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Hot tempers: Differential effects of heat and drought on domestic violence

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Abstract
Domestic violence (DV)–patterns of physical, sexual, economic, or psychological abuse by intimate partners and family members–persists as a serious national issue in Brazil despite public efforts to eliminate it. While the risk factors for and consequences of such violence are well studied, less is known about the potential impacts of global climate change on patterns of DV. Extreme weather (periods of extreme heat and prolonged drought) may impact patterns of DV through changing stress levels and agricultural household incomes. We test for such a relationship using administrative data from hospital reports, hotline calls, and female homicides, alongside weather and land use data. Our findings reveal a statistically significant, positive effect of higher daily maximum temperatures on violence but less evidence for a short- or long-run impact of rainfall. The results are consistent across different outcome variables and levels of aggregation, suggesting that climate change may exacerbate the risk of heat stress-related DV. Public policy should consider potential protective measures to insulate vulnerable households against extreme heat-related violence and consider the costs of interpersonal violence in analysis of climate change impacts.

Keywords Domestic violence · Extreme weather · Rainfall · Temperature · Brazil

JEL classification B54 · J12 · Q54

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1 Introduction

Domestic violence (DV)[1] is recognized worldwide as an immense public health problem that causes physical, sexual, and/or psychological harm to victims. One in three women and one in four men experience violence during their lifetimes, and DV comprises a large share of the total violent crime rate globally (World Health Organization 2024). This violence costs billions in lost revenue, wages, healthcare costs, and more (UN Women 2023). Developing effective policies to prevent DV is a massive challenge for policymakers that requires a nuanced understanding of the risk factors for household violence, and how these risk factors may worsen with increased global warming and the pressing challenges posed by climate change.

Heat and rising average temperatures are well established risk factors for violence (Mukherjee and Sanders 2021), including DV (Cohn 1990, 1993; Henke and Hsu 2020a). However, it remains unclear which mechanisms are at play and how these mechanisms interact together to induce specific types of crime, such as DV. Research is mixed on which outcomes of climate change—extreme heat, drought, or some other factor—are behind the observed climate-driven increases in domestic violence seen in the literature (Burke, Hsiang and Miguel 2015; Carleton and Hsiang 2016; Cohen and Gonzalez 2024). Ex ante, two main theories arise: income effects driven by negative weather realizations (such as drought in agriculturally dependent communities), and the acute stress generated by hotter temperatures. We contribute to this nascent literature by combining administrative data on the incidence of violence along several margins, including nonlethal mandatory reports, calls for service, and homicides of women. We then test for impacts of temperature and rainfall on observed violence in the short- and long-run using daily, weekly, and monthly analyses. In doing so, we offer insight into key temporal differences in risk factors for violence.

Empirical and population-level DV research has been limited in its ability to differentiate between immediate/short-term reactionary violence and chronic patterns of violence. DV is both a chronic and an acute public health problem, where acute stressors can precipitate individual acts of violence (Card and Dahl 2011) and patterns of violence evolve over time within relationships. Here, we differentiate between extreme weather (and, therefore, the impacts of climate change on DV) as an acute versus chronic stressor. The evidence we provide supports that the climate change-DV link in our context operates through an acute channel more so than a chronic one, supporting the idea of climate change as a short-term stressor rather than a long-term aggravator. This does not rule out other chronic stressors that can impact DV.

We hypothesize that extreme weather (periods of extreme heat and prolonged drought) may impact patterns of domestic violence through changing stress levels.

[1] DV may be defined as including violence against current/former intimate partners, parents, children, other family members, or cohabiting adults ("roommates"). In this paper, we use the inclusive language of "DV" rather than more specific language such as IPV (intimate partner violence) or violence against women. The data we use in our empirical analysis specifically refer to calls to a women's service hotline, hospital-reported assaults of women by men, and homicides of women. These proxy variables likely consist of largely DV, as DV is the largest precipitating factor for homicides of women (Dugan, Nagin and Rosenfeld 1999). However, these proxy variables do not capture the universe of DV and likely include some "false positives." We discuss this further in section 3.1.

This may occur due to: i) acute and immediate stress increases due to current weather (Mukherjee and Sanders 2021); ii) prolonged, chronic periods of heat increasing stress and emotional, violent responses, and iii) chronic stress imposed by the financial ramifications of patterns of adverse weather (specifically, prolonged drought). Research has shown that extreme heat and rainfall shortages are in fact salient to local producers, with ranchers responding to the lengthening dry season by changing cattle sale decisions (Skidmore 2022). We have little reason to believe that limited or no rainfall on any given day will affect violence. However, prolonged periods of little rain (as seen in the lengthening dry season) have substantial implications for farmers and cattle ranchers, especially those that rely on rain-fed agriculture. Therefore, we hypothesize that both acute, extreme heat and chronic hot weather may increase the likelihood of violence.

To conduct our analysis, we combine administrative data on DV assaults, homicides, and calls for service at the municipal level from 2010-2019.[2] Our fine-grain data allow us to take advantage of a two-way fixed effects specification to identify changes in violence resulting from increased temperatures and total rainfall at the daily, weekly, and monthly levels. This also allows us to speak to whether weather has impacts on chronic versus acute violence risk factors. We combine these data with daily rainfall and maximum temperature at the municipal level, as well as data on municipal land use for heterogeneity analysis and assessment of the income hypothesis.

Unlike prior work, we expand on the framework for understanding the links between global climate change and violence by studying two different forms of weather: high temperatures *and* periods of drought. We leverage daily data on maximum temperature and total rainfall to test for the acute and long-term implications of higher temperatures and worsening drought conditions. Because our first mechanism of action, income, would be largely driven by weather-dependent income such as from agriculture, we test for effect heterogeneity based on local land use. In doing so, we assess whether municipalities with higher shares of municipal land area in pasture and agricultural uses are more sensitive to temperature changes and lengthening dry seasons. This hypothesis is supported by research showing that rainfall levels significantly below the historical average significantly decreases farm profits (Pereda and Alves 2018).

We find a statistically significant and positive relationship between daily maximum temperature and our three violence measures (on the order of a $1 - 1.5\%$ increase in per-capita daily incidents within a municipality), with comparatively limited evidence regarding the influence of rainfall. The results are consistent across different outcome variables and levels of aggregation, pointing to the possibility that climate change–specifically in the form of heat stress–could intensify the risk of domestic violence in Brazil.

There is limited research on this issue specifically from Latin America (Carrasco-Portiho, Vives-Cases, Gil-González and Álvarez Dardet 2007; Garcia 2015; Pontecorvo et al. 2004), despite the prevalence of DV in the region. Some research has indicated that domestic violence rates are higher among Latino populations than

[2] Data availability vary the specific window used in each analysis. For hotline calls, we observe municipalities from 2014-2019, and for temperature we observe municipalities from 2010-2016.

other ethnic groups (Cho, Dreher and Neumayer 2014; Pontecorvo et al. 2004). Brazil ranks fifth in number of murders of women among the 84 countries surveyed by the World Health Organization (Waiselfisz 2015). The homicide rate of women in Brazil (3.5 per 100,000) is high relative to the region, with Bolivia (2.9), Argentina (1.3), Paraguay (1.9), Chile (0.7), and Uruguay (2.3) all having lower rates of homicide of women (World Bank Group 2025). In 2019, 23 Brazilian states (85.2%) had rates of more than 3.0 deaths per 100,000 women (Cerqueira, Ferreira and Bueno 2021), reaching the World Health Organizations threshold criteria for "high" or "very high" mortality rates (Cerqueira et al. 2021; Cerqueira and de Mello 2012; UNODC 2019). As a result, the research presented in this paper offers novel insight into patterns of violence against women in Latin America and specific risk factors for such violence.

