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 more pronounced effects in urban areas. Two mechanisms are identified: First, heat waves exacerbate stress and mental health issues among male spouses in urban settings, increasing the likelihood of violent behavior. Second, heat waves contribute to heightened community violence, which reinforces social norms that normalize aggressive behavior within households. 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. Specifically, this paper discusses the immediate response to the high temperature shock uncovering mediating pathways behind the relationship. My empirical approach for the causal relationship relies on matching the intimate partner violence occurrences to weather conditions at province and monthly level. I construct a panel data using geo-coded temperature data and monthly volume of helpline calls for intimate partner violence in Peru. Then, I apply two-way fixed effects regression models which yield estimates identified from

variation in weather conditions within a particular location and calendar month, controlling for annual local-level idiosyncrasies. Such variation is considered to be 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 province.

My principal finding is that heat waves promptly lead to an increase in intimate partner violence in Peru. Specifically, a one standard deviation (SD) increase in the number of hot days per month is associated with a 2.0% increase in IPV helpline calls compared to the mean number of calls. Moreover, the impact is more concentrated on urban areas. In urban provinces, a significant increase in IPV calls is observed, reaching a 2.3% increase compared to the mean number of calls. However, in rural provinces, an increase in the number of hot days does not significantly affect IPV calls.

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 channel explores the impact of heat waves on household income. Previous studies have shown that negative income shocks can increase 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 the impact of heat waves on household income across farm and non-farm households. The findings reveal no significant changes in income levels for either group, indicating that the income channel is unlikely to play a role in this context.

Exposure Channel: The second pathway explores whether heat waves alter patterns of indoor or outdoor activity, potentially affecting exposure to violent partners. This "exposure" mechanism has been extensively studied in the context of the Covid-19 pandemic recently. For instance, Leslie and Wilson (2020) and Bullinger et al. (2021) found that stay-at-home (SAH) policies increased time spent at home, thereby heightening the risk of IPV due to closer proximity to violent partners. To investigate this channel, I analyze mobility and time-use data during heat waves. The results show that time spent indoors decreases, while outdoor activity increases, which may reduce exposure to IPV in this setting.

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, which may normalize violent behavior and shift social norms toward greater acceptance of IPV. Existing literature highlights the role of community-level violence in driving IPV. For example, Mattina (2017) and Gutierrez and Gallegos (2016) demonstrate that early exposure to violence at the community level increases IPV risk in adulthood. Similarly, Noe and Rieackmann (2013) and Hossain et al. (2024) show that contemporaneous conflicts and rising conflict intensity increase IPV in Colombia and Nepal, respectively. Drawing on this framework, I analyze crime data in Peru to evaluate the relationship between heat waves and community violence. The results indicate that heat waves significantly increase community violence, potentially normalizing violent behaviors. Moreover, heat waves appear to influence attitudes toward violence, increasing male acceptance of IPV. This shift in acceptance suggests that heat waves may have a lasting impact on intra-household dynamics and IPV, extending beyond their immediate effects.

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 contributes to the existing literature in several ways. First, it provides new evidence that heat waves lead to an increase in intimate partner violence in developing coun-

tries. Prior research has largely focused on rainfall shocks in rural areas and their associated income channels, often overlooking the effects of temperature (Sekhri and Storeygard, 2014; Abiona and Koppensteiner, 2021; Díaz and Saldarriaga, 2023; Zhu et al., 2023). Only small body of research addresses temperature shocks (Sekhri and Storeygard, 2014; Abiona and Koppensteiner, 2021; Díaz and Saldarriaga, 2023; Bollman et al., 2023), but these studies typically rely on annually averaged temperatures to evaluate cumulative effects on IPV over the year. This long-term approach can obscure the acute impacts of heat waves because averaged temperatures can mask the presence of heat waves, as cooler days may lower the overall average. However, by focusing on daily temperature fluctuations and monthly incidents of IPV, this study reduces the risk that lower-temperature days will obscure the true occurrence and impact of heat waves and thus enhances our understanding of the impacts of heat waves.

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 improves upon existing research by utilizing helpline call data, which offers a more precise measure of IPV incidents. As an administrative source, this data reduces the inconsistencies that frequently arise from long-term reporting practices. Previous studies, including those by Zhu et al. (2023), Bollman et al. (2023), and Díaz and Saldarriaga (2023), use Demographic and Health Survey (DHS) that captures IPV experiences over the past year. This retrospective approach can introduce recall bias, as respondents may focus more on recent events rather than reflecting on the entire year, and it also depends on individuals' willingness to disclose their experiences. Especially, Díaz and Saldarriaga (2023) presents no impact of temperature using averaged temperature shocks over longer-term periods and longer-term reference period of IPV in Peru. In contrast, the monthly

helpline data enables more reliable tracking of variations in IPV over time, overcoming these issues.

The organization of the paper is as follows. Section 2 introduces data sources. Section 3 presents the empirical results. Section 4 introduces the mechanisms and uncover the mechanisms empirically. Section 5 provides robustness checks. Section 6 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). 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 ECMWF Reanalysis dataset (ERA-5 reanalysis), which provides hourly temperature and precipitation data from 2005 to 2022 at 0.25 $\times$ 0.25 degree resolution. I define monthly occurrences of heat waves at the provincial level based on the most populated district within each province. Specifically, the weather data

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

[2]Peru 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.

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 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.

