Temperature Variations and Domestic Violence

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Abstract

I combine detailed crime reports, independent helpline data, and high-frequency weather records to investigate how temperature variations influence domestic violence (DV) in Mexico City. I find a positive, contemporaneous, and linear relationship between daily temperature and DV, with a 1°C rise leading to a 2.8% increase in DV reports. This effect emerges even under moderate climatic conditions, suggesting continuous risk beyond extreme heat events. My findings rule out that changes in victims' reporting behavior entirely drive the relationship. Exploiting detailed census data from nearly 2,500 neighborhoods, I show that temperature-induced DV disproportionately affects poorer areas, revealing how environmental stressors exacerbate existing urban inequalities.

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E-mail address: martin.habets@eui.eu. Code for data processing and description available on my website at: https://martinhabets.github.io/mexico_build_data/

1 Introduction

Domestic violence (DV) is a global social crisis. In Mexico City alone, over 40% of women have experienced partner violence during their lifetime (ENDIREH, 2021). Its consequences span direct physical and psychological harm, as well as significant economic costs. Recognizing the severity of this issue, the Mexican government has made gender-based violence a national priority, explicitly committing to addressing its underlying determinants (SSPC, 2022). Yet, DV has attracted far less attention from economists than other dimensions of gender discrimination (Bhalotra et al., 2025), and its environmental triggers remain poorly understood.

In this paper, I examine how daily temperature variations influence the incidence of domestic violence in Mexico City, using rich, high-frequency data from police reports and an independent public helpline. Specifically, I construct a daily, neighborhood-level panel combining detailed crime reports from the Attorney General's Office and helpline calls with hourly meteorological measurements from ground monitoring stations for 2016-2020. This dataset allows me to precisely capture how slight day-to-day variations in ambient temperature – rather than *e.g.* extreme heat waves – influence DV incidence at a fine spatial and temporal scale.

The granularity and comprehensiveness of my data allow for credible identification of the short-term causal effect of temperature on domestic violence. I estimate neighborhood-by-day panel models with rich fixed effects that flexibly absorb time-invariant neighborhood characteristics and citywide shocks. I also explicitly address a key inherent threat in crime studies, the presence of a reporting bias. Through robust checks leveraging independent helpline data and an analysis of reporting dynamics, my findings suggest that temperature has a genuine effect on DV incidence and that sample selection is not the main driver of the core association.

I find robust evidence of a significant, positive, and nearly linear relationship between temperature and domestic violence. Specifically, a moderate increase in ambient temperature of just 1°C results in approximately a 2.8% rise in DV reports – a magnitude that remains consistent across various robustness checks, alternative measurement strategies, and different data sources. Crucially, this effect is not confined to extreme temperature ranges but emerges clearly even within the moderate temperatures typical of Mexico City. My results further indicate that the response to temperature variations is largely contemporaneous, with only negligible spillovers into subsequent days.

The average effect of temperature on domestic violence encompasses substantial heterogeneity. Leveraging detailed census data, I document a clear socioeconomic gradient: poorer neighborhoods experience significantly larger relative increases in DV compared to richer neighborhoods. For neighborhoods in the lowest income quintile, temperature-induced DV increases are about 50% larger relative to affluent areas, highlighting how even modest climatic stressors exacerbate existing inequalities within the city.

I contribute to this literature in three main ways. First, while estimates are consistent with other studies that identify the short-term relationship between temperature and crime (Cohen and Gonzalez, 2024; Heilmann et al., 2021; Blakeslee et al., 2021) or other forms of violence, such as maltreatment of young children or suicide (Evans et al., 2023; Burke et al., 2018), I focus specifically on domestic violence. DV is a type of crime that occurs primarily at home and is shaped by complex dynamics of control and power. These unique characteristics imply that domestic violence may respond to temperature differently than other types of crime: I find that domestic violence is more sensitive to temperature fluctuations than any other crime type in my data. Second, while much of the literature focuses on high temperatures or extreme heat events, I study a context characterized by moderate temperatures, with few days falling into extreme ranges. I show that the relationship between temperature and violence persists even in a temperate climate, using a novel measure of daily temperature exposure. Third, my analysis captures small-scale heterogeneity within a city. This level of granularity contrasts with most existing studies, which examine broader geographies. The interaction of the temperature-DV relationship with urban poverty highlights a potentially overlooked source of inequality within metropolitan areas.

These findings have clear implications for urban policy and climate adaptation. Temperature should be recognized as a continuous and substantial risk factor for DV, extending beyond the current focus on extreme events. The strong socioeconomic gradient further underscores the need for targeted investments in housing quality, public infrastructure, and social support in disadvantaged neighborhoods. Without such measures, we risk deepening existing urban inequalities in the face of environmental stress.

The remainder of the paper proceeds as follows. Section 2 provides context, outlines a conceptual framework for understanding temperature effects on DV, and describes the data as well as some raw associations between temperature and domestic violence. Section 3 presents the empirical strategy used to establish the main results presented in Section 4. Section 5 examines socioeconomic heterogeneity. In Section 6, I look into a potential reporting bias, explore the role of pollution, and discuss mechanisms. Section 7 concludes.

2 Context and Data

This section (i) sketches a brief conceptual framework linking temperature to domestic violence, (ii) describes the data, context, and how I construct the domestic-violence and environmental series for Mexico City, and (iii) presents preliminary descriptive patterns that motivate the empirical strategy.

Conceptual framework

An extensive literature documents a robust relationship between ambient temperature and aggressive behavior (Dell et al., 2014; Baysan et al., 2019; Blakeslee et al., 2021). Whether and how this relationship extends to domestic violence remains an open question. To guide the empirical analysis, I outline a brief conceptual framework.

Mechanisms linking temperature and domestic violence fall into three broad categories: direct physiological effects, changes in time-use/social exposure, and potential biases in reporting. While the first two may have an effect on the true incidence of DV, biases in reporting only distort observed counts by affecting the likelihood that a given incident appears in the data. I discuss each in turn.

A first channel involves direct physiological responses. Exposure to heat can have immediate and direct physiological effects, leading to a reduction of self-control and an increase in aggressiveness (Anderson et al., 2000; Baylis, 2020). These direct effects have been documented in the lab (Almås et al., 2025) or in controlled environments such as prisons (Mukherjee and Sanders, 2021), and may also be mediated by other physical reactions, such as sleep disruptions or deteriorations in mental health, both of which are strongly correlated with domestic violence risk (Janzen, 2025).

A second, complementary channel operates through changes in time use. Changes in temperature have been found to alter time allocation across activities and locations (Graff Zivin and Neidell, 2014; Garg et al., 2020a; Cohen and Gonzalez, 2024). These behavioral shifts may modify social exposure in a way that increases victimization and aggression risks (Cohen and Felson, 1979). In addition, these shifts can trigger changes in alcohol and substance use, risk factors repeatedly associated with domestic violence (Boles and Miotto, 2003; Heinz et al., 2011). This behavioral framework is consistent with the routine activity theory of crime developed by Cohen and Felson (1979), though its empirical relevance in the domestic sphere remains underexplored.

The third channel is related to an inherent limitation of crime data: we only observe a small share of the incidents. Government agencies, including police, have been shown to reduce effort on hotter days (Obradovich et al., 2018). However, this concern is somewhat mitigated in the context of domestic violence, which is typically reported directly by victims and less reliant on discretionary police activity. Instead, a more relevant threat is that victims' willingness to report may be affected by temperature. I examine this concern in detail in Section 6, and my analyses suggest that temperature has little influence on the timing or likelihood of reporting. While a reporting bias cannot be entirely ruled out, my findings support the interpretation that higher temperatures are associated with a genuine increase in DV incidence.

Data, Measurement, and Descriptive Patterns

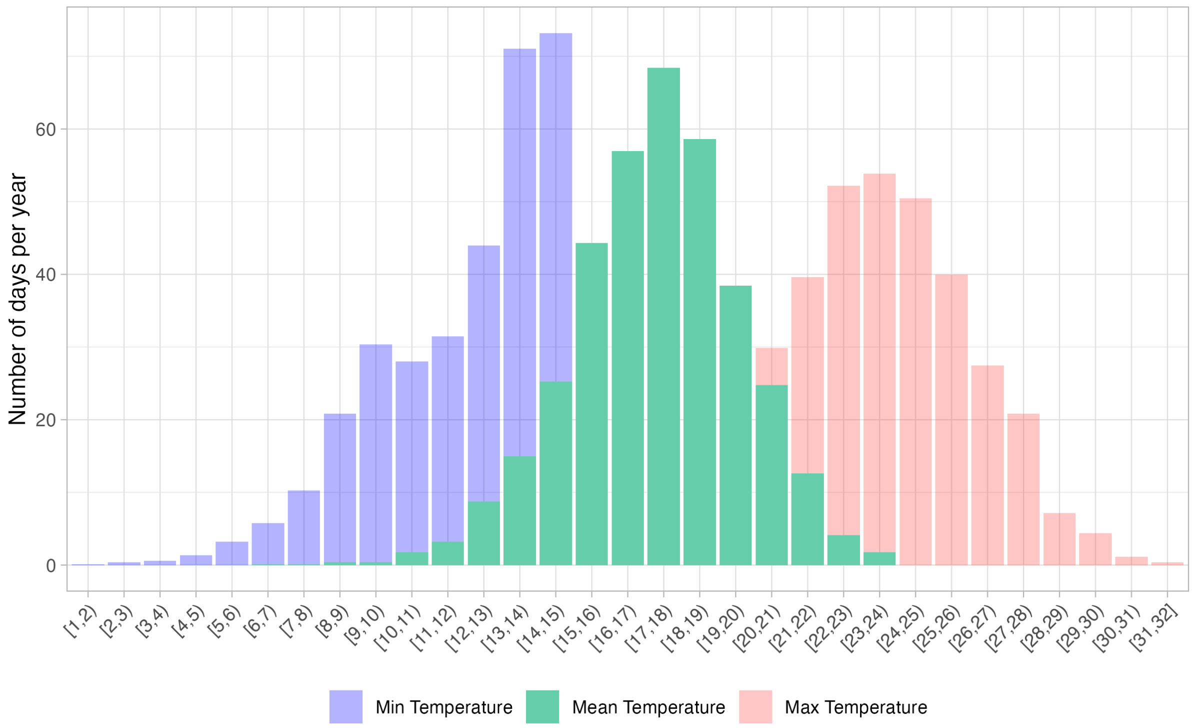
To measure domestic violence in Mexico City, I use detailed crime reports from the Attorney General's Office of Mexico City (Fiscalía General de Justicia, 2024). The reports are collected through police stations, emergency calls, online reports, and specialized crime units. I include all crime reports, regardless of whether they proceed to court. The dataset contains detailed information on the type of crime, the location of the crime, the dates and times when the crime occurred, and when the report was initiated.

I supplement the crime reports with data from an anti-domestic violence helpline, Línea Mujeres (Locatel, 2024). Operated by the Government of Mexico City, this public helpline offers 24/7 legal, psychological, and medical support to women experiencing violence. Calls are free and handled by trained psychologists and lawyers, who classify each incident by type. While many are coded as intimate partner violence, violence against children, or other family-related violence, not all calls are categorized. I therefore group all entries under a broad domestic violence definition. The data include the location of the incident, the time and date it occurred, and when the call was placed.