Our work is particularly timely given the threats posed by global climate change. Periods of drought and extreme heat are becoming increasingly common and expected to worsen in the coming decades. The Amazon and Cerrado biomes are home to rural areas that experience the type of extreme weather patterns we study in this paper. Further, these are areas that have also experienced high rates of migration in recent years. Public social services are much less readily available as the pace of government expansion has lagged behind the pace of migration. In many cases, and as we observe in our data, this means that the nearest hospital or women's police station is in another municipality or another state and may not be accessible by road. This relative geographic isolation compounds the social isolation created by DV. Our findings indicate that federal and state support to proactively place more social support programs in rural areas especially in the Northwest of the country may mitigate the harms caused by environmental-related DV.

2 Literature review and context

2.1 Extreme weather and interpersonal violence

Violence against women usually does not consist of isolated episodes, but rather a sequence of physical and non-physical behaviors that worsen over time (Barsted and Hermann 2001; Heise 1993; Johnson 1995; Krug, Mercy, Dahlberg and Zwi 2002). This violence impacts many aspects of survivors' lives and is reflected in various physical and mental health problems (Breiding, Black and Ryan 2008; Coker et al. 2002; Devries et al. 2011; Garcia-Moreno, Jansen, Ellsberg, Heise and Watts 2006; World Health Organization 2013), in negative effects on victims' children (Aizer 2011; Neggers, Goldenberg, Cliver and Hauth 2004; Rawlings and Siddique 2014), and in reduced productivity and employment (Leone, Johnson, Cohan and Lloyd 2004; Riger, Raja and Camacho 2002; Tolman and Rosen 2001). Elevated levels of violence, including homicide, put a heavy strain on public health services, especially in developing nations with limited resources (UNODC 2019).

The literature points to three pathways linking weather shocks and DV: (i) household economic insecurity, poverty-related stress, and emotional well-being (Buller et al. 2018; Cools, Flatø and Kotsadam 2015); (ii) women's empowerment (Bott 2012; Tankard and Iyengar 2018); and (iii) exposure to aggressive partners

(Anderson, Anderson, Dorr, DeNeve and Flanagan 2000; Piquero, Jennings, Jemison, Kaukinen and Knaul 2021). We address these pathways through considering the impacts of weather on income (pathways (i) and (ii)) and overall stress (pathway (iii)). We further consider temporal dimensions by identifying short-term versus long-term rainfall shortages and heat waves.

The theoretical and empirical literature on DV has extensively addressed the influence of household economic conditions and the distribution of resources within households on violence. Studies shed light on how factors such as income levels and relative income between partners can influence the prevalence of violence by reshaping the distribution of bargaining power within the household. On the one hand, the job market may represent opportunities to improve the victim's independence (Basu and Famoye 2004; Fajardo-Gonzalez 2021; Farmer and Tiefenthaler 1997; Gelles 1976; Henke and Hsu 2020b) by increasing women's economic status and decreasing the incidence of violence by raising the bargaining power of the woman in the household (Anderberg, Rainer, Wadsworth and Wilson 2016; Bowlus and Seitz 2006; Cerqueira, Moura and Pasinato 2019; Manser and Brown 1980). On the other hand, men may use violence to extract their partner's new or expanded income (Bloch and Rao 2002; Bobonis, González-Brenes and Castro 2013; Litwin, Perova and Reynolds 2019).

The heat hypothesis states that elevated temperatures serve as a motivator for general aggressive behavior (Anderson 1989; Anderson et al. 2000; Burke et al. 2015; Cohn 1990), increasing anger and lowering inhibitions. It is well documented that salient, negative emotional cues can spur impulsive or short-run violence (Card and Dahl 2011). Studies have shown that high temperatures lead to higher levels of aggression broadly (Baron and Bell 1976; Hsiang, Burke and Miguel 2013) and IPV (intimate partner violence) specifically (Cohn 1993; Henke and Hsu 2020a; Michael 1986; Rotton and Frey 1985). Mental health may also deteriorate as a function of poor sleep in hot conditions (Mullins and White 2019). Mukherjee and Sanders (2021) find that in already stressful environments (incarceration in US prisons), acute temperature spikes increase aggression and the incidence of interpersonal violence. Conversely, during periods of extreme heat, people are more likely to stay inside and therefore avoid aggressive strangers (Anderson et al. 2000; Cohn 1990). However, this increased proximity between abuser and victim could in turn increase DV rates, as seen in increased rates of DV during COVID-19 pandemic lockdowns (Piquero et al. 2021).

While crime rates have consistently been shown to correlate with local weather (Carleton and Hsiang 2016; Cohen and Gonzalez 2024; Heilmann, Kahn and Tang 2021; Ranson 2014), more recent work has aimed to address the underlying *mechanisms* by which extreme heat impacts crime and specifically DV. (Heilmann et al. 2021) find that the temperature-crime relationship is strongest in poorer neighborhoods and for crimes of passion, such as DV. Cohen and Gonzalez (2024) study crime patterns in Mexico using administrative records on charges, crime victimization survey data, and daily data on temperature. Their work suggests that increases in alcohol consumption and increased time spent outside the home on hotter days are the driving force undergirding the temperature-crime relationship. Colmer and Doleac (2023) consider how more or less restrictive concealed carry firearm laws may mediate the relationship between heat and violence. They find that more-prohibitive firearm laws indeed attenuate the effects of extreme heat on homicide, which they suggest is a function of firearm regulation limiting impulsive "crimes of passion." Pavanello and Zappalà (2024) consider the temperature-IPV relationship as mediated by another risk factor for violence: substance abuse. Their initial analysis shows that temperature shocks increase the prevalence of non-fatal IPV incidents in the United States. Using a triple-difference empirical methodology, they find that reformulating opioids to limit their abuse attenuates the effect of temperature. In Brazil specifically, Ishak (2022) finds that violent crimes do increase following droughts in rural parts of the country. That author points to agricultural yields as a particular mechanism of action, but does not differentiate between violent crime and violent crime against women/IPV. Our work expands on this by focusing in on a type of crime (DV), measured both in reported crime (homicide), mandatory reports (hospital assaults), and self-selected calls for service (hotline calls) at the daily level.

The Cohen and Gonzalez (2024) findings suggest that increased temperatures might actually *decrease* the proximity between abuser and victim by increasing time spent outside of the home, reducing the likelihood of DV (while perhaps increasing the likelihood of other types of crime victimization). Conversely, their finding that temperature leads to increased alcohol consumption does suggest a potential pathway for DV perpetration that we are, unfortunately, unable to test empirically in our setting.

