

Hot Weather, Hot Tempers: the Impact of Heat Waves on Intimate Partner Violence in Peru

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Abstract

This paper investigates the causal relationship between acute extreme temperature shocks—heat waves—and intimate partner violence (IPV) in Peru, highlighting the intersection between environmental stressors and gender-based violence. The findings demonstrate that heat waves increase IPV, with effects that are more pronounced in urban settings. Two mechanisms help explain this pattern. First, heat waves exacerbate stress and mental health challenges among male spouses in urban areas, raising the likelihood of violent behavior. Second, heat waves contribute to higher levels of community violence and greater acceptance of violent behavior, creating an environment where IPV becomes more likely. Together, these results emphasize the economic and social consequences of extreme heat and underscore the need for targeted interventions to mitigate IPV risks, particularly in urban populations, during heat waves.

Keywords: Heat Waves, Intimate partner violence, Gender-based Violence, Intra-household Behavior, Climate Change, Urban Stress

1 Introduction

As awareness of climate change continues to grow, the influence of high temperatures on human societies is becoming increasingly pronounced. An expanding body of research underscores the impacts of such climate shock on various aspects of human life, including income, health, and education (Carleton and Hsiang, 2016; Wu et al., 2016). These impacts also extend to agricultural and labor productivity (Deschênes and Greenstone, 2007; Somanathan et al., 2021) and even crime and human conflict (Ranson, 2014; Hsiang et al., 2013).

The negative effects of heat waves are particularly severe in low-income countries (IPCC, 2014; Hallegatte et al., 2016). This vulnerability is due to limited infrastructure to mitigate the effects of heat waves and a lack of access to cooling appliances. Furthermore, while social protection programs in low-income countries often assist victims of natural disasters, support specifically for heat wave victims is scarce, further increasing their vulnerability (Baez et al., 2017).

The disproportionate impact of heat waves also arises within households, exposing women to heightened risks of intimate partner violence. Increased stress and tension from extreme heat can exacerbate conflicts, particularly in households where social norms and gender roles create a significant gender gap between men and women. Economic pressures related to heat waves, such as reduced agricultural and labor productivity, can lead to greater financial strain on families, further intensifying these conflicts. Understanding how heat waves contribute to intimate partner violence is essential for addressing the specific vulnerabilities that women face during these climate events.

This paper examines the causal relationship between heat waves and intimate partner violence (IPV) in Peru. I focus on the immediate behavioral response to high temperature shocks and explore the pathways that may mediate this relationship. The analysis draws on administrative data from Peru’s national domestic violence helpline (Línea 100), measured as the number of calls per 10,000 residents in each province. Heat waves are defined as periods with unusually high numbers of “hot days,” where a hot day is one in which the daily maximum temperature exceeds the province-specific 90th percentile threshold (details

in Section 2). I further explore heterogeneity across urban and rural settings, classifying a province as urban if a majority of residents live in urbanized areas according to the national census.

My empirical approach relies on matching helpline call volumes to weather conditions at the province–month level. I construct a panel dataset combining geo-coded temperature data with IPV helpline calls from 2015 to 2022, and I apply two-way fixed effects regression models that exploit variation in weather conditions within a particular location and calendar month while controlling for annual local-level idiosyncrasies. Such variation is considered essentially random (Dell et al., 2014; Hsiang, 2016), because, for example, I am comparing IPV occurrences in a relatively warm January in a specific province with outcomes in a relatively cool January in that same province.

I find that heat waves lead to a prompt rise in intimate partner violence in Peru. A one–standard deviation increase in the number of hot days per month results in an additional 0.03–0.04 IPV helpline calls per 10,000 people, relative to the monthly mean of 1.405. This corresponds to a 2.1–3.1 percent increase in IPV calls. The effect is concentrated in urban areas: in urban provinces, IPV calls rise significantly by 0.06–0.08 per 10,000 (3.1–4.3 percent relative to the mean), whereas in rural provinces the impact is statistically insignificant.

Next, I investigate four potential pathways through which heat wave exposure could influence incidents of IPV: income, exposure, mental well-being, and community violence.

Income Channel: This mechanism posits that heat waves may reduce household income, thereby increasing stress and the risk of IPV. Previous studies have documented that negative income shocks can heighten IPV (Angelucci and Heath, 2020; Cools and Kotsadam, 2017; Abiona and Koppensteiner, 2021; Erten and Keskin, 2021; Díaz and Saldarriaga, 2023; Heath et al., 2020; Bollman et al., 2023). To test this pathway, I examine whether heat waves affect household income overall, and separately for agricultural households that are directly exposed to weather shocks through farming. Across both groups, however, I find no significant effect of hot days on household income. These results suggest that the income channel is unlikely to explain the short-run increase in IPV during heat waves.

Exposure Channel: The second pathway considers whether heat waves alter patterns of indoor or outdoor activity, potentially affecting exposure to violent partners. Prior work

during the Covid-19 pandemic shows that stay-at-home policies increased time spent indoors, heightening IPV risk due to closer proximity to violent partners (Leslie and Wilson, 2020; Bullinger et al., 2021). To examine this channel, I use mobility and time-use data. The analysis indicates that during heat waves, time spent indoors falls and out-of-home activity rises, which may reduce exposure to IPV. A likely explanation is the very low diffusion of residential cooling: according to Chilling Prospects: Tracking Sustainable Cooling for All 2025 (Sustainable Energy for All, 2025), just over one billion people in 77 countries remain at high risk from inadequate access to cooling, and Peru is classified among these high-risk countries. With limited access to cooling appliances such as air conditioning, households may find indoor environments less tolerable on hot days and instead seek relief outdoors or in public spaces. Evidence from Singapore supports this interpretation, showing that hotter days reallocate mobility toward air-conditioned destinations such as offices, malls, and schools, especially among residents lacking home cooling (Fesselmeier et al., 2024).

Mental Health Channel: The third pathway examines whether heat waves negatively affect male spouses' emotional well-being, potentially leading to increased stress and violent behavior. Previous research highlights the role of negative emotional cues in triggering family violence (Card and Dahl, 2011). This pathway also aligns with psychological studies suggesting that high temperatures can intensify aggressive motives and behaviors (Anderson, 2001). The analysis in this study finds evidence that heat waves worsen the mental well-being of male spouses, supporting the mental health channel. Moreover, this effect is particularly pronounced in urban areas, consistent with the stronger impact of heat waves on IPV observed in urban provinces.

Community Violence Channel: Finally, I assess whether heat waves contribute to higher levels of community violence. Community violence refers to violence occurring in the public sphere, outside the household, and affecting collective safety. Such incidents can make violent behavior more visible or seemingly more acceptable, which prior work links to a higher risk of IPV. Existing studies show that both early-life and contemporaneous exposure to violence at the community level can increase IPV risk (Mattina, 2017; Gutierrez and Gallegos, 2016; Noe and Rieackmann, 2013; Hossain et al., 2024). Building on this literature, I measure community violence using provincial-level police-reported crimes related to public safety (see

Section 2.3) and analyze how heat waves affect these outcomes. The results indicate that heat waves significantly raise community violence, with effects concentrated in urban areas. I also examine men’s attitudes toward violence using the World Values Survey and find that hot weather is associated with greater acceptance of violent behavior. While these shifts in acceptance may reflect heightened exposure rather than an immediate change in norms, together the results suggest that heat waves can intensify both community-level violence and tolerance of violence, creating conditions under which IPV is more likely to occur.

These findings highlight how extreme temperature shocks disproportionately affect women within households, with the impact being more pronounced in urban areas. The results emphasize the necessity for policies that prioritize rapid responses to climate shocks to mitigate intra-household violence. In particular, implementing mental health interventions in urban areas is essential to alleviate psychological stressors that contribute to adverse family dynamics. Furthermore, addressing community violence during heat waves is also critical, as it can normalize and reinforce harmful attitudes toward IPV.

This study makes a primary contribution by providing new evidence on the short-term impacts of heat waves on intimate partner violence in a low-income country setting. While much prior work has examined rainfall shocks and long-term income channels (Sekhri and Storeygard, 2014; Abiona and Koppensteiner, 2021; Díaz and Saldarriaga, 2023; Zhu et al., 2023), only a small body of research addresses temperature shocks (Sekhri and Storeygard, 2014; Abiona and Koppensteiner, 2021; Díaz and Saldarriaga, 2023; Bollman et al., 2023), and these studies typically rely on annually averaged temperatures to evaluate cumulative effects on IPV. Such long-term approaches may obscure the acute impacts of heat waves, as lower-temperature days reduce the overall average. Recent research on short-term fluctuations has largely focused on high-income contexts such as the United States (Henke and chi Hsu, 2020). By leveraging daily temperature variation and monthly IPV helpline call data in Peru, this paper provides novel evidence on how acute heat shocks affect IPV in a setting where household vulnerability and institutional capacity differ sharply from high-income countries. Beyond documenting this short-term relationship, I explore potential mechanisms. The results suggest that income effects play a limited role in the short run, whereas evidence is more consistent with alternative channels involving men’s mental distress and community

violence.

This study also contributes by identifying a particularly vulnerable subgroup with heightened exposure to heat risks: the urban population. To the best of my knowledge, it is the first to establish a causal relationship between urban heat risks and IPV in low-income countries. While previous studies, such as those by [Bollman et al. \(2023\)](#) and [Díaz and Saldarriaga \(2023\)](#), have primarily focused on rural areas and linked increases in IPV to poverty exacerbated by climate change, their findings may not fully capture the experiences of the entire population. By including data from all provinces and considering both rural and urban areas in Peru, this research reveals how heat risks differentially impact IPV in these settings.

Additionally, this study advances the literature by using administrative helpline call data, which provide a more precise and timely measure of IPV incidents. Prior work largely relies on Demographic and Health Surveys (DHS), which record whether IPV occurred at any point in the past 12 months but not when within that period. This design makes it impossible to link incidents to specific weather shocks, and the retrospective format can also introduce recall bias, as respondents may disproportionately emphasize recent events. Moreover, survey responses depend on individuals' willingness to disclose sensitive experiences, which may vary systematically with stigma or social norms. In contrast, monthly helpline calls capture IPV as it is reported, enabling closer alignment with short-term temperature shocks and reducing concerns about recall and disclosure bias.

