the brain which in turn affects aggression (Tiihonen, Rasanen, and Hakko, 1997) and recent molecular genetics studies have found gene-environment interactions whereby temperature affects neuro and hormonal pathways in the areas of thermoregulation and emotion regulation in the brain.

[4] Similarly, during the US Dust Bowl in the 1930s when prolonged drought lead to environmental disaster around Oklahoma, over 2 million people left the area and reports of violence are widespread. Whether these are effects on violence of weather via income, migration, or direct frustration is of course difficult to disentangle.

contain information on experience with wife-beating and GPS coordinates into one data set. The total sample size becomes 149,032 women in the age span 15-49 years, from 17 countries, interviewed in the years 2003-2013, living in 12,498 survey clusters. The distribution of the sample across SSA is shown in Figure 1.

Figure 1: Distribution of DHS clusters across SSA



These data are collected in the domestic violence module, implying that not all women are selected to answer these questions. Domestic violence is measured using a modified Conflict Tactics Scale (CTS), which has several advantages compared to many other datasets on violence (see Kishor (2005) for an extensive overview). A characteristic of CTS is that it uses several different questions regarding specific acts of violence. In this way the measure is less likely to be polluted by different understandings of what constitutes violence. CTS is also argued to reduce under-reporting as it gives respondents multiple opportunities to disclose their experiences of violence (Kishor, 2005; La Mattina, 2013).

The interviewers who use the domestic violence module are trained specifically to handle the sensitive questions of domestic violence, and they follow a strict protocol ensuring privacy. In particular, the interviewers are instructed to check all the surroundings within hearing distance for the presence of others. Only children young enough to not understand the questions are allowed to be present. The interviews are not allowed to proceed if privacy is not ensured, and the interview is terminated if someone enters the zone (ICF International, 2009).

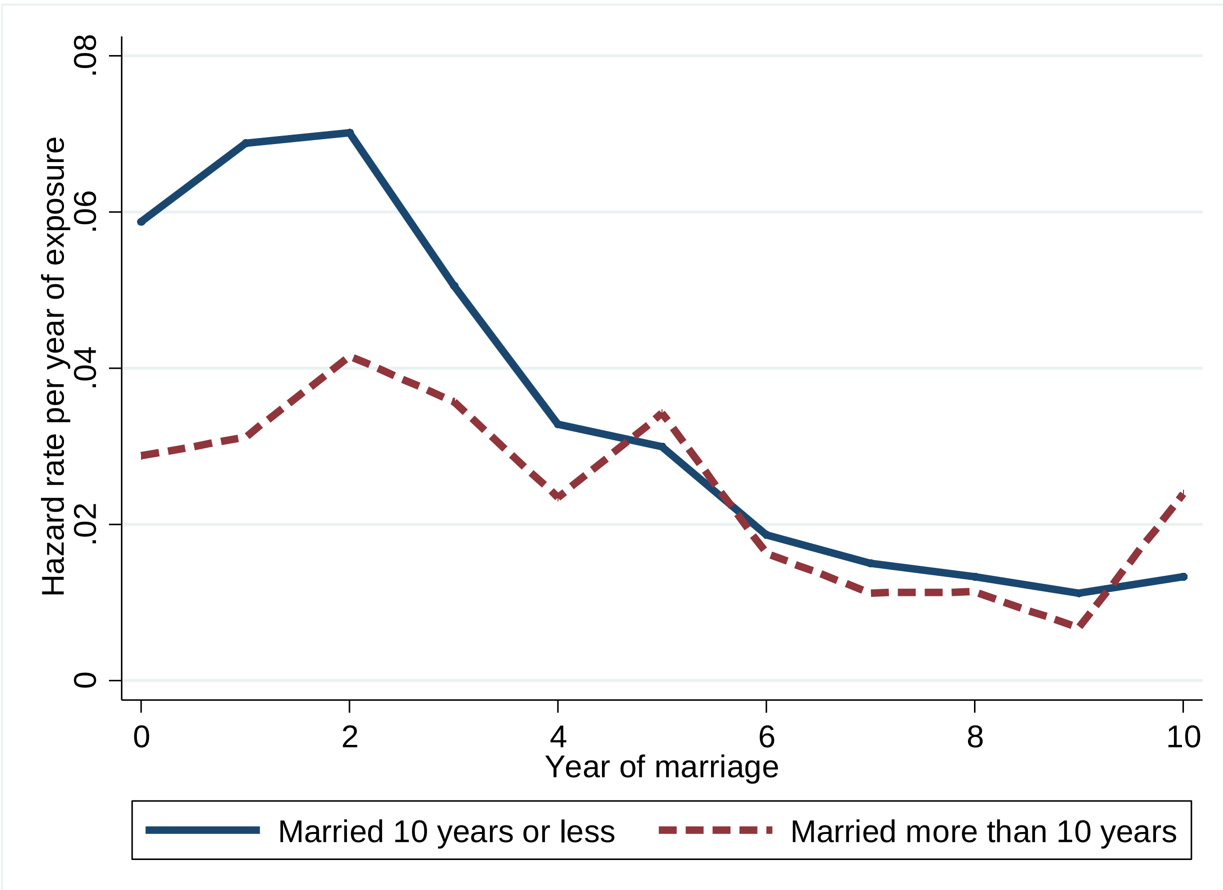
The care with which data is collected inspires confidence that the problem of under reporting is as low as possible. Furthermore, the high reported prevalence of violence across the region suggests that a considerable degree of women are willing to report violence. Likewise, the high acceptance of wife-beating in the region documented in Cools and Kotsadam (2014) suggests that social acceptability bias in reporting may be of less importance than in other settings. Palermo, Bleck, and Peterman (2014) use 24 DHS surveys to provide bounds for other sources of violence data such as health systems data or police records. They found that only 40 percent of the women having experienced domestic violence in the DHS surveys had reported this to someone and that only 7 percent had reported it to a formal source. Hence, while we may worry about under reporting, we are still likely to have one of the best sources of data.

Only women who are currently or have ever lived with a partner are selected to answer the questions about experience with intimate partner violence. The module includes questions about both emotional and physical (including sexual) violence. Our focus in this paper lies with physical violence. Violence is recorded as having occurred for women who answer that they have had a partner doing one of the following to them: Pushing, shaking, slapping, throwing something, or twisting an arm, striking with a fist or something that could cause injury, kicking or dragging, attempting to strangle or burn, threatening with a knife, gun, or other type of weapon, and attacking with a knife, gun, or other type of weapon, physically forcing intercourse or any other sexual acts, or forcing her to perform sexual acts with threats or in any other way. Using this definition, 26% of the women in our total sample were subject to abuse during the last twelve months and 32% have ever been victims of intimate partner violence.

All women stating that that they experienced abuse from their last partner are also asked when this first happened. The question asked in the module places the first violent episode in relation to either the year of marriage or the year of cohabitation of the *last* partner. A different question asks the women when they *first* married or entered cohabitation (married for short). We therefore had to limit the sample to women who only married once, and who were still married at time of interview. For consistency, we also removed women who were subjected to violence by their husbands before marrying, or reported a later occurrence than the time between marriage and the survey would allow for. Another worry is that the interviewed women misreport the timing of the first violent episode, which is likely to be a larger problem if the first occurrence happened a long time before the survey. We therefore reduce the sample to women who have been married less than ten years at the time of survey. The women thus enter the sample when they marry, and exit the sample when they are subjected to violence for the first time or in the year of interview, with the year of interview being less than ten years after marriage.

Hazard rates are the number of women who experience violence for the first time in a given year, divided by the number of women at risk that year. These are shown in Figure 2 for women who have been married ten years or less, and women who have been married more than ten years. The observed rates strengthen our suspicion that women who have been married for a long time tend to forget violent episodes that occurred early in marriage, and they also seem to remember the timing of the abuse with less precision as they heap the reporting of violent episodes on five and ten years more than women who have been married for a shorter period. For women married ten years or less, the risk of experiencing violence for the first time is the greatest after one-two years in marriage, and then falls sharply. Also these women display some heaping of violence at ten years of marriage; since the group who have been married exactly ten years is also suspiciously large, we exclude these women from further analysis. 25% of the 50,512 married women in the sample who have been married less than ten years experience violence in the period between their wedding and the survey. The expected probability of experiencing violence if staying married for ten years is 34% for these women.

Figure 2: Yearly risk of first violent episode



3.2 Weather data and construction of weather shocks

The data on total precipitation which we use comes from the ERA-Interim project, and is produced by the European Centre for Medium-Range Weather Forecasts. The data is recorded twice daily on a 0.75 x 0.75 degrees grid level from January 1 1979 to December 31 2011. The overwhelming majority of data comes from satellites, yet data from radiosondes, pilot balloons, aircrafts, wind profilers, ships, drifting buoys, and land stations is also used (Dee et al., 2011).

Our interest lies in violence that stems from income shocks created by extreme weather, and we therefore need to specify relevant seasons when agricultural yields are affected by rainfall. As the African continent generally does not enjoy abundant and reliable rainfall, adjusting crops, planting and harvest times to the rainy season is crucial to maximize agricultural production (Liebmann et al., 2012; Ati, Stigter, and Oladipo, 2002). If we assume that farmers make adjustments that are more or less optimal over time, we should therefore expect that rainfall during the rainy season when rainfall is plentiful matters the most for yields. We follow the method of Liebmann et al. (2012) in constructing rainy seasons that are consistent for Africa as a whole. First, we identified the rainy season in each grid cell as a continuous sequence of calendar months with average monthly rainfall above the yearly average. If there were multiple sequences, we chose the sequence during which the sum of monthly levels of precipitation was the largest.

There are studies which use absolute measures of droughts and floods, such as the number of reported deaths (Neumayer and Plumper, 2007), and in theory it should also be possible to use an absolute measure of rainfall in the analysis. An absolute analysis would ideally be able to identify shocks that were similar in terms of biological or economic impact. However, such an analysis would be less likely to be causal, as the effect of living in a drought-prone area would be indistinguishable from the effect of the drought itself. More flood-prone areas are for instance located closer to the coast, and were therefore for instance more affected by slave trade which is known to affect levels of income and trust between people living there today (Nunn, 2008; Nunn and Wantchekon, 2011). Furthermore, the effects of a given absolute shock, e.g., in terms of number of reported deaths, are obviously affected by the institutions and levels of income in the area and not only by exogenous factors.

To construct our relative measures of droughts and floods, we created a gamma distribution of rainfall during the rainy seasons between 1979 and 2011 for each grid cell. The gamma distributions were used because the distributions tend to be right-skewed, and we therefore wanted a model with full flexibility (Burke, Gong, and Jones, 2015). We study both the effects of droughts and floods that occurred during rainy seasons which ended during the same 12 months in which violence was recorded, and weather events that happened the year before the violent episode. The first effect will contain some that were affected after the bad yield had been harvested and the income shock was a fact, whereas others may have experienced violence before harvest, perhaps in anticipation of the crop failure. The latter captures effects during a complete year of exposure to a failed harvest.

Temperature is negatively correlated with rainfall, and temperature may at the same time have an independent effect on violence against women. To the extent that we are interested in increases in violence due to economic distress caused by droughts, controlling for temperature during the relevant rainy season will yield this conditional estimate of drought impact. We follow Ranson (2014) in using the fraction of days with temperature at noon GMT observed within 10-degree Fahrenheit bins. We also control for the average fraction of days in each bin in the cross sectional analysis.

With a complete model of violence, it should be straight-forward to estimate the effect of droughts and floods on experiences of violence in the year leading up to the interview. Whether an area experiences rainfall a particular year is, after all, plausibly random and exogenous. However with an incomplete model, other spatially correlated factors (in addition to temperature) may make any relationship found between droughts and violence spurious. This issue is due to that weather phenomena are spatially clustered, and that our drought and flood indicators only appear in a small number of cells. Thus it is likely correlated with other spatially determined factors that are important for our outcome variable, e.g., a culture of violence. As attempting to identify and control for all these factors is difficult, a solution proposed by Lind (2015) is to add Legendre polynomials on the coordinates and interactions between these polynomials.[5] In regressions with grid cell fixed effects, the only threat to identification lies in spatially correlated time trends, and Legendre polynomials are thus multiplied by these trends.

[5] Any polynomial can be used, yet Legendre polynomials are chosen due to their numerical stability (Lind, 2015).