Here, we do not test for mediating impacts by firearm restrictions (Colmer and Doleac 2023) or using the exogenous shock of the reformulation of OxyContin (Pavanello and Zappalà 2024) due to the low use of oxycodone HCL in Brazil during the period of study (Maia, Daldegan-Bueno and Fischer 2021) and the relatively low prevalence of personal firearms prior to the election of Jair Bolsonaro (Casado and Londoño 2020; Otis 2022; Prager and Martins 2020). However, these papers do raise interesting questions about how the temperature and violence relationship can be mediated by local community and policy characteristics. We explore local dependence on rain-fed agriculture as a mediating variable and the accessibility of hospitals and police stations (as measured by the prevalence of paved roads), discussed further in section 4.

Violence against women is linked to stress from adverse rainfall shocks (Abiona and Koppensteiner 2018; Miguel 2005). However, the introduction of an employment program can mitigate the impacts of rainfall shocks on DV (Sarma 2022). Henke and Hsu (2020a) find that an increase in the woman's relative wage is protective against weather-related IPV. Some studies have previously used rainfall as a measure of income shocks to show the implication for DV (Miguel 2005; Sekhri and Storeygard 2014a). Cools et al. (2015) find that women who have experienced a recent drought are more likely to have been abused during the last year. Díaz and Saldarriaga (2023) exploit the exposure to rainfall shocks and IPV in Peru and find that the probability of IPV increases after exposure to a dry shock during the cropping season. Importantly, rainfall may also prompt an alternative pathway to increased violence via proximity–in other words, if rainfall causes individuals to spend more time at home, they may be more subject to abuse in an already violent dynamic.

Our work expands on these prior papers by simultaneously assessing the impacts of both heat and rainfall using daily data on multiple reported forms of violence, offering heretofore unseen insight into the relationships between weather and DV and the mechanisms underneath. Rather than considering rainfall as a control variable in models of temperature, we intentionally consider the contravening impacts of rainfall on violence and utilize its unique relationship to income to better understand the mechanisms behind household violence. Further, we provide evidence on multiple dimensions of DV: calls for service, mandatory reports of assaults, and homicide of women. Whereas prior studies may focus on either fatal or nonfatal DV reported to policing authorities, by using multiple dimensions of violence we are able to overcome the reporting bias present in nonfatal police reports and the rarity of homicide events. Finally, we do this in a new and overlooked developing context (Brazil) where data on multiple dimensions of DV are rare and the ramifications of global climate change are already substantial.

2.2 Domestic violence policy and law in Brazil

Here, we describe the relevant policy and legal frameworks around our three primary measures of DV: hotline calls, homicides, and hospital-reported assaults.

Brazil has put in place a wide set of laws and locally available institutions to tackle domestic violence. These include the establishment of women's police stations (Portuguese acronym DEAMs) in 1985 to specifically prevent violence against women and provide specialized investigation and legal response. The 2006 Maria da Penha law expanded the role of these stations and encouraged the creation of interdisciplinary teams and specialized units. However, access to these programs is uneven across the country—as of 2018, 460 DEAMs were in operation across the 5,570 municipalities. Access to in-person services for survivors is therefore locally dependent, building the need for remote services like a nationwide hotline. The Women's Helpline (Ligue 180) was established in 2005 to fill this gap and is one of the main national channels for reporting DV in Brazil. Created to reduce barriers to formal complaints, it provides free, confidential, and round-the-clock support for victims and refers reports to appropriate agencies. Although widely available and officially promoted across public and private spaces, access to the helpline may still depend on factors such as internet or phone connectivity, local knowledge of the service, and trust in institutional responses.[3] These dynamics are particularly relevant when evaluating how external shocks—such as extreme rainfall—may shape reporting behavior.

Finally, in 2015 Brazil formally recognized femicide as a specific and aggravated form of homicide, reflecting the gender-based nature of many killings of women. The law redefined femicide as a qualifying circumstance within the criminal code, signaling the state's recognition of gender-based violence as a structural and systemic issue. It also introduced harsher penalties in cases involving specific vulnerabilities, such as when the victim was pregnant, elderly, disabled, or killed in front of family members. Given the specific importance of homicide of women as a national policy

[3] Importantly for our context, heavy rainfall should not impact cell phone connectivity except in extreme circumstances. However, heavy rainfall may impact transportation and therefore impact the number of phone operators who are able to report to work, which could have an impact on hotline wait times or operator availability. We discuss this further in the closing section of the paper.

priority, we specifically study this relatively rare outcome as one of our main outcomes of interest.

Despite the improved legal framework[4] to combat violence against women, such violence remains widespread in Brazil. According to a United Nations study, approximately 34% of Brazilian women reported having experienced intimate partner violence (IPV) (Department of Economic and Social Affairs 2010).

One of the main barriers to effective prevention and legal accountability is the persistent silence surrounding domestic violence. Victims often report abuse only when it reaches unbearable or life-threatening levels (Ribeiro 2017). Fear of retaliation, shame, economic dependency, and limited institutional support contribute to widespread under-reporting and low engagement with the criminal justice system (Amaral, Bhalotra and Prakash 2021). As a result, emergency services frequently serve as the first point of contact for women breaking the cycle of silence-typically after severe or repeated episodes of violence (Ribeiro 2017). This gap between legal protections and real-world access to justice underscores the fragility of institutional responses, particularly in contexts marked by structural inequality.

This paper provides analysis of the impacts of rainfall and heat on DV as measured in calls to the Ligue 180 hotline, incidence of female homicide, and hospital-based reports of DV assault. Due to data limitations, we are unable to study the other policies or programs to reduce DV (e.g., visits to Shelter Houses or cases adjudicated in Courts of Domestic and Family Violence Against Women). However, by studying the three outcomes of DV we do have data for, we are able to speak to different margins of violence, take-up of provided social services, and the relative impact of acute and chronic drought and heat on survivor's interaction with the state.

3 Methodology

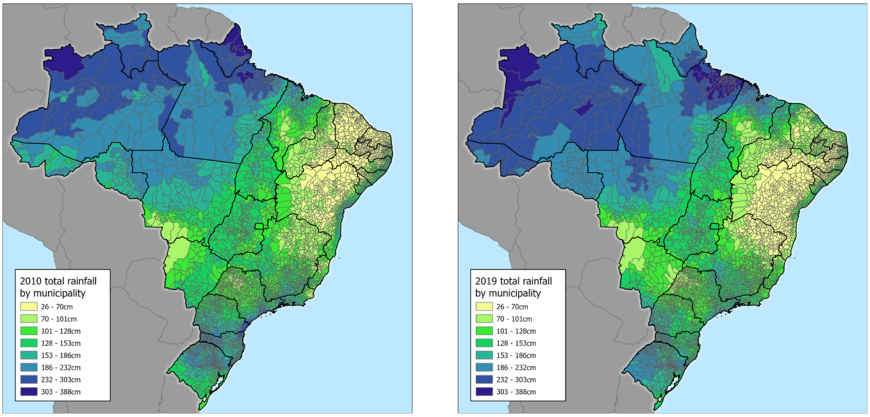
3.1 Data

We combine administrative data with data on weather and land use to conduct our empirical analysis.

