Essays on the Environmental Determinants of Crime

by

Justin Aubrey Ladner

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Doctoral Committee:

Associate Professor Dean Yang, Chair
Professor Charles C. Brown
Professor Brian A. Jacob
Professor James J. Prescott

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CHAPTER 1

Cloudy with a Chance of Crime: How Temperature Expectations and Forecast Errors Affect Criminal Activity

Abstract

In the extensive literature on temperature and crime, a clear positive correlation between observed temperature and criminal activity has been documented. The dominant explanation for this effect is that observed temperature conditions affect planning, which leads to changes in the number of opportunities for crime. Since planning necessarily applies to activities occurring in the future, it is more accurate to say that the plans one makes depend on temperature *expectations*, both in the current period and the near future. In this paper, I examine the impact of temperature expectations on daily violent crime and property theft levels for a set of 50 U.S. cities during the 2004-2012 period. I find that the effect of observed maximum temperature on a given day is largely captured by temperature expectations for that day. However, I also find that crime is affected by expectations about weather in the near future, and that forecast errors (i.e. unexpectedly hot or cold temperatures) significantly impact violent crime (but not property theft). This set of findings represents an important contribution to the temperature-crime literature, and provides new insight into the determinants of criminal labor supply. Furthermore, these results have significant policy implications for short-run crime forecasting.

1.1 Introduction

With a literature dating to the 19th century,[1] temperature is one of the most studied determinants of criminal activity. It is widely accepted that there is a strong positive correlation between temperature and many forms of crime, and this relationship is most often attributed to temperature's effect on the daily plans that people make. However, since any plan necessarily applies to future activities, it is more accurate to say that temperature *expectations* affect planning. This simple observation suggests a research agenda that may shed light on the temperature-crime relationship, especially with regard to understanding how expectations affect criminal labor supply. In this study, I decompose the effect of current day[2] observed temperature into two channels: one operating through temperature expectations for the current day, and the other operating through forecast errors (i.e. unexpectedly hot or cold temperatures). In addition, I examine how expectations about temperature conditions in the near future affect crime on the current day.

To understand why expectations are likely to play such an important role in this context, one must first consider the dominant explanation for the relationship between observed temperature and crime. This mechanism traces its roots to Cohen and Felson (1979), who established Routine Activity Theory (RAT) as a general model of criminal activity. According to this framework, a crime is likely to occur if three elements coincide in time and space: 1) a motivated offender, 2) a suitable target, and 3) the absence of a capable guardian. When these elements coincide more often, there are more opportunities

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[1] One of the earliest studies to touch on the subject is Morrison (1891).
[2] That is, temperature as measured in the same time period that the crime outcome of interest is being measured. Since the data in this paper are daily, and the variables included capture temperature (either observed or expected) in past periods and future periods, I will refer to contemporaneous variables as "current day" variables.

for crime, and we would expect the level of criminal activity to rise. The application of RAT to explaining temperature's effect on crime is straightforward: when the weather outside is favorable (e.g. a warm day), more people decide to leave their homes. This dispersion of people outside of residences increases the amount of human interaction, which creates more opportunities for person-to-person criminal acts. In addition, the shifting of people outside of residences increases the amount of unguarded or poorly guarded property (e.g. empty houses, cars parked in public places, etc.).

Past studies treat the RAT mechanism as a story about observed temperature: individuals see what the weather is like, and they adjust their plans accordingly. However, since planning is forward-looking by definition, it stands to reason that expectations will be a driving factor in determining those plans. If one accepts that expectations matter in the temperature-crime relationship, two questions immediately arise. Firstly, when people make plans, how forward-looking are they? One possibility is that expected temperature conditions on the current day are all that matter; however, expectations about future weather may also influence planning. The second question pertains to whether expectations are the *only* important factor in the temperature-crime relationship. In other words, if temperature affects crime by changing the plans that people make, and those plans are entirely determined by expectations, then is the effect of observed temperature on crime entirely due to temperature expectations? If not, then to what extent do forecast errors affect criminal activity?

The purpose of this study is to address these questions, none of which have been considered before. I begin by outlining a model in which the effect of temperature expectations and forecast errors is captured through a game of strategic interaction between “criminals” and “non-criminals.” In this two-period model, all agents are optimizing over a short time horizon, and choose to leave their residence in one period based on relative expected temperature conditions across time. The number of criminals and non-criminals who are away from home in a given period determines the number of opportunities for crime in that period. Furthermore, realized forecast errors affect the level of criminal activity by increasing or decreasing the chance that any opportunity for crime actually leads to a criminal act.

To test these predictions, I use a panel of 50 medium-to-large sized U.S. cities whose police departments report incident level crime data to the National Incident Based Reporting System (NIBRS). These data allow me to calculate daily crime counts for every city, covering all or most of the 2004-2012 period. For each city, I also gather weather forecasts and observed weather data. By combining these data sources, I am able to observe the following values for every city-day in my sample: forecast maximum temperature for the current day, forecast error for the current day, and forecast maximum temperatures for the next six days.

The analyses I conduct produce a number of compelling results. Firstly, I find that the relationship between current-day forecast maximum temperature and all types of crime studied is very similar to what is seen for observed maximum temperature. In other words, the effect of observed temperature on crime appears to be largely forecastable. However, there is also considerable evidence that forecast errors affect criminal activity in the case of violent crime. In particular, unexpectedly cold weather significantly decreases the incidence of violent offenses, especially for the major sub-category of assault. There is also evidence that unexpectedly hot temperatures increase violence, but that effect appears to diminish when the daily maximum temperature is much hotter (> 7 F) than expected. In a qualitative sense, there is some indication that forecast errors affect property theft in a similar way, but the estimates produced are much smaller in magnitude and generally lack statistical significance. The final significant finding of this paper is that expectations for higher future temperatures appear to significantly reduce crime on the current day. This result is clearly present for violent crime and property theft.

The findings of this study contribute to a number of literatures. The most obvious contribution is that I highlight two determinants of criminal activity (forecast errors and future temperature differences) that are completely novel concepts in the temperature-crime literature. In addition, my results shed light on the role that expectations play in short-term criminal labor supply. Specifically, the finding that crime falls when future temperatures are expected to be higher suggests that criminals intertemporally substitute their labor supply based on weather expectations. This is a unique result in the economics of crime literature, as past studies have generally found that criminals are either very myopic or have extremely high discount factors.[3] Furthermore, it underscores the importance of temperature as a parameter affecting criminal productivity, a fact that has received remarkably little attention amongst economists.

