# Supplemental Information: Weather impact on racial composition and citation activity of traffic stops in the United States

#### March 28, 2024

The following document presents supplemental information for the paper *Weather impact on racial composition and citation activity of traffic stops in the United States*. All data and code to recreate the analysis in the paper is available at https://www.github.com/trafficstops/Paper.

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### 1 Background and Literature Review

This section provides background information and a literature review associated with the topics covered in the main manuscript.

#### 1.1 Administrative Discretion

Street-level decision-making—such as traffic stops and citations—is marked by the application of administrative discretion (Maynard-Moody and Musheno, 2003). The need for discretion arises from the gap between broad regulations and their practical application in unique situations. Police officers must align their decisions with established laws, procedures, and standards, yet these guidelines do not always align perfectly with the complex realities encountered in frontline operations. Consequently, law enforcement is tasked with interpreting general rules and conflicting values in the process of decision-making (Lipsky, 1980). This process defines administrative discretion as "the freedom that street-level bureaucrats have in determining the type, quantity, and quality of sanctions [...] during policy implementation" (Tummers and Bekkers, 2014).

Administrative discretion can have both beneficial and detrimental effects on policing. Its primary benefit lies in leveraging officers' experiences, local insights, empathy, and flexibility, which are crucial for nuanced decision-making (Maynard-Moody and Musheno, 2003). However, the same discretion can also lead to adverse outcomes. For instance, in the presence of incomplete information, cognitive constraints, bounded rationality, and racial biases, police activities can create an unequal treatment of motorists (Simon, 1957; Kahneman, 2013; Tummers and Bekkers, 2014).

#### 1.2 Race and Traffic Stops

Measuring the relationship between race and traffic stops is empirically challenging as administrative data only includes information on stopped drivers and not on motorists that committed traffic offences (Grogger and Ridgeway, 2006; Simoiu et al., 2017). This leads to benchmark issues and survey errors. Benchmark issues refer to observing only the racial distribution of stopped drivers and not the distribution of drivers committing traffic offenses (Grogger and Ridgeway, 2006; Simoiu et al., 2017). For example, the Police-Public Contact Survey (PPCS) (Davis et al., 2018) suggests no difference between black and white drivers being stopped compared to their relative population shares. But if driving behavior differs between black and white motorists, then stopping them at the same rate could indicate racial bias. Results based on surveys may suffer from selection bias and recall errors (Pierson et al., 2020). The PPCS likely suffers from recall errors because participants are asked to remember their interactions with police over an entire year.

Two research designs emerged to overcome those challenges. First, researchers started to compare the racial distribution of speeding tickets from automated cameras with traffic stops by police officers (Lange et al., 2005; Lundman and Kowalski, 2009). Those studies found that age, gender, and race play an important role in speeding and that further research is necessary "to determine whether traffic stops for Driving While Black are in a small part the result of Speeding While Black" (Lundman and Kowalski, 2009). The large amount of time, effort, and financial resources necessary to conduct these studies make it unlikely that they will be replicated at a large scale.

As an alternative, a second, more cost-effective empirical strategy known as the "veil of darkness" (VOD) was proposed by Grogger and Ridgeway (2006). This strategy assumes that officers are less able to identify a driver's race at night and consequently, in the presence of racial bias, black drivers are less likely being stopped at night. Potential caveats of this strategy are uncontrolled differences in street lighting (Horrace and Rohlin, 2016), race-specific infractions that are more likely at night (Chohlas-Wood et al., 2018), or driving behavior according to visibility (Kalinowski et al., 2021). For instance, broken taillights are more likely to be detected during night time and could be an infraction that is more common among black drivers. As a result, studies using the VOD often provide little or no evidence of racial bias in police stops (Stacey and Bonner, 2021). An exception are Pierson et al. (2020) who find discrimination in traffic stops by employing a nationwide data set in addition to controlling for seasonality and non-race specific driving behavior. While the VOD literature relies on differences in visibility between day and night to evaluate racial bias in traffic stops, we introduce adverse weather as a new angle to quantify shifts in the racial distribution of drivers being stopped and cited.

Next to the already discussed literature using speed camera data or the veil of darkness, there is a large number of additional studies investigating the relationship between race and traffic stops, often coming to different conclusions. Some researchers find little or no evidence of racial disparities in traffic stops and citations. For instance, employing data for Cincinnati (Ohio), Ridgeway (2009) finds fewer citations being issued to black relative to white motorists and hypothesizes that this outcome is explained by black drivers being arrested as opposed to getting cited. The same author matches black drivers to motorists from other races based on infraction, time of day, and region in the City of Oakland, concluding that black drivers are treated equitably in terms of citation rates (Ridgeway, 2006). Using a driver survey conducted in North Carolina, Warren et al. (2006) suggest that racial bias is weak for highway patrol but strong for local police departments. The authors explain their results by differences in work patterns between state and local police and the higher speed of drivers on highways, relative to municipal roads, not allowing for racial profiling (Smith et al., 2001). Using nationwide data, Shane et al. (2017) argue that police killings of civilians are not motivated by race.

These studies are opposed by findings suggesting racial bias. Smith and Petrocelli (2001) find that black motorists are more likely to be stopped relative to their population share in Richmond, Virginia. Making use of data for North Carolina, Baumgartner et al. (2018) suggest racial bias after controlling for legally relevant factors for traffic stops, behavior of single police officers, and the outcomes for contraband searches. Based on administrative data from the Oakland police department, Hetey et al. (2016) demonstrate that officers stopped, searched, handcuffed, and arrested more blacks than whites. This result remained statistically significant after controlling for a large number of factors shaping police actions (e.g. crime rates, police officer characteristics).

An additional stream of research analyzes factors influencing the racial distribution of traffic stops and actions during them. Rojek et al. (2012) demonstrate that black (white) drivers are more likely to be searched in a predominantly white (black) neighborhood by white police officers. Analyzing audio recordings of traffic stops in Oakland (California), Hetey et al. (2016) find that "more severe legal language" is used by police officers during stops of black residents. Several researchers also find a relationship between officers' race and gender in the use of force during

encounters with the police (Ba et al., 2021; Hoekstra and Sloan, 2022). Stopping location and race of police officers play a role in assessing traffic stops as well, as shown by Roh and Robinson (2009) and Rojek et al. (2012).

#### 1.3 Crime and Weather

There is also a large amount of research related to the relationship between crime and weather with routine activities and heat-aggression theory as the two main strands (Sommer et al., 2018). Routine activities theory postulates that warm and dry weather leads to more outdoor activities and hence, higher probability of victim-offender interaction. We control for a potential shift in the amount of drivers on the road and the related greater likelihood of infractions, during warm and dry weather, by analyzing the racial distribution of drivers during stops and not the number of traffic stops. Heat-aggression theory postulates that high temperatures increases bad temper and annoyance, leading to more aggressive behavior. This behavior is, however, less likely for motorists, as most cars have air conditioning to reduce the temperature in cars.<sup>1</sup>

To analyze more rigorously if weather differently impacts crimes committed by race, we conducted a literature review spanning publications from 1970 to the most recent years (Anderson et al., 1995; Bell and Baron, 1976; Bushman et al., 2005; Cohen and Felson, 1979; Cohn, 1990, 1993; Cohn and Rotton, 1997, 2005; DeFronzo, 1984; Harries et al., 1984; Jacob et al., 2007; Mares, 2013; Rotton and Cohn, 2001; Sommer et al., 2018). Since the 1970s, researchers have consistently shown that weather influences crime rates, but none of these studies claim or find that rain or cold/heat have an effect on crime that differs by race. To our knowledge, there are also no studies demonstrating that adverse weather conditions influence traffic infractions differently between non-white and white drivers.

<sup>&</sup>lt;sup>1</sup>Already in the early 1960s about 80% of cars in the Southwest were equipped with air conditioning (Phelan and Sorge, 1990). Over the last two decades almost all cars sold had standard air conditioning according to Automotive Air Conditioning History published in *Motortrend* on 24 June 2010.

## 2 Summary Statistics on Race and Citations

Tables 1 and 2 summarize the distribution of black, Hispanic, and white drivers by city and state police, respectively. Note that for some cities and states, data is missing regarding the issuance of citations whereas for others, the summary statistics indicate that for 100% of stops a citation was issued. For the analysis with *citation* as the dependent variable, all cities and states with a value of 100% citations were removed.

City	State	Black	Hispanic	White	Citation
Connecticut	CT	14%	12%	74%	
Florida	FL	19%	22%	59%	
Georgia	GA	30%	3%	67%	
Michigan	MI	17%	2%	81%	76%
North Dakota	ND	3%	3%	94%	
New Hampshire	NH	3%	2%	96%	33%
New York	NY	12%	8%	80%	
Ohio	OH	13%	2%	84%	
Tennessee	TN	13%	4%	83%	100%
Texas	TX	11%	37%	53%	35%
Wisconsin	WI	6%	4%	90%	50%

Table 1. Percentage distribution of black, Hispanic, and white drivers during traffic stops by state police.

City	State	Black	Hispanic	White	Citation
Albany	NY	39%	5%	56%	
Arlington	TX	36%	24%	40%	
Aurora	CO	25%	5%	70%	100%
Bakersfield	CA	12%	33%	55%	100%
Burlington	VT	9%	1%	91%	
Camden	NJ	47%	34%	19%	
Charlotte	NC	54%	10%	36%	45%
Cincinnati	OH	59%	0%	41%	
Columbus	OH	46%	3%	51%	58%
Durham	NC	60%	12%	28%	45%
Fayetteville	NC	58%	6%	36%	47%
Garland	TX	19%	39%	42%	100%
<b>Grand Forks</b>	ND	9%	0%	91%	98%
Greensboro	NC	56%	5%	39%	51%
Hartford	CT	39%	28%	33%	64%
Henderson	NV	10%	13%	77%	100%
Little Rock	AR	54%	0%	46%	100%
Los Angeles	CA	27%	47%	26%	
Louisville	KY	32%	4%	64%	74%
Madison	WI	22%	9%	70%	70%
Mesa	AZ	8%	19%	73%	100%
Nashville	TN	39%	5%	56%	
New Orleans	LA	71%	3%	27%	31%
Oakland	CA	65%	22%	13%	38%
Oklahoma City	OK	22%	0%	78%	100%
Owensboro	KY	12%	0%	88%	100%
Philadelphia	PA	69%	10%	21%	
Plano	TX	16%	15%	69%	
Raleigh	NC	49%	9%	41%	46%
Saint Paul	MN	45%	8%	47%	26%
San Antonio	TX	10%	51%	39%	100%
San Diego	CA	13%	36%	51%	
San Francisco	CA	24%	20%	56%	65%
San Jose	CA	11%	67%	22%	
Tulsa	OK	23%	2%	74%	
Wichita	KS	17%	14%	69%	100%
Winston-Salem	NC	48%	11%	42%	64%

Table 2. Percentage distribution of black, Hispanic, and white drivers during traffic stops by city police.

# 3 Daily and Hourly Pattern of Traffic Stops by Race/Ethnicity

Figure 1 and 2 depict the patterns of traffic stops over a 24-hour period. Given the large variation in patterns, individual estimation by city and state police department using hourly dummy variables is preferred over a fixed effects logit model.

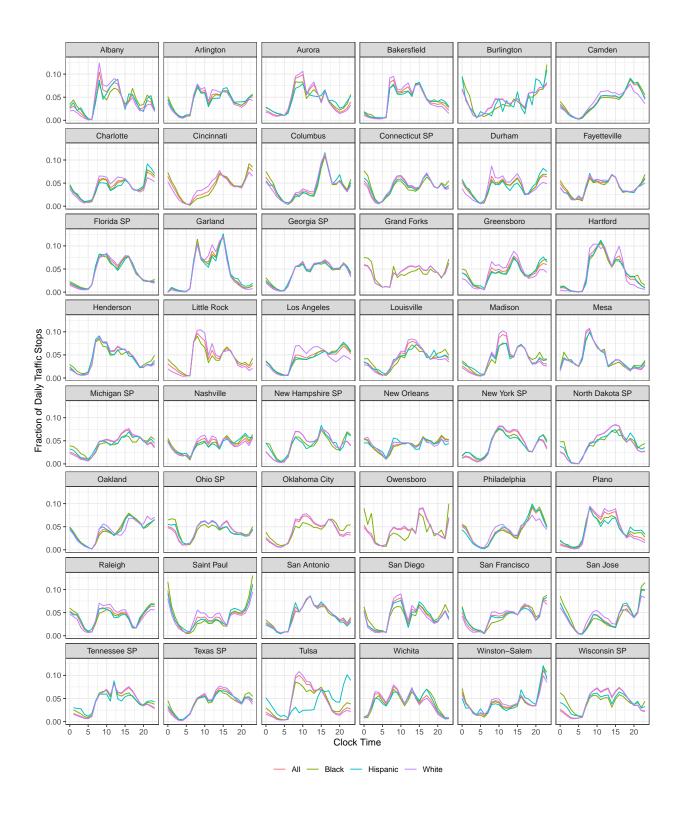


Figure 1. Fraction of Daily Traffic Stops by Time and Race/Ethnicity

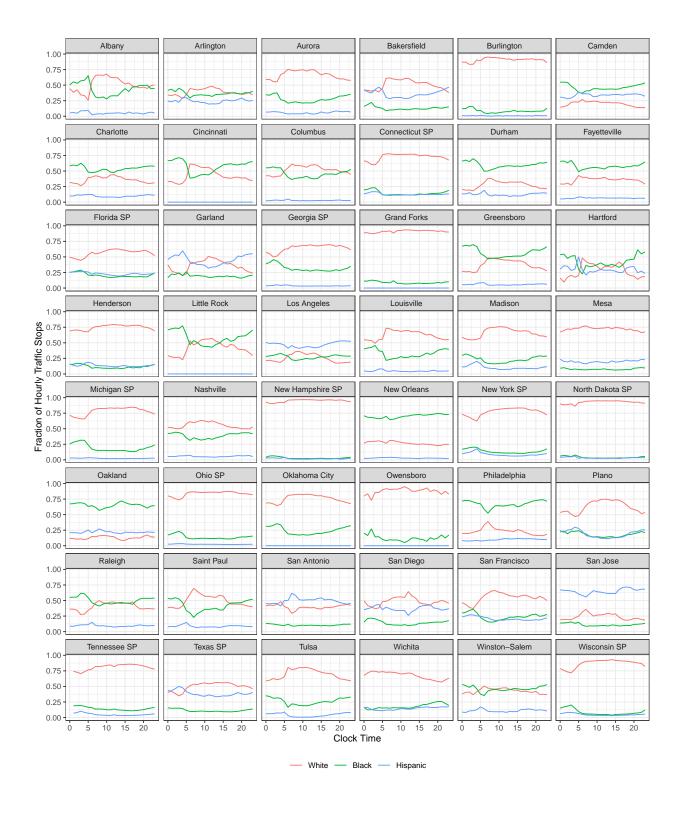


Figure 2. Fraction of Hourly Traffic Stops by Time and Race/Ethnicity

# **4 Temperature and Precipitation Patterns**

There are also differences in the intensity of rain and heat/cold across the jurisdictions in our model. Hence, the separation of the models by jurisdiction is warranted. Note that all the results presented for the jurisdiction-specific models are based on relative precipitation and temperature as described in the main manuscript.