3.1.1 Treatment

Rainfall data at the municipal level, including maximum daily rainfall, come from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) collected by the University of California at Santa Barbara Climate Hazards Center. We use each day's total rainfall value in centimeters in our main analysis. In Fig. 1, we

[4] Other forms of social support for survivors of violence in Brazil include the Brazilian Women's House ("Casa da Mulher Brasileira") which provide specialized services for survivors (e.g., counseling, police station accompaniment, and legal services); Courts of Domestic and Family Violence Against Women ("Juizados de Violência Doméstica e Familiar Contra Mulheres") process, judge, and carry out DV-specific cases; DV Women's Reference Centers ("Centro de Referência da Mulher") offer psychological services, counseling, and legal referral to women survivors of violence; and Shelter Houses ("Casa Abrigo") offer confidential safe housing and comprehensive care for women fleeing DV.



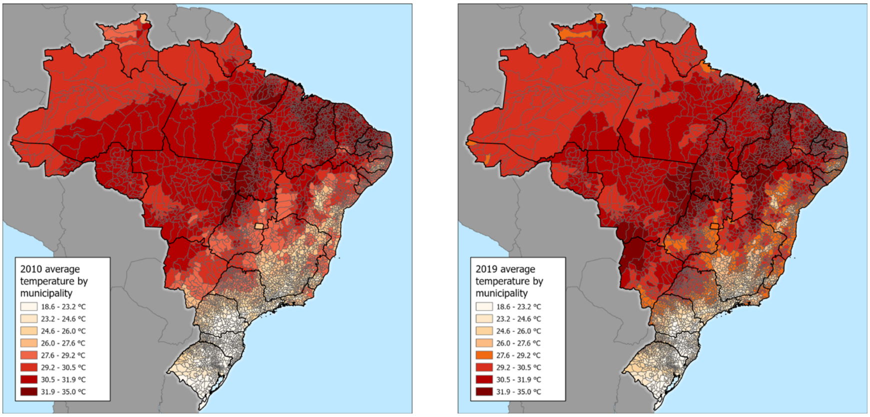
(a) 2010 (b) 2019

Fig. 1 Maximum daily rainfall in cm of each municipality for **a** 2010 and **b** 2019

present a map illustrating the maximum rainfall in centimeters for each municipality, comparing the patterns between our baseline year and the final year.

Maximum daily temperature data come from two sources. The first comes from Climate Hazards Center InfraRed Temperature with Stations data (CHIRTS) also collected by the University of California at Santa Barbara Climate Hazards Center. This data provides daily temperature at a 5km resolution through 2016. The second is the European Centre for Medium-Range Weather Forecasts ERA5-Land dataset (ERA), which has a 10km resolution and 2-meter air temperature. Since ERA reports hourly temperature for each day, we use the maximum temperature observed for each day. Our results are robust to the choice of CHIRTS or ERA for temperature data, so we present results using CHIRTS in the main body of the paper as it is commonly used in the literature. Results using ERA (and its wider sample window) are provided in the supplemental appendix. Figure 2 presents a map illustrating the maximum temperature, measured in degrees Celsius for each municipality, using ERA data to align with the time period shown in Fig. 1). This map highlights the temperature variations between our baseline year and the final year.

To account for omitted variable bias due to differential population distributions within the municipality (Auffhammer, Hsiang, Schlenker and Sobel 2013), we weight our municipal-level climate data by pixel-level population estimated by WorldPop. These data estimate the population within each pixel in Brazil for 2020. Because we do not have access to comparable data for other points in time, we use this as a proxy for population density over the course of the sample period. While this correction for pixel-level population density can correct for some of the within-municipality variation in temperature, with human behavior, it is much less plausible that the population stays in one area (let alone pixel) during the course of any given day. Movement patterns are likely different each day (for example, work days versus days where folks attend church). In this case, pixel-level data on population (or other sub-municipality population counts) are inherently noisy as people go to work, school, shops, church, etc. However, they still prove a substantial improvement over



(a) 2010 (b) 2019

Fig. 2 Maximum daily temperature of each municipality for **a** 2010 and **b** 2019

non-population weighted municipal averages, and we therefore use these weighted averages throughout the paper.

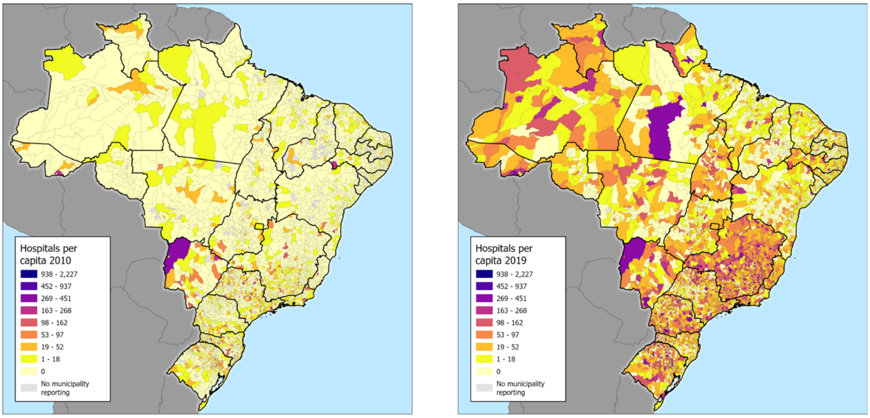
Data on land use, which we use in robustness tests and heterogeneity analysis, come from MapBiomas version 5, available via Google Earth Engine at up to the pixel level (30m spatial resolution).

3.1.2 Outcomes

We use three different measures of DV as our outcome variable. The first consists of data on assaults reported by hospitals from 2010 to 2019. Locations of reporting hospitals are mapped in A1, which includes an inset highlighting the Amazon and Cerrado biomes, where we would expect the most rainfall-driven agricultural production. The Notifiable Diseases Information System (Portuguese acronym SINAN) of the Ministry of Health includes data on all compulsory reported conditions and diseases, including assaults. SINAN includes assault-level data including municipality, year, the reporting health facility's ID, date and hour of occurrence, type of violence, whether the event occurred on a weekday or weekend, location of assault, whether the assault is a recurrence, means of aggression (e.g., firearms, threat), the victim's relationship with the aggressor, and referral to any other system (e.g., to a women's police station, hospital, public ministry).

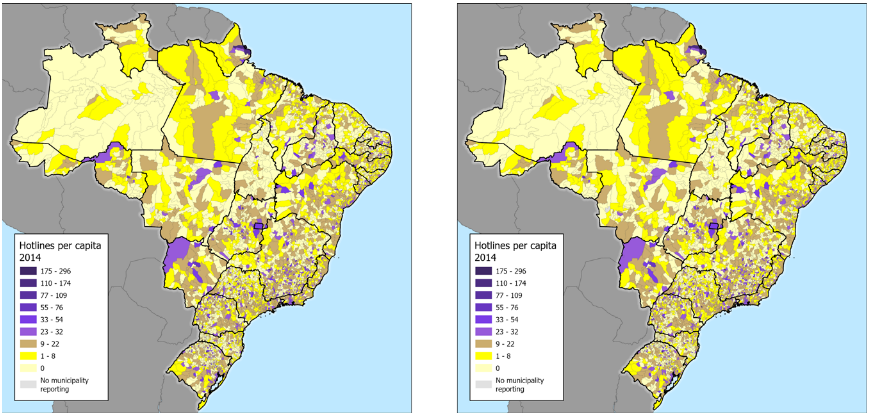
We exclude incidents of assaults where the attacker is not a male or the attacker was unknown, which means we are likely excluding some cases of DV where the victim was either unable or unwilling to name a partner or family member as the assailant. We further exclude the observations for 2009, the year in which violence reports were implemented, due to limited coverage across the country at the start of the reporting period. In Fig. 3, we map the patterns of hospital reports rates per capita from the baseline and the final year.

