

# Temperature Variation and Domestic Violence

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Tor Vergata Ph.D. Conference

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# Temperature Variation and Domestic Violence

- Domestic violence is common and costly:
  - In Mexico, 40% of women have experienced violence from a partner in their most recent or current relationship (in 2021)
  - Costly in terms of health care, lost productivity, social welfare...
- Identifying risk factors is crucial to inform prevention and intervention
  - Weather is one of them

# Today:

## What is the effect of temperature on domestic violence rates in Mexico City?

- Association between temperatures and crime is well documented ...  
... but is DV affected differentially?
  - Relationship between perpetrator and victim, involves a complex dynamic of power and control, mostly occurs at home ...
  - I find that DV reacts more strongly to temperature than other types of crime
- Small-scale heterogeneity
  - City's exposure to weather is approx. the same
  - Main source of heterogeneity is man-made (e.g. between neighborhoods)
  - Likely more responsive to interventions

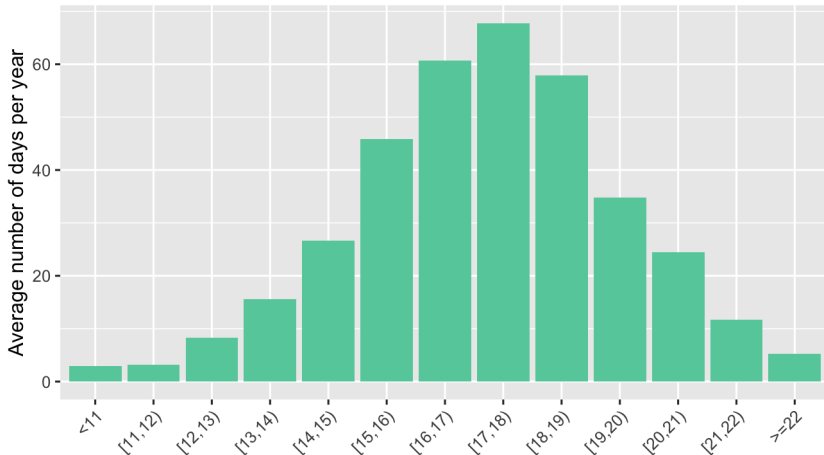
# Overview

- I document a positive association between temperatures and domestic violence
- On average, 1°C increase in daily temperature leads to a 2.7% [2.0% – 3.3%] increase in daily reported DV
- Lit. highlights two main complementary mechanisms
  - Routine Activity:  
variation in temperature leads to behavioural change
  - Physiological Effects:  
aggression increases with temperature because of physical irritation and discomfort

## Context: Mexico City

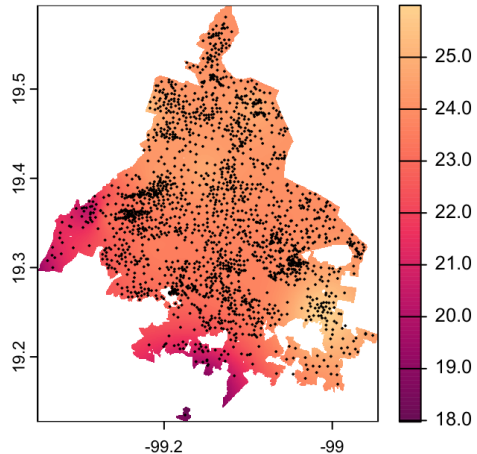
- Mild temperatures year round (altitude 2,250 masl)
- Temperature =  $t_{\text{mean}} = \text{sum}(\text{hourly measurements}) / 24$