The remainder of the paper is organized as follows. Section 2 outlines the data sources and variable construction. Sections 3 and 4 present the main results and heterogeneity analysis. Section 5 examines potential mechanisms and provides supporting evidence. Section 6 reports robustness checks. Section 7 concludes.

2 Data and Variables

2.1 Intimate Partner Violence

Information on IPV comes from the Ministry of Women and Vulnerable Populations (Ministerio de la Mujer y Poblaciones Vulnerables, MIMP). MIMP operates domestic violence

helpline called Línea 100. Línea 100 is a free 24-hour service, specialized in free telephone assistance nationwide in Peru. It provides information, guidance, counseling and emotional support in multiple languages for people affected by acts of violence against women and members of the family group or who know of a case (<https://www.gob.pe>). In addition to counseling, Línea 100 staff can refer cases to specialized services such as emergency centers for women (Centros de Emergencia Mujer, CEM), and in severe cases they can coordinate with the police or legal services. Thus, the helpline data likely reflect a wide range of IPV incidents, from those seeking emotional support to those requiring legal or protective intervention. Information on calls is publicly available on the website of the MIMP and is updated monthly.

I use the monthly volume of helpline calls for each province from 2015 to 2022^{1 2}. The primary outcome of interest is the monthly number of helpline calls per 10,000 people for each province. MIMP provides the total number of calls for each province, and I divide the number of calls by the total population of the province, with population data obtained from the 2007 Peruvian Census.

2.2 Temperature

As my main data source on weather, I use the ERA5 database from the European Center for Medium-Range Weather Forecasts. ERA5 provides hourly temperature and precipitation data from 2005 to 2022 at 0.25×0.25 degree resolution which corresponds to approximately a 27.5×27.5 kilometer grid at the equator. I define monthly occurrences of heat waves at the provincial level based on the most populated district within each province. Specifically, the weather data from the grid point closest to the centroid of the most populated district represents the province's weather.

To generate the variable *Z-Hotdays* for time t in province p for the main analysis, I follow [Baez et al., 2017](#). The construction process involves several steps:

First, I use hourly temperature data from the ERA5 reanalysis dataset to compute the

¹The years 2020 and 2021 are excluded due to the significant impact of COVID-19.

²Peru is administratively divided into 25 regions (departments), which are further subdivided into 196 provinces and 1,869 districts. This study primarily uses data at the provincial level.

daily mean and maximum temperatures for each province. Second, for each date, I determine the 90th percentile of daily maximum and mean temperatures. This percentile is based on a 5-year rolling window of past temperatures. For instance, to find the 90th percentile for January 15, 2015, I consider temperatures from January 15, 2010, to January 14, 2015. Third, I count the number of days each month where the daily maximum or mean temperature exceeds the 90th percentile for that province. Finally, to standardize heat exposure across provinces, I compute the mean and standard deviation of the number of hot days per month over the sample period. I then convert the number of hot days into a z-score. As per [Baez et al., 2017](#), provinces with a z-score of zero or below are considered “unaffected” and are assigned a value of zero.

In a similar way, I construct a variable for cold days (*Z-Colddays*). Here, I use the 10th percentile of daily maximum and mean temperatures, again based on a 5-year rolling window, as the cutoff. For each province and month, I count the number of days when the daily maximum or mean temperature falls below this 10th percentile threshold. As with hot days, I standardize the count into a z-score across the sample period.

For the analysis of income and mental health channels, I adjust the weather variable as follows. I count the number of hot days in the 30 days preceding the interview date. The 90th percentile threshold to define the hot days is derived similarly using a 5-year rolling window based on the interview date. Next, I calculate the mean and standard deviation of the number of hot days for 30 days over the sample period to create an individual exposure z-score. For the exposure channel analysis, I create a binary indicator that marks whether the daily maximum (or mean) temperature exceeds the 90th percentile.

Additionally, I explore alternative specifications using temperature bins as described by [Mullins and White, 2019](#). I group daily maximum temperatures for each province into $5^{\circ}C$ -wide bins, ranging from $< 10^{\circ}C$ to $> 30^{\circ}C$. Similarly, I group daily mean temperatures into bins from $< 5^{\circ}C$ to $> 25^{\circ}C$. Then, I count the number of days each month where daily mean or maximum temperatures fall into each bin.

Summary statistics for IPV occurrences and each temperature variable are reported in [Table 1](#). Additionally, [Panel A of Figure 1](#) illustrates the average number of hot days per month from 2015 to 2022, defined as days when the daily maximum temperature exceeds the

90th percentile, while Panel B depicts the average number of helpline calls per month per 10,000 residents across all provinces over the sample period. Triangles on each map represent metropolitan areas with populations exceeding 300,000. Panel B shows that helpline calls are not always most frequent in urban areas. This suggests that helpline data capture IPV occurrences beyond metropolitan areas, making it a suitable measure for analyzing the impact of heat waves on IPV across different regions rather than being limited to urban settings.

Table 1: Summary Statistics

	count	mean	sd	min	max
Number of helpline calls per 10,000	13680	1.405	1.379	0	14.786
Z-score of number of hot days (max temp)	13680	0.399	0.860	0	6.595
Z-score of number of hot days (mean temp)	13680	0.398	0.925	0	6.860
Number of days with temp below 10	13680	1.178	3.701	0	31.000
Number of days with temp 10-15	13680	8.778	11.142	0	31.000
Number of days with temp 15-20	13680	7.657	10.416	0	31.000
Number of days with temp 20-25	13680	5.855	10.241	0	31.000
Number of days with temp 25-30	13680	4.370	8.291	0	31.000
Number of days with temp above 30	13680	2.593	6.679	0	31.000

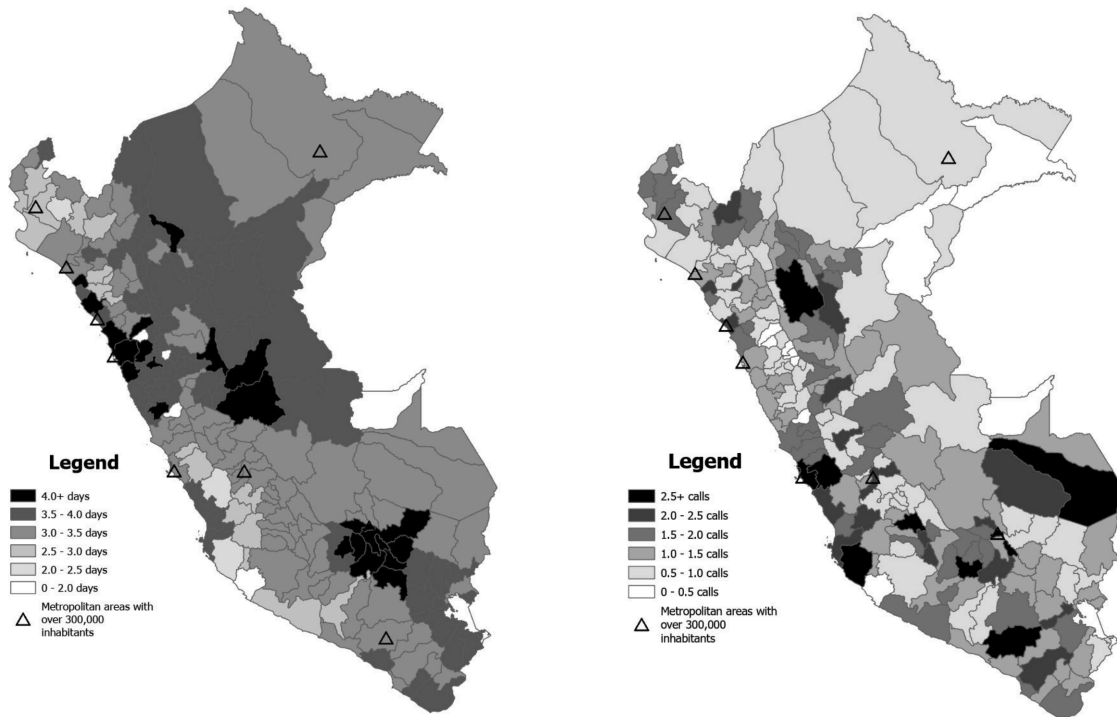
2.3 Channel Outcome Variables

2.3.1 Income

To explore the mediating factors, I gather data from various sources. For the income channel, I utilize the Peru National Household Survey (ENAHO). ENAHO is a longitudinal survey conducted from 2016 to 2018, covering a representative sample of the national population. It provides detailed information on employment, income, education, expenditures, assets, household demographics, and housing, with a focus on recent economic and social conditions³. Given the study’s focus on the short-term effects of heat waves, ENAHO is a valuable data source for examining short-term economic status.

My main income measure is per capita household net income. I construct this by summing

³The detailed information on this data can be found below: <https://ghdx.healthdata.org/record/peru-national-household-survey-2016>



Panel A: Heat Wave Map

Panel B: IPV Map

Figure 1: Heat Waves and IPV Maps

the monetary earnings of all household members from their main and secondary occupations, including both wage employment and self-employment. These income components are reported for the previous month (or shorter recall periods such as weekly or biweekly), making them suitable for capturing short-term fluctuations relevant to heat shocks. In-kind payments from employment are excluded because they are collected with a twelve-month recall window, which is not directly comparable to the monthly income measures. I then divide household net income by household size to obtain per capita values and take logarithms to construct the main outcome variable used in the analysis.

Because weather shocks are expected to affect agricultural households more strongly, I classify households into farm and non-farm groups. A household is coded as a farm household if at least one member is engaged in agriculture or fishery in any survey wave, either as a self-employed producer or as a wage laborer. All other households are classified as non-farm.

This definition ensures that households with even partial reliance on agriculture at some point during the panel are treated as more directly exposed to weather risk.