The second outcome consists of data records on calls to the Women's Service Center, known as Ligue 180, from 2014 to 2019. Ligue 180 registers complaints of



(a) 2010 (b) 2019

Fig. 3 Hospital reported assault rates per capita for **a** 2010 and **b** 2019



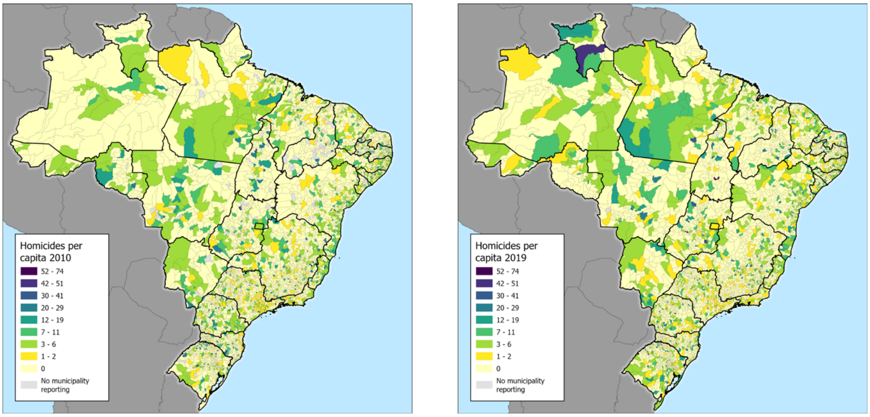
(a) 2010 (b) 2019

Fig. 4 Hotline calls per capita for **a** 2010 and **b** 2019

aggression against women and refer victims to other systems for care, support, and related services. The data we use are at the level of the call and provide information on the person making the call, the victim's race and sex, the sex of the aggressor, the date of the call for service, and the state and municipality of the aggression. Data on individual calls to Ligue 180 are available starting in 2014.[5] For this reason, regressions using the number of calls by municipality are limited to the period beginning in 2014. We map hotline calls per capita in Fig. 4.

Finally, we use data on female homicides by assault tracked in the the Mortality Information System (Portuguese acronym SIM) by Ministry of Health from 2010 to 2019. Deaths are registered using International Statistical Classification of Diseases

[5] Even though it was established in 2010, the General Coordination of the Women's Service Center (Ligue 180) does not have the microdata available for the period from 2005 to 2013.



(a) 2010 (b) 2019

Fig. 5 Homicide rates per capita for **a** 2010 and **b** 2019

and Related Health Problems (ICD-10) codes to denote the cause of death. We limit the sample to those deaths by assault of women (ICD-10 codes X92-Y09), which provides a coarse measure of DV homicide fatalities. The SIM data include the date and the cause of death, as well as the age, sex, and race of the victim. Appendix figure A2 presents a timeline showing the sample period covered by each database used in our analysis (temperature, rainfall, and DV measures). We map homicide rates per capita in Fig. 5.

In all studies of sensitive topics and illegal behaviors, there is substantial concern about the potential for sample selection and/or non-reporting. In our case, hospitals, hotline attendants, and police/medical examiners responding to homicides are all mandated to report cases of DV. This mitigates some concern over underreporting, but there is still a risk that record-keeping is inconsistent or mandatory reporters do not comply. Homicide cases in general tend to exhibit greater reliability compared to hotline calls or hospital reports, primarily due to the elevated prevalence of under-reporting in instances of self-reported violence (DeRiviere 2008). As a result, our results are a lower bound of the total incidence of DV against women.

3.1.3 Descriptive statistics

Table 1 presents descriptive statistics for the outcome and treatment variables used in our analysis, as well as two municipal-level control variables used in our heterogeneity analysis. (Note that we do not present control variable descriptives as our main analysis uses fixed effects which would be collinear with state or region control variables.) We provide summary statistics of treatment (rainfall and maximum temperature) for the current day and prior day using both our primary and secondary data sources. Values are presented in degrees Celsius for temperature and millimeters for rainfall.

Given the frequency of our data (daily), our outcome variable averages are quite small. This is intuitive, as it is unlikely that on an average day a single municipality

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Treatments					
Max daily temperature (current day)	19,670,908	28.89948	4.460577	1.631264	42.44538
Daily rainfall (current day)	27,772,335	0.3788956	0.9113823	0	91.15752
Max daily temperature (prior day)	19,670,908	28.89948	4.460577	1.631264	42.44538
Daily rainfall (prior day)	27,772,334	0.3788956	0.9113823	0	91.15752
Avg. max temperature (current week)	3,953,514	20.54154	13.64	0	47.10166
Avg. daily rainfall (current week)	3,953,514	0.3802337	0.4856717	0	13.0225
Avg. max temperature (prior week)	3,947,945	20.557052	13.62782	0	47.10166
Avg. daily rainfall (prior week)	3,947,945	0.3798934	0.4855463	0	13.0225
Avg. max temperature (current month)	912,408	22.25191	14.68882	0	41.63028
Avg. daily rainfall (current month)	912,408	0.4118934	0.3704135	0	5.171108
Avg. max temperature (prior month)	906,839	22.38856	14.62966	0	41.63028
Avg. daily rainfall (prior month)	906,839	0.4110549	0.3701137	0	5.171108
Max daily temperature (current day - ERA)	27,772,335	27.84451	4.626152	0	42.93454
Max daily temperature (prior day - ERA)	27,772,334	27.84451	4.626152	0	42.93454
Avg. max temperature (current week - ERA)	27,772,335	27.9704	4.414644	0	47.90781
Avg. max temperature (prior week - ERA)	27,733,352	27.95682	4.400661	0	47.90781
Avg. max temperature (current month - ERA)	912,408	30.26947	4.41164	0	42.48889
Avg. max temperature (prior month - ERA)	906,839	30.25619	4.413974	0	42.48889
Controls					
Percentage of paved roads	24,420,011	0.3929645	0.2368934	5.23e-06	0.9999451
Percentage of agricultural land use	27,772,335	0.5553492	0.2731895	1.57e-07	0.9856619
Outcomes					
Hospital rates (daily)	21,667,162	0.0685327	1.172778	0	575.1943
Hotline rates (daily)	21,667,162	0.0269114	0.6282621	0	216.0145
Homicide rates (daily)	21,667,162	0.0042052	0.2220478	0	121.0434
Hospital rates (weekly)	3,953,514	0.3755921	2.930161	0	575.1943
Hotline rates (weekly)	3,953,514	0.1474872	1.54572	0	370.3105
Homicide rates (weekly)	3,953,514	0.0230464	0.520623	0	121.0434
Hospital rates (monthly)	912,408	1.627461	7.119535	0	575.1943
Hotline rates (monthly)	912,408	0.63907	3.537579	0	431.8385
Homicide rates (monthly)	912,408	0.0998615	1.086319	0	121.0434
Homicide (at home - daily)	21,667,162	0.022602	0.063233	0	136
Hospital (assault at home - daily)	21,667,162	0.0230323	0.2670475	0	145
Hospital (assault is a recurrence - daily)	21,667,162	0.0161865	0.209228	0	81

has even one homicide of a woman–indeed, our average is 0.004 homicides per capita. Hospital reports of assaults and hotline calls are more common (at 0.07 and 0.027 incidents per 100,000 municipal population per day). The maximums are much higher, but this is driven by nonzero values in small municipalities with populations below 100,000.