In addition to these academic contributions, this paper has important policy implications with regard to crime prediction. Aside from highlighting new determinants of criminal activity that may improve forecasting techniques, my findings make a general statement about the efficacy of predicting the effect of future temperature conditions on crime. On the one hand, I show that the effect of temperature on property theft is almost

[3] See, for example, Lee and McCrary (2005).

fully forecastable, since forecast errors have little-to-no impact on this type of criminal activity. Unfortunately, this positive result does not extend to violent crime, which is significantly affected by unexpectedly hot or cold weather. As such, some of the effect of temperature on violence cannot be predicted in advance.

The remainder of this paper is organized as follows: Section 1.2 presents the theoretical model and its predictions, Section 1.3 discuses the empirical methodology, Section 1.4 provides an overview of the data used, Section 1.5 presents results, Section 1.6 discusses potential mechanisms, and Section 1.7 concludes.

1.2 Model

In this section, I outline a simple framework in which the effect of temperature on crime is attributable to three mechanisms: temperature expectations for the current period, realized forecast errors in the current period, and temperature expectations for the near future. The model itself is a discrete-choice variant of the classic Cournot game with many players. In this model, there are a total of P players, each of whom is one of two types. Type A players are non-criminals who value time spent away from their residence, but are deterred from leaving home by the possibility of being the victim of a crime. Type B players are criminals whose sole motivation for leaving home during the day is to engage in criminal activity. I assume that there are P^A type A players and P^B type B players, so that $P = P^A + P^B$. Importantly, I also assume that all players are risk neutral.

There are two periods in this model, one representing the present day and the other representing the near future. Before the first period begins, all players must choose whether to stay at home or leave their residence in each period, with the restriction that players cannot choose the same location in both periods. The intuition for this restriction is that, over a short time horizon, one may have a fixed set of tasks scheduled, including activities inside and outside of one's residence. In this setting, expected temperature conditions simply serve to determine the timing of these activities. The reader should note that this model is static, since all players are restricted to making a single set of irreversible decisions before period 1, after which point the payoffs to each period are realized. In any event, the primary purpose of the model is to describe a setting wherein the number of people who choose to leave their residence during the present day depends on the temperature conditions expected today relative to those expected in the near future.

1.2.1 Type A Players

I begin the exposition of this model by outlining the maximization problems for each type of player. Player i, a type A player, receives two pieces of information at the beginning of period 1 that inform her about the expected utility of leaving her residence in each period: the expected temperature in period 1 (T_1^e), and the expected temperature in period 2 (T_2^e). Player i can expect to receive $b_1 = b(T_1^e)$ units of utility from leaving her residence in period 1, and $b_2 = b(T_2^e)$ units of utility from doing so in period 2. Furthermore, player i is assumed to have a player-specific discount factor δ_i drawn from the uniform distribution on the unit interval; as a result, the discounted value of leaving her residence in period 2 is given by $\delta_i b_2$.

Naturally, player i also faces a cost to leaving her residence, since she exposes herself to being victimized by type B players. This victimization can happen in one of two ways: Either player i can become the victim of a crime in a direct player-to-player interaction with a type B player, or a type B player can commit a crime against player i's unguarded property.[4] All told, player i can expect to face N_t^B opportunities for victimization if she leaves home in period t. I assume that this value is directly proportional to the number of type B players who have left their homes during the same period. Any one of these opportunities has a probability $\pi(\omega_t) = \pi_0 + g(\omega_t)$ of becoming criminal, in which case player i faces a fixed utility loss of L. In the expression for π, ω equals the forecast error $T_t - T_t^e$ (i.e. the realized temperature less the expected temperature during period t). I assume that $E[g(\omega_t)] = 0$, so that $E[\pi(\omega_t)] = \pi_0$. Since all agents are risk neutral, type A players treat $\pi(\omega)$ as if it were a constant equal to π_0 in their maximization problem. Ultimately, player i must weigh the net expected utility from leaving her residence in period 1 against the expected utility from doing so in the next period. Player i's problem is written formally below:[5]

$$\begin{gathered} \max\{b_1 - N_1^B \pi_0 L \,, \delta_i[b_2 - N_2^B \pi_0 L]\} \\ where \;\; \delta_i \sim U[0,1] \\ and \; N_1^B = \lambda P^B \rho^c \,, N_2^B = \lambda P^B (1-\rho^c) \end{gathered} \qquad (1)$$

1.2.2 Type B Players

Now consider player j, who is a type B player. This player is also trying to decide when to leave home, but his motivation for going outside is the utility he will receive from committing criminal acts against type A players who have left their residence during the same period. Player j can expect to have N_t^A opportunities for criminal activity against type A players and their property, a value that I assume to be directly proportional to the number of type A players who have chosen to leave their residence. Each of these

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[4] For instance, during the period in which she has left home her residence may be burglarized.
[5] The value ρ^c represents the critical value of the discount factor for type B players.

opportunities results in a crime with probability $\pi(\omega_t)$, in which case player j receives G units of utility. Once again, the assumption of risk neutrality implies that all type B agents treat $\pi(\omega_t)$ as π_0 in their maximization problem. Player j has a player-specific discount factor given by ρ_j, also drawn from the uniform distribution on the unit interval. As was the case with type A agents, player j weighs the net benefit of leaving home in the first period against that of doing so in the following period instead. Player j's maximization problem is written formally below:

$$\begin{gathered} \max\{N_1^A \pi_0 G, \rho_j N_2^A \pi_0 G\} \\ where\ \rho_j \sim U[0,1] \\ and\ N_1^A = \lambda P^A \delta^c, N_2^A = \lambda P^A (1-\delta^c) \end{gathered} \tag{2}$$

Before period 1, all players simultaneously decide what their location will be in each period. To solve for the unique pure strategy Nash equilibrium in this problem, we must identify critical values of δ and ρ.