Temperatures in Mexico City are mild despite its latitude due to a combination of altitude, geography, and climate patterns. Figure 1 shows the distribution of daily mean, minimum, and maximum temperatures in the years of the sample. To reflect the exposure of the average inhabitant, temperature data are weighted by the population of each neighborhood. The daily mean temperature fluctuates between 16°C and 19°C for half of the year. At the extremes of the distribution for mean temperature, there are, on average, 1 day per year below 10°C and 6 days above 22°C. This approximately translates to 2.5 days per year with minimum temperatures below 5°C and 1.5 days with maximum temperatures exceeding 30°C.

Temperatures do not vary significantly over the year. Figure B1 shows a relatively

Figure 1: Average Population Exposure to Temperatures



Note: Average number of days per year falling within 1°C bins for 2016–2020. Min. (max.) is lowest (highest) hourly value, and mean is the average of the 24 hourly readings. Temperature data are aggregated across neighborhoods and weighted by population to reflect exposure of the average resident.

small difference in mean temperature between the warmest and coolest months. In contrast, the city experiences highly seasonal precipitation, with the majority of rainfall occurring during the rainy season from May to October. During these months, frequent afternoon thunderstorms and heavy rains help clear pollutants from the air, resulting in improved air quality. Still, levels of particulate matter remain high in Mexico City throughout the year. In almost 3 out of 4 days between 2016 and 2023, residents in Mexico City experienced pollution levels above the WHO Air Quality Guidelines for 24-hour concentrations of particulate matter (WHO, 2021). I discuss pollution and its interaction with temperatures in greater detail in Section 6.

I obtained weather and air pollution variables, *i.e.*, temperature, wind speed, relative humidity, and levels of particulate matter data at the hour level from the Secretary of the Environment's (SEDEMA) website (SEDEMA, 2024). These data are collected by about 30 ground monitoring stations in and around Mexico City. I create hourly weather and air pollution series for each neighborhood by weighting the data from each monitoring station within 20 km of the neighborhood in proportion to the inverse of the distance between the centroid of the neighborhood and the monitoring station. I then average the 24 hourly measurements to construct daily measures. Additionally, I use daily total precipitation data from the National Water Commission's website (CONAGUA, 2024) and create a daily series for each neighborhood by weighting data from the 95 ground monitoring stations.

I match the environmental data to the domestic violence data by the location of the crime, as reported by the victim. For the main analysis using crime data, I use AGEBs (*Áreas Geoestadísticas Básicas*) as the unit of observation. These are census-defined statistical areas created by Mexico's national statistical office (INEGI) and allow me to incorporate detailed socioeconomic information into the analysis. In contrast, the helpline call data is geolocalized by *colonia* (neighborhood) whose boundaries are distributed by the National Population Council (CONAPO). *Colonias* reflect administrative rather than statistical delineations.

The use of these two spatial units is a constraint imposed by the structure of the data. To improve readability, I refer to both units as "neighborhoods" throughout the text. However, it is important to note that colonias and AGEBs do not align perfectly: larger or denser *colonias* are often divided into multiple AGEBs. There are 2,431 AGEBs and 1,948 *colonias*. Figure B2 shows a map of the AGEBs and their centroids, along with the locations of weather, pollution, and precipitation ground monitoring stations used to construct the environmental exposure series.

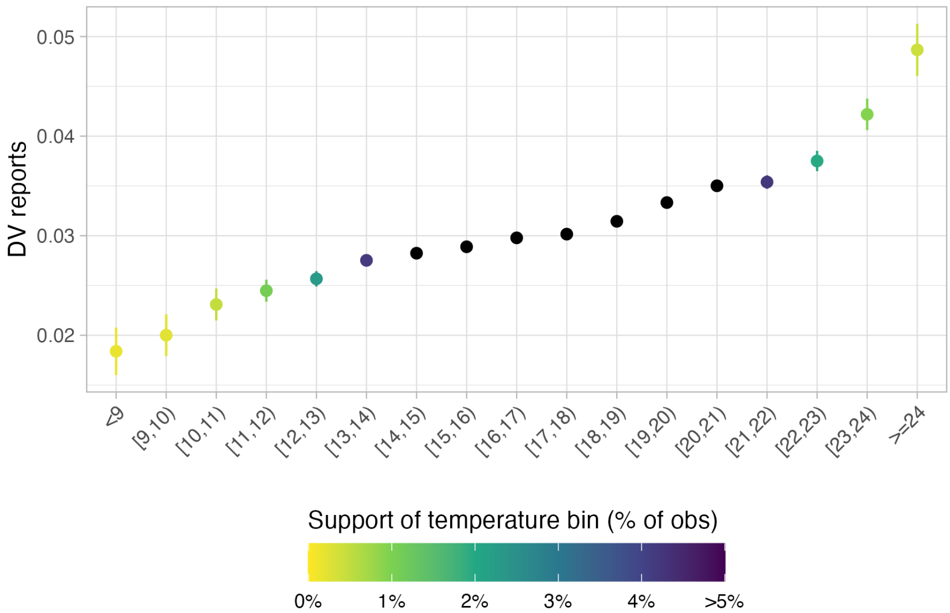
I combine data from the sources described above to create daily series of domestic violence and environmental data for Mexico City over the years 2016-2020 at the neighborhood level.[1] In Table A1, I provide summary statistics to characterize the sample that I use in the empirical analysis. The data shows an average of 73.6 domestic violence reports per day, with the helpline registering 18.5 calls related to DV incidents daily. In both data sources, approximately two-thirds of these incidents were reported as occurring during daytime hours (7 am to 7 pm included).

As a first look into the relationship between daily temperatures and domestic violence, I plot the average number of reported DV incidents per day per neighborhood across bins of daily mean temperature in Figure 2. A positive correlation between temperature and domestic violence is clearly apparent. On days with a mean temperature between 11°C and 12°C, there are on average 0.025 domestic violence crimes recorded per neighborhood. In contrast, the number of recorded incidents doubles on days with mean temperatures between 21°C and 22°C.[2] However, these raw associations may capture both temperature and seasonal effects, among others. To address this, I introduce an econometric framework in the next section that allows for a clean identification of the relationship between temperature and DV.

[1]As of now, I work with the sub-sample of days that preceded the pandemic (until mid-February 2020), but I have more recent data at hand.

[2]Figure B3 shows a similar trend for DV incidents measured through calls to the helpline. In addition, Figure B4 and B5 average DV incidence at a monthly level and show that warmer months record higher incidence of DV.

Figure 2: Average Count of DV Reports by Temperature Bin



Note: Average count of daily DV reports per neighborhood plotted across 1°C bins of daily mean temperature. Tail bins are grouped so that each contains at least 0.1% of observations cumulatively.

3 Empirical Strategy

My objective is to identify the short-term causal effect of temperature on the incidence of domestic violence. Both domestic violence and temperature may be affected by unobserved time-invariant factors, such as urban environment features, and time-varying determinants, such as seasonality patterns and holidays. My empirical specifications include a broad range of time-varying weather controls and a rich set of fixed effects to address these concerns.

I estimate the impact of temperature on same-day DV events by leveraging within-neighborhood temporal variations in temperature. I conduct the analysis at a daily level to isolate the short-term, non-economic determinants of DV. Since the domestic violence outcomes follow an implicit count process, I implement the following Poisson count fixed effect regression model (estimated using Quasi Maximum Likelihood to handle overdispersion):

$$C_{i,d} = exp\left(\mu_i + \lambda_d + \theta \cdot Temp_{i,d} + \gamma \cdot W_{i,d} + \varepsilon_{i,d}\right) \tag{1}$$

where the unit of observation is neighborhood i on day d.

The outcome $C_{i,d}$ is the daily count of DV which occurred in neighborhood i on day d. $Temp_{i,d}$ is the 24-hour mean of daily temperature in neighborhood i on day d. The use of 24-hour daily mean, rather than maximum or minimum temperature, is conceptually better suited to the DV context, since it reflects the cumulative thermal burden rather than short-lived extremes. The parameter of interest, θ, captures the marginal effect of an increase in mean temperature on DV rates. This specification assumes a log-linear relationship between temperature and DV, an assumption that I relax below. $W_{i,d}$ is a vector of time-varying weather controls that includes total daily precipitation, 24-hour mean of relative humidity, and 24-hour mean of windspeed in neighborhood i on day d, each entered as quintile indicators to flexibly account for potential nonlinear effects.

Neighborhood fixed effects μ_i account for time-invariant unobserved determinants of domestic violence specific to a neighborhood. To control for any unobserved determinants of domestic violence that vary over time but are common across Mexico City, I include λ_d, a comprehensive set of temporal fixed effects. These include year-by-month fixed effects to capture long-term trends in DV, day-of-week fixed effects to control for within-week patterns, and day-of-year fixed effects to absorb calendar-related variations, such as pay-day effects or potential misreporting on the first day of each month.

In addition, I specify a more flexible model to capture potential non-linearities in the temperature and domestic violence relationship:

$$C_{i,d} = exp\left(\mu_i + \lambda_d + \sum_b \theta^b \cdot Temp_{i,d}^b + \gamma \cdot W_{i,d} + \varepsilon_{i,d}\right) \tag{2}$$

where b denotes temperature bins of width 1°C. The vector $Temp_{it}^b$ includes binary indicators for each bin b, which take the value 1 if the temperature in neighborhood i on day d falls within the corresponding temperature interval. The parameters of interest θ^b capture changes in domestic violence rates on days with temperature falling in bin b relative to those in the reference bin. I set the omitted reference bin to days with 24-hour mean temperature in the bin [16°C − 17°C), which occur on about 60 days per year. This range reflects typical conditions in Mexico City, with average daily lows around 13°C and highs near 23°C. To avoid sparse bins at the extremes, adjacent bins are grouped until each contains at least 1% of observations cumulatively (bin support shown in Figure B6).

In both specifications, identification relies on the assumption that, conditional on the set of controls and fixed effects, temperature is as good as random. This ensures that estimating Eqs. 1 and 2 yields unbiased estimates of θ and θ^b. These parameters are identified by exploiting the variation of temperature within neighborhood over time. Standard errors are clustered at the neighborhood level, the level at which I measure temperatures.

4 Effects of Temperature Variation on DV

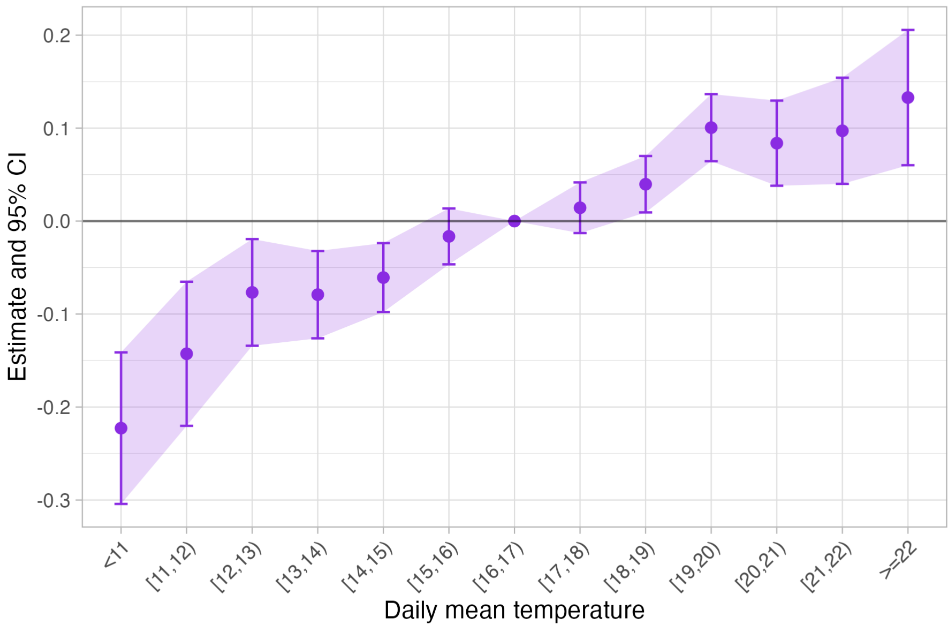
Contemporaneous effects

I exploit my high-frequency data to document a positive, nearly linear relationship between temperature and domestic violence. To account for potential non-linearities in the temperature-DV relationship, I use the semi-parametric bin estimator described in Equation 2. The resulting estimates for θ^b, along with 95% confidence intervals, are displayed in Figure 3. The figure shows that moving from the reference bin (14–16°C) to colder days is associated with a reduction in DV, while warmer days are associated with an increase in DV.