In the raw data, the maximum number of reports at the hospital is 453, indicating potential outliers. To ensure that our results were not driven by extreme cases, such as a mass casualty event in a small municipality during a heat wave, we trimmed the sample to include only a maximum of 200 reports per hospital. The trimmed results indicate slight variations in the daily and weekly data, while the monthly data remains unaffected. Detailed results of the trimmed analysis are presented in appendix tables A26–A28.

3.2 Empirical strategy

We use a two-way fixed effects (TWFE) estimation strategy[6] using fixed effects for municipality-by-year and time unit of observation (most often, calendar date). Our treatment variable is a measure of maximum temperature or total rainfall (in centimeters) on the prior day, over the preceding week, and over the preceding month, weighted by pixel-level population.[7] This allows us to untangle the immediate effects of weather shocks (such as increased stress from extreme heat (Mukherjee and Sanders 2021)) versus the effects of chronic stress from prolonged periods of drought or extreme heat.

Our outcome variable, $Y_{i,t}$, represents either the municipal-level per capita homicide events, per capita assault events, or per capita calls to 180. Outcome variables are aggregated to the relevant time window (i.e., the day, the week, or the month), depending on the specific analysis. Because our empirical specifications include fixed effects for calendar date and municipality-by-year, we do not include municipality or region control variables as they would be collinear. We estimate the following:

$$Y_{i,t} = \alpha + \beta_1 * temp_{[i,t-1]} + \gamma_i + \lambda_t + e_{it} \quad (1)$$

$$Y_{i,t} = \alpha + \beta_1 * rainfall_{[i,t-1]} + \gamma_i + \lambda_t + e_{it}. \quad (2)$$

We hypothesize that acute stress is likely to be a cause of short-term violence, and therefore most likely to be picked up using the prior day and preceding week's cumulative rainfall and average maximum temperature as the treatment variable of interest. Chronic stress, on the other hand, would be most correlated with a long-term trend, and therefore should be best measured using the preceding 28 days' cumulative rainfall or maximum average temperature.

[6] Substantial attention has been paid recently to the bias caused by traditional TWFE models with varying treatment timing, intensity, and permanence (Borusyak, Jaravel and Spiess 2022; Callaway 2021; Goodman-Bacon and Marcus 2020). While recent estimators can account for this bias in cases where treatment is binary but time-varying, our treatment variable is a continuous measure that varies non-monotonically each observed period. We could, however, measure our treatment variable as a binary for whether the preceding day/week's maximum temperature or total rainfall were above or below rainfall in the prior year (or whether the deviation is above or below some threshold) and then use the contemporary econometric estimators. However, this is unsatisfying as deviation from historical levels does not speak to deviation from recent patterns. We leave this for future work.

[7] Note that including total rainfall over a seven-day period is empirically similar to using the average maximum temperature over seven days, with the latter simply scaled down by 7.

Table 2 Regression analysis of weather on DV outcomes, daily data

Variables	Hospital	Hotline	Homicide
Panel A: Daily Data			
Max daily temperature (current day)	0.000936***	0.000370***	3.96e-05
	(0.000138)	(0.000139)	(2.43e-05)
Daily rainfall (current day)	0.000655*	0.000448	− 0.000232***
	(0.000359)	(0.000368)	(6.71e-05)
Panel B: Prior Day Data			
Max daily temperature (prior day)	0.000954***	0.000463***	4.92e-05**
	(0.000136)	(0.000143)	(2.44e-05)
Daily rainfall (prior day)	0.000255	0.000642*	− 2.48e-05
	(0.000342)	(0.000386)	(6.78e-05)
Observations	13,789,209	6,070,744	13,789,209
R-squared	0.017	0.007	0.003
Date FE	X	X	X
Municipio x Year FE	X	X	X
Standard Errors	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS
Outcome mean	0.0608	0.0412	0.00452

Outcome variables (incidents per municipality per day) are normalized per 100,000 municipal population. Cluster-robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Our use of administrative reporting does also circumvent some issues with sample selection – survivors of DV often do not report their experiences for fear of reprisal, judgment, and other consequences. However, we do face sample selection in that only some victims of DV assault will go to a hospital for treatment or call a hotline for assistance. In this way, our outcome variable measuring homicide incidents is the best measure of those available.

4 Results

Next, we present results estimating the relationship between short- and medium-run temperature and rainfall on different measures of DV.

Table 2 panel A presents the estimates testing for a contemporary effect of maximum temperature and total daily rainfall on hospital reports, hotline calls, and homicide of women. There is a positive relationship between daily maximum temperature and the three measures of violence, but less evidence for the impact of rainfall. We find that a one-degree Celsius increase in the maximum temperature on the present or prior day corresponds to a 1.5% increase in the per capita daily assault rate and a 0.9% increase in hotline calls, with no significant impact on homicides. Our effects are therefore small when compared to single-degree Celsius increases in daily maximum temperature. However, when we consider larger daily deviations such as a five- or ten-degree Celsius increase (as may be seen in the case of an acute

Table 3 Regression analysis of weather on DV outcomes, weekly data

Variables	Hospital	Hotline	Homicide
Panel A: Current Week Data			
Avg. max temperature (current week)	0.000858**	0.000482***	0.000522***
	(0.000130)	(0.000133)	(0.000228)
Avg. daily rainfall (current week)	0.00866*	− 0.00617	− 0.000156
	(0.00504)	(0.00438)	(0.000974)
Panel B: Prior Week Data			
Avg. max temperature (prior week)	0.00441**	0.00377***	0.000449**
	(0.00122)	(0.000332)	(0.000216)
Avg. daily rainfall (prior week)	0.00487	− 0.00127	− 0.00234***
	(0.00474)	(0.00450)	(0.000894)
Observations	2,826,778	1,727,914	2,827,200
R-squared	0.113	0.050	0.021
Week FE	X	X	X
Municipio x Year FE	X	X	X
Standard Errors	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS
Outcome mean	0.522	0.337	0.0322

Outcome variables (incidents per municipality per week) are normalized per 100,000 municipal population. Cluster-robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

heat wave where the daily maximum temperature is 35 instead of 30), these effects become larger and more economically meaningful. This is suggestive evidence in favor of the aggression and proximity hypotheses. Conversely, we would not expect daily rainfall to impact DV except through proximity, for which we do not find evidence.

However, it is also possible that incidents of violence are not immediately reported to hotlines or hospitals, therefore yielding stronger results the next day or in following days. We test this in Table 2 panel B, where we again find robust evidence of an impact of temperature on DV outcomes. A one-degree Celsius increase in the prior day's maximum temperature increases hospital assaults by 1.6%, hotline calls by 1.1%, and homicides by 1.1%. However, the results remain statistically insignificant and small for prior day's rainfall.