4 Empirical strategies

4.1 Cross sectional analysis

In analyzing the effects of weather on violence against women, we perform several different types of analyses. First, we ask whether having experienced a drought or a flood during a recent rainy season is related to having been abused during the last year. The estimation will be of the following form:

$$\begin{aligned} Abused\, Last\, Year_{i,g,t} = \beta_1 D_{g,t-1} + \beta_2 D_{g,t-2} + \beta_3 F_{g,t-1} + \beta_4 F_{g,t-2} \\ + T_{g,t-1} + T_{g,t-2} + T_g + \alpha_s \times L_g(x,y) + Age_i + e_{i,g,t} \end{aligned} \quad (1)$$

The dependent variable is a variable for whether a woman i living in grid cell g was abused in the year before the time of interview t. $D_{g,t-1}$ and $D_{g,t-2}$ are negative shocks to precipitation in grid g below a predetermined percentile in the grid-specific gamma distribution during the last and next-to-last completed rainy seasons before the month of interview, respectively. $F_{g,t-1}$ and $F_{g,t-2}$ are the corresponding positive precipitation shocks. Matrices of fraction of days in 10 degree Fahrenheit temperature bins during the two last rainy seasons, as well as average temperatures, are entered in the terms $T_{g,t-1} + T_{g,t-2} + T_g$. We include survey fixed effects, α_s, which control both for country and the year of survey, and as such, we are only comparing the effects of shocks within a given country and year. These survey fixed effects are interacted with Legendre polynomials

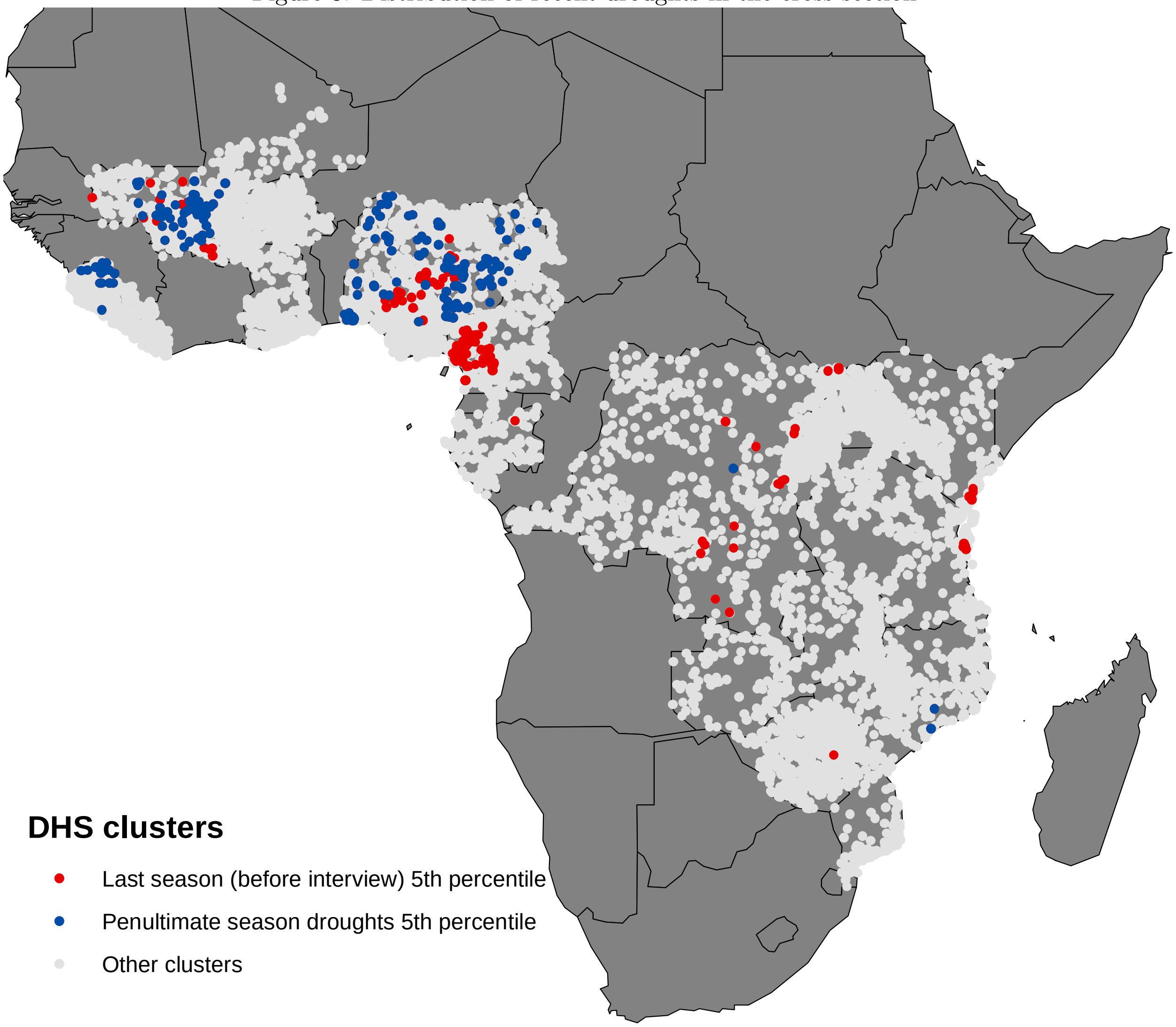
$$L_g(x,y) = \sum_{k=0}^{K}\sum_{l=0}^{L} P_k(x)P_l(y)$$

Where $P_k(x)$ and $P_l(y)$ are Legendre polynomials of order k and l on the coordinates x and y. Age_i is the woman's age. As the shocks occur at the grid level, we cluster the standard errors at this level.

As the same percentile cutoff is used in each grid cell, all cells have the same probability of experiencing a shock in a given year (Burke, Gong, and Jones, 2015). It is only because the shocks occur at different times that some areas will experience shocks and some will not. Nonetheless, the results may still be driven by some unobservable features that are correlated with both the shocks and violence. This is due to the relatively short time window of our data and spatial correlation in rainfall across areas. This implies that a shock in one place is correlated with shocks in places nearby. Places nearby are likely to be similar in terms of other characteristics, some of which may be correlated with abuse, thereby causing omitted variable bias in our estimates. As we see in Figure 3, the geographical location of the clusters who experienced a drought during either the last or the next-to-last rainy season are concentrated in a few regions only. We investigate this potential problem by running a Moran's I test on the residuals in each model. This widely used test of spatial dependence rests on the premise that if error terms are independent and identically distributed, the distribution of Moran's I is known (Cliff and Ord, 1972).

Since we only have data on each individual observed during one year, we are not able to control for area fixed effects in investigating the probability of having experienced violence using the total sample. Controlling for area fixed effects requires that we have several observations from the same areas, and is greatly beneficial in terms of identification as it controls for all time invariant factors that may differ across areas. In what follows, we pursue two strategies whereby we can control for grid level fixed effects.

Figure 3: Distribution of recent droughts in the cross section



4.2 Repeated cross section

Our first strategy for controlling for area specific factors uses the fact that we have a repeated cross section of surveys in nine of our DHS countries, with at least five years between each survey. Aggregating the data to the grid level in these countries allows us to investigate whether areas that have experienced a drought or flood between each of the two survey rounds is related to a change in the level of violence during the year leading up to the interview. We estimate the following specification for our 553 grid cells that have two observations over time:

$$\begin{aligned}\triangle\overline{Abused\,Last\,Year}_{g,t} &= \beta_1\Delta D_{g,t-1} + \beta_2\Delta D_{g,t-2} + \beta_3\Delta F_{g,t-1} + \beta_4\Delta F_{g,t-2} \\ &+ \Delta T_{g,t-1} + \Delta T_{g,t-2} + \Delta\alpha_c \times L_g(x,y) + \Delta\bar{Age}_g + e_{g,t} \qquad (2)\end{aligned}$$

The dependent variable is the difference between the second and first surveys in the grid cell average probability of experiencing violence last year. We control for country fixed effects so that only differences within a country are compared, and interact this control with our Legendre polynomials to handle spatial correlation in the country-specific changes.

The main advantage of this specification is that it allows us to use grid fixed effects and we are therefore not worried about time invariant omitted variables at the grid level. Thereby, the low spread of the shocks is of less concern for internal validity in this analysis than in the previous one. However, spatial correlation in trends in violence may still be a concern, which we ease by interacting a linear time trend with polynomials on the coordinates. Another potential issue is that we have to assume that any differences affecting violence between populations interviewed in the two different surveys are unrelated to weather characteristics (e.g., not affected by climate-induced migration). This is why we again control for differences in age composition.

4.3 Duration analyses of first time abuse

In the violence module of DHS surveys, women who had experienced violence from their partners were also asked how long it took after they got married or started living together until the first violent episode occurred in the partnership. From this information, we can construct a time series as the interviewed women got married in different years, which we then use to control for unobserved omitted variables that differ across space and time. To that end, we employ duration analysis to study whether the time from marriage until the first violent episode is affected by extreme values of rainfall.

The duration models are specified in the following way:

$$\log\left(\frac{First\,violence_{i,g,t}}{1-First\,violence_{i,g,t}}\right) = \alpha_t + \beta_1 \bar{D}_{g,m+t} + \beta_2 \bar{F}_{g,m+t} + (m+t)\times\alpha_s \times L_g + \alpha_a + \alpha_g \tag{3}$$

Where the dependent variable is the relative risk that woman i in grid cell g is abused for the first time in year t after her marriage year m, $\bar{D}_{g,t}$ and $\bar{F}_{g,t}$ equal 1 if there was a drought or flood in year m+t or m+t-1, α_a are 5-year age of marrying groups, α_g are grid cell fixed effects, and α_t are piecewise constants by year of marriage. The piecewise constants ensure full flexibility in the baseline rate, which is preferred as we do not wish to impose any particular time-dependence on the process (Blossfeld, Golsch, and Rohwer, 2012). Once again, we may worry that our specification is affected by spatial patterns in period trends in violence that are correlated with weather fluctuations, which is less likely to be a problem in this case as we use a ten year time series in each grid for each survey. Such spatial correlation can be captured by controlling for interactions of period time trends with Legrenge polynomials, and once again we allow these interactions to be survey specific. As the sample is restricted to include only older women if they married at a late age, we included 5-year age of marrying groups to make sure that the period effects we are studying are not confounded with age or cohort effects.

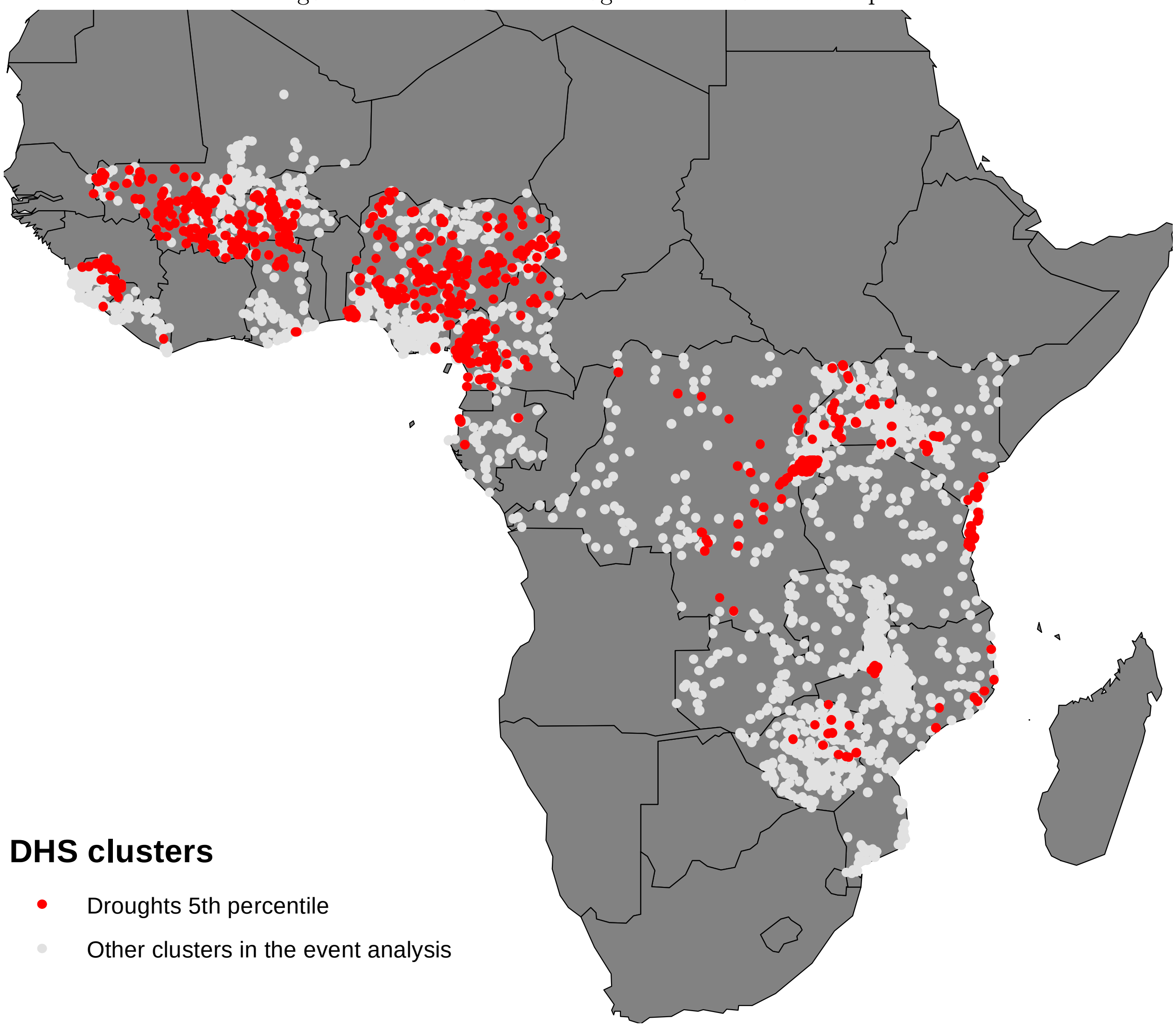
This sample consists of 50,512 women in 1,060 different grid cells, sampled in 24 surveys in 17 countries, who entered marriage between 1993 and 2013. In total, we make use of 233,755 years at risk, i.e., marriage years up to an eventual violent episode in our sample. The distribution of droughts in this sample is shown in Figure 4. At the 5% drought level, 12,686 women were affected by at least one drought while still in the sample and 10,911 by at least one flood, which equals 25% and 22% of the total sampled women, respectively.