		Max. Pre	Max. Precipitation		Temperature				
Jurisdiction	State	1-hour	20-min	Min.	Q1	Q2	Mean	Q3	Max.
Connecticut	CT	8.59	2.86	-24.00	2.77	13.49	11.84	20.83	33.32
Florida	FL	21.48	7.16	-9.17	21.88	26.05	24.85	29.01	40.56
Georgia	GA	30.28	10.09	-16.15	12.81	21.02	19.64	27.03	43.45
Michigan	MI	15.03	5.01	-25.87	1.29	11.99	11.18	21.20	41.35
New Hampshire	NH	7.91	2.64	-27.94	0.77	11.09	9.66	19.18	32.96
New York	NY	16.76	5.59	-28.08	1.98	11.69	10.90	20.12	35.95
North Dakota	ND	8.56	2.85	-33.75	-2.88	10.35	8.99	21.35	43.07
Ohio	OH	14.11	4.70	-24.72	4.69	14.85	13.63	22.66	41.23
Tennessee	TN	20.13	6.71	-17.90	8.92	17.61	16.70	24.96	44.53
Texas	TX	20.05	6.68	-17.41	16.56	24.29	23.00	30.08	46.47
Wisconsin	WI	11.50	3.83	-32.48	0.11	11.42	10.67	21.46	43.38

		Max. Pre	ecipitation	Temperature					
Jurisdiction	State	1-hour	20-min	Min.	Q1	Q2	Mean	Q3	Max.
Albany	NY	8.02	2.67	-22.86	1.06	10.96	10.23	19.72	33.80
Arlington	TX	7.48	2.49	-7.71	13.10	20.64	20.26	27.60	41.28
Aurora	CO	5.69	1.90	-21.80	7.52	15.63	15.18	23.16	39.12
Bakersfield	CA	1.57	0.52	-2.86	13.09	19.71	20.49	27.78	43.41
Burlington	VT	6.05	2.02	-28.02	-2.60	5.61	6.14	16.52	31.37
Camden	NJ	12.98	4.33	-17.65	4.25	12.94	12.86	21.47	36.60
Charlotte	NC	9.89	3.30	-12.73	9.17	17.91	17.06	25.02	40.37
Cincinnati	ОН	12.33	4.11	-19.84	4.29	13.92	13.47	22.60	40.70
Columbus	ОН	7.52	2.51	-21.24	3.37	13.81	13.07	22.90	37.81
Durham	NC	11.06	3.69	-12.05	8.09	17.32	16.54	24.86	41.77
Fayetteville	NC	8.26	2.75	-11.66	10.24	18.75	17.79	25.40	41.64
Garland	TX	7.68	2.56	-9.42	15.79	24.15	23.01	30.99	44.46
<b>Grand Forks</b>	ND	11.02	3.67	-31.93	-3.82	10.00	8.13	20.29	42.52
Greensboro	NC	10.26	3.42	-14.10	7.71	16.77	16.14	24.51	39.20
Hartford	CT	3.37	1.12	-19.23	2.11	11.77	11.30	20.76	32.93
Henderson	NV	1.60	0.53	-6.96	12.63	20.43	20.43	28.45	43.44
Little Rock	AR	11.82	3.94	-7.32	16.15	22.88	21.35	27.60	35.98
Los Angeles	CA	3.29	1.10	-1.37	12.87	17.92	18.23	23.24	37.74
Louisville	KY	9.17	3.06	-25.67	6.47	16.37	15.18	24.36	34.77
Madison	WI	11.70	3.90	-28.59	0.75	13.20	11.67	22.57	42.97
Mesa	AZ	2.28	0.76	-0.43	15.41	22.36	22.70	29.99	45.80
Nashville	TN	13.72	4.57	-15.93	7.99	17.28	16.25	24.95	39.22
New Orleans	LA	13.76	4.59	-4.27	17.92	23.50	22.26	27.59	37.77
Oakland	CA	2.82	0.94	-0.48	12.55	16.63	17.54	21.94	42.21
Oklahoma City	OK	15.19	5.06	-14.64	11.65	21.14	20.16	28.86	45.85
Owensboro	KY	4.65	1.55	-11.79	8.38	17.66	16.65	25.39	36.14
Philadelphia	PA	26.76	8.92	-18.23	4.29	12.99	12.77	21.42	35.65
Plano	TX	7.56	2.52	-10.05	14.10	22.94	22.07	30.42	45.20
Raleigh	NC	13.23	4.41	-13.12	8.17	17.38	16.53	24.79	42.58
Saint Paul	MN	14.59	4.86	-33.69	-3.42	7.17	6.93	17.87	41.65
San Antonio	TX	11.73	3.91	-6.11	18.33	25.23	24.16	30.63	42.98
San Diego	CA	2.65	0.88	1.80	13.78	18.64	18.84	23.40	38.40
San Francisco	CA	4.44	1.48	2.74	11.31	12.86	13.03	14.68	25.05
San Jose	CA	2.86	0.95	-2.26	10.81	14.80	15.94	20.15	42.82
Tulsa	OK	9.12	3.04	-18.04	10.61	19.97	19.48	28.24	46.76
Wichita	KS	9.64	3.21	-20.30	7.28	17.45	16.81	26.14	44.78
Winston-Salem	NC	8.85	2.95	-13.03	7.61	15.88	15.41	23.24	38.56

# 5 Regression Results: Black

## **5.1** City Police Departments

#### 5.1.1 Albany (New York)

		Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	0.188**	0.187**	0.182**	0.183**	0.180**	0.182**		
	(0.088)	(0.088)	(0.089)	(0.089)	(0.089)	(0.089)		
Precip.	0.084	0.077	0.085		3.709	3.908		
•	(0.087)	(0.099)	(0.087)		(2.899)	(3.052)		
$Night \times Precip.$		0.032				-0.046		
		(0.210)				(0.220)		
Temp.			-0.003	-0.003	-0.003	-0.003		
•			(0.003)	(0.003)	(0.003)	(0.003)		
$Precip. \times Temp.$					-0.012	-0.013		
					(0.010)	(0.010)		
Constant	-0.249*	-0.249*	0.501	0.484	0.480	0.471		
	(0.138)	(0.138)	(0.909)	(0.909)	(0.910)	(0.911)		
Observations	21,296	21,296	21,296	21,296	21,296	21,296		
Log Likelihood	-13,871.360	-13,871.340	-13,871.010	-13,871.490	-13,870.220	-13,870.190		
Akaike Inf. Crit.	27,840.710	27,842.690	27,842.010	27,840.970	27,842.430	27,844.390		

*Note*: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.2 Arlington (Texas)

		Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	0.027	0.026	0.030	0.030	0.030	0.029		
Precip.	(0.050) $-0.030$	(0.050) -0.091	(0.050) $-0.030$	(0.050)	(0.050) 1.267	(0.050) -0.972		
$Night \times Precip.$	(0.055)	(0.075) 0.133	(0.055)		(2.851)	(3.540) 0.148		
Temp.		(0.112)	0.002	0.002	0.002	(0.137) 0.002		
			(0.002)	(0.002)	(0.002)	(0.002)		
$Precip. \times Temp.$					-0.004 (0.010)	0.003 (0.012)		
Constant	0.178*** (0.066)	0.178*** (0.066)	-0.403 (0.558)	-0.404 (0.558)	-0.397 (0.558)	-0.374 (0.559)		
Observations	76,152	76,152	76,152	76,152	76,152	76,152		
Log Likelihood Akaike Inf. Crit.	-52,293.970 104,673.900	-52,293.250 104,674.500	-52,293.420 104,674.800	-52,293.570 104,673.100	-52,293.310 104,676.600	-52,292.720 104,677.400		

## 5.1.3 Aurora (Colorado)

		Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	0.018	0.018	-0.004	-0.004	-0.003	-0.003		
-	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)		
Precip.	0.079	0.078	0.045		3.302	3.560		
	(0.078)	(0.085)	(0.079)		(2.862)	(3.009)		
$Night \times Precip.$		0.004				-0.061		
•		(0.211)				(0.223)		
Temp.			-0.007***	-0.007***	-0.007***	-0.007***		
_			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					-0.011	-0.012		
					(0.010)	(0.010)		
Constant	-0.580***	-0.580***	1.485***	1.500***	1.443***	1.439***		
	(0.060)	(0.060)	(0.348)	(0.347)	(0.350)	(0.350)		
Observations	150,600	150,600	150,600	150,600	150,600	150,600		
Log Likelihood	-86,046.090	-86,046.090	-86,028.000	-86,028.150	-86,027.340	-86,027.300		
Akaike Inf. Crit.	172,186.200	172,188.200	172,152.000	172,150.300	172,152.700	172,154.600		

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.4 Bakersfield (California)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.099*	0.101*	0.101*	0.100*	0.103*	0.103*	
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	
Precip.	0.311	0.364	0.320		-19.663	-19.288	
	(0.229)	(0.260)	(0.230)		(12.263)	(12.495)	
$Night \times Precip.$		-0.223				-0.085	
		(0.535)				(0.547)	
Temp.			0.001	0.001	0.001	0.001	
			(0.002)	(0.002)	(0.002)	(0.002)	
$Precip. \times Temp.$					0.070	0.069	
					(0.043)	(0.044)	
Constant	-1.627***	-1.628***	-1.876***	-1.777***	-1.859***	-1.864***	
	(0.097)	(0.097)	(0.679)	(0.675)	(0.679)	(0.680)	
Observations	90,424	90,424	90,424	90,424	90,424	90,424	
Log Likelihood	-41,557.620	-41,557.540	-41,557.550	-41,558.490	-41,556.280	-41,556.270	
Akaike Inf. Crit.	83,215.240	83,217.070	83,217.110	83,216.970	83,216.560	83,218.540	

## **5.1.5** Burlington (Vermont)

		Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	-0.021	-0.029	-0.042	-0.044	-0.041	-0.053		
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)		
Precip.	0.119	-0.009	0.143		-1.681	-3.833		
-	(0.136)	(0.208)	(0.135)		(5.107)	(5.512)		
$Night \times Precip.$		0.251				0.354		
		(0.279)				(0.284)		
Temp.			-0.014***	-0.013***	-0.014***	-0.014***		
			(0.004)	(0.004)	(0.004)	(0.004)		
$Precip. \times Temp.$					0.006	0.013		
					(0.018)	(0.019)		
Constant	-2.141***	-2.137***	1.656	1.593	1.655	1.750		
	(0.167)	(0.167)	(1.203)	(1.201)	(1.203)	(1.205)		
Observations	27,346	27,346	27,346	27,346	27,346	27,346		
Log Likelihood	-7,969.127	-7,968.712	-7,964.064	-7,964.587	-7,964.000	-7,963.209		
Akaike Inf. Crit.	16,034.250	16,035.420	16,026.130	16,025.170	16,028.000	16,028.420		

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.6 Camden (New Jersey)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	0.184***	0.190***	0.179***	0.178***	0.179***	0.185***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Precip.	0.038	0.072**	0.040		0.326	0.912
•	(0.027)	(0.032)	(0.027)		(1.014)	(1.049)
$Night \times Precip.$		-0.137**				-0.142**
		(0.062)				(0.063)
Temp.			-0.003**	-0.003*	-0.003**	-0.003*
_			(0.001)	(0.001)	(0.001)	(0.001)
$Precip. \times Temp.$					-0.001	-0.003
					(0.003)	(0.004)
Constant	1.239***	1.234***	2.014***	1.997***	2.014***	1.965***
	(0.059)	(0.059)	(0.391)	(0.390)	(0.391)	(0.391)
Observations	119,651	119,651	119,651	119,651	119,651	119,651
Log Likelihood	-70,558.340	-70,555.960	-70,556.320	-70,557.450	-70,556.280	-70,553.830
Akaike Inf. Crit.	141,212.700	141,209.900	141,210.600	141,210.900	141,212.600	141,209.700