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 $5°C$-wide bins, ranging from $< 10°C$ to $> 30°C$. Similarly, I group daily mean temperatures into bins from $< 5°C$ to $> 25°C$. 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	18240	1.801	1.780	0	17.670
Z-score of number of hot days (max temp)	18240	0.386	0.828	0	6.595
Z-score of number of hot days (mean temp)	18240	0.375	0.865	0	6.860
Number of days with temp below 10	18240	1.183	3.718	0	31.000
Number of days with temp 10-15	18240	8.712	11.102	0	31.000
Number of days with temp 15-20	18240	7.751	10.477	0	31.000
Number of days with temp 20-25	18240	5.849	10.231	0	31.000
Number of days with temp 25-30	18240	4.326	8.235	0	31.000
Number of days with temp above 30	18240	2.617	6.722	0	31.000

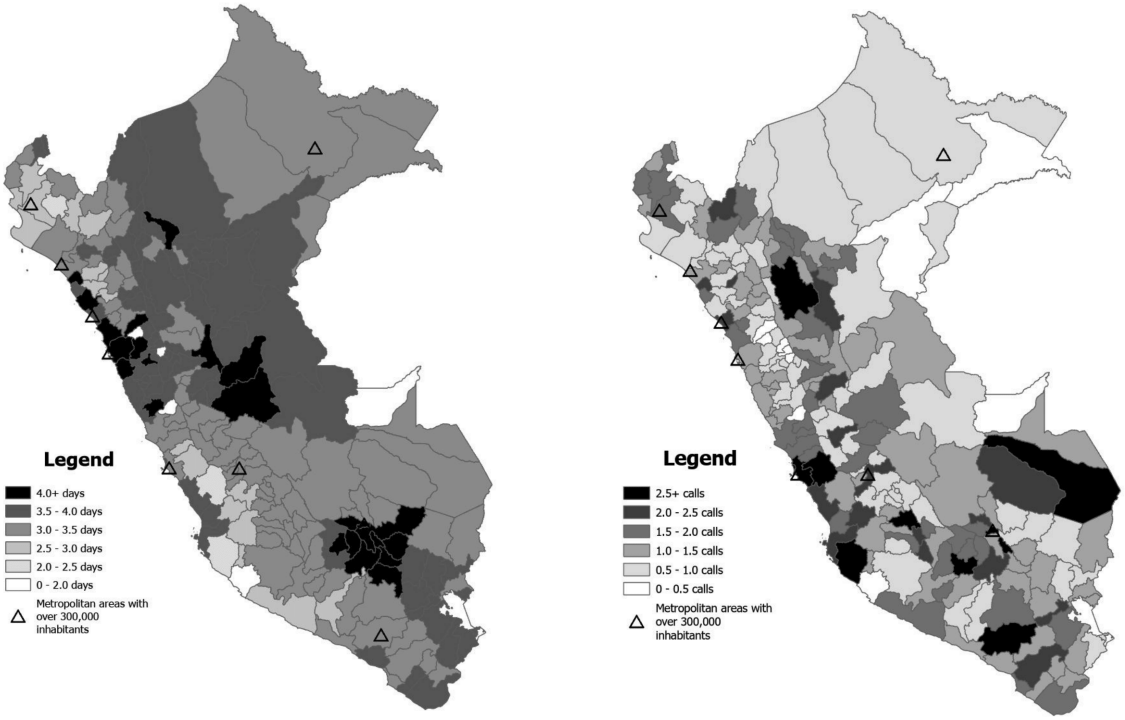
2.3 Channel Outcome Variables

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 conditions[3]. 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.

Using data on total gross and net income for each household, recorded daily, weekly,

[3]The 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

biweekly, or monthly, I construct real monthly income variables: the logarithms of monthly gross income and monthly net income.

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 days[4].

[4]The 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

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 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.

2.4 Sub-samples: urbanization

To estimate the heterogeneous impact of heat waves based on urbanization, I utilize data from the 2007 Peruvian Census, which provides information on the level of urbanization in each province, ranging from 0% to 100%. I construct a variable, *urban*, to reflect the degree of urbanization. Provinces with a scale greater than 50 are classified as urban ($urban = 1$), while those with a scale of 50 or below are classified as rural ($urban = 0$). For the province of Callao, where urbanization data was unavailable in the 2007 Census, I imputed the value using data from the 2017 Census. As a results, among the 196 sample provinces, 91 provinces are classified as urban and 105 provinces are classified 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.

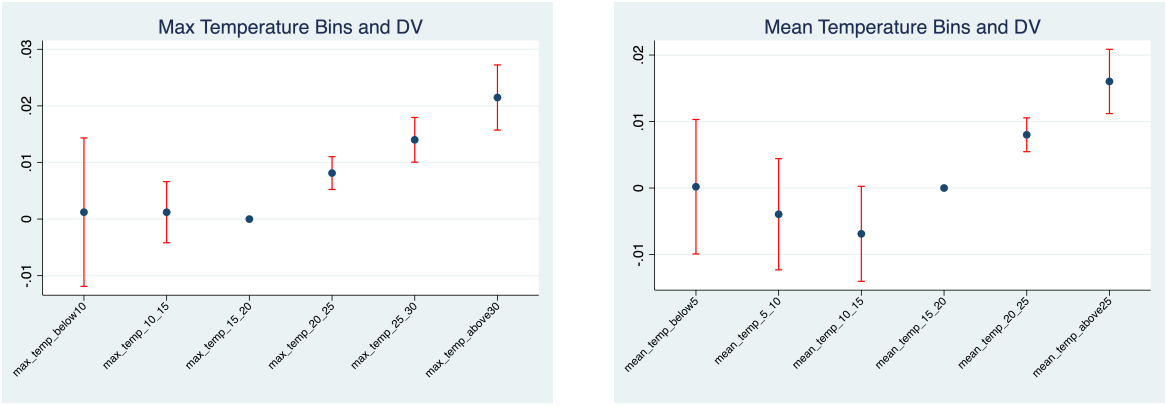
3.1 Absolute Measure of Heat Wave: Temperature Bins Specification

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. Equation (1) describes the first model for estimating the effects of temperature on IPV.

$$IPV_{prmy} = \alpha + \beta \sum_{k} Tbin_{k,prmy} + \mu_{my} + \delta_{py} + \epsilon_{prmy} \tag{1}$$

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 Equation (1) are summarized in Figure 2, which plots the point estimates and 95% intervals for the estimates of the β_j terms using daily mean and maximum temperatures respectively. For both outcomes, there is a clear upward-sloping pattern for the temperature bins above 15°C, indicating that additional hot days increase IPV occurences. 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. Equation (2) outlines the model used to estimate the impact of relative measures of heat waves on IPV:

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

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 Equation (2) are presented in Table 2. I find that a one standard

deviation (1SD) increase in the number of hot days which is measured using daily maximum temperature in a month increases helpline calls by 2.0%[5] in column (2). Also, a 1SD increase in the number of hot days which is measured using daily mean temperature in a month increases helpline calls by 3.1% in column (4) of Table 2.

