Too Cold to Cope, Too Hot to Work: Temperature Extremes and Intimate Partner Violence*

Julieth Saenz-Molina†

November 15, 2025

Abstract

The increasing frequency of extreme weather events poses significant socioeconomic challenges, particularly for vulnerable populations in developing countries. This paper investigates the impact of temperature exposure on intimate partner violence (IPV) using individual-level data from the 2008 Bolivian Demographic and Health Survey matched with high-resolution daily climate data. Employing a temperature binning approach with fixed effects, I find substantial heterogeneous effects by altitude: in low-altitude areas, ten additional days of extreme cold (below 21°C) or extreme heat (33°C or higher) significantly increase IPV incidence by 3.6 and 2.2 percentage points, respectively, while moderate cold temperatures reduce IPV incidence. Moreover, cold exposure increases IPV through heightened male alcohol consumption and income instability, particularly in rural and indigenous communities, while heat exposure reduces women's employment in urban, non-indigenous households. Overall, the results demonstrate that the effects of temperature exposure are highly contextual and heterogeneous, underscoring the need for climate adaptation policies that are sensitive to socioeconomic status and gender so that they can contribute to the broader goal of reducing violence against women.

JEL codes: I14, J12, Q54, O54

Keywords: intimate partner violence; temperature shocks; climate change effects; Latin America

*Acknowledgments: I am grateful to Subha Mani, Sophie Mitra, and Andrew Simons for their invaluable guidance, feedback, and suggestions. I am also grateful to Claus Pörtner, Shamma Alam, Emily Pakhtigian, Xinde Ji, and Teevrat Garg for their insightful comments and suggestions. I thank Elizabeth Lockwood, Heather Schofield, Eeshani Kandpal, Francois Cohen, Julien Daubanes, and Anna Shostya for their advice. I am also grateful for the helpful conversations with participants of the 7th Nordic Annual Environmental and Resource Economics (NAERE) Workshop, the Association of Environmental and Resource Economists Virtual Workshop (AERE@OSWEET), and Fordham University's Applied Microeconomics Workshop. All errors are my own.

†Dept. of Economics, Fordham University, Bronx, NY 10458. Email: jsaenzmolina@fordham.edu.

1 Introduction

Rising temperatures and the increasing frequency and magnitude of extreme weather events associated with climate change pose significant economic and social costs. These impacts are especially grave for low- and middle-income countries (LMICs) that have weak and often unstable social and economic structures and institutions (Adom, 2024; International Monetary Fund, 2023). Various studies estimate climate change's detrimental effects on economic growth (Dell et al., 2012; Deryugina and Hsiang, 2014), poverty (Guivarch et al., 2021), productivity (Hsiang, 2016), risk preferences (Purcell, 2021), and human health (Zhao et al., 2021). A growing body of research also examines how rising temperatures and changing weather patterns influence aggressive behavior, including violent crime (Zhao et al., 2024), civil unrest (Hsiang et al., 2011; Stechemesser et al., 2022), and domestic violence (Evans et al., 2025; Díaz and Saldarriaga, 2023; Henke and Hsu, 2020). However, the effects of climate change on intimate partner violence (IPV) remain understudied, particularly in contexts where social vulnerability, limited legal protections, and gender inequality amplify the risks faced by women (UN Women, 2022).

Despite decades of policy efforts, IPV remains a pervasive global issue. According to the World Health Organization, nearly one-third of women aged 15–49 who have ever been in a long-term relationship report having experienced some form of IPV (WHO, 2021). Such violence has short- and long-term consequences for women's health, productivity, and well-being, and it also affects children's development, behavior, and future outcomes (Bedoya et al., 2020; Bhuller et al., 2023; WHO, 2021).

Given growing evidence linking high temperatures to increased aggression and conflict (Baylis, 2020; Hsiang et al., 2013), it is crucial to understand how temperature shocks influence IPV, and whether these effects vary across populations with different climatic and social characteristics. This paper examines the heterogeneous relationship between temperature and IPV using individual-level data from the 2008 Demographic and Health Surveys (DHS) for Bolivia, matched with high-resolution daily climate data. Bolivia offers a unique context to study these effects because its geography spans both tropical lowlands and mountainous highlands, which differ substantially in climate, economic activity, and cultural norms. These natural contrasts allow for a detailed analysis of how climatic adaptation and social vulnerability shape the relationship between temperature shocks and IPV.

The empirical strategy builds on previous literature on the health and economic impacts of temperature exposure (Barreca et al., 2016; Burke et al., 2015; Deschênes and Greenstone, 2011; Evans et al., 2025; Graff Zivin et al., 2018). I construct a set of temperature bins that capture the number of days in the 12 months preceding the survey with maximum temperatures within each 2°C range. This approach allows for nonlinear responses and avoids imposing a restrictive functional form on the relationship between temperature and IPV. The specification includes month-of-survey and region fixed effects to account for seasonal patterns and unobserved regional characteristics that may confound the estimated effects. This empirical strategy exploits the variation in the timing of the DHS interviews, comparing individuals within the same region and season who experienced marginally different temperature days due to variations in the 12-month period. Identification relies on the assumption that the timing of the survey interviews is exogenous to household characteristics and unrelated to local patterns of IPV.

Because Bolivia exhibits significant differences in climate and adaptation capacity across altitudes,[1] I estimate the effect of temperature on IPV separately for low- and high-altitude regions. The results reveal that differences in climatic adaptation translate into a strongly heterogeneous relationship between temperature and IPV. In low-altitude areas, ten more days of extreme cold (< 21°C) and hot (≥ 33°C) temperatures increase IPV incidence by 3.6 and 2.2 percentage points, respectively, while days with moderate cold temperatures, $[21, 23)$, reduce violence by 6.0 percentage points. In contrast, the effects in high-altitude areas are small and statistically insignificant, likely reflecting more stable climates and greater adaptation to cooler temperatures.

Further disaggregation shows that within low-altitude areas, the magnitude and mechanisms of these effects differ across demographic groups. Cold temperature shocks increase IPV among rural and indigenous households, largely through declines in household

[1] A cutoff of 1000 meters above sea level is used to distinguish low- and high-altitude areas.

wealth and increases in men's alcohol consumption. Hot temperature shocks, in turn, raise IPV incidence among urban and non-indigenous households by reducing women's employment and increasing daily interactions between partners. These results indicate that the same climatic shock can have opposite or offsetting effects depending on local conditions and socioeconomic characteristics.

This paper contributes to the literature on climate change and violence in several important ways. First, it is the first to document the heterogeneous effects of temperature on intimate partner violence (IPV) and identify the mechanisms through which they operate. The results show that temperature shocks have context-dependent effects that vary by altitude, population group, and type of temperature exposure. Second, by employing a flexible temperature-binning approach with fixed effects, I capture nonlinear and non-monotonic responses that reveal both cold and hot shocks impact IPV. This approach, which combines high-frequency climate data with self-reported measures of IPV, allows for stronger causal inference and overcomes the reporting biases common in administrative records that often undercount violence within the household (Palermo et al., 2014). Third, I estimate cumulative effects over the prior year, reflecting more sustained disruptions in economic and social conditions. To the best of my knowledge, this is the first study to analyze the causal relationship between temperature and IPV beyond contemporaneous effects. Together, these contributions provide new evidence on how climatic adaptation and social vulnerability shape the link between temperature and IPV.

Most existing studies on temperature and violence assume homogeneous effects of temperature shocks, masking important differences in exposure and adaptation across populations (Henke and Hsu, 2020; Mannell et al., 2024; Sanz-Barbero et al., 2018; Zhu et al., 2023). However, some studies show that the association between temperature and violent crime is influenced by social and demographic factors (Heilmann et al., 2021; Mahendran et al., 2021; Xu et al., 2020, 2021). Such differences in vulnerability are also reflected in the literature on extreme precipitation shocks and IPV, which finds varying effects of wet and dry shocks across regions (Cools et al., 2020; Díaz and Saldarriaga, 2023; Rai et al., 2021; Sekhri and Hossain, 2023). My findings extend this evidence by highlighting how climatic adaptation and socioeconomic vulnerability jointly determine the magnitude and direction of the temperature–IPV relationship. The results have important policy implications for the design of gender-sensitive climate adaptation and public health programs that consider local climatic and social contexts.

The rest of the paper is organized as follows. Section 2 describes the data used and discusses the climatic and demographic differences in low- and high-altitude areas. Section 3 provides the empirical specifications. Section 4 presents the results on all dimensions of IPV for the high-altitude and low-altitude samples. Section 5 provides an in-depth analysis of the mechanisms in low-altitude areas. Section 6 discusses the heterogeneous effects of temperature. Section 7 presents robustness checks. Section 8 concludes with a summary of the findings and offers some policy recommendations.

2 Data

Bolivia presents a unique case study, with several demographic subgroups that experience the effects of climate change differently. First, the significant differences in altitude within the country's regions allow for a separate analysis of populations accustomed to different climates. This is important because recent studies have found that the effects of temperature on health outcomes are more likely to be influenced by 'de-adaption' to atypical temperatures rather than by the ranges of temperatures that they typically experience in their areas (Heutel et al., 2021; Helo Sarmiento, 2023). Second, Bolivia's demographic diversity, with its large rural and indigenous populations, makes it particularly useful for analyzing those demographic groups that are vulnerable to and disproportionately affected by climate change. Studies show that rural indigenous women are at risk, both in terms of their vulnerability to climate change (Chapola et al., 2024; Coen, 2021; Johnson et al., 2022) and their exposure to IPV (Heidinger, 2021; Meekers et al., 2013). In fact, the large rural and indigenous population of women in Bolivia may explain why it is one of 19 countries in the world, and the only one in Latin America, where more than

40% of ever-partnered women have experienced IPV at least once in their lifetime. This high incidence of IPV makes it easier to capture the marginal effects of high-frequency variables, such as daily temperature.

To empirically analyze the effect of temperature on IPV, I combine data from two sources: (1) the 2008 Bolivian Demographic and Health Survey (DHS), and (2) the ERA5Land dataset provided by the European Center for Medium-Range Weather Forecasts (ECMWF).

2.1 *Survey Data and Outcome Variables*

The IPV data come from the DHS conducted in Bolivia between February and June of 2008. The 2008 survey is the only Bolivian survey that includes GPS coordinates at the DHS cluster level, allowing for the alignment of IPV data with climate data. Also, due to the time of the survey, the period of measurement for IPV (12 months prior to the survey) covers the effects of La Nina, the Southern Oscillation (ENSO) effect characterized by cooler temperatures and increased rainfall. This facilitates the analysis of cold temperature shocks, which are rarely analyzed in the violence literature (Hsiang et al., 2011). Additionally, the DHS questionnaire on domestic violence is very comprehensive. Unlike other DHS questionnaires from similar countries like Colombia and Peru, it includes more questions on psychological abuse, specifying the time period and the frequency of each act.

The DHS survey randomization happens at the cluster level. A DHS cluster, drawn from the census data and population density, consists of a village in rural areas or a few street blocks in urban areas. Within each cluster, twenty households were randomly selected for the interview. The survey data contains cross-sectional information on the general characteristics of each household, as well as the sociodemographic and health status of a representative sample of women 15–49 years old.

Under strict privacy-protection protocols, women who had an intimate relationship in the year prior to the survey were asked about their experience of intimate partner mistreatment, including physical and sexual IPV and psychological abuse.[2] The module is based on a modified and shortened version of the Conflict Tactic Scales (CTS) elaborated by Straus (1979; 1990), which was designed to minimize definitional bias, provide multiple opportunities for disclosure, and increase the likelihood of reporting less severe forms of violence (Garcia-Moreno et al., 2006; Straus et al., 1996; WHO, 2005). The main outcome variable, IPV Incidence, indicates whether the woman reported that a partner has done any of the following acts to her in the last 12 months:

1. pushed or tugged
2. hit with the hand or foot
3. hit with an object
4. tried to strangle or burn
5. forced to have unwanted sexual relations

I created several variables to measure the frequency and severity of IPV. The frequency variables, *often* and *sometimes*, indicate whether at least one of the acts occurred often, and whether all of the acts occurred sometimes or once, respectively. The severity variables are based on the WHO classifications of each act (WHO, 2021). *Less severe* is set to 1 if the woman only chose any of the first acts, while *Severe* equals 1 if the woman suffered from any of the last three acts.

One of the United Nations' Sustainable Development Goals (SDG) related to violence against women, SDG 5.2, includes a target to eliminate all forms of violence against women and girls, with indicator 5.2.1 specifically measuring psychological violence alongside physical and sexual violence (UN General Assembly, 2015). Although there is no internationally standard measure, the Bolivian laws define psychological abuse as situations of controlling behavior (Coa and Ochoa, 2009). In the Domestic Violence module of the DHS, respondents were asked whether their partner exhibited each of the following eight behaviors in the past 12 months: accused her of unfaithfulness, was jealous of other men, limited contact with her family, humiliated or insulted her[3], threatened to aban-

[2]In this paper, the IPV definition includes physical and sexual violence. Since there is no standardized measure of psychological abuse, including it as part of IPV would limit the external validity of the results.

[3]Examples given for this question included the expressions: "You're useless", "You never do anything", "You're so dumb", and "My mom used to do things better for me".

don her, threatened to take her children, threatened to stop economic support, or broke household objects in anger. I use this question to create an indicator of psychological abuse, which is equal to 1 if the woman experienced at least one of these behaviors.