min max



## Data from ground-based stations

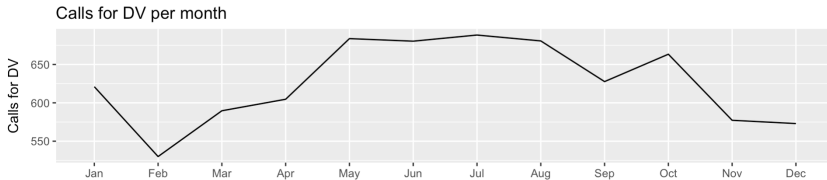
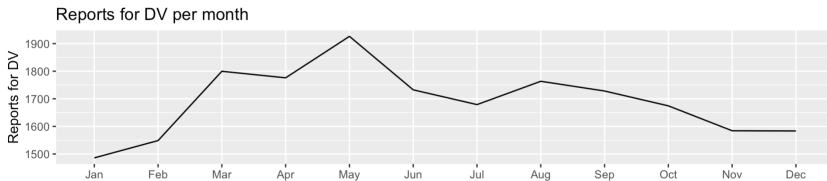
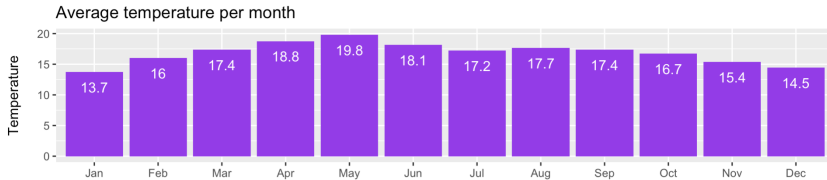
- Hourly weather data from 26 stations
  - Temperature
  - Humidity
  - Windspeed
- Precipitations from 84 weather stations
  - Total daily precipitations (mm)
- Hourly pollution data from 24 stations
  - PM2.5



# Domestic violence data

- Two sources of data, to investigate a potential reporting bias
  - Incident-level crime data from Mexico City Attorney General's Office ( $\approx 56$  per day)
  - Calls to a helpline ( $\approx 25$  per day)
- Time and date of **occurrence**, geo-coded
- 2016 – Pandemic
- Daily count for each of 1,948 neighborhoods ( $\approx 95\%$  zeroes)

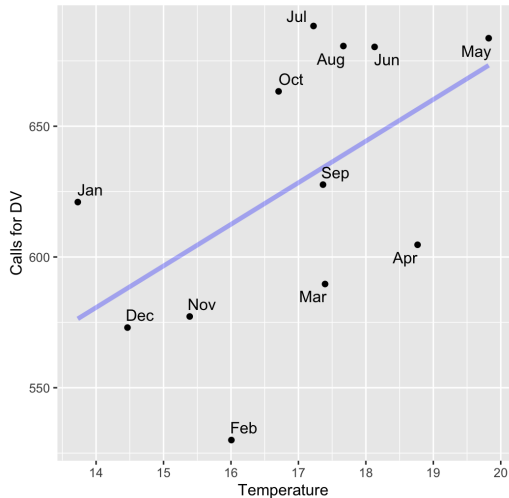
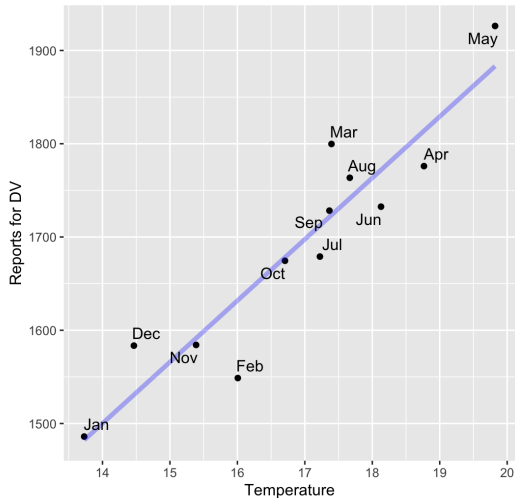
# Raw data: monthly averages I