Table 2: The effects of heat waves on IPV incidents

	IPV Calls			
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.0297***	0.0279***		
	(0.010)	(0.010)		
Z-Colddays (max)		-0.0159		
		(0.012)		
Z-Hotdays (mean)			0.0435***	0.0432***
			(0.010)	(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<.001

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

[5]For comparability,the coefficients are divided by the mean dependent variable so that they can be interpreted as percent changes from the mean.

heat waves and IPV still holds using DHS data. Equation (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.

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

	IPV Indicator			
	(1)	(2)	(3)	(4)
Panel A: Heat wave for 12 months				
Z-Hotdays (max)	-0.0005	-0.0002		
	(0.002)	(0.002)		
Z-Colddays (max)		0.0029		
		(0.004)		
Z-Hotdays (mean)			0.0017	0.0012
			(0.002)	(0.002)
Z-Colddays (mean)				-0.0074
				(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)	-0.0017	-0.0016		
	(0.002)	(0.002)		
Z-Colddays (max)		0.0013		
		(0.002)		
Z-Hotdays (mean)			-0.0013	-0.0013
			(0.002)	(0.002)
Z-Colddays (mean)				0.0000
				(0.002)
Observations	109180	109180	109180	109180
ymean	0.190	0.190	0.190	0.190
Year X Month FE	Yes	Yes	Yes	Yes
Province X 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<.001

This reduces potential biases that can arise from self-reported survey data.

4 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 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).

Heterogeneity analysis shows that the adverse effects of heat waves on mental health are more pronounced in urban areas than in rural areas. A reexamination of the main causal analysis confirms that the rise in IPV is concentrated in urban settings.

4.1 Income Channel

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

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

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.[6] $Z_Hotdays_{hpt}$ 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.

[6]The income variables are all deflated and logged values.

Table 4 presents the estimated impact of heat waves on household income based on Equation (4). The results show that heat waves in the past month do not significantly affect monthly per-capita gross or net income, indicating no short-term impact on household income. I estimate the same model separately for agricultural and non-agricultural households, and no significant impact was observed for either group, as shown in columns (2) and (3) of Table 4.

Table 4: The effects of heat wave on per-capita income

	Per-Capita Gross Income		
	(1)	(2)	(3)
Z-Hotdays (max)	-0.0084	-0.0063	-0.0019
	(0.007)	(0.017)	(0.009)
Z-Colddays (max)	-0.0025	0.0079	-0.0141*
	(0.007)	(0.012)	(0.009)
	Per-Capita Net Income		
Z-Hotdays (max)	-0.0086	-0.0060	-0.0024
	(0.007)	(0.016)	(0.008)
Z-Colddays (max)	-0.0031	0.0083	-0.0159*
	(0.007)	(0.012)	(0.008)
Observations	31789	12619	17004
ymean	6.331	5.795	6.742
Household FE	Yes	Yes	Yes
Year X Month FE	Yes	Yes	Yes
Province X Year FE	Yes	Yes	Yes
Sample	All	Farm HH	Non-farm HH

Note: The outcome variables are all deflated and logged values. 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<.001

To further investigate, I examine whether heat waves might specifically affect income in rural areas differently from general household income, given that agriculture is a primary income source in rural areas. To address this, I estimate Equation (4) separately for urban and rural areas, with results provided in Table A.1. Table A.1 confirms the findings from Table 4, showing no significant short-term impact of heat waves on income in either urban or rural areas.[7] This indicates that income in rural areas is not significantly affected by

[7]I also estimated Equation (4) using heat wave shocks measured by daily mean temperatures, which

short-term heat waves. Consequently, the immediate increase in IPV associated with heat waves is not driven by income-related factors.

These findings contrast with existing literature that shows that high temperatures reduce agricultural income in the long term. Long-term studies typically use average annual temperatures to capture the cumulative effects of prolonged heat exposure, such as gradual reductions in crop yields. This discrepancy underscores the importance of considering both short-term and long-term temperature variations when evaluating their impact on income.

4.2 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. Equation (5) describes the model specification used to estimate the relationship between heat waves and mobility.

$$Y_{pdmy} = \beta_0 + \beta_1 Hotday_{pdmy} + \beta_2 Colddday_{pdmy} + \psi_{my} + \mu_d + \delta_{pm} + \epsilon_{prmy} \tag{5}$$

In this model specification, the dependent variable Y_{pdmy} 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 $Hotday_{pdmy}$ 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 5 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

yielded similar outcomes.

points on hot days, while they decrease by 2.75 percentage points on cold days, as shown in Column (1) of Panel A[8]. 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 suggests that hot weather encourages more outdoor activity, contrary to initial expectations. It can be inferred that individuals cope with hot weather by spending time outdoors, such as in parks, thereby reducing indoor time and decreasing exposure to IPV.