It is important to note that whether a drought and flood occurs one year or the next in a specific place is essentially random (e.g., Dell, Jones, and Olken (2013)). The control group in this analysis consists of marriage years in the same grid cell that were unaffected by the shock, which are experienced by the drought-affected woman herself earlier in time, other women who married earlier and therefore had more marriage experience before the shock, and/or women who married later and were therefore unaffected by the shock.

How these groups are divided is random. This is different from the repeated cross section analysis, as we are here able to exploit the exact timing of the weather incident in relation to the violent episode within each survey. We therefore no longer worry about compositional changes between rounds of studies.

The duration model analyzes factors that contribute to violence against women who have not previously experienced violence in their relationship. It is thus useful in revealing what might make husbands crossing that important boundary it is to start becoming abusive towards their wives. However, it does not capture the intensity nor likelihood of re-occurrence of violence within a relationship. If previous abstention from violence is an inhibiting factor, the results may be viewed as a lower bound on the total effect of rainfall shocks on violence.

Figure 4: Distribution of droughts in the duration sample



5 Results

5.1 Cross-sectional analysis

In Table 1, we present OLS regressions of how the reported incidence of abuse last year is affected by incidences of drought and flood during the last and next-to-last rainy seasons before the interview. The shock variables are droughts and floods defined as rainfall observations below the 2.5th, 5th, 10th and 15th percentile or above the inverse of these percentiles in the precipitation distribution respectively. From the regressions in columns 1-3, there appears to be a correlation in the data between droughts during the last season before the interview and violence, especially with shocks below the 5th percentile. However, when temperature is controlled for in column 4, the coefficient is more than halved for that percentile as high temperatures seem to explain much of the correlation.

As discussed in the empirical strategy, we may worry that these results are driven by some factor that is correlated with both the shocks and violence.[6] We note that there is strong spatial autocorrelation in all the regressions without spatial polynomials. Although adding more covariates and particularly survey fixed effects reduce the autocorrelation, these models remain invalid. As we add more polynomials, we see that the autocorrelation is further reduced. With polynomials of the second order, the autocorrelation is only weakly significant using 2.5% and 5% droughts, and insignificant when studying 10% and 15% droughts. The preferred model is displayed in column 7 and contains polynomials of the 3rd order, at which point there is virtually no and insignificant spatial autocorrelation across all cut-offs. This model displays point estimates of the effect of drought the last season on violence between 0.1 percentage points and 0.8 percentage points. Using the 5% cut-off which yields the highest estimate, we can exclude impacts above 3.3 percentage points with 95% confidence. For the penultimate season, the effect is significantly negative using the 10% and 15% cut-offs. Using the 5% cut-off which yields the most positive effect, we can exclude impacts above 1.2 percentage points. It thus seems that there is little support in the cross-sectional analysis for our hypothesis that droughts increase the likelihood of experiencing violence. However, we must keep in mind that this is based on information only stemming from rainfall at two time points before each survey, and thus has very limited external validity to assess impacts of rainfall variation across years.

In table 2, we study whether drought shocks are related to poverty in the sense that we test its association with observing wealth index levels in the bottom two quintiles of the survey-wide distribution. From this analysis, we see that there is no proof of such a relationship once we increase the number of degrees in the polynomials, and that even with fourth order polynomials, we are not able to fully control for spatial autocorrelation. The fact that we do not see an association with lower levels of wealth makes us reluctant to draw conclusions from the analysis in Table 1 as to the relationship between income shocks and violence.[7] In what follows, we instead use specifications that make use of variation across time in the same locations.

[6] Another proof of this is found by using whether her father was violent against her mother as outcome variable, which is highly correlated with violence against women but not plausibly affected by current rainfall. We find correlations between weather shocks and this outcome as is shown in Appendix A.

[7] In Appendix B, we exclude urban households from the analysis and then find an effect of droughts on wealth levels. The effect of droughts on violence is negative or insignificant in this sample.

Table 1: Cross sectional analysis of the effect of weather shocks on having experienced violence the last year before interview

DV: Experienced violence last year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	All	All	All
Drought (2.5%) last season	0.026	0.044*	0.043*	0.010	0.005	0.011	0.002
	(0.026)	(0.024)	(0.024)	(0.024)	(0.026)	(0.024)	(0.024)
Flood (2.5%) last season	0.173***	0.048	0.048	0.036	0.023	-0.006	-0.0005
	(0.022)	(0.044)	(0.044)	(0.034)	(0.029)	(0.031)	(0.029)
Drought (2.5%) penultimate season	-0.105***	-0.004	-0.005	0.011	0.026*	-0.003	-0.004
	(0.021)	(0.016)	(0.016)	(0.016)	(0.014)	(0.016)	(0.016)
Flood (2.5%) penultimate season	0.081	0.055*	0.054*	0.031	-0.007	-0.022	-0.023
	(0.049)	(0.030)	(0.030)	(0.031)	(0.028)	(0.019)	(0.023)
R^2	0.004	0.068	0.071	0.079	0.090	0.099	0.103
Moran's I of residuals	0.140***	0.025***	0.025***	0.020***	0.006***	0.001*	0.000
Z-score	*135.90*	*24.49*	*24.50*	*20.28*	*6.59*	*1.72*	*0.26*
Drought (5%) last season	0.033**	0.048***	0.047***	0.021	0.003	0.012	0.008
	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
Flood (5%) last season	0.154***	0.009	0.009	0.006	-0.002	-0.001	-0.0005
	(0.021)	(0.030)	(0.030)	(0.022)	(0.022)	(0.020)	(0.020)
Drought (5%) penultimate season	-0.106***	-0.022*	-0.023*	-0.022*	-0.005	-0.018	-0.017
	(0.015)	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)	(0.015)
Flood (5%) penultimate season	0.067***	0.043**	0.043**	0.024	0.009	0.022	0.020
	(0.024)	(0.020)	(0.020)	(0.018)	(0.017)	(0.015)	(0.015)
R^2	0.009	0.069	0.072	0.080	0.090	0.099	0.103
Moran's I of residuals	0.125***	0.024***	0.024***	0.021***	0.006***	0.001*	0.000
Z-score	*121.05*	*24.15*	*24.16*	*20.35*	*6.70*	*1.68*	*0.78*
Drought (10%) last season	0.011	0.024*	0.024*	0.001	-0.010	0.001	0.003
	(0.013)	(0.014)	(0.014)	(0.012)	(0.010)	(0.009)	(0.009)
Flood (10%) last season	0.056**	0.002	0.002	-0.009	-0.043***	-0.035***	-0.031**
	(0.025)	(0.015)	(0.015)	(0.013)	(0.016)	(0.013)	(0.014)
Drought (10%) penultimate season	-0.119***	-0.027**	-0.027**	-0.022**	-0.027**	-0.034***	-0.036***
	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Flood (10%) penultimate season	0.015	0.005	0.004	-0.014	-0.023**	-0.015	-0.018*
	(0.017)	(0.014)	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)
R^2	0.014	0.068	0.071	0.080	0.091	0.099	0.103
Moran's I of residuals	0.115***	0.025***	0.025***	0.021***	0.006***	0.001	0.001
Z-score	*111.72*	*24.63*	*24.63*	*20.65*	*5.86*	*1.43*	*0.97*
Drought (15%) last season	-0.008	-0.010	-0.010	-0.021**	-0.017**	-0.005	0.001
	(0.012)	(0.011)	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)
Flood (15%) last season	0.087***	0.032***	0.032***	0.018	0.001	-0.008	-0.005
	(0.020)	(0.012)	(0.012)	(0.011)	(0.014)	(0.013)	(0.013)
Drought (15%) penultimate season	-0.102***	0.002	0.0015	0.006	-0.013	-0.029***	-0.036***
	(0.012)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)
Flood (15%) penultimate season	0.009	0.010	0.010	-0.009	-0.017*	-0.009	-0.013
	(0.015)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
R^2	0.017	0.068	0.071	0.080	0.090	0.099	0.103
Moran's I of residuals	0.111***	0.026***	0.026***	0.021***	0.006***	0.001	0.000
Z-score	*107.79*	*25.38*	*25.38*	*20.54*	*6.57*	*1.63*	*0.85*
Survey F.E.	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legrenge polynomials of degree 1	no	no	no	no	yes	yes	yes
Legrenge polynomials of degree 2	no	no	no	no	no	yes	yes
Legrenge polynomials of degree 3	no	no	no	no	no	no	yes
N	149,032	149,032	149,022	149,022	149,032	149,032	149,032

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2: Cross sectional analysis of the effect of weather shocks on the probability of observing wealth index levels in the lowest two quintiles of the survey-wide distribution

DV: Lowest two wealth quintiles	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All	All	All	All	All	All
Drought (2.5%) last season	-0.109***	-0.098***	-0.072***	-0.045**	-0.029	-0.024
	(0.036)	(0.031)	(0.025)	(0.022)	(0.021)	(0.022)
Flood (2.5%) last season	0.027	0.045	0.075***	0.063**	0.049**	0.035*
	(0.037)	(0.031)	(0.029)	(0.026)	(0.023)	(0.021)
Drought (2.5%) penultimate season	0.117**	0.064**	0.074**	0.081***	0.041	0.045
	(0.054)	(0.029)	(0.031)	(0.030)	(0.029)	(0.028)
Flood (2.5%) penultimate season	-0.014	0.049*	0.058*	0.045*	0.039	0.024
	(0.041)	(0.028)	(0.031)	(0.025)	(0.026)	(0.023)
R^2	0.016	0.097	0.128	0.165	0.182	0.194
Moran's I of residuals	0.039***	0.017***	0.012***	0.003***	0.001***	0.001*
Z-score	*59.84*	*26.37*	*18.54*	*5.76*	*2.72*	*1.94*
Drought (5%) last season	-0.083**	-0.073***	-0.074***	-0.055**	-0.026	-0.021
	(0.034)	(0.027)	(0.026)	(0.023)	(0.022)	(0.021)
Flood (5%) last season	-0.029	-0.021	0.043	0.025	0.006	-0.0002
	(0.032)	(0.030)	(0.028)	(0.024)	(0.023)	(0.023)
Drought (5%) penultimate season	0.092**	0.019	-0.007	-0.021	-0.016	-0.025
	(0.038)	(0.029)	(0.028)	(0.028)	(0.026)	(0.027)
Flood (5%) penultimate season	-0.057	0.010	-0.009	0.001	-0.028	-0.031
	(0.037)	(0.026)	(0.036)	(0.024)	(0.023)	(0.019)
R^2	0.017	0.097	0.128	0.165	0.182	0.194
Moran's I of residuals	0.038***	0.017***	0.012***	0.004***	0.002***	0.001**
Z-score	*58.20*	*26.36*	*19.10*	*5.99*	*2.84*	*1.99*
Drought (10%) last season	-0.035	-0.018	-0.044**	-0.012	0.018	0.017
	(0.026)	(0.020)	(0.021)	(0.020)	(0.020)	(0.019)
Flood (10%) last season	-0.019	0.010	0.051**	0.024	-0.003	-0.003
	(0.023)	(0.021)	(0.025)	(0.020)	(0.019)	(0.018)
Drought (10%) penultimate season	0.148***	0.071***	0.001	-0.001	0.008	0.004
	(0.027)	(0.020)	(0.020)	(0.019)	(0.017)	(0.017)
Flood (10%) penultimate season	-0.077***	-0.009	-0.045*	-0.014	-0.025	-0.022
	(0.027)	(0.019)	(0.024)	(0.020)	(0.018)	(0.017)
R^2	0.021	0.097	0.128	0.164	0.182	0.194
Moran's I of residuals	0.035***	0.016***	0.012***	0.004***	0.002***	0.001**
Z-score	*54.16*	*25.51*	*18.53*	*6.03*	*2.89*	*2.00*
Drought (15%) last season	-0.004	-0.008	-0.023	-0.011	0.009	0.002
	(0.023)	(0.018)	(0.015)	(0.016)	(0.015)	(0.015)
Flood (15%) last season	-0.041*	-0.008	0.016	-0.014	-0.023	-0.026
	(0.022)	(0.018)	(0.020)	(0.017)	(0.016)	(0.016)
Drought (15%) penultimate season	0.172***	0.087***	0.038**	0.024	0.034**	0.025
	(0.021)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Flood (15%) penultimate season	-0.067***	-0.013	-0.029	-0.016	-0.017	-0.017
	(0.023)	(0.018)	(0.020)	(0.016)	(0.015)	(0.014)
R^2	0.026	0.098	0.128	0.164	0.182	0.194
Moran's I of residuals	0.032***	0.016***	0.012***	0.004***	0.002***	0.001**
Z-score	*49.47*	*25.42*	*18.88*	*6.10*	*2.91*	*2.03*
Survey F.E.	yes	yes	yes	yes	yes	yes
Age controls	no	yes	no	no	no	no
Temperature controls	no	yes	no	no	no	no
Legrenge polynomials of degree 1	no	no	yes	yes	yes	yes
Legrenge polynomials of degree 2	no	no	no	yes	yes	yes
Legrenge polynomials of degree 3	no	no	no	no	yes	yes
Legrenge polynomials of degree 4	no	no	no	no	no	yes
N	560,558	559,427	560,558	560,558	560,558	560,558

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

5.2 Repeated cross section

The first strategy we employ to control for area fixed effects is a repeated cross sectional analysis in the nine countries for which we have repeated surveys. The data is now aggregated to the grid level as defined by our rainfall data, and in Table 3, we present the results of estimating Equation 2 for our 553 repeated grid cells. The dependent variable is now the difference between the second and first survey in the grid cell average probability of experiencing violence the year before the interview. We see that the model which includes temperature controls in column 4 is now complete enough not to display significant spatial autocorrelation. For the full drought impact where temperature is not controlled for, the model with one or two polynomials performs the best in terms of spatial independence of residuals. None of the coefficients display any significant positive effect of droughts on violence against women, and droughts in the penultimate season seem to reduce violence using the 5% cut-off. We can exclude drought effects greater than 10 percentage points in the last season and 4.4 percentage points in the penultimate season.

