DV and climate in Brazil

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Abstract

Domestic violence (DV)–injury, physical, sexual, or psychological suffering, and moral or property damage committed by intimate partners and family members–persists as a serious national issue in Brazil despite the public efforts to eliminate it. While the risk factors and consequences of such violence are well studied, less is known about the potential impacts of global climate change on patterns of DV. Consistent with existing literature, extreme weather (periods of extreme heat and prolonged drought) may impact patterns of DV through changing stress levels and household income. We test for such a relationship in Brazil 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 and suggest that climate change may exacerbate the risk of 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 the impacts of climate change.

Key words: Domestic violence; extreme weather; rainfall; temperature; Brazil

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1 Introduction

Domestic violence (DV) is recognized worldwide as a public health problemthat causes physical, sexual, or psychological harm to victims.. One in three women and one in four men experience violence during their lifetimes, costing billions in lost revenue, wages, healthcare costs, and more (UN Women, 2023). However, effective DV prevention requires understanding the risk factors for household violence, and how these risk factors may become worse over time with increased global warming, stressors caused by late-stage capitalism, and other pressing global challenges.

Heat and rising average temperatures are well established risk factors for violence (Mukherjee and Sanders, 2021), including DV (Henke and Hsu, 2020a; Cohn, 1993, 1990). However, it remains unclear which mechanisms are at play when temperatures rise and droughts worsen. Ex ante, two main theories arise: income effects driven by negative weather realizations (such as drought), 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 homicide. We then test for impacts of temperature and rainfall on observed violence in the short- and long-run using daily, weekly, and monthly analyses. Further, 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 impacts. We provide evidence supporting climate change as a short-term stressor rather than a long-term aggravator.

We hypothesize that extreme weather (periods of extreme heat and prolonged drought) may impact patterns of domestic violence through changing stress levels. 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 this 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. Conversely, 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 2014-2019. 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 level. 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.

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.

Our findings indicate a statistically significant positive correlation between daily maximum temperature and the three violence measures, 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 could intensify the risk of domestic violence in Brazil.

There is a limited amount of data on this issue specifically from Latin America (Garcia, 2015; Carrasco-Portiho et al., 2007; Pontecorvo et al., 2004) while some research has indicated that domestic violence rates are higher among Latino populations than other ethnic groups (Cho et al., 2014; Pontecorvo et al., 2004). Brazil ranks fifth in number of murders of women among 84 countries surveyed by the World Health Organization (Waiselfisz, 2015). In 2019, 23 Brazilian states (85.2%) had rates of more than 3.0 deaths per 100,000 women (Cerqueira et al., 2021), reaching the World Health Organizations threshold criteria for high or very high mortality rates (UNODC, 2019; Cerqueira and de Mello, 2012; Cerqueira et al., 2021). 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 are becoming increasingly common and expected to worsen in the coming decades. The Amazon and Cerrado biomes are home to rural areas that very much feel the kinds of extreme weather patterns we study in this paper. Further, these areas are also where more recent migration has occurred. Public social services are much less readily available as the pace of government expansion has lagged behind the pace of migration. In many cases, 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 isolation compounds on the 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 hypothesized effects

Violence against women usually does not involve isolated episodes, but rather a sequence of physical and non-physical behaviors that worsen over time (Krug et al., 2002; Johnson, 1995;

Heise, 1993; Barsted and Hermann, 2001). This violence impacts several aspects of their lives and is reflected in various physical and mental health problems (Breiding et al., 2008; Coker et al., 2002; Devries et al., 2011; Garcia-Moreno et al., 2006; World Health Organization, 2013), on victims' children (Aizer, 2011; Neggers et al., 2004; Rawlings and Siddique, 2014), and for productivity and employment (Leone et al., 2004; Riger et al., 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 et al., 2015); (ii) women's empowerment (Bott, 2012; Tankard and Iyengar, 2018); and (iii) exposure to aggressive partners (Anderson et al., 2000; Piquero et al., 2021).