1.2.3 Solving for Critical Values

For type A and type B players, the critical values of δ^c (for type A) and ρ^c (for type B) can be found by identifying the players who are just indifferent between leaving home in period 1 or period 2. The marginal Type A player's value of δ is given by the following condition:

$$b_1 - N_1^B \pi_0 L = \delta_i [b_2 - N_2^B \pi_0 L]$$

$$\Rightarrow \delta^c = \frac{b_1 - N_1^B \pi_0 L}{b_2 - N_2^B \pi_0 L}$$

$$Define\ \phi = \lambda P^B \pi_0 L$$

$$\Rightarrow \delta^c = \frac{b_1 - \rho^c \phi}{b_2 - (1-\rho^c)\phi} \quad (3)$$

For type B players, one can solve for the critical value of ρ in a similar fashion:

$$N_1^A \pi_0 G = \rho_j N_2^A \pi_0 G$$

$$\Rightarrow \rho^c = \frac{N_1^A \pi_0 G}{N_2^A \pi_0 G}$$

$$\Rightarrow \rho^c = \frac{\delta^c}{1-\delta^c}$$

Since it is necessary that $\rho^c \in [0,1]$, the formula for ρ^c must be re-expressed to account for values of δ^c greater than 0.5:

$$\rho^c = \begin{cases} \dfrac{\delta^c}{1-\delta^c} & if\ \delta^c < 0.5 \\ 1 & if\ \delta^c \geq 0.5 \end{cases} \quad (4)$$

The system of equations given by (3) and (4) does not have a straightforward linear solution, but solving the system is not particularly interesting for our purposes anyway.[6] Instead, we are interested in how these critical values change with b_1 and b_2:[7]

$$\frac{\partial \delta^c}{\partial b_1} = \frac{(1-\delta^c)^2 \mathrm{K}_2}{\mathrm{K}_2^2(1-\delta^c)^2 + \mathrm{K}_2\phi + \mathrm{K}_1\phi} \quad (5)$$

$$\frac{\partial \delta^c}{\partial b_2} = \frac{-(1-\delta^c)^2 \mathrm{K}_1}{\mathrm{K}_2^2(1-\delta^c)^2 + \mathrm{K}_2\phi + \mathrm{K}_1\phi} \quad (6)$$

$$\frac{\partial \rho^c}{\partial b_1} = \frac{\frac{\partial \delta^c}{\partial b_1}}{(1-\delta^c)^2} \quad (7)$$

[6] I derive this solution in Appendix 1.A.

[7] See Appendix 1.A for the derivation of these derivatives.

$$\frac{\partial \rho^c}{\partial b_2} = \frac{\frac{\partial \delta^c}{\partial b_2}}{(1-\delta^c)^2} \quad (8)$$

$$Where \quad \begin{aligned} \mathrm{K}_1 &= b_1 - \rho^c \phi \\ \mathrm{K}_2 &= b_2 - (1-\rho^c)\phi \end{aligned}$$

I assume that the model coefficients and the function b are such that: 1) type A players are always comparing positive net benefits, and 2) an interior solution is guaranteed for any combination of T_1^e and T_2^e. Under these conditions, it is clear that $\frac{\partial \delta^c}{\partial b_1}, \frac{\partial \rho^c}{\partial b_1} > 0$ and $\frac{\partial \delta^c}{\partial b_2}, \frac{\partial \rho^c}{\partial b_2} < 0$. In other words, *ceteris paribus*, an increase in b_1 leads to more players of both types leaving their residence in the first period, while a similar increase in b_2 leads more players of both types to delay this action until the second period.

1.2.4 Expected Temperature and the Level of Criminal Activity

Let I_t be the number of criminal incidents occurring during period t in equilibrium. Using expressions (3) and (4), together with our knowledge of the derivatives expressed above, we can solve for this value and identify the effect of expected temperature (T_t^e) and forecast error ($\omega_t = T_t - T_t^e$) on criminal activity during period t. In words, I_t will equal the total number of opportunities for crime during period t, multiplied by the probability that each opportunity actually results in a criminal incident. Recall that any type A player will face $N_1^B = \lambda P^B \rho^c$ opportunities for victimization should she leave her home in period 1, and $N_2^B = \lambda P^B (1-\rho^c)$ opportunities should she go out in period 2 instead. A total of $P^A \delta^c$ type A players leave their residence in period 1, while $P^A(1-\delta^c)$ do so in period 2. Combining all of these values, we can reach expressions for I_1 and I_2:

$$I_1 = \pi(\omega_1)\lambda P^A P^B \delta^c \rho^c$$
$$I_2 = \pi(\omega_2)\lambda P^A P^B (1 - \delta^c)(1 - \rho^c) \quad (9)$$

Expression (9) highlights the two independent channels through which temperature expectations and realized forecast errors affect crime. Firstly, temperature expectations affect the expected benefit type A players receive from leaving their residence in either period, which determines the equilibrium values of δ^c and ρ^c. Simply put, a higher value of b_t causes more players of all types to leave home in period t, resulting in more criminal activity during that period. As of yet, I have not placed any restriction on the relationship between b_t and T_t^e, but it is reasonable to assume that $\frac{db_t}{dT_t^e}$ is positive for most values of T_t^e.[8] Under this assumption, the model predicts that crime in period t will be increasing in T_t^e.

While the number of people outside of their residence in each period is determined before the start of period 1, the forecast errors ω_1 and ω_2 are not determined until the actual temperatures of their respective periods are realized. Thus, in this model forecast errors do not affect crime by changing the number of criminal opportunities in each period; rather, they affect crime by altering the probability that any one of those opportunities results in criminal activity. The rationale for this modeling choice is that unexpected heat and cold affect the manner in which people interact. There are a variety of potential reasons for this to be the case, as I will discuss in Section 1.6.

[8] It is certainly not necessary to assume that $\frac{db_t}{dT_t^e} > 0$ for all T_t^e. A more realistic assumption would be to assume that this derivative is positive below some critical threshold, above which the temperature is so high that the benefit to going outside declines. In this case, the model predicts that crime in period t would decline at very high expected temperatures.

1.2.5 *A Graphical Representation*

An example equilibrium for this model is depicted graphically in Figure 1.A.1, with comparative statics given in Figures 1.A.2 and 1.A.3. In Figure 1.A.1, expressions (3) and (4) are drawn in gray and black (respectively) for general values of T_1^e and T_2^e. Recall that (3) expresses δ^c as a function of ρ^c, and (4) expresses ρ^c as a function of δ^c. Equilibrium requires that both expressions be satisfied simultaneously, which is graphically represented by the intersection of the two functions.