The second dependent variable that we wanted to study is whether droughts increase the risk of ever having experienced violence in a relationship. Column 5 in Table 4 shows that droughts during the last season before the interview do not affect violence at this extensive margin, and that droughts in the penultimate season below the 5th percentile significantly decrease this risk.[8]

Finally, we ran this model using as outcome variable whether the women live in households whose score on the wealth index lies in the lowest two quintiles of the survey-wide wealth distribution. The model with one Legendre polynomial proved to have the least spatial autocorrelation. According to these results, droughts during the last season before the interview increase the low wealth incidence, but the effect is only weakly significant with the 10% shocks and otherwise not significant. However, droughts during the penultimate season significantly increase the low wealth incidence using the 2.5% and 15% cut-offs, and weakly so using the 10% cut-off. As the wealth index is constructed based on observing household durables which are results of long-term investments (such as the quality of housing), we would expect droughts to impact with some delay. The effect of floods take both positive and negative values. This is expected if rainfall increases agricultural output until some tipping point, after which more rain reduces output. Hence, with varying tipping points we are unlikely to get consistent results in any one direction.

We are more confident in interpreting these results causally as we now control for spatial fixed effects and because we find that household wealth is affected. Nonetheless, as the analysis uses a limited number of agricultural seasons in each location, we proceed to the third type of analysis where we use information on the timing of the first occurrence of abuse.

[8]We also tested for effects of droughts in any of the last five seasons before each survey round and did not find any significant correlation in analyses without spatial autocorrelation (available upon request).

Table 3: Repeated cross sectional analysis of the effect of weather shocks on having experienced violence the last year before interview

DV: Experienced violence last year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	All	All	All
Drought (2.5%) last season	-0.014	-0.024	-0.020	-0.015	0.012	0.047*	0.042
	(0.027)	(0.030)	(0.029)	(0.026)	(0.025)	(0.027)	(0.029)
Flood (2.5%) last season	-0.043	-0.025	-0.020	-0.006	0.024	-0.041	-0.083
	(0.065)	(0.041)	(0.040)	(0.039)	(0.052)	(0.059)	(0.061)
Drought (2.5%) penultimate season	-0.030	-0.026	-0.027	-0.015	-0.030	-0.011	0.002
	(0.018)	(0.020)	(0.020)	(0.022)	(0.025)	(0.028)	(0.029)
Flood (2.5%) penultimate season	-0.083**	-0.037	-0.033	-0.006	-0.028	-0.059*	-0.095**
	(0.041)	(0.039)	(0.039)	(0.043)	(0.042)	(0.035)	(0.039)
R^2	0.021	0.281	0.301	0.328	0.396	0.476	0.534
Moran's I of residuals	0.045***	0.010***	0.009***	0.004	0.001	-0.004	-0.008
Z-score	*12.48*	*3.17*	*2.99*	*1.49*	*0.72*	*-0.54*	*-1.52*
Drought (5%) last season	-0.018	-0.036	-0.036	-0.030	-0.0003	0.036	0.032
	(0.019)	(0.022)	(0.022)	(0.020)	(0.019)	(0.023)	(0.023)
Flood (5%) last season	0.054	-0.005	-0.006	0.0002	0.040	-0.001	-0.027
	(0.056)	(0.026)	(0.025)	(0.025)	(0.033)	(0.036)	(0.037)
Drought (5%) penultimate season	-0.025***	-0.013	-0.013	-0.007	-0.043***	-0.044***	-0.028
	(0.010)	(0.013)	(0.013)	(0.014)	(0.016)	(0.016)	(0.018)
Flood (5%) penultimate season	-0.017	0.023	0.022	0.037	0.033	0.034	0.009
	(0.031)	(0.026)	(0.025)	(0.026)	(0.027)	(0.025)	(0.029)
R^2	0.016	0.285	0.306	0.336	0.403	0.477	0.526
Moran's I of residuals	0.042***	0.011***	0.010***	0.004	0.000	-0.004	-0.008
Z-score	*11.49*	*3.29*	*3.11*	*1.57*	0.58	*-0.68*	*-1.53*
Drought (10%) last season	-0.015	-0.029*	-0.025	-0.022	-0.005	0.031	0.026
	(0.013)	(0.017)	(0.017)	(0.016)	(0.017)	(0.021)	(0.021)
Flood (10%) last season	-0.017	-0.027	-0.029	-0.024	0.001	0.007	0.012
	(0.030)	(0.020)	(0.020)	(0.021)	(0.026)	(0.026)	(0.029)
Drought (10%) penultimate season	-0.024**	-0.014	-0.016	-0.002	-0.021	-0.026	-0.035
	(0.011)	(0.013)	(0.013)	(0.016)	(0.020)	(0.021)	(0.022)
Flood (10%) penultimate season	-0.040*	0.001	-0.00004	0.002	0.009	0.008	-0.001
	(0.020)	(0.016)	(0.016)	(0.019)	(0.019)	(0.020)	(0.020)
R^2	0.025	0.285	0.306	0.332	0.394	0.472	0.527
Moran's I of residuals	0.045***	0.010***	0.009***	0.004	0.001	-0.004	-0.008
Z-score	*12.36*	*3.03*	*2.85*	*1.45*	*0.66*	*-0.60*	*-1.58*
Drought (15%) last season	-0.017	-0.026*	-0.022	-0.022*	-0.009	0.014	0.017
	(0.012)	(0.014)	(0.015)	(0.013)	(0.014)	(0.015)	(0.017)
Flood (15%) last season	-0.016	-0.013	-0.016	-0.003	0.016	0.010	0.021
	(0.024)	(0.020)	(0.020)	(0.020)	(0.023)	(0.026)	(0.029)
Drought (15%) penultimate season	-0.013	0.004	0.002	0.021	0.009	-0.004	-0.019
	(0.013)	(0.013)	(0.013)	(0.015)	(0.018)	(0.019)	(0.020)
Flood (15%) penultimate season	-0.040**	-0.007	-0.005	-0.009	0.009	0.011	-0.006
	(0.017)	(0.014)	(0.013)	(0.015)	(0.017)	(0.019)	(0.020)
R^2	0.027	0.280	0.300	0.334	0.394	0.468	0.525
Moran's I of residuals	0.044***	0.009***	0.009***	0.002	0.001	-0.004	-0.008
Z-score	*12.10*	*2.92*	*2.75*	*1.13*	*0.63*	*-0.48*	*-1.52*
Grid F.E.	yes	yes	yes	yes	yes	yes	yes
Country trends	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
n (women)	104,207	104,207	104,207	104,207	104,207	104,207	104,207
N (grids)	553	553	553	553	553	553	553

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4: Repeated cross sectional analysis of the effect of weather shocks on ever having experienced violence

DV: Ever experienced violence	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	All	All	All
Drought (2.5%) last season	-0.008	0.013	0.015	0.007	0.006	0.051*	0.040
	(0.024)	(0.023)	(0.022)	(0.024)	(0.026)	(0.027)	(0.029)
Flood (2.5%) last season	-0.008	-0.009	-0.004	-0.008	0.019	-0.041	-0.093
	(0.057)	(0.052)	(0.052)	(0.056)	(0.059)	(0.062)	(0.064)
Drought (2.5%) penultimate season	-0.027	-0.039	-0.041	-0.024	-0.039	-0.014	-0.001
	(0.023)	(0.025)	(0.027)	(0.031)	(0.034)	(0.030)	(0.028)
Flood (2.5%) penultimate season	-0.081	-0.058	-0.057	-0.043	-0.052	-0.075	-0.120**
	(0.050)	(0.058)	(0.058)	(0.064)	(0.063)	(0.048)	(0.051)
R^2	0.016	0.205	0.220	0.230	0.286	0.422	0.485
Moran's I of residuals	0.046***	0.020***	0.019***	0.017***	0.003	-0.005	-0.007
Z-score	*12.65*	*5.79*	*5.42*	*4.98*	*1.36*	*-0.85*	*-1.40*
Drought (5%) last season	-0.027	-0.005	-0.003	-0.010	-0.008	0.034	0.028
	(0.019)	(0.019)	(0.019)	(0.021)	(0.022)	(0.026)	(0.027)
Flood (5%) last season	0.027	-0.005	-0.005	-0.016	0.034	-0.011	-0.036
	(0.038)	(0.030)	(0.030)	(0.033)	(0.035)	(0.043)	(0.045)
Drought (5%) penultimate season	-0.015	-0.034**	-0.035**	-0.025	-0.068***	-0.058***	-0.042*
	(0.012)	(0.015)	(0.016)	(0.018)	(0.022)	(0.019)	(0.022)
Flood (5%) penultimate season	-0.045	0.003	0.001	0.011	0.015	0.018	-0.002
	(0.033)	(0.033)	(0.033)	(0.033)	(0.036)	(0.031)	(0.035)
R^2	0.018	0.204	0.219	0.232	0.297	0.422	0.474
Moran's I of residuals	0.043***	0.019***	0.018***	0.016***	0.003	-0.005	-0.007
Z-score	*11.77*	*5.51*	*5.17*	*4.67*	*1.21*	*-0.90*	*-1.43*
Drought (10%) last season	-0.025*	-0.010	-0.006	-0.012	-0.023	0.022	0.012
	(0.013)	(0.016)	(0.016)	(0.017)	(0.020)	(0.022)	(0.022)
Flood (10%) last season	-0.028	-0.045*	-0.046*	-0.055**	-0.019	-0.002	-0.003
	(0.028)	(0.027)	(0.027)	(0.028)	(0.031)	(0.032)	(0.036)
Drought (10%) penultimate season	-0.015	-0.026*	-0.029*	-0.024	-0.038	-0.041*	-0.047*
	(0.013)	(0.016)	(0.016)	(0.018)	(0.025)	(0.024)	(0.025)
Flood (10%) penultimate season	-0.052**	-0.011	-0.012	-0.009	-0.011	-0.005	-0.013
	(0.026)	(0.022)	(0.022)	(0.025)	(0.025)	(0.023)	(0.024)
R^2	0.039	0.210	0.226	0.242	0.287	0.417	0.475
Moran's I of residuals	0.043***	0.019***	0.018***	0.015***	0.004	-0.005	-0.008
Z-score	*11.98*	*5.51*	*5.13*	*4.51*	*1.42*	*-0.89*	*-1.52*
Drought (15%) last season	-0.023*	-0.013	-0.011	-0.013	-0.020	0.008	0.012
	(0.012)	(0.013)	(0.013)	(0.014)	(0.016)	(0.017)	(0.019)
Flood (15%) last season	-0.014	-0.027	-0.028	-0.023	-0.001	-0.004	0.0058
	(0.023)	(0.024)	(0.024)	(0.024)	(0.027)	(0.032)	(0.035)
Drought (15%) penultimate season	0.011	0.010	0.009	0.024	0.019	-0.004	-0.016
	(0.015)	(0.017)	(0.017)	(0.019)	(0.021)	(0.021)	(0.023)
Flood (15%) penultimate season	-0.048**	-0.013	-0.012	-0.022	-0.010	0.006	-0.009
	(0.022)	(0.018)	(0.018)	(0.019)	(0.023)	(0.021)	(0.021)
R^2	0.038	0.203	0.216	0.239	0.285	0.411	0.470
Moran's I of residuals	0.043***	0.022***	0.021***	0.018***	0.003	-0.005	-0.007
Z-score	*11.90*	*6.32*	*5.94*	*5.17*	*1.26*	*-0.77*	*-1.43*
Grid F.E.	yes	yes	yes	yes	yes	yes	yes
Country trends	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
n (women)	104,568	104,568	104,568	104,568	104,568	104,568	104,568
N (grids)	553	553	553	553	553	553	553

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: Repeated cross sectional analysis of the effect of weather shocks on the probability of observing wealth index levels in the lowest two quintiles of the survey-wide distribution