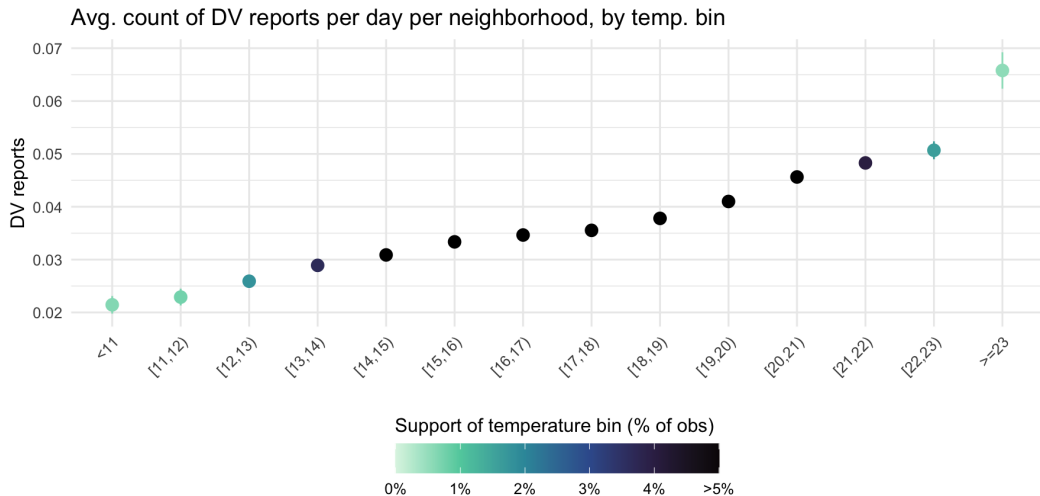
# Raw data: monthly averages II

Monthly averages for DV cases and temperature



## Relating temp and DV cases: Raw data per day $\times$ neighborhood

scatter






## Poisson count FE model estimated using Pseudo Maximum Likelihood

$$Y_{i,d} = \mu_i + \mu_d + \theta \cdot f(T_{i,d}) + \gamma \cdot W_{i,d} + \varepsilon_{i,d}$$

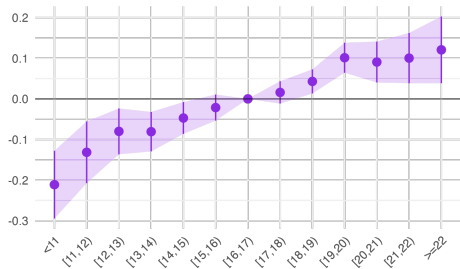
- $Y_{i,d}$  is a daily count for DV crime in neighborhood  $i$  on day  $d$
- $\mu_i$  are neighborhoods' FE and  $\mu_d$  are temporal FE: year-month, day of year, day of week
- $T_{i,d}$  is the average daily temp. in a neighborhood and  $f(\cdot)$ :
  - Either:  $f(T_{i,d}) = T_{i,d}$
  - Or:  $f(T_{i,d}) = \sum_b^B T_{i,d}^b$  where  $T_{i,d}^b$  indicates if  $T_{i,d}$  falls in bin  $b$ .
- $W_{i,d}$  controls for other weather variables (precipitation, windspeed, humidity) in quintiles
- $\varepsilon_{i,d}$  clustered at the neighborhood level

## Identifying variation:

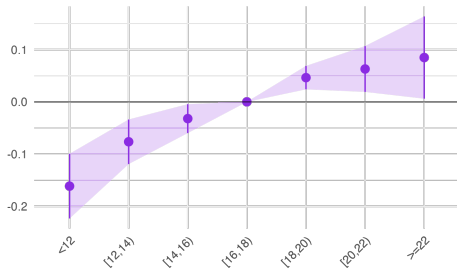
### Idiosyncratic, short-term fluctuations within neighborhoods

- Within-neighborhood: I control for all static neighborhood characteristics 
- Within-year-month: Since systematic seasonal and annual variations for that month in any year are adjusted. 
- Adjusting for day of the week and day of the year 

## Linear over temperature support



(a) Temperature bins of width 1°C



(b) Temperature bins of width 2°C

- Semi-parametric bin estimator to capture non linear relationship
- Interpreted with reference to the omitted category: [16°C – ...°C)

## Temperature enters linearly

	(i) Poisson	(ii) Poisson	(iii) OLS	(iv) Poisson
Temperature	0.034*** (0.003)	0.026*** (0.003)	0.0008*** (0.0001)	0.027*** (0.003)
pm25_mean				-0.0008 (0.0006)
Observations	2,933,688	2,933,688	2,933,688	2,933,688
Effect size (in %)	3.42%	2.67%	2.68%	2.73%
Neighborhood FEs (1,948)	✓	✓	✓	✓
Year-Month FEs (50)	✓	✓	✓	✓
Day of Week FEs (7)	✓	✓	✓	✓
Day of Year FEs (366)	✓	✓	✓	✓
Prec, hum, and wsp quintiles		✓	✓	✓

- Significant positive association between temperature and DV
- A 1°C increase in avg. temp. corresponds to a 2.7% increase in daily DV reporting