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 (Farmer and Tiefenthaler, 1997; Henke and Hsu, 2020b; Gelles, 1976; Basu and Famoye, 2004; Fajardo-Gonzalez, 2021) by increasing women's economic status and decreasing the incidence of violence by raising the bargaining power of the woman in the household (Anderberg et al., 2016; Bowlus and Seitz, 2006; Cerqueira et al., 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 et al., 2013; Litwin et al., 2019).

The heat hypothesis states that elevated temperatures serve as a motivator for general aggressive behavior (Anderson et al., 2000; Anderson, 1989; Cohn, 1990), increasing anger and lowering inhibitions. Studies have shown that high temperatures leads to higher levels of aggression broadly (Baron and Bell, 1976; Hsiang et al., 2013) as well as IPV (intimate partner violence) specifically

(Cohn, 1993; Henke and Hsu, 2020a; Michael, 1986; Rotton and Frey, 1985). 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. Violence against women is linked to stress from adverse rainfall shocks (Miguel, 2005; Abiona and Koppensteiner, 2018). 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. Finally, 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 could increase DV given the increased proximity between abuser and victim, as seen in increased rates of DV during COVID-19 pandemic lock-downs (Piquero et al., 2021).

Some studies have previously used rainfall as a measure of income shocks to show the implication for DV (Miguel, 2005; Sekhri and Storeygard, 2014). 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.

3 Background

In 1985, Brazil took the lead in introducing women's police stations within Latin America. These specialized stations were established to address the incidence of violence against women and are part of the structure of the Civil Police, which is an organ of the Public Security System of each State of Brazil. Women's police stations (Portuguese acronym DEAMs) are responsible for violence prevention, investigation, and legal response, which must be guided by respect for human rights and the principles of the Democratic State of Law.

However, it was only after the enactment of Law nº 11,340/2006 (known as the Maria da Penha Law), the first legal provision to combat violence against women and promote public policies in

Brazil, that the women's police station expanded its role. This legal framework not only broadened the scope and duties of DEAMs and other police facilities but also delineated precise protocols for addressing DV cases. Consequently, the legislation introduced a structured collaboration among federal, state, and municipal governments and non-governmental organizations to establish DEAMs. The law fortified the efforts of various public institutions by stipulating the formation of interdisciplinary teams specializing in medical, psychological, and holistic support for survivors of DV. Finally, the legislation enhanced funding mechanisms at the state level, with the federal government allocating resources to states dedicated to implementing the Maria da Penha law specifically to establish DEAMs. In 2018, according to Brazilian Institute of Geography and Statistics (IBGE) data, there were 460 DEAMs, which corresponds to approximately one women's police station for every twelve municipalities.

In March 2015, Brazil introduced a second significant legal enactment aimed at enhancing the security and protection of women, formally known as Law nº 13,104/2015 or the Femicide Law. Femicide is defined as the deliberate killing of women due to their gender. Notably, the Femicide Law incorporated femicide as an aggravating factor within the context of homicide, carrying potential sentences ranging from twelve to thirty years of imprisonment for the perpetrator. The law also stipulated an escalation of penalties, ranging from one-third to one-half, if the crime of femicide is committed under specific circumstances: i) during pregnancy or within three months post-partum; ii) against individuals under fourteen years of age, over sixty years of age, or those with disabilities; or iii) in the presence of the victim's direct descendants or ascendants.

The enactment of these laws is a notable accomplishment in women's rights and represents a foundational toolset in the ongoing battle against DV targeting women. In addition to these legal protections, the Women's Helpline (Ligue 180) was created to reduce the barrier to making formal complaints about experienced DV and ensure the well-being of victims. In 2003, the government passed a Law nº 10.714/2003 authorizing the Executive Branch to make available nationwide a telephone number to respond to complaints of violence against women. However, only in 2010, through presidential Decree nº 7.393/2010, the Women's Service Center - Ligue 180 was established, and in 2011, the reports became mandatory. Ligue 180 is operated by the Ministry of Human Rights and Citizenship, which receives, analyzes, and forwards reports of disclosed violence against women. The helpline operates 24 hours a day, seven days a week, offering free and confidential assistance. It is available not only in Brazil but also in an expansive international reach encompassing 16 additional countries.[1].