Figure 1.A.2 demonstrates the effect of an increase in $b_1 = b(T_1^e)$ due to a change in T_1^e. Since expression (4) is not a function of b_1 directly, it remains fixed in its original position. Expression (3), on the other hand, shifts upwards, so that every possible critical value of ρ is now associated with a higher value of δ. As our previous discussion would suggest, this shift results in higher values for δ^c and ρ^c, which leads to more crime in period 1. In a similar fashion, Figure 1.A.3 considers an increase in T_2^e, which encourages all players to delay leaving their residence until period 2. The end result of this improvement in future weather is that crime falls in period 1.

1.3 Empirical Methodology

1.3.1 *Defining "Expectations"*

Before discussing the regression model estimated in this study, it is necessary to consider how temperature expectations are defined. The question of expectation formation is an old debate crossing many fields in economics, often with conflicting evidence in different contexts. However, in the case of weather expectations, the answer is more straightforward. This is because accurate weather forecasts have become ubiquitous in the modern world, and there is significant evidence to suggest that people use them frequently.

In fact, a small literature has developed covering this specific topic, with several near-unanimous conclusions: 1) most people use weather forecasts frequently, 2) people believe the forecasts they have access to, and 3) people make plans based on these forecasts. These issues are all investigated in detail in Lazo, Morss, and Demuth (2009), who conduct a survey on the subject.[9] The most basic finding of this study is that the vast majority of people surveyed (96.4%) use weather forecasts at least occasionally, and most people use forecasts multiple times per day. In fact, among respondents who report using weather forecasts, the average person receives forecast information 115 times per month (equivalent to nearly 4 times per day).[10] Furthermore, 74% of the respondents who use forecasts report that they are satisfied or very satisfied with the information provided in those forecasts, and only 8% express some level of dissatisfaction. Perhaps most importantly, the authors find strong evidence that individuals incorporate weather forecasts into their daily planning, and that they place significant monetary value on this information.[11]

In other words, the extant literature on the subject suggests that weather forecasts are, at the very least, strongly correlated with the subjective expectations that people have about temperature in the near future. As such, I will treat the forecast data used in this

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[9] The authors report 1,520 completed surveys. The survey was managed by a survey research company, and all responses were gathered over the internet using unique e-mail links.
[10] This figure may strike the reader as unreasonably high. However, one should note that daily television scheduling is designed to provide viewers with at least two forecasts per day, one in the morning and one in the evening. With the proliferation of the internet and smart phones, it is not inconceivable to think that a typical person views 3-4 weather forecasts per day.
[11] Based on valuation questions in their survey, the authors report a median household value of weather forecasting of $286/year.

paper as representing these expectations. This assertion is roughly equivalent to assuming that individuals have rational expectations about temperature in the near future, since temperature forecast errors are approximately mean-zero and weakly correlated over time.[12]

1.3.2 Regression Model

The empirical methods used in this paper represent a very basic extension of what has been done in the past. Generally speaking, most studies using regression analysis to examine the relationship between observed temperature and crime estimate models of the following form:

$$\theta_{i,t} = \alpha + X_{i,t}'\gamma + f\left(T_{i,t}\right) + \varepsilon_{i,t} \quad (11)$$

In (11), $\theta_{i,t}$ is a measure for some type of criminal activity pertaining to time period t in city i (e.g. a monthly assault rate), and $X_{i,t}$ is a set of fixed effects and other controls that are specific to city i and day t. There is considerable variation in the time scales studied; many researchers look at monthly crime data,[13] but annual, weekly, and daily data are also common. Throughout this study, I examine daily variation in crime and temperature, and the terminology used below will reflect that choice.

The centerpiece of (11) is $f\left(T_{i,t}\right)$, which represents some function of observed temperature in city i on day t. Many different forms of $f\left(T_{i,t}\right)$ have been studied over the

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[12] In the study sample used in this paper, the Pearson correlation coefficient between day t forecast errors and day $t-1$ forecast errors is about 0.2. Looking at individual cities, this value fluctuates between about 0.1 and 0.26. Correlation between day t errors and longer lags is also statistically significant, but the correlation coefficients are quite low. Incidentally, controlling for lagged forecast errors has no effect on the results discussed in Section 1.5.

[13] To a large extent, this is because many well-established crime databases provide crime counts at the monthly level (for example, the FBI's Uniform Crime Reports).

years, but the most basic option is to assume a linear relationship between temperature and crime (i.e. $f\left(T_{i,t}\right) = \beta T_{i,t}$). A central idea of this study is that people are likely to have well-developed expectations about temperature, both during the current day and in the near future. Since these expectations influence the plans people make, they should be accounted for in any examination of the effect of observed temperature on crime. Consider the regression model given in (12) below:

$$\theta_{i,t} = \beta_0 + X'_{i,t}\gamma + \beta_1 T_{i,t} + \varepsilon_{i,t} \quad (12)$$

In this model, β_1 is interpreted as the effect of a one-degree increase in current-day observed temperature on crime during the same day, conditional on the variables held constant in $X_{i,t}$. By accounting for expectations, one can increase the information contained in (12) in two distinct ways. First, it is possible to rewrite $T_{i,t}$ as $T_{i,t} = T^e_{i,t} + e_{i,t}$, where $T^e_{i,t}$ is the expected temperature on day t and $e_{i,t}$ is the realized forecast error on the same day. Using a multi-day forecast, one can also control for expectations beyond the current day. For simplicity, this expectation is defined as the average expected temperature conditions in the near future (I will refer to this value as $\overline{T^e_{\iota,f}}$). The forecasts used in this study cover seven days; as such, $\overline{T^e_{\iota,f}}$ is defined as the average expected temperature in the six days after the current day (i.e. $\overline{T^e_{\iota,f}} = \frac{1}{6}\sum_{j=1}^{6} T^e_{i,t+j}$). However, the theoretical model in Section 1.2 suggests that we are truly interested in how expected future temperature conditions *differ* from the current day; therefore, I define the variable $D^e_{\iota,f} = \overline{T^e_{\iota,f}} - T^e_{i,t}$, which I refer to as the "future temperature difference." Using these new definitions and terms, one can estimate the regression model given in (13).

$$\theta_{i,t} = \alpha_0 + X'_{i,t}\tau + aT^e_{i,t} + be_{i,t} + cD^e_{i,f} + \mu_{i,t} \quad (13)$$

Note that the variables $T_{i,t}^e$ and $e_{i,t}$ decompose the variation that $T_{i,t}$ captured in (12), while the inclusion of $D_{i,f}^e$ accounts for an entirely new source of variation. The coefficients of interest in this new model (a, b, and c) have the potential to significantly increase our understanding of the temperature-crime relationship. This is particularly true of the latter two, which capture channels that are conceptually unique in the literature on temperature and crime.