# Displacement effects and spillovers

	1 lag	3 lags	7 lags
Temperature	0.022*** (0.005)	0.022*** (0.005)	0.022*** (0.005)
l(tmean,1)	0.006 (0.004)	0.007 (0.006)	0.007 (0.006)
l(tmean,2)		-0.004 (0.006)	-0.004 (0.006)
l(tmean,3)		0.005 (0.004)	0.004 (0.006)
l(tmean,4)			0.004 (0.005)
l(tmean,5)			-0.005 (0.005)
l(tmean,6)			-0.000 (0.006)
l(tmean,7)			0.001 (0.004)
Cumulative effects	0.028	0.030	0.030
Observations	2,931,740	2,927,844	2,920,052

- Cumulative effects stable and not larger than previously:
  - Crimes are really additional
  - Temperature does not only cause DV that would have happened anyway at a later point

## Stronger associations for violent crimes

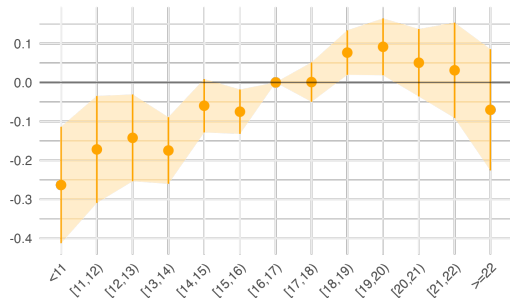
Table: Different types of crime

	Domestic violence (i)	Homicide (ii)	Theft (iii)	Drugs possession (iv)	Fraud (v)
Temperature	0.026*** (0.003)	0.024** (0.012)	0.003** (0.001)	-0.003 (0.008)	0.006 (0.004)
Mean DV	0.029	0.002	0.147	0.006	0.018
Observations	2,933,688	2,933,688	2,933,688	2,933,688	2,933,688



## Alternative data for domestic violence

- 30k+ calls to an domestic violence support helpline, operates year round, 24/7, free of charge
- Provides legal, psychological, and medical advice to women who experience violence
- Captures more than DV *crimes*



Linear estimate:

0.0294\*\*\* (0.007) [1.5% – 4.4%]

# Effect of Temperature on Reporting Behavior

## Probability of Same Day Reporting

Table: Logistic regression

	Same day reporting (i)
Temperature	0.007 (0.008)
Observations	80,502
Weather FEs	✓
Neighborhood FEs	✓
Time FEs	✓

- Report level data
- Higher temperatures do not seem to influence whether victims report incidents on the same day

# Effect of Temperature on Reporting Behavior

## Positive Delays (in days)

	Delay (in days) (i)
Temp. crime day	-0.023* (0.013)
Temp. report day	-0.007 (0.007)
Observations	56,078
Weather FEs	✓
Neighborhood FEs	✓
Time FEs	✓

- Negbin for crimes reported with a delay
  - Higher temp. on crime day associated with shorter reporting delays
  - Higher temp. on report day does not significantly affect the length of reporting delays for cases with positive delays.
- Higher temperatures may slightly encourage quicker reporting

## Effect on Main Analysis: back to daily neighborhood counts

	Same day reports (i)	Next day reports (ii)	Reports days 2-7 (iii)	Reports days 7-14 (iv)	Reports days 14+ (v)
Temperature	0.031*** (0.006)	0.032*** (0.007)	0.035*** (0.007)	0.022* (0.013)	0.003 (0.008)
Observations	2,390,022	2,356,890	2,349,360	1,736,418	2,252,976

- Disaggregate DV Reports by categories of delay
- Higher temperatures increase DV reporting primarily in the immediate and short-delay categories

## Are the costs of higher temperature unequally distributed?

- Augment earlier regressions with interactions of neighborhood poverty measures
- Higher exposure:
  - e.g. live in overcrowded homes, lack adequate insulation/ventilation, work outside
- Resource Constraints:
  - limited adaptive behaviors e.g. may be unable to modify living spaces or routines

## Urban poverty (from census data 2020)

	Urban poverty level:				
	Very low	Low	Medium	High	W. avg
Share of population (%):					
... living in home with dirt floor	0.2	0.5	1.2	3.8	0.6
... living in home without running water	0.0	0.2	1.4	24.3	0.9
... living in home without access to a refrigerator	1.0	4.1	8.5	16.2	5.2
... living in overcrowded home	6.8	20.0	29.2	38.1	21.2
... not entitled to health care services	20.6	26.3	30.7	36.0	27.2
... aged 15+ without basic education	7.8	16.8	24.0	29.4	17.7
... aged 6 to 14 that does not attend school	4.1	5.0	6.2	6.3	5.3
Population share	17%	51%	29%	3%	
Mean DV (day × neighborhood)	0.020	0.032	0.034	0.012	

Last column (in bold) is the population average (population-weighted mean of neighborhoods).