Since this paper focuses on women who are in a long-term relationship and could be exposed to IPV, I limited the sample to respondents who were partnered (married/cohabiting) at the time of the survey and shared a household with their partners. Due to the time period specified by the IPV question and to ensure that the temperature shocks are correctly assigned, I dropped all women who have lived in the current location for less than a year. The final sample consists of 9,812 women. To capture differences in climate based on altitude, I also created two subsamples, low- and high-altitude, using 1000 meters above sea level as the cutoff (Díaz and Saldarriaga, 2023; Helo Sarmiento, 2023).

Table 1 summarizes the demographic characteristics of the full country sample and the two altitude subsamples. Column (1) shows that the average woman in the sample is 33 years old and has completed an average of 7.5 years of schooling. More than a third of the sample lives in rural areas, and 23 percent work in agriculture. Also, 64% of the sample has indigenous ethnicity, reflective of the large indigenous communities in the country. About a quarter of the women in the sample were victims of IPV, with 10% of them suffering from severe forms of IPV and 4% experiencing it often. Additionally, 42% of women suffered from psychological abuse.

Columns (2) and (3) of Table 1 show that the altitude subsamples are demographically different. Compared to women in the high-altitude areas, the respondents in the low-altitude areas are less likely to be rural, more likely to work in agriculture, and more likely to identify themselves as indigenous. They also have more years of education, on average. While IPV incidence is lower in low-altitude areas, psychological abuse is higher. These statistically significant demographic differences, combined with substantial regional variation in temperature exposure described in the next section, provide a basis for differentiating the effects of temperature shocks on violence between low- and high-altitude areas.

Table 1: Summary Statistics by Altitude

	(1) Full Country	(2) Low Altitude	(3) High Altitude	(4) Difference (3) − (2)
IPV Incidence	0.26	0.23	0.27	0.05***
				(0.01)
Often	0.04	0.04	0.04	0.01
				(0.00)
Severe physical IPV	0.10	0.09	0.11	0.01
				(0.01)
Psychological abuse	0.42	0.45	0.41	−0.03*
				(0.01)
Rural	0.38	0.26	0.44	0.17***
				(0.01)
Age (years)	33.44	32.54	33.87	1.33***
				(0.23)
Indigenous Ethnicity	0.64	0.37	0.76	0.39***
				(0.01)
Schooling years completed	7.58	8.32	7.23	−1.08***
				(0.13)
Worked in the past 12 months	0.75	0.71	0.77	0.06***
				(0.01)
Works in agriculture	0.23	0.11	0.28	0.17***
				(0.01)
Observations	9812	3479	6309	

Notes: The sample is restricted to women currently partnered and have lived at their current location for at least one year. The Low Altitude sample consists of all the observations located in DHS clusters with altitude less than 1000m above sea level. High altitude is all the remaining clusters. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.2 *Weather Data*

Temperature and precipitation data come from the ERA5-Land dataset, which uses observation data and climatic models to obtain reanalysis data available on a $0.1° \times 0.1°$ (approx. 10km) quadrilateral grid from January 1980 to present. Estimates from the reanalysis data have been used extensively in the economics literature. This is because they are regarded as the most consistent estimates of weather in a grid cell, compared to other measures that only use observational data, especially for areas with low coverage from weather stations (Auffhammer et al., 2013). Each survey cluster is matched to the closest cell on the grid using the GPS coordinates provided by the DHS. One caveat of this method is that the DHS coordinates are provided with a random displacement error to ensure individuals' anonymity, and thus, the assignment of weather variables could be misaligned with the next corresponding grid cell. That is, the analysis relies on the assumption that the difference in the daily maximum temperature between neighboring grid cells is statistically insignificant.

I transformed the hourly data into daily data by taking the maximum temperature and the total accumulation of precipitation for each day. Figure 1 shows the population-weighted distribution of maximum temperature in Bolivia over the two-year period of interest, 2007–2008. The height of each bar represents the number of days in which the average maximum temperature was in the respective bin. The figure depicts a key feature of tropical nations: the temperature range over the year is narrow due to the lack of seasonality. Therefore, unlike previous literature that used 5°C or 10°F temperature bins, the main empirical analysis of this paper relies on 2°C temperature bins to capture enough spatial and temporal variation (Garg et al., 2020; Helo Sarmiento, 2023). In doing so, I am following the research by Helo Sarmiento (2023), who studied the effect of temperature on mortality in Colombia, another tropical country in South America.

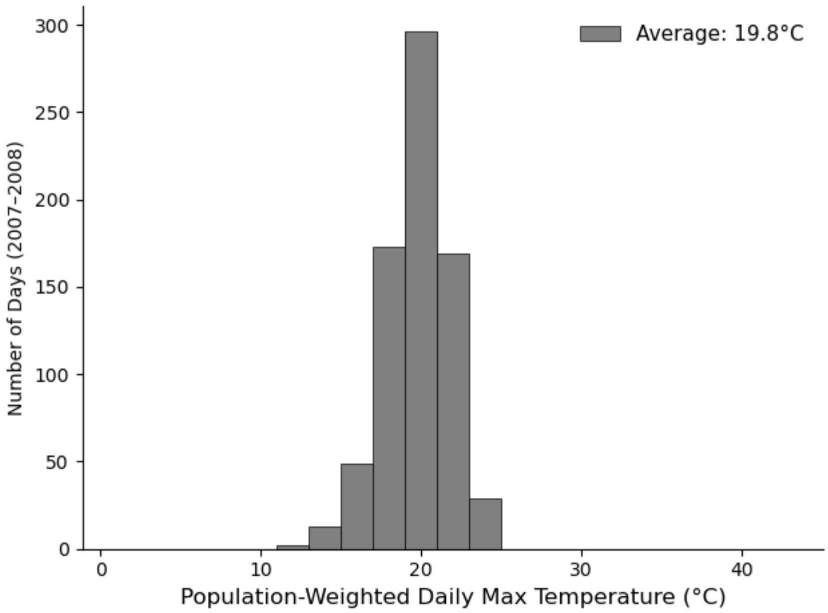

Figure 1: Distribution of Daily Maximum Temperature by Altitude

Notes: Each bar represents the number of days the population-weighted daily maximum temperature fell within the corresponding 2°C range (bin width = 2°C). Population weights are based on DHS cluster counts, defined as the number of individuals within 2 km (urban) or 10 km (rural) of each cluster, using the national census closest to 2010. The histograms cover daily maximum temperatures from January 2007 to December 2008.

Due to Bolivia's location within the Andes Mountain range and its proximity to the equator, another important characteristic of this country is that its temperatures depend on altitude instead of seasonal patterns. Figure 2 depicts the difference in the range of daily maximum temperatures between the low- and high-altitude subsamples. While mountainous, high-altitude areas rarely experience temperatures above 23°C, the average daily maximum temperature in the lowlands is 27°C. The low-altitude areas also experience a wider range of temperatures with more outliers on the colder side. The left-skewed distribution reflects occasional cold fronts, locally known as surazos, which originate in Patagonia and can reach the Bolivian lowlands (Garreaud, 1999; Lanfredi and de Camargo, 2018).

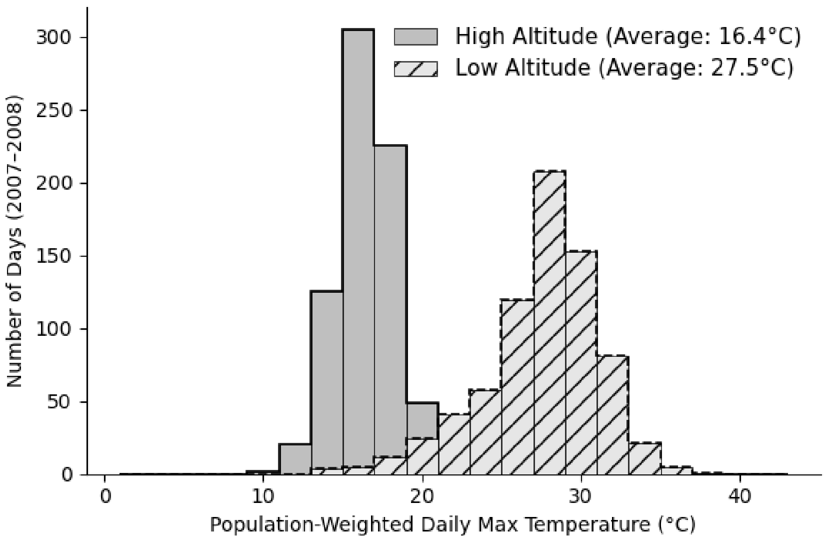

Figure 2: Distribution of Daily Maximum Temperature by Altitude

Notes: Each bar represents the number of days the population-weighted daily maximum temperature fell within the corresponding 2°C range (bin width = 2°C). Population weights are based on DHS cluster counts, defined as the number of individuals within 2 km (urban) or 10 km (rural) of each cluster, using the national census closest to 2010. The histograms cover daily maximum temperatures from January 2007 to December 2008. Low altitude is defined as clusters below 1,000 m above sea level, and high altitude as clusters at or above 1,000 m.

3 Empirical Specification

In line with the standard approach in environmental economics, I employ a flexible parametric model that uses discrete temperature bins to estimate the temperature effect. This specification captures potential nonlinearities and avoids restrictive functional-form assumptions (Deschênes and Greenstone, 2011; Ranson, 2014).[4]

$$Y_{icm} = \alpha + \sum_{j=1}^{T} \beta_j TMAX_{icm} + \nu P_{icm} + \eta' Z_{icm} + \kappa_c + \gamma_m + \varepsilon_{icm} \tag{1}$$

Y_{icm} is the outcome variable for individual i in region c in month m. The key variables of interest, $TMAX_{icm}$, is a series of $2°C$ bins: $< 11, [11, 13), ..., [31, 33), \geq 33$. Each bin j indicates the number of days in the previous 12 months in which the maximum temperature is within the jth range. Since the survey was conducted from February to June 2008,

[4]Results remain robust when using a probit specification. A detailed discussion comparing probit estimates and the rationale for using the Linear Probability Model (LPM) as the primary specification is provided in Section 7.3.

this variable leverages the variation in the interview date. Thus, for each observation, bin j denotes the number of days experienced by individual i in the corresponding 365 days prior to the survey. Since for all observations the number of days across all temperature bins adds up to 365, the bin $[21, 23)°C$ is omitted and used as the reference category. Thus, β_j is interpreted as the effect on IPV from one more day in the j^{th} bin (relative to the omitted category), based on exposure in the 12 months prior to the survey.

P_{icm} is the total accumulated precipitation in the previous 12 months. It is used as a control variable, given previous evidence of the high correlation between temperature and precipitation, as well as between extreme precipitation shocks and IPV (Díaz and Saldarriaga, 2023; Sekhri and Storeygard, 2014). Z_{icm} is a set of demographic and day-of-interview controls. Demographic factors include age, rural status, ethnicity, and education. Additionally, I control for the maximum temperature on the day of the survey to capture any short-term effects that temperature could have on survey response, due to recall or cognitive performance (Gaoua, 2010; Pilcher et al., 2002; Sharma et al., 1985), or interviewer productivity (LoPalo, 2023). Similarly, I include a morning-survey indicator to control for any possible measurement error arising from the time of the day at which the interview is conducted. Previous evidence suggests that women are more likely to self-report IPV in the morning, since the risk of retaliation increases with time of day (Theiss, 2024).

Finally, κ_c and γ_m are region and month-of-survey fixed effects. κ_c captures any time-invariant observed and unobserved region-specific characteristics, while γ_m controls for any possible seasonal patterns in IPV reporting. Standard errors are clustered at the DHS cluster level. To match the survey design and ensure representativeness at the country level, all observations are weighted using the DHS sample weights.

The empirical strategy relies on the identification assumption that the temperature bins are orthogonal to individual characteristics, ensuring that exposure to each temperature bin is as good as randomly determined among respondents. To empirically test this assumption, I estimate equation (1) using demographic characteristics that are not expected to be systematically affected by the previous year's temperature, including age, height, years of schooling, and indigenous ethnicity.

Tables A.1 and A.2 present the results for the low- and high-altitude samples, respectively.[5] The temperature bins are uncorrelated to age, height, and years of schooling for both samples. Parental IPV is also uncorrelated with temperature bins in high-altitude areas, although in low-altitude areas, the coefficients for the moderate temperature shocks, $[21, 23)$ and $[31, 33)$, are statistically significant. The significant coefficients, however, could be due to spurious correlation, as the Type I error increases with the number of outcomes estimated. Following Benjamini et al. (2006), I calculate sharpened False Discovery Rate (FDR) q-values for the temperature bins in each table. Most coefficients do not survive multiple-testing adjustment at the 10% level, and thus, there is no evidence of systematic imbalance.

As an additional validity check, I examine whether the timing of survey interviews was correlated with respondents' observable characteristics. This test assesses whether data collection within each region and survey month was systematically related to demographic composition, which could indirectly bias the temperature exposure distribution. Specifically, I regress each demographic characteristic on the number of days since the start of fieldwork, controlling for region and month-of-interview fixed effects. Tables A.3 and A.4 report the results for the low- and high-altitude samples, respectively. In the low-altitude sample, coefficients on interview timing are small and statistically insignificant across outcomes. In the high-altitude sample, the coefficient for years of schooling is negative and statistically significant at the 1 percent level. However, other observables are not significantly associated with interview timing. Overall, the evidence indicates a limited association between survey timing and respondent composition, with one significant relationship for schooling in high-altitude areas. For the low-altitude sample, the results suggest that the within-region-month timing of interviews was as good as random with respect to respondent demographics, supporting the exogeneity of survey timing and temperature exposure around the interview date.