When using daily outcome data, we are left with incredibly small incident counts on any given day given the infrequency of these outcomes, especially homicide, at the municipal-day level. To account for this, we use the aggregated current and prior week (Table 3) data, where treatment is the average maximum temperature over seven days or the average daily rainfall in centimeters. The outcome variables of interest are therefore the total number of incidents/calls made over that seven-day period. Our results here are consistent with the prior story of increased violence during and after hotter periods. A one-degree Celsius increase in the prior week's maximum temperature increases hospital assaults by 0.8%, hotline calls by 1.1%, and homicides by 1.4%. Again, we find no effect for rainfall.

Table 4 Regression analysis of weather on DV outcomes, monthly data

Variables	Hospital	Hotline	Homicide
Panel A: Current Month Data			
Avg. max temperature (current month)	0.00249***	0.0226***	0.00221*
	(0.00633)	(0.000755)	(0.00115)
Avg. daily rainfall (current month)	0.0454	0.0117	− 0.0184***
	(0.0342)	(0.0321)	(0.00589)
Panel B: Prior Month Data			
Avg. max temperature (prior month)	0.0122**	0.0145**	0.00194*
	(0.00609)	(0.00675)	(0.00117)
Avg. daily rainfall (prior month)	0.0683**	0.0211	− 0.00921
	(0.0321)	(0.0297)	(0.00588)
Observations	652,392	398,808	652,392
R-squared	0.362	0.183	0.088
Month FE	X	X	X
Municipio x Year FE	X	X	X
Standard Errors	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS
Outcome mean	2.261	1.462	0.140

Outcome variables (incidents per municipality per month) are normalized per 100,000 municipal population. Cluster-robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4 presents the same exercise but aggregated at the month level. Here, we find again evidence of temperatures increasing violence, but the effects are more imprecisely estimated and coefficients are small. Current month temperature increases hospital assaults by 0.1%, and prior month average maximum temperature increases of one degree Celsius increase hospital assaults by 0.5%. Estimates for rainfall are inconsistent in sign, magnitude, and statistical precision. We take this as evidence that monthly treatment measures are limited in their ability to precisely measure impacts of climate on household violence. This is supportive of a more short-run impact of heat on violence, rather than long-term, chronic stressors or droughts.

As a placebo test, we use the maximum temperature and rainfall from six months prior to the observation period (in this case, the month). This relies on the assumption that weather from a particular month in the prior rainy or dry season will have minimal effect on the current month's weather. Results are provided in Table 5. We find no consistent evidence of a statistically significant effect of weather shocks far removed from the observation period on violence measured as hospital assaults or homicides of women. However, we do find a significant (at the 5% level) and negative correlation of temperature and rainfall on hotline calls. This may reflect the unique differences in hotline calls as compared to hospital assaults or homicides. Hospital attendance is likely due to a time-sensitive need (medical care) and homicides are relatively quickly reported. On the contrary, hotline calls can be made by a DV victim at any time, even months or years after an assault or other form of violence has taken place. This further supports the idea that hotline calls may be less

Table 5 Regression analysis of weather on DV outcomes, placebo test

Variables	Hospital	Hotline	Homicide
Avg. max temperature (6 months prior)	−0.000643	−0.00203**	0.000217
	(0.000878)	(0.000944)	(0.000218)
Avg. daily rainfall (6 months prior)	−0.00859	−0.00884**	0.00118
	(0.00575)	(0.00422)	(0.00122)
Observations	652,362	398,802	652,362
R-squared	0.098	0.086	0.083
Date FE	X	X	X
Municipio x Year FE	X	X	X
Standard Errors	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS
Outcome mean	0.0733	0.0475	0.00463

Outcome variables (incidents per municipality) are normalized per 100,000 municipal population. Cluster-robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

immediately receptive to climate-related triggers and therefore a noisier proxy for current violence rates.

4.1 Mechanisms

Next, we turn to mechanisms. We test for four main mechanisms: drought-related income shocks; access to hospitals and resources via paved roads; repeated instances of violence (rather than marginal or 'one-off' violent incidents); and violence spurred by proximity within the home.

Our findings suggest that the weather-crime relationship, in our context and for this type of crime, is largely a story of temperature, rather than rainfall shocks or drought. To further unpack this mechanism, we consider specifically those municipalities who should be most impacted by weather shocks via income effects: municipalities with a high percentage of land area in agricultural uses. If drought-driven income shocks are the mechanism behind DV in these municipalities, we would expect a negative and significant coefficient on rainfall for these specifications. Total land area in agricultural uses (using a single point in time estimate for each municipality) is presented in figure A3. Consistent with prior work (Skidmore, Sims and Gibbs 2023), we restrict our sample to municipalities with at least 25% and 50% of municipal land area in agricultural land use (tables A1–A6). While our impacts for temperature are consistent, we see little movement on the rainfall variable *except* for on hospital assaults. However, the coefficient on assaults is positive, indicating that as rainfall increases, hospital-reported assaults also increase. We similarly provide analysis for the converse–limiting the sample to those municipalities defined by the Brazilian Institute of Geography and Statistics (Portuguese acronym IBGE) as "highly urban." Results for this sub-sample are presented in appendix tables A7–A9, and are again consistent with the sample in high-agriculture municipalities. We take this as evidence *against* a rain-fed agriculture story negatively shocking household incomes and driving our results.

We also narrow the sample to municipalities with more than 40% paved roads. We use this as a proxy for accessibility to services, such as policing and hospital care. The percentage of paved roads (using a single point in time estimate for each municipality) is presented in appendix figure A4. Using this sub-sample, the outcomes consistently align with our main findings related to hospitals and homicides (tables A10–A12). Notably, the effects on hotline calls are statistically indistinguishable from zero in the daily model. It is crucial to emphasize that our observed effects remain consistent even with this sample restriction, though it is noteworthy that these specific municipalities do not significantly influence the overall outcomes.

We look to characteristics of reported violence next. Our hospital data include whether the violence is a 'recurrence,' meaning that the victim self-reported that violence has occurred before, regardless of whether they have sought medical care for or reported prior instances of violence. This allows us to identify whether our results are driven by marginal changes to violent behavior (e.g., an unprecedented instance of violence) or increasing violence in already violent relationships. We limit our outcomes to those recurrent assaults (appendix tables A13–A15). Our results are consistent for both temperature and rainfall, with the strongest results in terms of significance and magnitude (relative to the outcome variable mean) seen in the prior day and week estimates. We take this as evidence that the change we are identifying in the short-run estimates are driven by an increase in violence in previously violent relationships, rather than inducing new or first-time violence.

We similarly can identify if homicides of women or hospital-reported assaults occurred within the home, allowing us to identify whether proximity between victim and abuser is an important mechanism for this violence. When we limit the outcome variable to these in-home incidents, we again find robust relationships between temperature and hospital assaults, but no significant relationship with homicides at the daily level (appendix tables A16–A18). However, at the weekly (current and prior) and current month levels, we find a significant effect of heat on homicides committed within the home. This suggests that prolonged exposure to extreme heat increases the risk of domestic violence homicides, likely by escalating stress over time, which in turn creates conditions for violent behavior. This aligns with theories that extended time spent at home under stressful conditions can foster environments conducive to violence. While we interpret the effect on assaults as primarily driven by proximity, the relationship with homicides is more complex. Homicides tend to be rarer and are influenced by unique, context-specific factors within each household, rather than being directly tied to proximity, as was observed during the COVID-19 pandemic (Kim and Royle 2024).