The estimates indicate a substantial effect: a 1°C increase in daily mean temperature is associated with just over a 2.4% increase in DV.[3] Moreover, these estimates suggest that the relationship between temperature and DV is approximately linear across the observed temperature range.

[3]This is based on a back-of-the-envelope average of the differences between the estimates for consecutive temperature bins.

Figure 3: Semi-Parametric Estimates of Temperature on DV Reports



Note: Estimates $\hat{\theta}^b$ and 95% confidence intervals from a semi-parametric bin estimator using 1°C bins of daily mean temperature, as specified in Equation 2. Each estimate reflects the change in domestic violence reports relative to the omitted reference bin [16°C – 17°C). Mean temperature is computed as the average of 24 hourly readings per day.

Given this apparent linearity, I estimate the baseline specification of Equation 1, imposing linearity on the temperature-DV relationship. Panel A of Table 1 presents the results of this baseline specification, where daily temperature is measured as the mean of the 24 hourly measurements of temperature. The point estimate indicates that a 1°C increase in daily mean temperature leads to a 2.8% increase in reported DV, aligning closely with the semi-parametric estimates[4].

Panel B of Table 1 explores the distinct effects of daytime and nighttime temperatures on domestic violence. I define daytime temperatures as the average of the hourly measurements of temperature between 7 am and 8 pm. To measure nighttime temperature, I average the hourly measurements from 9 pm on the previous night to 7 am on the morning in which the DV event is reported. Results in (i) and (ii) show that daytime temperature has a stronger association with DV than nighttime temperature when either enters the specification separately. The estimate for daytime temperature is close to the baseline estimate, while the estimate for nighttime temperature is about

[4]Percent change = $(e^{0.0274} - 1 \times 100) \approx 2.78\%$

Table 1: The Effect of Temperature on Reported DV

	Reports for DV		
	(i)	(ii)	(iii)
Panel A:			
24-hour Mean Temperature	0.0274***		
	(0.0034)		
Observations	3,624,826		
Panel B:			
Daytime temperature	0.0246***		0.0220***
	(0.0030)		(0.0041)
Nighttime temperature		0.0188***	0.0039
		(0.0031)	(0.0042)
Observations	3,624,815	3,624,809	3,624,797
Panel C:			
Maximum temperature	0.0197***		0.0159***
	(0.0026)		(0.0030)
Minimum temperature		0.0178***	0.0097***
		(0.0029)	(0.0034)
Observations	3,624,826	3,624,826	3,624,826
Prec., hum., windsp. quintiles	✓	✓	✓
Neighborhood FEs (1,798)	✓	✓	✓
Year-Month FEs (50)	✓	✓	✓
Day of Week FEs (7)	✓	✓	✓
Day of Year FEs (366)	✓	✓	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Panel A presents estimates from the baseline specification (Equation 1), where temperature is measured as the mean of 24 hourly readings. Panel B replaces mean temperature with daytime (7:00–20:00) and nighttime (21:00–7:00) temperatures. Column (i) includes only daytime temperature; Column (ii) includes only nighttime temperature; Column (iii) includes both jointly. Panel C adopts the same approach using the minimum and maximum of the 24 hourly readings instead. The dependent variable is the count of reported domestic violence incidents per neighborhood per day.

25% smaller but still significant. When both are included jointly in (iii), the nighttime temperature effect drops and becomes statistically insignificant, while the daytime effect remains strong. This suggests that DV is primarily driven by daytime temperature exposure, aligning with patterns of increased social and household interactions during these hours.

Temperature extremes are commonly used in the literature to measure exposure. Panel C of Table 1 examines daily maximum and minimum temperatures as predictors of DV. While both are significant – whether estimated separately or jointly – their effects are smaller and less comprehensive than those in Panel A, which uses the 24-hour mean temperature.[5] The literature often relies on maximum temperature as a proxy for heat exposure, emphasizing extreme heat during the hottest part of the day. While practical due to data availability, this approach may overlook the effects of sustained temperature exposure throughout the day. The results of Table 1 suggest that relying uniquely on maximal temperature could underestimate the effects of temperature on DV.

In all the estimations, I control for precipitation, relative humidity, and wind speed – each included as quintiles – to isolate the role of temperature. These weather factors can independently influence behavior and interact with temperature. Omitting these controls increases the temperature estimate by approximately 20%, indicating that they capture important variations in weather conditions. Table A2 presents these results, including specifications where each quintile is included separately. Additionally, Figure B8 shows the estimates across quintiles for the baseline specification, though no clear pattern emerges.

In Table A3, I estimate the baseline specification and vary the set of fixed effects. The results reveal their critical role in isolating the relationship between temperature and domestic violence. Neighborhood fixed effects are crucial, as structural differ-

[5]Figure B7 presents semi-parametric estimates of daily maximum and minimum temperatures, using temperature bins and estimating their effects jointly. The relationship for both variables remains approximately linear, and the effect of maximum temperature is larger than that of minimum temperature. These findings align closely with the results in Table 1 from the simpler specification where linearity is imposed.

ences across neighborhoods drive much of the observed variation in DV. Accounting for seasonality is also essential: while removing either day-of-year or month fixed effects individually does not substantially affect the results (as they largely capture the same seasonal patterns), removing both demonstrates the importance of controlling for seasonal variation. Interestingly, controlling for day-of-week fixed effects has little impact on the results, suggesting that within-week patterns are less relevant for explaining DV dynamics in this context.

Dynamic adjustments and cumulative effects

A common concern when analyzing the influence of short-term variations in temperature is whether the observed relationship between temperature and domestic violence (DV) incidents is purely contemporaneous or whether there exist meaningful temporal dynamics – such as displacement (harvesting) or persistence effects.

To address these possibilities, I estimate distributed lag models, allowing DV incidents to respond to temperature not only contemporaneously but also on preceding and subsequent days. Specifically, I estimate the following specification, which mirrors the structure of Equation 1 but incorporates leads and lags of temperature:

$$C_{i,d} = exp\left(\mu_i + \lambda_d + \sum_{\ell=-F}^{L} \theta^{\ell} \cdot Temp_{i,d}^{\ell} + \gamma \cdot W_{i,d} + \varepsilon_{i,d}\right) \tag{3}$$

This formulation allows me to test two distinct but not mutually exclusive dynamic hypotheses. First, higher contemporaneous DV induced by higher temperature may represent violence incidents that would otherwise have occurred in subsequent days. Under the presence of such "harvesting" effect, a positive contemporaneous temperature effect would be offset by negative coefficients in subsequent lags. Second, the temperature shock might trigger not only contemporaneous violence but also maintain elevated DV levels across subsequent days, resulting in positive lagged coefficients. This is a "persistence" effect. Importantly, these dynamics are not mutually exclusive: if harvesting effects and persistence effects coexist, they may cancel each other out, resulting in near-zero estimates for lags.

Table 2 presents estimates of distributed lag models with 1, 3, and 7 daily lags of temperature. The contemporaneous temperature coefficient remains highly significant across specifications (approximately 2.3% – 2.7%), while lagged temperature effects beyond the first day are small in magnitude and statistically insignificant. In particular, the first lag's coefficient is small and positive (approximately 0.5% – 0.8%), suggesting minimal spillover into the subsequent day. Beyond this, coefficients fluctuate around zero without statistical significance, indicating neither substantial persistence nor meaningful displacement.

In addition, the cumulative effect – the sum of contemporaneous and lagged coefficients – remains very close to the contemporaneous baseline estimate (2.7% in baseline, ranging from 2.8% to 3.1% with lags). This reinforces the interpretation that temperature shocks predominantly induce immediate, short-lived responses in DV incidents, with negligible net carry-over effects into subsequent days.

To further validate these findings, I estimate a specification including leads (future temperature values) alongside lags. The leads serve as a falsification test, as future temperature should logically not influence current DV incidents. Figure B9 clearly illustrates that lead coefficients are consistently close to zero and statistically insignificant, further corroborating the contemporaneous nature of the temperature-DV relationship and the absence of spurious temporal dynamics.

Taken together, these results robustly confirm that the temperature-driven increase in domestic violence is primarily an immediate, contemporaneous phenomenon, without meaningful persistence or displacement effects.

5 Heterogeneous Responses: The Role of Urban Poverty

In this section, I examine how the effect of temperature on domestic violence varies over neighborhood characteristics, particularly income and housing quality. I find that

Table 2: Lagged Effects of Temperature on Reported DV

	Reports			
	(i)	(ii)	(iii)	(iv)
Temperature	0.0274***	0.0234***	0.0236***	0.0237***
	(0.0034)	(0.0046)	(0.0047)	(0.0047)
l(tmean,1)		0.0051	0.0073	0.0078
		(0.0041)	(0.0056)	(0.0056)
l(tmean,2)			-0.0060	-0.0063
			(0.0056)	(0.0057)
l(tmean,3)			0.0059	0.0058
			(0.0041)	(0.0055)
l(tmean,4)				0.0026
				(0.0056)
l(tmean,5)				-0.0041
				(0.0056)
l(tmean,6)				-0.0006
				(0.0054)
l(tmean,7)				0.0019
				(0.0040)
Cumulative effect	0.0274	0.0285	0.0309	0.0308
Observations	3,624,826	3,622,403	3,617,557	3,607,865
Date FEs	✓	✓	✓	✓
Prec, hum, wsp quintiles	✓	✓	✓	✓
Neighborhood FEs	✓	✓	✓	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Column (i) reports the baseline specification (Equation 1), where temperature is measured as the mean of 24 hourly readings. Columns (ii), (iii), and (iv) sequentially include 1, 3, and 7 daily lags of temperature, respectively. The bottom row reports the cumulative effect, defined as the sum of the coefficients on same-day temperature and its lags. The dependent variable is the count of reported domestic violence incidents per neighborhood per day. All specifications include year-month fixed effects, day-of-week fixed effects, and day-of-year fixed effects, controls for precipitation, humidity, and wind speed (in quintiles), and neighborhood fixed effects.

an unequal response of domestic violence to temperature variations exacerbates pre-existing disparities in quality of life across the city.

I begin by augmenting earlier regressions with interactions between temperature and neighborhood average income, categorized into population-weighted quintiles. The top income quintile earns almost twice as much as the fourth, reflecting a strong concentration of income at the top. In contrast, income differences among the bottom 80% of the distribution are more modest, suggesting a compressed distribution in the lower quintiles.

The estimates presented in Table 3 reveal a clear income gradient with the impact of temperature on domestic violence declining as income increases. In the poorest neighborhoods (income quintile 1), a 1°C increase in mean temperature is associated with a 3.4% increase in reported domestic violence incidents. In contrast, the corresponding estimate for the richest neighborhoods (quintile 5) is only 2.2%. This pattern suggests that lower-income areas are more sensitive to heat-related stress.