[5] Balance-check results for the full national sample are reported in Appendix B, Table B.1. The extreme temperature bins are largely uncorrelated with demographic characteristics.

4 Results

As discussed earlier, due to its location within the Andes and its varied topography, large portions of the country sit at altitudes above 1,000 meters, with some areas exceeding 3,000 meters above sea level. This significant altitudinal variation leads to substantial differences in climatic conditions across regions, shaping both temperature exposure and population adaptation, and resulting in heterogeneous behavioral responses to weather shocks. To capture these effects more accurately, I stratify the sample into low- and high-altitude groups, using a cutoff of 1,000 meters above sea level.[6] The bin structures for each altitude subsample are adjusted to reflect their distinct climatic ranges, enabling more meaningful comparisons relative to local norms of temperature exposure.

I estimated the effect of temperature on IPV for each altitude subsample using equation (1), but with distinct sets of temperature bins. Specifically, the low-altitude bins are set as follows: $< 21, [21, 23), \ldots, [31, 33), \geq 33$, with $[27, 29)$ as the reference bin. For the high-altitude subsample, the bins are: $< 11, [11, 13), \ldots, [19, 21), \geq 21$, with $[15, 17)$ as the reference category. These reference bins were chosen based on the population-weighted average maximum temperatures observed during 2007–2008 (Figure 2).

The results for IPV incidence by altitude category are shown in Figure 3. The point estimates for the high-altitude subsample are all very small and statistically insignificant, even at the 10 percent level. Thus, there is no evidence of a temperature effect on IPV incidence in the mountainous, high-altitude areas of Bolivia. Since the climate of this subsample is generally cooler and rarely reaches temperatures above $23°C$, it is possible that individuals were not exposed to temperatures sufficiently high to affect temperament and intrafamily interactions over the preceding year.

In contrast, for the low-altitude subsample, the effect of temperature on IPV incidence seems to be nonlinear. While extremely cold and hot days have a significantly positive effect on IPV, relative to the reference bin, days with moderate temperatures have a

[6]Results for the full national sample are provided in Appendix B for reference. These aggregate estimates show no statistically significant effect of temperature on IPV incidence. However, due to the climatic differences between regions, such point estimates may obscure the heterogeneous effects of temperature and its associated mechanisms.

negative effect on the incidence of IPV. The colder temperature bins, however, tend to have larger coefficients than the hotter temperature bins, implying that the population in low altitudes is more susceptible to cold shocks.

This difference between low- and high-altitude areas may be a result of the distribution of temperatures experienced by each area. While high-altitudes experienced a narrow range of temperatures (between 9°C and 23°C) with few outliers, the low-altitude areas had a wider range of temperatures (between $13°C$ and $37°C$). The lowlands experienced the effect of the cooler Southern Oscillation (ENSO) climate pattern, La Niña, between November 2007 and April 2008, which brought about outlying cold days (Climate Prediction Center, 2008; Global Facility for Disaster Reduction and Recovery, 2008). Due to their infrequency, low-altitude areas may be 'de-adapted' to such colder temperatures (Heutel et al., 2021). Additionally, they experienced high temperatures, which previous research has shown to be associated with increased violence (Zhao et al., 2024).

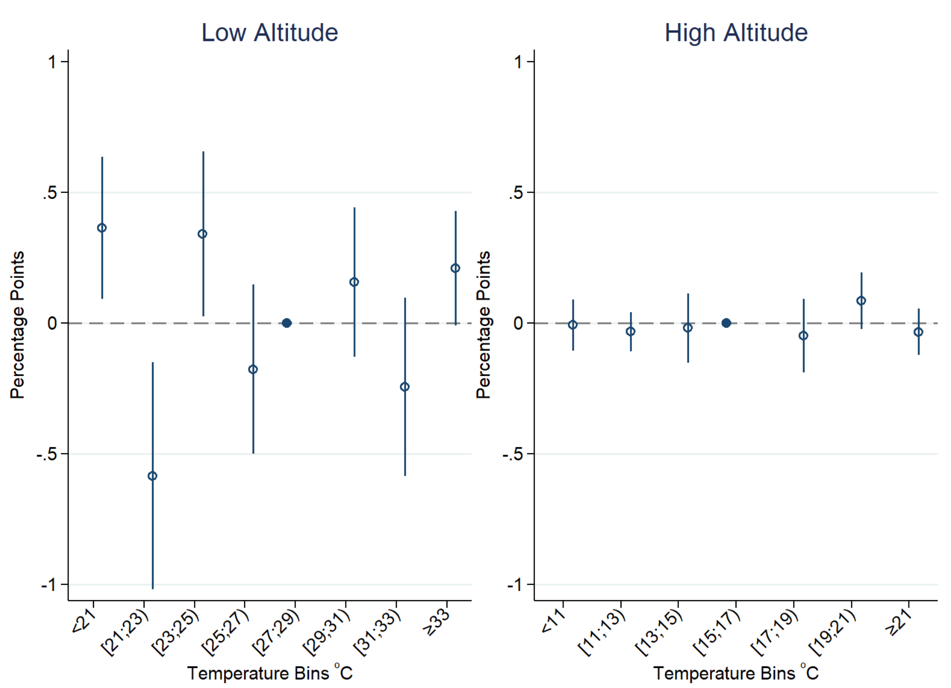

Figure 3: Estimated Effect of Temperature on IPV Incidence by Altitude

Notes: Low altitude is defined as clusters below 1,000 m above sea level, and high altitude as clusters at or above 1,000 m. Dots show the coefficients estimated using equation (1); lines are 95% CI with SEs clustered at the DHS cluster level. Coefficients are scaled by 100 (percentage points) and represent the marginal effect of one extra day in each 2°C bin relative to the omitted bin $[21, 23)$°C. Controls include 12-month precipitation, age, rural status, ethnicity, education, survey-day max temperature, and morning-survey indicator. Region and month fixed effects also included.

Given that only the low-altitude areas experience sufficient temperature shocks to have a detrimental impact on IPV incidence, I further investigate the effect of temperature on other dimensions of IPV for this subsample only.[7] Table 2 shows the point estimates. As presented in columns (2)–(4), the sign of the coefficients remains the same for all temperature bins across all levels of severity. Exchanging a day in the reference bin for a day in the extreme cold or hot bins, < 21°C and ≥ 33°C, increases all levels of IPV. However, only the point estimates for severe IPV are significant (p-value < 0.10), indicating that ten extra days with extreme temperatures increase the likelihood of severe IPV by 2.0 percentage points, relative to the omitted category.

The point estimates for < 21 and $[23, 25)$ in column (5) reveal that ten extra days in each bin increase the proportion of women who report suffering from IPV only sometimes

[7]A similar analysis for high-altitude areas can be found in Appendix A.

by 4.4 and 4.6 percentage points, respectively, relative to the reference bin. These changes are not offset by the statistically insignificant decrease in the proportion of women who report suffering from IPV often after experiencing days in the same bins, suggesting that the increase in IPV incidence due to experiencing such temperatures arises from new cases of IPV, instead of shifts in frequency. Similarly, exposure to ten extremely hot days, ≥ 33°C, increases reports of experiencing IPV only sometimes by 2.8 percentage points, which is not offset by the reduction in reports of women suffering from violence often.

Table 2: Temperature Effect in All Dimensions of IPV – Low Altitude

	(1) IPV Incidence	(2) IPV Severity Less severe	(3) Severe	(4) IPV Frequency Sometimes	(5) Often	(6) Psychological Abuse
< 21 (%)	0.36***	0.16	0.20*	0.44***	-0.08	0.30*
	(0.14)	(0.10)	(0.12)	(0.13)	(0.05)	(0.17)
$[21, 23)$ (%)	-0.60***	-0.33*	-0.28	-0.46**	-0.14	-0.43*
	(0.22)	(0.18)	(0.17)	(0.23)	(0.10)	(0.25)
$[23, 25)$ (%)	0.34**	0.27**	0.07	0.46***	-0.11	0.36*
	(0.16)	(0.11)	(0.10)	(0.15)	(0.09)	(0.18)
$[25, 27)$ (%)	-0.19	-0.16	-0.02	-0.02	-0.17**	-0.06
	(0.16)	(0.13)	(0.14)	(0.17)	(0.07)	(0.18)
$[27, 29)$ omitted category						
$[29, 31)$ (%)	0.15	0.03	0.12	0.31**	-0.16***	0.30*
	(0.15)	(0.10)	(0.14)	(0.15)	(0.06)	(0.17)
$[31, 33)$ (%)	-0.26	-0.04	-0.22	-0.10	-0.16**	0.10
	(0.17)	(0.13)	(0.15)	(0.17)	(0.07)	(0.18)
≥ 33 (%)	0.22*	0.01	0.21*	0.28**	-0.07	0.20
	(0.11)	(0.10)	(0.12)	(0.12)	(0.04)	(0.15)
Observations	3476	3476	3476	3476	3476	3476
R-squared	0.0402	0.0329	0.0228	0.0445	0.0317	0.0377

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To verify that spatial dependence in the regression residuals does not bias the low-altitude estimates, I compute global Moran's I statistics using cluster-level residuals from equation 1. The tests use inverse-distance spatial weights within 100, 150, and 200 km radii based on DHS cluster coordinates. At shorter distances (50 km), a large share of clusters have no spatial neighbors ("islands"), so those results are excluded. The results are presented in Table A.5. Across the 100–200 km thresholds, Moran's I values are small ($|I| < 0.05$) and statistically insignificant ($p > 0.10$) for all IPV outcomes. The only marginal case is the overall IPV measure at 100 km ($I = -0.04$, $p_{\text{perm}} = 0.07$), which indicates weak and statistically uncertain spatial dependence that is not robust across larger radii. These findings suggest that the estimated temperature–IPV relationships are not driven by spatially correlated unobservables, and that cluster-robust standard errors appropriately account for local dependence.

5 Mechanisms in Low-Altitude Areas

There are different possible mechanisms by which temperature impacts IPV in low-altitude areas. They are discussed in this section.

5.1 *Alcohol Consumption*

Alcohol-induced IPV is one of the most common forms of violence against women in Latin American countries (Angelucci, 2008; Díaz and Saldarriaga, 2023). Temperature shocks could influence men's drinking behavior, adding to alcohol consumption patterns associated with cultural norms and financial distress. Extreme temperatures could lead to increased drinking due to changes in social interactions, such as spending more time indoors because of cold temperatures. Alcohol could also be used to reduce stress during temperature shocks that affect income stability and mental health. Although an empirical analysis of the relationship between temperature and alcohol consumption is beyond the scope of this study due to data limitations, I use a more direct variable to estimate alcohol-related violence. Based on the women's reports, I constructed an indicator for whether the partner was intoxicated when the violence occurred. Column (1) of Table 3 shows that the relationship between temperature bins and alcohol-induced IPV follows the same pattern as overall IPV incidence (presented in Table 2), with the coldest bin having a positive effect and a moderate cold shock having a negative one. The results indicate that ten days in the < 21 bin increases the likelihood of alcohol-induced IPV by

4 percentage points, relative to the reference bin. However, moderately cold days with a maximum temperature in the $[21, 23)$ have fewer alcohol-induced cases of violence, by 5.3 percentage points. Furthermore, the point estimates for the two coldest temperature bins are larger for alcohol-induced IPV than for total IPV incidence. This suggests that men's alcohol consumption is a key driver of the relationship between cold temperature shocks and violence.

Conversely, column (2) of Table 3 shows that only the extreme temperature bins have a positive relationship with the probability of a woman indicating she drinks alcohol, while milder temperatures have a negative relationship. However, the point estimates are not statistically significant, even at the ten percent level. While this does not rule out that temperature shocks influence the frequency of women's alcohol consumption, it provides conditional evidence that women's behavior is not significantly affected by temperature shocks.

Table 3: Alcohol Consumption

	(1) Partner drunk during IPV	(2) Drinks alcohol
< 21 (%)	0.40***	0.07
	(0.11)	(0.18)
$[21, 23)$ (%)	-0.53***	-0.30
	(0.18)	(0.31)
$[23, 25)$ (%)	0.11	-0.17
	(0.12)	(0.24)
$[25, 27)$ (%)	-0.11	-0.30
	(0.11)	(0.21)
$[27, 29)$ omitted category		
$[29, 31)$ (%)	0.08	-0.21
	(0.09)	(0.18)
$[31, 33)$ (%)	-0.14	-0.23
	(0.11)	(0.21)
≥ 33 (%)	0.12*	0.18
	(0.07)	(0.16)
Observations	3476	3474
R-squared	0.0284	0.0295

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 *Norms and Attitudes*

One of the determining factors of IPV is societal norms (Flake and Forste, 2006; Heise and Kotsadam, 2015; Obot and Room, 2005). Thus, I posit that, in addition to an increase in violence in society, such as crime and political unrest, temperature shocks could affect IPV incidence through a change in norms, particularly those related to the acceptance of violence (La Mattina, 2017; Steenkamp, 2005). To test this hypothesis, I built an index of women's "wife-beating attitudes", which indicates the number of circumstances (0 to 5) that the respondent finds acceptable for partner abuse: going out without telling her partner, neglecting the children, arguing with him, refusing to have sex with him, and burning the food. The point estimates for this index are presented in Table 4. The coefficients for all the temperature bins are small and not significant, suggesting that women's acceptance of wife-beating is not affected by temperature.