#### 5.1.7 Charlotte (North Carolina)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.058***	0.059***	0.062***	0.064***	0.063***	0.063***	
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	
Precip.	-0.056***	-0.051**	-0.057***		-2.182***	-2.194***	
•	(0.019)	(0.025)	(0.019)		(0.745)	(0.763)	
$Night \times Precip.$		-0.014				0.003	
		(0.039)				(0.040)	
Temp.			0.002***	0.002***	0.002***	0.002***	
•			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.007***	0.007***	
•					(0.003)	(0.003)	
Constant	0.568***	0.568***	-0.088	-0.084	-0.070	-0.070	
	(0.026)	(0.026)	(0.184)	(0.184)	(0.184)	(0.185)	
Observations	527,560	527,560	527,560	527,560	527,560	527,560	
Log Likelihood	-352,457.800	-352,457.700	-352,451.300	-352,455.700	-352,447.200	-352,447.20	
Akaike Inf. Crit.	705,009.600	705,011.400	704,998.600	705,005.400	704,992.500	704,994.500	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.8 Cincinnati (Ohio)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.029	-0.027	-0.034	-0.034	-0.034	-0.032	
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	
Precip.	-0.037	0.012	-0.032		-1.162	-0.578	
	(0.029)	(0.038)	(0.029)		(1.217)	(1.260)	
$Night \times Precip.$		-0.119**				-0.106*	
		(0.059)				(0.060)	
Temp.			-0.003***	-0.003***	-0.003***	-0.003***	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.004	0.002	
					(0.004)	(0.004)	
Constant	0.604***	0.603***	1.351***	1.367***	1.351***	1.333***	
	(0.039)	(0.039)	(0.262)	(0.262)	(0.262)	(0.263)	
Observations	195,030	195,030	195,030	195,030	195,030	195,030	
Log Likelihood	-128,918.100	-128,916.100	-128,914.000	-128,914.600	-128,913.600	-128,912.000	
Akaike Inf. Crit.	257,936.300	257,934.100	257,930.000	257,929.200	257,931.100	257,930.100	

## 5.1.9 Columbus (Ohio)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.157***	0.159***	0.157***	0.157***	0.157***	0.160***	
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	
Precip.	-0.065	0.011	-0.066		0.613	1.967	
_	(0.048)	(0.065)	(0.048)		(1.776)	(1.898)	
$Night \times Precip.$		-0.170*				-0.207**	
•		(0.097)				(0.104)	
Temp.			0.0001	-0.00003	0.0001	0.0002	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.002	-0.007	
•					(0.006)	(0.006)	
Constant	-0.017	-0.018	-0.043	-0.010	-0.042	-0.069	
	(0.047)	(0.047)	(0.331)	(0.330)	(0.331)	(0.331)	
Observations	113,111	113,111	113,111	113,111	113,111	113,111	
Log Likelihood	-76,977.520	-76,976.000	-76,977.510	-76,978.440	-76,977.440	-76,975.45	
Akaike Inf. Crit.	154,049.000	154,048.000	154,051.000	154,050.900	154,052.900	154,050.90	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 5.1.10 Durham (North Carolina)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.017	0.017	0.012	0.012	0.012	0.012	
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	
Precip.	0.026	0.026	0.027		0.120	0.101	
	(0.036)	(0.042)	(0.036)		(1.419)	(1.460)	
$Night \times Precip.$		-0.001				0.005	
		(0.081)				(0.083)	
Temp.			-0.002*	-0.002*	-0.002*	-0.002*	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.0003	-0.0003	
					(0.005)	(0.005)	
Constant	1.205***	1.205***	1.869***	1.864***	1.868***	1.869***	
	(0.061)	(0.061)	(0.395)	(0.395)	(0.395)	(0.396)	
Observations	113,001	113,001	113,001	113,001	113,001	113,001	
Log Likelihood	-69,928.200	-69,928.200	-69,926.760	-69,927.040	-69,926.760	-69,926.750	
Akaike Inf. Crit.	139,950.400	139,952.400	139,949.500	139,948.100	139,951.500	139,953.500	

## **5.1.11** Fayetteville (North Carolina)

		Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	-0.004	-0.003	-0.004	-0.004	-0.005	-0.003		
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)		
Precip.	-0.032	-0.026	-0.032		1.182	1.512		
	(0.024)	(0.029)	(0.025)		(1.017)	(1.083)		
$Night \times Precip.$		-0.023				-0.051		
•		(0.055)				(0.058)		
Temp.			-0.0001	-0.0001	-0.0001	-0.00001		
			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					-0.004	-0.005		
					(0.003)	(0.004)		
Constant	0.761***	0.760***	0.779***	0.795***	0.776***	0.764***		
	(0.043)	(0.043)	(0.295)	(0.295)	(0.295)	(0.296)		
Observations	195,610	195,610	195,610	195,610	195,610	195,610		
Log Likelihood	-129,042.000	-129,041.900	-129,042.000	-129,042.900	-129,041.300	-129,040.900		
Akaike Inf. Crit.	258,178.000	258,179.800	258,180.000	258,179.700	258,180.500	258,181.800		

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.12 Garland (Texas)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	-0.012	-0.010	-0.014	-0.014	-0.014	-0.011
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
Precip.	-0.035	-0.015	-0.036		-0.568	-0.218
	(0.056)	(0.057)	(0.056)		(2.364)	(2.352)
$Night \times Precip.$		-0.296				-0.291
		(0.239)				(0.240)
Temp.			-0.001	-0.001	-0.001	-0.001
			(0.002)	(0.002)	(0.002)	(0.002)
$Precip. \times Temp.$					0.002	0.001
					(0.008)	(0.008)
Constant	-0.809	-0.811	-0.510	-0.520	-0.507	-0.523
	(0.610)	(0.610)	(0.760)	(0.759)	(0.760)	(0.760)
Observations	88,013	88,013	88,013	88,013	88,013	88,013
Log Likelihood	-53,836.560	-53,835.690	-53,836.340	-53,836.550	-53,836.310	-53,835.490
Akaike Inf. Crit.	107,771.100	107,771.400	107,772.700	107,771.100	107,774.600	107,775.000

#### 5.1.13 Grand Forks (North Dakota)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.166*	0.169*	0.158	0.158	0.160	0.161	
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	
Precip.	0.035	0.165	0.034		-8.000*	-7.498*	
_	(0.105)	(0.171)	(0.105)		(4.169)	(4.385)	
$Night \times Precip.$		-0.199				-0.091	
•		(0.225)				(0.245)	
Temp.			-0.003	-0.003	-0.003	-0.003	
_			(0.003)	(0.003)	(0.003)	(0.003)	
$Precip. \times Temp.$					0.028*	0.026*	
•					(0.014)	(0.015)	
Constant	-2.491***	-2.493***	-1.628*	-1.625*	-1.560*	-1.566*	
	(0.148)	(0.148)	(0.919)	(0.919)	(0.919)	(0.919)	
Observations	35,467	35,467	35,467	35,467	35,467	35,467	
Log Likelihood	-10,284.920	-10,284.530	-10,284.470	-10,284.520	-10,282.490	-10,282.42	
Akaike Inf. Crit.	20,665.850	20,667.070	20,666.940	20,665.040	20,664.980	20,666.840	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### **5.1.14** Greensboro (North Carolina)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.084***	0.089***	0.089***	0.089***	0.090***	0.094***	
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	
Precip.	-0.012	0.050	-0.013		-2.672**	-2.356*	
	(0.036)	(0.044)	(0.036)		(1.274)	(1.282)	
$Night \times Precip.$		-0.182**				-0.180**	
•		(0.075)				(0.076)	
Temp.			0.002**	0.002**	0.002**	0.002**	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.009**	0.008*	
					(0.004)	(0.004)	
Constant	0.725***	0.723***	0.075	0.075	0.098	0.059	
	(0.046)	(0.046)	(0.299)	(0.300)	(0.300)	(0.300)	
Observations	188,242	188,242	188,242	188,242	188,242	188,242	
Log Likelihood	-124,442.600	-124,439.700	-124,440.200	-124,440.300	-124,438.000	-124,435.200	
Akaike Inf. Crit.	248,979.300	248,975.400	248,976.400	248,974.600	248,974.000	248,970.400	

## **5.1.15** Hartford (Connecticut)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.108 (0.126)	0.118 (0.126)	0.113 (0.126)	0.110 (0.126)	0.113 (0.126)	0.125 (0.126)	
Precip.	0.332** (0.139)	0.385*** (0.146)	0.321** (0.139)	(	-2.169 (5.624)	-2.550 (5.547)	
$Night \times Precip.$	(3, 2, 2, 2,	-0.522 (0.415)	(3, 2, 2, 2,		(2.2.2.)	-0.573 (0.421)	
Temp.		(3)	0.006 (0.004)	0.006 (0.004)	0.006 (0.004)	0.006 (0.004)	
$Precip. \times Temp.$			(3123.1)	(31331)	0.009 (0.020)	0.010 (0.019)	
Constant	0.212 (0.279)	0.199 (0.279)	-1.351 (1.128)	-1.502 (1.126)	-1.348 (1.128)	-1.424 (1.129)	
Observations Log Likelihood Akaike Inf. Crit.	12,841 -8,520.514 17,133.030	12,841 -8,519.810 17,133.620	12,841 -8,519.490 17,132.980	12,841 -8,522.215 17,136.430	12,841 -8,519.391 17,134.780	12,841 -8,518.570 17,135.140	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.16 Henderson (Nevada)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	0.089	0.093	0.087	0.087	0.087	0.091
Precip.	(0.066) 0.563*	(0.066) 0.749**	(0.066) 0.554*	(0.066)	(0.066) -3.083	(0.066) -0.961
$Night \times Precip.$	(0.291)	(0.331) -0.735	(0.292)		(7.900)	(8.155) -0.688
		(0.683)				(0.702)
Temp.			-0.001 (0.003)	-0.002 (0.003)	-0.001 (0.003)	-0.001 (0.003)
$Precip. \times Temp.$					0.012 (0.027)	0.006 (0.028)
Constant	-1.814***	-1.815***	-1.398*	-1.307	-1.388	-1.433*
	(0.119)	(0.119)	(0.849)	(0.847)	(0.849)	(0.850)
Observations	85,355	85,355	85,355	85,355	85,355	85,355
Log Likelihood Akaike Inf. Crit.	-30,902.470 61,904.930	-30,901.870 61,905.730	-30,902.350 61,906.690	-30,904.050 61,908.100	-30,902.240 61,908.480	-30,901.740 61,909.490

#### 5.1.17 Little Rock (Arkansas)

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	-0.078	-0.081	-0.087	-0.087	-0.087	-0.094		
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)		
Precip.	0.035	0.008	0.035		-8.186*	-9.727*		
	(0.070)	(0.081)	(0.070)		(4.925)	(5.133)		
Night $\times$ Precip.		0.117				0.218		
		(0.181)				(0.202)		
Temp.			-0.004	-0.004	-0.004	-0.004		
			(0.004)	(0.004)	(0.004)	(0.004)		
$Precip. \times Temp.$					0.028*	$0.033^{*}$		
					(0.017)	(0.017)		
Constant	0.738***	0.737***	1.800	1.800	1.889	1.969*		
	(0.186)	(0.186)	(1.163)	(1.163)	(1.164)	(1.166)		
Observations	12,719	12,719	12,719	12,719	12,719	12,719		
Log Likelihood	-8,534.166	-8,533.936	-8,533.738	-8,533.864	-8,532.318	-8,531.63		
Akaike Inf. Crit.	17,152.330	17,153.870	17,153.470	17,151.730	17,152.640	17,153.27		

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### **5.1.18** Los Angeles (California)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.010 (0.008)	-0.008 (0.008)	-0.013 (0.008)	-0.013 (0.008)	-0.013 (0.008)	-0.011 (0.008)	
Precip.	0.012 (0.030)	0.140*** (0.036)	-0.001 (0.030)	(0.000)	-3.515* (2.078)	0.277 (2.179)	
$Night \times Precip.$	()	-0.377*** (0.062)	(******)		(,	-0.368*** (0.065)	
Temp.		, ,	-0.002*** (0.0004)	-0.002*** (0.0004)	-0.002*** (0.0004)	-0.002*** (0.0004)	
$Precip. \times Temp.$			(,	(******/	0.012* (0.007)	-0.001 (0.008)	
Constant	0.174*** (0.013)	0.174*** (0.013)	0.684*** (0.121)	0.684*** (0.121)	0.689*** (0.121)	0.654*** (0.121)	
Observations Log Likelihood Akaike Inf. Crit.	2,268,217 -1,525,331.000 3,050,762.000	2,268,217 -1,525,313.000 3,050,727.000	2,268,217 -1,525,322.000 3,050,746.000	2,268,217 -1,525,322.000 3,050,744.000	2,268,217 -1,525,321.000 3,050,745.000	2,268,217 -1,525,305.000 3,050,715.000	

## **5.1.19** Louisville (Kentucky)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.203***	0.207***	0.198***	0.199***	0.197***	0.202***	
ŭ.	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	
Precip.	0.170***	0.214***	0.173***		3.319**	5.355***	
•	(0.038)	(0.044)	(0.038)		(1.650)	(1.790)	
$Night \times Precip.$		-0.169*				-0.271***	
•		(0.086)				(0.096)	
Temp.			-0.003**	-0.002*	-0.003**	-0.002*	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					$-0.011^*$	-0.017***	
					(0.006)	(0.006)	
Constant	-0.547***	-0.549***	0.192	0.127	0.191	0.144	
	(0.059)	(0.059)	(0.374)	(0.373)	(0.374)	(0.374)	
Observations	100,623	100,623	100,623	100,623	100,623	100,623	
Log Likelihood	-63,084.970	-63,083.060	-63,082.970	-63,093.310	-63,081.140	-63,077.040	
Akaike Inf. Crit.	126,262.000	126,260.100	126,259.900	126,278.600	126,258.300	126,252.100	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.20 Madison (Wisconsin)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	-0.118*** (0.033)	-0.113*** (0.033)	-0.122*** (0.033)	-0.121*** (0.033)	-0.119*** (0.033)	-0.118*** (0.033)
Precip.	-0.042 (0.035)	0.009 (0.040)	-0.039 (0.035)	(0.022)	-5.378*** (1.135)	-5.040*** (1.189)
$Night \times Precip.$	(0.033)	-0.174** (0.077)	(0.033)		(1.133)	-0.073 (0.079)
Temp.		(0.077)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)
$Precip. \times Temp.$			(0.001)	(0.001)	0.018***	0.017*** (0.004)
Constant	-0.593*** (0.052)	-0.595*** (0.052)	-0.124 (0.287)	-0.111 (0.287)	-0.095 (0.287)	-0.105 (0.287)
Observations Log Likelihood Akaike Inf. Crit.	172,252 -92,563.630 185,225.300	172,252 -92,561.020 185,222.000	172,252 -92,562.250 185,224.500	172,252 -92,562.900 185,223.800	172,252 -92,550.700 185,203.400	172,252 -92,550.270 185,204.500