2.3.2 Exposure

To explore the exposure channel, I use province-level daily mobility data provided by Google, following [Bollman et al., 2023](#). In response to COVID-19, Google has constructed mobility data regarding people’s frequency of visits and lengths of stays at categorized places such as (i) retail and recreation, (ii) parks, (iii) transit stations, (iv) workplaces, and (v) residential areas. The data show how visitors to and time spent in the categorized places change compared to baseline days⁴.

I use the percentage change in visits to each categorized area from October 16, 2021, to October 15, 2022. Although Google provides mobility data from 2020 to 2022, I focus on this later period to avoid distortions in mobility trends caused by COVID-19-related restrictions during 2020 and early 2021. To preserve anonymity, data are missing for any dates with an insufficient number of visitors to a place category. For the missing data, which represent an insufficient number of visitors, I impute values as the average of the maximum negative value and the minimum positive value for each province.

2.3.3 Mental Health

To explore the mental health, I leverage the Peru Continuous Demographic and Health Survey from 2013 to 2017. The DHS survey is repeated cross-section survey conducted annually by the Peruvian National Bureau of Statistics. DHS surveys on health outcomes and socio-demographic characteristics of individuals including questions on intimate partner violence and mental health.

The DHS surveys include questions on mental distress symptoms using the Patient Health Questionnaire-9 (PHQ-9), a widely used tool for screening, diagnosing, monitoring, and measuring the mental health. This questionnaire consists of nine questions that ask about the frequency of specific symptoms over the past two weeks. The symptoms covered by

⁴The detailed information on this data can be found below: https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927&sjid=12464980794855916007-NC

the questionnaire include: (1) Little interest or pleasure in doing things, (2) Feeling down, depressed, or hopeless, (3) Trouble falling or staying asleep, or sleeping too much, (4) Feeling tired or having little energy, (5) Poor appetite or overeating, (6) Feeling bad about yourself or that you are a failure or have let yourself or your family down, (7) Trouble concentrating on things, such as reading the newspaper or watching television, (8) Moving or speaking so slowly that other people could have noticed, or the opposite, being so fidgety or restless that you have been moving a lot more than usual, and (9) Thoughts that you would be better off dead or of hurting yourself in some way. I use the PHQ-9 scores and construct an index of mental distress for male spouses by calculating the standardized Z-scores of the total scores from each question.

2.3.4 Community Violence

Data on community violence are obtained from the National Register of Crime and Offense Reports for the years 2015 to 2017, which include police-reported crime statistics at the provincial level. I focus on crimes related to public safety, including offenses against (1) body, life, and health, (2) freedom, (3) public safety, (4) public tranquility, (5) humanity, and (6) state and national defense. Using these data, I calculate the number of public safety-related crimes per 10,000 people for each province to measure community violence.

To analyze norms surrounding violence among males, I use data from the World Value Survey (WVS) conducted in 2012 and 2018. The WVS provides data on the acceptance of various forms of violence, including wife-beating, child-beating, violence against others, and suicide. Based on responses to these questions, I construct an index of violence acceptance among male spouses, which serves as a proxy for societal norms related to violence.

2.3.5 Sub-samples: Urbanization

To estimate the heterogeneous impact of heat waves by degree of urbanization, I use data from the 2007 Peruvian Census, which reports the share of the population living in urban areas for each province (ranging from 0% to 100%). I construct a binary variable, *urban*, equal to one for provinces with an urbanization rate above 58.4—the 75th percentile of the distribution—and zero otherwise. For the province of Callao, where the 2007 Census did

not report urbanization, I impute the value using data from the 2017 Census. Based on this classification, among the 190 provinces in my sample, 48 are categorized as urban and 142 as rural.

3 Main Results

In this section, I utilize two distinct models to examine the effect of high temperatures on IPV: one based on temperature bins and the other using a relative concept of heat waves. I first present evidence from the two-way fixed effects approach using temperature bins. Next, I show results from the second specification, where heat waves are defined relative to each province’s temperature distribution. Thereafter, I compare the results with the results using DHS data.

3.1 Absolute Measure of Heat Wave: Temperature Bins Specification

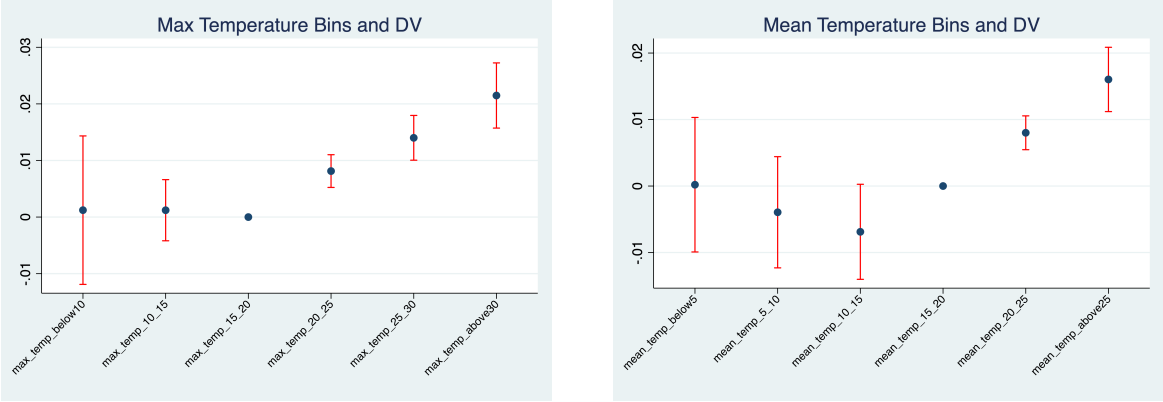
The first model employs temperature bins to capture the effect of temperature in absolute terms. This approach have been widely used in the climate economics literature (Mullins and White, 2019; Barreca et al., 2016; Hsiang, 2016) and enables a detailed examination of how specific temperature ranges influence IPV. Additionally, the results are easily interpretable and communicable, as they capture the impact of well-defined temperature thresholds. Eq.1 describes the first model for estimating the effects of temperature on IPV.

$$IPV_{prmy} = \alpha + \beta \sum_k Tbin_{k,prmy} + \mu_{my} + \delta_{py} + \epsilon_{prmy} \quad (1)$$

where IPV_{prmy} is the outcome variable, representing the number of helpline calls per 10,000 population in province p , region r , in month m of year y . $Tbin_{k,prmy}$ denotes the number of days in each month where the daily mean or maximum temperature falls within the specified temperature bin. The temperature bins for daily maximum temperature are: below 10°C, 10-15°C, 15-20°C, 20-25°C, 25-30°C, and above 30°C. Similarly, the temperature bins for daily mean temperature are: below 5°C, 5-10°C, 10-15°C, 15-20°C, 20-25°C,

and above 25°C. The main specification includes month-by-year and province-by-year fixed effects. Standard errors are clustered at the province level.

The estimation results from Eq.1 are summarized in Figure 2, which plots the point estimates and 95% intervals for the estimates of the β_j terms using daily maximum and mean temperatures respectively (the corresponding regression table is reported in Appendix Table A.1). For both outcomes, there is a clear upward-sloping pattern for the temperature bins above 15°C, indicating that additional hot days increase IPV occurrences. Specifically, in Panel (b) of Figure 2, IPV decreases as temperature initially increases. However, once the temperature exceeds a certain threshold (in this case, 15°C), IPV starts to increase rapidly.



(a) Daily Max Temperature

(b) Daily Mean Temperature

Figure 2: Temperature bins

Notes: Vertical lines represent 95% confidence intervals. In each case, the coefficient can be interpreted as the effect of one additional day in the baseline bin, relative to a day between 15-20°C

3.2 Relative Measures of Heat Wave

In addition to traditional temperature bin models, I incorporate an alternative approach following Baez et al., 2017. This method defines a hot day as one where the temperature exceeds the 90th percentile threshold of historical data specific to each province. By employing this relative measure, the model accounts for temperature extremes relative to local climatic norms rather than using fixed thresholds. This approach adjusts for the variability

in local climate conditions across provinces, acknowledging that what constitutes a hot day can differ significantly between regions. Eq.2 outlines the model used to estimate the impact of relative measures of heat waves on IPV:

$$IPV_{prmy} = \beta_0 + \beta_1 Z_Hotdays_{prmy} + \beta_2 Z_Colddays_{prmy} + \mu_{my} + \delta_{py} + \epsilon_{prmy} \quad (2)$$

In this model, $Z_Hotdays_{prmy}$ represents the Z-scores of the number of hot days in province p , region r , month m , and year y . The specification also includes $Z_Colddays_{prmy}$, which denotes the Z-scores of the number of cold days in province p and month m . The model controls for month-by-year (μ_{my}) and province-by-year (δ_{py}) fixed effects. Standard errors are clustered at the province level.

The estimates from Eq.2 are reported in Table2. Heat waves are found to significantly increase IPV. In column (1), a one standard deviation (SD) increase in the number of hot days, measured using daily maximum temperature within a month, raises helpline calls by 0.028 per 10,000 people relative to a monthly mean of 1.405. This corresponds to a 2.0 percent increase in calls.⁵ Similarly, column (4) shows that a one standard deviation increase in hot days based on daily mean temperature raises helpline calls by 0.043 per 10,000, or 3.1 percent relative to the mean.

3.3 Revisit to Main Analysis: Limitation of DHS Data

In this subsection, I explore the impact of heat waves on IPV using DHS data and compare the results with those obtained from helpline data. DHS surveys include detailed questions about IPV experiences and have been widely utilized in related research (Díaz and Saldarriaga, 2023; Bollman et al., 2023; Zhu et al., 2023). However, these surveys rely on a 12-month recall period for IPV experiences. I expect this annual reporting nature poses challenges in attributing IPV incidents to within-year and short-term variations in environmental factors like heat waves. To verify this expectation, I investigate whether the relationship between

⁵For comparability, coefficients are scaled by the mean of the dependent variable and can be interpreted as percent changes from the mean.