Table 4: Women's Attitudes About Violence

	(1) Wife-beating Index
< 21	0.0005
	(0.0044)
$[21, 23)$	-0.0012
	(0.0082)
$[23, 25)$	-0.0030
	(0.0057)
$[25, 27)$	-0.0005
	(0.0040)
$[27, 29)$ omitted category	
$[29, 31)$	-0.0009
	(0.0042)
$[31, 33)$	0.0032
	(0.0050)
≥ 33	-0.0044
	(0.0028)
Observations	3475
R-squared	0.0800

Notes: The coefficients in this table represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. The regression includes controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. It also includes region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 *Changes in Labor Market Outcomes*

Since this research focuses on the 12-month period, there could be pathways that are not contemporaneous. For example, climate has an effect on income, particularly for families that depend on agricultural yields (Deryugina and Hsiang, 2014; Lobell et al., 2011). Changes in labor and earnings can alter women's bargaining power and increase the likelihood of IPV, as men use violence to extract resources from women or to re-establish power in the relationship (Bloch and Rao, 2002; Bobonis et al., 2013; Calvi and Keskar, 2023). Additionally, as financial instability and stress increase, violence may be used as an emotional release (Angelucci, 2008; Buller et al., 2016; Jewkes, 2002). For example, previous literature has found that recent precipitation shocks, such as floods and droughts, can increase IPV incidence over subsequent months. (Díaz and Saldarriaga, 2023).

To empirically measure the effect of temperature on bargaining power, I use the respondent's and her partner's labor market outcomes over the last year prior to the interview. The results in Table 5 suggest that hot and cold temperature shocks affect labor market outcomes differently. Column (1) suggests that only extreme heat impacts the probability that the respondent has a job. Ten extra days in the $[31, 33)$ and ≥ 33 bins change the probability of the women having a job by 4.0 and -3.1 percentage points, respectively. However, both of these coefficients are significant at the ten percent level only. Similarly, Column (4) shows that extra days in the hottest temperature bin also decrease the probability that the partner has a job. Although this coefficient is not statistically significant even at the ten percent level, the effect may not be fully captured due to the high rate of men's labor participation, with 99% of partners having a job.

While extreme cold days do not have a significant effect on job incidence, they do affect the type of jobs women and their partners have. On the one hand, Columns (3) and (5) show that ten extra days with temperatures below 21°C decrease the likelihood that both women and men work in the non-agricultural manual sector by 2.0 and 4.9 percentage points, respectively. On the other hand, agricultural employment goes up due to extreme cold shocks, though differently for women and men. Women increase their self-employment in agriculture, while men increase their work for an employer in an agricultural enterprise. Interestingly, the < 21 bin is the only one that has a positive effect on women's agricultural self-employment. The gradient in women's agricultural self-employment for a moderate cold shock, $[21, 23)$, is negative and significant. For every ten extra days with maximum temperature in the $[21, 23)$ range, the probability that the woman is self-employed in agriculture decreases by 8.4 percentage points. The effect of the two coldest bins on women's agricultural self-employment aligns with the pattern in IPV incidence presented in Table 2. This suggests that extreme cold increases household reliance on agriculture, thereby raising their vulnerability to income shocks, which may partially explain the corresponding rise in IPV.

Table 5: Temperature Effects on Labor Market Outcomes

	Panel A: Women's Outcomes			Panel B: Partner's Outcomes		
	(1) Worked last year	(2) Agric self-emp.	(3) Non-Ag Manual	(4) Husband works	(5) Agric employee	(6) Non-Ag Manual
< 21 (%)	0.00	0.49***	-0.20**	0.03	0.11**	-0.52**
	(0.16)	(0.19)	(0.10)	(0.03)	(0.05)	(0.22)
$[21, 23)$ (%)	0.12	-0.84***	0.16	-0.03	-0.01	0.64*
	(0.23)	(0.30)	(0.17)	(0.04)	(0.09)	(0.38)
$[23, 25)$ (%)	0.08	-0.42**	0.06	0.03	0.07	-0.19
	(0.16)	(0.18)	(0.12)	(0.02)	(0.06)	(0.19)
$[25, 27)$ (%)	-0.12	-0.01	-0.19*	0.02	0.11**	-0.17
	(0.17)	(0.13)	(0.10)	(0.03)	(0.05)	(0.19)
$[27, 29)$ (omitted)		*omitted category*			*omitted category*	
$[29, 31)$ (%)	-0.12	-0.33***	-0.00	0.03	0.13**	-0.07
	(0.17)	(0.12)	(0.09)	(0.03)	(0.05)	(0.17)
$[31, 33)$ (%)	0.40*	-0.13	-0.01	0.06	0.05	-0.36*
	(0.22)	(0.16)	(0.15)	(0.04)	(0.06)	(0.20)
≥ 33 (%)	-0.31*	-0.02	-0.12	-0.06	0.06	0.02
	(0.17)	(0.09)	(0.10)	(0.04)	(0.04)	(0.15)
Observations	3476	3476	3476	3470	3470	3476
R-squared	0.0888	0.2732	0.0164	0.0133	0.0526	0.0934

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Other temperature bins also decrease the probability of women's self-employment in agriculture, which could indicate that only extreme temperature shocks impact women's bargaining power. Lack of a job in hotter temperatures or the shift to self-employment due to colder shocks could affect the woman's resources relative to those of her partner. If a woman earns less than her husband, she may not be able to leave the relationship, and thus, she would have low bargaining power and be vulnerable to abuse. I use two proxy variables to measure bargaining power: comparative earning capacity and a decision-making index. The former, "earns same or more than partner", is an indicator variable based on women's reports. The latter is a count of how many out of six household decisions she is involved in, including: how to spend her earnings, health care, making large purchases, making daily household purchases, visiting family or relatives, and how to spend his earnings.

The results are presented in Table 6. The coefficients in Column (1) indicate that relative to the reference bin, women who spend ten more days in the hottest bin, ≥ 33, are 4.0 percentage points less likely to earn the same or more than their partner. This is reflective of the decrease in women's participation in the labor market for the same bin, as presented in Table 5. In contrast, none of the coefficients on the decision-making index, presented in Column (2), are statistically significant even at the ten percent level. This suggests that none of the labor or earnings changes due to temperature shocks have a significant impact on the woman's power within the relationship.

Table 6: Bargaining Power Proxies

	(1) Earns $\geq$ partner's earnings	(2) Decision-making Index
< 21	0.07	-0.0028
	(0.16)	(0.0053)
$[21, 23)$	-0.47	0.0059
	(0.29)	(0.0079)
$[23, 25)$	-0.28	-0.0049
	(0.19)	(0.0057)
$[25, 27)$	-0.39**	0.0028
	(0.16)	(0.0053)
$[27, 29)$ omitted category		
$[29, 31)$	-0.33**	-0.0020
	(0.17)	(0.0057)
$[31, 33)$	0.07	0.0071
	(0.20)	(0.0078)
≥ 33	-0.40**	-0.0045
	(0.15)	(0.0057)
Observations	3476	3476
R-squared	0.1099	0.0671

Notes: The coefficients in this table represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. Column (1) presents the coefficients in percentage points. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

One caveat, however, is that the questions used for building the decision-making index do not specify a timeframe, e.g., who has the final say on large household purchases? Thus, it is likely that women are answering based on their most recent interactions. If the temperature shock only affected the woman's earnings or decision-making power temporarily, this proxy would not fully reflect the impact of temperature on bargaining power beyond the immediate period of the shock.

In addition to extreme temperature shocks affecting labor outcomes, moderate temperatures also have an impact. Extra days in the $[25, 27)$ and $[29, 31)$ bins have a positive gradient in the partner's agricultural employment, while a negative gradient is observed in the "earned same or more" variable. This means that during moderate shocks, men are more likely to be employed in agriculture and earn more than women. However, as shown in Table 2, this shift in income does not seem to impact IPV incidence significantly. It is possible that agricultural yields thrive during these moderate temperatures, improving the household's economic stability. This mechanism is discussed in further detail in Section 6.1 for rural areas. However, empirical testing of such a hypothesis is beyond the scope of this paper.

6 Heterogeneous Effects and Mechanisms in Low-Altitude Areas

There are other factors, besides differences in altitude, that can influence the relationship between temperature and IPV. For example, if one of the mechanisms by which temperature impacts violence is changes in agricultural labor (as shown in Section 5.3), then it is expected that the rural population will be more affected by temperature than the urban population. In this section, I examine the potential heterogeneous effects of temperature in low-altitude areas, comparing rural and urban residence status, as well as the indigenous population.

6.1 *Rural Areas*

Table 7 presents the results for the rural subgroup. Similar to the entire low-altitude sample, Column (1) shows that colder bins have a non-monotonic, significant effect on IPV incidence. Specifically, relative to the omitted category, exposure to ten extra days in the < 21 and $[23, 25)$ bins increases the probability of violence by 4.4 and 4.9 percentage points, respectively. Meanwhile, ten extra days in the $[21, 23)$ bin decreases the probability of IPV by 5.9 percentage points. This pattern remains consistent in both levels of severity. This suggests that there is no change in severity level due to the temperature, and thus, the increase in incidence is due to new cases of IPV, especially the less-severe type of violence.

I explore three factors that could determine the relationship between temperature and violence: partner's alcohol consumption during IPV events, the likelihood that the women work, and the household's wealth index. Columns (5)–(7) show the point estimates for each of these variables, in the respective order. The results suggest that it is not one specific determinant that drives the effect of temperature on violence. Additional exposure to the coldest bin, < 21°C, increases the likelihood of alcohol-induced IPV, while decreasing the household's wealth and the probability that the woman will be at home during the day. Thus, extremely cold days were highly disruptive to daily life, affecting men's alcohol consumption, causing economic distress, and reducing exposure between couples. Meanwhile, days in the ≥ 33°C bin also significantly decreased household wealth in a similar magnitude to days in the < 21°C bin, but such extremely hot days did not lead to a statistically significant positive effect in IPV incidence or its severity.

Additionally, neither of the three mechanisms explored fully explains the effect of the mild cold temperatures on IPV. Ten extra days in the $[21, 23)$ bin lead to a decrease in alcohol-induced violence by 3.2 percentage points, relative to the omitted bin. However, this estimate is only significant at the ten percent level, and is much smaller in magnitude than the 5.9 percentage points decrease in overall IPV incidence. Similarly, although the results in the $[23, 25)$ bin suggest an increase in new incidences of IPV, the effect on alcohol-induced violence is close to zero. These findings indicate that men's alcohol consumption is not a significant driver of violence during moderate temperature changes, and thus, other factors must be at play.

Table 7: Temperature Effect in Rural Areas – Low Altitude

	(1) IPV Incidence (%)	(2) IPV Severity Less Severe (%)	(3) Severe (%)	(4) Partner Drunk During IPV (%)	(5) At home During Day (%)	(6) Household Wealth Index
< 21	0.44***	0.31***	0.12	0.31***	-0.87***	-0.0013**
	(0.16)	(0.11)	(0.10)	(0.11)	(0.26)	(0.0007)
$[21, 23)$	-0.59**	-0.35	-0.24	-0.32*	0.52	0.0015
	(0.29)	(0.22)	(0.21)	(0.18)	(0.39)	(0.0010)
$[23, 25)$	0.49**	0.37**	0.12	0.01	0.29	< 0.0001
	(0.21)	(0.15)	(0.15)	(0.15)	(0.28)	(0.0008)
$[25, 27)$	-0.21	-0.05	-0.16	-0.11	0.79***	-0.0005
	(0.22)	(0.14)	(0.17)	(0.15)	(0.25)	(0.0007)
$[27, 29)$ omitted category						
$[29, 31)$	0.29*	0.28*	0.02	0.15	0.42*	-0.0003
	(0.17)	(0.14)	(0.13)	(0.13)	(0.23)	(0.0006)
$[31, 33)$	-0.29	-0.03	-0.26	-0.31**	-0.11	-0.0001
	(0.20)	(0.13)	(0.16)	(0.13)	(0.25)	(0.0006)
≥ 33	0.09	0.05	0.04	0.16	-0.26	-0.0011**
	(0.18)	(0.13)	(0.14)	(0.13)	(0.22)	(0.0006)
Observations	1331	1331	1331	1331	1331	1331
R-squared	0.0330	0.0347	0.0345	0.0499	0.1400	0.2863

Notes: The coefficients in this table represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. Columns (1)–(5) present the coefficients in percentage points. The sample is restricted to rural DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

It is worth noting, though, that the $[21, 23)$ bin is the only positive point estimate for household wealth, though not statistically significant even at the ten percent level. However, assuming that household income is highly dependent on agricultural yields, this positive effect suggests that agricultural crops benefit from temperatures in this range. This finding aligns with crop-specific temperature sensitivities: soybeans, which comprise almost half of the cultivated area in Bolivia's low-altitude Santa Cruz region (Trase, 2024), are highly sensitive to temperature variation depending on their growth stage (Alsajri, 2020). The optimal temperature for soybean cultivation is generally reported to be $22 - 24$°C (Hatfield et al., 2011), which coincides closely with the $[21, 23)$ temperature bin where positive wealth effects are observed.