Population share is the share of population living in neighborhoods of each poverty level.

Mean DV is the average count of domestic violence incidents per day per neighborhood.

## Temperature and domestic violence, across urban poverty levels

	Reports (i)
Temp. $\times$ Marginality = Very Low	0.014*** (0.005)
Temp. $\times$ Marginality = Low	0.027*** (0.004)
Temp. $\times$ Marginality = Medium	0.030*** (0.004)
Temp. $\times$ Marginality = High	0.037 (0.036)
Observations	2,933,688

## Temperature as a non-economic driver of DV crime

- I document a positive and linear effect of temperature on Domestic Violence
  - Slight variations (*not* extreme events) in a mild climate (less prepared to acclimatize)
  - Stronger for poorer neighborhoods → exacerbates differences in quality of life
- Need for targeted support for vulnerable populations
- Need for urban planning for climate resilience



# Temperature as a non-economic driver of DV crime

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Thanks!

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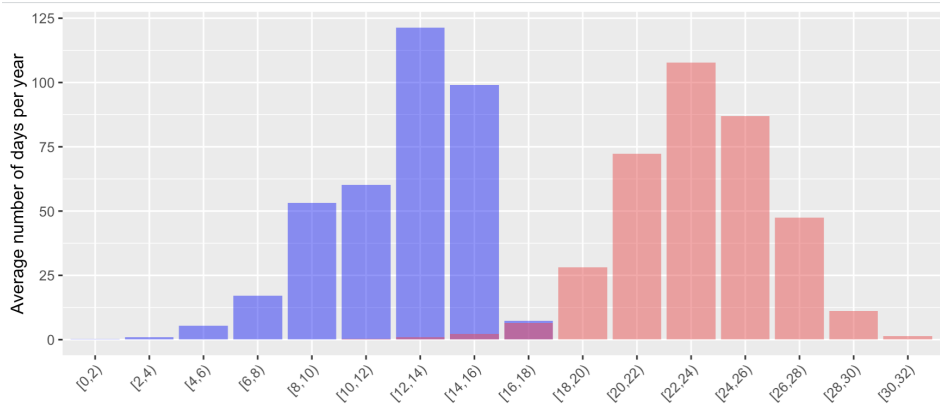
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# Appendix

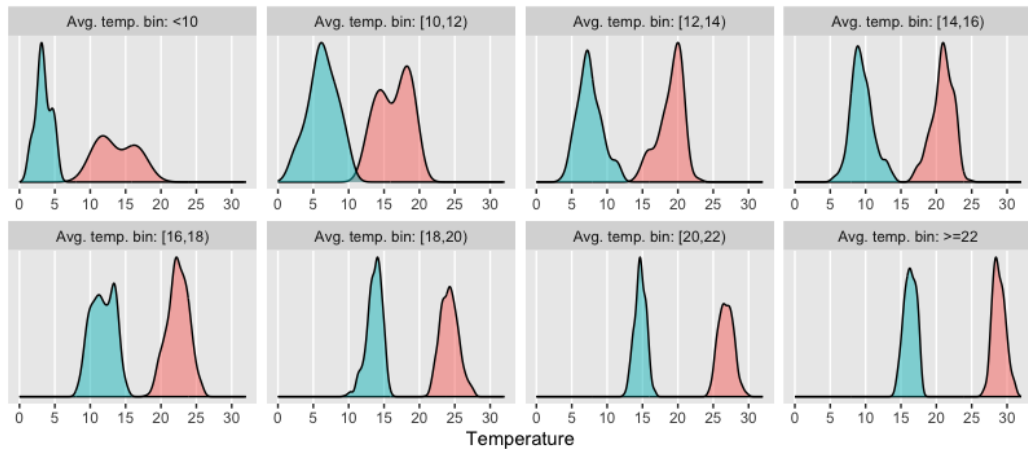
## Average exposure to tmin, tmax (in days per year)