Table 2: The effects of heat waves on IPV incidents

	IPV Calls			
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.0297*** (0.010)	0.0279*** (0.010)		
Z-Colddays (max)		-0.0159 (0.012)		
Z-Hotdays (mean)			0.0435*** (0.010)	0.0432*** (0.010)
Z-Colddays (mean)				-0.0072 (0.011)
Observations	13680	13680	13680	13680
ymean	1.405	1.405	1.405	1.405
Year X Month FE	Yes	Yes	Yes	Yes
Province X Year FE	Yes	Yes	Yes	Yes

Note: The regressions include month-by-year and province-by-year fixed effects. Standard errors clustered at the province level in parenthesis. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

heat waves and IPV still holds using DHS data. Eq.3 presents the model used to estimate the impact of heat waves on IPV using DHS data:

$$IPV_{ipmy} = \alpha + \beta Z_Hotdays_{ipmy} + \gamma Z_Colddays_{ipmy} + X_{ipmy}\phi + \mu_{py} + \delta_{my} + \epsilon_{ipmy} \quad (3)$$

where IPV_{ipmy} indicates whether the female spouse i has experienced any type of IPV during the past 12 months. $Z_Hotdays_{ipmy}$ and $Z_Colddays_{ipmy}$ are the Z-scores of the number of hot days and cold days during the 12 months, respectively. The vector X_{ipmy} includes information on the woman's age and education, her husband's age and education, and household wealth. Month-by-year and province-by-year fixed effects are included, and standard errors are clustered at the province level.

One possibility to consider in the model is that although the survey asks about IPV experiences over the past 12 months, respondents may be more likely to recall more recent incidents. Therefore, I next replaced $Z_Hotdays_{ipmy}$ and $Z_Colddays_{ipmy}$ for the past 12 months with those for the past 1 month to consider a more recent exposure window. The estimates from both models are presented in Panel A and B of Table 3. The estimates indicate

no significant impact of heat waves on IPV using DHS data. The causal relationship between IPV and extreme temperature events that last only a few days or weeks is difficult to capture using DHS data. This limitation can be attributed to the longer recall period of the DHS survey compared to the shorter reference period in helpline data.

With a longer reference period, DHS data may complicate the isolation of direct influences from heat waves due to other factors that vary throughout the year. Specifically, an increase in IPV due to heat waves can be compensated by a temporary fall in IPV in subsequent months (Deschênes and Moretti, 2009; Ranson, 2014). Additionally, self-reporting over a long reference period can cause recall bias, where women may underreport true incidents due to faulty memory or social stigma (Beegle et al., 2012; Aggero and Frisancho, 2018). In contrast, helpline data is updated monthly, ensuring that the timing of incidents aligns more closely with the actual occurrence of heat waves, allowing for the observation of immediate responses to short-term weather shocks. Furthermore, the administrative data from helpline calls is often systematically recorded and maintained, ensuring consistency and reliability. This reduces potential biases that can arise from self-reported survey data.

4 Heterogeneity by Urbanization and Geography

An important question is whether the effects of heat waves on IPV differ across urban and rural contexts. Urban areas may be more vulnerable to temperature shocks due to higher population density, the urban heat island effect, and limited opportunities for households to adapt their daily routines compared to rural settings. To examine this heterogeneity, I classify provinces as urban if their 2007 Census urbanization rate exceeds the 75th percentile of the national distribution (58.4%), and as rural otherwise (Section 2.3.5).

Table 4 reports the heterogeneity results by urbanization. Panel A shows that the effects of hot days are concentrated in urban provinces: a one standard deviation (SD) increase in hot days raises helpline calls by 0.058 per 10,000 people (3.1 percent relative to the mean) when using daily maximum temperature and by 0.079 calls (4.3 percent relative to the mean) when using daily mean temperature. By contrast, Panel B shows small and statistically insignificant effects in rural provinces. The bottom rows of Table 4 confirm that

Table 3: The effects of heat wave on IPV with DHS

	IPV Indicator			
	(1)	(2)	(3)	(4)
Panel A: Heat wave for 12 months				
Z-Hotdays (max)	-0.000 (0.002)	-0.000 (0.002)		
Z-Colddays (max)		0.003 (0.004)		
Z-Hotdays (mean)			0.002 (0.002)	0.001 (0.002)
Z-Colddays (mean)				-0.007 (0.005)
Observations	109180	109180	109180	109180
ymean	0.190	0.190	0.190	0.190
	IPV Indicator			
	(1)	(2)	(3)	(4)
Panel B: Heat wave for 1 month				
Z-Hotdays (max)	-0.002 (0.002)	-0.002 (0.002)		
Z-Colddays (max)		0.001 (0.002)		
Z-Hotdays (mean)			-0.001 (0.002)	-0.001 (0.002)
Z-Colddays (mean)				0.000 (0.002)
Observations	109180	109180	109180	109180
ymean	0.190	0.190	0.190	0.190
Year \times Month FE	Yes	Yes	Yes	Yes
Province \times Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the province level in parenthesis. The regressions control for month-by-year and province-by-year fixed effects. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

the urban–rural differences are statistically significant, indicating that urban areas are more sensitive to heat.

A potential concern is that the urban–rural split may simply proxy for underlying climate differences across Peru rather than “urban-ness” per se. Much of the most urbanized population is concentrated along the coast, where heat extremes are more common, while the Peruvian Highlands are largely rural and have lower absolute temperatures. To address this, I re-estimate the model separately for the Lowlands (coastal and low-elevation areas) and the Highlands (Andean provinces).⁶

Table A.2 shows that the urban gradient in heat sensitivity remains visible within regions. In the Lowlands (Panel A), the effects of hot days are strong overall and particularly pronounced in urban provinces, whereas rural lowlands show weaker responses. In the Highlands (Panel B), where absolute temperatures are lower, effects are generally attenuated; nevertheless, urban highland provinces still exhibit positive and significant responses to hot days, while rural highlands do not.

As an additional robustness exercise, Appendix Table A.3 re-estimates the absolute temperature–bin specification separately for urban and rural provinces. The results mirror the relative-threshold findings: IPV rises monotonically across higher temperature bins in urban areas, whereas rural responses are comparatively flat and weaker. Taken together, the evidence indicates that (i) heat raises IPV primarily in urban areas, and (ii) this urban–rural heterogeneity persists even after conditioning on geography (Lowlands vs. Highlands) and when using absolute temperature thresholds.

5 Mechanism

In this section, I examine four potential channels through which exposure to heat waves can affect IPV: income, exposure, mental health, and community violence. To identify the pathways that mediate the observed increase in IPV in Peru, I estimate the effects of heat waves on these factors while ruling out alternative explanations. The results indicate that

⁶Departments classified as highlands are Cajamarca, Áncash, La Libertad, Huánuco, Pasco, Junín, Huanavelica, Ayacucho, Apurímac, Cusco, Puno, Arequipa, Moquegua, and Tacna.

Table 4: The effects of heat waves on IPV calls: Urban vs. Rural heterogeneity

	IPV calls	
	(1)	(2)
Panel A: Urban areas		
Z-Hotdays (max)	0.058*** (0.019)	
Z-Colddays (max)	-0.024 (0.017)	
Z-Hotdays (mean)		0.079*** (0.018)
Z-Colddays (mean)		-0.015 (0.019)
Observations	3456	3456
ymean	1.850	1.850
Panel B: Rural areas		
Z-Hotdays (max)	0.002 (0.013)	
Z-Colddays (max)	0.009 (0.014)	
Z-Hotdays (mean)		0.015 (0.012)
Z-Colddays (mean)		0.012 (0.013)
Observations	10224	10224
ymean	1.255	1.255
Year \times Month FE	Yes	Yes
Province \times Year FE	Yes	Yes
Hot: diff (Urban–Rural)	.037	.03
p-value	.019	.011

Note: Standard errors clustered at the province level in parentheses. All models include month-by-year and province-by-year fixed effects. Regressions are estimated in levels; coefficients are reported as percent changes from the mean monthly call rate. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

income and exposure do not significantly change during heat waves, suggesting these are not operative channels in the short term. Instead, the analysis identifies two plausible pathways: deteriorating mental health among male spouses and increased community violence, including shifts in attitudes toward violence. These mechanisms may operate simultaneously and interact in complex ways, with some reinforcing each other and others offsetting their effects (Díaz and Saldarriaga, 2023; Roy et al., 2019).

5.1 Income Channel

In order to explore the income channels, I employ a two-way fixed effects model as described in Eq.4.

$$Y_{hpt} = \alpha + \beta Z_Hotdays_{hpt} + \gamma Z_Colddays_{hpt} + \psi_h + \mu_p + \delta_t + \epsilon_{hpt} \quad (4)$$

The dependent variable Y_{hpt} represents the outcome of interest for household h : per-capita monthly gross income and per-capita monthly net income in province p at time t . $Z_Hotdays_{hpt}$ and $Z_Colddays_{hpt}$ are the Z-scores of hot and cold days over the past month from the interview date. The model includes household, month-by-year, and province-by-year fixed effects. Standard errors are clustered at the province level.

Table 5 reports the estimates. Across all specifications, there is no evidence that heat waves in the past month significantly affect per-capita household net income. Columns (1)–(3) use the definition of hot and cold days based on daily maximum temperatures, while columns (4)–(6) use daily mean temperatures. In both cases, the coefficients on hot and cold days are small in magnitude and statistically insignificant. Because weather shocks are expected to affect farm households more strongly, given their greater reliance on climate-sensitive activities, I estimate the model separately for farm and non-farm households. Columns (2) and (5) restrict the sample to farm households, and columns (3) and (6) to non-farm households. The results show no significant effects for either group, suggesting that even among households most directly exposed to weather conditions, short-term income does not respond to heat waves.

I further estimate the model separately for urban and rural households (results in Table A.4), which again shows no significant effects of hot or cold days on household net income.