4.2 Tests of robustness

Next, we describe the results of a series of tests for robustness and of mechanisms, with empirical results reported in the online supplemental appendix. We first show robustness to functional form by checking for impacts of temperature in two binned specifications. We create a series of dummy variables for the maximum daily temperature falling in bins of 2.5 and 5 degrees Celsius. This specification allows us to identify whether truly extreme values of heat are driving our effects. Results are presented in appendix tables A19–A20. The results for hospital reports and hotline calls are consistent with our main results. At the hottest temperatures, the magnitude of the impact is higher for hospital reports and hotline calls, suggesting that high temperatures have a causal impact on nonlethal forms of physical violence. The effects on homicide are statically indistinguishable from zero *except* for the largest and smallest bins in the 2.5 degree Celsius model. On the hottest days, the impact of temperature on homicide is positive, and on the coolest days, it is negative. From this, we can conclude that our identified effects are indeed capturing the effect of *heat*, not just relative increases in temperature.

We further show robustness to alternative fixed effects specifications (appendix tables A21–A22) and to including both current and prior day's weather data simultaneously to account for heat waves (appendix tables A23–A25). We additionally trim the dataset to exclude outliers in our hospital reporting data (descriptive statistics for this trimmed sample in appendix table A26 and results in A27–A28). We also estimate a model where the treatment of interest is the average maximum temperature over the week before and the week after the observation day (appendix table A29). The results for temperature and hotline calls are relatively precise nulls, but the spotty statistical significance yields concern about serial autocorrelation between weather realizations at different points in time. We also show robustness to using the ERA as an alternative source of data on temperature (appendix tables A30–A32). Our findings remain consistent.

Finally, we consider an alternative measure of rainfall to better capture the impacts of drought, specifically. According to Skidmore (2022), focus groups in cattle ranching regions of the Amazon indicate that farmers are less likely to measure precipitation on any given day. In that study, "Farmers reported that measuring rainfall is uncommon, and most have low awareness of the centimeters of rain that fall on their property. Instead, they conceptualize rainfall based on whether a day passes without any rain." Given this information, that author instead measures drought as the number of days with zero rainfall. We follow this precedent and present results where the treatment variable (for rainfall) is whether there was a nonzero value of rainfall (on the current or prior day) or an integer for how many days of rainfall there were in the current or prior period (the week or month). Our results (presented in appendix tables A33–A35) on temperature remain robust both in terms of sign and magnitude.

We do find significant and positive associations of binary rainfall and total days of rain on current day hospital assaults and hotline calls. We take the latter result as consistent with the idea that hotline calls are made more 'on your schedule'–if women are home during rainy days, then today's rainfall may provide an opportunity to call a DV hotline.

In these analyses, we find that an additional day with rainfall in the current or prior week and month corresponds to a decrease in homicides of women. Also, previous studies have found that a one standard deviation decrease in annual rainfall increases the incidence of domestic violence by 13.1% in Tanzania (Abiona and Koppensteiner 2018) and reported dowry deaths by 7.8% in India (Sekhri and Storeygard 2014b).[8] By comparison, our findings suggest that an additional day of rainfall in the prior

[8] The standard deviation for rainfall in those papers is reported as 15% of long-run annual rainfall (Abiona and Koppensteiner 2018) or 0.237 m (Sekhri and Storeygard 2014b).

week or month decrease the homicide rate for women by 2.2% or 0.4%, respectively. However, prior work has found that homicide rates in general decrease when it rains (Wesselbaum 2022). Here, we argue in favor of caution of our results—because we do not have information on whether the homicide was specifically committed by an intimate partner or family member, it is possible that these results are simply picking up the reduced homicide rate overall when it rains.

5 Discussion

We estimate the causal effect between extreme weather events and DV in Brazil. Our main result indicates that hotter temperatures lead to a short- and medium-term (up to weeks-long) increase in violence. Conversely, rainfall shocks, including contemporaneous rainfall (suggestive of proximity effects) or long-term rainfall, (suggestive of patterns of drought) have no significant effect. Further analysis reveals that the results are consistent across different outcome variables, levels of aggregation (including over time), and sample restrictions to those municipalities with higher percentages of land area in agriculture.

We do not interpret our findings as suggesting that there is no relationship between rainfall and DV–rather, at a population-level, rainfall does not appear to have a statistically identifiable impact. This does not rule out a relationship between, for example, rainfall-dependent income and violence in certain households or certain communities. Instead, we see this as an avenue for future research, especially qualitative work and case studies, to understand why a factor (like rainfall) can have locally specific effects but not be identified at a large scale.

Our work suggests that climate change–specifically in the form of extreme heat–may exacerbate the risk of DV. As global climate change continues and worsens, there is a pressing need to understand the potential social impacts of such heat. Climate change-related events compound the preexisting high levels of poverty in the country, impacting a significant number of individuals and inflicting damage on property. Also, these events increase economic stress, social isolation, and cultural norms that perpetuate DV. Therefore, our findings highlight the need for a more comprehensive approach to addressing DV that considers the broader social and environmental context in which it occurs.

Because this study relies on administrative data, further research is needed to understand specific mechanisms of action at a micro-level. First, the infrastructure of the houses is not known, especially with regards to thermal insulation or access to air conditioning, which would reduce the effect of heat. The quality of infrastructure directly impacts how much households can mitigate their own heat shocks by staying indoors. Further, we do not know the employment conditions of any household whose violence is reflected in our data, including whether the victim of violence worked for pay outside the home or if the household's income is agriculturally-dependent. Future work can build on these results to address several questions. First, it can incorporate access to protective measures in the analysis. Secondly, it could include some measures of women's employment given the income effects driven by negative weather shocks. Finally, further dedicated study of Ligue 180 could provide extensive insight into how DV survivors engage with state-sponsored services and how limitations or funding cuts impact survivor outcomes. For example, as discussed earlier, it is possible that extreme weather may impact whether phone line operators are able to report in to work. Researchers could study this more explicitly through collaboration with hotline service agencies to understand how threats to operator accessibility (as through funding cuts in the United States) impact survivor wellbeing.

Our findings have important policy implications for Brazil, especially as the country is geographically large and dispersed. We document that extreme heat, via temperature-induced stress, increases DV across a variety of intensity margins for both highly urban and agriculturally dependent areas. This points to a need for integrated climate adaptation strategies that account for gender-based violence risks. For example, this could include local cooling centers during heat waves where social service providers (including DV agencies) offer on-site services. In many cases, the nearest hospital or women's police station is in another municipality or another state and may not be accessible by road (see appendix figure A1). Federal and state policymakers may proactively address this issue by funding health and social supportive services in these underserved areas to mitigate the impacts of global climate change and extreme heat on household violence. Finally, Brazil may consider investing in mobile crisis units to do specific outreach during heatwaves, extending the reach of Ligue 180 and ensuring its climate resilience, and incorporating gender-sensitive protocols into heatwave response and climate adaptation plans. Such measures are especially important in regions where women face greater barriers to reporting violence and accessing protection.

Data Availability Details on data sources (including publicly available ones) are provided within the manuscript.

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