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 survivors (e.g., psychological, police station accompaniment, legal services, accommodation, and transportation). Under the Maria da Penha law, Courts of Domestic and Family Violence Against Women ("Juizados de Violência Doméstica e Familiar Contra Mulheres") may be created by the Union (in the Federal District and in the Territories) and by the States to process, judge, and carry out cases arising from the practice of domestic and family violence against women. Women's Reference Centers ("Centro de Referência da Mulher") offer reception spaces, psychological and social care, and guidance and legal referral to women survivors of violence. And finally, Shelter Houses ("Casa Abrigo") offer confidential and temporary protected housing and comprehensive care for women whose lives are at imminent risk due to DV.

In this paper, we focus on reports made at the hospital, calls to the Ligue 180 hotline, and incidences of femicide. We do not include use of other supportive care, such as visits to Shelter Houses or cases adjudicated in Courts of Domestic and Family Violence Against Women due to data limitations. However, by studying these three outcomes of DV, 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.

[1]The 16 countries are Argentina, Belgium, Spain, USA (San Francisco and Boston), France, French Guiana, Netherlands, England, Italy, Luxembourg, Norway, Paraguay, Portugal, Switzerland, Uruguay and Venezuela.

4 Data

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

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.

Maximum daily temperature data come from two sources. The first comes from Climate Hazards Center InfraRed Temperature with Stations data (CHIRTS) collected by the University of California at Santa Barbara Climate Hazards Center. This data is a 5km resolution and is the daily temperature. However, it ended in 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 are provided in the supplemental appendix.

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.

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. 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, referral to any other system (e.g., to a women's police station, hospital, public ministry). SINAN also includes victim-level data such as date of birth, sex, age, pregnancy status, race, level of schooling, marital status, occupation, and disability status. We 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.

The second 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 aggression against women and refer them 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, and the state and municipality of the aggression. Data on individual calls to Ligue 180 are available starting in 2014. For this reason, regressions using the number of hotline calls by municipality are limited to the period beginning in 2014.

Finally, we use data on female homicides by assault tracked in the the Mortality Information System (Portuguese acronym SIM) by the Ministry of Health from 2010 to 2019. Deaths are registered using International Statistical Classification of Diseases 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. We exclude incidents of homicide and assault where the attacker as 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.Homicide cases tend to exhibit greater reliability compared to hotline calls or hospital reports, primarily due to the elevated prevalence of underreporting in instances of self-reported violence. As a result, our results are a lower bound of the total incidence of DV against women.

Table 1 presents descriptive statistics for the outcome and treatment variables used in our 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.)

5 Methodology

We use a two-way fixed effects (TWFE) estimation strategy 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 rainfall (in centimeters) on the prior day, over the preceding week, and over the preceding month (30 days). 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 the municipal-level per capita homicide events, per capita assault events, and per capita calls to 180. 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. When investigating mechanisms, we will use

$$Y_{i,t} = \alpha + \beta_1 * temp_{[i,t-1]} + \beta_2 * X + \gamma_i + \lambda_t + e_i t \tag{1}$$

$$Y_{i,t} = \alpha + \beta_1 * rainfall_{[i,t-1]} + \beta_2 * X + \gamma_i + \lambda_t + e_i t \tag{2}$$

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 cumulative preceding week's rainfall and 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 30 days' cumulative rainfall or maximum average temperature.

As a robustness test, we run the models excluding observations during the COVID-19 pandemic. We argue that the pandemic generated a substantial shock to behavior patterns, especially as they relate to the perpetration and reporting of IPV. We conduct separate analysis of observations during the pandemic and discuss observed heterogeneity and disrupted use of different services.

Substantial attention has been paid recently to the bias caused by traditional TWFE models with varying treatment timing, intensity, and permanence (Callaway, 2021; Goodman-Bacon and Marcus, 2020; Borusyak et al., 2022). 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 each observed period. We can, 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 prior levels does not speak to deviation from recent patterns.

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 not all in the event that record-keeping is inconsistent or mandatory reporters do not comply.

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 measured.

6 Results

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

Table 2 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. 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, which we do not see evidence for.

However, it is also possible that incidences 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 3, where we again find robust evidence of an impact of temperature on DV outcomes. However, the results remain statistically insignificant and small for prior day's rainfall.