Table 5: The effects of heat wave on per-capita household net income

	Log of real per-capita household net income during the last month					
	(1)	(2)	(3)	(4)	(5)	(6)
Z-Hotdays (max)	-0.020 (0.021)	0.001 (0.032)	-0.029 (0.033)			
Z-Colddays (max)	0.023 (0.017)	0.033 (0.024)	0.016 (0.025)			
Z-Hotdays (mean)				-0.018 (0.025)	-0.001 (0.036)	-0.017 (0.040)
Z-Colddays (mean)				0.002 (0.018)	0.001 (0.027)	-0.007 (0.029)
Observations	31789	15623	16085	31789	15623	16085
ymean	5.266	4.875	5.653	5.266	4.875	5.653
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year \times Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Province \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Farm	Non-farm	All	Farm	Non-farm

Note: The outcome variable is per-capita household net income for the last month, deflated and expressed in logs. Columns 2 and 4 restrict the sample to farm households, defined as those in which at least one member works in agriculture in any wave. Columns 3 and 6 restrict the sample to non-farm households. Standard errors clustered at the province level in parenthesis. The regressions control for household, month-by-year and province-by-year fixed effects. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

These findings imply that short-term increases in IPV associated with heat waves are not mediated by household income shocks.

In sum, this evidence stands in contrast to the broader literature documenting long-term income losses from higher temperatures, especially in agriculture. Studies relying on annual average temperatures capture gradual reductions in yields and earnings, while the present analysis focuses on month-to-month variation. The divergence underscores the importance of distinguishing between the short-run transitory impacts of heat waves and the longer-term cumulative effects of sustained warming on income.

5.2 Exposure Channel

The exposure channel implies that environmental conditions, like heat waves, may increase IPV by causing individuals to spend more time at home, leading to greater interaction and

potential conflict between partners (Leslie and Wilson, 2020; Bullinger et al., 2021). This section investigates whether outdoor activities decrease during heat waves and, if so, whether IPV increases as increased at-home time leads to greater exposure to IPV. To this end, I analyze how people’s mobility patterns—both to indoor and outdoor locations—change on hot days. Eq.5 describes the model specification used to estimate the relationship between heat waves and mobility following the approach in Bollman et al. (2023).

$$Y_{pdm_y} = \beta_0 + \beta_1 Hotday_{pdm_y} + \beta_2 Coldday_{pdm_y} + \psi_{my} + \mu_d + \delta_{pm} + \epsilon_{prmy} \quad (5)$$

In this model specification, the dependent variable Y_{pdm_y} represents the percentage change in visits to five categories of places in province p on day d in month m and year y . The variable $Hotday_{pdm_y}$ is an indicator equal to 1 if the daily maximum (mean) temperature exceeds the 90th percentile of the historical temperature distribution for the province. The model includes fixed effects for month-by-year (ψ_{my}), day-of-week (μ_d), and province-by-month (δ_{pm}). Standard errors are clustered at the province level.

Table 6 presents the estimation results where hot days measured by daily maximum and mean temperature tend to increase outdoor activities and decrease indoor time while cold days exhibit the opposite trend. Specifically, visits to park areas increase by 2.60 percentage points on hot days, while they decrease by 2.75 percentage points on cold days, as shown in Column (1) of Panel A⁷. This pattern remains consistent when hot days are measured by daily mean temperature, as depicted in Panel B. Conversely, visits and lengths of stay at residential areas significantly decrease by 0.21 percentage points on hot days in Panel A and by 0.24 percentage points in Panel B.

This finding suggests that hot weather encourages more outdoor activity, contrary to initial expectations that extreme heat would discourage mobility. A plausible explanation lies in the very limited diffusion of residential cooling technologies. According to Chilling Prospects: Tracking Sustainable Cooling for All 2025 (Sustainable Energy for All, 2025), just over one billion people across 77 countries face high risks from inadequate access to cooling,

⁷The estimates for cold days are consistent with Bollman et al., 2023 where people tend to reduce visits to parks, transit stations, and retail/recreational areas

and Peru is classified among these high-risk countries. With few households owning air conditioning or other effective cooling appliances, indoor environments can become hotter and less tolerable than shaded or public outdoor areas during heat waves. As a result, individuals may cope by reallocating time toward outdoor spaces such as parks or public venues. This interpretation is consistent with evidence from Singapore, where hotter days increase mobility to air-conditioned destinations like offices, malls, and schools, especially among residents without home cooling (Fesselmeyer et al., 2024).

Table 6: The effects of heat wave on mobility

	(1) Parks	(2) Workplace	(3) Transit	(4) Residential	(5) Retail/Rec
Panel A: Max temp					
Hotday (d)	2.604*** (0.475)	0.059 (0.496)	0.210 (0.236)	-0.207*** (0.075)	0.051 (0.308)
Coldday (d)	-2.754*** (0.402)	-0.250 (0.329)	-0.754*** (0.262)	0.353*** (0.075)	-0.425* (0.244)
Observations	37466	37466	37466	37466	37466
ymean	23.603	28.188	-7.634	5.129	12.101
Panel B: Mean temp					
Hotday(Mean) (d)	2.127*** (0.496)	-0.391 (0.477)	0.081 (0.312)	-0.244*** (0.070)	0.281 (0.338)
Coldday(Mean) (d)	-1.340*** (0.440)	0.994*** (0.361)	-0.550* (0.293)	0.244*** (0.074)	-0.027 (0.241)
Observations	37466	37466	37466	37466	37466
ymean	23.603	28.188	-7.634	5.129	12.101
Year \times Month FE	Yes	Yes	Yes	Yes	Yes
Province \times Month FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the province level in parenthesis. All specifications include month-by-year, province-by-month, and day-of-week fixed effects. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The heterogeneous impact of heat waves on mobility is also examined based on urbanization, as discussed in Section 4, Table A.5 estimates Eq.5 for urban and rural areas separately. Both urban and rural areas exhibit the same pattern: visits to parks increase, while visits to

residential areas decrease on hot days. Consequently, the exposure channel can be excluded as a potential mechanism for increased IPV during hot days, since individuals tend to engage in more outdoor activities and do not spend more time at home. This finding suggests that the acute increase in IPV following hot days cannot be attributed to increased at-home time and exposure to IPV.

5.3 Mental Health Channel

Extreme temperatures can affect individuals' mental well-being. In this section, I examine the impact of heat waves on mental health using an index of mental distress, measured by the PHQ-9, a widely used screening tool for psychological distress. Eq.6 describes the specification:

$$MentalDistress_{ipt} = \alpha + \beta Z_Hotdays_{ipt} + \gamma Z_Colddays_{ipt} + X_{ipt}\phi + \mu_p + \delta_t + \epsilon_{ipt} \quad (6)$$

The dependent variable, $MentalDistress_{ipt}$, represents the standardized mental distress index for the husband of woman i in province p at time t . $Z_Hotdays_{ipt}$ and $Z_Colddays_{ipt}$ are the z-scores of hot and cold days, defined using daily maximum or mean temperatures over the past month prior to the interview date. X_{ipt} includes controls for age, education, marital status, household wealth, and household size. All regressions include month-by-year and province-by-year fixed effects, and standard errors are clustered at the province level.

Table 7 reports the main results. Columns (1) and (2) show that a one standard deviation increase in hot days measured by maximum temperature significantly raises men's mental distress, whereas cold days have no detectable effect. By contrast, columns (3) and (4), which use daily mean temperature, yield positive but insignificant coefficients for hot days. Taken together, these results suggest that extreme heat is the primary driver of short-term deterioration in men's mental health.

To investigate heterogeneity by urbanization, I estimate Eq.6 separately for urban and rural provinces. The results in Table 8 show a clear divergence. In urban areas (Panel A), hot days measured by maximum temperature significantly increase mental distress: a one standard deviation rise in hot days leads to an increase of 0.024 standard deviations in the

Table 7: The effects of heat wave on mental distress

	Mental Distress Index			
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.012*** (0.004)	0.012*** (0.003)		
Z-Colddays (max)		-0.003 (0.008)		
Z-Hotdays (mean)			0.002 (0.003)	0.003 (0.003)
Z-Colddays (mean)				0.013 (0.009)
Observations	56312	56312	56312	56312
y _{mean}	-0.165	-0.165	-0.165	-0.165
Year × Month FE	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: The analyses control for age, wealth level, cohabitation status, and education level. The regressions include month-by-year and province-by-year fixed effects. Standard errors clustered at the province level in parenthesis. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

index. In rural areas (Panel B), however, the effect of hot days is small and statistically insignificant. Instead, rural provinces display a modest increase in distress in response to cold days, but not to hot days. Formal tests confirm that the urban–rural difference in the maximum-temperature specification is statistically significant ($p = 0.001$), while the difference in the mean-temperature specification is smaller and not significant.

These results indicate that the adverse mental health effects of heat waves are concentrated in urban populations. When combined with the heterogeneous IPV findings in Section 4, the evidence points to urban men being more vulnerable to heat-induced mental distress, which in turn mediates the observed increase in IPV calls during heat waves.

To further validate the role of urbanization, I build on the same 2007 Peruvian Census measure of the degree of urbanization that I used for the baseline urban–rural split. In that analysis, provinces above the 75th percentile of urbanization (58.4 percent) were classified as urban, while those below were rural. Here, instead of a binary cutoff, I exploit the continuous variation by dividing provinces into five groups: 0–20 percent (Group 1), 20–40

percent (Group 2), 40–60 percent (Group 3), 60–80 percent (Group 4), and 80–100 percent (Group 5).⁸

Figure 3 reports the impact of hot days on IPV calls by degree of urbanization, showing a near-linear increase in the effect as urbanization rises. Figure 4 provides complementary evidence for the mental health pathway: hot days significantly increase mental distress in highly urbanized provinces (Groups 4 and 5), but not in less urbanized ones. Moreover, the coefficient for Group 5 is larger than that for Group 4, consistent with the stronger IPV effects observed in more urbanized areas.