#### 5.1.21 Mesa (Arizona)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.166*	0.161	0.166*	0.168*	0.166*	0.160	
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	
Precip.	-0.976**	-1.402**	-0.980**		-12.772	-15.163	
_	(0.384)	(0.553)	(0.385)		(12.585)	(12.583)	
$Night \times Precip.$		0.886				0.997	
•		(0.756)				(0.757)	
Temp.			-0.001	0.0002	-0.001	-0.001	
_			(0.004)	(0.004)	(0.004)	(0.004)	
$Precip. \times Temp.$					0.040	0.047	
•					(0.043)	(0.043)	
Constant	-2.277***	-2.274***	-2.073*	-2.330*	-2.034	-1.925	
	(0.148)	(0.148)	(1.242)	(1.236)	(1.243)	(1.246)	
Observations	67,000	67,000	67,000	67,000	67,000	67,000	
Log Likelihood	-20,662.870	-20,662.190	-20,662.850	-20,666.660	-20,662.410	-20,661.560	
Akaike Inf. Crit.	41,417.730	41,418.380	41,419.710	41,425.330	41,420.820	41,421.120	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### **5.1.22** Nashville (Tennessee)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.019** (0.008)	0.024*** (0.008)	0.015* (0.008)	0.015* (0.008)	0.015* (0.008)	0.021*** (0.008)	
Precip.	0.108*** (0.006)	0.162*** (0.007)	0.111*** (0.006)		1.748*** (0.234)	2.609*** (0.243)	
$Night \times Precip.$		-0.150*** (0.012)				-0.177*** (0.013)	
Temp.			-0.002*** (0.0003)	-0.002*** (0.0003)	-0.002*** (0.0003)	-0.002*** (0.0003)	
$Precip. \times Temp.$					-0.006*** (0.001)	-0.008*** (0.001)	
Constant	-0.141*** (0.011)	-0.144*** (0.011)	0.395*** (0.074)	0.327*** (0.074)	0.388*** (0.074)	0.332*** (0.074)	
Observations Log Likelihood Akaike Inf. Crit.	2,444,249 -1,642,473.000 3,285,046.000	2,444,249 -1,642,398.000 3,284,899.000	2,444,249 -1,642,446.000 3,284,994.000	2,444,249 -1,642,621.000 3,285,341.000	2,444,249 -1,642,422.000 3,284,947.000	2,444,249 -1,642,324.000 3,284,755.000	

#### 5.1.23 New Orleans (Louisiana)

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	0.013	0.013	0.011	0.011	0.012	0.011		
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)		
Precip.	-0.031**	-0.028*	-0.030**		-1.909**	-2.420**		
•	(0.014)	(0.017)	(0.014)		(0.910)	(1.067)		
$Night \times Precip.$		-0.010				0.033		
		(0.031)				(0.036)		
Temp.			-0.001	-0.001	-0.001	-0.001		
·			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$			, ,	, ,	0.006**	0.008**		
					(0.003)	(0.004)		
Constant	0.979***	0.979***	1.283***	1.293***	1.276***	1.289***		
	(0.031)	(0.031)	(0.283)	(0.283)	(0.283)	(0.284)		
Observations	406,499	406,499	406,499	406,499	406,499	406,499		
Log Likelihood	-236,901.800	-236,901.700	-236,901.200	-236,903.500	-236,899.100	-236,898.70		
Akaike Inf. Crit.	473,903.600	473,905.500	473,904.400	473,907.100	473,902.100	473,903.300		

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 5.1.24 Oakland (California)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.202*** (0.049)	-0.200*** (0.049)	-0.192*** (0.049)	-0.192*** (0.049)	-0.192*** (0.049)	-0.183*** (0.049)	
Precip.	0.112 (0.133)	0.315 (0.224)	0.122 (0.133)	(0.049)	33.540** (14.742)	59.554*** (17.592)	
$\textit{Night} \times \textit{Precip}.$	(0.155)	-0.325 (0.277)	(0.155)		(14.742)	-0.924*** (0.325)	
Temp.		(0.277)	0.005* (0.003)	0.005* (0.003)	0.006** (0.003)	0.006** (0.003)	
$Precip. \times Temp.$			(0.003)	(0.003)	-0.117** (0.052)	-0.206*** (0.061)	
Constant	1.902*** (0.076)	1.901*** (0.076)	0.344 (0.809)	0.374 (0.808)	0.310 (0.809)	0.049 (0.815)	
Observations Log Likelihood Akaike Inf. Crit.	91,049 -40,178.890 80,451.780	91,049 -40,178.180 80,452.370	91,049 -40,177.020 80,450.030	91,049 -40,177.450 80,448.890	91,049 -40,174.340 80,446.680	91,049 -40,170.170 80,440.330	

## 5.1.25 Oklahoma City (Oklahoma)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.014	-0.013	-0.019	-0.019	-0.019	-0.018	
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	
Precip.	0.057***	0.088***	0.057***		0.808	1.017	
	(0.019)	(0.026)	(0.019)		(0.859)	(0.863)	
$Night \times Precip.$		-0.061*				-0.063*	
•		(0.037)				(0.037)	
Temp.			-0.002***	-0.002***	-0.002***	-0.002***	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.003	-0.003	
					(0.003)	(0.003)	
Constant	-0.836***	-0.837***	-0.362**	-0.359**	-0.367**	-0.380**	
	(0.028)	(0.028)	(0.173)	(0.173)	(0.173)	(0.173)	
Observations	667,262	667,262	667,262	667,262	667,262	667,262	
Log Likelihood	-346,357.700	-346,356.300	-346,353.800	-346,358.400	-346,353.400	-346,352.000	
Akaike Inf. Crit.	692,813.400	692,812.600	692,807.600	692,814.900	692,808.900	692,808.100	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.26 Owensboro (Kentucky)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.564** (0.235)	0.569** (0.235)	0.536** (0.236)	0.535** (0.235)	0.543** (0.236)	0.543** (0.236)	
Precip.	-0.082	0.013	-0.046	(0.233)	-15.525	-15.415	
$Night \times Precip.$	(0.254)	(0.348) -0.184	(0.251)		(13.982)	(14.474) -0.014	
Temp.		(0.505)	-0.012	-0.012	-0.011	(0.482) -0.011	
$Precip. \times Temp.$			(0.008)	(0.007)	(0.008) 0.052	(0.008) $0.052$	
Constant	-1.927*** (0.339)	-1.930*** (0.340)	1.435 (2.205)	1.470 (2.196)	(0.047) 1.321 (2.208)	(0.048) 1.320 (2.208)	
Observations Log Likelihood Akaike Inf. Crit.	6,652 -2,367.721 4,825.443	6,652 -2,367.655 4,827.310	6,652 -2,366.531 4,825.062	6,652 -2,366.549 4,823.097	6,652 -2,365.879 4,825.759	6,652 -2,365.879 4,827.758	

## 5.1.27 Philadelphia (Pennsylvania)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.057***	0.060***	0.057***	0.057***	0.057***	0.060***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	
Precip.	-0.018**	0.020	-0.018**		-0.737**	-0.381	
_	(0.009)	(0.012)	(0.009)		(0.341)	(0.353)	
$Night \times Precip.$		-0.090***				-0.086***	
•		(0.019)				(0.019)	
Temp.			0.0001	0.0001	0.0001	0.0002	
_			(0.0004)	(0.0004)	(0.0004)	(0.0004)	
$Precip. \times Temp.$					0.002**	0.001	
•					(0.001)	(0.001)	
Constant	1.087***	1.085***	1.059***	1.069***	1.060***	1.033***	
	(0.015)	(0.015)	(0.115)	(0.115)	(0.115)	(0.115)	
Observations	1,540,120	1,540,120	1,540,120	1,540,120	1,540,120	1,540,120	
Log Likelihood	-825,179.500	-825,167.800	-825,179.500	-825,181.400	-825,177.200	-825,167.000	
Akaike Inf. Crit.	1,650,453.000	1,650,432.000	1,650,455.000	1,650,457.000	1,650,452.000	1,650,434.000	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.28 Plano (Texas)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.063	0.065	0.065	0.065	0.066	0.067	
Precip.	(0.041) $-0.072$	(0.041) 0.008	(0.041) $-0.072$	(0.041)	(0.041) -4.597	(0.041) $-3.533$	
$Night \times Precip.$	(0.062)	(0.074) -0.239*	(0.062)		(2.819)	(2.875) -0.203	
		(0.138)	0.001	0.001	0.001	(0.140)	
Temp.			0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	
$Precip. \times Temp.$					0.015 (0.009)	0.012 (0.010)	
Constant	-0.987***	-0.986***	-1.297***	-1.299***	-1.287***	-1.306***	
	(0.068)	(0.068)	(0.374)	(0.374)	(0.374)	(0.374)	
Observations	179,181	179,181	179,181	179,181	179,181	179,181	
Log Likelihood Akaike Inf. Crit.	-85,140.340 170,372.700	-85,138.740 170,371.500	-85,139.980 170,374.000	-85,140.680 170,373.400	-85,138.660 170,373.300	-85,137.560 170,373.100	

## 5.1.29 Raleigh (North Carolina)

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	0.074***	0.079***	0.072**	0.071**	0.072**	0.076***		
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)		
Precip.	0.108***	0.184***	0.109***		0.524	1.057		
Î	(0.024)	(0.035)	(0.024)		(0.903)	(0.914)		
$Night \times Precip.$		-0.159***				-0.163***		
		(0.049)				(0.049)		
Temp.			-0.001	-0.001	-0.001	-0.001		
			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					-0.001	-0.003		
					(0.003)	(0.003)		
Constant	0.265***	0.262***	0.606***	0.585**	0.604***	0.561**		
	(0.036)	(0.036)	(0.234)	(0.234)	(0.234)	(0.234)		
Observations	288,739	288,739	288,739	288,739	288,739	288,739		
Log Likelihood	-196,500.100	-196,494.700	-196,499.000	-196,509.300	-196,498.900	-196,493.40		
Akaike Inf. Crit.	393,094.100	393,085.500	393,094.000	393,112.600	393,095.800	393,086.800		

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### **5.1.30** Saint Paul (Minnesota)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	-0.175***	-0.176***	-0.173***	-0.174***	-0.173***	-0.175***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Precip.	-0.036	-0.083	-0.037		-0.825	-1.073
	(0.038)	(0.058)	(0.038)		(1.460)	(1.486)
$Night \times Precip.$		0.083				0.088
•		(0.077)				(0.078)
Temp.			0.0005	0.0004	0.0005	0.0004
_			(0.001)	(0.001)	(0.001)	(0.001)
$Precip. \times Temp.$					0.003	0.003
					(0.005)	(0.005)
Constant	0.548***	0.549***	0.420	0.432	0.419	0.427
	(0.044)	(0.044)	(0.300)	(0.299)	(0.300)	(0.300)
Observations	117,975	117,975	117,975	117,975	117,975	117,975
Log Likelihood	-79,394.110	-79,393.510	-79,394.010	-79,394.500	-79,393.870	-79,393.210
Akaike Inf. Crit.	158,884.200	158,885.000	158,886.000	158,885.000	158,887.700	158,888.400

## 5.1.31 San Antonio (Texas)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.056**	0.057**	0.058**	0.058**	0.058**	0.058**	
	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	
Precip.	-0.050*	-0.047	-0.049*		-1.430	-1.552	
•	(0.028)	(0.034)	(0.028)		(1.505)	(1.626)	
$Night \times Precip.$		-0.006				0.012	
		(0.058)				(0.062)	
Temp.			0.001	0.001	0.001	0.001	
_			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.005	0.005	
					(0.005)	(0.005)	
Constant	-1.293***	-1.293***	-1.525***	-1.540***	-1.519***	-1.516***	
	(0.035)	(0.035)	(0.249)	(0.249)	(0.249)	(0.249)	
Observations	470,451	470,451	470,451	470,451	470,451	470,451	
Log Likelihood	-241,408.900	-241,408.900	-241,408.500	-241,410.100	-241,408.000	-241,408.00	
Akaike Inf. Crit.	482,915.800	482,917.800	482,916.900	482,918.100	482,918.100	482,920.000	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.32 San Diego (California)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	-0.097**	-0.098***	-0.096**	-0.097**	-0.096**	-0.095**
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Precip.	0.153	0.130	0.157		8.786*	9.278*
	(0.097)	(0.119)	(0.098)		(5.037)	(5.323)
Night $\times$ Precip.		0.070				-0.062
		(0.205)				(0.216)
Temp.			0.001	0.0003	0.001	0.001
			(0.002)	(0.002)	(0.002)	(0.002)
$Precip. \times Temp.$					$-0.030^*$	-0.032*
					(0.018)	(0.019)
Constant	-1.103***	-1.102***	-1.307**	-1.195**	-1.346**	-1.358**
	(0.049)	(0.049)	(0.552)	(0.548)	(0.553)	(0.554)
Observations	198,938	198,938	198,938	198,938	198,938	198,938
Log Likelihood	-99,679.570	-99,679.510	-99,679.500	-99,680.760	-99,677.910	-99,677.870
Akaike Inf. Crit.	199,451.100	199,453.000	199,453.000	199,453.500	199,451.800	199,453.700