To test for long-term effects of individual rainfall shocks, we consider the rainfall and temperature outcomes from 30 days prior to the observation day in table 4. Results on hotline and hospital calls remain consistent, while the others are statstically indistinguishable from zero.

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 (table 5) and prior week (table 6) 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, but our results on hotline calls, while similar in magnitude, lose statistical significant. Again, we find no effect for rainfall.

Tables 7 and 8 do the same exercise but aggregated at the month level. Here, we find no consistency in our results and overall lose statistical significance. We take this as evidence that monthly treatment is too coarse or distanced to identify impacts 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 9. We find no consistent evidence of a statistically significant effect of weather shocks far removed from the observation period on violence.

As a robustness check, 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. Total land area in agricultural uses (using a single point in time estimate for each municipality) is presented in figure 1. Consistent with prior work (Skidmore et al., 2023), we restrict our sample to municipalities with more than 25% of municipal land area in agricultural land use. We test for impacts of weather in these municipalities using both daily violence (table 14) and violence occurring on the prior day (table 15). The results for hospitals and homicides are consistent with our main results. Effects on hotline calls are statically indistinguishable from zero. Importantly, our effects are *consistent* to this sample restriction, but effects are not driven by these municipalities.

Further, we check for impacts of temperature in a binned specification to identify whether truly extreme values of heat are driving our effects (table 17). 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, suggesting that high temperatures have a causal impact on nonlethal forms of physical violence. However, the effects on hotline calls are not driven by the highest temperature bins, and the effects on homicide are statically indistinguishable from zero.

We also conducted additional tests by narrowing the sample to municipalities with more than 40% paved roads. The percentage of paved roads (using a single point in time estimate for each municipality) is presented in figure 2. We used daily (table 18) and violence occurring on the prior day (table 19). The outcomes consistently align with our main findings related to hospitals and homicides. Notably, the effects on hotline calls are statistically indistinguishable from zero. It is crucial to emphasize that our observed effects remain consistent even with this sample restriction, though it's noteworthy that these specific municipalities do not significantly influence the overall outcomes.

Finally, we also test for robustness to use of the ERA as an alternative source of data on temperature. Our findings remain consistent.

7 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 longer-term (up to weeks-long) increase in violence, while 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..

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, which would reduce the effect of heat. This impacts how much households are able to 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.

Our findings have important policy implications for Brazil, especially as the country is geographically large and dispersed. 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. Federal and state policymakers may proactively address this issue by funding health and social supportive services in these areas to mitigate the impacts of global climate change and extreme heat on household violence.

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)
Variables	N	Mean	sd	min	max
Daily temperature (ERA)	21,667,162	27.865	4.502	2.166	41.624
Daily temperature (CHIRTS)	15,603,989	28.852	4.467	1.411	42.520
Daily rainfall	21,667,161	0.382	0.884	0.000	85.892
Hospital	21,667,162	0.070	1.159	0.000	453.515
Homicide	21,667,162	0.004	0.223	0.000	115.009
Hotline	21,667,162	0.027	0.623	0.000	194.444
Max daily temperature (prior day - ERA)	21,6671,62	27.865	4.501	2.166	41.624
Max daily temperature (prior day - CHIRTS)	15,609,523	28.853	4.467	1.411	42.520
Daily rainfall (t-1)	21,6671,,61	0.382	0.884	0.000	85.892
Max daily temperature (t-30 - ERA)	21,667,162	27.854	4.498	2.166	41.624
Max daily temperature (t-30 - CHIRTS)	15,770,009	28.863	4.458	1.411	42.520
Daily rainfall (t-30)	21,667,161	0.383	0.886	0.000	85.892
Avg. max temperature (current week ERA)	21,667,162	27.979	4.271	8.885	47.890
Avg. max temperature (current week CHIRTS)	21,667,162	20.870	13.484	0.000	46.883
Avg. daily rainfall (current week)	21,667,162	0.384	0.479	0.000	12.270
Avg. max temperature (prior week ERA)	21,667,127	27.983	4.279	8.885	47.890
Avg. max temperature (prior week CHIRTS)	21,667,127	20.939	13.477	0.000	46.883
Avg. daily rainfall (prior week)	21,667,127	0.385	0.481	0.000	12.270
Avg. max temperature (current month ERA)	21,667,162	27.962	3.962	11.804	39.747
Avg. max temperature (current month CHIRTS)	21,667,162	20.857	13.401	0.000	38.204
Avg. daily rainfall (current month)	21,667,162	0.384	0.349	0.000	4.750
Avg. max temperature (prior month ERA)	21,667,022	27.962	3.961	11.804	39.747
Avg. max temperature (prior month CHIRTS)	21,667,022	21.086	13.317	0.000	38.204
Avg. daily rainfall (prior month)	21,667,022	0.385	0.351	0.000	4.750
Percentage of agriculture land use	21,667,162	0.556	0.272	0.000	0.986