DV: Lowest two wealth quintiles	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	All	All	All
Drought (2.5%) last season	-0.001	-0.001	0.003	0.002	0.002	0.004	-0.003
	(0.020)	(0.022)	(0.022)	(0.023)	(0.025)	(0.027)	(0.030)
Flood (2.5%) last season	0.003	-0.004	-0.0003	0.005	-0.014	0.008	-0.001
	(0.018)	(0.018)	(0.018)	(0.020)	(0.019)	(0.020)	(0.021)
Drought (2.5%) penultimate season	0.062**	0.062**	0.066**	0.072**	0.059**	0.107***	0.099***
	(0.028)	(0.029)	(0.030)	(0.032)	(0.030)	(0.035)	(0.038)
Flood (2.5%) penultimate season	0.013	0.010	0.006	0.011	0.021	0.023	0.028
	(0.020)	(0.018)	(0.018)	(0.017)	(0.018)	(0.022)	(0.023)
R^2	0.005	0.019	0.045	0.053	0.118	0.177	0.227
Moran's I of residuals	0.005***	0.005***	0.005***	0.004***	-0.001	-0.002	-0.003
Z-score	*3.41*	*3.32*	*3.14*	*2.66*	*-0.08*	*-0.85*	*-1.07*
Drought (5%) last season	0.028	0.030	0.029	0.031	0.036	0.045*	0.040
	(0.019)	(0.022)	(0.021)	(0.022)	(0.026)	(0.027)	(0.027)
Flood (5%) last season	-0.007	-0.019	-0.015	-0.011	-0.032**	-0.031*	-0.037**
	(0.015)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.018)
Drought (5%) penultimate season	0.035*	0.046**	0.054**	0.055**	0.026	0.042	0.033
	(0.019)	(0.021)	(0.021)	(0.021)	(0.024)	(0.032)	(0.033)
Flood (5%) penultimate season	-0.011	-0.016	-0.014	-0.013	-0.010	-0.028**	-0.028**
	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)
R^2	0.009	0.025	0.052	0.060	0.122	0.178	0.228
Moran's I of residuals	0.005***	0.005***	0.005***	0.004***	-0.001	-0.002	-0.003
Z-score	*3.28*	*3.42*	*3.18*	*2.68*	*-0.08*	*-0.83*	*-1.03*
Drought (10%) last season	0.023*	0.028	0.024	0.027	0.035*	0.033	0.027
	(0.014)	(0.018)	(0.017)	(0.018)	(0.020)	(0.021)	(0.020)
Flood (10%) last season	0.026**	0.019	0.022*	0.031**	0.023	0.023	0.020
	(0.013)	(0.012)	(0.012)	(0.014)	(0.015)	(0.015)	(0.016)
Drought (10%) penultimate season	0.042***	0.051***	0.050***	0.058***	0.038*	0.046**	0.048**
	(0.015)	(0.016)	(0.016)	(0.016)	(0.020)	(0.024)	(0.025)
Flood (10%) penultimate season	-0.007	-0.012	-0.009	-0.012	-0.007	-0.016	-0.014
	(0.013)	(0.015)	(0.015)	(0.015)	(0.018)	(0.018)	(0.018)
R^2	0.021	0.037	0.060	0.073	0.127	0.181	0.231
Moran's I of residuals	0.004***	0.005***	0.004***	0.003**	-0.001	-0.002	-0.003
Z-score	*3.09*	*3.32*	*3.01*	*2.49*	*-0.35*	*-0.83*	*-1.03*
Drought (15%) last season	0.013	0.019	0.019	0.019	0.010	-0.003	-0.005
	(0.014)	(0.017)	(0.016)	(0.016)	(0.018)	(0.02)	(0.021)
Flood (15%) last season	0.023**	0.021**	0.021**	0.028**	0.022*	0.018	0.018
	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)
Drought (15%) penultimate season	0.041**	0.048***	0.048***	0.058***	0.042**	0.055**	0.061**
	(0.016)	(0.016)	(0.016)	(0.017)	(0.020)	(0.022)	(0.024)
Flood (15%) penultimate season	0.005	0.006	0.009	0.008	0.011	0.002	-0.001
	(0.011)	(0.015)	(0.014)	(0.015)	(0.017)	(0.017)	(0.018)
R^2	0.018	0.033	0.058	0.071	0.124	0.178	0.231
Moran's I of residuals	0.005***	0.005***	0.004***	0.003**	-0.001	-0.002	-0.002
Z-score	*3.22*	*3.23*	*2.93*	*2.47*	*-0.23*	*-0.70*	*-0.96*
Grid F.E.	yes	yes	yes	yes	yes	yes	yes
Country trends	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
n (women)	455,342	455,342	455,342	455,342	455,342	455,342	455,342
N (grids)	1,217	1,217	1,217	1,217	1,217	1,217	1,217

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

5.3 Duration analysis

In the final strategy, we instead use information on when the women were abused for the first time in their relationship. By using the DHS survey questions on how many years it took after marriage or cohabitation before women who experienced violence were abused for the first time, we conduct a duration analysis which allows us to control for grid level fixed effects. The analysis thus compares shock-affected marriage years with marriage years that have not been affected by a shock in the same place, and we have controlled for differences in risk of violence based on marriage duration and age composition at time of marriage.

Results using the full sample are presented in Table 6. Since this is a conditional logistic regression, we are not able to obtain residuals and test for spatial autocorrelation. However, we observe that R^2 increases when adding survey-specific time trends, whereas adding Legendre polynomials has practically no impact, suggesting that adding the survey-specific time trend controls alone is sufficient to handle spatial autocorrelation. Starting with droughts at the 2.5% level, we see that these droughts reduce the propensity of experiencing violence by 13.4% which is a significant reduction. This equals an average reduction of 0.6 percentage points in the yearly risk of experiencing violence. If every marriage year was affected by a drought at this level, we would expect a 3.8 percentage points decline in the risk of experiencing violence in a ten year marriage. Less severe droughts have insignificant impacts with close to an even odds ratio. From column 2, the maximum positive drought effect in the 95% confidence interval is an 8% increase which would amount to 0.3 percentage points per year and a 2.2 percentage points increase in a ten year marriage with constant droughts.

For a limited sample, we have information about how long they have lived in the place of interview. For this subsample, we can thus limit the analysis to marriage years spent in that location. As shown in Table 7, this yields very similar results and we can exclude positive drought effects larger than 13.7%. The negative effect on violence of most extreme droughts that we found in Table 6 is no longer significant at the 5% level. However, the odds ratio indicates that a violence-reducing effect may be present also in this limited sample.

Table 6: Duration analysis of the effect of weather shocks on first incidence of violence in marriage

DV: First violent episode	(1)	(2)	(3)	(4)	(5)
Sample	All	All	All	All	All
Drought (2.5%)	0.907	0.866**	0.865**	0.867**	0.865**
	(0.054)	(0.055)	(0.056)	(0.055)	(0.055)
Flood (2.5%)	1.029	1.019	1.051	1.008	0.996
	(0.063)	(0.050)	(0.053)	(0.050)	(0.051)
R^2	0.024	0.031	0.029	0.032	0.033
Drought (5%)	0.970	0.943	0.921*	0.945	0.943
	(0.042)	(0.042)	(0.043)	(0.043)	(0.042)
Flood (5%)	0.991	1.004	1.018	0.998	0.991
	(0.039)	(0.034)	(0.036)	(0.035)	(0.035)
R^2	0.024	0.031	0.029	0.032	0.033
Drought (10%)	1.013	0.997	0.989	0.996	0.997
	(0.033)	(0.034)	(0.035)	(0.033)	(0.034)
Flood (10%)	1.019	1.019	1.040	1.012	1.008
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)
R^2	0.024	0.031	0.029	0.032	0.033
Drought (15%)	1.025	1.015	1.000	1.009	1.007
	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)
Flood (15%)	1.009	1.014	1.042	1 .010	1.006
	(0.029)	(0.028)	(0.030)	(0.029)	(0.029)
R^2	0.024	0.031	0.029	0.032	0.033
Piecewise constants	yes	yes	yes	yes	yes
Age at marriage (grouped)	yes	yes	yes	yes	yes
Survey-specific time trends	no	yes	yes	yes	yes
Temperature controls	no	no	yes	no	no
Legendre polynomials of degree 1	no	no	no	yes	yes
Legendre polynomials of degree 2	no	no	no	no	yes
n (marriage-years at risk)	233,755	233,755	219,138	233,755	233,755
N (women)	50,512	50,512	48,715	50,512	50,512

Droughts and floods refer to rainfall below the threshold in rainy seasons terminating during the relevant marriage year or the year before. The age of marriage variable is grouped in five year intervals. Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 7: Duration analysis of the effect of weather shocks on first incidence of violence in marriage, years in residence only

DV: First violent episode	(1)	(2)	(3)	(4)
Sample	In location	In location	In location	In location
Drought (2.5%)	0.946	0.809	0.810	0.788*
	(0.126)	(0.110)	(0.108)	(0.113)
Flood (2.5%)	1.025	1.039	1.039	1.037
	(0.092)	(0.078)	(0.077)	(0.079)
R^2	0.027	0.033	0.033	0.034
Drought (5%)	1.074	0.946	0.947	0.935
	(0.088)	(0.082)	(0.081)	(0.084)
Flood (5%)	1.030	1.077	1.082*	1.074
	(0.054)	(0.050)	(0.051)	(0.052)
R^2	0.027	0.033	0.033	0.034
Drought (10%)	1.089*	1.033	1.043	1.026
	(0.056)	(0.053)	(0.054)	(0.053)
Flood (10%)	1.053	1.074	1.091*	1.076
	(0.051)	(0.048)	(0.049)	(0.052)
R^2	0.027	0.033	0.033	0.034
Drought (15%)	1.019	0.990	0.997	0.971
	(0.049)	(0.044)	(0.046)	(0.043)
Flood (15%)	1.004	1.038	1.056	1.039
	(0.041)	(0.039)	(0.041)	(0.041)
R^2	0.027	0.032	0.033	0.034
Piecewise constants	yes	yes	yes	yes
Age at marriage (grouped)	yes	yes	yes	yes
Survey-specific time trends	no	yes	yes	yes
Temperature controls	no	no	yes	no
Legendre polynomials of degree 1	no	no	no	yes
Legendre polynomials of degree 2	no	no	no	no
n (marriage-years at risk)	104,392	104,392	104,392	104,392
N (women)	24,884	24,884	24,884	24,884

Droughts and floods refer to rainfall below the threshold in rainy seasons terminating during the relevant marriage year or the year before. The age of marriage variable is grouped in five year intervals. Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

6 Conclusion

We use variation in rainfall to study how income shocks affect intimate partner violence in Sub-Saharan Africa. We encounter two main obstacles in conducting this analysis. First, weather phenomena show strong patterns of spatial clustering. This feature means that although constructing a measure of droughts which is relative and thus independent of location when the full period with weather data is used, it will be spatially autocorrelated in a given year. We prove that this is a problem in our analysis by testing regression residuals using the Moran's I test. We furthermore add spatial polynomials and show that this successfully handles the problem.

A second and related issue is the scarcity of time series data on violence against women in Sub-Saharan Africa. Although the threat to internal validity from this can be dealt with using spatial polynomials, the issue of external validity is more problematic. In the cross-section, the only weather variation used for the analysis is the seasons leading up to the interview. If these particular drought-affected areas or drought-affected years are not representative of drought effects in general, this is problematic for drawing conclusions of the relationship between droughts and violence across space and time.

A slight improvement on addressing this problem comes from using changes in drought occurrence before each of two survey rounds, which can be done where we have two surveys in the same geographical place. This controls for the average level of violence in each place across time, and reduces the concern about representativeness to whether the effect of the difference between rounds in weather events leading up to each survey is representative.

Our third attempt at addressing this issue comes from using recall data collected in each survey on the first occurrence of violence in a marriage. This raises some methodological issues of its own, most notably about how representative women who continue their first marriage are of the total population of women at risk of experiencing intimate partner violence, and also about the accuracy of recalled violent episodes. Nevertheless, this approach allows us to use a ten-year time series of droughts prior to each survey, which vastly improves the external validity of these findings for past and future drought events in Sub-Saharan Africa.

Contrary to our expectations, we generally do not find any association between droughts and intimate partner violence. This holds both on the intensive margin when studying violence during the last year before each survey, and on the extensive margin when studying the probability of ever having experienced violence in a relationship or the propensity of a marriage to turn violent. In the latter case, the most severe droughts may even reduce the likelihood that violence is initiated. The lack of association is in spite of evidence that droughts cause relative wealth loss in affected communities. Very similar effects are also found when limiting the sample to rural areas only, both on relative wealth loss and on violence against women.[9] We can only speculate why this is the case. First, the strong association between wealth and intimate partner violence in Sub-Saharan Africa may be related to other aspects of relative deprivation than the economic situation itself in this narrow sense, such as historical violence and extortion. Secondly, there may be aspects of the particular income shock from lack of rainfall which makes it less likely to trigger intimate partner violence than other income shocks. In particular, the collective nature and slow onset of droughts may trigger less aggression and more adherence to social norms than other income shocks.