[Back](#)

# Daily min. and max. by average temperature bins

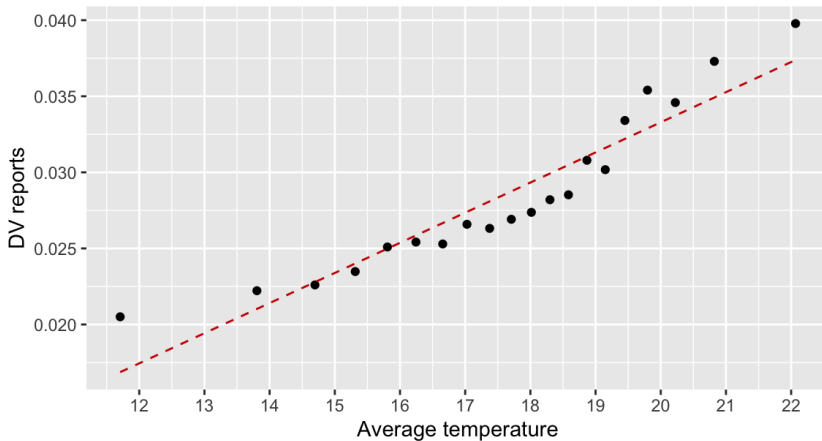
Reference omitted category is [16,18)



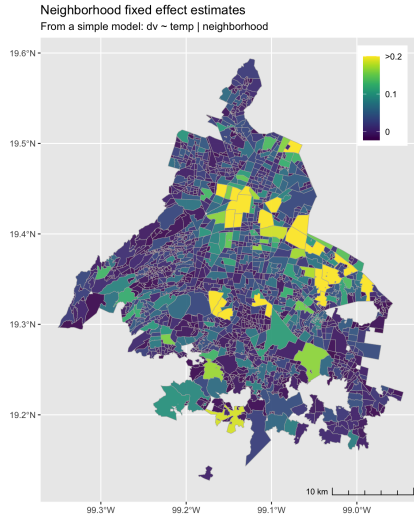
## Scatter plots: day $\times$ neighborhood

Temperatures and daily DV reports at neighborhood level

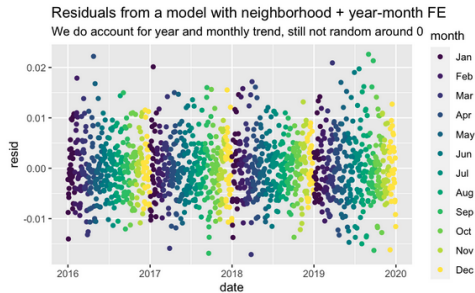
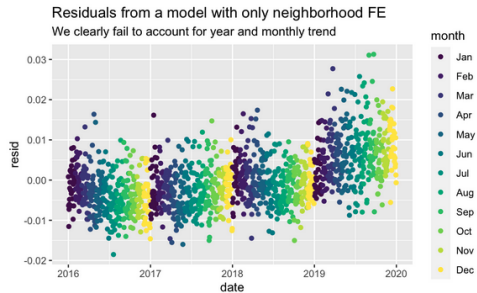
20 bins of equal n (based on temperature)



# Fixed effects: neighborhoods



# Fixed effects: year $\times$ month



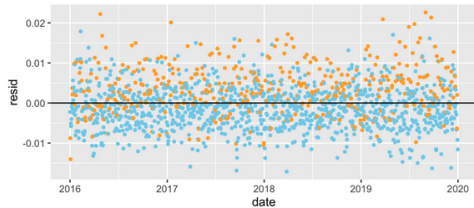
[Back](#)



# Fixed effects: day of the week

Residuals from a model with neighborhood + year-month FE

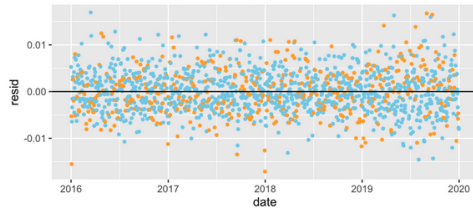
We do account for year and monthly trend, still not random around 0