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2: Daily data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Max daily temperature	0.000913***	0.000370***	5.92e-05**			
	(0.000133)	(0.000132)	(2.43e-05)			
Daily rainfall				-9.38e-05	-0.000259	-0.000244***
				(0.000331)	(0.000299)	(6.23e-05)
Observations	13,789,209	6,070,744	13,789,209	19,852,381	12,133,916	19,852,381
R-squared	0.018	0.007	0.003	0.019	0.008	0.003
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0624	0.0419	0.00477	0.0757	0.0489	0.00479

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Prior day data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Max daily temperature (prior day)	0.000956***	0.000443***	5.26e-05**			
	(0.000132)	(0.000137)	(2.40e-05)			
Daily rainfall (t-1)				-0.000455	-0.000360	-0.000110*
				(0.000332)	(0.000289)	(6.03e-05)
Observations	13,789,204	6,070,743	13,789,204	19,852,381	12,133,916	19,852,381
R-squared	0.018	0.007	0.003	0.019	0.008	0.003
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0624	0.0419	0.00477	0.0757	0.0489	0.00479

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4: Prior 30 days data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Max daily temperature (t-30)	0.000276**	0.000293**	3.11e-05			
	(0.00461)	(0.000137)	(2.33e-05)			
Daily rainfall (t-30)				0.000272	-3.69e-05	-7.22e-06
				(0.000347)	(0.000305)	(6.83e-05)
Observations	13,955,229	6,236,884	13,955,229	19,852,381	12,133,916	19,852,381
R-squared	0.018	0.008	0.004	0.019	0.008	0.003
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0627	0.0426	0.00478	0.0757	0.0489	0.00479

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Current week data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Avg. max temperature (current week)	0.000696*	0.000410	0.000234***			
	(0.000365)	(0.000409)	(8.63e-05)			
Avg. daily rainfall (current week)				0.000513	-0.00155	-0.000105
				(0.00196)	(0.00155)	(0.000389)
Observations	2,826,778	1,727,914	2,826,778	2,826,778	1,727,914	2,826,778
R-squared	0.042	0.023	0.020	0.042	0.023	0.020
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0777	0.0490	0.00512	0.0777	0.0490	0.00512

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Prior week data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Avg. max temperature (prior week)	0.00101***	0.000279	0.000219**			
	(0.000365)	(0.000426)	(8.65e-05)			
Avg. daily rainfall (prior week)				-0.000123	-0.00138	-0.000480
				(0.00171)	(0.00147)	(0.000374)
Observations	2,826,773	1,727,913	2,826,773	2,826,773	1,727,913	2,826,773
R-squared	0.042	0.023	0.020	0.042	0.023	0.020
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0777	0.0490	0.00512	0.0777	0.0490	0.00512

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Current month data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Avg. max temperature (current month)	-0.000219	0.000267	0.000564*			
	(0.000806)	(0.000887)	(0.000294)			
Avg. daily rainfall (current month)				0.0140***	-0.00168	-0.000687
				(0.00459)	(0.00461)	(0.00149)
Observations	706,758	432,042	706,758	706,758	432,042	706,758
R-squared	0.096	0.082	0.077	0.096	0.082	0.077
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0786	0.0483	0.00534	0.0786	0.0483	0.00534