#### 5.1.33 San Francisco (California)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.088***	-0.087***	-0.082***	-0.082***	-0.082***	-0.080***	
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	
Precip.	-0.187***	-0.103	-0.184***		2.232	5.518	
_	(0.063)	(0.082)	(0.063)		(9.514)	(9.563)	
$Night \times Precip.$		-0.192				$-0.237^*$	
•		(0.125)				(0.128)	
Temp.			0.016***	0.016***	0.016***	0.017***	
•			(0.004)	(0.004)	(0.004)	(0.004)	
$Precip. \times Temp.$					-0.008	-0.020	
•					(0.033)	(0.034)	
Constant	-0.448***	-0.448***	-5.012***	-5.053***	-5.036***	-5.184***	
	(0.035)	(0.035)	(1.063)	(1.062)	(1.067)	(1.070)	
Observations	251,569	251,569	251,569	251,569	251,569	251,569	
Log Likelihood	-150,861.500	-150,860.300	-150,852.200	-150,856.700	-150,852.200	-150,850.500	
Akaike Inf. Crit.	301,818.900	301,818.600	301,802.500	301,809.400	301,804.400	301,802.900	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.34 San Jose (California)

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	0.012 (0.061)	0.014 (0.061)	0.013 (0.062)	0.013 (0.062)	0.013 (0.062)	0.017 (0.062)
Precip.	-0.032 (0.124)	0.118 (0.206)	-0.031 (0.124)	(31332)	-1.314 (13.325)	3.595 (14.283)
$Night \times Precip.$	(***= *)	-0.227 (0.255)	(**-= *)		()	-0.258 (0.275)
Temp.		(******)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)
$Precip. \times Temp.$			(31332)	(31332)	0.005 (0.047)	-0.012 (0.050)
Constant	-0.108 (0.092)	-0.109 (0.092)	-0.255 (0.880)	-0.261 (0.880)	-0.253 (0.880)	-0.353 (0.887)
Observations Log Likelihood Akaike Inf. Crit.	38,581 -24,247.400 48,590.810	38,581 -24,247.010 48,592.030	38,581 -24,247.390 48,592.780	38,581 -24,247.420 48,590.840	38,581 -24,247.380 48,594.770	38,581 -24,246.950 48,595.900

## 5.1.35 Tulsa (Oklahoma)

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.007	0.008	0.001	0.0005	0.001	0.002	
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	
Precip.	0.048	0.071**	0.049		0.163	0.413	
Î	(0.032)	(0.036)	(0.032)		(1.250)	(1.257)	
$Night \times Precip.$		-0.108				-0.106	
		(0.081)				(0.081)	
Temp.			-0.002***	-0.002***	-0.002***	-0.002***	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.0004	-0.001	
					(0.004)	(0.004)	
Constant	-0.511***	-0.512***	0.205	0.205	0.205	0.195	
	(0.050)	(0.050)	(0.253)	(0.253)	(0.253)	(0.253)	
Observations	280,612	280,612	280,612	280,612	280,612	280,612	
Log Likelihood	-152,118.600	-152,117.600	-152,114.400	-152,115.500	-152,114.400	-152,113.50	
Akaike Inf. Crit.	304,333.100	304,333.300	304,326.800	304,327.000	304,328.800	304,329.000	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.1.36 Wichita (Kansas)

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	-0.005	-0.005	-0.009	-0.009	-0.008	-0.009		
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)		
Precip.	0.010	0.009	0.010		-0.940	-1.083		
	(0.023)	(0.028)	(0.023)		(0.904)	(0.954)		
$Night \times Precip.$		0.003				0.024		
		(0.049)				(0.051)		
Temp.			-0.002*	-0.002*	-0.002*	-0.002**		
			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					0.003	0.004		
					(0.003)	(0.003)		
Constant	-1.321***	-1.321***	-0.825***	-0.826***	-0.820***	-0.814***		
	(0.061)	(0.061)	(0.263)	(0.263)	(0.263)	(0.263)		
Observations	290,091	290,091	290,091	290,091	290,091	290,091		
Log Likelihood	-142,928.400	-142,928.400	-142,926.500	-142,926.600	-142,925.900	-142,925.800		
Akaike Inf. Crit.	285,952.700	285,954.700	285,951.000	285,949.200	285,951.900	285,953.600		

## 5.1.37 Winston-Salem (North Carolina)

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	0.040	0.040	0.040	0.040	0.039	0.040		
	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)		
Precip.	-0.014	-0.011	-0.014		1.041	1.103		
-	(0.032)	(0.045)	(0.032)		(1.218)	(1.246)		
Night $\times$ Precip.		-0.005				-0.016		
		(0.065)				(0.066)		
Temp.			-0.0001	-0.0001	-0.0001	-0.0001		
_			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					-0.004	-0.004		
					(0.004)	(0.004)		
Constant	0.160***	0.159***	0.195	0.199	0.186	0.183		
	(0.045)	(0.045)	(0.333)	(0.333)	(0.334)	(0.334)		
Observations	150,475	150,475	150,475	150,475	150,475	150,475		
Log Likelihood	-103,239.800	-103,239.800	-103,239.800	-103,239.900	-103,239.400	-103,239.40		
Akaike Inf. Crit.	206,573.700	206,575.600	206,575.600	206,573.800	206,576.900	206,578.800		

# **5.2** State Police Departments

#### 5.2.1 Connecticut

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.016	-0.013	-0.013	-0.013	-0.013	-0.009	
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	
Precip.	0.079***	0.143***	0.075***		0.221	1.753**	
	(0.019)	(0.025)	(0.019)		(0.629)	(0.720)	
$Night \times Precip.$		-0.140***				-0.191***	
		(0.038)				(0.044)	
Temp.			0.002***	0.002***	0.002***	0.002***	
_			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.001	-0.005**	
					(0.002)	(0.002)	
Constant	-1.418***	-1.420***	-1.943***	-1.995***	-1.941***	-1.970***	
	(0.024)	(0.024)	(0.198)	(0.197)	(0.198)	(0.198)	
Observations	948,360	948,360	948,360	948,360	948,360	948,360	
Log Likelihood	-413,040.400	-413,033.600	-413,036.800	-413,044.200	-413,036.800	-413,027.100	
Akaike Inf. Crit.	826,170.700	826,159.100	826,165.600	826,178.400	826,167.500	826,150.100	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.2.2 Florida

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.087*** (0.007)	-0.086*** (0.007)	-0.088*** (0.007)	-0.088*** (0.007)	-0.088*** (0.007)	-0.087*** (0.007)	
Precip.	0.009* (0.005)	0.014** (0.005)	0.009* (0.005)	(0.007)	-0.733* (0.395)	-0.322 (0.420)	
$Night \times Precip.$	(0.000)	-0.064*** (0.020)	(0.000)		(0.070)	-0.057*** (0.021)	
Temp.		(*** *)	-0.001*** (0.0003)	-0.001*** (0.0003)	-0.001*** (0.0003)	-0.001*** (0.0003)	
$Precip. \times Temp.$			(******)	(31332)	0.002* (0.001)	0.001 (0.001)	
Constant	-0.698*** (0.011)	-0.698*** (0.011)	-0.478*** (0.083)	-0.477*** (0.083)	-0.475*** (0.084)	-0.483*** (0.084)	
Observations Log Likelihood Akaike Inf. Crit.	5,231,498 -2,897,591.000 5,795,282.000	5,231,498 -2,897,585.000 5,795,273.000	5,231,498 -2,897,587.000 5,795,277.000	5,231,498 -2,897,589.000 5,795,278.000	5,231,498 -2,897,586.000 5,795,275.000	5,231,498 -2,897,582.000 5,795,270.000	

## 5.2.3 Georgia

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	-0.009	-0.007	0.024*	0.023*	0.024*	0.026**		
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)		
Precip.	$0.017^{*}$	0.031***	0.010		-1.024**	-0.448		
•	(0.010)	(0.011)	(0.010)		(0.469)	(0.498)		
$Night \times Precip.$		-0.074***				-0.098***		
		(0.027)				(0.029)		
Temp.			0.017***	0.017***	0.017***	0.017***		
			(0.0005)	(0.0005)	(0.0005)	(0.0005)		
$Precip. \times Temp.$					0.003**	0.002		
					(0.002)	(0.002)		
Constant	-0.435***	-0.435***	-5.490***	-5.493***	-5.488***	-5.508***		
	(0.022)	(0.022)	(0.144)	(0.144)	(0.144)	(0.144)		
Observations	900,697	900,697	900,697	900,697	900,697	900,697		
Log Likelihood	-552,599.400	-552,595.700	-551,968.000	-551,968.400	-551,965.600	-551,959.80		
Akaike Inf. Crit.	1,105,293.000	1,105,287.000	1,104,032.000	1,104,031.000	1,104,029.000	1,104,020.00		

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.2.4 Michigan

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	0.022 (0.025)	0.023 (0.025)	0.071*** (0.025)	0.071*** (0.025)	0.071*** (0.025)	0.073*** (0.025)
Precip.	-0.062* (0.033)	-0.042 (0.039)	-0.113*** (0.035)	(0.023)	-3.121*** (1.057)	-2.725** (1.117)
$Night \times Precip.$	(0.033)	-0.070	(0.033)		(1.037)	-0.083
Temp.		(0.075)	0.027***	0.027***	0.027***	(0.081) 0.027***
$Precip. \times Temp.$			(0.001)	(0.001)	(0.001) 0.010***	(0.001) 0.009**
Constant	-1.418*** (0.056)	-1.417*** (0.056)	-9.026*** (0.267)	-8.983*** (0.267)	(0.004) -8.999*** (0.267)	(0.004) -9.011*** (0.268)
Observations Log Likelihood Akaike Inf. Crit.	298,815 -136,361.000 272,818.100	298,815 -136,360.600 272,819.200	298,815 -135,934.200 271,966.400	298,815 -135,939.900 271,975.800	298,815 -135,930.100 271,960.200	298,815 -135,929.600 271,961.100

## 5.2.5 New Hampshire

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.265***	-0.261***	-0.239**	-0.243**	-0.240**	-0.229**	
Ü	(0.098)	(0.098)	(0.099)	(0.099)	(0.099)	(0.099)	
Precip.	0.209**	0.241**	0.186*		5.976	8.429**	
•	(0.095)	(0.098)	(0.097)		(3.711)	(3.837)	
$Night \times Precip.$		-0.232				-0.529*	
•		(0.282)				(0.310)	
Temp.			0.019***	0.019***	0.019***	0.019***	
•			(0.004)	(0.004)	(0.004)	(0.004)	
$Precip. \times Temp.$					-0.020	-0.028**	
					(0.013)	(0.013)	
Constant	-2.733***	-2.734***	-7.925***	-8.001***	-7.910***	-8.015***	
	(0.138)	(0.138)	(1.009)	(1.009)	(1.009)	(1.012)	
Observations	151,953	151,953	151,953	151,953	151,953	151,953	
Log Likelihood	-18,246.620	-18,246.260	-18,233.070	-18,234.640	-18,231.860	-18,230.24	
Akaike Inf. Crit.	36,581.240	36,582.520	36,556.140	36,557.270	36,555.730	36,554.490	
Note:					*p<0.1; **p<0.05; ***p<0.01		

#### **5.2.6** New York

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	-0.202***	-0.200***	-0.170***	-0.170***	-0.170***	-0.168***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Precip.	-0.141***	-0.109***	-0.166***		-4.693***	-4.155***
•	(0.010)	(0.011)	(0.010)		(0.349)	(0.363)
$Night \times Precip.$		-0.118***				-0.113***
		(0.022)				(0.023)
Temp.			0.026***	0.026***	0.026***	0.026***
_			(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Precip. \times Temp.$					0.016***	0.014***
					(0.001)	(0.001)
Constant	-1.444***	-1.444***	-8.755***	-8.727***	-8.723***	-8.737***
	(0.014)	(0.014)	(0.073)	(0.073)	(0.073)	(0.073)
Observations	5,646,136	5,646,136	5,646,136	5,646,136	5,646,136	5,646,136
Log Likelihood	-2,186,106.000	-2,186,092.000	-2,180,900.000	-2,181,056.000	-2,180,815.000	-2,180,803.00
Akaike Inf. Crit.	4,372,311.000	4,372,284.000	4,361,900.000	4,362,210.000	4,361,733.000	4,361,710.000

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01 Note:

#### 5.2.7 North Dakota

	Dependent variable: Black					
	(1)	(2)	(3)	(4)	(5)	(6)
Night	-0.145** (0.059)	-0.144** (0.059)	-0.145** (0.059)	-0.145** (0.059)	-0.145** (0.059)	-0.143** (0.059)
Precip.	0.065 (0.106)	0.093 (0.117)	0.064 (0.106)	,	1.211 (3.655)	1.667 (3.692)
$Night \times Precip.$	, ,	-0.127 (0.259)	, ,		•	-0.152 (0.269)
Temp.			0.0003 (0.002)	0.0003 (0.002)	0.0004 (0.002)	0.0004 (0.002)
$Precip. \times Temp.$					-0.004 (0.012)	-0.005 (0.013)
Constant	-3.041*** (0.093)	-3.041*** (0.093)	-3.134*** (0.531)	-3.134*** (0.531)	-3.141*** (0.531)	-3.146*** (0.531)
Observations Log Likelihood Akaike Inf. Crit.	221,428 -32,529.040 65,152.090	221,428 -32,528.920 65,153.840	221,428 -32,529.030 65,154.060	221,428 -32,529.200 65,152.410	221,428 -32,528.980 65,155.960	221,428 -32,528.810 65,157.620