Table 5: The effects of heat wave on mobility

	(1) Parks	(2) Workplace	(3) Transit	(4) Residential	(5) Retail/Rec
Panel A: Max temp					
Hotday (d)	2.6039***	0.0587	0.2097	-0.2071***	0.0506
	(0.475)	(0.496)	(0.236)	(0.075)	(0.308)
Coldday (d)	-2.7537***	-0.2496	-0.7543***	0.3525***	-0.4248*
	(0.402)	(0.329)	(0.262)	(0.075)	(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)	2.1271***	-0.3911	0.0806	-0.2444***	0.2807
	(0.496)	(0.477)	(0.312)	(0.070)	(0.338)
Coldday(Mean) (d)	-1.3399***	0.9941***	-0.5504*	0.2440***	-0.0267
	(0.440)	(0.361)	(0.293)	(0.074)	(0.241)
Observations	37466	37466	37466	37466	37466
ymean	23.603	28.188	-7.634	5.129	12.101
Year X Month FE	Yes	Yes	Yes	Yes	Yes
Province X 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<.001

[8]The 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

The heterogeneous impact of heat waves on mobility is also examined based on urbanization, as discussed in Section 4.1, Table A.2 estimates Equation (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.

4.3 Mental Health Channel

Extreme temperatures can affect mental well-being of individuals. In this section, I explore the impact of heat waves on mental health using a measure of depressive symptoms and mental distress. Equation (6) describes the model specification to examine the mental health channel.

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

The dependent variable, $MentalDistress_{ipt}$, represents the index of mental distress for the husband of woman i in province p at time t measured by PHQ-9. $Z_Hotdays_{ipt}$ and $Z_Colddays_{ipt}$ are the z-scores of the number of hot and cold days, based on daily maximum temperatures during the past month or two weeks prior to the interview date. The vector X_{ipt} includes control variables of the husband's age, education, marital status, health status, household wealth, and household size. The model includes month-by-year fixed effects and province-by-year fixed effects. Standard errors are clustered at the province level.

Table 6 presents the estimation results of the heat wave on *Mental distress* for males in all provinces. Columns (1) and (2) show that a 1 standard deviation in the number of hot days during the past month or two weeks leads to a significant increase in mental distress. This suggests that men are more likely to experience heightened mental distress during heat waves.

Table 6: The effects of heat wave on mental distress

	Mental Distress			
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.0064**			
	(0.002)			
Z-Hotdays (2w, max)		0.0043*		
		(0.002)		
Z-Hotdays (mean)			0.0001	
			(0.003)	
Z-Hotdays (2w, mean)				-0.0001
				(0.004)
Observations	56382	56382	56382	56382
ymean	-0.118	-0.118	-0.118	-0.118
Year X Month FE	Yes	Yes	Yes	Yes
Province X Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the province level in parenthesis. The anayses control for cold days, age, wealth level, indicator of overweight, and education level. The regressions include month-by-year and province-by-year fixed effects. Significance is indicated at * p<0.1, ** p<0.05, *** p<.001

I also estimate the heterogeneous impact of heat waves in urban and rural areas. Columns (1) and (3) of Table 7 present the estimation results of Equation (6) in urban and rural areas separately. Interestingly, the increased level of mental distress is concentrated in urban areas. Heat waves significantly increase mental distress in urban areas. However, they do not have a significant impact in rural areas.

Next, I revisit the impact of heat waves on IPV occurrences to estimate the heterogeneity depending on urbanization, using Equation (2). This estimation aims to check whether the results are consistent with the heterogeneous outcomes observed for mental distress in column (1) and (3).

The estimates are presented in column (2) and (4) of Table 7. In urban areas, heat waves are found to increase IPV calls, whereas no such relationship is observed in rural areas. Specifically, column (2) indicate that a 1 standard deviation increase in hot days results in a rise in IPV calls by 0.0391 per 10,000 people. This figure corresponds to 2.4% increase of

IPV calls compared to the mean.

In contrast, column (4) shows null results for rural areas. Neither hot days nor cold days significantly affect the IPV calls in these areas. These results indicate that the impact of heat waves on IPV is concentrated in urban areas. Therefore, it can be concluded that individuals in urban areas are more susceptible to heat-induced mental distress, and the rise in IPV driven by deteriorating mental health is primarily concentrated in urban areas. These findings provide empirical support for the mental health channel as a mediating factor linking heat waves to IPV.

Table 7: The effects of heat wave on stress index in urban and rural areas

	(1) Mental distress (Urban)	(2) DV calls (Urban)	(3) Mental distress (Rural)	(4) DV calls (Rural)
Z-Hotdays (max)	0.0115***	0.0391***	-0.0016	0.0114
	(0.003)	(0.014)	(0.007)	(0.015)
Z-Colddays (max)	-0.0082	-0.0380***	-0.0038	0.0165
	(0.007)	(0.014)	(0.009)	(0.019)
Observations	33956	6480	22425	7200
ymean	-0.123	1.644	-0.112	1.191
Year X Month FE	Yes	Yes	Yes	Yes
Province X Year FE	Yes	Yes	Yes	Yes
Controls	Yes		Yes	

Note: The outcome variables are all deflated and logged values. 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<.001

To further confirm the relationship between urbanization and the impact of heat waves on IPV, I examine the robustness of my findings using an alternative measure of urbanization. The 2007 Peruvian Census provides data on the degree of urbanization for each province, ranging from 0 to 100%[9]

Since the urbanization values range from 0% to 100%, I divide provinces into five groups based on urbanization ranges: 0 to 20% (Group 1), 20 to 40% (Group 2), 40 to 60% (Group 3), 60 to 80% (Group 4), and 80 to 100% (Group 5).

[9]Since the degree of urbanization for the province of Callao was not available, I imputed the value based on the 2017 Census.

I then estimate Equation (2) separately for each group. Figure 3 presents the coefficients estimating the impact of heat waves on IPV calls for these groups. The results indicate that the impact of heat waves increases consistently with higher levels of urbanization. This relationship appears approximately linear, with greater urbanization corresponding to a larger increase in IPV calls during heat waves.