6.2 *Urban Areas*

Given that urban areas are less reliant on agricultural income, the relationship between temperature and IPV is likely to have different pathways. The results for this subgroup of the lowlands are presented in Table 8. Columns (1)–(3) suggest that the pattern of point estimates is consistent with the full low-altitude sample. However, cold and hot temperature shocks impact violence differently.

Cold shocks impact the severity of IPV, which increases in the < 21 bin and decreases in the $[21, 23)$ bin. This effect is directly linked to men's alcohol consumption. Column (5) shows that experiencing ten more days with < 21°C temperature increases alcohol-induced violence by 5.7 percentage points, a much larger effect than the increase of 3.5 percentage points in severe IPV. Conversely, ten more days in the $[21, 23)$ bin decreases alcohol-induced IPV by 7.8 percentage points, compared to the 6.4 percentage points decrease on severe IPV. These results suggest that the relationship between cold temperature shocks and alcohol is a key driver of the increase in severity.

In contrast, hot temperature shocks significantly increase the incidence and the severity of IPV. Specifically, exposure to ten more days with a maximum temperature of ≥ 33°C increases the probability of IPV by 3.2 percentage points, with 2.7 percentage points attributed to an increase in severe types of violence. The pathways by which hot temperature shocks affect violence are also different than those of cold shocks. Alcohol-induced violence is not the main driver of the increase in IPV. However, ten more days in the extremely hot bin decreases women's labor participation and increases the likelihood that they drink alcohol by 3.8 and 4.9 percentage points, respectively. These findings suggest that an increase in temperatures in urban areas can lead to a decrease in women's bargaining power and inhibitions.

Table 8: Temperature Effect in Urban Areas – Low Altitude

	(1) IPV Incidence	(2) IPV Severity Less Severe	(3) Severe	(4) Partner Drunk During IPV	(5) Respondant Drinks Alcohol	(6) Worked Last Year
< 21 (%)	0.32	-0.03	0.35**	0.57**	0.32	-0.30
	(0.27)	(0.19)	(0.17)	(0.22)	(0.31)	(0.27)
$[21, 23)$ (%)	-0.59	0.05	-0.64**	-0.78***	-0.59	0.45
	(0.41)	(0.32)	(0.27)	(0.26)	(0.63)	(0.43)
$[23, 25)$ (%)	0.22	0.25	-0.03	0.07	0.13	0.43*
	(0.25)	(0.18)	(0.17)	(0.16)	(0.41)	(0.24)
$[25, 27)$ (%)	-0.29	-0.10	-0.19	-0.16	-0.42	0.09
	(0.27)	(0.23)	(0.17)	(0.19)	(0.36)	(0.21)
$[27, 29)$ omitted category						
$[29, 31)$ (%)	0.00	-0.02	0.02	-0.01	-0.15	-0.10
	(0.20)	(0.14)	(0.16)	(0.12)	(0.29)	(0.20)
$[31, 33)$ (%)	-0.40	-0.02	-0.38	-0.12	-0.26	0.71**
	(0.27)	(0.22)	(0.24)	(0.13)	(0.35)	(0.32)
≥ 33 (%)	0.32**	0.05	0.27*	0.09	0.49**	-0.38*
	(0.15)	(0.14)	(0.16)	(0.08)	(0.22)	(0.22)
Observations	2145	2145	2145	2145	2144	2145
R-squared	0.0517	0.0481	0.0338	0.0291	0.0338	0.0882

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to urban DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.3 *Indigenous Ethnicity*

Given its large indigenous population, Bolivia presents a unique opportunity to study the differential effects of temperature shocks based on ethnicity (Canessa, 2012; World Bank, 2015). Table 9 presents the estimated effect of temperature on IPV incidence and severity for the indigenous and non-indigenous groups separately. The results indicate that indigenous groups are more vulnerable to temperature shocks than non-indigenous groups. Although the pattern of the point estimates for IPV incidence is the same for both groups, Column (1) shows that the magnitude of the effect is larger for the indigenous population.

Cold and hot temperature shocks seem to influence the severity of violence differently for each population. Among the non-indigenous group, only the cold temperature bins significantly change the likelihood of experiencing severe IPV. Meanwhile, for the indigenous group, cold shocks significantly affect the likelihood of experiencing less-severe forms of IPV, and hot shocks impact severe types of violence. Such a heterogeneous effect of temperature likely highlights the existing vulnerabilities of the indigenous population due to cultural or economic differences.

Table 9: Temperature Effect by Indigenous Status – Low Altitude

	Panel A: Indigenous			Panel B: Non-Indigenous		
	(1)	(2)	(3)	(4)	(5)	(6)
	IPV	IPV Severity		IPV	IPV Severity	
	Incidence	Less severe	Severe	Incidence	Less severe	Severe
< 21 (%)	0.63***	0.51***	0.12	0.17	-0.10	0.27**
	(0.23)	(0.15)	(0.16)	(0.18)	(0.15)	(0.12)
$[21, 23)$ (%)	-0.86**	-0.64**	-0.22	-0.31	0.01	-0.32**
	(0.42)	(0.27)	(0.34)	(0.25)	(0.26)	(0.16)
$[23, 25)$ (%)	0.50*	0.59***	-0.09	0.30	0.07	0.23**
	(0.27)	(0.18)	(0.17)	(0.21)	(0.17)	(0.12)
$[25, 27)$ (%)	-0.08	-0.03	-0.04	-0.25	-0.21	-0.04
	(0.31)	(0.18)	(0.25)	(0.21)	(0.18)	(0.12)
$[27, 29)$ (omitted)		*omitted category*			*omitted category*	
$[29, 31)$ (%)	0.41	0.37**	0.04	-0.04	-0.20	0.17
	(0.26)	(0.15)	(0.21)	(0.15)	(0.14)	(0.12)
$[31, 33)$ (%)	-0.33	0.20	-0.53**	-0.19	-0.19	-0.01
	(0.31)	(0.18)	(0.26)	(0.21)	(0.19)	(0.14)
≥ 33 (%)	0.35	-0.14	0.49**	0.18	0.15	0.03
	(0.24)	(0.14)	(0.22)	(0.16)	(0.14)	(0.08)
Observations	1178	1178	1178	2298	2298	2298
R-squared	0.0468	0.0502	0.0350	0.0507	0.0477	0.0279

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Robustness Tests

7.1 *Average Mean Temperature*

In this section, I use the same empirical specification as described in equation (1), but replace the temperature bins with the average daily mean temperature over the 12 months prior to the survey as the main independent variable. Previous literature has found that such a measurement of temperature has a positive relationship with IPV incidence, particularly in South Asian countries (Zhu et al., 2023). Similarly, the results presented in Table 10 show that the average temperature has a positive relationship with IPV incidence in the full-country and high-altitude samples. In the low-altitude sample, however, average temperature has a negative relationship with IPV incidence, reflecting the high impact of cold days on violence. However, the coefficients in all samples are not statistically significant, even at the ten percent level. The findings highlight the importance of understanding the full impact of temperature across various contexts and groups.

Table 10: Effect of Average Mean Temperature Over Previous Year on IPV Incidence

	(1) IPV Incidence	(2) IPV Incidence	(3) IPV Incidence
Average Daily Temp (%)	0.22	-1.22	0.80
	(0.34)	(1.18)	(0.53)
Sample	National	Low Altitude	High Altitude
Observations	9772	3476	6296
R-squared	0.0257	0.0326	0.0244

Notes: In this table, each column presents the point estimate for IPV incidence for different subsamples. The low-altitude sample includes DHS clusters with an elevation less than 1000m above sea level. The high-altitude sample includes all remaining clusters. The coefficients in this table represent the effect in percentage points of a 1°C increase in the average daily mean temperature experienced over the 12 months prior to the survey interview. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2 *ENSO Effect 2007–2008*

From November 2007 to April 2008, Bolivia was affected by La Niña, the cooler phase of the El Niño–Southern Oscillation (ENSO). During this period, the country's lowland regions experienced heavy rainfall, flooding, and below-average temperatures (Global Facility for Disaster Reduction and Recovery, 2008). Additionally, in July 2007, southern South America experienced an exceptional cold-air outbreak, which reached Bolivia and led to unusually cold conditions in the low-altitude Amazon Basin, where minimum temperatures dropped well below seasonal norms (Lanfredi and de Camargo, 2018). Thus, to investigate whether the cold shock is the main driver of the relationship between cold temperatures and IPV in low-altitude areas, I use the following empirical specification:

$$Y_{icm} = \alpha + \beta_1 TCOLD_{icm} + +\beta_2 THOT_{icm} + \nu P_{icm} + \eta' Z_{icm} + \kappa_c + \gamma_m + \varepsilon_{icm} \qquad (2)$$

$TCOLD_{icm}$ and $THOT_{icm}$ are the number of days in the 12 months prior to the survey in which the maximum daily temperature exceeded one standard deviation (SD) below or above the local historical average, respectively. The historical average is calculated as the mean of all daily maximum temperatures from 1980 to 2005 for each square in the grid. Such that β_1 and β_2 can be interpreted as the effect of one more abnormally cold or hot day relative to a day within 1SD of the average. The remaining variables are kept as specified in equation (1).

The point estimates for IPV incidence for each sample (full country, low-altitude, and high-altitude) are presented in Table 11. Consistent with the results in equation (1), Columns (1) and (3) show no statistically significant relationship between temperature shocks and IPV for the full national sample and the high-altitude regions. In contrast, Column (2) reveals that, in low altitudes, the overall effect of abnormally cold days is positive, whereby an extra day in $TCOLD$ leads to an increase in reported IPV of 0.6 percentage points, relative to the reference bin. Meanwhile, the point estimate for $THOT$ shows that an extra day with a hot temperature shock decreases the likelihood of reported IPV by 0.3 percentage points, although statistically significant at the 10 percent level only. For context, the average respondent in the low-altitude regions experienced 53 days with maximum temperature more than 1SD below the historical average, and 60 days with abnormally hot temperatures (more than 1SD above the average).

Table 11: Effect of Abnormal Temperatures on IPV Incidence

	(1) IPV Incidence	(2) IPV Incidence	(3) IPV Incidence
TCOLD (%)	0.19	0.62**	0.04
	(0.13)	(0.26)	(0.17)
THOT (%)	-0.11	-0.28*	0.02
	(0.09)	(0.16)	(0.13)
Sample	National	Low Altitude	High Altitude
Observations	9772	3476	6296
R-squared	0.0267	0.0368	0.0237

Notes: In this table, $TCOLD$ and $THOT$ indicate the number of days in the 12 months prior to the survey in which the maximum daily temperature exceeded one standard deviation (SD) below or above the local historical average, respectively. The omitted temperature bin is [-1, 1] standard deviations away from the historical average. The coefficients represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to women currently partnered and have lived at their current location for at least one year. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Despite the non-monotonic pattern presented in Table 2, with the two extreme bins in the cold and hot temperatures having opposite effects, the results in Table 10 are evidence that abnormally cold days have an overall positive effect on IPV incidence and abnormally hot days have a negative effect in low altitudes. Additionally, Table 12 shows that the abnormally cold days significantly impacted different mechanisms. Experiencing extra $TCOLD$ days increases the likelihood that the partner was drunk during the IPV events, while lowering women's bargaining power due to reduced agricultural employment and relative earnings. On the other hand, of the mechanisms explored, only men's alcohol consumption is a key driver of the decrease in IPV incidence due to experiencing more $THOT$ days.

Table 12: **Mechanisms Using Z-score Anomalies - Low Altitude**

	(1) IPV Incidence (%)	(2) Partner drunk during IPV (%)	(3) Worked: Agric Self-employed (%)	(4) Earns $\geq$ partner's earnings (%)	(5) Decision-making Index
TCOLD (%)	0.62**	0.46**	-0.47*	-0.61*	-2.95***
	(0.26)	(0.21)	(0.25)	(0.31)	(0.86)
THOT (%)	-0.28*	-0.24**	-0.27	0.10	-0.50
	(0.16)	(0.10)	(0.18)	(0.20)	(0.56)
Observations	3476	3476	3476	3476	3476
R-squared	0.0368	0.0223	0.2377	0.0991	0.0712

Notes: In this table, *TCOLD* and *THOT* indicate the number of days in the 12 months prior to the survey in which the maximum daily temperature exceeded one standard deviation (SD) below or above the local historical average, respectively. The omitted temperature bin is [-1, 1] standard deviations away from the historical average. The coefficients represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. Columns (1)–(4) present the coefficients in percentage points. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.3 *Probit Specification*

While my primary specification employs an Ordinary Least Squares (OLS) approach (Linear Probability Model, LPM), some authors advocate using nonlinear probability models, such as probit, for a binary dependent variable. The main concerns with using an LPM are that: (1) predicted values are not constrained to lie within the [0,1] interval, which may lead to nonsensical probability predictions in some cases; and, (2) the model inherently exhibits heteroskedasticity due to the binary nature of the outcome variable, which can result in biased standard errors if not corrected using robust or clustered variance estimators.

While the second concern is mitigated using clustered standard errors, I examine the predicted probabilities from my LPM specification to address the first concern empirically. None of the predicted probabilities exceed 1, and only about 0.2% of predictions fall below 0. With such a small proportion of predicted probabilities outside the unit interval, it is unlikely that the estimates are substantially biased (Friedman, 2012). Nonetheless, as a robustness check, I replicate my main analysis using a probit model for the incidence of IPV and each of its dimensions. Table 13 presents marginal effects derived from the probit regression for the low-altitude sample. The direction, magnitude, and significance of the estimated coefficients remain consistent across both modeling approaches, reinforcing the robustness of the original findings.