Importantly, baseline DV levels are also lower in richer areas: neighborhoods in the top income quintile report, on average, 0.016 incidents per neighborhood-day, compared to approximately 0.025 in the other four quintiles. As a result, the increase in DV associated with higher temperatures is larger for disadvantaged neighborhoods both in relative terms (higher percentage change) and in absolute terms (more additional incidents). These findings underscore how rising temperatures may compound existing inequalities.

Next, I turn to a complementary measure of deprivation: the Housing Quality and Crowding Index (HQCI). This composite index captures both the quality of housing materials (walls, roof, flooring) and the degree of household crowding (number of rooms, bedrooms, kitchen per person). I hypothesize that differences in living conditions – beyond income alone – play a central role in shaping vulnerability to temperature variations.

As with income, I divide neighborhoods into HQCI quintiles, each containing equal shares of the population. The gradient in the temperature–DV relationship persists,

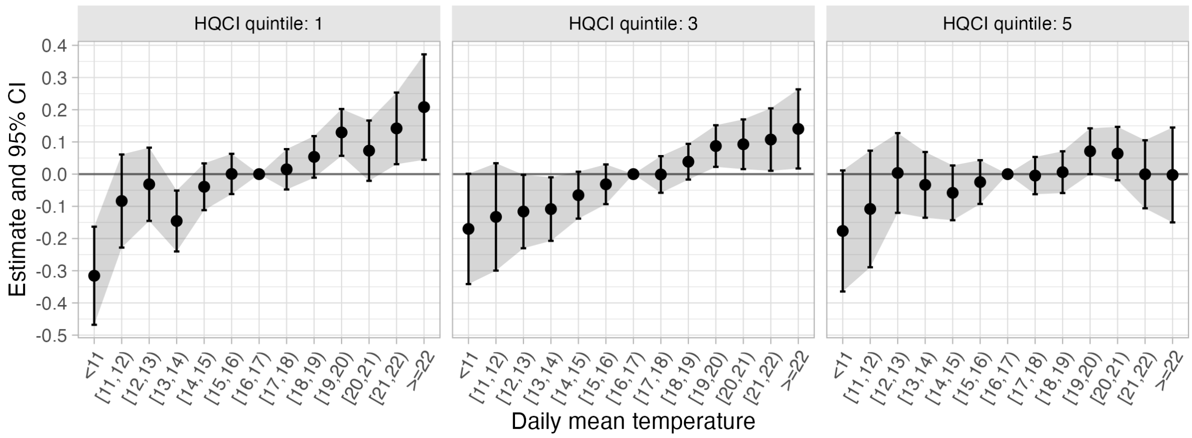
Table 3: The Effect of Temperature on Reported DV by Neighborhood Income Level

	Reports for DV
	(i)
Temperature × income_quintile = 1	0.0342***
	(0.0048)
Temperature × income_quintile = 2	0.0297***
	(0.0044)
Temperature × income_quintile = 3	0.0254***
	(0.0045)
Temperature × income_quintile = 4	0.0239***
	(0.0046)
Temperature × income_quintile = 5	0.0216***
	(0.0048)
Observations	3,578,253
Date FEs	✓
Prec, hum, wsp quintiles	✓
Neighborhood FEs (2,376)	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Estimates are from a modified version of Equation 1, in which mean daily temperature is interacted with neighborhood-level income quintile indicators. Quintiles are defined using population-weighted neighborhood-level average income, with Quintile 1 representing the poorest and Quintile 5 the richest areas. The dependent variable is the count of reported domestic violence incidents per neighborhood per day. This specification includes year-month fixed effects, day-of-week fixed effects, and day-of-year fixed effects, controls for precipitation, humidity, and wind speed (in quintiles), and neighborhood fixed effects.

mirroring the income-based results. However, I also explore whether the shape of the relationship varies with HQCI alongside the temperature distribution. Figure 4 reports semi-parametric estimates for the lowest, middle, and highest HQCI quintiles.

Figure 4: Semi-Parametric Estimates of Temperature on DV by HQCI Quintile



Note: Estimates $\hat{\theta}^b$ and 95% confidence intervals from a modified version of Equation 2, in which temperature bin indicators $Temp^b_{i,d}$ are interacted with Housing Quality and Crowding Index (HQCI) quintile indicators. All coefficients are estimated jointly in a single regression. The omitted reference bin is $[16°C - 17°C)$. Only HQCI quintiles 1, 3, and 5 are plotted for clarity.

The contrast is striking: in HQCI quintile 1 (worst housing conditions), we observe a strong, upward-sloping curve – domestic violence increases steadily with higher temperatures. In quintile 3, the slope is notably flatter, and in quintile 5 (best housing conditions), the curve is virtually flat, with no discernible temperature effect.

This pattern suggests that housing conditions mediate vulnerability to temperature shocks. Poor housing quality and crowding likely exacerbate the psychological and physiological stress associated with heat exposure. In contrast, households in better-constructed, less crowded dwellings may be more protected, buffering residents against heat-related stress and the risk of violence.

The results presented in this section point to a clear and consistent pattern: urban deprivation – whether measured by income or by housing quality – sharply increases sensitivity to temperature-induced domestic violence. These findings highlight how climate impacts are not evenly distributed, but rather follow existing lines of inequality, with the most disadvantaged neighborhoods facing the greatest costs.

6 Mechanisms, Robustness and Alternative Channels

Having established that daily temperature leads to an increase in reports for domestic violence, I now turn to potential alternative explanations. Specifically, I investigate whether the documented temperature-DV relationship might reflect biases arising from reporting behaviors, measurement issues, or other correlated environmental factors. The analyses in this section demonstrate robust evidence supporting a genuine causal effect of temperature on domestic violence incidence.

I start by confirming that the temperature-DV relationship remains consistent when measured using helpline calls – an independent data source unaffected by legal thresholds. Next, I show through reporting-delay diagnostics that temperature does not significantly influence the time between reporting and incidence of DV, suggesting that a reporting bias on the extensive margin is unlikely to be substantial. Benchmarking across crime types further confirms that the estimated effects are specific to violent interpersonal conflicts. Finally, I investigate the role of pollution as a potential environmental confounder, concluding that air quality neither mediates nor confounds the documented temperature-DV relationship in any meaningful way. Together, these tests indicate that the observed temperature effects reflect real changes in violent behavior, rather than measurement or reporting biases.

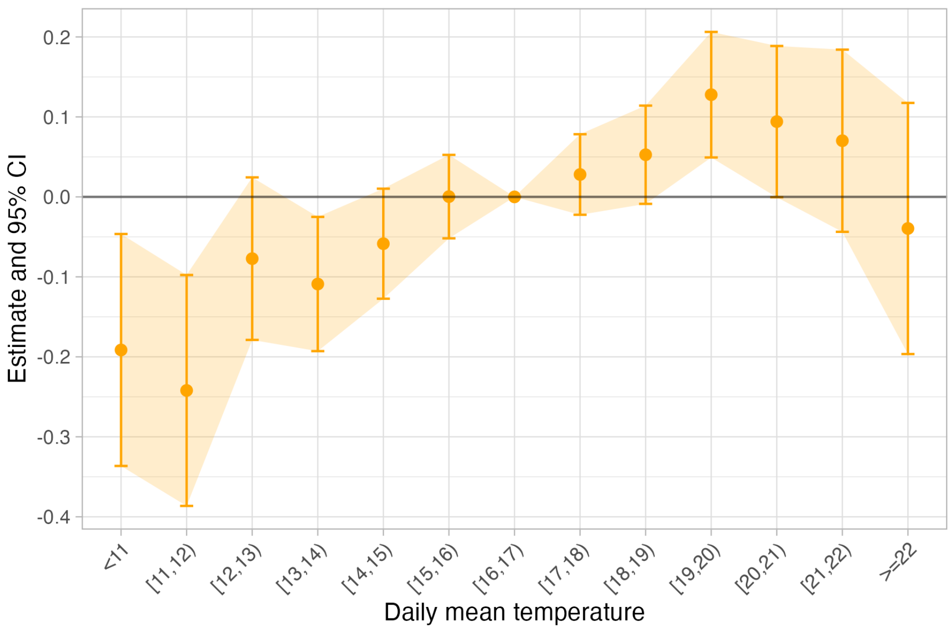
Could the pattern be driven by measurement or reporting?

Alternative outcome: helpline calls

Because all of the main evidence so far relies on police reports, a first robustness step is to test whether the temperature–DV gradient survives in a data set that is generated outside the criminal-justice pipeline. Calls to the public helpline *Línea Mujeres* are ideal for this purpose. Calling the helpline is free, anonymous, available around the clock, and unconnected to any legal procedure. Victims do not need to travel, fill out forms, or face police officers. These differences matter in two key ways. First, they eliminate some of the logistical and psychological frictions that could make formal reporting more sensitive to weather than the underlying incidence of violence. Second, the helpline records a broader spectrum of abuse – from threats and escalating arguments to physical attacks – that often never reaches the courts. Calls provide an independent view of the phenomenon and are less constrained by legal thresholds.

If weather mainly affected cost of reporting rather than true incidence, the elasticity in calls should diverge from that found with report data. Re-estimating the baseline specification of Eq. 1 with daily helpline calls yields a coefficient of 0.029 (s.e. 0.007), statistically indistinguishable from the 0.027 based on crime reports. The semi-parametric version of the model confirms the same near-linear slope across most of the temperature range. Figure 5 shows that only the hottest bins display a modest flattening relative to the results with reports data. But with generally wide confidence intervals, and in particular for extreme bins, any difference is not statistically significant.

Figure 5: Semi-Parametric Estimates of Temperature on DV Calls



Note: Estimates $\hat{\theta}^b$ and 95% confidence intervals from a semi-parametric bin estimator using 1°C bins of daily mean temperature, as specified in Equation 2. Each estimate reflects the change in calls for DV relative to the omitted reference bin [16°C – 17°C).

This concordance across two data sources reinforces and informs the main result in two ways. First, it makes a pure reporting-bias story implausible. If hotter days simply affected reporting costs, the elasticity in calls – generated under very different reporting incentives – should look different. Second, it shows that temperature already acts early in the escalation ladder. This is inconsistent with an economic or opportunity mechanism that would affect only severe violence.

Reporting-delay diagnostics

Only 13.1% of the women in Mexico City who experienced physical and/or sexual violence by their intimate partner filed a report, according to survey evidence (ENDIREH, 2021)[6]. Now, if weather conditions correlate with the likelihood that reports show up in our data, sample selection could bias the estimates documented above. Ideally, one would directly test whether temperature affects that extensive margin, but such a direct test is unfeasible, as data on unreported incidents are, by construction, unavailable.