In addition, I estimate Equation (6) for each group to examine the mental health pathway. Figure 4 presents the coefficients estimating the impact of heat waves on the mental distress index for each group. The results show that heat waves significantly increase the mental distress of male spouses in Groups 4 and 5, with no significant effects observed for males in Groups 1, 2, and 3. Moreover, the coefficient for Group 5 is larger than that for Group 4, aligning with the findings in Figure 3, which demonstrate a greater impact of heat waves in more urbanized areas.

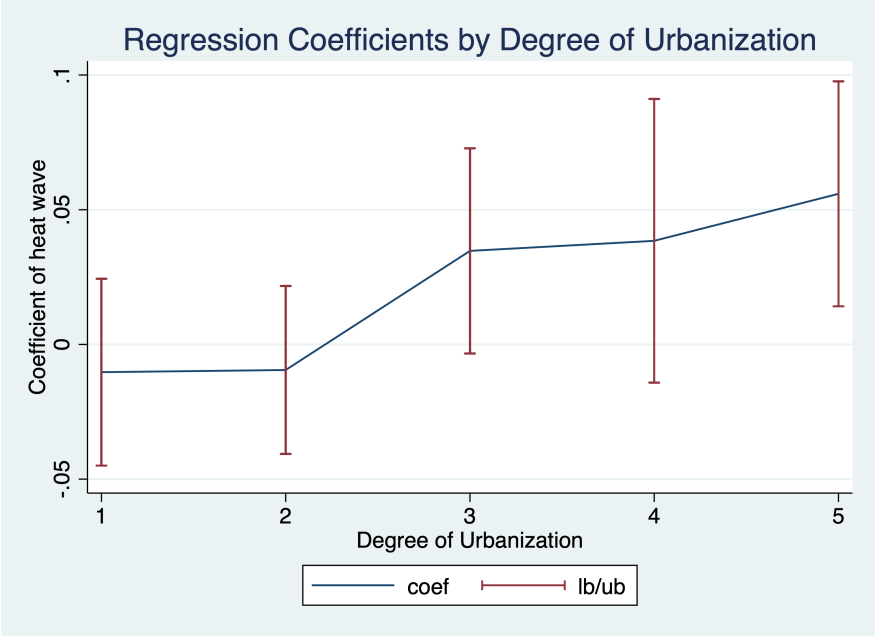


Figure 3: The impact of heat waves on DV calls for each group

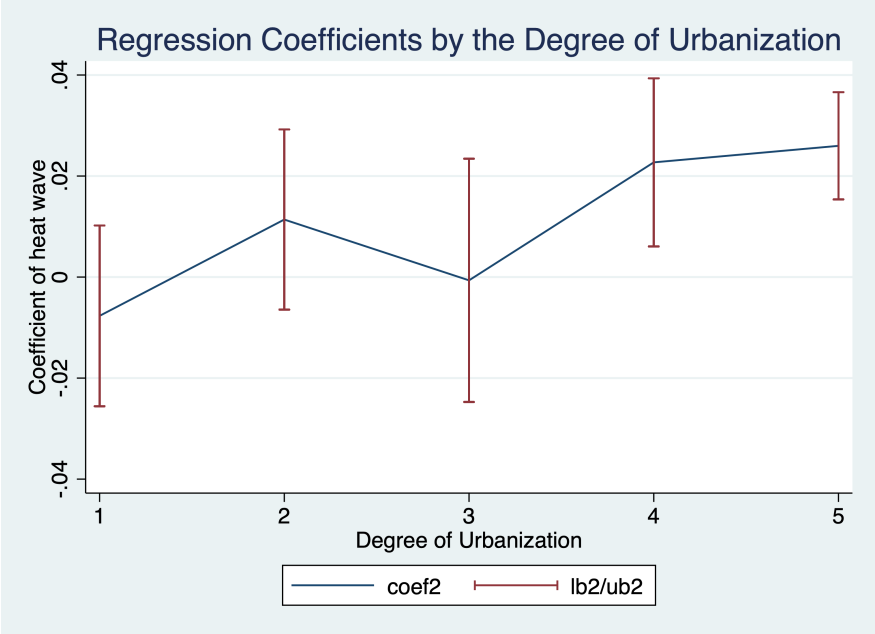


Figure 4: The impact of heat waves on the stress index for each group

4.4 Community Violence Channel

Heat waves, as climate shocks, can intensify social unrest and violence at the community level, potentially normalizing violent behavior and altering social norms (Ranson, 2014; Hsiang et al., 2013). Research finds that exposure to community violence increases the incidence of IPV (Mattina, 2017; Gutierrez and Gallegos, 2016; Noe and Rieackmann, 2013; Hossain et al., 2024). Building on this literature, this section examines the relationship between heat waves and community violence, investigating whether increased exposure to violence due to hot weather leads to higher IPV rates.

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

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

where the dependent variable, $Crime_{pmy}$, represents the number of public safety-related crimes per 10,000 in province p, month m, and year y. The public safety-related crimes include 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 Z-scores of the number of hot days in province p, month m, and year y. The specification also includes $Z_Colddays_{pmy}$, which denotes the Z-scores of the number of cold days. The model incorporates province-by-year fixed effects (μ_{py}) and month-by-year fixed effects (δ_{my}), with standard errors clustered at the province level.

The estimates in Table 8 suggests that heat waves significantly increase community violence, providing a plausible pathway through which IPV may also rise during these periods. Column (1) shows that a one standard deviation increase in the number of hot days, defined using daily maximum temperature (Z-Hotdays (max)), significantly increases public safety-related crimes. Column (2) replaces this with the mean temperature measure (Z-Hotdays (mean)), and while the coefficient is not statistically significant, it remains positive. These findings suggest that heat waves intensify social tensions, potentially leading to spillover effects on intra-household dynamics.