This study has uncovered that if there is a relationship between poverty and violence against women in Sub-Saharan Africa, it is likely to be a complex and contextual one. More data is needed to uncover such patterns, preferably panel data, which would allow for following a marriage through better and worse with detailed accounts of violence. We have taken full advantage of the spatial and temporal aspects found in currently available data and we have used an exogenous source of income variation to identify causal effects. Through these means, we have not been able to identify any stable and statistically significant relationship between droughts and violence against women in Sub-Saharan Africa.

References

Alesina, A., B. Brioschi, and E. L. Ferrara (2016): "Violence Against Women: A Cross-cultural Analysis for Africa," Working Paper 21901, National Bureau of Economic Research.

Anderson, C., and M. DeLisi (2011): *The Psychology of Social Conflict and Aggression*chap. Implications of global climate change for violence in developed and developing countries, pp. 249–265. Psychology Press, New York.

[9] See Appendix B.

Anderson, C. A. (2001): "Heat and Violence," *Current Directions in Psychological Science*, 10(1), 33–38.

Ati, O. F., C. J. Stigter, and E. O. Oladipo (2002): "A Comparison of Methods to Determine the Onset of the Growing Season in Northern Nigeria," *International Journal of Climatology*, 22(6), 731–742.

Barlett, C. P., and C. A. Anderson (2013): "The General Aggression and General Learning Models," in *The International Encyclopedia of Media Studies*, ed. by A. N. Valdivia, pp. 1–20, Oxford. Blackwell Publishers.

Benson, M., G. Fox, A. DeMaris, and J. Van Wyk (2003): "Neighborhood Disadvantage, Individual Economic Distress and Violence Against Women in Intimate Relationships," *Journal of Quantitative Criminology*, 19(3), 207–235.

Benton, T., and I. Craib (2011): *Philosophy of Social Science*. Palgrave Macmillan, Basingstoke and New York.

Berkowitz, L. (1983): "Aversively Stimulated Aggression: Some Parallels and Differences in Research with Animals and Humans," *American Psychologist*, 38(11), 1135–1144.

Bloch, F., and V. Rao (2002): "Terror as a Bargaining Instrument: A Case Study of Dowry Violence in Rural India," *American Economic Review*, 92(4), 1029–1043.

Blossfeld, H., K. Golsch, and G. Rohwer (2012): *Event History Analysis With Stata*. Psychology Press, New York and London.

Bohlken, A. T., and E. J. Sergenti (2010): "Economic Growth and Ethnic Violence: An Empirical Investigation of Hindu-Muslim Riots in India," *Journal of Peace Research*, 47(5), 589–600.

Burke, M., E. Gong, and K. Jones (2015): "Income Shocks and HIV in Africa," *The Economic Journal*, 125(585), 1157–1189.

Card, D., and G. B. Dahl (2011): "Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior," *The Quarterly Journal of Economics*, 126(1), 103–143.

Cliff, A., and K. Ord (1972): "Testing for Spatial Autocorrelation Among Regression Residuals," *Geographical Analysis*, 4(3), 267–284.

Cools, S., and A. Kotsadam (2014): "Resources and Domestic Violence in Sub-Saharan Africa," Working paper.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A. C. M. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A. J. Geer, L. Haimberger, S. B. Healy, H. Hersbach, E. V. Holm, L. Isaksen, P. Kallberg, M. Kohler, M. Matricardi, A. P. McNally, B. M. Monge-Sanz, J.-J. Morcrette, B.-K. Park, C. Peubey, P. de Rosnay, C. Tavolato, J.-N. Thepaut, and F. Vitart (2011): "The ERA-Interim Reanalysis: Configuration and Performance of the Data Assimilation System," *Quarterly Journal of the Royal Meteorological Society*, 137(656), 553–597.

Dell, M., B. F. Jones, and B. A. Olken (2013): "What Do We Learn from the Weather? The New Climate-Economy Literature," Working Paper 19578, National Bureau of Economic Research.

DeWall, C. N., C. A. Anderson, and B. J. Bushman (2011): "The General Aggression Model: Theoretical Extensions to Violence," *Psychology of Violence*, 1(3), 245–258.

Doepke, M., and M. Tertilt (2009): "Women's Liberation: What's in It for Men?," *The Quarterly Journal of Economics*, 124(4), 1541–1591.

Duflo, E. (2012): "Women Empowerment and Economic Development," *Journal of Economic Literature*, 50(4), 1051–1079.

Eswaran, M., and N. Malhotra (2011): "Domestic Violence and Women's Autonomy in Developing Countries: Theory and Evidence," *Canadian Journal of Economics*, 44(4), 1222–1263.

Fagan, B. (2000): *The Little Ice Age: How Climate Made History, 1300-1850*. Basic Books, New York.

Farmer, A., and J. Tiefenthaler (1997): "An Economic Analysis of Domestic Violence," *Review of Social Economy*, 55(3), 337–358.

Frey, B. S., D. A. Savage, and B. Torgler (2011): "Behavior under Extreme Conditions: The Titanic Disaster," *The Journal of Economic Perspectives*, 25(1), 209–221.

Goode, W. (1971): "Force and Violence in the Family," *Journal of Marriage and the Family*, 33, 624–636.

Harari, M., and E. La Ferrara (2013): "Climate and Cells: A Disaggregated Analysis," CEPR Discussion Paper 9277, Centre for Economic Policy Research, London.

Hornung, C., C. McCullough, and T. Sugimoto (1981): "Status Relationships in Marriage: Risk Factors in Spouse Abuse," *Journal of Marriage and the Family*, 43, 679–692.

ICF International (2009): "Ethical and Safety Guidelines for Implementing the DHS Domestic Violence Module," Discussion paper.

IPCC (2014): "Climate Change 2014 Synthesis Report," in *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. by IPCC The Core Writing Team, R. K. Pachauri, and L. Meyer, Geneva. IPCC.

Jacob, B., L. Lefgren, and E. Moretti (2007): "The Dynamics of Criminal Behavior: Evidence from Weather Shocks," *Journal of Human Resources*, XLII(3), 489–527.

Jewkes, R. (2002): "Intimate Partner Violence: Causes and Prevention," *The Lancet*, 359, 1423–1429.

Kishor, S. (2005): "Domestic Violence Measurement in the Demographic and Health Surveys: The History and the Challenges," Discussion paper, United Nations Expert Paper 1-9.

Kudamatsu, M., T. Persson, and D. Strömberg (2012): "Weather and Infant Mortality in Africa," CEPR Discussion Paper 9222, Center for Economic Policy Research.

La Mattina, G. (2013): "Armed Conflict and Domestic Violence: Evidence from Rwanda," Working Paper.

Liebmann, B., I. Blade, G. N. Kiladis, L. M. V. Carvalho, G. B. Senay, D. Allured, S. Leroux, and C. Funk (2012): "Seasonality of African Precipitation from 1996 to 2009," *Journal of Climate*, 25(12), 4304–4322.

Lind, J. T. (2015): "Spurious Weather Effects," CESifo Working Paper Series 5365, CESifo.

Lundberg, S., and R. A. Pollak (1996): "Bargaining and Distribution in Marriage," *Journal of Economic Perspectives*, 10(4), 139–158.

Mani, A., S. Mullainathan, E. Shafir, and J. Zhao (2013): "Poverty Impedes Cognitive Function," *Science*, 341(6149), 976–980.

Mehlum, H., E. Miguel, and R. Torvik (2006): "Poverty and Crime in 19th Century Germany," *Journal of Urban Economics*, 59(3), 370 – 388.

Miguel, E. (2005): "Poverty and Witch Killing," *The Review of Economic Studies*, 72(4), 1153–1172.

Miguel, E., S. Satyanath, and E. Sergenti (2004): "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, 112(4), 725–753.

Munyo, I., and M. Rossi (2013): "Frustration, Euphoria, and Violent Crime," *Journal of Economic Behavior & Organization*, 89, 136–142.

Neumayer, E., and T. Plumper (2007): "The Gendered Nature of Natural Disasters: The Impact of Catastrophic Events on the Gender Gap in Life Expectancy, 1981-2002," *Annals of the Association of American Geographers*, 97(3), 551–566.

Nunn, N. (2008): "Slavery, Inequality, and Economic Development in the Americas," in *Institutions and Economic Performance*, ed. by E. Helpman, Boston. Harvard University Press.

Nunn, N., and L. Wantchekon (2011): "The Slave Trade and the Origins of Mistrust in Africa," *American Economic Review*, 101(7), 3221–52.

Palermo, T., J. Bleck, and A. Peterman (2014): "Tip of the Iceberg: Reporting and Gender-Based Violence in Developing Countries," *American Journal of Epidemiology*, 179(5), 602–612.

Pollak, R. A. (2005): "Bargaining Power in Marriage: Earnings, Wage Rates and Household Production," NBER Working Papers 11239, National Bureau of Economic Research.

Ranson, M. (2014): "Crime, Weather, and Climate Change," *Journal of Environmental Economics and Management*, 67(3), 274–302.

Schneider, D., K. Harknett, and S. McLanahan (2016): "Intimate Partner Violence in the Great Recession," *Demography*, 53(2), 471–505.

Sekhri, S., and A. Storeygard (2013): "Dowry Deaths: Consumption Smoothing in Response to Climate Variability in India," Virginia Economics Online Papers 407, University of Virginia.

Tiihonen, J., P. Rasanen, and H. Hakko (1997): "Seasonal Variation in the Occurrence of Homicide in Finland," *American Journal of Ppsychiatry*, 154(12), 1711–1714.

True, J. (2012): *The Political Economy of Violence Against Women*. Oxford University Press, Oxford.

Uthman, O. A., T. Moradi, and S. Lawoko (2009): "The Independent Contribution of Individual-, Neighbourhood-, and Country-Level Socioeconomic Position on Attitudes Towards Intimate Partner Violence Against Women in Sub-Saharan Africa: A Multilevel Model of Direct and Moderating Effects," *Social Science & Medicine*, 68(10), 1801–1809.

Vyas, S., and C. Watts (2009): "How Does Economic Empowerment Affect Women's Risk of Intimate Partner Violence in Low and Middle Income Countries? A Systematic Review of Published Evidence," *Journal of International Development*, 21(5), 577–602.

World Health Organization (2013): *Global and Regional Estimates of Violence against Women: Prevalence and Health Effects of Intimate Partner Violence and Non-Partner Sexual Violence*. World Health Organization, Geneva.

A Robustness check: Effect on violence by father towards mother

As a robustness check, we use whether the respondent's father was violent against her mother as outcome variable, which is highly correlated with violence against women but not plausibly affected by current rainfall. 24% of the women answer affirmatively on the question and these women are 122% more likely to have been abused by their partners (from 23 to 51 percentage points). The models with the least spatial autocorrelation are found in columns 6 and 7, which still display Moran's I's in the outskirts of the expected distributions. We see that many of the models without spatial controls display strongly significant correlations with droughts and floods. These are fewer and less strong in the cases where polynomials enter the regressions, although not completely absent.

Table 8: Repeated cross sectional analysis of the effect of weather shocks on the probability of observing wealth index levels in the lowest two quintiles of the survey-wide distribution