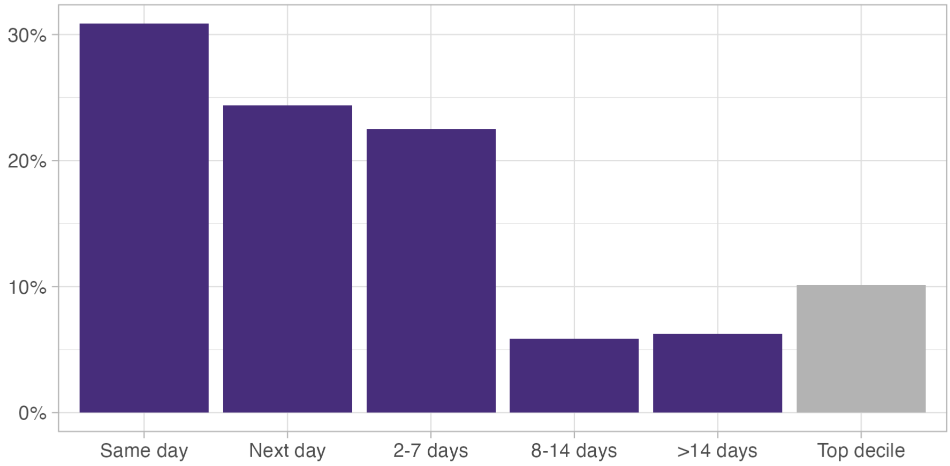
Still, we can test a closely related aspect of reporting behavior: the timing of incident reporting. If temperature systematically influenced the propensity to report, we might expect it to also affect the delay with which the incident is reported. To examine this possibility, I investigate whether temperature affects the delay between crime occurrence and reporting.

Figure 6 shows the distribution of the number of days between the domestic violence incident and the corresponding report. Reporting tends to be prompt: more than half of incidents are reported within one day (30% on the same day, 25% the next day), with less than 10% reported on the third day, and a long right-tail thereafter. Because very long delays are likely driven by different dynamics – such as follow-up procedures, legal requirements, or delayed disclosure – I exclude the top decile of the reporting delay distribution (reports made more than a month after the incident). These extreme delays are less likely to reflect immediate behavioral responses

[6]While these figures pertain to intimate partner violence, they highlight the importance of understanding reporting dynamics also in the wider context of domestic violence.

and more likely to introduce noise or measurement error.

Figure 6: Distribution of Reporting Delays for DV Reports



Note: Incident level data. Reporting delays is the number of days between the date of the domestic violence incident (as reported by the victim) and the date of reporting. Observations with a delay in the top decile (33+ days, final bar) are excluded from the analysis in Table 4.

To formally assess the influence of temperature on reporting delays, I first estimate a logit regression where the dependent variable indicates whether the incident was reported on the same day it occurred. Column (i) of Table 4 shows that temperature on the incident day has no meaningful impact on the likelihood of same-day reporting. This suggests that temperature is not a strong predictor of same-day reporting in this context.

Next, for incidents with at least one-day delays, I model the length of the delay using a negative binomial model (to account for over-dispersion in the delay counts). Column (ii) of Table 4 shows a modest yet negative estimate, indicating that each additional degree Celsius reduces reporting delay by about 1.3%. In Column (iii), including both incident-day and reporting-day temperatures simultaneously, estimates remain similarly small and negative. Thus, higher temperatures slightly shorten reporting delays, but these effects are minor and unlikely to meaningfully distort our primary contemporaneous results.

Finally, in Table 5, I estimate the baseline DV regression separately for subsets of incidents categorized by delay intervals (same day, next day, 2–7 days, 8–14 days, and 15+ days). This approach allows me to test whether the core temperature effect differs

Table 4: Temperature and Reporting Delays in DV Incidents

	Same day report	Positive delay	
	(i)	(ii)	(iii)
	Logit	Neg. Bin.	Neg. Bin.
Temperature on incident day	0.0035	-0.0124**	-0.0109*
	(0.0083)	(0.0061)	(0.0062)
Temperature on reporting day			-0.0117**
			(0.0046)
# Neighborhood	2,297	2,384	2,384
Observations	72,378	47,764	47,764
Date FEs	✓	✓	✓
Prec, hum, wsp quintiles	✓	✓	✓
Neighborhood FEs	✓	✓	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Incident level data. Incidents with a delay in the top decile (33+ days) are excluded from all estimations. Column (i) reports the coefficient estimate from a logistic regression where the dependent variable is an indicator for same-day reporting. Columns (ii) and (iii) report estimates from negative binomial models, estimated on the subsample of incidents reported with a delay of at least one day. Column (ii) includes only temperature on the incident day; Column (iii) includes temperature on both the incident and reporting days. All models year-month fixed effects, day-of-week fixed effects, and day-of-year fixed effects, controls for precipitation, humidity, and wind speed (in quintiles), and neighborhood fixed effects.

between reports made shortly after an incident versus those reported with significant delays. The estimates remain stable across incidents reported within the first week, slightly dip for incidents with delays of 8-14 days, and disappear for incidents reported with more than two weeks' delay. This consistency reinforces that the contemporaneous temperature-DV relationship is robust among promptly reported incidents.

These analyses on reporting delay clearly demonstrate that temperature has minimal impact on the timing of reporting. Given this negligible effect on reporting delays, it seems plausible to assume that temperature does not strongly influence the extensive margin – the likelihood of reporting DV incidents at all. Although it is unfeasible to conclusively rule out a reporting bias, these diagnostics substantially alleviate such concerns. I therefore interpret the documented positive contemporaneous relationship between temperature and domestic violence as primarily reflecting a genuine increase in incidence rather than an artifact of reporting behavior.

Table 5: The Effect of Temperature on Reported DV by Delay in Reporting

	Same day (i)	Next day (ii)	2-7 days (iii)	8-14 days (iv)	>14 days (v)
Temperature on incident day	0.0330***	0.0327***	0.0342***	0.0233*	0.0044
	(0.0061)	(0.0068)	(0.0070)	(0.0132)	(0.0078)
# Neighborhood	2,318	2,294	2,293	1,849	2,247
Observations	3,490,792	3,454,648	3,453,142	2,784,491	3,383,869
Dependent variable mean	0.007	0.006	0.005	0.002	0.004
Date FEs	✓	✓	✓	✓	✓
Prec, hum, wsp quintiles	✓	✓	✓	✓	✓
Neighborhood FEs	✓	✓	✓	✓	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Dependent variable is the daily count of reported domestic violence incidents per neighborhood within each delay category. Columns (i) through (v) report estimates from separate regressions, each estimated on a distinct subsample defined by reporting delay: same day, next day, 2–7 days, 8–14 days, and more than 14 days after the incident. Year-month fixed effects, day-of-week fixed effects, and day-of-year fixed effects, controls for precipitation, humidity, and wind speed (in quintiles), and neighborhood fixed effects are included in each specification.

Cross-crime benchmark

An additional way to assess whether the documented effect of temperature on domestic violence reflects genuine increases in incidence rather than reporting artifacts is to compare it with temperature effects on other crime types, especially those less susceptible to reporting biases. In Table A4, I re-estimate the baseline specification using different crime outcomes: homicides, theft, and fraud.

Among these outcomes, homicides represent an especially valuable benchmark. They have a very high likelihood of being reported, minimizing concerns related to a temperature-driven selection bias. The estimate shows a 2.4% increase in homicides for each additional degree Celsius. This result closely aligns with findings from other contexts and datasets. For example, Cohen and Gonzalez (2024) estimates a similar effect for the country of Mexico, finding a 2.6% increase in homicides per additional degree Celsius. Garg et al. (2020b) document a comparable 2.1% increase in daily homicide risk in Mexico. They use mortality statistics, which are generally subject to less underreporting than judicial data.

Estimates for theft and fraud indicate small and statistically insignificant effects.

Unlike domestic violence and homicide, theft and fraud are economically motivated crimes less clearly linked to impulsive or aggressive behavior triggered by heat. The weak results for these economically driven crimes provide indirect evidence that the temperature effect documented for domestic violence and homicide is driven specifically by temperature-induced changes in aggressive or impulsive behaviors rather than general increases in criminal activity or changes in crime reporting.

Finally, although my primary focus is domestic violence, it is reassuring that my main estimate is very close to Cohen and Gonzalez (2024)'s estimate for the effect of temperature on family violence in Mexico (3.5% per 1°C increase). Overall, benchmarking across crime types supports the argument that the temperature-driven increases observed in domestic violence are unlikely to be driven primarily by biases in crime reporting, and instead reflect a genuine behavioral response to higher temperatures.

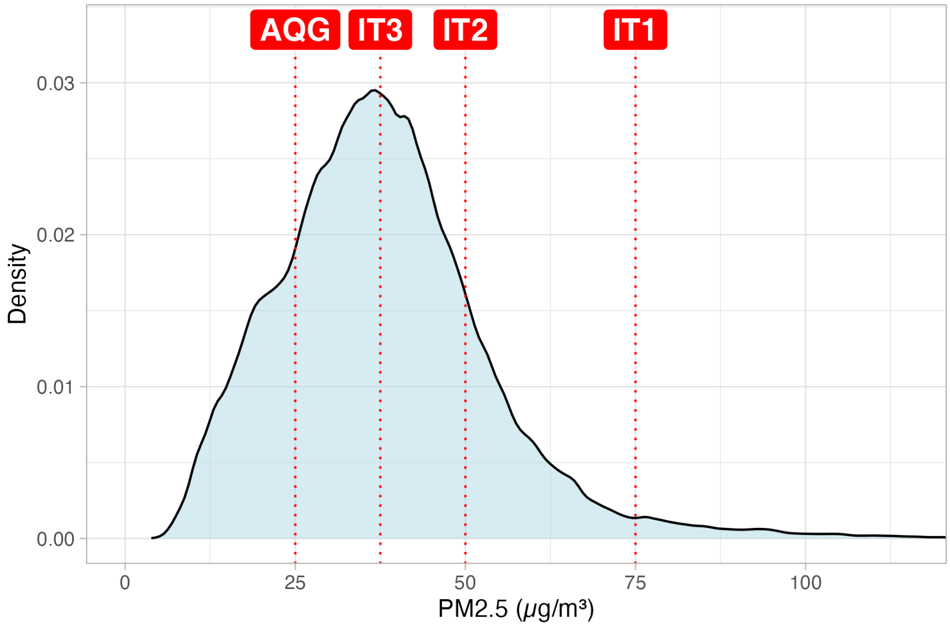
Environmental Interactions: The Role of Pollution

Beyond reporting behaviors and cross-crime comparisons, environmental factors – particularly air pollution – could potentially influence the relationship between temperature and domestic violence (DV). Given Mexico City's chronic air-quality challenges, it is plausible that pollution acts either as a confounder or as an indirect mechanism, altering social behaviors and interactions.

Mexico City consistently experiences elevated air pollution levels, notably particulate matter (PM 2.5). Figure 7 illustrates the distribution of the daily maximum PM 2.5 hourly readings per neighborhood relative to the World Health Organization's (WHO) Air Quality Guideline (AQG) and Interim Targets (IT1–IT3). The figure highlights the widespread exceedance of recommended pollution thresholds, reflecting Mexico City's persistently high pollution levels, with many neighborhood days experiencing at least one hour above the recommended levels.

If pollution were systematically correlated with temperature and simultaneously affected DV incidence, the previously documented temperature-DV relationship could

Figure 7: Distribution of maximum daily PM 2.5 reading per neighborhood



Note: Density of the daily maximum PM 2.5 hourly reading per neighborhood for 2016-2020. Vertical lines indicate the WHO Air Quality Guideline (AQG) and Interim Targets (IT1–IT3).

be biased. I first tested this possibility by directly including daily average PM 2.5 levels in the baseline specification. However, this simple linear specification revealed no statistically significant relationship between average daily pollution and DV incidents, suggesting a more nuanced approach to pollution exposure measurement may be required.