While these findings provide suggestive evidence that mental health may mediate the relationship between heat and IPV, a couple of limitations remain. First, the analysis cannot rule out the possibility that heat waves affect both IPV and mental distress simultaneously, or that IPV itself worsens men’s mental health. In addition, the PHQ-9 primarily captures depressive symptoms, which may not perfectly align with the psychological mechanisms such as heightened aggression that the literature often associates with heat and violence. To address this concern, I complement the PHQ-9 results with an alternative measure of mental well-being in Section 6.1, based on the World Values Survey, which also shows significant deterioration during heat waves. Taken together, the results should be interpreted as suggestive evidence consistent with a mental health pathway, rather than definitive proof.

⁸Since the value for the province of Callao was unavailable in 2007, I imputed it using the 2017 Census.

Table 8: The effects of heat wave on mental distress: Urban vs. Rural heterogeneity

	Mental Distress Index	
	(1)	(2)
Panel A: Urban areas		
Z-Hotdays (max)	0.024*** (0.005)	
Z-Colddays (max)	-0.011 (0.013)	
Z-Hotdays (mean)		0.006 (0.010)
Z-Colddays (mean)		0.000 (0.015)
Observations	25025	25025
ymean	-0.175	-0.175
Panel B: Rural areas		
Z-Hotdays (max)	0.002 (0.007)	
Z-Colddays (max)	-0.004 (0.006)	
Z-Hotdays (mean)		-0.007 (0.006)
Z-Colddays (mean)		0.016** (0.007)
Observations	31286	31286
ymean	-0.157	-0.157
Year \times Month FE	Yes	Yes
Province \times Year FE	Yes	Yes
Controls	Yes	Yes
Hot: diff (Urban–Rural)	.035	.01
p-value	.001	.153

Note: The analyses control for age, wealth level, cohabitation status, and education level. The regressions include month-by-year and province-by-year fixed effects. Standard errors clustered at the province level in parenthesis. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

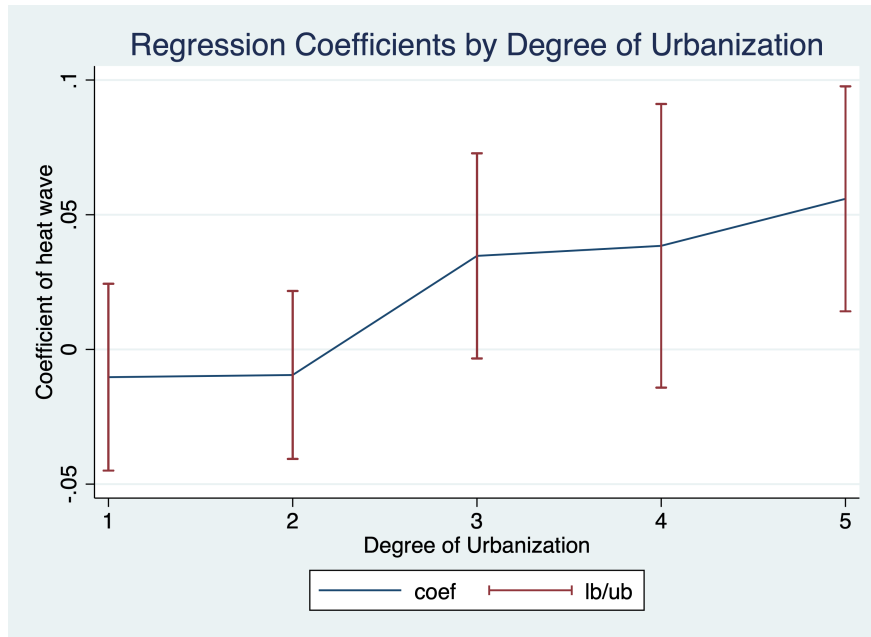


Figure 3: The impact of heat waves on IPV calls for each group

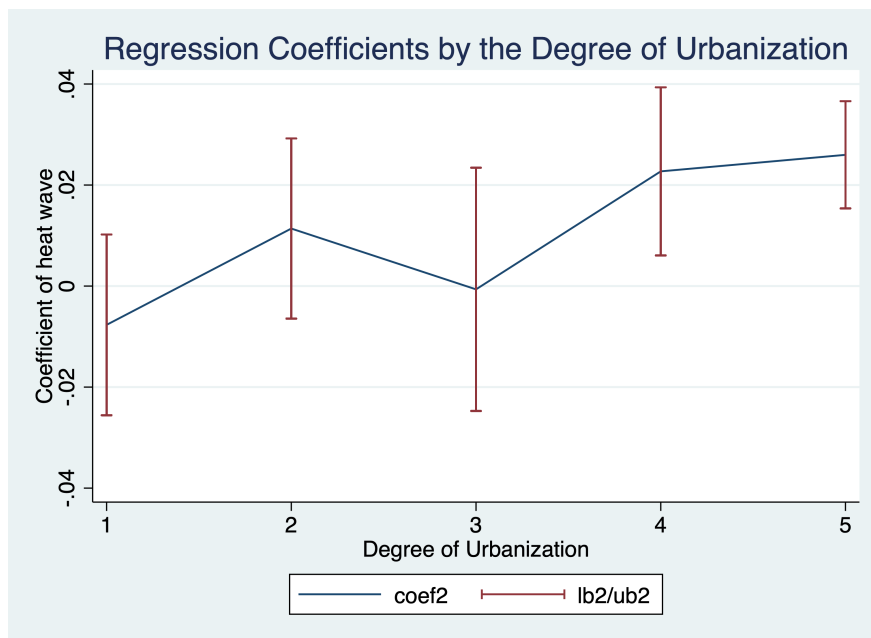


Figure 4: The impact of heat waves on the stress index for each group

5.4 Community Violence Channel

(Ranson, 2014; Hsiang et al., 2013). These spikes in community violence may make violent

behavior more visible and seemingly more acceptable, which prior research links to higher IPV risk (Mattina, 2017; Gutierrez and Gallegos, 2016; Noe and Rieackmann, 2013; Hossain et al., 2024). Building on this literature, this section examines whether heat-induced increases in community violence, along with greater tolerance of violent behavior, contribute to higher IPV rates.

To analyze this pathway, I estimate the relationship between heat waves and community crimes using the following model:

$$Crime_{pmy} = \alpha + \beta Z_Hotdays_{pmy} + \gamma Z_Colddays_{pmy} + \mu_{py} + \delta_{my} + \epsilon_{pmy} \quad (7)$$

where the dependent variable, $Crime_{pmy}$, represents the number of crimes per 10,000 people in province p , month m , and year y . I separately examine total crimes and public safety-related crimes, the latter including offenses against body, life, and health; freedom; public safety; public tranquility; humanity; and state and national defense. The key independent variable, $Z_Hotdays_{pmy}$, captures the standardized number of hot days in province p , month m , and year y , while $Z_Colddays_{pmy}$ denotes the number of cold days. The model incorporates province-by-year and month-by-year fixed effects, and standard errors are clustered at the province level.

Table 9 reports the baseline results. Columns (1) and (3) show that when hot days are measured using maximum temperature, heat waves significantly increase both total crimes and public-safety-related crimes. In contrast, columns (2) and (4), which use mean temperature, yield small and statistically insignificant coefficients. Cold days do not appear to have robust effects in either specification. Overall, the evidence indicates that extreme heat, not cold, is the main climatic driver of community violence.

Table 9: The effects of heat waves on community violence

	All Crimes		Public Safety-Related Crimes	
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.072** (0.035)		0.063*** (0.019)	
Z-Colddays (max)	0.063 (0.113)		-0.017 (0.052)	
Z-Hotdays (mean)		0.004 (0.032)		0.028 (0.020)
Z-Colddays (mean)		0.015 (0.071)		-0.037 (0.036)
Observations	6367	6367	6367	6367
ymean	5.446	5.446	2.237	2.237
Year \times Month FE	Yes	Yes	Yes	Yes
Province \times Year FE	Yes	Yes	Yes	Yes

Note: Columns (1) and (2) use as the dependent variable the total number of crimes reported per 10,000 people. Columns (3) and (4) use public-safety-related crimes reported per 10,000 people as the dependent variable. Standard errors are clustered at the province level and are presented in parentheses. Significance is indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 examines heterogeneity by urbanization. The results indicate a clear urban effect: for public-safety-related crimes, heat waves raise crime significantly in urban provinces, with effects of 0.127 and 0.108 per 10,000 people in columns (3) and (4). In contrast, the corresponding rural coefficients are close to zero and statistically insignificant, and the difference between urban and rural effects is itself significant, confirming that the impact is concentrated in urban settings. For total crimes, the urban effect is also positive, with weaker significance, suggesting that heat-induced violence is more robustly detected when focusing on public-safety-related offenses. Taken together, these results highlight that urban areas are not only the primary locus of heat-induced increases in community violence but also systematically more affected than rural provinces. This urban-centered pattern is consistent with the main IPV findings, reinforcing the interpretation that community-level unrest may amplify intra-household tensions in cities.

Table 10: The effects of heat waves on community violence: Urban vs. Rural heterogeneity

	All Crimes		Public Safety-Related Crimes	
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.040 (0.035)		0.030 (0.021)	
Z-Hotdays (max) × Urban	0.090 (0.082)		0.097** (0.042)	
Z-Colddays (max)	0.090 (0.136)		-0.024 (0.060)	
Z-Colddays (max) × Urban	-0.104 (0.175)		0.033 (0.091)	
Z-Hotdays (mean)		-0.039 (0.031)		-0.013 (0.019)
Z-Hotdays (mean) × Urban		0.128* (0.073)		0.121*** (0.038)
Z-Colddays (mean)		0.020 (0.078)		-0.036 (0.037)
Z-Colddays (mean) × Urban		-0.028 (0.137)		-0.014 (0.082)
Observations	6367	6367	6367	6367
y _{mean}	5.446	5.446	2.237	2.237
Year × Month FE	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes
Urban effect (hot)	.13	.089	.127	.108
p-val (urban hot)	.088	.192	.001	.003

Note: Columns (1) and (2) use as the dependent variable the total number of crimes reported per 10,000 people. Columns (3) and (4) use public-safety-related crimes reported per 10,000 people as the dependent variable. Standard errors are clustered at the province level and are presented in parentheses. Significance is indicated as follows: * p<0.1, ** p<0.05, *** p<0.01.