In column (4), the coefficient on Z-Hotdays (mean) is -0.0003 and not statistically signif-

icant, indicating that in non-urban areas, heat waves do not have a statistically discernible effect on public safety-related violence. However, the positive and significant interaction term indicates that in urban areas, an increase in the number of hot days leads to a 0.0548 increase in reported violence incidents per 10,000 people. These results highlight spatial heterogeneity in the effects of heat waves, with urban areas experiencing a more pronounced increase in public safety-related violence. These findings align with the main analysis, which shows a significant rise in IPV in urban settings.

Table 8: The effects of heat waves on community violence per 10,000

	Police Reports of Public Safety-Related Violence			
	(1)	(2)	(3)	(4)
Z-Hotdays (max)	0.0632***		0.0465**	
	(0.019)		(0.021)	
Z-Hotdays (max) × Urban			0.0340	
			(0.031)	
Z-Hotdays (mean)		0.0276		-0.0003
		(0.020)		(0.020)
Z-Hotdays (mean) × Urban				0.0548*
				(0.029)
Observations	6367	6367	6367	6367
ymean	2.237	2.237	2.237	2.237
Year × Month FE	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes

Note: 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<.001.

Additionally, I examine whether heat waves influence male spouses' attitudes toward violence, including acceptance of violence against others, wife-beating, and self-harm. To assess this, I estimate:

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

The dependent variable, $ViolenceAccept_{irmy}$, represents the index of violence acceptance for individual i in region r in month m and year y, constructed from responses on the justifiability of wife-beating, child-beating, violence against others, and suicide. The key independent variable, $Z_Hotdays_{irmy}$, is the Z-score of the number of hot days in the 30

days prior to the interview date. The model includes controls for cold days, education level, age, and the number of children, as well as fixed effects for year-by-month and region levels. Standard errors are clustered at the region level.

Table 9 presents the estimation results for the impact of heat waves on violence acceptance. Column (1) of Panel A shows that a one standard deviation increase in hot days (measured by daily maximum temperature) significantly raises the overall violence acceptance index. Column (2) indicates a significant increase in justification for wife-beating (coefficient: 0.1848). Columns (4) and (5) also show significant increases in justification for violence against others and suicide. However, column (3) finds no significant relationship between hot days and justification for child-beating.

Panel B, which defines hot days using daily mean temperature, shows similar but generally weaker patterns. Significant increases are observed in the justification for wife-beating and suicide, but no significant effects are found for child-beating or violence against others.

Table 9: 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***	0.1848***	0.0611	0.0958*	0.1920***
	(0.046)	(0.058)	(0.043)	(0.056)	(0.057)
Panel B: Mean Temp					
Z-Hotdays (mean)	0.1177		0.0750	0.0706	0.1608*
	(0.071)		(0.062)	(0.078)	(0.089)
Observations	1303	1309	1302	1297	1285
ymean	0.021	0.155	0.013	0.000	0.032
Year × 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<.001.

These results suggest that heat waves significantly increase the acceptance of violence

among males, particularly in justifications for wife-beating, violence against others, and suicide. Although the causal direction cannot be empirically disentangled, these shifts in attitudes, likely influenced by exposure to community violence during heat waves, contribute to an environment where IPV becomes more likely, and increased IPV itself may reinforce these attitudes. The findings indicate that the effects of heat waves extend beyond temporary spikes in IPV, potentially leaving lasting impacts on social norms and behaviors.

Overall, the results on community violence and attitudes toward violence illustrate how heat waves influence both observable violence and societal norms, providing deeper insights into how climate shocks exacerbate intra-household violence.

5 Robustness Checks

5.1 Alternative Measure of Mental Health

In Section 3, I document an increase in IPV during heat waves, and in Section 4, 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 (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 Equation (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 10 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-being [10]. 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 6.

Table 10: The Impact of Hot Days on Mental Health

	(1)	(2)	(3)
	Mental Health Index	Z-Happy	Z-Life Satis
Z-Hotdays (max)	-0.0925**	-0.1121**	-0.0738*
	(0.036)	(0.043)	(0.038)
Z-Colddays (max)	0.0413	0.0634	0.0198
	(0.051)	(0.063)	(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<.001.

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

5.2 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 Equation (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 11. 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.

Table 11: Falsification Test

	(1)	(2)	(3)	(4)	(5)
Z_hotdays_max_org	0.0488***				
	(0.0139)				
fal_Z_hotdays_3		-0.0074			
		(0.0139)			
fal_Z_hotdays_4			-0.0127		
			(0.0137)		
fal_Z_hotdays_5				0.0186	
				(0.0125)	
fal_Z_hotdays_6					-0.0007
					(0.0140)
Year X Month FE	Yes	Yes	Yes	Yes	Yes
Province X Year FE	Yes	Yes	Yes	Yes	Yes
ymean	1.5093	1.5093	1.5093	1.5093	1.5093
N	5940	5940	5940	5940	5940
r2	0.7302	0.7297	0.7297	0.7298	0.7297

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.

5.3 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 between the outdoor environment and human well-being (Napoli et al., 2021). The UTCI is expressed as an equivalent ambient temperature (°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 $\geq 26°C$, Strong heat stress at $\geq 32°C$, and Very strong heat stress at $\geq 38°C$ (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 12 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 4.3. 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 12: The correlation between heat stress and urbanization

	(1) Moderate Heat stress	(2) Strong Heat stress	(3) Very strong Heat stress
z_urban	0.1098***	0.1055***	0.0113*
	(0.029)	(0.028)	(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<.001

6 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.

References

Tamma A. Carleton and Solomon M. Hsiang. Social and economic impacts of climate, 2016. ISSN 10959203.

Xiaoxu Wu, Yongmei Lu, Sen Zhou, Lifan Chen, and Bing Xu. Impact of climate change on human infectious diseases: Empirical evidence and human adaptation, 2016. ISSN 18736750.