Thus far, I have only used the term "temperature" generally, without being specific about which temperature measure I will be using. The only two observed temperature variables for which I have a forecast counterpart are daily maximum and daily minimum temperature, and the latter value is conceptually problematic.[14] In any case, the vast majority of past research has focused on the effect of maximum temperature on crime, and a primary goal of this paper is to extend the understanding of that particular effect by accounting for expectations. As such, the reader should henceforth take the general term "temperature" to mean "daily maximum temperature."

In the discussion above, I considered a hypothetical regression model in which the variables of interest ($T_{i,t}^e$, $e_{i,t}$, and $D_{i,f}^e$) were related to temperature in a linear manner. This simplification was convenient for expository purposes, and I do report the results of estimating equation (13) in Table 1.C.5, but there is strong evidence in past research to suggest that the effect of temperature on crime may be non-linear.[15] As such, for nearly all

[14] People are very unlikely to form expectations about daily absolute minimum temperature. This is because the absolute minimum temperature during a day almost always occurs in the early morning, right around sunrise. Knowing what the weather will be like at 5:00am is of no value to most people, since they don't expect to be outside of their residence at that time anyway. As a consequence, the most common minimum temperature predicted in a forecast published by a media outlet is the evening minimum temperature (which is not available in my data).

[15] See, for example, Cohn and Rotton (1997) and Cohn and Rotton (2000).

of the analyses that follow here I will use semi-parametric bin estimators for each variable, in the spirit of Ranson (2012) and Deschennes and Greenstone (2011). The estimators used for each variable are defined as follows:

1. Expected Maximum Temperature ($T^e_{i,j,t}$) – 14 bins (indexed by j), beginning at < 35 F, and then proceeding in five-degree steps to the highest bin of ≥ 95 F (i.e. < 35 F, 35-39 F, 40-44 F, … , 90-94 F, ≥ 95 F). The omitted category is < 35 F ($T^e_{i,1,t}$).
2. Forecast Error ($e_{i,k,t}$) – 9 bins (indexed by k), beginning at < -7 F, and then proceeding in two-degree steps to the highest bin of > 7 F (i.e. < -7 F, [-7 F, -5 F), … , [-1 F, 1 F] , (1 F, 3 F], … , > 7 F). The omitted category is [-1 F, 1 F] ($e_{i,5,t}$).
3. Future Temperature Difference ($D^e_{i,h,f}$) – 9 bins (indexed by h), beginning at < -13 F, and then proceeding in four-degree steps to the highest bin of > 13 F (i.e. < -13 F, [-13 F, -9 F), … , [-1 F, 1 F] [16] , (1 F, 5 F], … , > 13 F). The omitted category is [-1 F, 1 F] ($D^e_{i,5,f}$).

The regression model I focus on in this paper is given by (14) below:

$$\theta_{i,t} = \rho_0 + X'_{i,t}\tau + \sum_{j\neq 1} a_j T^e_{i,j,t} + \sum_{k\neq 5} b_k e_{i,k,t} + \sum_{h\neq 5} c_h D^e_{i,h,f} + \eta_{i,t} \quad (14)$$

In all cases, the dependent variable is the log of daily criminal activity for a particular crime type (I discuss the crime categories studied in Section 1.4). Though fairly uncommon, there are city-days in the sample that have no recorded crime for a particular category, so I use the inverse hyperbolic sine transformation proposed by Burbidge et al. (1988).[17] The vector $X_{i,t}$ includes year-by-city fixed effects, month-by-city fixed effects, day-

[16] The central bin of [-1 F, 1 F] obviously does not have a width of 4 F, but it is chosen to represent conditions that are essentially the same as the current day.
[17] Thus, if y is the number of offenses of a particular type occurring on day t, then $ln(y) = ln\left(y + \sqrt{1+y^2}\right)$.

of-week fixed effects, an indicator for the first of each month, controls for major holidays and other significant days (e.g. Black Friday), controls for one lag of observed maximum temperature[18] and one lag of observed precipitation, controls for total precipitation[19] on day t, controls for forecast daytime chance of precipitation on day t,[20] and controls for the average forecast chance of daytime precipitation in the near future.[21] The controls for precipitation expectations come from the same forecasts used for expected daily maximum temperature; a summary of the controls contained in $X_{i,t}$ is given in Table 1.C.4. For all regressions in this paper, standard errors are clustered by city.

The numerous controls contained in $X_{i,t}$ (especially the weather variables) are included in order to allow for a particular interpretation of the a_j, b_k, and c_h coefficients. Specifically, the coefficient estimates discussed in Section 1.5 capture the effect of $T_{i,t}^e$, $e_{i,t}$, and $D_{i,f}^e$ *conditional* on other factors that are likely to influence daily planning. For instance, weather conditions on the previous day may affect how people value weather on the current day, and precipitation on the current day will almost certainly do the same.

[18] The set of controls included for observed maximum temperature on the previous day is also a semi-parametric bin estimator, using the same bin definitions as $T_{i,t}^e$.

[19] Current day and lagged total precipitation are both captured by semi-parametric bin estimators as well. In each case, six bins are defined (0," (0"-0.25"), [0.25"-0.5"), [0.5"-0.75"), [0.75"-1"), and ≥ 1"). The first bin (no precipitation) is the omitted category.

[20] Daytime chance of precipitation is defined as the probability that at least 0.01" of rain will fall between 6:00am and 6:00pm. This probability is conditional on the weather conditions observed at the time the forecast is made. Once again, a semi-parametric bin estimator is used to control for this variable. The bins used are [0%, 10%], (10%, 30%], (30%, 50%], (50%, 70%], (70%, 90%] , and > 90%. [0%, 10%] is the omitted category.

[21] This variable is defined in a similar manner to $D_{i,f}^e$. Specifically, I average the forecast chance of daytime precipitation over the six future days in the forecast, and then subtract the chance of precipitation for the current day from that average. The variable that results can take positive or negative values (between -100% and 100%), with more negative values implying that the average chance of precipitation is lower in the future than it is on the current day. As the reader has undoubtedly come to expect, this variable is also captured using a semi-parametric bin estimator, with bins of < - 70%, (-70%, -50%], (-50%, -30%], (-30%, -10%), [-10%, 10%], (10%, 30%], > 30%.
[-10%, 10%] is the omitted category.