To better quantify pollution exposure, I adopt the approach of Hoffmann and Rud (2024), coding daily air pollution as the number of hours above the WHO's AQG and IT1–IT3 thresholds. Table 6 summarizes these pollution targets and the corresponding exposure levels in Mexico City. Pollution above these thresholds is common: approximately one-third of all hours, and over 80% of days, exceed the WHO AQG threshold in sample. Even the least stringent Interim Target (IT1) was exceeded on roughly 2.5% of days.

To assess whether air pollution confounds the temperature effect, I augment Eq. 1 by adding, for each WHO threshold $\tau \in$ AQG, IT3, IT2, IT1, a variable $H_{i,d}^{\tau}$ counting the number of hours in day d that PM2.5 in neighborhood i exceeds τ. The specification keeps the same fixed effects and weather controls as before, so the coefficient on Hi, d^{τ}

Table 6: WHO Air Quality Guidelines for PM 2.5 and Pollution Incidence

	Target PM 2.5	Hour-Neighborhood	Days-Neighborhood
Air Quality Guideline (AQG)	25 $\mu g/m^3$	35.8 %	80.2 %
Interim Target 3 (IT3)	37.5 $\mu g/m^3$	11.5 %	47.8 %
Interim Target 2 (IT2)	50 $\mu g/m^3$	3.3 %	17.8 %
Interim Target 1 (IT1)	75 $\mu g/m^3$	0.5 %	2.6 %

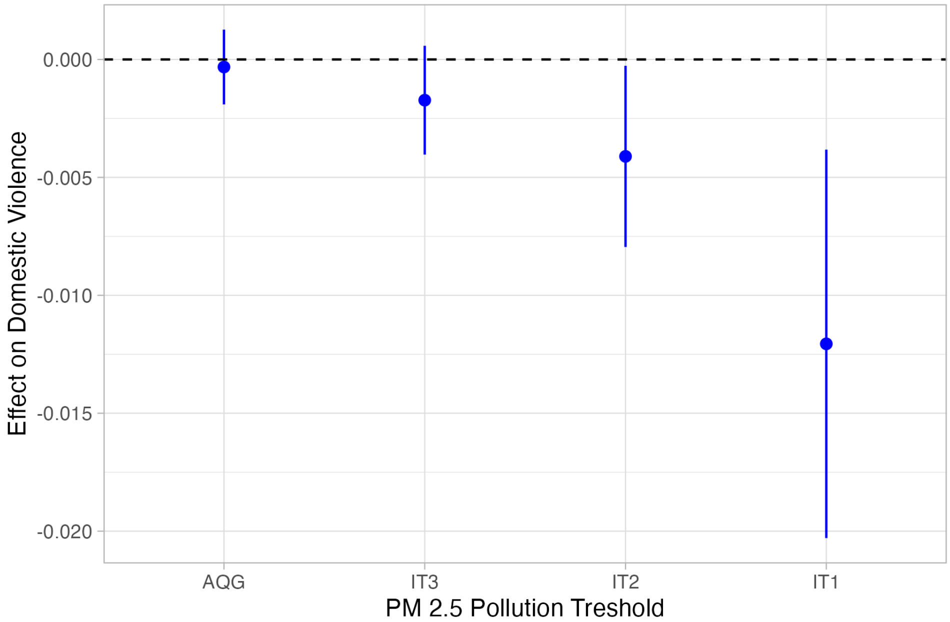
is interpreted as the percent change in DV associated with one additional hour above that threshold, conditional on mean temperature and other meteorological factors.

Figure 8 plots estimates from separate regressions of DV incidence on hours above each WHO threshold. For lower pollution thresholds (AQG and IT3), estimates are small and statistically insignificant. Given that these thresholds are exceeded frequently, it is unsurprising that modest pollution levels do not meaningfully influence DV reports. Interestingly, however, at more extreme pollution thresholds (IT2 and especially IT1), the estimates become negative and statistically significant. Specifically, each additional hour above the IT1 threshold is associated with approximately a 1.2% reduction in daily DV reports. This negative relationship suggests that very high pollution may indirectly reduce DV incidence, possibly by limiting outdoor activities or social interactions, thereby reducing opportunities for conflict.

Importantly, even after accounting for these pollution measures, the estimated effect of temperature on DV remains virtually unchanged in both magnitude and statistical significance. This indicates clearly that pollution neither mediates nor confounds the core temperature-DV relationship documented previously. While pollution – especially at extreme levels – might independently affect DV, its influence is quantitatively minor compared to the influence of temperature variations.

In sum, the pollution analysis confirms the robustness of the documented temperature-DV relationship. Despite Mexico City's high pollution levels, variations in air quality do not significantly bias or confound the relationship between temperature and domestic violence. This further strengthens confidence in the main results, underscoring that the temperature-driven increase in DV incidence is a distinct and robust phenomenon.

Figure 8: Daily hours above WHO thresholds and Domestic Violence



Note: Coefficient estimates and 95% confidence intervals from separate regressions augmenting Equation 1 with a count of hourly exceedances of each WHO $PM_{2.5}$ threshold (AQG, IT3, IT2, IT1). Each estimate reflects the change in DV reports associated with one additional hour above the corresponding threshold, conditional on mean temperature and other weather variables.

What mechanism survives these tests?

The robustness exercises in this section strongly suggest that the temperature effect reflects a genuine rise in domestic-violence incidence rather than a reporting artifact. What, then, drives this observed relationship? Three empirical regularities documented above help narrow the possible mechanisms.

First, consider the timing and functional form of the relationship. The effect is strictly contemporaneous, approximately linear across a moderate temperature range of 11°C–23°C, and distributed-lag estimates reveal neither persistence nor displacement. Any plausible mechanism must therefore operate within the same day and without a sharp physiological threshold. A purely physiological explanation – such as heat-induced stress – struggles to explain the absence of nonlinearities or threshold effects. In addition, moving between two temperatures that are within the human body comfort zone should not trigger physiological stress. The stability of the estimates across the full temperature support points to a complementary behavioral or social dimension.

Second, the robustness of the estimates to variations in reporting incentives and administrative frictions indicates that temperature affects the occurrence of violence itself, rather than the likelihood of reporting. Similar elasticities from police reports and the lower-cost, anonymous helpline calls confirm that variations in reporting costs or administrative constraints cannot entirely drive the observed effects.

Third, the amplification of temperature effects by socioeconomic vulnerability – housing quality and income – points toward mechanisms involving stress and interpersonal contact. The elasticity more than triples in neighborhoods characterized by crowded living conditions and poor housing materials. This distributional pattern supports the argument that higher temperatures increase interpersonal friction, especially when households have limited means to mitigate heat stress or to physically separate arguing parties.

Taken together, these three findings strongly favor a short-run behavioral mechanism that combines mild physiological stress with temperature-driven changes in social interactions, leading to increased interpersonal contact. Higher ambient temperature, even within moderate comfort ranges, may plausibly lower self-control and increase irritability. Coincidentally, variations in temperature alter social routines and prompt household members to spend more time together, increasing interpersonal contact and the likelihood for escalation and aggression.

7 Conclusion

This paper provides robust evidence of a relationship between daily temperature and domestic violence (DV) in Mexico City. Leveraging fine-grained data from police reports and independent helpline records, my findings show that even moderate increases in ambient temperature significantly raise DV incidence, with a nearly linear relationship and immediate contemporaneous effects. Specifically, I find that a 1°C rise in daily mean temperature is associated with approximately a 2.7% increase in

DV reports, a relationship that remains consistent across various robustness checks and alternative measurement strategies.

The observed patterns strongly support a combined physiological and behavioral mechanism. Moderate heat stress reduces self-control and increases irritability, while temperature variations shift social interactions and time use, heightening the risk of conflict and aggression. In addition, while a reporting bias cannot be entirely ruled out, my findings suggest that sample selection cannot be the main driver of the relationship between temperature and DV.

Importantly, this impact is unequally distributed across the city. Neighborhoods in the lowest income quintiles experience notably stronger effects, with each degree increase in temperature producing up to 50% greater relative increases in DV incidents compared to affluent areas. Similarly, poor housing quality amplifies temperature-induced DV, highlighting how climatic stressors compound pre-existing urban inequalities.

These findings carry two key policy implications. First, the near-linearity of the relationship suggests that policies should consider temperature as a continuous risk factor rather than focusing exclusively on extreme events. Second, the strong gradient observed across income levels and housing conditions indicates that residents of poorer neighborhoods have more limitations to avoidance behavior. Policies aimed at improving housing quality and living conditions could therefore effectively mitigate the adverse social impacts of increasing environmental stress.

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A Appendix Tables

Table A1: Summary Statistics: Domestic Violence, Weather, and Pollution

	N	Mean	Std Dev	Min	Max
Domestic violence – Daily					
Reports for DV	2,922	73.4	25.69	20	174
Reports for DV in daytime	2,922	41.9	14.99	9	100
Reports for DV in nighttime	2,922	25.0	11.15	5	78
Calls for DV	2,130	25.9	9.56	0	83
Calls for DV in daytime	2,130	18.5	7.16	0	50
Calls for DV in nighttime	2,130	7.5	3.84	0	38
Domestic violence – Day × AGEB					
Reports for DV	7,097,538	0.030	0.18	0	6
Domestic violence – Day × Neighborhood					
Calls for DV	2,939,400	0.019	0.15	0	7
Weather and pollution – Daily					
Mean temperature (°C)	2,922	17.3	2.31	6.9	23.6
Minimum temperature (°C)	2,922	12.4	2.55	1.7	18.0
Maximum temperature (°C)	2,922	23.4	2.76	10.7	31.4
Precipitation (mm)	2,922	1.8	3.43	0	28.0
Relative humidity (%)	2,922	52.6	13.49	14.3	88.1
Windspeed (km/h)	2,922	2.1	0.45	1.2	6.3
Mean PM2.5 (μg/m^3)	2,922	21.1	8.95	2.9	88.2

Note: The number of observations varies across variables due to shorter coverage of DV call data compared to reports. Domestic violence reports are aggregated by day and AGEB (a census block–level unit), while domestic violence calls are aggregated by day and neighborhood. This distinction reflects differences in the underlying geographic identifiers of the two datasets.

Table A2: Sensitivity to Controls for Precipitation, Humidity, and Wind Speed

	Reports				
	(i)	(ii)	(iii)	(iv)	(v)
Temperature	0.0277***	0.0335***	0.0307***	0.0285***	0.0332***
	(0.0034)	(0.0027)	(0.0029)	(0.0033)	(0.0028)
Observations	3,624,826	3,624,883	3,624,883	3,624,826	3,624,883
Precipitation FEs (5)	✓		✓		
Humidity FEs (5)	✓			✓	
Windspeed FEs (5)	✓				✓
Neighborhood FEs (2,407)	✓	✓	✓	✓	✓
Year-Month FEs (50)	✓	✓	✓	✓	✓
Day of Week FEs (7)	✓	✓	✓	✓	✓
Day of Year FEs (366)	✓	✓	✓	✓	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Dependent variable is the daily count of reported domestic violence incidents per neighborhood. Column (i) (baseline) includes quintile fixed effects for precipitation, humidity, and wind speed. Columns (ii)–(v) include none or only one set of weather controls at a time.