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8: Prior month data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
	-0.000779	0.000202	0.000466*			
Avg. max temperature (prior month)						
	(0.000948)	(0.000880)	(0.000257)			
				0.0104*	-0.00250	-0.00118
Avg. daily rainfall (prior month)						
				(0.00554)	(0.00426)	(0.00115)
Observations	706,753	432,041	706,753	706,753	432,041	706,753
R-squared	0.096	0.082	0.077	0.096	0.082	0.077
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0786	0.0483	0.00534	0.0786	0.0483	0.00534

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 9: Placebo test

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
	0.000998	0.000197	-0.000394			
Avg. max temperature (6 months prior)						
	(0.000732)	(0.000841)	(0.000266)			
				-0.0181***	-0.000664	0.000888
Avg. daily rainfall (6 months prior)						
				(0.00473)	(0.00462)	(0.00126)
Observations	706,723	432,035	706,723	706,723	432,035	706,723
R-squared	0.096	0.082	0.077	0.096	0.082	0.077
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0786	0.0483	0.00534	0.0786	0.0483	0.00534

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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8 Appendix

Table 10: Daily data - ERA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Max daily temperature	0.00104***	0.000800***	9.78e-05***						
	(0.000119)	(0.000102)	(2.04e-05)						
Max daily temperature (prior day)				0.00110***	0.000731***	7.39e-05***			
				(0.000120)	(0.000102)	(2.03e-05)			
Max daily temperature (t-30)							0.000219**	0.000295***	5.44e-05***
							(0.000107)	(0.000109)	(2.02e-05)
Observations	19,852,382	12,133,917	19,852,382	19,852,382	12,133,917	19,852,382	19,852,382	12,133,917	19,852,382
R-squared	0.019	0.008	0.003	0.019	0.008	0.003	0.019	0.008	0.003
Date FE	X	X	X	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	ERA	ERA	ERA	ERA	ERA	ERA	ERA	ERA	ERA
Outcome mean	0.0757	0.0489	0.00479	0.0757	0.0489	0.00479	0.0757	0.0489	0.00479

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 11: Weekly data - ERA

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Avg. max temperature (current week)	0.000784**	0.000999***	0.000200***			
	(0.000338)	(0.000310)	(7.60e-05)			
Avg. max temperature (prior week)				0.000803**	0.00105***	0.000197**
				(0.000340)	(0.000306)	(8.07e-05)
Observations	2,826,778	1,727,914	2,826,778	2,826,773	1,727,913	2,826,773
R-squared	0.042	0.023	0.020	0.042	0.023	0.020
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	ERA	ERA	ERA	ERA	ERA	ERA
Outcome mean	0.0777	0.0490	0.00512	0.0777	0.0490	0.00512

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 12: Monthly data - ERA

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Avg. max temperature (current month)	-0.000508	0.000959	0.000245			
	(0.000715)	(0.000719)	(0.000195)			
Avg. max temperature (prior month)				-0.00150*	0.00108	0.000342*
				(0.000816)	(0.000705)	(0.000183)
Observations	706,758	432,042	706,758	706,753	432,041	706,753
R-squared	0.096	0.082	0.077	0.096	0.082	0.077
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	ERA	ERA	ERA	ERA	ERA	ERA
Outcome mean	0.0786	0.0483	0.00534	0.0786	0.0483	0.00534

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 13: Placebo test - ERA

	(1)	(2)	(3)
VARIABLES	Hospital	Hotline	Homicide
Avg. max temperature (6 months prior)	0.00126*	-0.000428	-0.000163
	(0.000740)	(0.000768)	(0.000224)
Observations	706,723	432,035	706,723
R-squared	0.096	0.082	0.077
Date FE	X	X	X
Municipio x Year FE	X	X	X
Standard Errors	Municipality	Municipality	Municipality
Data	ERA	ERA	ERA
Outcome mean	0.0786	0.0483	0.00534

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 14: Daily Data - Agriculture land use

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Max daily temperature	0.000842***	0.000237	6.91e-05**			
	(0.000154)	(0.000153)	(2.81e-05)			
Daily rainfall				-4.48e-05	-0.000317	-0.000255***
				(0.000386)	(0.000339)	(6.87e-05)
Observations	11,284,463	4,996,673	11,284,463	16,288,228	10,000,438	16,288,228
R-squared	0.017	0.007	0.003	0.019	0.008	0.003
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0686	0.0434	0.00482	0.0830	0.0502	0.00481

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regressions include a linear control variable for the percentage of municipal land area that is in any agricultural land use.