Given that the LPM predicted values remain predominantly within the valid probability range and that robust standard errors are employed to correct for heteroskedasticity, the practical advantages of using probit diminish significantly. Conversely, as articulated by Friedman (2012), the LPM provides straightforward, easily interpretable coefficients directly representing percentage-point changes in probability, facilitating clearer communication of results. Additionally, probit and logit models impose specific distributional assumptions of the error term, which, if incorrectly specified, can lead to significant biases (Friedman, 2012). The close alignment between the probit and LPM results provides strong support for maintaining OLS as the preferred specification in my analysis.

Table 13: Marginal Effects of Temperature on IPV Dimensions Using Probit Regression – Low Altitude

	(1)	(2)	(3)	(4)	(5)	(6)
	IPV	IPV Severity		IPV Frequency		Psychological
	Incidence	Less severe	Severe	Sometimes	Often	Abuse
< 21 (%)	0.37***	0.17	0.20**	0.42***	-0.09	0.31*
	(0.14)	(0.10)	(0.10)	(0.13)	(0.06)	(0.17)
$[21, 23)$ (%)	-0.65***	-0.36**	-0.32*	-0.49**	-0.14	-0.43*
	(0.22)	(0.18)	(0.18)	(0.23)	(0.08)	(0.25)
$[23, 25)$ (%)	0.35**	0.26**	0.09	0.46***	-0.10	0.36*
	(0.16)	(0.11)	(0.11)	(0.15)	(0.08)	(0.19)
$[25, 27)$ (%)	-0.20	-0.17	-0.04	-0.05	-0.19***	-0.06
	(0.16)	(0.13)	(0.12)	(0.17)	(0.07)	(0.17)
$[27, 29)$ (%)			*omitted category*			
$[29, 31)$ (%)	0.13	0.02	0.10	0.28**	-0.17***	0.30*
	(0.14)	(0.10)	(0.11)	(0.14)	(0.05)	(0.17)
$[31, 33)$ (%)	-0.30*	-0.05	-0.25*	-0.13	-0.20***	0.10
	(0.17)	(0.14)	(0.13)	(0.17)	(0.07)	(0.18)
≥ 33 (%)	0.24**	0.02	0.21**	0.29**	-0.05	0.20
	(0.11)	(0.10)	(0.10)	(0.12)	(0.05)	(0.15)
Observations	3476	3467	3476	3476	3467	3476

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted DHS clusters with an elevation less than 1000m above sea level. All regressions use a probit specification and include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8 Conclusion

This paper presents new evidence on the effects of recent temperature shocks on intimate partner violence (IPV), emphasizing both the nonlinear nature of the relationship and its heterogeneity across populations. While the short-term impact of temperature on violence has been studied extensively (Blakeslee et al., 2021; Evans et al., 2025; Hsiang et al., 2013; Mukherjee and Sanders, 2021; Sanz-Barbero et al., 2018), analysis of the longer-lasting effects has been limited. The literature has found that hot temperatures have direct effects, such as psychological and physiological changes, increased irritability, temperament changes, and cognitive function decline (Almås et al., 2025; Baylis, 2020; Stechemesser et al., 2022). However, we should expect that the effects of temperature shocks over the preceding year are indirect, operating through socioeconomic channels. Thus, sustained exposure to temperature extremes is likely to disproportionately affect vulnerable groups of the population, such as rural and indigenous women.

Using self-reported IPV data from the 2008 Bolivian DHS, matched with high-resolution daily climate data, I estimate the cumulative effect of temperature exposure over the 12 months preceding the survey. This strategy allows me to capture sustained changes rather than short-lived fluctuations. Bolivia's distinct topography creates wide variation in climate across regions: the highlands experience cooler and more stable temperatures, while the lowlands are exposed to both extreme heat and occasional cold fronts. To account for these differences in climatic adaptation, I estimate separate models for low- and high-altitude areas. The results show that the relationship between temperature and IPV is strongly influenced by de-adaptation to atypical temperatures: in low-altitude areas, ten additional days below 21°C or above 33°C significantly increase IPV incidence, while moderate cold temperatures ($[21, 23)$°C) appear protective. In contrast, high-altitude areas exhibit no statistically significant effects, consistent with their narrower range of temperature variation.

Due to its geographical location, Thus, the national results mask important heterogeneity in the effect of temperatures, as different populations are accustomed to and adapted to different climates. Dividing the sample into low-altitude and high-altitude areas reveals that the effect of temperature on IPV is strongly influenced by de-adaptation to atypical temperatures. In low-altitude areas, where populations were exposed to both cold and heat shocks, IPV increases with temperature deviations in both directions: ten additional days below 21°C or above 33°C raise IPV incidence significantly, while moderate cold shocks ($[21, 23)$°C) appear protective. By contrast, high-altitude areas show no significant effects, likely due to having less exposure to extreme temperature shocks.

Even within low altitudes, the effects of temperature shocks and the mechanisms behind them differ by temperature type and population group. Extremely cold shocks are associated with increased IPV incidence in rural and indigenous households, likely driven by male alcohol consumption and income shocks, including shifts from formal or non-agricultural labor to informal agricultural work. In urban areas, both extreme cold and hot temperatures increase the incidence and severity of IPV. For these areas, the effect of cold temperatures appears to be positively related to men's alcohol consumption. Hot shocks, meanwhile, decrease the likelihood that women work and increase the likelihood that they drink alcohol, which could result in more contentious interactions between the couple.

These findings underscore the need for gender-sensitive climate adaptation policies, particularly in countries with high IPV prevalence, weak legal protections of women's rights, and high vulnerability to climate change. As both hot and cold temperature extremes become more frequent with phenomena such as La Niña and El Niño, the long-term social costs will increasingly burden women, especially those in marginalized groups. To effectively meet the goals of SDG 5.2, interventions must account for both the climatic and socioeconomic dimensions of IPV risk: improving resilience through diversified income sources, targeted alcohol abuse prevention, and community-based awareness programs that reflect local vulnerabilities. This study highlights that climate change is not just an environmental or economic issue, but also a gendered social one, with lasting consequences for women's safety and autonomy. This understanding is critical for estimations of the cost of climate change on economic growth and for designing public policies to prevent and reduce partner abuse, especially in developing and less developed countries.

References

Adom, P. K. (2024). The socioeconomic impact of climate change in developing countries over the next decades: A literature survey. *Environmental Research Communications*, 6(4):042001.

Almås, I., Auffhammer, M., Bold, T., Bolliger, I., Dembo, A., Hsiang, S. M., Kitamura, S., Miguel, E., and Pickmans, R. (2025). Destructive Behaviour, Judgement, and Economic Decision-making under Thermal Stress*. *The Economic Journal*, page ueae116.

Alsajri, F. A. (2020). *Temperature Effects on Soybean Vegetative, Physiological, Reproductive, and Seed Quality*. PhD thesis, Mississippi State University.

Angelucci, M. (2008). Love on the rocks: Alcohol abuse and domestic violence in rural mexico. *The B.E. Journal of Economic Analysis & Policy*, 8(1):Article 43.

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Review of Environmental Economics and Policy*, 7(2):181–198.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*, 124(1):105–159.

Baylis, P. (2020). Temperature and temperament: Evidence from Twitter. *Journal of Public Economics*, 184:104161.

Bedoya, M., Espinoza, K., and Sánchez, A. (2020). Alcohol-induced physical intimate partner violence and child development in Peru. *Oxford Development Studies*, 48(3):271–286.

Benjamini, Y., Krieger, A. M., and Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3):491–507.

Bhuller, M., Dahl, G. B., Løken, K. V., and Mogstad, M. (2023). Domestic Violence Reports and the Mental Health and Well-being of Victims and Their Children. *Journal of Human Resources*.

Blakeslee, D., Chaurey, R., Fishman, R., Malghan, D., and Malik, S. (2021). In the heat of the moment: Economic and non-economic drivers of the weather-crime relationship. *Journal of Economic Behavior & Organization*, 192:832–856.

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

Bobonis, G. J., González-Brenes, M., and Castro, R. (2013). Public Transfers and Domestic Violence: The Roles of Private Information and Spousal Control. *American Economic Journal: Economic Policy*, 5(1):179–205.

Buller, A. M., Hidrobo, M., Peterman, A., and Heise, L. (2016). The way to a man's heart is through his stomach?: A mixed methods study on causal mechanisms through which cash and in-kind food transfers decreased intimate partner violence. *BMC Public Health*, 16(1):488.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Calvi, R. and Keskar, A. (2023). 'Til Dowry Do Us Part: Bargaining and Violence in Indian Families. *The Review of Economics and Statistics*, pages 1–45.

Canessa, A. (2012). New Indigenous Citizenship in Bolivia: Challenging the Liberal Model of the State and its Subjects. *Latin American and Caribbean Ethnic Studies*, 7(2):201–221.

Chapola, E., Cunsolo, A., Harper, S. L., Edge, V. L., Berrang-Ford, L., and Group, I. R. (2024). Climate change and its impact on the mental health well-being of Indigenous women in Western cities, Canada. *Journal of Community & Applied Social Psychology*, 34(3):e2807.

Climate Prediction Center (2008). El niño/southern oscillation (ENSO) diagnostic discussion. ENSO Diagnostic Discussion, National Centers for Environmental Prediction, NOAA/National Weather Service, Camp Springs, MD.

Coa, R. and Ochoa, L. H. (2009). Bolivia encuesta nacional de demografía y salud - ENDSA - 2008. DHS Final Report FR228, Ministerio de Salud y Deportes and Macro International, Calverton, Maryland.

Coen, S. E. (2021). Voices in the background: Environmental degradation and climate change as driving forces of violence against indigenous women. *Global Studies Quarterly*, 1(3):ksab018.

Cohen, F. and Gonzalez, F. (2024). Understanding the Link between Temperature and Crime. *American Economic Journal: Economic Policy*, 16(2):480–514.

Cools, S., Flatø, M., and Kotsadam, A. (2020). Rainfall shocks and intimate partner violence in sub-Saharan Africa. *Journal of Peace Research*, 57(3):377–390.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Deryugina, T. and Hsiang, S. M. (2014). Does the Environment Still Matter? Daily Temperature and Income in the United States.

Deschênes, O. and Greenstone, M. (2011). Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. *American Economic Journal: Applied Economics*, 3(4):152–185.

Díaz, J.-J. and Saldarriaga, V. (2023). A drop of love? Rainfall shocks and spousal abuse: Evidence from rural Peru. *Journal of Health Economics*, 89:102739.

Evans, M. F., Gazze, L., and Schaller, J. (2025). Temperature and Maltreatment of Young Children. *The Review of Economics and Statistics*, pages 1–37.

Flake, D. F. and Forste, R. (2006). Fighting families: Family characteristics associated with domestic violence in five Latin American countries. *Journal of Family Violence*, 21:19–29.

Friedman, J. (2012). Whether to probit or to probe it: in defense of the linear probability model. world bank blogs.

Gaoua, N. (2010). Cognitive function in hot environments: A question of methodology, exposure duration, and temperature levels. *Scandinavian Journal of Medicine & Science in Sports*, 20:60–70.

Garcia-Moreno, C., Jansen, H. A., Ellsberg, M., Heise, L., and Watts, C. (2006). Prevalence of intimate partner violence: Findings from the WHO multi-country study on women's health and domestic violence. *The Lancet*, 368(9543):1260–1269.

Garg, T., Jagnani, M., and Taraz, V. (2020). Temperature and Human Capital in India. *Journal of the Association of Environmental and Resource Economists*, 7(6):1113–1150.

Garreaud, R. (1999). Cold air incursions over subtropical and tropical south america: A numerical case study. *Monthly Weather Review*, 127(12):2823 – 2853.

Global Facility for Disaster Reduction and Recovery (2008). Bolivia– 2007/2008 –la niña phenomenon causes severe losses in agriculture. Disaster Risk Management Report, World Bank Group.

Graff Zivin, J., Hsiang, S. M., and Neidell, M. (2018). Temperature and Human Capital in the Short and Long Run. *Journal of the Association of Environmental and Resource Economists*, 5(1):77–105.

Guivarch, C., Mejean, A., and Taconet, N. (2021). Linking climate and inequality. *Finance & Development*, 58(3).

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., Thomson, A. M., and Wolfe, D. (2011). Climate impacts on agriculture: Implications for crop production. *Agronomy Journal*, 103(2):351–370.

Heidinger, L. (2021). Intimate partner violence: Experiences of first nations, métis and inuit women in canada, 2018. *Juristat: Canadian Centre for Justice Statistics*, pages 1–21.

Heilmann, K., Kahn, M. E., and Tang, C. K. (2021). The urban crime and heat gradient in high and low poverty areas. *Journal of Public Economics*, 197:104408.

Heise, L. L. and Kotsadam, A. (2015). Cross-national and multilevel correlates of partner violence: An analysis of data from population-based surveys. *The Lancet Global Health*, 3(6):e332–e340.

Helo Sarmiento, J. (2023). Into the tropics: Temperature, mortality, and access to health care in Colombia. *Journal of Environmental Economics and Management*, 119:102796.

Henke, A. and Hsu, L.-c. (2020). The gender wage gap, weather, and intimate partner violence. *Review of Economics of the Household*, 18(2):413–429.