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.2.8 Ohio

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.032*** (0.008)	-0.033*** (0.008)	-0.040*** (0.008)	-0.040*** (0.008)	-0.040*** (0.008)	-0.041*** (0.008)	
Precip.	-0.015 (0.009)	-0.027** (0.013)	-0.004 (0.009)	(0.000)	0.458 (0.347)	0.246 (0.366)	
$\textit{Night} \times \textit{Precip}.$	(0.005)	0.030 (0.019)	(0.005)		(0.017)	0.038*	
Temp.		(*** * /	-0.004*** (0.0002)	-0.004*** (0.0002)	-0.004*** (0.0002)	-0.004*** (0.0002)	
$Precip. \times Temp.$			(*****_)	(******_/	-0.002 (0.001)	-0.001 (0.001)	
Constant	-1.701*** (0.011)	-1.700*** (0.011)	-0.548*** (0.071)	-0.546*** (0.071)	-0.549*** (0.071)	-0.543*** (0.071)	
Observations Log Likelihood Akaike Inf. Crit.	5,290,376 -2,096,305.000 4,192,708.000	5,290,376 -2,096,304.000 4,192,708.000	5,290,376 -2,096,169.000 4,192,439.000	5,290,376 -2,096,169.000 4,192,437.000	5,290,376 -2,096,168.000 4,192,439.000	5,290,376 -2,096,167.000 4,192,437.000	

## 5.2.9 Tennessee

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	0.161***	0.164***	0.208***	0.208***	0.209***	0.213***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	
Precip.	-0.009	0.031**	-0.037***		-2.807***	-1.473***	
•	(0.013)	(0.014)	(0.013)		(0.525)	(0.553)	
$Night \times Precip.$		-0.177***				-0.228***	
		(0.032)				(0.035)	
Temp.			0.026***	0.026***	0.026***	0.026***	
_			(0.0004)	(0.0004)	(0.0004)	(0.0004)	
$Precip. \times Temp.$					0.009***	0.005***	
					(0.002)	(0.002)	
Constant	-1.600***	-1.600***	-9.031***	-9.018***	-9.023***	-9.066***	
	(0.021)	(0.021)	(0.128)	(0.128)	(0.128)	(0.128)	
Observations	1,789,219	1,789,219	1,789,219	1,789,219	1,789,219	1,789,219	
Log Likelihood	-706,514.300	-706,498.100	-704,769.000	-704,773.200	-704,755.200	-704,732.100	
Akaike Inf. Crit.	1,413,123.000	1,413,092.000	1,409,634.000	1,409,640.000	1,409,608.000	1,409,564.000	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### **5.2.10** Texas

	Dependent variable: Black						
	(1)	(2)	(3)	(4)	(5)	(6)	
Night	-0.023*** (0.006)	-0.022*** (0.006)	-0.015*** (0.006)	-0.015*** (0.006)	-0.015*** (0.006)	-0.014** (0.006)	
Precip.	0.111*** (0.007)	0.142*** (0.008)	0.112*** (0.007)	` ,	-0.416 (0.335)	0.647* (0.355)	
$Night \times Precip.$	, ,	-0.128*** (0.016)	, ,		,	-0.144*** (0.017)	
Temp.			0.004*** (0.0002)	0.004*** (0.0002)	0.004*** (0.0002)	0.004*** (0.0002)	
$Precip. \times Temp.$					0.002 (0.001)	-0.002 (0.001)	
Constant	-1.143*** (0.008)	-1.143*** (0.008)	-2.239*** (0.056)	-2.232*** (0.056)	-2.238*** (0.056)	-2.252*** (0.056)	
Observations Log Likelihood Akaike Inf. Crit.	8,641,146 -3,867,711.000 7,735,521.000	8,641,146 -3,867,680.000 7,735,460.000	8,641,146 -3,867,515.000 7,735,131.000	8,641,146 -3,867,640.000 7,735,378.000	8,641,146 -3,867,514.000 7,735,130.000	8,641,146 -3,867,479.000 7,735,061.000	

## 5.2.11 Wisconsin

	Dependent variable: Black							
	(1)	(2)	(3)	(4)	(5)	(6)		
Night	-0.114***	-0.112***	-0.082***	-0.082***	-0.082***	-0.080***		
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)		
Precip.	-0.078*	-0.040	-0.103**		-1.172	-0.583		
	(0.042)	(0.050)	(0.042)		(1.447)	(1.472)		
$Night \times Precip.$		-0.114				-0.147		
0 1		(0.090)				(0.094)		
Temp.			0.014***	0.014***	0.014***	0.014***		
			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					0.004	0.002		
					(0.005)	(0.005)		
Constant	-1.588***	-1.589***	-5.485***	-5.466***	-5.480***	-5.493***		
	(0.037)	(0.037)	(0.231)	(0.230)	(0.231)	(0.231)		
Observations	795,948	795,948	795,948	795,948	795,948	795,948		
Log Likelihood	-189,542.500	-189,541.600	-189,395.700	-189,399.000	-189,395.500	-189,394.2		
Akaike Inf. Crit.	379,180.900	379,181.300	378,889.500	378,893.900	378,890.900	378,890.40		

# 6 Regression Results: Citation

## **6.1** City Police Departments

#### 6.1.1 Charlotte (North Carolina)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.165***	0.165***	0.165***	0.165***	0.165***	0.165***	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	
Night	-0.184***	-0.182***	-0.185***	-0.184***	-0.185***	-0.183***	
-	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	
Precip.	-0.057***	-0.028	-0.057***		-1.098	-0.841	
•	(0.019)	(0.024)	(0.019)		(0.702)	(0.722)	
$Night \times Precip.$		-0.073*				-0.063	
•		(0.038)				(0.039)	
Temp.			-0.001	-0.001	-0.001	-0.001	
·			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.004	0.003	
					(0.002)	(0.002)	
Constant	-0.162***	-0.163***	0.019	0.023	0.028	0.015	
	(0.025)	(0.025)	(0.175)	(0.175)	(0.175)	(0.175)	
Observations	584,129	584,129	584,129	584,129	584,129	584,129	
Log Likelihood	-391,124.500	-391,122.700	-391,124.000	-391,128.700	-391,122.900	-391,121.600	
Akaike Inf. Crit.	782,345.100	782,343.400	782,346.000	782,353.400	782,345.800	782,345.200	
Note:	*p<0.1; **p<0.05; ***p<0.01						

## 6.1.2 Columbus (Ohio)

	Dependent variable: Citation							
	(1)	(2)	(3)	(4)	(5)	(6)		
Nonwhite	-0.074***	-0.074***	-0.074***	-0.074***	-0.074***	-0.074***		
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)		
Night	-0.654***	-0.660***	-0.652***	-0.652***	-0.652***	-0.659***		
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)		
Precip.	-0.186***	-0.328***	-0.191***		-3.825**	-6.606***		
_	(0.049)	(0.066)	(0.049)		(1.751)	(1.861)		
$Night \times Precip.$		0.317***				0.428***		
		(0.097)				(0.103)		
Temp.			0.001	0.001	0.001	0.001		
			(0.001)	(0.001)	(0.001)	(0.001)		
$Precip. \times Temp.$					0.012**	0.021***		
					(0.006)	(0.006)		
Constant	0.555***	0.557***	0.169	0.270	0.165	0.223		
	(0.048)	(0.048)	(0.340)	(0.339)	(0.340)	(0.341)		
Observations	116,263	116,263	116,263	116,263	116,263	116,263		
Log Likelihood	-74,497.990	-74,492.740	-74,497.340	-74,504.950	-74,495.170	-74,486.54		
Akaike Inf. Crit.	149,092.000	149,083.500	149,092.700	149,105.900	149,090.300	149,075.10		
Note:					*p<0.1; **p<0	0.05; ***p<0.0		

## 6.1.3 Durham (North Carolina)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	
Night	-0.348***	-0.347***	-0.351***	-0.350***	-0.351***	-0.350***	
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	
Precip.	-0.150***	-0.139***	-0.149***		-1.511	-1.446	
	(0.033)	(0.040)	(0.033)		(1.303)	(1.336)	
$Night \times Precip.$		-0.036				-0.016	
		(0.073)				(0.074)	
Temp.			-0.002	-0.002	-0.002	-0.002	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.005	0.004	
					(0.004)	(0.005)	
Constant	-0.236***	-0.236***	0.237	0.269	0.246	0.242	
	(0.053)	(0.053)	(0.350)	(0.349)	(0.350)	(0.350)	
Observations	128,656	128,656	128,656	128,656	128,656	128,656	
Log Likelihood	-86,868.560	-86,868.440	-86,867.620	-86,878.030	-86,867.070	-86,867.050	
Akaike Inf. Crit.	173,833.100	173,834.900	173,833.200	173,852.100	173,834.100	173,836.100	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## **6.1.4** Fayetteville (North Carolina)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.225***	0.225***	0.225***	0.226***	0.225***	0.225***	
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	
Night	-0.197***	-0.197***	-0.203***	-0.202***	-0.202***	-0.203***	
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	
Precip.	-0.087***	-0.089***	-0.084***		-0.994	-1.198	
·	(0.025)	(0.029)	(0.025)		(1.014)	(1.075)	
$Night \times Precip.$		0.007				0.033	
0 1		(0.055)				(0.058)	
Temp.			-0.003***	-0.003***	-0.003***	-0.003***	
•			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.003	0.004	
					(0.003)	(0.004)	
Constant	0.270***	0.270***	1.061***	1.102***	1.063***	1.070***	
	(0.043)	(0.043)	(0.288)	(0.288)	(0.288)	(0.289)	
Observations	209,106	209,106	209,106	209,106	209,106	209,106	
Log Likelihood	-135,887.800	-135,887.800	-135,884.000	-135,889.800	-135,883.600	-135,883.400	
Akaike Inf. Crit.	271,871.700	271,873.700	271,866.000	271,875.500	271,867.200	271,868.800	

## 6.1.5 Grand Forks (North Dakota)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.700***	0.700***	0.697***	0.696***	0.697***	0.697***	
	(0.184)	(0.184)	(0.184)	(0.184)	(0.184)	(0.184)	
Night	-0.256	-0.261	-0.292	-0.289	-0.294	-0.296	
	(0.180)	(0.180)	(0.181)	(0.181)	(0.181)	(0.182)	
Precip.	0.595	0.330	0.606		16.837	16.050	
_	(0.577)	(0.862)	(0.580)		(15.090)	(16.061)	
$Night \times Precip.$		0.423				0.132	
		(1.155)				(1.013)	
Temp.			-0.012*	-0.012*	-0.012*	$-0.012^*$	
			(0.007)	(0.007)	(0.007)	(0.007)	
$Precip. \times Temp.$					-0.056	-0.053	
					(0.051)	(0.054)	
Constant	3.183***	3.187***	6.515***	6.501***	6.464***	6.468***	
	(0.269)	(0.269)	(1.906)	(1.906)	(1.906)	(1.906)	
Observations	35,467	35,467	35,467	35,467	35,467	35,467	
Log Likelihood	-2,914.282	-2,914.218	-2,912.718	-2,913.533	-2,912.180	-2,912.171	
Akaike Inf. Crit.	5,926.564	5,928.436	5,925.437	5,925.066	5,926.359	5,928.342	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## **6.1.6** Greensboro (North Carolina)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.022**	0.022**	0.022**	0.022**	0.022**	0.022**	
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	
Night	-0.407***	-0.408***	-0.404***	-0.402***	-0.403***	-0.405***	
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	
Precip.	-0.115***	-0.135***	-0.116***		-2.205*	-2.316*	
•	(0.035)	(0.044)	(0.035)		(1.237)	(1.242)	
$Night \times Precip.$		0.057				0.062	
•		(0.074)				(0.074)	
Temp.			0.002	0.002	0.002	0.001	
_			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					$0.007^{*}$	0.007*	
					(0.004)	(0.004)	
Constant	0.074*	0.075*	-0.379	-0.377	-0.361	-0.347	
	(0.043)	(0.043)	(0.291)	(0.291)	(0.292)	(0.292)	
Observations	199,143	199,143	199,143	199,143	199,143	199,143	
Log Likelihood	-131,790.900	-131,790.600	-131,789.600	-131,795.100	-131,788.200	-131,787.900	
Akaike Inf. Crit.	263,677.800	263,679.200	263,677.300	263,686.100	263,676.400	263,677.700	

## **6.1.7** Hartford (Connecticut)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	-0.988***	-0.988***	-0.988***	-0.989***	-0.988***	-0.988***	
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	
Night	-0.074	-0.070	-0.076	-0.078	-0.076	-0.073	
	(0.107)	(0.108)	(0.107)	(0.107)	(0.107)	(0.108)	
Precip.	-0.266**	-0.250*	-0.258**		-2.099	-2.248	
_	(0.124)	(0.133)	(0.124)		(4.847)	(4.898)	
$Night \times Precip.$		-0.123				-0.125	
		(0.374)				(0.371)	
Temp.			-0.003	-0.003	-0.003	-0.003	
			(0.004)	(0.004)	(0.004)	(0.004)	
$Precip. \times Temp.$					0.006	0.007	
					(0.017)	(0.017)	
Constant	1.495***	1.492***	2.271**	2.441**	2.273**	2.257**	
	(0.223)	(0.224)	(1.030)	(1.027)	(1.030)	(1.032)	
Observations	17,794	17,794	17,794	17,794	17,794	17,794	
Log Likelihood	-10,158.070	-10,158.010	-10,157.770	-10,159.930	-10,157.700	-10,157.640	
Akaike Inf. Crit.	20,410.140	20,412.030	20,411.540	20,413.860	20,413.400	20,415.280	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6.1.8 Louisville (Kentucky)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	-0.365***	-0.366***	-0.365***	-0.365***	-0.365***	-0.365***	
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	
Night	-1.059***	-1.053***	-1.049***	-1.049***	-1.046***	-1.043***	
Ü	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	
Precip.	-0.090**	-0.005	-0.096**		-7.402***	-6.551***	
1	(0.044)	(0.059)	(0.044)		(1.925)	(2.076)	
$Night \times Precip.$	` '	-0.250**	, ,		, ,	-0.143	
0 1		(0.100)				(0.105)	
Temp.		, ,	0.005***	0.005***	0.005***	0.005***	
· · <b>r</b> ·			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$			(/	(	0.025***	0.022***	
r					(0.007)	(0.007)	
Constant	1.647***	1.644***	0.282	0.322	0.284	0.259	
	(0.065)	(0.065)	(0.421)	(0.421)	(0.421)	(0.422)	
Observations	105,271	105,271	105,271	105,271	105,271	105,271	
Log Likelihood	-52,074.020	-52,070.720	-52,068.650	-52,070.970	-52,061.080	-52,060.120	
Akaike Inf. Crit.	104,242.000	104,237.400	104,233.300	104,235.900	104,220.200	104,220.200	
Nota:	*n<0.1 **n<0.05 ***n>0.01						