Table 15: Prior day Data - Agriculture land use

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Hospital	Hotline	Homicide	Hospital	Hotline	Homicide
Max daily temperature (prior day)	0.000928***	0.000354**	5.95e-05**			
	(0.000152)	(0.000158)	(2.75e-05)			
Daily rainfall (t-1)				-0.000575	-0.000275	-6.43e-05
				(0.000386)	(0.000333)	(6.96e-05)
Observations	11,284,459	4,996,672	11,284,459	16,288,228	10,000,438	16,288,228
R-squared	0.017	0.007	0.003	0.019	0.008	0.003
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0686	0.0434	0.00482	0.0830	0.0502	0.00481

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regressions include a linear control variable for the percentage of municipal land area that is in any agricultural land use.

Table 16: Agriculture land use - ERA

	(1)	(2)	(3)
VARIABLES	Hospital	Hotline	Homicide
	0.00104***	0.000703***	0.000103***
Max daily temperature			
	(0.000138)	(0.000116)	(2.37e-05)
	0.00110***	0.000636***	8.28e-05***
Max daily temperature (prior day)			
	(0.000139)	(0.000116)	(2.36e-05)
Observations	16,288,228	10,000,438	16,288,228
R-squared	0.019	0.008	0.003
Date FE	X	X	X
Municipio x Year FE	X	X	X
Standard Errors	Municipality	Municipality	Municipality
Data	ERA	ERA	ERA
Outcome mean	0.0830	0.0502	0.00481

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regressions include a linear control variable for the percentage of municipal land area that is in any agricultural land use.

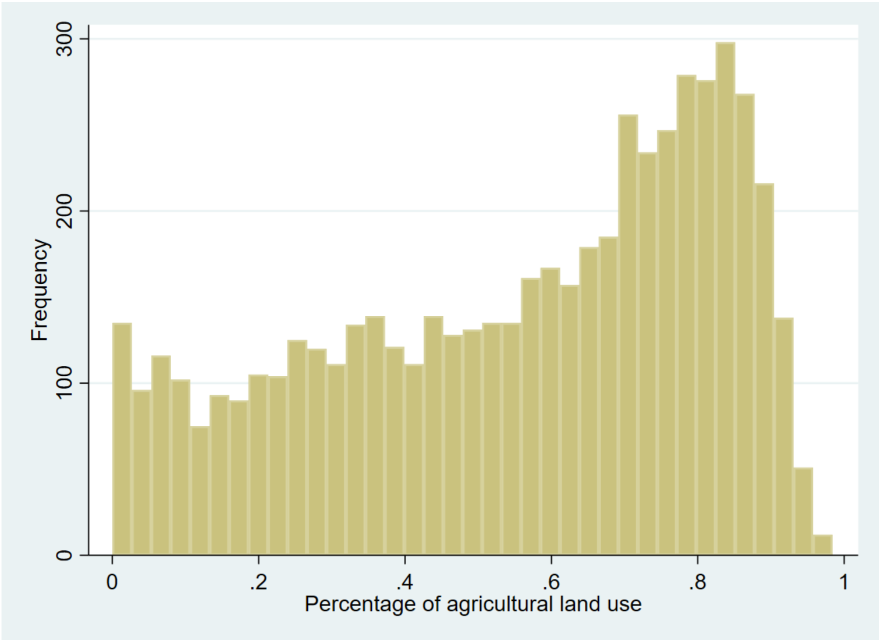

Figure 1: Frequency of percentage agricultural land use

Table 17: Extreme temperature - binned maximum daily temperature

VARIABLES	(1) Hospital	(2) Hotline	(3) Homicide
Daily temp (20 to 25ºC)	0.00577***	0.003	-0.0003
	(0.002)	(0.0019)	(0.0004)
Daily temp (25 to 30ºC)	0.0112***	0.005**	-0.00004
	(0.002)	(0.0019)	(0.0004)
Daily temp (30 to 35ºC)	0.0136***	0.006***	0.00004
	(0.002)	(0.0019)	(0.0004)
Daily temp (>35ºC)	0.0169***	0.004*	0.00004
	(0.002)	(0.0019)	(0.0006)
Observations	13,789,209	6,070,744	13,789,209
R-squared	0.017	0.004	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	0.0624	0.0419	0.00476