Weekend: • FALSE • TRUE

Residuals from a model with neighborhood + year-month FE + day

We do account for many time trends, looks random around 0



Weekend: • FALSE • TRUE

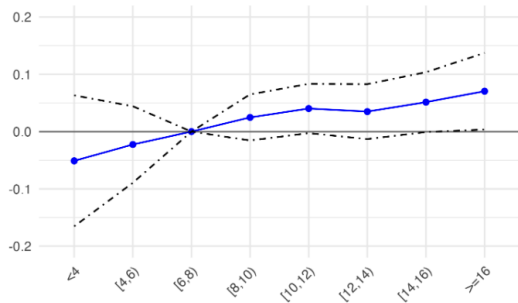
[Back](#)

## Linear effect of temp (i), tmin (ii), tmax (iii) and tmin/tmax jointly (iv)

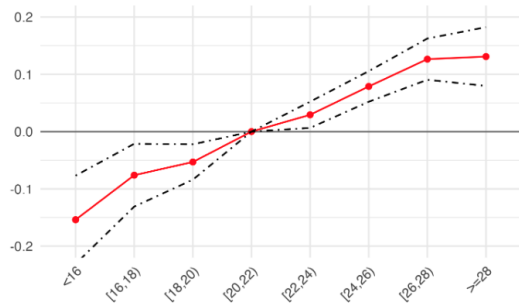
	(i)	(ii)	(iii)	(iv)
Temperature	0.034*** (0.003)			
Daily min. temperature		0.018*** (0.003)		0.007** (0.003)
Daily max. temperature			0.025*** (0.002)	0.023*** (0.002)
Observations	2,933,688	2,933,688	2,933,688	2,933,688

Dependent variable is the daily count of domestic violence police reports per neighborhood. Temperature is the baseline measure, i.e. the average of the daily minimal and maximal temperatures. All regressions are estimated with controls for precipitation, neighborhood fixed effects, year-month, day-of-week, and day-of-year fixed effects. Clustered (Neighborhood-Month-Year) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

## Non-linear effect of tmin and tmax jointly



(a)  $T_{\min}$



(b)  $T_{\max}$

[Back to main results](#)

## Different ways to model the LHS

	binary(reports_dv) (i)	log(1+reports_dv) (ii)	reports_dv**(1/4) (iii)	asinh(reports_dv) (iv)
Temperature	0.0009*** (0.00008)	0.0006*** (0.00005)	0.0008*** (0.00007)	0.0008*** (0.00007)
Precipitation	0.000003 (0.00003)	0.000001 (0.00002)	0.000001 (0.00003)	0.000002 (0.00002)
Observations	2,933,688	2,933,688	2,933,688	2,933,688
Mean DV	0.029	0.019	0.027	0.025
Effect size (temp)	3.29%	3.19%	3.11%	3.19%
95% CI (temp)	[2.74 - 3.83]	[2.66 - 3.72]	[2.59 - 3.63]	[2.66 - 3.73]
Neighborhood FEs	✓	✓	✓	✓
Year-Month FEs	✓	✓	✓	✓
Day of Week FEs	✓	✓	✓	✓
Day of Year FEs	✓	✓	✓	✓

## Clustering of standard errors

SE Type	SE in %	CI in %
Baseline (neighborhood x month x year)	0.29	[2.84 – 3.98]
IID	0.28	[2.86 – 3.96]
Clustered by neighborhood	0.29	[2.84 – 3.98]
Clustered by district	0.37	[2.68 – 4.14]
<b>Robust to spatial correlation (à la Conley, 1999):</b>		
cutoff 1km	0.30	[2.82 – 4.00]
cutoff 2km	0.32	[2.78 – 4.04]
cutoff 5km	0.39	[2.65 – 4.17]
cutoff 10km	0.54	[2.35 – 4.47]
cutoff 15km	0.53	[2.37 – 4.45]
cutoff 20km	0.44	[2.55 – 4.27]
cutoff 30km	0.44	[2.55 – 4.27]

Estimated effects in p.p. are:  $\exp(\text{estimated coefficients}) - 1 \times 100\%$

Point estimate is 0.0335  $\rightarrow$  3.41%