Table A3: Sensitivity to Fixed Effects Specification

	Reports					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Temperature	0.0277***	0.0141**	0.0245***	0.0285***	0.0348***	0.0275***
	(0.0034)	(0.0062)	(0.0031)	(0.0029)	(0.0019)	(0.0033)
Observations	3,624,826	3,657,955	3,624,826	3,624,826	3,624,826	3,624,826
Precipitation FEs (5)	✓	✓	✓	✓	✓	✓
Humidity FEs (5)	✓	✓	✓	✓	✓	✓
Windspeed FEs (5)	✓	✓	✓	✓	✓	✓
Neighborhood FEs (2,407)	✓		✓	✓	✓	✓
Year-Month FEs (50)	✓	✓		✓		✓
Day of Week FEs (7)	✓	✓	✓	✓	✓	
Day of Year FEs (366)	✓	✓	✓			✓
Year FEs (5)			✓		✓	

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Dependent variable is the daily count of reported domestic violence incidents per neighborhood. Each column reports estimates from a variation of the baseline specification in which a different set of fixed effects is omitted. All regressions include quintile controls for precipitation, humidity, and wind speed.

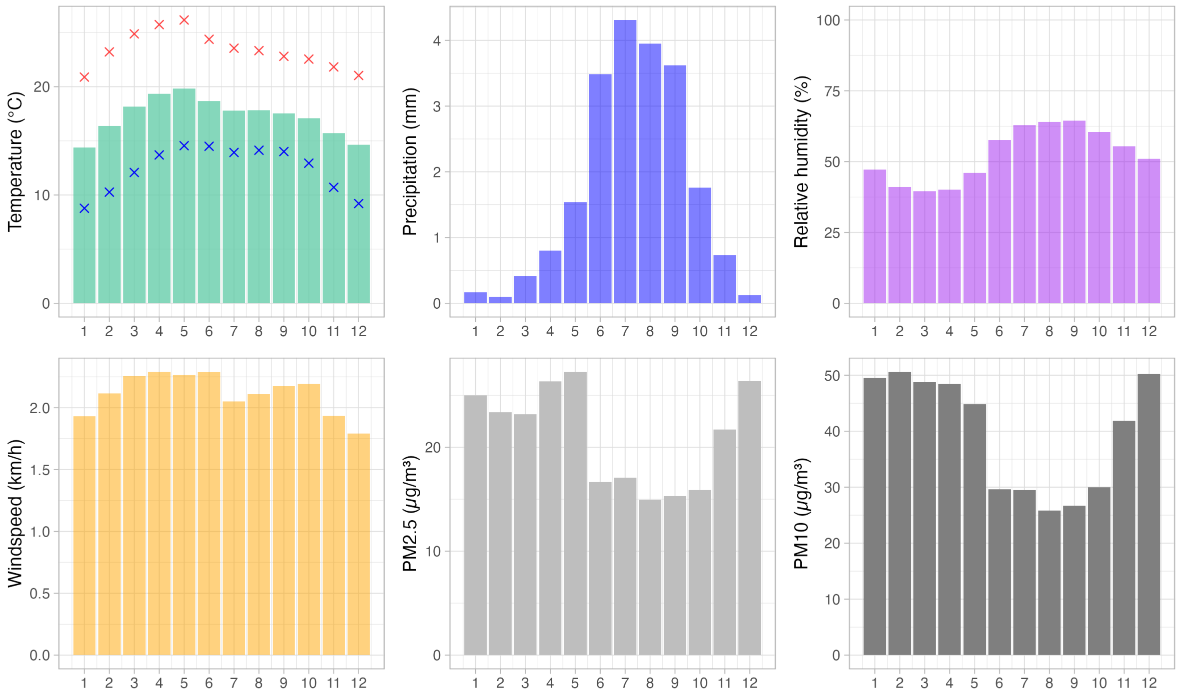
Table A4: Temperature Effects on Reports for Other Types of Crime

	Domestic violence (i)	Homicide (ii)	Theft (iii)	Fraud (iv)
tmean	0.0274***	0.0268**	0.0023	0.0052
	(0.0034)	(0.0111)	(0.0015)	(0.0046)
Observations	3,624,826	2,843,215	3,636,874	3,454,739
Dependent variable mean	0.023	0.002	0.119	0.015
Prec, hum, wsp quintiles	✓	✓	✓	✓
ageb FEs	✓	✓	✓	✓
year-month FEs	✓	✓	✓	✓
day_of_week FEs	✓	✓	✓	✓
day_of_year FEs	✓	✓	✓	✓

Notes: Standard errors clustered by neighborhood in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level. Each column reports results from a separate regression of daily crime counts on temperature and weather controls. All regressions include neighborhood fixed effects, day-of-year fixed effects, year fixed effects, and quintile controls for precipitation, humidity, and wind speed. The dependent variable varies across columns and corresponds to daily counts per neighborhood for the indicated crime category.

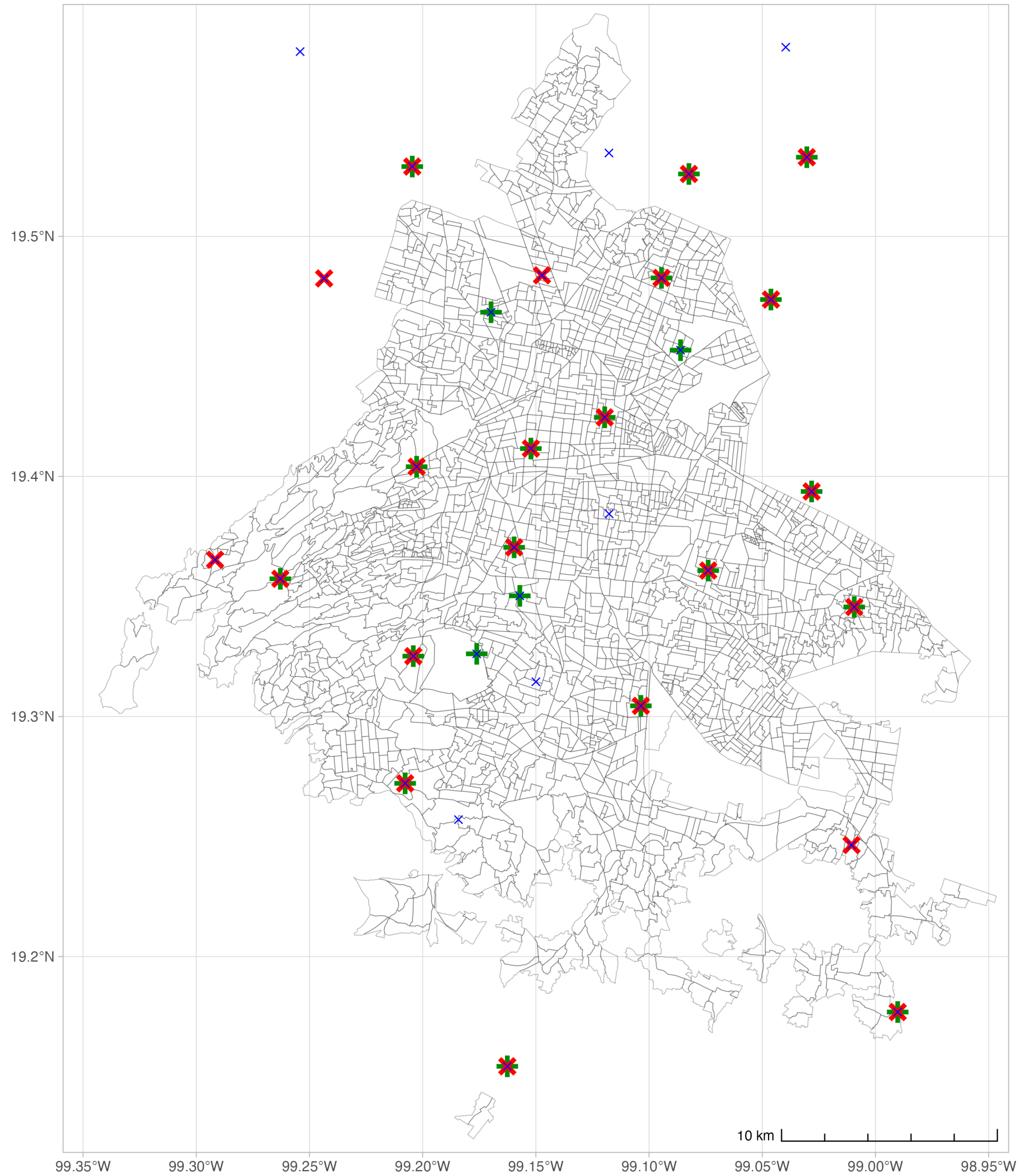
B Appendix Figures

Figure B1: Monthly averages of weather and pollution indicators



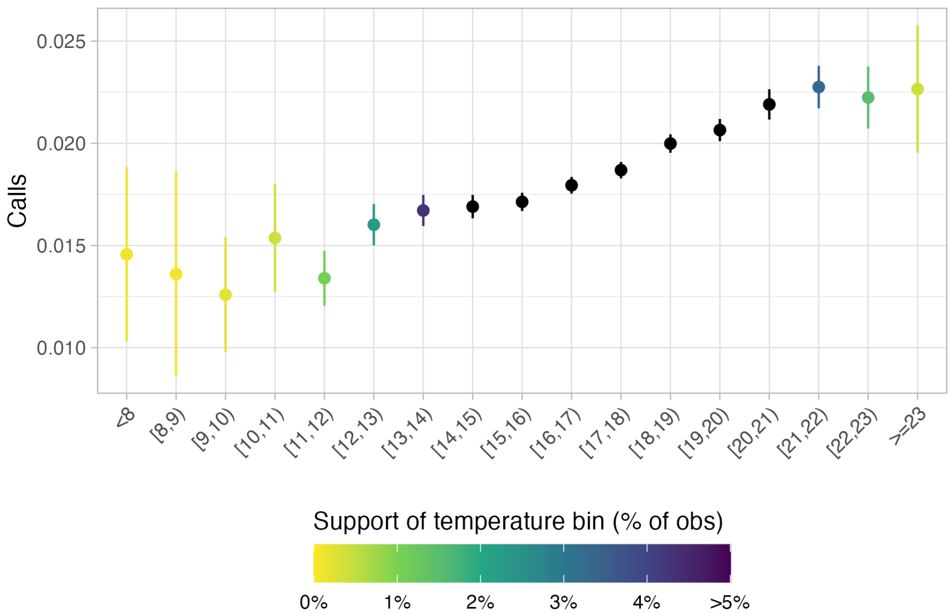
Note: Monthly averages for daily weather and pollution measures in Mexico City, 2016–2020.

Figure B2: Monitoring stations and AGEBs of Mexico City



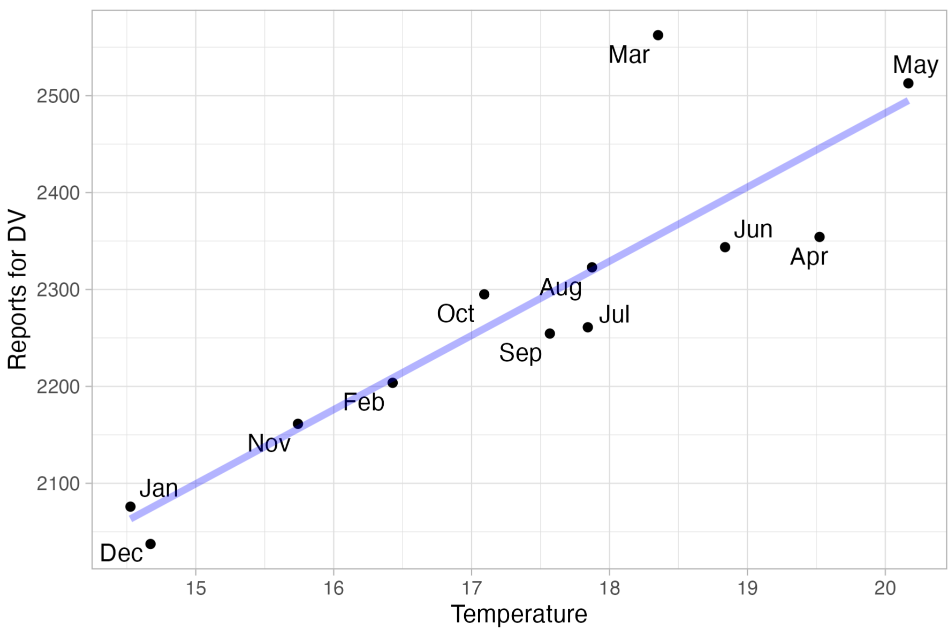
Note: The 2,431 AGEBs of Mexico City, along with weather monitoring stations in red, pollution monitoring in green, and precipitation stations in blue. There are a total of 27, 24, and 51 stations used for weather, pollution, and precipitation, respectively, that are within a 20km radius of the centroid of any neighborhood. Some do not appear the map due to their location outside the displayed area.