Precipitation expectations (both for the current day and in the future) may also be important.[22]

1.4 Data

The data used in this study come from three primary sources, covering crime, observed weather, and forecast weather. In this section, I describe each of these sources, and provide a number of summary measures for the data. In determining the final set of cities to include in my analyses, a number of criteria were followed; for brevity's sake, I have removed a detailed discussion of these restrictions to Appendix 1.B.

1.4.1 Crime Data

The crime data used in this study are drawn from extracts produced by the National Incident Based Reporting System (NIBRS) and made publicly available by the Interuniversity Consortium for Political and Social Research (ICPSR). As the name suggests, the NIBRS database includes information about crime at the incident level, including a myriad of details about offenses committed, offense characteristics, as well as information about the offenders and victims (if available). The sample used in this study includes the largest[23] 50 NIBRS city police departments for which I have all necessary data. Most of the included cities are present in the NIBRS database for the entire 2004-2012 period; however, a minority of included cities only have data spanning 2005-2012 or 2006-2012.

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[22] Dropping some or all of these weather controls has little meaningful impact on the a_j, b_k, and c_h coefficients (the magnitudes change in some cases, but the qualitative interpretation remains the same, and significance levels are not meaningfully altered).

[23] As measured by average population during the 2006-2012 period

In the NIBRS data, an offense is identified by one of over 40 numeric codes; for example, an aggravated assault receives the code 131. There is a temptation to examine every type of crime independently, but this is not a viable option in the space of one paper.[24] Instead, I group crimes into two major categories: violent crime and property theft. These two categories collectively account for about 70% of all criminal activity[25] on an average day, and include all crimes that have received significant attention in the temperature-crime literature. In addition to these major categories, I also examine the subcategories of assault and larceny.[26] For the main results of the paper, I also independently consider the effect of temperature on crimes occurring in all locations, and outside of residences only. All categories studied are defined in Table 1.C.1, and sample summary statistics for daily crime counts are provided in Panels 1 and 2 of Table 1.1.

1.4.2 Observed Weather Data

As discussed above, all 50 police departments included in this analysis have jurisdiction over a single city. To obtain observed weather outcomes for each of these cities, I use data drawn from Wunderground, an online archive for weather data. For each city, I choose the closest single weather station that has a complete (or very nearly complete) daily time series during the 2004-2012 period. For every city in my sample, the weather station used is located at a local airport or military base. The two observed weather elements I use in

[24] It also would be redundant and, in many cases, uninformative. Many of the 46 codes describe very similar crimes, which makes grouping them together very natural. In addition, some types of crime are too rare to examine independently.
[25] The largest omitted category is vice crime (which is dominated by drug-related offenses), followed by property damage crimes (mostly vandalism).
[26] Assaults account for the vast majority of violent crimes, and larcenies account for a majority of property theft.

my analyses are daily maximum temperature and daily total precipitation. Panel 3 of Table 1.1 provides sample summary statistics for these two variables.

1.4.3 Forecast Weather Data

The most unique data source used in this paper comes from weather forecast data published by the National Weather Service (NWS). The NWS is by far the largest producer of basic weather forecasts in the United States, though the weather forecasts that most people use on a daily basis are NWS reports that have been customized by a third party.[27] Given their ubiquity in day-to-day life, historical weather forecast data is surprisingly hard to come by in a convenient form, as most forecasts are not archived once the time they pertain to has passed. However, the National Climatic Data Center (NCDC) publicly provides all of its archived forecast data via its online Hierarchical Data Storage System (HDSS).[28] Even so, extracting and preparing this data is challenging, and the production of the dataset used in this study may prove to be a significant contribution to future research.

There are a few archived forecast products to choose from, but the Tabular State Forecast (TSF) report is the best fit for the purposes of this study. TSF reports are generally produced twice a day,[29] and include simple weather forecasts for a set of cities in a particular U.S. state.[30] I limit my attention to TSF reports published after 12:00pm; these forecasts include predicted daytime maximum and early morning minimum temperatures for the next seven days, along with nighttime and daytime[31] chance of precipitation. A short

[27] For example, local news stations take NWS forecast data and use them in reporting their own forecasts.
[28] Go to http://has.ncdc.noaa.gov/pls/plhas/has.dsselect.
[29] Typically, once early in the morning (around 2:00am-4:00am), and again in the afternoon/evening (usually about 4:00pm, but sometimes in the late evening). However, forecast times vary by weather forecast office.
[30] For larger states, a single TSF report will only cover a region of that state.
[31] Nighttime is defined as 6:00pm-6:00am, while daytime is 6:00am-6:00pm.

word or phrase is also included to describe the general weather conditions during the day (e.g. "partly cloudy"). Thus, the information provided for each city in a TSF report is very similar to the sort of forecast that one would find in a newspaper.

Since the forecasts I use are all published in the afternoon, the first day of each forecast pertains to weather conditions on the day following the forecast's publication (this is the "current day" forecast). The choice of using afternoon forecasts is deliberate, in order to best capture the expectations that people have at the end of day $t-1$ (i.e. heading into the current day). The remaining six days form my definition of the "near future," as discussed in Section 1.3. Panel 3 of Table 1.1 includes sample summary statistics for forecast maximum temperature, time of forecast publication (expressed in hours on day $t-1$), and forecast error. As these summary statistics suggest, temperature forecasts for the current day are quite accurate, with errors larger than 5 degrees being rare. In fact, temperature forecasts pertaining to the near future are also very reliable. More details about forecast accuracy can be found in Appendix 1.B.

1.5 Results

The results discussed below are divided into several subsections. I begin with an examination of the regression model given by (13), in which the variables of interest enter linearly. This is followed by simplified version of (14) in which all forecast information has been removed. The main results begin with Section 1.5.3, where I estimate (14) including all city-days in the study sample. Afterwards, I re-estimate (14) for a variety of subsamples of interest. Given the large number of coefficients estimated for each effect, I find it more intuitive and convenient to report my results in a graphical form. In each figure, coefficient values and their associated 95% confidence intervals are plotted. Every figure also includes a small table that reports other values of interest. In the main results of the paper, the dependent variable in every regression model is the natural log of a daily crime count. Each of these daily counts includes all offenses of a given type occurring in a department's jurisdiction. Since temperature may have a particularly powerful effect on crimes outside of residences, I repeat the central results of the paper after restricting the dependent variable to include only such offenses. These findings are reported in Appendix 1.C.