I then turn to attitudes toward violence. If hot weather heightens exposure to violent behavior, it may also shape individuals' acceptance of violence. Using male responses on whether wife-beating, child-beating, violence against others, or suicide are justifiable, I construct an index of violence acceptance and estimate:

$$ViolenceAccept_{irmy} = \alpha + \beta Z_Hotdays_{irmy} + \gamma Z_Colddays_{irmy} + X_{irmy}\phi + \mu_r + \delta_{my} + \epsilon_{irmy} \quad (8)$$

where $ViolenceAccept_{irmy}$ is the standardized index for individual i in region r , month m , and year y . Controls include age, education, number of children, and household characteristics. Region and month-by-year fixed effects are included, with standard errors clustered at the region level.

Table 11 reports the results. Panel A shows that a one standard deviation increase in hot days (measured by maximum temperature) significantly raises the violence acceptance index (column 1), with especially strong effects on justification for wife-beating (0.185) and suicide (0.192). Significant increases are also found for violence against others, while no effect appears for child-beating. Panel B, using mean temperature, shows similar but somewhat weaker patterns, with positive and significant effects for wife-beating and suicide. These findings suggest that hot weather increases men’s acceptance of violence, particularly toward spouses and others, consistent with greater exposure to violent environments.

While these results support the interpretation that community violence and the acceptance of violence are mechanisms linking heat waves to IPV, some caveats remain. It is possible that heat simultaneously increases IPV and community violence, and that the higher acceptance of violence observed in the data reflects this greater exposure rather than a clear shift in norms. Moreover, social norms rarely change after brief exposure, so the observed increases may capture short-term tolerance rather than lasting attitudinal change. Nonetheless, these patterns suggest that sustained or repeated exposure to extreme heat could gradually erode norms against violence, amplifying both community-level unrest and IPV over time.

6 Robustness Checks

6.1 Alternative Measure of Mental Health

In Section 3, I document an increase in IPV during heat waves, and in Section 5.3, I identify a mental health pathway that can mediate the rise in IPV calls, using PHQ-9 scores as an indicator. To further validate this mental health channel, I employ an alternative data source to measure mental health. Specifically, I use data from the World Values Survey

Table 11: The Impact of Hot Days on Males' Acceptance of Violence

	(1) Violence Accept Index	(2) Justify Beat wife	(3) Justify Beat child	(4) Justify violence(others)	(5) Justify suicide
Panel A: Max Temp					
Z-Hotdays (max)	0.1317*** (0.046)	0.1848*** (0.058)	0.0611 (0.043)	0.0958* (0.056)	0.1920*** (0.057)
Z-Colddays (max)	0.0531 (0.068)	0.0829 (0.082)	-0.0123 (0.059)	0.0525 (0.079)	0.0846 (0.073)
Panel B: Mean Temp					
Z-Hotdays (mean)	0.1177 (0.071)	0.1709** (0.076)	0.0750 (0.062)	0.0706 (0.078)	0.1608* (0.089)
Z-Colddays (mean)	0.0480 (0.071)	0.1500 (0.090)	-0.0212 (0.062)	-0.0052 (0.097)	0.0653 (0.092)
Observations	1303	1301	1302	1297	1285
ymean	0.021	0.030	0.013	0.000	0.032
Year \times month FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Note: The sample for the analysis is males. The regressions control for cold days, education level, age, and the number of children. Standard errors are clustered at the region level and are presented in parentheses. Significance is indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(WVS) Wave 6 (2012) and Wave 7 (2018) to investigate whether heat waves worsen mental health among male spouses.

The WVS includes two relevant survey questions: one measuring general happiness on a scale of 1–4, and the other assessing current life dissatisfaction on a scale of 1–10. Using the responses to these questions, I recode, standardize the scores and construct a composite mental well-being index. I then estimate Eq. 6 to evaluate the impact of heat waves occurring within the 30 days prior to the survey date on this index. Importantly, heat waves in this analysis are defined at the region level rather than the province level, as the WVS dataset provides only region-level information for survey participants.

Since this alternative measure of mental well-being is based on individuals' assessments of general life satisfaction, one concern is whether a recent heat wave could significantly influence a measure typically associated with long-term well-being. While much of the literature

on life satisfaction and climate focuses on long-term impacts of climatic attributes, recent studies also show short-term effects. For instance, [Levinson \(2012\)](#) examines the impact of daily temperature on life satisfaction, [Connolly \(2013\)](#) investigates the effects of daily rain and high temperatures, and [Li et al. \(2024\)](#) analyze the role of monthly temperature. These findings suggest that short-term climatic variations can meaningfully influence self-reported life satisfaction, supporting its use in this analysis.

Table 12 presents the estimation results for the impact of heat waves on mental well-being among male spouses. Column (1) shows that a one standard deviation increase in the number of hot days leads to a significant decrease in the mental well-being⁹. This result can be further decomposed into significant increases in both the happiness z-score and the life satisfaction z-score, which are components of the index, as shown in Columns (2) and (3). These estimates are consistent with and further support the robustness of the mental health channel reported in Table 7.

Table 12: The Impact of Hot Days on Mental Health

	(1)	(2)	(3)
	Mental Health Index	Z-Happy	Z-Life Satis
Z-Hotdays (max)	-0.0925** (0.036)	-0.1121** (0.043)	-0.0738* (0.038)
Z-Colddays (max)	0.0413 (0.051)	0.0634 (0.063)	0.0198 (0.047)
Observations	771	769	770
ymean	0.025	-0.005	0.057
YearXmonth FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Sample	Married males	Married males	Married males

Note: The sample for the analysis is married males. The regressions control for cold days, education level, age, and the number of children. Standard errors are clustered at the region level and are presented in parentheses. Significance is indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

⁹I also estimate the impact of heat waves measured by daily mean temperatures, which similarly presents a significant decrease in the mental well-being index.

6.2 Falsification Test

To ensure that the relationship between heat waves and IPV calls is not driven by underlying trends or systematic factors, I conduct a falsification test. This involves assessing the effect of future heat waves on IPV calls to verify that the observed impact is due to exogenous weather shocks rather than pre-existing trends.

Specifically, I estimate a modified version of Eq.2 for urban areas, replacing the current month's heat wave variable with heat waves occurring three or more months after the survey month. This approach tests whether future weather events, which should not influence current IPV calls, show any significant effects.

The results of this falsification test are presented in Table 13. Due to the availability of weather data only up to June 2022, I begin by estimating the baseline specification for the period from January 2015 to June 2022, excluding the years 2020 and 2021, in urban provinces only. The baseline results, shown in column 1, confirm that current-month heat waves significantly increase IPV calls in urban areas.

Next, in column 2, I substitute the current month's heat wave with a heat wave occurring 3 months later. In columns 3 to 5, I progressively replace the heat wave variable with those occurring 4, 5, and 6 months later, respectively. In these future-period analyses, I find no statistically significant relationship between IPV calls and future heat waves.

These findings suggest that households do not anticipate and respond to future heat waves, and that the heat wave variable is not merely capturing unobserved factors influencing IPV trends. Therefore, the absence of significant effects in the falsification test provides robust evidence that the observed relationship between heat waves and IPV calls in the main analysis is indeed causal.

6.3 Heat Index in Urban

As an additional robustness check to better understand how urbanization influences mental well-being, I utilize a thermal comfort index to explore the correlation between human thermal strain and the degree of urbanization. The Universal Thermal Climate Index (UTCI) is widely recognized in human biometeorology as a parameter to assess the linkages be-

Table 13: Falsification Test

	IPV Calls				
	(1)	(2)	(3)	(4)	(5)
Z-Hotdays (max)	0.049*** (0.014)				
Placebo hot days (max, +3)		-0.007 (0.014)			
Placebo hot days (max, +4)			-0.013 (0.014)		
Placebo hot days (max, +5)				0.019 (0.012)	
Placebo hot days (max, +6)					-0.001 (0.014)
Observations	5940	5940	5940	5940	5940
ymean	1.509	1.509	1.509	1.509	1.509
Year \times Month FE	Yes	Yes	Yes	Yes	Yes
Province \times Year FE	Yes	Yes	Yes	Yes	Yes

Note: The regressions include month-by-year and province-by-year fixed effects. Standard errors clustered at the province level in parenthesis. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

tween the outdoor environment and human well-being (Napoli et al., 2021). The UTCI is expressed as an equivalent ambient temperature ($^{\circ}\text{C}$) in a reference environment, providing the same physiological response of a reference person as the actual environment. This measure accounts for various factors, including air temperature, humidity, wind speed, and solar radiation, as well as considerations for clothing (Blazejczyk et al., 2012). The UTCI categorizes heat stress into several levels: Moderate heat stress at $\geq 26^{\circ}\text{C}$, Strong heat stress at $\geq 32^{\circ}\text{C}$, and Very strong heat stress at $\geq 38^{\circ}\text{C}$ (Bröde et al., 2012; Napoli et al., 2018, 2021).

In this section, I use UTCI data retrieved from ERA5-Heat to investigate the correlation between urbanization and heat stress. The dataset covers January to March—the summer season in Peru—from 2017 to 2019 for each grid cell. Following the approach in Section 2.2, a province’s weather is represented using data from the grid point closest to the centroid of its most populated district.

To quantify heat stress, dummy variables are generated for *Moderate Heat Stress*, *Strong*

Heat Stress, and *Very Strong Heat Stress*, set to 1 if the daily maximum UTCI is greater than or equal to 26°C, 32°C, and 38°C, respectively. Additionally, *z_urban* is constructed as a standardized Z-score of the degree of urbanization obtained from the 2017 Census. This variable provides a standardized measure for comparing urbanization levels across provinces, enabling a more rigorous evaluation of the association between urbanization and heat stress.

Table 14 presents the correlations between urbanization and each level of heat stress. A one standard deviation increase in the degree of urbanization is associated with a higher probability of experiencing heat stress. Specifically, a one standard deviation increase in urbanization is correlated with an 11% increase in the likelihood of moderate heat stress, a 10.6% increase in strong heat stress, and a 1.1% increase in very strong heat stress.