DV: Lowest two wealth quintiles	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	All	All	All
Drought (2.5%) last season	0.025	0.075***	0.075***	0.045*	0.040	0.036	0.028
	(0.033)	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.021)
Flood (2.5%) last season	0.176***	0.050*	0.050*	0.014	0.012	-0.024	0.007
	(0.017)	(0.027)	(0.028)	(0.033)	(0.030)	(0.033)	(0.032)
Drought (2.5%) penultimate season	-0.113***	-0.006	-0.006	0.015	0.032**	0.028*	0.028*
	(0.019)	(0.017)	(0.017)	(0.014)	(0.014)	(0.015)	(0.016)
Flood (2.5%) penultimate season	0.114***	0.063***	0.064***	0.056**	0.003	-0.011	-0.009
	(0.037)	(0.021)	(0.021)	(0.022)	(0.020)	(0.018)	(0.022)
R^2	0.005	0.086	0.086	0.095	0.112	0.120	0.125
Moran's I of residuals	0.214***	0.033***	0.033***	0.025***	0.007***	0.001	-0.002
Z-score	*180.10*	*28.60*	*28.58*	*21.23*	*6.77*	*1.58*	*-1.48*
Drought (5%) last season	0.021	0.050***	0.050***	0.027	0.014	0.015	0.008
	(0.020)	(0.016)	(0.016)	(0.016)	(0.015)	(0.017)	(0.016)
Flood (5%) last season	0.165***	0.066***	0.066***	0.036*	0.032	0.011	0.026
	(0.028)	(0.019)	(0.019)	(0.022)	(0.021)	(0.024)	(0.021)
Drought (5%) penultimate season	-0.132***	-0.028**	-0.028**	-0.020**	0.010	0.005	-0.0002
	(0.015)	(0.013)	(0.013)	(0.010)	(0.011)	(0.011)	(0.011)
Flood (5%) penultimate season	0.088***	0.046**	0.047**	0.028	0.004	-0.004	-0.005
	(0.020)	(0.019)	(0.019)	(0.018)	(0.015)	(0.013)	(0.014)
R^2	0.013	0.086	0.086	0.095	0.112	0.120	0.125
Moran's I of residuals	0.187***	0.033***	0.033***	0.025***	0.008***	0.001*	-0.002
Z-score	*157.44*	*27.97*	*27.95*	*21.11*	*6.84*	*1.70*	*-1.47*
Drought (10%) last season	0.004	0.013	0.014	-0.007	-0.011	-0.008	-0.005
	(0.015)	(0.016)	(0.016)	(0.014)	(0.012)	(0.010)	(0.011)
Flood (10%) last season	0.070**	0.051***	0.051***	0.033**	-0.004	-0.011	-0.013
	(0.027)	(0.015)	(0.015)	(0.015)	(0.014)	(0.012)	(0.014)
Drought (10%) penultimate season	-0.145***	-0.034***	-0.034***	-0.026***	-0.009	-0.014	-0.018**
	(0.013)	(0.011)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)
Flood (10%) penultimate season	0.054***	0.015	0.015	0.005	-0.009	-0.008	-0.020*
	(0.016)	(0.015)	(0.015)	(0.014)	(0.010)	(0.011)	(0.010)
R^2	0.025	0.086	0.086	0.095	0.112	0.120	0.126
Moran's I of residuals	0.157***	0.033***	0.033***	0.025***	0.008***	0.001*	-0.002
Z-score	*132.28*	*28.03*	*28.01*	*21.16*	*6.86*	*1.68*	*-1.50*
Drought (15%) last season	-0.006	-0.017	-0.017	-0.025**	-0.010	-0.001	0.002
	(0.014)	(0.012)	(0.012)	(0.011)	(0.008)	(0.007)	(0.007)
Flood (15%) last season	0.085***	0.042***	0.042***	0.025**	0.001	-0.010	-0.008
	(0.019)	(0.013)	(0.013)	(0.012)	(0.013)	(0.011)	(0.012)
Drought (15%) penultimate season	-0.133***	-0.020*	-0.019*	-0.012	-0.012	-0.021**	-0.027***
	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
Flood (15%) penultimate season	0.049***	0.022	0.022	0.010	0.0004	-0.004	-0.014
	(0.014)	(0.014)	(0.014)	(0.013)	(0.010)	(0.011)	(0.010)
R^2	0.031	0.086	0.086	0.095	0.112	0.120	0.126
Moran's I of residuals	0.143***	0.033***	0.033***	0.025***	0.008***	0.001*	-0.002
Z-score	*120.73*	*28.64*	*28.63*	*21.51*	*6.98*	*1.71*	*-1.48*
Survey F.E.	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
N	154,316	154,316	154,316	154,316	154,316	154,316	154,316

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

B Rural sample

We here investigate whether droughts have an effect on violence in rural areas, as it has been argued that the effect of rainfall on household income is stronger in these households (Kudamatsu, Persson, and Strömberg, 2012). Columns 6 and 7 in Table 9 show that there is no impact of severe droughts on violence, and that milder droughts at the 10th and 15th percentile may lead to less violence.

When studying how droughts impact wealth levels in the rural sample, we are able to tackle spatial autocorrelation using 3rd order Legendre polynomials, unlike what was the case when using the whole sample. We also see that the coefficients from the penultimate season drought events have the expected sign, that is, droughts increase the share in the lowest wealth quintiles in rural areas. There is a significant impact of experiencing a season in the driest 2.5% of the distribution, and a weakly significant effect using the 15% cut-off. This strengthens the interpretation of droughts as negative income shocks in this sample.

From Table 11, we see from column 5 that there is no effect of droughts on violence the year before the interview, using the repeated cross-sections.

Table 12 shows that the effect of droughts on wealth in rural areas is similar to that in the total population using the repeated cross-section, with only slightly higher estimates. A drought in the penultimate season causes a significant increase in the share in the lowest two quintiles of the distribution if the drought is at the 2.5% level or 15% level (as seen in column 6), which is the specification which performs best in terms of spatial autocorrelation. Drought have weakly significant effects at if within the 5% and 10% driest seasons.

Finally, we ran the duration model on the rural sample. As shown in Table 13, this confirms the finding of there not being any relationship between droughts and violence against women. Note that the significant negative results in the larger sample are also not present, although point estimates still indicate odds ratios smaller than unity.

Table 9: Cross sectional analysis of the effect of weather shocks on having experienced violence the last year before interview, rural sample

DV: Experienced violence last year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Rural	Rural	Rural	Rural	Rural	Rural	Rural
Drought (2.5%) last season	0.050**	0.078***	0.077***	0.040*	0.031	0.031	0.012
	(0.022)	(0.024)	(0.024)	(0.022)	(0.022)	(0.022)	(0.022)
Flood (2.5%) last season	0.163***	0.037	0.037	0.029	0.019	-0.010	-0.015
	(0.029)	(0.049)	(0.049)	(0.035)	(0.031)	(0.034)	(0.031)
Drought (2.5%) penultimate season	-0.093***	0.002	0.001	0.016	0.031*	0.021	0.006
	(0.025)	(0.021)	(0.021)	(0.018)	(0.017)	(0.019)	(0.018)
Flood (2.5%) penultimate season	0.093*	0.055*	0.054*	0.036	-0.009	-0.027	-0.022
	(0.049)	(0.032)	(0.032)	(0.034)	(0.027)	(0.022)	(0.028)
R^2	0.004	0.068	0.071	0.081	0.095	0.104	0.110
Moran's I of residuals	0.133***	0.025***	0.025***	0.018***	0.004***	0.000	-0.002
Z-score	*121.75*	*23.01*	*23.01*	*16.52*	*4.11*	*0.11*	*-1.27*
Drought (5%) last season	0.046***	0.071***	0.070***	0.040**	0.015	0.016	0.009
	(0.016)	(0.016)	(0.016)	(0.015)	(0.014)	(0.015)	(0.014)
Flood (5%) last season	0.158***	0.010	0.010	0.004	0.001	-0.003	-0.013
	(0.020)	(0.032)	(0.033)	(0.024)	(0.024)	(0.024)	(0.023)
Drought (5%) penultimate season	-0.098***	-0.015	-0.016	-0.011	0.006	0.001	0.004
	(0.016)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.015)
Flood (5%) penultimate season	0.067***	0.043**	0.043**	0.023	0.010	0.021	0.021
	(0.025)	(0.021)	(0.021)	(0.019)	(0.018)	(0.017)	(0.016)
R^2	0.008	0.069	0.071	0.081	0.095	0.104	0.110
Moran's I of residuals	0.118***	0.024***	0.024***	0.018***	0.004***	0.000	-0.002
Z-score	*108.35*	*22.46*	*22.47*	*16.53*	*4.21*	*0.17*	*1.21*
Drought (10%) last season	0.016	0.033**	0.033**	0.007	-0.006	-0.003	-0.007
	(0.014)	(0.016)	(0.016)	(0.013)	(0.010)	(0.010)	(0.010)
Flood (10%) last season	0.062***	0.011	0.012	-0.002	-0.034**	-0.034**	-0.037**
	(0.024)	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)	(0.015)
Drought (10%) penultimate season	-0.117***	-0.028**	-0.028**	-0.018	-0.027**	-0.031***	-0.033***
	(0.014)	(0.013)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)
Flood (10%) penultimate season	0.017	0.009	0.009	-0.013	-0.022*	-0.017	-0.019
	(0.019)	(0.016)	(0.016)	(0.013)	(0.013)	(0.012)	(0.012)
R^2	0.013	0.068	0.070	0.081	0.096	0.105	0.110
Moran's I of residuals	0.107***	0.025***	0.025***	0.018***	0.004***	0.000	-0.002
Z-score	*97.95*	*23.26*	*23.26*	*16.93*	*3.85*	*0.11*	*-1.29*
Drought (15%) last season	-0.010	-0.008	-0.008	-0.020**	-0.016**	-0.009	-0.006
	(0.013)	(0.012)	(0.012)	(0.010)	(0.008)	(0.008)	(0.007)
Flood (15%) last season	0.083***	0.037***	0.036***	0.020*	0.004	-0.002	-0.001
	(0.019)	(0.012)	(0.012)	(0.012)	(0.015)	(0.013)	(0.014)
Drought (15%) penultimate season	-0.101***	0.001	0.001	0.009	-0.018*	-0.030***	-0.035***
	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.011)
Flood (15%) penultimate season	0.017	0.015	0.015	-0.008	-0.011	-0.008	-0.014
	(0.016)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
R^2	0.017	0.067	0.070	0.081	0.095	0.104	0.110
Moran's I of residuals	0.103***	0.026***	0.026***	0.018***	0.004***	0.000	-0.002
Z-score	*94.43*	*24.16*	*24.15*	*16.82*	*4.25*	*0.10*	*1.29*
Survey F.E.	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
N	103,945	103,945	103,937	103,937	103,945	103,945	103,945

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 10: Cross sectional analysis of the effect of weather shocks on the probability of observing wealth index levels in the lowest two quintiles of the survey-wide distribution, rural sample

DV: Lowest two wealth quintiles	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Rural	Rural	Rural	Rural	Rural	Rural	Rural
Drought (2.5%) last season	-0.060**	-0.090***	-0.089***	-0.069***	-0.042	-0.027	-0.013
	(0.030)	(0.031)	(0.031)	(0.027)	(0.025)	(0.022)	(0.022)
Flood (2.5%) last season	0.004	0.011	0.011	0.013	0.066***	0.028	0.015
	(0.025)	(0.029)	(0.029)	(0.025)	(0.025)	(0.022)	(0.022)
Drought (2.5%) penultimate season	0.109***	0.120***	0.120***	0.044	0.070***	0.082***	0.058**
	(0.035)	(0.035)	(0.035)	(0.029)	(0.027)	(0.027)	(0.026)
Flood (2.5%) penultimate season	-0.072	-0.053	-0.053	0.011	0.046	0.035	0.028
	(0.047)	(0.047)	(0.047)	(0.033)	(0.031)	(0.025)	(0.026)
R^2	0.002	0.032	0.033	0.093	0.126	0.153	0.166
Moran's I of residuals	0.057***	0.049***	0.049***	0.018***	0.011***	0.001***	-0.001
Z-score	*83.50*	*71.32*	*71.35*	*26.01*	*15.82*	*2.60*	*-0.37*
Drought (5%) last season	-0.013	-0.046*	-0.046*	-0.039*	-0.032	-0.033*	-0.015
	(0.025)	(0.026)	(0.026)	(0.020)	(0.020)	(0.019)	(0.019)
Flood (5%) last season	-0.016	-0.044	-0.044	-0.040	0.008	-0.030	-0.037
	(0.026)	(0.030)	(0.030)	(0.030)	(0.027)	(0.025)	(0.025)
Drought (5%) penultimate season	0.085***	0.125***	0.125***	0.057**	0.048**	0.041*	0.030
	(0.024)	(0.029)	(0.029)	(0.022)	(0.021)	(0.022)	(0.022)
Flood (5%) penultimate season	-0.102***	-0.068**	-0.069**	-0.007	-0.013	-0.020	-0.040**
	(0.030)	(0.031)	(0.031)	(0.019)	(0.026)	(0.020)	(0.019)
R^2	0.004	0.034	0.035	0.094	0.126	0.153	0.166
Moran's I of residuals	0.054***	0.047***	0.047***	0.017***	0.011***	0.001***	-0.001
Z-score	*79.27*	*69.44*	*69.47*	*25.54*	*16.16*	*2.67*	*-0.41*
Drought (10%) last season	0.010	-0.029	-0.029	-0.012	-0.026	-0.016	0.004
	(0.019)	(0.022)	(0.022)	(0.017)	(0.018)	(0.017)	(0.016)
Flood (10%) last season	0.023	-0.022	-0.022	-0.002	0.055***	0.034*	0.012
	(0.029)	(0.021)	(0.021)	(0.019)	(0.021)	(0.019)	(0.016)
Drought (10%) penultimate season	0.092***	0.171***	0.170***	0.085***	0.011	0.017	0.012
	(0.021)	(0.027)	(0.027)	(0.018)	(0.019)	(0.018)	(0.018)
Flood (10%) penultimate season	-0.068***	-0.040*	-0.040*	0.013	0.003	0.001	-0.015
	(0.020)	(0.022)	(0.022)	(0.018)	(0.017)	(0.016)	(0.015)
R^2	0.007	0.038	0.039	0.094	0.126	0.153	0.166
Moran's I of residuals	0.052***	0.044***	0.044***	0.017***	0.011***	0.001***	-0.001
Z-score	75.89	65.16	65.21	25.01	15.89	2.67	-0.42
Drought (15%) last season	0.029*	-0.005	-0.005	0.004	-0.016	-0.005	0.013
	(0.016)	(0.021)	(0.021)	(0.015)	(0.015)	(0.015)	(0.014)
Flood (15%) last season	0.025	-0.037*	-0.037*	-0.020	0.019	-0.012	-0.026*
	(0.026)	(0.021)	(0.021)	(0.020)	(0.019)	(0.016)	(0.015)
Drought (15%) penultimate season	0.094***	0.173***	0.173***	0.087***	0.038**	0.037**	0.032*
	(0.020)	(0.022)	(0.022)	(0.017)	(0.015)	(0.016)	(0.016)
Flood (15%) penultimate season	-0.053***	-0.035*	-0.035*	0.014	0.014	0.002	-0.005
	(0.018)	(0.019)	(0.019)	(0.016)	(0.016)	(0.015)	(0.014)
R^2	0.009	0.041	0.041	0.095	0.126	0.153	0.166
Moran's I of residuals	0.049***	0.042***	0.042***	0.017***	0.011***	0.002***	-0.001
Z-score	*72.29*	*61.68*	*61.72*	*24.99*	*16.15*	*2.77*	*0.77*
Survey F.E.	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
N	369,380	369,380	368,605	368,605	369,380	369,380	369,380