1.5.1 Estimation of Linear Model

As discussed in Section 1.3, the regression model given in (13) requires that all of the channels of interest (T_t^e, e_t, and D_f^e) affect crime in a linear fashion. This is a very rigid assumption, and will be relaxed in the main results. However, the estimates I report in this section establish a few basic points that are important to discuss.

Table 1.C.5 reports coefficients obtained from estimating (13) for the full sample of 141,359 city-days. As expected, there is a clear positive relationship between expected maximum temperature and criminal activity, especially in the case of violent crime. Forecast errors also appear to have a positive effect on all types of crime, and in all cases one can reject the null hypothesis that a 1-degree increase T_t^e has the same effect on crime as a 1-degree increase in e_t. The effect of forecast errors on property theft is statistically significant but small in magnitude; as will be shown in Section 1.5.3, the relationship between property theft and forecast errors becomes largely insignificant in the more complex specification given by (14). Table 1.C.5 also suggests that D_f^e does not significantly affect violent crime, and has a *positive* effect on property theft. This finding also deviates

strongly from the main results of the paper, and emphasizes the benefit of allowing for a more flexible empirical specification.

As the remainder of Section 5 will show, the model given in (13) is not complex enough to accurately examine the relationship between temperature expectations, forecast errors, and criminal activity. However, Table 1.C.5 does provide evidence that T_t^e and e_t do not have the same effect on crime, which reinforces the argument that past studies have fallen short by not decomposing the effect of observed temperature on crime into its constituent parts. This is an important first step, and significantly motivates the analyses to follow.

1.5.2 Observed Maximum Temperature

For comparative purposes, I begin this series of results by estimating a simplified version of the model given in (14) in which expectations are ignored. Every measure of current day or future weather expectations has been dropped, including those for temperature and precipitation. Instead, the only variable of interest here is observed maximum temperature on the current day, which is represented with the same semi-parametric bin estimator used to represent current day expected temperature (see Section 1.3 for details). The results of this exercise are presented in Figure 1.1.

Figure 1.1 demonstrates a strong positive relationship between observed maximum temperature and crime for all categories studied, though the effects are clearly more pronounced for violent crime. In fact, the trend for property theft is only marginally increasing for temperatures above 70 F, while the trend for violent crime is clearly upward sloping until temperatures rise above 90 F. In all ways, these findings are consistent with what has been found repeatedly in past studies. Furthermore, Figure 1.C.1 demonstrates that the effect of observed maximum temperature on crimes occurring outside of residences is very similar.

1.5.3 Full Model

Figures 1.2 through 1.4 contain the results obtained from estimating the regression model given in (14) for all city-days in my sample. The use of multiple figures is necessary due to the large number of coefficients: Figure 1.2 reports the effect of expected temperature on the current day, Figure 1.3 does the same for current day forecast errors, and Figure 1.4 reports the effect of future temperature differences.

Given the high correlation between expected and observed daily maximum temperature, it is not surprising that the coefficient estimates plotted in Figure 1.2 look very similar to those shown for observed maximum temperature in the previous figure. In other words, the vast majority of the effect of observed maximum temperature on crime can be attributed to expected maximum temperature. In the context of the model outlined in Section 1.2, Figure 1.2 is consistent with the prediction that crime rises when conditions on the current day are expected to be better. As Figure 1.C.2 demonstrates, the effect of expected maximum temperature on crimes outside of residences is very similar.

Figure 1.3 plots the results for current day forecast errors. In the case of violent crime, especially its largest subcategory of assault, there is a clear relationship between forecast errors and criminal activity. The estimated effects are especially strong on days that are much colder than expected, where violent crime falls by up to nearly 4%. Warmer-than-expected temperatures have the opposite effect of increasing violence (again, especially assault), though the magnitude of these effects are somewhat smaller (typically between 1% and 3%). In fact, for temperatures that are *much* hotter than expected (> 7 F), the positive effect on violence diminishes and becomes insignificant.

In stark contrast to the results for violent crime, the effect of forecast errors on property theft is muted and largely insignificant. Taken at face value, the property theft and larceny coefficient estimates plotted in Figure 1.3 suggest the same general trend that applies to violent crime (i.e. colder than expected days reduce crime, and unexpectedly warm days have the opposite effect), but only a handful of these coefficients are significant at an acceptable level. Forecast errors affect crimes outside of residences in a similar way, as shown in Figure 1.C.3.

Figure 1.4 completes the central results of this paper by reporting the effect of future temperature differences on current day criminal activity. The consistent finding in this case is that, across almost every category of crime,[32] the expectation of much warmer temperatures in the future significantly reduces crime during the current day. These effects are especially strong in the highest possible bin (i.e. > 13 F warmer over the next six days, on average), though several categories of crime see significant reductions at lower bins as well. Interestingly, there is very little evidence to support an equivalent effect operating in the opposite direction. In fact, an expectation of colder temperatures in the future does not affect property theft at all, and only marginally influences violent crime. For crimes outside of residences (see Figure 1.C.4), the effect of future temperature differences is qualitatively similar, but the property theft coefficients generally lose a degree of statistical significance.

[32] The sole exception is larcenies occurring outside of residences, which do not appear to be affected by future temperature differences.

The results presented thus far provide several new insights into the relationship between temperature and crime, but also raise new questions. For example, it seems likely that the effect of forecast errors and future temperature differences will depend of the level of expected temperature. In addition, one wonders if these effects are significantly different during the weekend (when weather is more likely to influence planning). Both of these questions are addressed in the subsections to follow. To avoid an overwhelming number of figures, I do not report separate results for crimes outside of residences.[33]

1.5.4 Expected Temperature Ranges

In Figures 1.3 and 1.4, the estimates reported reflect the average effect of forecast errors and future temperature differences over all city-days in the study sample. Of course, there are ways of dividing this sample to provide more insight into these effects. One of the most interesting options is to consider different ranges of expected temperature on the current day. For example, crime might only be affected by future temperature differences if the weather today is expected to be at some temperature extreme. Similarly, forecast errors may be important in certain temperature ranges, but not in others. To explore these possibilities, I divide the study sample into three subsamples covering days that are expected to have cold (< 50 F), moderate (50 F – 79 F), or hot (80+ F) maximum temperatures. I then re-estimate (14) for each of these subsamples, and discuss the coefficient estimates for forecast errors and future temperature differences.

[33] As the results discussed thus far suggest, the effects seen for crimes outside or residences are quite similar to those seen overall.