This analysis highlights a strong correlation between urbanization and thermal strain, offering a potential explanation for the higher mental distress observed in urban areas in Section 5.3. These findings suggest that the higher prevalence of heat stress in urban settings likely contributes to the observed disparity in mental health outcomes between urban and rural areas.

Table 14: The correlation between heat stress and urbanization

	(1) Moderate Heat stress	(2) Strong Heat stress	(3) Very strong Heat stress
<i>z_urban</i>	0.1098*** (0.029)	0.1055*** (0.028)	0.0113* (0.007)
Observations	47520	47520	47520
ymean	0.492	0.258	0.024
Dep. X Year FE	Yes	Yes	Yes
Month X Day FE	Yes	Yes	Yes

Note: Each column represents a separate regression of each degree of heat stress on the Z-score of urbanization. Standard errors clustered at the province level in parenthesis. The regressions include month-by-day and department-by-year fixed effects. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

7 Conclusion

This paper examines the causal relationship between extreme heat and the incidence of IPV. Unlike existing studies, it focuses on short-term and acute weather events—specifically, heat waves—and identifies a particularly vulnerable group: urban populations. The findings demonstrate that heat waves significantly increase the risk of IPV, with the impact being more pronounced in urban areas. Moreover, suggestive evidence indicates that male spouses in urban settings experience greater mental health deterioration compared to their rural counterparts, which serves as a key channel contributing to the rise in violence. Additionally, the results highlight community violence as a potential mechanism, showing that heat waves intensify public safety-related crimes, particularly in urban areas, thereby creating an environment that fosters IPV.

This paper has a couple of limitations. First, using helpline call data may present certain challenges. If temperature shocks lead to behavioral changes—such as a reduced likelihood of seeking third-party help during IPV incidents—then using helpline call data might introduce bias or only capture the patterns of individuals who actively seek help. Nevertheless, this would likely result in an underestimation of the true impact of heat waves, suggesting that the actual effect could be even greater in the same direction. Additionally, using helpline call data effectively captures instances that are severe enough to require immediate assistance, thereby reflecting the most critical cases of domestic violence.

Second, this study cannot fully disentangle the specific pathways through which heat waves influence IPV because of potential violations of exclusion restrictions. Exclusion restrictions require that the identified pathways—such as mental well-being and community violence—are not influenced by other unobserved factors that simultaneously affect IPV. In this case, heat waves may trigger broader changes which could interact with multiple pathways, making it challenging to isolate the independent effect of each mechanism. While my findings provide suggestive evidence for certain pathways, the violation of exclusion restrictions limits the ability to draw definitive causal conclusions about their roles.

This paper highlights several policy implications. First, it emphasizes the importance of targeted heat mitigation strategies in urban areas, including infrastructure improvements

such as expanding green spaces and adopting cool roofs to reduce heat exposure. Addressing the mental health impacts of extreme heat is equally crucial. Expanding access to mental health services, such as tele-health initiatives and mobile mental health units, can help mitigate the link between heat waves and violence. Public awareness campaigns can further educate residents on coping strategies for heat-induced stress. Additionally, this study underscores the need to address community violence during heat waves, as rising violent crimes can reinforce harmful attitudes toward IPV. Policies should focus on strengthening community-based violence prevention programs and challenging norms that justify violence during periods of extreme heat.

Future research should further explore the psychological dimensions associated with extreme heat and their impact on behavior. Conducting short-term longitudinal surveys could offer valuable insights into how stress and violence patterns evolve in response to temperature fluctuations over days, weeks, or months. Additionally, investigating the effectiveness of psychological strategies in mitigating stress and reducing domestic violence is a promising area for study. This approach can provide a deeper understanding of how urban stressors interact with climate variables over time, further informing policy and intervention strategies.

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Appendix Tables

Table A.1: The effects of temperature on IPV

	IPV calls	
	(1) est1	(2) est2
Max temp: Below 10°C	0.001 (0.006)	
Max temp: 10°C - 15°C	0.001 (0.003)	
Max temp: 20°C - 25°C	0.008*** (0.001)	
Max temp: 25°C - 30°C	0.014*** (0.002)	
Max temp: Above 30°C	0.021*** (0.003)	
Mean temp: Below 5°C		0.000 (0.005)
Mean temp: 5°C - 10°C		-0.004 (0.004)
Mean temp: 10°C - 15°C		-0.007* (0.003)
Mean temp: 20°C - 25°C		0.008*** (0.001)
Mean temp: Above 25°C		0.016*** (0.002)
Observations	13680	13680
ymean	1.405	1.405
Year × Month FE	Yes	Yes
Province × Year FE	Yes	Yes

Note: Standard errors clustered at the province level in parenthesis. The regressions control for month-by-year and province-by-year fixed effects. All regressions are estimated in levels, though estimates are reported as percent changes from the mean monthly call rate. The baseline temperature bin is 15°C-20°C. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: The effects of heat waves on IPV calls: Lowlands vs. Highlands

	IPV calls					
	(1) All	(2) Urban	(3) Rural	(4) All	(5) Urban	(6) Rural
Panel A: Lowlands						
Z-Hotdays (max)	0.053*** (0.019)	0.055* (0.031)	0.023 (0.027)			
Z-Colddays (max)	-0.061*** (0.020)	-0.031 (0.028)	-0.046 (0.033)			
Z-Hotdays (mean)				0.074*** (0.018)	0.091** (0.035)	0.045** (0.021)
Z-Colddays (mean)				-0.051** (0.021)	-0.053 (0.032)	-0.036 (0.031)
Observations	4176	1656	2520	4176	1656	2520
ymean	1.599	2.010	1.329	1.599	2.010	1.329
Panel B: Highlands						
Z-Hotdays (max)	0.013 (0.013)	0.061*** (0.020)	-0.009 (0.015)			
Z-Colddays (max)	0.005 (0.013)	-0.013 (0.023)	0.024 (0.015)			
Z-Hotdays (mean)				0.024* (0.013)	0.074*** (0.019)	-0.001 (0.015)
Z-Colddays (mean)				0.011 (0.013)	0.001 (0.024)	0.027* (0.015)
Observations	9504	1800	7704	9504	1800	7704
ymean	1.320	1.703	1.231	1.320	1.703	1.231
Year \times Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Province \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the province level in parentheses. All models include month-by-year and province-by-year fixed effects. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: The effects of temperature on IPV: Urban vs. Rural

	IPV calls			
	(1) Urban	(2) Rural	(3) Urban	(4) Rural
Max temp: Below 10°C	-0.007 (0.011)	0.006 (0.008)		
Max temp: 10°C - 15°C	0.002 (0.006)	0.002 (0.003)		
Max temp: 20°C - 25°C	0.007*** (0.002)	0.002 (0.002)		
Max temp: 25°C - 30°C	0.012*** (0.003)	0.004 (0.004)		
Max temp: Above 30°C	0.018*** (0.004)	0.011** (0.005)		
Mean temp: Below 5°C			-0.004 (0.010)	0.005 (0.005)
Mean temp: 5°C - 10°C			-0.006 (0.008)	-0.001 (0.004)
Mean temp: 10°C - 15°C			-0.008 (0.008)	-0.004 (0.004)
Mean temp: 20°C - 25°C			0.007*** (0.001)	0.002 (0.003)
Mean temp: Above 25°C			0.013*** (0.003)	0.011*** (0.004)
Observations	3456	10224	3456	10224
y _{mean}	1.850	1.255	1.850	1.255
Year × Month FE	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the province level in parenthesis. The regressions control for month-by-year and province-by-year fixed effects. All regressions are estimated in levels, though estimates are reported as percent changes from the mean monthly call rate. The baseline temperature bin is 15°C-20°C. Significance is indicated at * p<0.1, ** p<0.05, *** p<0.01

Table A.4: The effects of heat wave on per-capita household net income

	Log of real per-capita household net income during the last month			
	(1) Urban	(2) Rural	(3) Urban	(4) Rural
Z-Hotdays (max)	-0.021 (0.029)	-0.022 (0.035)		
Z-Colddays (max)	0.034 (0.026)	0.005 (0.023)		
Z-Hotdays (mean)			-0.007 (0.035)	-0.039 (0.033)
Z-Colddays (mean)			0.009 (0.027)	-0.015 (0.027)
Observations	17698	13992	17698	13992
ymean	5.593	4.855	5.593	4.855
Household FE	Yes	Yes	Yes	Yes
Year \times Month FE	Yes	Yes	Yes	Yes
Province \times Year FE	Yes	Yes	Yes	Yes

Note: The outcome variable is the log of real per-capita household net income during the last month. Columns 1 and 3 restrict the sample to urban households, and Columns 2 and 4 to rural households. Standard errors clustered at the province level in parenthesis. The regressions control for household, month-by-year and province-by-year fixed effects. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: The effects of heat wave on mobility: Urban vs. Rural heterogeneity

	(1) Parks (Urban)	(2) Residential (Urban)	(3) Parks (Rural)	(4) Residential (Rural)
Panel A: Max temp				
Hotday (d)	1.471** (0.675)	-0.238 (0.158)	3.044*** (0.589)	-0.212** (0.083)
Coldday (d)	-1.837*** (0.522)	0.431*** (0.129)	-3.503*** (0.555)	0.292*** (0.092)
Observations	16136	16136	21330	21330
ymean	15.017	8.394	30.099	2.658
Panel B: Mean temp				
Hotday(Mean) (d)	2.109*** (0.779)	-0.474*** (0.163)	2.224*** (0.624)	-0.147** (0.069)
Coldday(Mean) (d)	-1.036* (0.562)	0.333*** (0.115)	-1.397** (0.582)	0.196* (0.099)
Observations	16136	16136	21330	21330
ymean	15.017	8.394	30.099	2.658
Year \times Month FE	Yes	Yes	Yes	Yes
Province \times Month FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the province level in parenthesis. All specifications include month-by-year, province-by-month, and day-of-week fixed effects. Significance is indicated at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$