Figure B3: Average Count of DV Calls by Temperature Bin



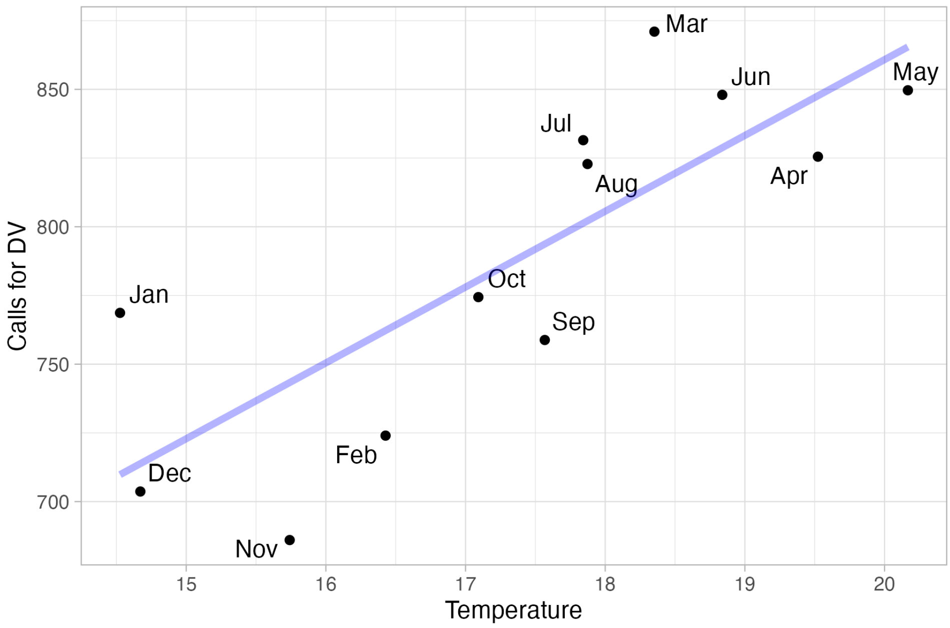
Note: Average count of daily DV calls per neighborhood plotted across 1°C bins of daily mean temperature. Bins with less than 0.01% of observations at the distributional extremes are grouped.

Figure B4: Monthly DV Reports and Mean Temperature



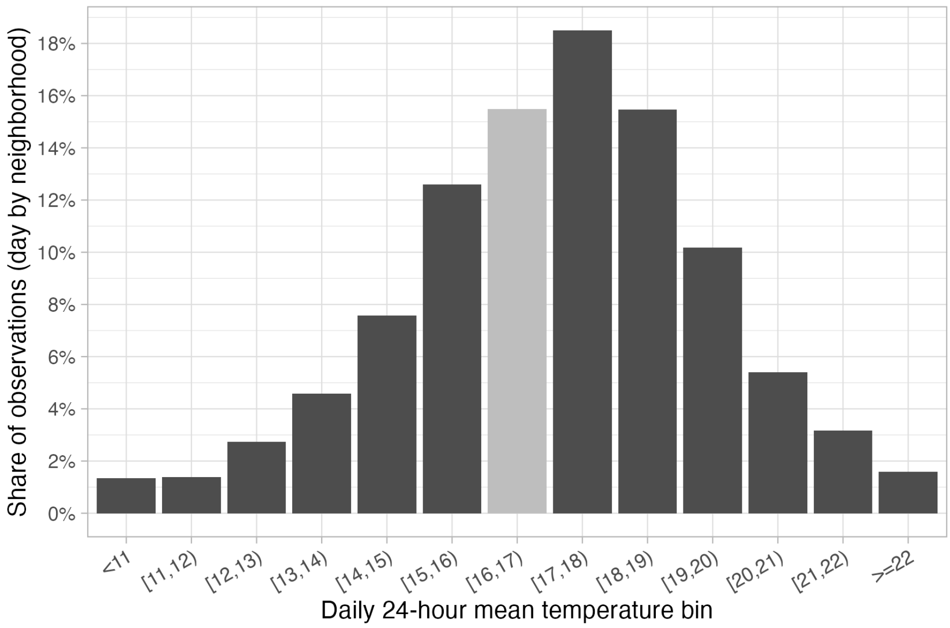
Note: Monthly averages of DV reports and mean temperature for 2016-2020. Each point represents a calendar month, with the fitted line from a bivariate linear regression of monthly DV reports on monthly mean temperature.

Figure B5: Monthly DV Calls and Mean Temperature



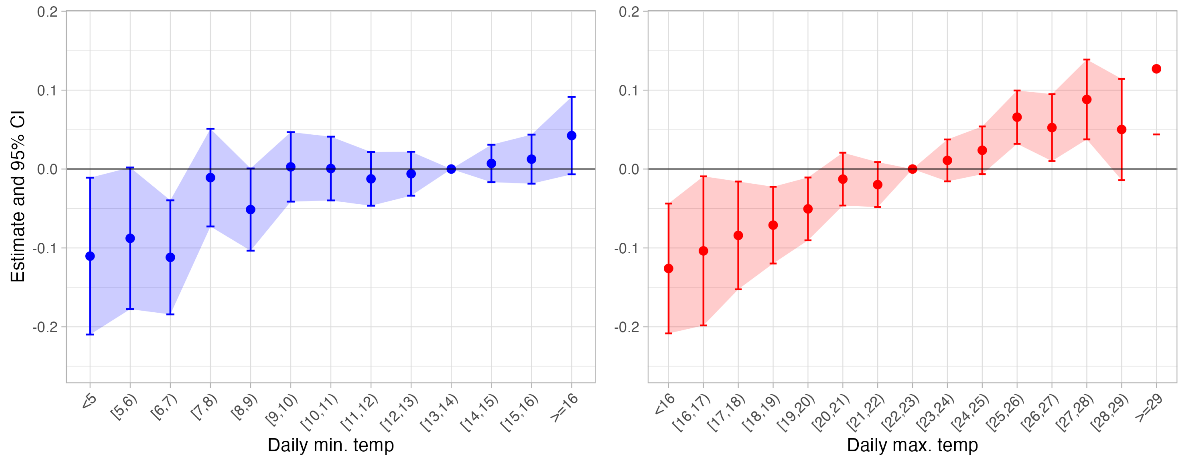
Note: Monthly averages of DV calls and mean temperature for 2016-2020. Each point represents a calendar month, with the fitted line from a bivariate linear regression of monthly DV calls on monthly mean temperature.

Figure B6: Distribution of Mean Temperature Regression Bins



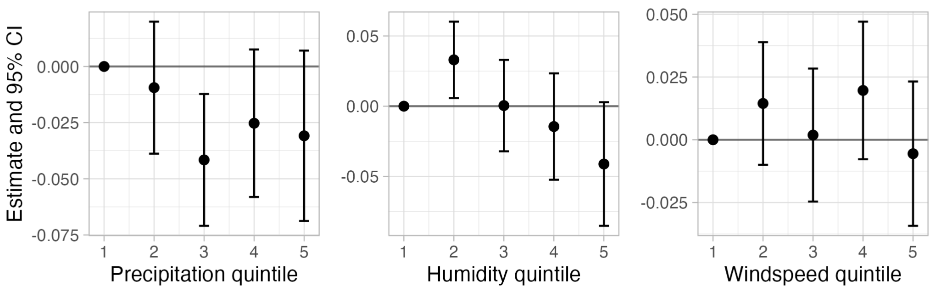
Note: Histogram of daily mean temperature observations across 1°C bins. Each bin corresponds to a binary indicator in the vector $Temp_{it}^{b}$ in Eq. 2. The omitted reference category, [16°C – 17°C) (shaded) represents typical weather conditions in Mexico City. At the tails, adjacent bins are grouped until each contains at least 1% of observations cumulatively

Figure B7: Semi-Parametric Estimates of Minimum and Maximum Temperature Effects on Domestic Violence



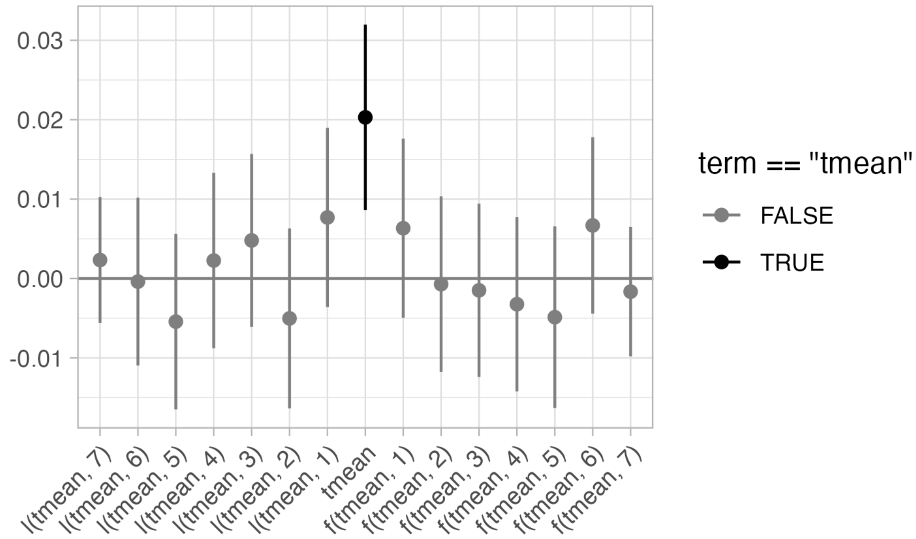
Note: Estimates $\hat{\theta}^b$ and 95% confidence intervals from a semi-parametric bin estimator using 1°C bins of daily minimum and maximum temperature, jointly included in place of mean temperature in a modified version of Equation 2. Each estimate reflects the change in DV reports relative to the omitted reference bin: [13°C, 14°C) for minimum temperature and [22°C, 23°C) for maximum temperature. Minimum and maximum temperature are defined as the lowest and highest of the 24 hourly readings recorded each day.

Figure B8: Estimates on Weather Quintiles from the Baseline Specification



Note: Coefficient estimates and 95% confidence intervals for precipitation, relative humidity, and wind speed quintiles from the baseline specification with temperature entering linearly (Panel A of Table 1). Each quintile is included as a categorical variable, with the first quintile omitted as the reference.

Figure B9: Estimates from a Distributed Lags and Leads Model



Note: Estimates $\hat{\theta}_\ell$ and 95% confidence intervals from the distributed lag and lead model specified in Equation 3, which includes seven daily lags and seven daily leads of mean temperature.