#### 6.1.9 Madison (Wisconsin)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.182***	0.182***	0.182***	0.181***	0.182***	0.182***	
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	
Night	-0.145***	-0.150***	-0.150***	-0.151***	-0.152***	-0.156***	
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	
Precip.	0.258***	0.191***	0.262***		4.717***	4.140***	
	(0.036)	(0.043)	(0.037)		(1.105)	(1.134)	
$Night \times Precip.$		0.203**				0.143*	
		(0.079)				(0.079)	
Temp.			-0.002***	-0.002**	-0.002**	-0.002**	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.015***	-0.013***	
					(0.004)	(0.004)	
Constant	0.584***	0.586***	1.232***	1.148***	1.206***	1.223***	
	(0.048)	(0.048)	(0.255)	(0.255)	(0.255)	(0.255)	
Observations	189,195	189,195	189,195	189,195	189,195	189,195	
Log Likelihood	-113,225.300	-113,221.900	-113,222.000	-113,251.200	-113,214.100	-113,212.400	
Akaike Inf. Crit.	226,550.700	226,545.900	226,545.900	226,602.400	226,532.100	226,530.700	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6.1.10 New Orleans (Louisiana)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	-0.173***	-0.173***	-0.173***	-0.173***	-0.173***	-0.173***	
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	
Night	-0.298***	-0.301***	-0.290***	-0.290***	-0.290***	-0.295***	
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	
Precip.	-0.044***	-0.073***	-0.045***		-2.571***	-5.616***	
	(0.014)	(0.017)	(0.014)		(0.955)	(1.135)	
Night $\times$ Precip.		0.104***				0.195***	
		(0.031)				(0.037)	
Temp.			0.005***	0.005***	0.005***	0.005***	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.008***	0.018***	
					(0.003)	(0.004)	
Constant	-1.552***	-1.551***	-3.074***	-3.063***	-3.080***	-3.011***	
	(0.031)	(0.031)	(0.284)	(0.284)	(0.284)	(0.284)	
Observations	418,011	418,011	418,011	418,011	418,011	418,011	
Log Likelihood	-248,317.400	-248,311.900	-248,302.800	-248,308.000	-248,299.200	-248,285.700	
Akaike Inf. Crit.	496,736.700	496,727.700	496,709.600	496,718.000	496,704.500	496,679.400	

## 6.1.11 Oakland (California)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	-0.336***	-0.336***	-0.336***	-0.337***	-0.337***	-0.336***	
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	
Night	-0.182***	-0.188***	-0.183***	-0.183***	-0.183***	-0.188***	
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	
Precip.	-0.454***	-0.838***	-0.454***		26.245***	15.141	
	(0.095)	(0.156)	(0.096)		(9.598)	(10.953)	
$Night \times Precip.$		0.641***				0.504**	
		(0.196)				(0.219)	
Temp.			-0.0002	0.0002	-0.0002	-0.001	
			(0.002)	(0.002)	(0.002)	(0.002)	
$Precip. \times Temp.$					-0.094***	-0.056	
					(0.034)	(0.038)	
Constant	0.119**	0.121**	0.189	0.070	0.167	0.304	
	(0.054)	(0.054)	(0.544)	(0.543)	(0.544)	(0.547)	
Observations	116,323	116,323	116,323	116,323	116,323	116,323	
Log Likelihood	-75,323.240	-75,317.770	-75,323.230	-75,335.340	-75,319.350	-75,316.630	
Akaike Inf. Crit.	150,742.500	150,733.500	150,744.500	150,766.700	150,738.700	150,735.300	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## **6.1.12** Raleigh (North Carolina)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.019** (0.007)	0.019** (0.007)	0.019** (0.007)	0.018** (0.007)	0.019** (0.007)	0.019** (0.007)	
Night	-0.319*** (0.027)	-0.322*** (0.027)	-0.320*** (0.027)	-0.318*** (0.027)	-0.319*** (0.027)	-0.323*** (0.027)	
Precip.	-0.154*** (0.024)	-0.200*** (0.032)	-0.153*** (0.024)		-2.000** (0.892)	-2.397*** (0.906)	
$Night \times Precip.$		0.106** (0.048)				0.125*** (0.048)	
Temp.			-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	
$Precip. \times Temp.$					0.006** (0.003)	0.007** (0.003)	
Constant	-0.140*** (0.035)	-0.139*** (0.035)	0.023 (0.227)	0.052 (0.227)	0.033 (0.227)	0.066 (0.227)	
Observations Log Likelihood Akaike Inf. Crit.	317,899 -210,837.700 421,771.400	317,899 -210,835.300 421,768.500	317,899 -210,837.400 421,772.900	317,899 -210,859.200 421,814.400	317,899 -210,835.300 421,770.500	317,899 -210,831.900 421,765.800	

#### 6.1.13 Saint Paul (Minnesota)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.447***	0.448***	0.448***	0.448***	0.448***	0.448***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	
Night	-0.271***	-0.270***	-0.281***	-0.281***	-0.281***	-0.280***	
-	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	
Precip.	-0.002	0.016	0.003		-0.267	-0.178	
	(0.041)	(0.058)	(0.041)		(1.563)	(1.584)	
$Night \times Precip.$		-0.037				-0.031	
		(0.083)				(0.084)	
Temp.			-0.003***	-0.003***	-0.003***	-0.003***	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.001	0.001	
					(0.005)	(0.005)	
Constant	-1.326***	-1.327***	-0.417	-0.417	-0.417	-0.419	
	(0.049)	(0.049)	(0.322)	(0.321)	(0.322)	(0.322)	
Observations	128,623	128,623	128,623	128,623	128,623	128,623	
Log Likelihood	-72,743.490	-72,743.390	-72,739.390	-72,739.390	-72,739.370	-72,739.310	
Akaike Inf. Crit.	145,585.000	145,586.800	145,578.800	145,576.800	145,580.700	145,582.600	

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6.1.14 San Francisco (California)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	-0.458***	-0.458***	-0.458***	-0.458***	-0.458***	-0.458***	
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	
Night	-0.106***	$-0.107^{***}$	-0.104***	-0.104***	-0.104***	-0.105***	
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	
Precip.	-0.139***	-0.173***	-0.139***		-6.161	-7.084	
	(0.050)	(0.066)	(0.050)		(7.442)	(7.501)	
$Night \times Precip.$		0.075				0.083	
		(0.099)				(0.100)	
Temp.			0.004	0.004	0.003	0.003	
			(0.003)	(0.003)	(0.003)	(0.003)	
$Precip. \times Temp.$					0.021	0.024	
					(0.026)	(0.026)	
Constant	0.690***	0.690***	-0.360	-0.387	-0.293	-0.239	
	(0.031)	(0.031)	(0.913)	(0.913)	(0.917)	(0.919)	
Observations	314,682	314,682	314,682	314,682	314,682	314,682	
Log Likelihood	-198,686.400	-198,686.100	-198,685.700	-198,689.600	-198,685.400	-198,685.100	
Akaike Inf. Crit.	397,470.800	397,472.200	397,471.500	397,477.200	397,472.800	397,474.100	

## 6.1.15 Winston-Salem (North Carolina)

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.120***	0.120***	0.120***	0.120***	0.120***	0.120***	
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	
Night	-0.380***	-0.376***	-0.384***	-0.381***	-0.382***	-0.379***	
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	
Precip.	-0.107***	-0.049	-0.105***		-2.606**	-2.270*	
•	(0.031)	(0.046)	(0.031)		(1.195)	(1.231)	
$Night \times Precip.$		-0.111*				-0.086	
•		(0.063)				(0.064)	
Temp.			-0.002*	-0.002*	-0.002*	-0.002*	
•			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.009**	0.008*	
					(0.004)	(0.004)	
Constant	0.683***	0.680***	1.224***	1.255***	1.245***	1.225***	
	(0.044)	(0.044)	(0.330)	(0.330)	(0.330)	(0.331)	
Observations	168,963	168,963	168,963	168,963	168,963	168,963	
Log Likelihood	-108,086.000	-108,084.400	-108,084.600	-108,090.200	-108,082.400	-108,081.50	
Akaike Inf. Crit.	216,268.000	216,266.800	216,267.200	216,276.400	216,264.800	216,265.000	

## **6.2** State Police Departments

## 6.2.1 Connecticut

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.065***	0.065***	0.065***	0.065***	0.065***	0.065***	
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Night	-0.391***	-0.392***	-0.388***	-0.388***	-0.388***	-0.389***	
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	
Precip.	-0.081***	$-0.085^{***}$	-0.086***		-0.968**	-1.212**	
	(0.014)	(0.019)	(0.014)		(0.471)	(0.524)	
$Night \times Precip.$		0.009				0.033	
		(0.029)				(0.032)	
Temp.			0.002***	0.002***	0.002***	0.002***	
			(0.0005)	(0.0005)	(0.0005)	(0.0005)	
$Precip. \times Temp.$					0.003*	0.004**	
					(0.002)	(0.002)	
Constant	0.039**	0.039**	-0.627***	-0.573***	-0.635***	-0.630***	
	(0.017)	(0.017)	(0.138)	(0.137)	(0.138)	(0.138)	
Observations	1,081,642	1,081,642	1,081,642	1,081,642	1,081,642	1,081,642	
Log Likelihood	-731,625.400	-731,625.300	-731,613.500	-731,631.900	-731,611.700	-731,611.200	
Akaike Inf. Crit.	1,463,343.000	1,463,345.000	1,463,321.000	1,463,356.000	1,463,319.000	1,463,320.000	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6.2.2 Michigan

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	-0.086***	-0.086***	-0.091***	-0.091***	-0.091***	-0.091***	
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	
Night	-0.175***	-0.174***	-0.164***	-0.164***	-0.164***	-0.162***	
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	
Precip.	0.106***	0.118***	0.094***		2.571***	3.046***	
•	(0.030)	(0.036)	(0.030)		(0.896)	(0.943)	
$Night \times Precip.$		-0.047				$-0.120^{*}$	
		(0.068)				(0.069)	
Temp.			0.007***	0.007***	0.007***	0.007***	
·			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					-0.008***	-0.010***	
					(0.003)	(0.003)	
Constant	1.194***	1.194***	-0.689***	-0.723***	-0.713***	-0.729***	
	(0.048)	(0.048)	(0.231)	(0.231)	(0.231)	(0.232)	
Observations	305,899	305,899	305,899	305,899	305,899	305,899	
Log Likelihood	-168,488.900	-168,488.700	-168,454.200	-168,459.400	-168,450.400	-168,448.900	
Akaike Inf. Crit.	337,075.800	337,077.300	337,008.500	337,016.700	337,002.700	337,001.700	

## 6.2.3 New Hampshire

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.203***	0.203***	0.195***	0.193***	0.195***	0.195***	
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	
Night	-0.346***	-0.346***	-0.328***	-0.323***	-0.328***	-0.332***	
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	
Precip.	-0.379***	-0.380***	-0.408***		-14.933***	-15.694***	
_	(0.051)	(0.055)	(0.052)		(1.856)	(1.922)	
$Night \times Precip.$		0.011				0.252	
		(0.155)				(0.158)	
Temp.			0.017***	0.017***	0.017***	0.017***	
			(0.001)	(0.001)	(0.001)	(0.001)	
$Precip. \times Temp.$					0.050***	0.053***	
					(0.006)	(0.007)	
Constant	-1.532***	-1.532***	-6.311***	-6.197***	-6.320***	-6.299***	
	(0.058)	(0.058)	(0.348)	(0.347)	(0.348)	(0.348)	
Observations	154,494	154,494	154,494	154,494	154,494	154,494	
Log Likelihood	-94,577.940	-94,577.940	-94,480.560	-94,517.080	-94,448.030	-94,446.810	
Akaike Inf. Crit.	189,245.900	189,247.900	189,053.100	189,124.200	188,990.100	188,989.600	

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### **6.2.4** Texas

Dependent variable: Citation						
(1)	(2)	(3)	(4)	(5)	(6)	
0.445***	0.445***	0.446***	0.446***	0.446***	0.446***	
(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
-0.378***	-0.379***	-0.379***	-0.380***	-0.379***	-0.378***	
(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
0.377***	0.347***	0.377***		14.524***	15.411***	
(0.005)	(0.006)	(0.005)		(0.286)	(0.308)	
	0.141***	, ,		, ,	-0.118***	
	(0.014)				(0.015)	
	, ,	-0.001***	-0.001***	-0.0004***	-0.0004***	
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	
		, ,	, ,	-0.047***	-0.050***	
				(0.001)	(0.001)	
-0.402***	-0.402***	-0.244***	-0.207***	-0.283***	-0.293***	
(0.005)	(0.005)	(0.034)	(0.034)	(0.034)	(0.034)	
13,629,162	13,629,162	13,629,162	13,629,162	13,629,162	13,629,162	
-8,742,844.000	-8,742,788.000	-8,742,833.000	-8,745,547.000	-8,741,476.000	-8,741,443.000	
17,485,788.000	17,485,678.000	17,485,768.000	17,491,193.000	17,483,055.000	17,482,992.000	
	0.445*** (0.001) -0.378*** (0.003) 0.377*** (0.005)  -0.402*** (0.005)  13,629,162 -8,742,844.000	0.445***	(1) (2) (3)  0.445*** 0.445*** 0.446*** (0.001) (0.001) (0.001) -0.378*** -0.379*** -0.379*** (0.003) (0.003) (0.003) 0.377*** 0.347*** 0.377*** (0.005) (0.006) (0.005) 0.141*** (0.014) -0.001*** (0.0001)  -0.402*** -0.402*** -0.244*** (0.005) (0.005) (0.005) 0.13,629,162 13,629,162 13,629,162 -8,742,844.000 -8,742,788.000 -8,742,833.000	(1) (2) (3) (4)  0.445*** 0.445*** 0.446*** 0.446*** (0.001) (0.001) (0.001) (0.001) -0.378*** -0.379*** -0.379*** -0.380*** (0.003) (0.003) (0.003) (0.003) 0.377*** 0.347*** 0.377*** (0.005) (0.006) (0.005) 0.141*** (0.014) -0.001*** -0.001*** (0.0001) (0.0001)  -0.402*** -0.402*** -0.244*** -0.207*** (0.005) (0.005) (0.005) 0.141**- (0.0001) (0.0001)	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6.2.5 Wisconsin