Olivier Deschênes and Michael Greenstone. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97, 2007. ISSN 00028282. doi: 10.1257/aer.97.1.354.

E Somanathan, Rohini Somanathan, Anant Sudarshan, and Meenu Tewari. The impact of temperature on productivity and labor supply: Evidence from indian manufacturing, 2021.

Matthew Ranson. Crime, weather, and climate change. *Journal of Environmental Economics and Management*, 67:274–302, 2014. ISSN 10960449. doi: 10.1016/j.jeem.2013.11.008.

Solomon M. Hsiang, Marshall Burke, and Edward Miguel. Quantifying the influence of climate on human conflict. *Science*, 341, 2013. ISSN 10959203. doi: 10.1126/science.1235367.

IPCC. Climate change 2014 synthesis report summary chapter for policymakers. *Ipcc*, 2014. ISSN 1476-4687.

Stephane Hallegatte, Mook Bangalore, Laura Bonzanigo, Marianne Fay, Tamaro Kane, Ulf Narloch, Julie Rozenberg, David Treguer, and Adrien Vogt-Schilb. *Shock Waves: Managing the Impacts of Climate Change on Poverty*. 2016. doi: 10.1596/978-1-4648-0673-5.

Javier Baez, German Caruso, Valerie Mueller, and Chiyu Niu. Heat exposure and youth migration in central america and the caribbean. volume 107, pages 446–450. American Economic Association, 5 2017. doi: 10.1257/aer.p20171053.

Melissa Dell, Benjamin F Jones, and Benjamin A Olken. What do we learn from the weather? the new climate-economy literature what do we learn from the weather? the new climate-economy literature1. *Source: Journal of Economic Literature*, 52:740–793, 2014. doi: 10.1257/jel.

Solomon Hsiang. Climate econometrics. *Annual Review of Resource Economics*, 8:43–75, 10 2016. ISSN 19411359. doi: 10.1146/annurev-resource-100815-095343.

Manuela Angelucci and Rachel Heath. Women empowerment programs and intimate partner violence. *AEA Papers and Proceedings*, 110, 2020. ISSN 2574-0768. doi: 10.1257/pandp.20201047.

Sara Cools and Andreas Kotsadam. Resources and intimate partner violence in sub-saharan africa. *World Development*, 95, 2017. ISSN 18735991. doi: 10.1016/j.worlddev.2017.02.027.

Olukorede Abiona and Martin Foureaux Koppensteiner. The impact of household shocks on domestic violence: Evidence from tanzania. *SSRN Electronic Journal*, 2021. doi: 10.2139/ssrn.3301756.

Bilge Erten and Pinar Keskin. Female employment and intimate partner violence: Evidence from syrian refugee inflows to turkey. *Journal of Development Economics*, 150, 2021. ISSN 03043878. doi: 10.1016/j.jdeveco.2020.102607.

Juan José Díaz and Victor Saldarriaga. A drop of love? rainfall shocks and spousal abuse: Evidence from rural peru. *Journal of Health Economics*, 89, 5 2023. ISSN 18791646. doi: 10.1016/j.jhealeco.2023.102739.

Rachel Heath, Melissa Hidrobo, and Shalini Roy. Cash transfers, polygamy, and intimate partner violence: Experimental evidence from mali. *Journal of Development Economics*, 143, 2020. ISSN 03043878. doi: 10.1016/j.jdeveco.2019.102410.

Katie Bollman, Judhajit Chakraborty, Leah Lakdawala, and Eduardo Nakasone. Frosty climate, icy relationships: Frosts and intimate partner violence in rural peru, 2023.

Emily Leslie and Riley Wilson. Sheltering in place and domestic violence: Evidence from calls for service during covid-19. *Journal of Public Economics*, 189, 2020. ISSN 00472727. doi: 10.1016/j.jpubeco.2020.104241.

Lindsey Rose Bullinger, Jillian B. Carr, and Analisa Packham. Covid-19 and crime effects of stay-at-home orders on domestic violence. *American Journal of Health Economics*, 7:249–280, 6 2021. ISSN 23323507. doi: 10.1086/713787.

David Card and Gordon B. Dahl. Family violence and football: The effect of unexpected emotional cues on violent behavior. *Quarterly Journal of Economics*, 126:103–143, 2 2011. ISSN 00335533. doi: 10.1093/qje/qjr001.

Craig A. Anderson. Heat and violence. *Current Directions in Psychological Science*, 10, 2001. ISSN 09637214. doi: 10.1111/1467-8721.00109.

Giulia La Mattina. Civil conflict, domestic violence and intra-household bargaining in post-genocide rwanda. *Journal of Development Economics*, 124, 2017. ISSN 03043878. doi: 10.1016/j.jdeveco.2016.08.001.

Italo A. Gutierrez and Joss V. Gallegos. The effect of civil conflict on domestic violence: The case of peru. *SSRN Electronic Journal*, 2016. doi: 10.2139/ssrn.2851158.

Dominik Noe and Johannes Rieackmann. The effect of civil conflict on domestic violence in colombia. *Poverty, Equity and Growth in Developing and Transition Countries: Statistical Methods and Empirical Analysis - Discussion Papers*, 2013.

Iqbal Hossain, Dana Bazarkulova, and Janice Compton. Effects of conflicts on labor market outcome and intimate partner violence: Evidence from nepal. *Feminist Economics*, 30:75–105, 10 2024. ISSN 1354-5701. doi: 10.1080/13545701.2024.2413369. URL https://www.tandfonline.com/doi/full/10.1080/13545701.2024.2413369.

Sheetal Sekhri and Adam Storeygard. Dowry deaths: Response to weather variability in india. *Journal of Development Economics*, 111:212–223, 11 2014. ISSN 03043878. doi: 10.1016/j.jdeveco.2014.09.001.