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 18: Daily Data - Percentage of paved roads

VARIABLES	(1) Hospital	(2) Hotline	(3) Homicide	(4) Hospital	(5) Hotline	(6) Homicide
Max daily temperature	0.000960***	0.000325*	8.23e-05**			
	(0.000199)	(0.000185)	(3.39e-05)			
Daily rainfall				3.86e-05	-0.000660	-0.000254***
				(0.000465)	(0.000461)	(8.86e-05)
Observations	5,426,332	2,377,224	5,426,332	7,800,738	4,751,630	7,800,738
R-squared	0.020	0.008	0.004	0.020	0.008	0.004
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0603	0.0446	0.00510	0.0739	0.0528	0.00522

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regressions include a linear control variable for the percentage of a municipality's roads that are paved divided by the total municipal area (in hectares).

Table 19: Prior day Data - Percentage of paved roads

VARIABLES	(1) Hospital	(2) Hotline	(3) Homicide	(4) Hospital	(5) Hotline	(6) Homicide
Max daily temperature	0.000665***	0.000283	6.42e-05*			
(prior day)	(0.000206)	(0.000195)	(3.39e-05)			
Daily rainfall (t-1)				-0.000412	-0.000369	-9.16e-05
				(0.000465)	(0.000419)	(8.47e-05)
Observations	5,426,330	2,377,224	5,426,330	7,800,738	4,751,630	7,800,738
R-squared	0.020	0.008	0.004	0.020	0.008	0.004
Date FE	X	X	X	X	X	X
Municipio x Year FE	X	X	X	X	X	X
Standard Errors	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Data	CHIRTS	CHIRTS	CHIRTS	CHIRPS	CHIRPS	CHIRPS
Outcome mean	0.0603	0.0446	0.00510	0.0739	0.0528	0.00522

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regressions include a linear control variable for the percentage of a municipality's roads that are paved divided by the total municipal area (in hectares).

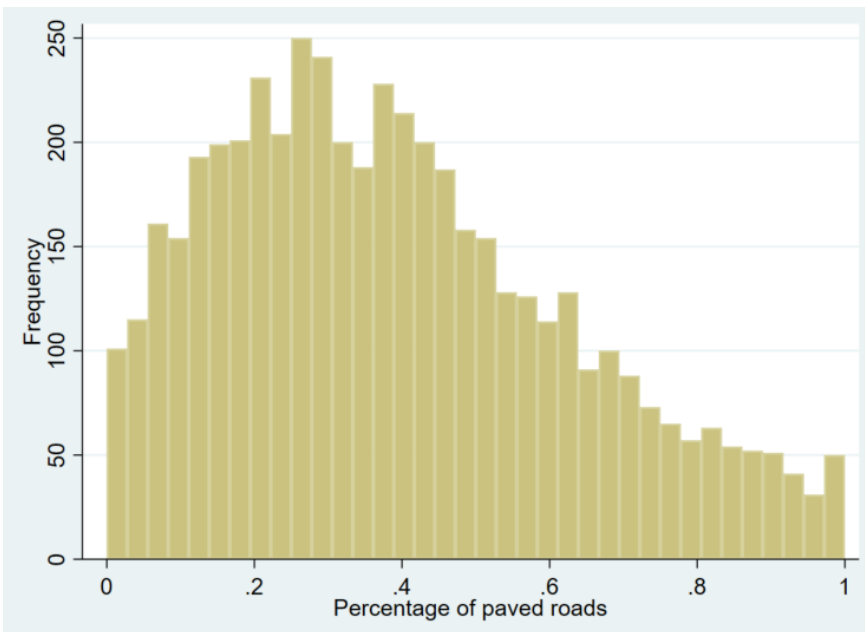

Figure 2: Frequency of percentage of paved roads