Heutel, G., Miller, N. H., and Molitor, D. (2021). Adaptation and the Mortality Effects of Temperature across U.S. Climate Regions. *The Review of Economics and Statistics*, 103(4):740–753.

Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics*, 8(Volume 8, 2016):43–75.

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the Influence of Climate on Human Conflict. *Science*, 341(6151):1235367.

Hsiang, S. M., Meng, K. C., and Cane, M. A. (2011). Civil conflicts are associated with the global climate. *Nature*, 476(7361):438–441.

International Monetary Fund (2023). Climate challenges in fragile and conflict-affected states. IMF Staff Climate Note, International Monetary Fund.

Jacob, B., Lefgren, L., and Moretti, E. (2007). The Dynamics of Criminal Behavior: Evidence from Weather Shocks. *The Journal of Human Resources*, 42(3):489–527.

Jewkes, R. (2002). Intimate partner violence: Causes and prevention. *The Lancet*, 359(9315):1423–1429.

Johnson, D. E., Parsons, M., and Fisher, K. (2022). Indigenous climate change adaptation: New directions for emerging scholarship. *Environment and Planning E: Nature and Space*, 5(3):1541–1578.

La Mattina, G. (2017). Civil conflict, domestic violence and intra-household bargaining in post-genocide Rwanda. *Journal of Development Economics*, 124:168–198.

Lanfredi, I. S. and de Camargo, R. (2018). Classification of extreme cold incursions over south america. *Weather and Forecasting*, 33(5):1183–1203.

Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. *Science*, 333(6042):616–620.

LoPalo, M. (2023). Temperature, Worker Productivity, and Adaptation: Evidence from Survey Data Production. *American Economic Journal: Applied Economics*, 15(1):192–229.

Mahendran, R., Xu, R., Li, S., and Guo, Y. (2021). Interpersonal violence associated with hot weather. *The Lancet Planetary Health*, 5(9):e571–e572.

Mannell, J., Brown, L. J., Jordaan, E., Hatcher, A., and Gibbs, A. (2024). The impact of environmental shocks due to climate change on intimate partner violence: A structural equation model of data from 156 countries. *PLOS Climate*, 3(10):e0000478.

Meekers, D., Pallin, S. C., and Hutchinson, P. (2013). Intimate partner violence and mental health in Bolivia. *BMC Women's Health*, 13(1):28.

Mukherjee, A. and Sanders, N. J. (2021). The Causal Effect of Heat on Violence: Social Implications of Unmitigated Heat Among the Incarcerated. Technical Report w28987, National Bureau of Economic Research.

Obot, I. S. and Room, R. (2005). *Alcohol, Gender and Drinking Problems: Perspectives from Low and Middle Income Countries*. World Health Organization, Geneva.

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

Pilcher, J. J., Nadler, E., and Busch, C. (2002). Effects of hot and cold temperature on human performance: A meta-analytical review. *Ergonomics*, 45(10):682–698.

Purcell, H. (2021). *The Heterogeneous Impacts of Natural Disasters on Risk Preferences in Indonesia*. PhD thesis, University of Pennsylvania.

Rai, A., Sharma, A. J., and Subramanyam, M. A. (2021). Droughts, cyclones, and intimate partner violence: A disastrous mix for Indian women. *International Journal of Disaster Risk Reduction*, 53:102023.

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management*, 67(3):274–302.

Sanz-Barbero, B., Linares, C., Vives-Cases, C., González, J. L., López-Ossorio, J. J., and Díaz, J. (2018). Heat wave and the risk of intimate partner violence. *Science of The Total Environment*, 644:413–419.

Sekhri, S. and Hossain, M. A. (2023). Water in Scarcity, Women in Peril. *Journal of the Association of Environmental and Resource Economists*, 10(6):1475–1513.

Sekhri, S. and Storeygard, A. (2014). Dowry deaths: Response to weather variability in India. *Journal of Development Economics*, 111:212–223.

Sharma, V. M., Panwar, S. K., and Panwar, M. S. (1985). Effects of raised body temperature on reasoning, memory, and mood. *Journal of Applied Physiology*, 59(6):1823–1827.

Stechemesser, A., Levermann, A., and Wenz, L. (2022). Temperature impacts on hate speech online: Evidence from 4 billion geolocated tweets from the USA. *The Lancet Planetary Health*, 6(9):e714–e725.

Steenkamp, C. (2005). The Legacy of War: Conceptualizing a 'Culture of Violence' to Explain Violence after Peace Accords. *The Round Table*, 94(379):253–267.

Straus, M. A. (1979). Measuring Intrafamily Conflict and Violence: The Conflict Tactics (CT) Scales. *Journal of Marriage and Family*, 41(1):75–88.

Straus, M. A. and Gelles, R. J. (1990). *Physical Violence in American Families: Risk Factors and Adaptations to Violence in 8,145 Families.* Transaction Publishers, New Brunswick, NJ.

Straus, M. A., Hamby, S. L., Boney-McCoy, S., and Sugarman, D. B. (1996). The revised conflict tactics scales (CTS2): Development and preliminary psychometric data. *Journal of Family Issues*, 17(3):283–316.

Theiss, K. (2024). Uncounted: How survey implementation methods miss 3 million annual cases of intimate partner violence worldwide. World Bank Blogs: Development Impact.

Trase (2024). Deforestation and climate change threaten Bolivia's soy sector. Trase Insights.

UN General Assembly (2015). Transforming our world: The 2030 agenda for sustainable development. Resolution 70/1.

UN Women (2022). Gender equality and climate change: A closer look at existing evidence.

WHO (2005). WHO multi-country study on women's health and domestic violence against women. Report, World Health Organization, Geneva.

WHO (2021). Violence against women prevalence estimates, 2018. Technical report, World Health Organization, Geneva.

World Bank (2015). *Indigenous Latin America in the Twenty-First Century: The First Decade*. World Bank.

Xu, R., Xiong, X., Abramson, M. J., Li, S., and Guo, Y. (2020). Ambient temperature and intentional homicide: A multi-city case-crossover study in the US. *Environment International*, 143:105992.

Xu, R., Xiong, X., Abramson, M. J., Li, S., and Guo, Y. (2021). Association between ambient temperature and sex offense: A case-crossover study in seven large US cities, 2007–2017. *Sustainable Cities and Society*, 69:102828.

Zhao, J., Andresen, M. A., Farrell, G., and Tilley, N. (2024). Temperature, crime, and violence: A systematic review and meta-analysis. *Environmental Health Perspectives*, 132(10):107001.

Zhao, Q., Guo, Y., Ye, T., Gasparrini, A., Tong, S., Overcenco, A., Urban, A., Schneider, A., Entezari, A., Vicedo-Cabrera, A. M., et al. (2021). Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: A three-stage modelling study. *The Lancet Planetary Health*, 5(7):e415–e425.

Zhu, Y., He, C., Bell, M., Zhang, Y., Fatmi, Z., Zhang, Y., Zaid, M., Bachwenkizi, J., Liu, C., Zhou, L., Chen, R., and Kan, H. (2023). Association of Ambient Temperature With the Prevalence of Intimate Partner Violence Among Partnered Women in Low- and Middle-Income South Asian Countries. *JAMA Psychiatry*, 80(9):952–961.

A Additional Tables

Table A.1: Balance Check – Low Altitude

	(1) Age (years)	(2) Height (cms)	(3) Years of schooling	(4) Indigenous Ethnicity	(5) Parental IPV	(6) Age at first marriage (in years)
< 21	0.027	-0.024	-0.005	0.003	0.003	0.005
	(0.027)	(0.024)	(0.021)	(0.002)	(0.002)	(0.016)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[21, 23)$	0.004	0.009	0.014	-0.004	-0.007**	0.058**
	(0.051)	(0.044)	(0.032)	(0.004)	(0.003)	(0.026)
	[1.000]	[1.000]	[1.000]	[1.000]	[0.429]	[0.429]
$[23, 25)$	0.033	0.027	0.019	0.000	0.001	0.005
	(0.031)	(0.023)	(0.023)	(0.003)	(0.002)	(0.018)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[25, 27)$	0.016	-0.022	0.006	0.000	-0.002	0.029
	(0.030)	(0.030)	(0.022)	(0.002)	(0.002)	(0.021)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[27, 29)$ omitted category						
$[29, 31)$	0.005	-0.010	-0.008	-0.001	0.001	0.019
	(0.027)	(0.023)	(0.021)	(0.002)	(0.002)	(0.018)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[31, 33)$	-0.006	0.006	0.020	-0.005	-0.004**	0.043**
	(0.046)	(0.032)	(0.027)	(0.003)	(0.002)	(0.020)
	[1.000]	[1.000]	[1.000]	[1.000]	[0.518]	[0.429]
≥ 33	0.031	-0.009	-0.007	0.007***	0.002	-0.023
	(0.034)	(0.027)	(0.019)	(0.002)	(0.002)	(0.015)
	[1.000]	[1.000]	[1.000]	[0.087]	[1.000]	[1.000]
Observations	3476	3426	3476	3476	3280	3476
R-squared	0.010	0.068	0.154	0.137	0.021	0.045

Notes: The coefficients in this table represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. Anderson (2008) sharpened False Discovery Rate (FDR) q-values are reported for the temperature bins in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Balance Check – High Altitude

	(1) Age (years)	(2) Height (cms)	(3) Years of schooling	(4) Indigenous Ethnicity	(5) Parental IPV	(6) Age at first marriage (in years)
< 11	-0.005	0.002	-0.001	0.000	0.001	-0.004
	(0.008)	(0.006)	(0.007)	(0.000)	(0.001)	(0.005)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[11, 13)$	0.002	0.004	0.009*	-0.001**	0.000	0.001
	(0.006)	(0.005)	(0.005)	(0.000)	(0.000)	(0.004)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[13, 15)$	-0.014	0.003	0.000	0.000	0.001	-0.008
	(0.012)	(0.009)	(0.010)	(0.001)	(0.001)	(0.007)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[15, 17)$ omitted category						
$[17, 19)$	-0.013	0.002	0.004	-0.001	0.001	-0.012
	(0.012)	(0.010)	(0.011)	(0.001)	(0.001)	(0.008)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[19, 21)$	-0.003	0.007	0.010	0.000	0.000	0.009*
	(0.009)	(0.006)	(0.007)	(0.000)	(0.001)	(0.005)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
≥ 21	-0.007	0.004	0.005	-0.001	0.000	-0.007
	(0.007)	(0.005)	(0.006)	(0.000)	(0.000)	(0.005)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Observations	6296	6144	6296	6296	5811	6296
R-squared	0.010	0.038	0.166	0.178	0.014	0.025

Notes: The coefficients in this table represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. The sample is restricted DHS clusters with an elevation greater than 1000m above sea level. All regressions include controls for: total accumulated precipitation in the previous 12 months, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. Anderson (2008) sharpened False Discovery Rate (FDR) q-values are reported for the temperature bins in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Balance Test: Exogeneity of Interview Timing to Respondent Characteristics – Low Altitude

	(1) Age (years)	(2) Height (cms)	(3) Years of schooling	(4) Indigenous Ethnicity	(5) Parental IPV	(6) Years lived in residence
Days since first survey	0.015	0.024	0.016	<-0.001	<0.001	-0.012
	(0.025)	(0.021)	(0.018)	(0.002)	(0.002)	(0.047)
Observations	3479	3429	3479	3479	3283	3463
R-squared	0.0051	0.0578	0.1416	0.1231	0.0155	0.0259

Notes: The coefficients in this table represent the marginal effect of being interviewed one day later. The sample is restricted to DHS clusters with an elevation less than 1000m above sea level. All regressions include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Balance Test: Exogeneity of Interview Timing to Respondent Characteristics – High Altitude

	(1) Age (years)	(2) Height (cms)	(3) Years of schooling	(4) Indigenous Ethnicity	(5) Parental IPV	(6) Years lived in residence
Days since first survey	-0.0174	-0.0022	-0.0359***	0.0007	-0.0007	-0.0073
	(0.0166)	(0.0130)	(0.0133)	(0.0010)	(0.0010)	(0.0379)
Observations	6309	6156	6309	6309	5824	6251
R-squared	0.0068	0.0359	0.1608	0.1701	0.0111	0.0129

Notes: The coefficients in this table represent the marginal effect of being interviewed one day later. The sample is restricted to DHS clusters with an elevation greater than 1000m above sea level. All regressions include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Moran's I Test for Spatial Autocorrelation in Regression Residuals (Low-Altitude Sample)

IPV Dimension	Radius (km)	Moran's I	p (Normal)	p (Permutation)
IPV Incidence	100	−0.042	0.186	0.074
	150	−0.034	0.232	0.102
	200	−0.030	0.255	0.130
Less Severe IPV	100	−0.016	0.668	0.353
	150	−0.012	0.706	0.385
	200	−0.011	0.726	0.399
Severe IPV	100	−0.034	0.543	0.257
	150	−0.012	0.725	0.399
	200	−0.011	0.726	0.399
IPV Sometimes	100	−0.009	0.820	0.431
	150	−0.007	0.870	0.448
	200	−0.006	0.893	0.458
IPV Often	100	−0.035	0.283	0.140
	150	−0.043	0.115	0.032
	200	−0.041	0.114	0.034
Psychological IPV	100	−0.021	0.530	0.261
	150	−0.013	0.688	0.351
	200	−0.007	0.871	0.466
Number of clusters		308		

Notes: Moran's I tests are computed on cluster-level residuals from the low-altitude regressions using inverse-distance weights and 999 random permutations. The 50 km radius is excluded because approximately 5% of clusters have no spatial neighbors. Non-significant results (p > 0.10) indicate no evidence of global spatial autocorrelation.