Yixiang Zhu, Cheng He, Michelle Bell, Yuqiang Zhang, Zafar Fatmi, Ying Zhang, Maryam Zaid, Jovine Bachwenkizi, Cong Liu, Lu Zhou, Renjie Chen, and Haidong Kan. Association of ambient temperature with the prevalence of intimate partner violence among partnered women in low- and middle-income south asian countries. *JAMA psychiatry*, 80:952–961, 9 2023. ISSN 21686238. doi: 10.1001/jamapsychiatry.2023.1958.

Jamie T. Mullins and Corey White. Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics*, 68, 12 2019. ISSN 18791646. doi: 10.1016/j.jhealeco.2019.102240.

Alan Barreca, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro. Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century, 2016.

Olivier Deschênes and Enrico Moretti. Extreme weather events, mortality, and migration. *Review of Economics and Statistics*, 91, 2009. ISSN 00346535. doi: 10.1162/rest.91.4.659.

Kathleen Beegle, Joachim De Weerdt, Jed Friedman, and John Gibson. Methods of household consumption measurement through surveys: Experimental results from tanzania. *Journal of Development Economics*, 98, 2012. ISSN 03043878. doi: 10.1016/j.jdeveco.2011.11.001.

Jorge Aggero and Verrnica Frisancho. Misreporting in sensitive health behaviors and its impact on treatment effects: An application to intimate partner violence. *SSRN Electronic Journal*, 2018. doi: 10.2139/ssrn.3103802.

Shalini Roy, Melissa Hidrobo, John Hoddinott, and Akhter Ahmed. Transfers, behavior change communication, and intimate partner violence: Postprogram evidence from rural bangladesh. *Review of Economics and Statistics*, 101:865–877, 12 2019. ISSN 15309142. doi: 10.1162/rest_a_00791.

Arik Levinson. Valuing public goods using happiness data: The case of air quality. *Journal of Public Economics*, 96:869–880, 10 2012. ISSN 00472727. doi: 10.1016/j.jpubeco.2012.06.007.

Marie Connolly. Some like it mild and not too wet: The influence of weather on subjective well-being. *Journal of Happiness Studies*, 14:457–473, 4 2013. ISSN 13894978. doi: 10.1007/s10902-012-9338-2.

Haoyang Li, Yifeng Chen, and Mingming Ma. Temperature and life satisfaction: Evidence from chinese older adults. *Ecological Economics*, 225, 11 2024. ISSN 09218009. doi: 10.1016/j.ecolecon.2024.108342.

Claudia Di Napoli, Christopher Barnard, Christel Prudhomme, Hannah L. Cloke, and Florian Pappenberger. Era5-heat: A global gridded historical dataset of human thermal comfort indices from climate reanalysis. *Geoscience Data Journal*, 8:2–10, 6 2021. ISSN 20496060. doi: 10.1002/gdj3.102.

Krzysztof Blazejczyk, Yoram Epstein, Gerd Jendritzky, Henning Staiger, and Birger Tinz. Comparison of utci to selected thermal indices. *International Journal of Biometeorology*, 56:515–535, 2012. ISSN 00207128. doi: 10.1007/s00484-011-0453-2.

Peter Bröde, Dusan Fiala, Krzysztof Błażejczyk, Ingvar Holmér, Gerd Jendritzky, Bernhard Kampmann, Birger Tinz, and George Havenith. Deriving the operational procedure for the universal thermal climate index (utci). *International Journal of Biometeorology*, 56, 2012. ISSN 00207128. doi: 10.1007/s00484-011-0454-1.

Claudia Di Napoli, Florian Pappenberger, and Hannah L. Cloke. Assessing heat-related health risk in europe via the universal thermal climate index (utci). *International Journal of Biometeorology*, 62, 2018. ISSN 00207128. doi: 10.1007/s00484-018-1518-2.

7 Appendix Tables

Table A.1: The effects of heat wave on per-capita income (Urban & Rural)

	(1) Per-Capita Gross Income (Urban)	(2) Per-Capita Gross Income (Rural)
Z-Hotdays (max)	-0.0033	-0.0215
	(0.008)	(0.019)
Z-Colddays (max)	-0.0008	-0.0073
	(0.008)	(0.016)
Observations	22431	9222
ymean	6.544	5.915
	(1) Per-Capita Net Income (Urban)	(2) Per-Capita Net Income (Rural)
Z-Hotdays (max)	-0.0033	-0.0215
	(0.008)	(0.019)
Z-Colddays (max)	-0.0008	-0.0073
	(0.008)	(0.016)
Observations	22431	9222
ymean	6.544	5.915
Household FE	Yes	Yes
Year X Month FE	Yes	Yes
Province X Year FE	Yes	Yes

Note: The outcome variables are all deflated and logged. 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<.001

Table A.2: The effects of heat wave on mobility in urab and rural areas

	(1) Parks (Urban)	(2) Residential (Urban)	(3) Parks (Rural)	(4) Residential (Rural)
Panel A: Max temp				
Hotday (d)	2.3394***	-0.2112**	2.8525***	-0.2135**
	(0.557)	(0.104)	(0.831)	(0.101)
Coldday (d)	-2.4718***	0.4108***	-3.5903***	0.2176*
	(0.460)	(0.098)	(0.686)	(0.123)
Observations	24809	24809	12657	12657
ymean	19.152	6.654	32.329	2.139
Panel B: Mean temp				
Hotday(Mean) (d)	2.2005***	-0.3872***	1.8458**	-0.0507
	(0.599)	(0.106)	(0.851)	(0.070)
Coldday(Mean) (d)	-1.5084***	0.2617**	-1.1635	0.2106**
	(0.457)	(0.100)	(0.844)	(0.097)
Observations	24809	24809	12657	12657
ymean	19.152	6.654	32.329	2.139
Year X Month FE	Yes	Yes	Yes	Yes
Province X 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<.001