	Dependent variable: Citation						
	(1)	(2)	(3)	(4)	(5)	(6)	
Nonwhite	0.689***	0.689***	0.689***	0.689***	0.689***	0.689***	
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	
Night	-0.617***	-0.618***	-0.614***	-0.614***	-0.615***	-0.615***	
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	
Precip.	0.005	-0.014	0.004		2.281***	2.115***	
Î	(0.019)	(0.021)	(0.019)		(0.653)	(0.663)	
$Night \times Precip.$		0.093**				0.065	
•		(0.047)				(0.047)	
Temp.			0.001***	0.001***	0.001***	0.001***	
*			(0.0004)	(0.0004)	(0.0004)	(0.0004)	
$Precip. \times Temp.$					-0.008***	-0.007***	
•					(0.002)	(0.002)	
Constant	-0.165***	-0.165***	-0.543***	-0.543***	-0.555***	-0.551***	
	(0.021)	(0.021)	(0.114)	(0.114)	(0.114)	(0.114)	
Observations	829,437	829,437	829,437	829,437	829,437	829,437	
Log Likelihood	-557,215.800	-557,213.900	-557,210.100	-557,210.200	-557,204.000	-557,203.100	
Akaike Inf. Crit.	1,114,530.000	1,114,528.000	1,114,520.000	1,114,518.000	1,114,510.000	1,114,510.000	

# 7 Marginal Effects

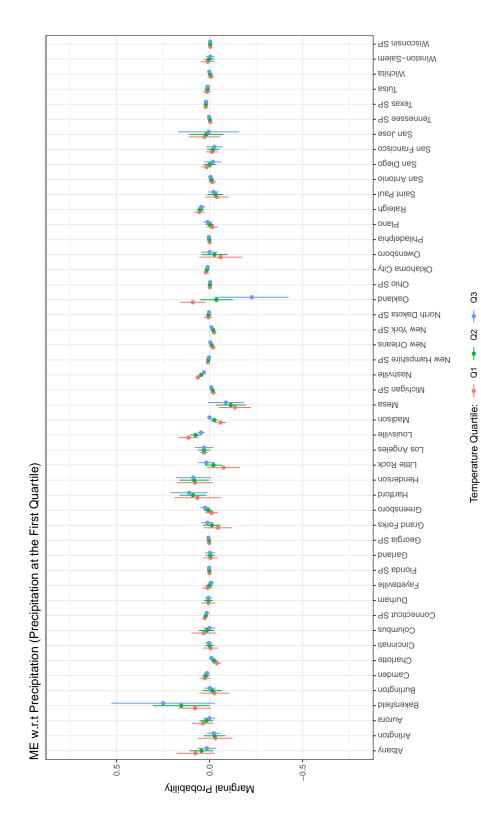


Figure 3. Marginal effects of a stopped driver being black with respect to precipitation being at the first quartile.

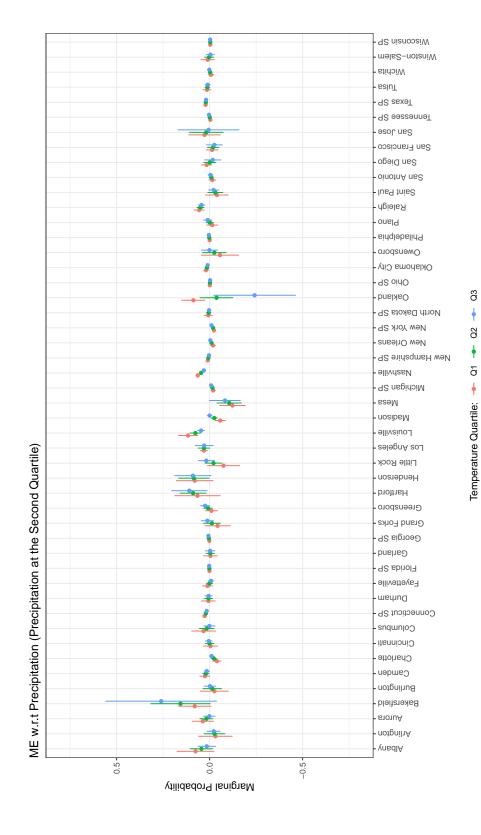


Figure 4. Marginal effects of a stopped driver being black with respect to precipitation being at the second quartile.

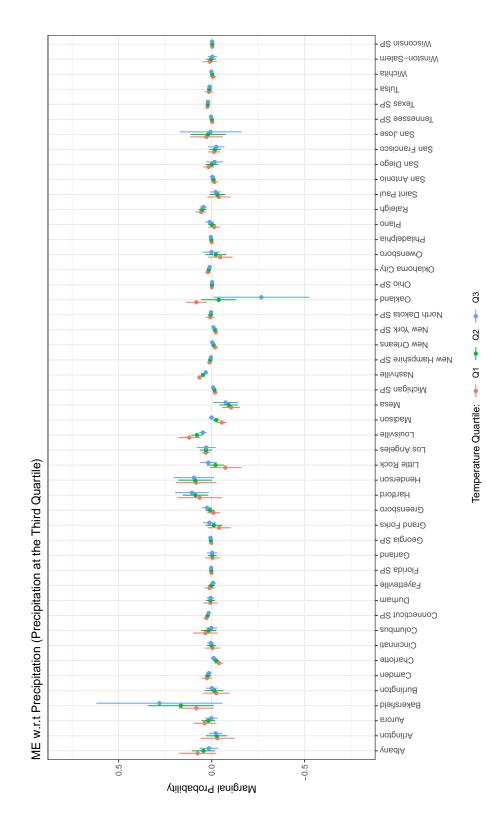


Figure 5. Marginal effects of a stopped driver being black with respect to precipitation being at the third quartile.

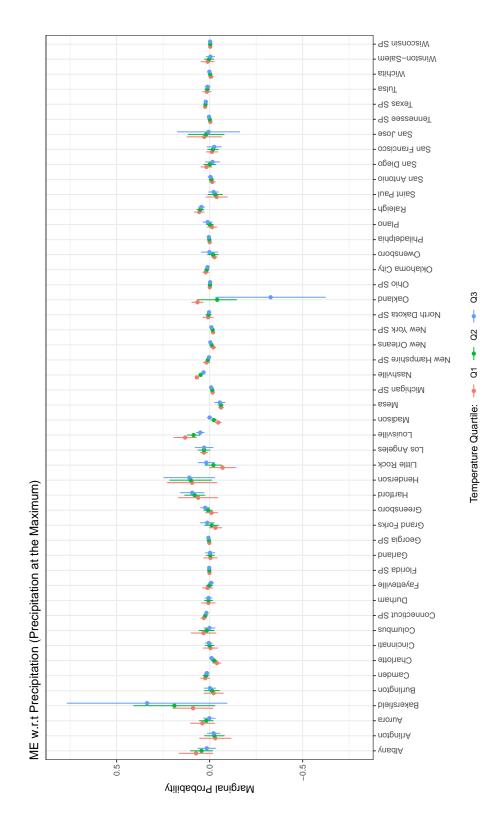


Figure 6. Marginal effects of a stopped driver being black with respect to precipitation being at the maximum.

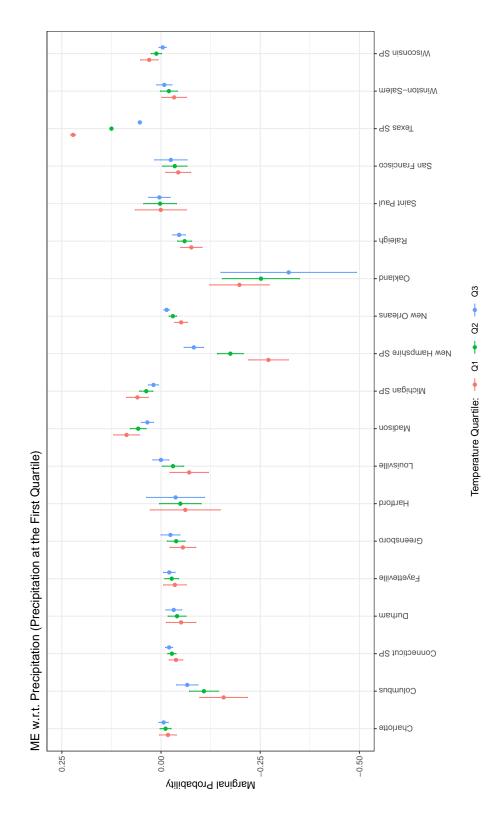


Figure 7. Marginal effects of a citation issuance with respect to precipitation being at the first quartile.

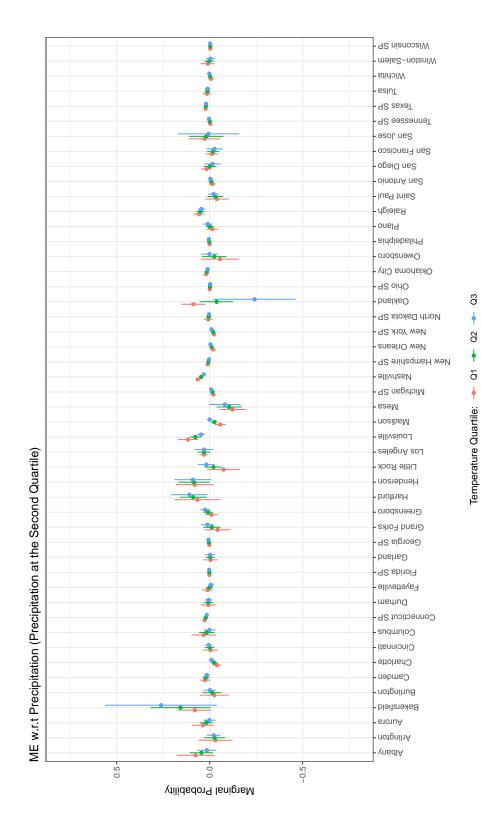


Figure 8. Marginal effects of a citation issuance with respect to precipitation being at the second quartile.

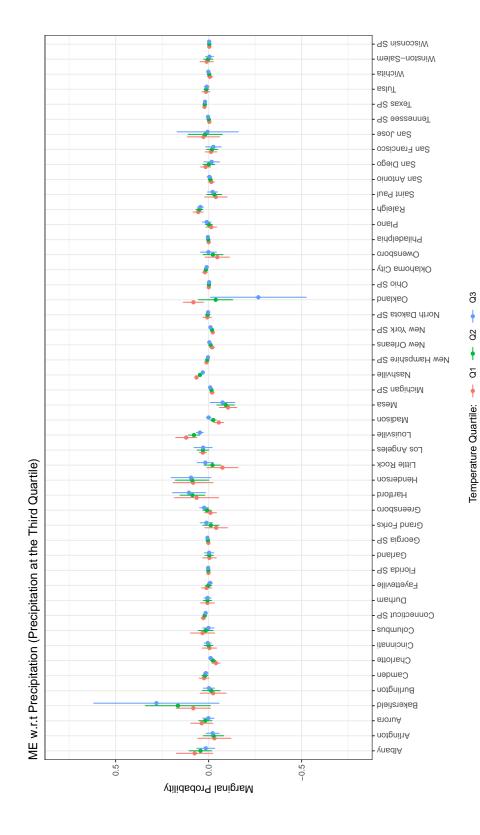


Figure 9. Marginal effects of a citation issuance with respect to precipitation being at the third quartile.

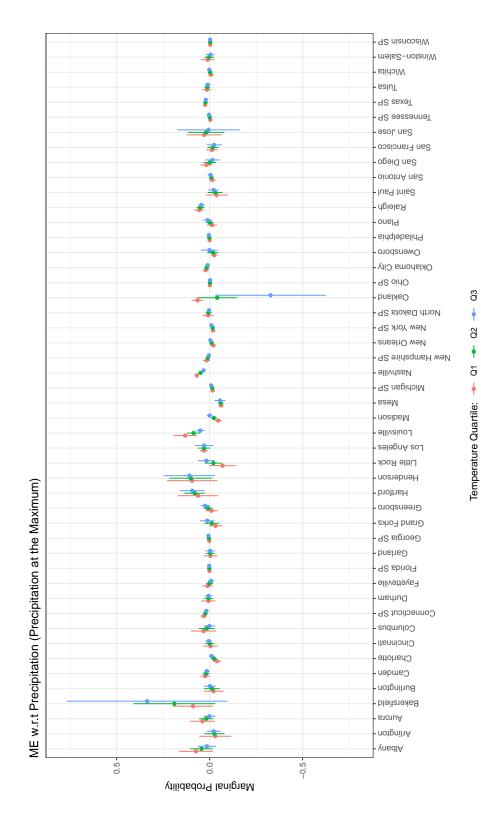


Figure 10. Marginal effects of a citation issuance with respect to precipitation being at maximum.

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