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 11: Repeated cross sectional analysis of the effect of weather shocks on having experienced violence the last year before interview, rural sample

DV: Experienced violence last year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Rural	Rural	Rural	Rural	Rural	Rural	Rural
Drought (2.5%) last season	-0.028	-0.019	-0.025	-0.030	0.013	0.033	0.013
	(0.033)	(0.039)	(0.038)	(0.037)	(0.034)	(0.039)	(0.039)
Flood (2.5%) last season	0.002	0.015	0.009	0.016	0.063	0.007	-0.002
	(0.093)	(0.062)	(0.069)	(0.069)	(0.064)	(0.069)	(0.072)
Drought (2.5%) penultimate season	-0.019	-0.026	-0.017	-0.002	-0.009	0.009	0.011
	(0.027)	(0.027)	(0.028)	(0.032)	(0.034)	(0.037)	(0.039)
Flood (2.5%) penultimate season	-0.051	0.001	-0.001	0.032	0.004	-0.027	-0.072
	(0.050)	(0.044)	(0.040)	(0.044)	(0.045)	(0.043)	(0.047)
R^2	0.007	0.291	0.306	0.335	0.395	0.472	0.531
Moran's I of residuals	0.039***	0.011***	0.010***	0.004	-0.002	-0.006	-0.009*
Z-score	*9.81*	*3.22*	*2.92*	*1.49*	*0.10*	*-0.96*	*-1.78*
Drought (5%) last season	-0.019	-0.009	-0.012	-0.009	0.014	0.036	0.019
	(0.023)	(0.025)	(0.025)	(0.025)	(0.027)	(0.035)	(0.037)
Flood (5%) last season	0.042	-0.017	-0.023	-0.019	0.010	-0.042	-0.061
	(0.050)	(0.037)	(0.039)	(0.040)	(0.043)	(0.050)	(0.051)
Drought (5%) penultimate season	-0.017	-0.025	-0.019	-0.012	-0.037*	-0.032	-0.010
	(0.014)	(0.016)	(0.017)	(0.018)	(0.021)	(0.022)	(0.025)
Flood (5%) penultimate season	0.016	0.048*	0.048*	0.060**	0.055**	0.057**	0.023
	(0.035)	(0.027)	(0.026)	(0.027)	(0.026)	(0.022)	(0.025)
R^2	0.007	0.300	0.315	0.346	0.405	0.483	0.531
Moran's I of residuals	0.038***	0.012***	0.011***	0.004	-0.002	-0.006	-0.009*
Z-score	*9.66*	*3.37*	*3.10*	*1.57*	*0.06*	*-1.06*	*-1.69*
Drought (10%) last season	-0.022	-0.008	-0.006	-0.007	0.005	0.029	0.006
	(0.015)	(0.019)	(0.019)	(0.020)	(0.022)	(0.027)	(0.028)
Flood (10%) last season	-0.037	-0.036	-0.039	-0.037	-0.011	-0.031	-0.019
	(0.033)	(0.025)	(0.025)	(0.025)	(0.028)	(0.032)	(0.034)
Drought (10%) penultimate season	-0.020	-0.029*	-0.029*	-0.018	-0.039	-0.048*	-0.049*
	(0.014)	(0.017)	(0.017)	(0.019)	(0.025)	(0.026)	(0.028)
Flood (10%) penultimate season	-0.040	0.002	0.001	-0.0005	0.015	0.004	-0.013
	(0.028)	(0.022)	(0.021)	(0.023)	(0.024)	(0.028)	(0.026)
R^2	0.021	0.297	0.313	0.338	0.397	0.477	0.531
Moran's I of residuals	0.039***	0.011***	0.009***	0.004	-0.002	-0.007	-0.009*
Z-score	*9.98*	*3.01*	*2.70*	*1.45*	*0.02*	*-1.14*	*-1.81*
Drought (15%) last season	-0.015	-0.002	0.001	0.001	0.006	0.029	0.021
	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.021)	(0.023)
Flood (15%) last season	-0.043	-0.017	-0.025	-0.016	0.008	0.001	0.013
	(0.029)	(0.023)	(0.022)	(0.023)	(0.026)	(0.029)	(0.032)
Drought (15%) penultimate season	-0.017	-0.010	-0.010	0.003	-0.011	-0.021	-0.031
	(0.017)	(0.017)	(0.017)	(0.019)	(0.021)	(0.022)	(0.024)
Flood (15%) penultimate season	-0.030	0.005	0.005	-0.002	0.022	0.015	-0.009
	(0.023)	(0.019)	(0.018)	(0.019)	(0.022)	(0.027)	(0.026)
R^2	0.022	0.290	0.306	0.333	0.395	0.474	0.530
Moran's I of residuals	0.042***	0.011***	0.010***	0.002	-0.002	-0.006	-0.009*
Z-score	*10.48*	*3.21*	*2.84*	*1.13*	*0.05*	*-1.00*	*-1.79*
Grid F.E.	yes	yes	yes	yes	yes	yes	yes
Country trends	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
n (women)	104,207	104,207	104,207	104,207	104,207	104,207	104,207
N (grids)	510	510	510	510	510	510	510

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 12: Repeated cross sectional analysis of the effect of weather shocks on the probability of observing wealth index levels in the lowest two quintiles of the survey-wide distribution, rural sample

DV: Lowest two wealth quintiles	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	All	All	All
Drought (2.5%) last season	-0.003	-0.010	-0.009	-0.009	0.011	0.011	-0.0003
	(0.034)	(0.034)	(0.035)	(0.034)	(0.037)	(0.038)	(0.041)
Flood (2.5%) last season	-0.018	-0.025	-0.021	-0.019	-0.028	-0.013	-0.008
	(0.022)	(0.023)	(0.023)	(0.026)	(0.024)	(0.024)	(0.026)
Drought (2.5%) penultimate season	0.043	0.051	0.050	0.039	0.043	0.094**	0.091*
	(0.038)	(0.039)	(0.040)	(0.042)	(0.043)	(0.048)	(0.052)
Flood (2.5%) penultimate season	-0.002	-0.008	-0.011	-0.001	0.025	0.025	0.032
	(0.021)	(0.021)	(0.023)	(0.022)	(0.022)	(0.027)	(0.028)
R^2	0.002	0.023	0.039	0.056	0.162	0.232	0.277
Moran's I of residuals	0.007***	0.008***	0.008***	0.004***	0.001	-0.001	-0.001
Z-score	*4.26*	*4.56*	*4.53*	*2.66*	*1.27*	*-0.09*	*-0.18*
Drought (5%) last season	0.034	0.029	0.029	0.031	0.043	0.056	0.051
	(0.033)	(0.036)	(0.034)	(0.035)	(0.036)	(0.037)	(0.038)
Flood (5%) last season	-0.023	-0.035	-0.032	-0.035	-0.048**	-0.046**	-0.043*
	(0.021)	(0.022)	(0.022)	(0.025)	(0.022)	(0.021)	(0.023)
Drought (5%) penultimate season	0.035	0.059**	0.062**	0.051*	0.040	0.064*	0.052
	(0.025)	(0.028)	(0.028)	(0.027)	(0.029)	(0.034)	(0.037)
Flood (5%) penultimate season	-0.024*	-0.028*	-0.031*	-0.024	-0.015	-0.018	-0.022
	(0.014)	(0.015)	(0.016)	(0.017)	(0.019)	(0.016)	(0.017)
R^2	0.010	0.034	0.051	0.066	0.171	0.241	0.283
Moran's I of residuals	0.007***	0.008***	0.008***	0.004***	0.001	-0.001	-0.001
Z-score	*4.34*	*4.52*	*4.52*	*2.68*	*1.22*	*-0.06*	*-0.18*
Drought (10%) last season	0.023	0.019	0.015	0.014	0.023	0.014	0.009
	(0.023)	(0.027)	(0.025)	(0.026)	(0.027)	(0.029)	(0.029)
Flood (10%) last season	0.024	0.016	0.020	0.024	0.026	0.021	0.018
	(0.014)	(0.015)	(0.015)	(0.017)	(0.018)	(0.016)	(0.017)
Drought (10%) penultimate season	0.040**	0.058***	0.060***	0.065***	0.047*	0.058*	0.056*
	(0.020)	(0.022)	(0.021)	(0.022)	(0.026)	(0.032)	(0.033)
Flood (10%) penultimate season	-0.019	-0.028	-0.028	-0.032	-0.022	-0.028	-0.028
	(0.018)	(0.022)	(0.021)	(0.022)	(0.023)	(0.022)	(0.022)
R^2	0.015	0.039	0.056	0.073	0.170	0.236	0.281
Moran's I of residuals	0.007***	0.007***	0.007***	0.003**	0.001	-0.001	-0.001
Z-score	*4.17*	*4.31*	*4.27*	*2.49*	*0.88*	*-0.11*	*-0.29*
Drought (15%) last season	0.028	0.031	0.027	0.022	0.023	0.007	0.011
	(0.018)	(0.022)	(0.021)	(0.022)	(0.021)	(0.024)	(0.024)
Flood (15%) last season	0.028**	0.022*	0.024*	0.025	0.029*	0.022	0.021
	(0.012)	(0.012)	(0.013)	(0.016)	(0.015)	(0.014)	(0.014)
Drought (15%) penultimate season	0.038*	0.051**	0.053***	0.064***	0.051**	0.064**	0.066**
	(0.020)	(0.020)	(0.020)	(0.021)	(0.023)	(0.028)	(0.029)
Flood (15%) penultimate season	0.003	0.004	0.004	0.002	0.012	0.004	-0.0005
	(0.016)	(0.021)	(0.020)	(0.021)	(0.023)	(0.022)	(0.023)
R^2	0.017	0.040	0.056	0.074	0.173	0.237	0.284
Moran's I of residuals	0.007***	0.007***	0.007***	0.003**	0.001	-0.001	-0.001
Z-score	*4.27*	*4.25*	*4.17*	*2.47*	*0.86*	*-0.05*	*-0.23*
Grid F.E.	yes	yes	yes	yes	yes	yes	yes
Country trends	no	yes	yes	yes	yes	yes	yes
Age controls	no	no	yes	yes	no	no	no
Temperature controls	no	no	no	yes	no	no	no
Legendre polynomials of degree 1	no	no	no	no	yes	yes	yes
Legendre polynomials of degree 2	no	no	no	no	no	yes	yes
Legendre polynomials of degree 3	no	no	no	no	no	no	yes
n (women)	455,342	455,342	455,342	455,342	455,342	455,342	455,342
N (grids)	1,123	1,123	1,123	1,123	1,123	1,123	1,123

Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 13: Duration analysis of the effect of weather shocks on first incidence of violence in marriage, rural sample

DV: First violent episode	(1)	(2)	(3)	(4)
Sample	Rural	Rural	Rural	Rural
Drought (2.5%)	0.932	0.888	0.896	0.896
	(0.076)	(0.073)	(0.078)	(0.077)
Flood (2.5%)	1.039	1.028	1.059	1.018
	(0.067)	(0.058)	(0.061)	(0.059)
R^2	0.023	0.029	0.026	0.030
Drought (5%)	0.956	0.924	0.903*	0.934
	(0.052)	(0.054)	(0.056)	(0.056)
Flood (5%)	1.016	1.007	1.023	0.999
	(0.044)	(0.041)	(0.043)	(0.042)
R^2	0.023	0.029	0.026	0.030
Drought (10%)	0.992	0.976	0.975	0.988
	(0.038)	(0.040)	(0.043)	(0.041)
Flood (10%)	1.047	1.039	1.060	1.032
	(0.040)	(0.038)	(0.041)	(0.040)
R^2	0.023	0.029	0.026	0.030
Drought (15%)	0.995	0.984	0.978	0.985
	(0.036)	(0.036)	(0.037)	(0.037)
Flood (15%)	1.031	1.031	1.056	1.026
	(0.035)	(0.033)	(0.036)	(0.035)
R^2	0.023	0.029	0.026	0.030
Piecewise constants	yes	yes	yes	yes
Age at marriage (grouped)	yes	yes	yes	yes
Survey-specific time trends	no	yes	yes	yes
Temperature controls	no	no	yes	no
Legendre polynomials of degree 1	no	no	no	yes
n (marriage-years at risk)	152,750	152,750	143,944	152,750
N (women)	32,874	32,874	32,874	32,874

Droughts and floods refer to rainfall below the threshold in rainy seasons terminating during the relevant marriage year or the year before. The age of marriage variable is grouped in five year intervals. Standard errors clustered on the ERA-Interim grid level in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.