B National Results

B.1 Endogeneity of Temperature At the National Level

Table B.1 shows that, at the national level, the temperature bins are uncorrelated with age, height, and parental IPV. However, the hottest bin, $\geq 33°\text{C}$, is significantly correlated with more years of education and a higher likelihood of having indigenous ethnicity. Also, the colder temperature bins are significantly correlated with indigenous ethnicity. These results show that, at the national level, exposure to certain temperatures is not exogenous. This finding is expected, as Table 1 shows that the low- and high-altitude samples experience different temperatures and are significantly different demographically.

B.2 Temperature Effects on IPV Using National Sample

The point estimates for IPV Incidence are shown in Figure B.1. While most coefficients are positive, none of them are statistically significant even at the 10 percent level. That is, I find no evidence that temperature affected IPV occurrences over the preceding year, which is contrary to the current literature on heat and violence in the short term (Blakeslee et al., 2021; Henke and Hsu, 2020; Ranson, 2014). A possible explanation is that violent acts arising from contemporaneous shocks, such as an increase in temperature, are offset by less violence on other days. For example, previous studies have found evidence of a somewhat offsetting decline in violent crime in the weeks after a temperature shock (Jacob et al., 2007; Cohen and Gonzalez, 2024).

Table B.1: Balance Check – Full Country

	(1) Age (years)	(2) Height (cms)	(3) Years of schooling	(4) Indigenous Ethnicity	(5) Parental IPV	(6) Age at first marriage (in years)
< 11	0.015	0.006	0.003	0.002*	0.001	0.010
	(0.011)	(0.008)	(0.009)	(0.001)	(0.001)	(0.007)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[11, 13)$	0.021*	0.007	0.014	0.001	0.000	0.014*
	(0.011)	(0.009)	(0.010)	(0.001)	(0.001)	(0.008)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[13, 15)$	0.005	0.004	0.001	0.002**	0.001	0.004
	(0.012)	(0.009)	(0.010)	(0.001)	(0.001)	(0.008)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[15, 17)$	0.020	0.004	0.005	0.002*	0.000	0.013
	(0.013)	(0.010)	(0.010)	(0.001)	(0.001)	(0.009)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[17, 19)$	0.003	0.001	0.003	0.001	0.001	-0.002
	(0.009)	(0.009)	(0.009)	(0.001)	(0.001)	(0.006)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[19, 21)$	0.022	0.015	0.021	0.002	0.001	0.025*
	(0.019)	(0.014)	(0.015)	(0.001)	(0.001)	(0.013)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[21, 23)$ omitted category						
$[23, 25)$	0.013	0.008	0.012	0.002	0.001	0.003
	(0.021)	(0.017)	(0.017)	(0.002)	(0.001)	(0.014)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[25, 27)$	0.026*	0.004	0.015	-0.001	0.000	0.018*
	(0.015)	(0.013)	(0.011)	(0.001)	(0.001)	(0.010)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[27, 29)$	-0.004	0.015	0.012	0.002	0.001	-0.001
	(0.018)	(0.015)	(0.014)	(0.001)	(0.001)	(0.012)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[29, 31)$	0.006	-0.004	-0.007	0.000	0.002	0.010
	(0.017)	(0.013)	(0.017)	(0.002)	(0.001)	(0.013)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
$[31, 33)$	0.022	0.006	-0.008	-0.001	-0.001	0.036***
	(0.037)	(0.021)	(0.020)	(0.002)	(0.001)	(0.014)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
≥ 33	0.003	0.020	0.051***	0.005**	0.001	-0.021
	(0.038)	(0.021)	(0.018)	(0.002)	(0.002)	(0.014)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Observations	9772	9570	9772	9772	9091	9772
R-squared	0.012	0.074	0.159	0.275	0.015	0.045

Notes: The coefficients in this table represent the marginal effect of experiencing one more day in the respective bin, relative to the omitted bin. All regressions include controls for: total accumulated precipitation in the previous 12 months, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [27, 29)°C. Anderson (2008) sharpened False Discovery Rate (FDR) q-values are reported for the temperature bins in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

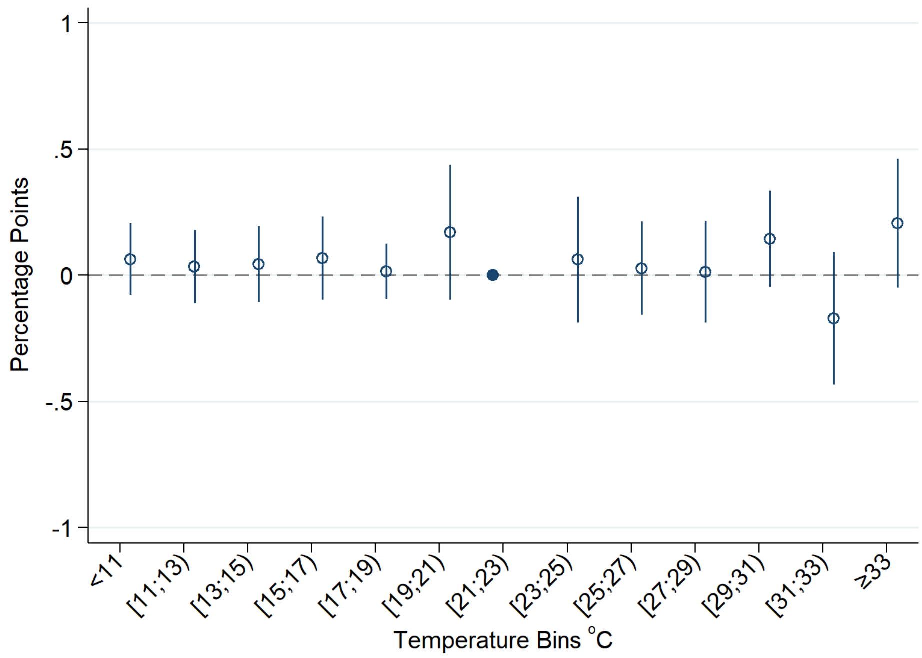

Figure B.1: Estimated Effect of Temperature on IPV Incidence

Notes: Dots show the coefficients estimated using equation (1); lines are 95% CI with SEs clustered at the DHS cluster level. Coefficients are scaled by 100 (percentage points) and represent the marginal effect of one extra day in each 2°C bin relative to the omitted bin $[21, 23)$°C. Controls include 12-month precipitation, age, rural status, ethnicity, education, survey-day max temperature, and morning-survey indicator. Region and month fixed effects were also included.

To explore any possible temporal displacement in IPV, I run equation (1) on the two frequency variables: *often* and *sometimes*. Figure B.2 shows the point estimates for each variable. Most of the coefficients on the variable *often* are negative and statistically significant, indicating that exposure to more days in the hotter or colder bins (relative to the reference bin) has a significant negative effect on the likelihood that a woman experiences IPV often. In contrast, most of the coefficients on the variable *sometimes* are positive, though not statistically significant. The results of these two variables together suggest that the IPV induced by temperature shocks is offset in later periods, such that the overall effect is a decrease in the frequency of violence, but not in its prevalence.

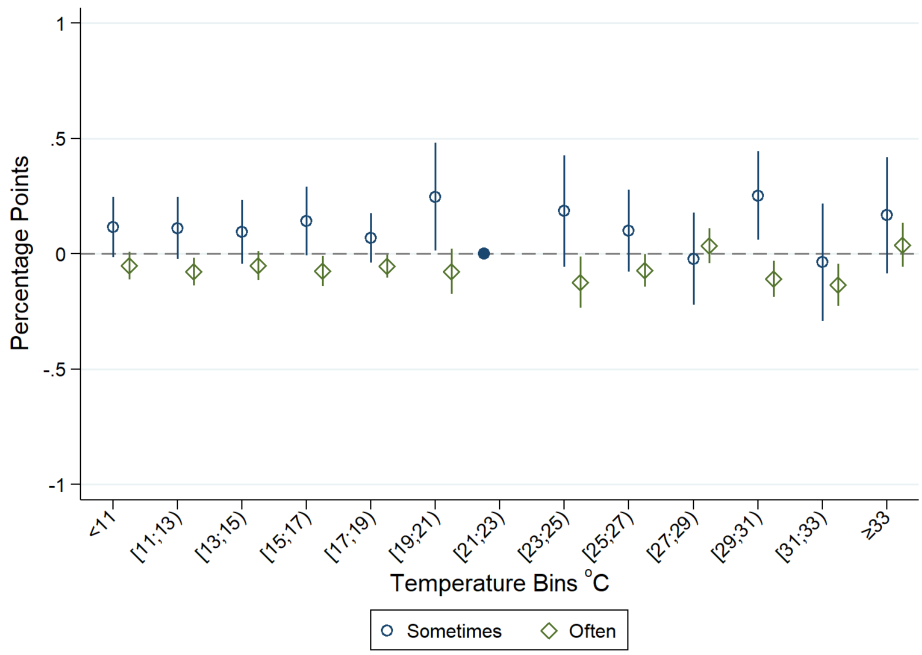

Figure B.2: Estimated Effect of Temperature on IPV Frequency

Notes: Dots show the coefficients estimated using equation (1); lines are 95% CI with SEs clustered at the DHS cluster level. Coefficients are scaled by 100 (percentage points) and represent the marginal effect of one extra day in each 2°C bin relative to the omitted bin $[21, 23)$°C. Controls include 12-month precipitation, age, rural status, ethnicity, education, survey-day max temperature, and morning-survey indicator. Region and month fixed effects were also included.

Besides having an effect on the frequency of IPV, temperature could also affect other aspects of intimate partner mistreatment, such as IPV severity and psychological abuse. The estimates for these outcome variables are presented in Table B.2. Columns (1) and (2) show no evidence that temperature has a significant effect on the severity of IPV occurrences. Only the coefficient for severe IPV in the $[31, 33)$ bin shows a statistically significant negative effect. Exchanging ten extra days in the reference bin for days with a maximum temperature in the $[31, 33)$ range lowers severe IPV by 2.2 percentage points (p-value < 0.10). While the decrease in the experience of severe IPV is not linked to an increase in less-severe acts of IPV, it seems to be related to a statistically significant increase in psychological abuse. The point estimates presented in column (7) for bins $[29, 31)$ and $[31, 33)$ indicate a significant increase in psychological abuse of 2.8 percentage points and 2.7 percentage points, respectively, for an extra ten days in each range. These results suggest that additional exposure to hot days may affect the severity and type of abuse women are subjected to.

Table B.2: Temperature Effect IPV Severity

	(1) IPV Incidence	(2) IPV Severity Less severe	(3) Severe	(4) Psychological Abuse
< 11 (%)	0.06	0.08	-0.02	0.08
	(0.07)	(0.05)	(0.06)	(0.08)
$[11, 13)$ (%)	0.03	0.06	-0.03	0.06
	(0.07)	(0.06)	(0.06)	(0.08)
$[13, 15)$ (%)	0.04	0.06	-0.02	0.07
	(0.08)	(0.06)	(0.07)	(0.08)
$[15, 17)$ (%)	0.07	0.08	-0.01	0.09
	(0.08)	(0.06)	(0.07)	(0.09)
$[17, 19)$ (%)	0.02	0.04	-0.03	0.01
	(0.06)	(0.05)	(0.05)	(0.06)
$[19, 21)$ (%)	0.17	0.15	0.01	0.23*
	(0.14)	(0.10)	(0.12)	(0.12)
$[21, 23)$ omitted category				
$[23, 25)$ (%)	0.06	0.09	-0.03	0.17
	(0.13)	(0.10)	(0.10)	(0.14)
$[25, 27)$ (%)	0.03	0.05	-0.02	0.07
	(0.09)	(0.07)	(0.07)	(0.09)
$[27, 29)$ (%)	0.01	0.04	-0.02	-0.03
	(0.10)	(0.08)	(0.10)	(0.12)
$[29, 31)$ (%)	0.14	0.08	0.06	0.28**
	(0.10)	(0.08)	(0.11)	(0.12)
$[31, 33)$ (%)	-0.18	0.04	-0.22*	0.27**
	(0.14)	(0.10)	(0.12)	(0.13)
≥ 33 (%)	0.22	0.07	0.14	-0.00
	(0.13)	(0.09)	(0.12)	(0.15)
Observations	9772	9772	9772	9772
R-squared	0.0297	0.0188	0.0163	0.0305

Notes: The coefficients in this table represent the marginal effect in percentage points of experiencing one more day in the respective temperature bin, relative to the omitted bin. All regressions include controls for: total accumulated precipitation in the previous 12 months, age, rural status, ethnicity, education, maximum temperature on the day of the survey, and a morning-survey indicator. They also include region and month-of-survey fixed effects. Standard errors are clustered at the DHS cluster level and shown in parentheses. The omitted temperature bin is [21, 23)°C. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Nonetheless, substantial climatic differences between low- and high-altitude areas may complicate the interpretation of these results. According to Figure 2, a day with maximum temperature in the chosen reference bin of $[21, 23)$ is a very hot day that is rarely experienced by the average individual in high-altitude areas. Yet, it is a moderately cold day for those living in low-altitude areas. Therefore, the point estimates from the full-country sample may obscure the heterogeneous effects of temperature and its associated mechanisms.