Figures 1.5 and 1.6 present the results of this exercise for the lowest temperature category, including all days where the expected maximum temperature falls below 50 F. The estimates for forecast errors are provided in Figure 1.5, and those for future temperature differences are given in Figure 1.6. Since it is quite rare to have a future temperature differences that is less than -13 F in this temperature range, I have redefined the future temperature difference bins so that the lowest bin is now < - 9 F.

In this temperature range, forecast errors have no apparent effect on property theft, and the effect observed for violent crime is rarely significant. In other words, as long as it is expected to be cold, unexpectedly hot or cold temperatures have no additional effect on criminal activity.[34] On the other hand, Figure 1.6 reveals that expectations of warmer weather in the future significantly reduce crime on the current day. This effect is found to some extent for all crime categories studied, but it is clearly strongest for property theft (and its subcategory larceny). In fact, I find that property theft crime falls by nearly 6% on days where the next six days are expected to be more than 13 F warmer, on average. The equivalent effect for violent crime is smaller (just under 5%), but still highly significant.

Figure 1.7 (forecast errors) and Figure 1.8 (future temperature differences) report the results produced for the moderate temperature range, which I define to include all city-days with expected temperatures from 50 F to 79 F. In this particular case, future temperature differences appear to have no consistent effect on any category of crime; in addition, forecast errors have no effect on property theft. However, forecast errors do significantly impact violent crime. This is especially true for higher-than-expected

[34] There is some marginal evidence that unexpectedly cold temperatures reduce violence in this temperature range, but it is only supported by significant coefficients in the [-7 F, -5 F) temperature bin.

temperatures, which increase violent crime by as much as 4%. There is also compelling evidence that days that are at least 5 F colder than expected experience a significant reduction (nearly 4%) in violent crime. As was the case with the full sample, there appears to be a nonlinear relationship between forecast errors and violence, since the impact of positive forecast errors falls considerably in the highest error range (though it remains positive and significant).

Figure 1.9 (forecast errors) and Figure 1.10 (future temperature differences) complete the examination of different temperature ranges by reporting results for the highest expected temperature category (≥ 80 F). This range can be thought of as including all days that one would consider "hot." As was the case with the moderate range, there is little consistent evidence that property theft responds to forecast errors or future temperature differences on hot days. Violence, on the other hand, responds to both (although only marginally in the case of forecast errors). For instance, hot days that are at least 5 F cooler than expected appear to experience lower levels of violence, including a nearly 3% reduction in assaults for days that are at least 7 F cooler. Furthermore, expectations of cooler temperatures in the future appear to increase violence on the current day (by as much as 3%).

1.5.5 Workweek vs. Weekend

To complement the results presented thus far, I re-estimate (14) separately for workweek and weekend subsamples.[35] The rationale for this division is that people tend to have more flexible schedules on the weekend, so that the effect of the variables of interest may differ

[35] Where the workweek is defined as Monday through Friday.

markedly on these city-days. All of the figures associated with this exercise are located in Appendix 1.C.

Figures 1.C.5 and 1.C.6 report the coefficient estimates for expected maximum temperature during the workweek and weekend, respectively. Broadly speaking, these results indicate that expected maximum temperature is positively correlated with criminal activity during all times of the week. However, in the case of violent crime it is also clear that the coefficient values are somewhat smaller during the weekend.

Figures 1.C.7 and 1.C.8 report the coefficient estimates for forecast errors during the workweek and weekend, respectively. During the workweek, colder-than-expected temperatures reduce violent crime by as much as 3.5%, while hotter-than-expected temperatures have the same non-linear effect that was observed in Figure 1.6. There is even some evidence that unexpectedly cold temperatures reduce property theft, though the coefficient magnitudes are smaller and only marginally significant. The qualitative trends observed in weekend coefficient estimates are similar, but statistical significance is greatly reduced.

Figure 1.C.9 (workweek) and Figure 1.C.10 (weekend) complete the workweek-weekend comparison by reporting coefficient estimates for future temperature differences. Figure 1.C.9 shows strong evidence that violent crime falls on workweek city-days in which it is expected to be much warmer in the future, but this finding almost completely disappears for weekend city-days. Property theft also appears to decline during workweek city-days, but only for the > 13 F bin. In contrast, Figure 1.C.10 reveals a strong negative correlation between warmer expected future temperatures and property theft on weekend city-days.

1.6 Possible Mechanisms

The results reported in this paper establish that: 1) current day expected maximum temperatures are positively correlated with criminal activity on the same day, and 2) forecast errors and future temperature differences matter in certain contexts. These empirical results have definite value, but they do not establish the underlying mechanisms responsible for the effects estimated. Disentangling and quantifying these channels cannot be done in the space of one paper, and will likely involve years of further investigation. However, in part to motivate future work, I will outline some possible explanations below.

Recall from Section 1.2 that the theoretical model presented in this paper suggests two mechanisms through which temperature affects crime. The first of these is that current and future temperature expectations determine the time use and labor supply decisions of non-criminals and criminals, respectively. This channel captures the RAT-based argument that has been popular in the temperature-crime literature for decades. The second mechanism in the model operates through forecast errors, which are theorized to affect the probability that any interaction between player types becomes criminal. Several explanations for why this would happen are discussed below.

One possibility is that all of the effects reported in Section 1.5 can be traced back to changes in the number of people outside of residences. This is especially plausible if one views the plans that people make as being reversible at low cost, or if one rejects the idea that advanced planning is an important determinant of daily routines. If this were the case, then unexpected heat or cold would simply encourage or discourage one to leave home. Consequently, forecast errors would affect crime by altering the plans that people make, just as temperature expectations are thought to. Ladner (2015c) examines this possibility by studying daily levels of crime and public transit ridership in Chicago, IL. Using a regression model similar to (14), I show that current day and future expected temperatures affect ridership levels in the manner predicted by my theoretical model. Since ridership is a strong proxy for the number of people outside of residences, this finding supports the conclusion that people's temperature expectations affect the probability that they leave home on a given day. Coefficient estimates from the same regression demonstrate that unexpectedly cold weather appears to reduce ridership, but unexpectedly hot weather has no significant effect. In contrast, these positive forecast errors significantly increase violent crime in the city (but not property theft).

If one rejects the notion that forecast errors affect crime only by changing the number of people outside of residences, then what other options are available? One possibility is that errors in expectations trigger positive or negative emotional cues that affect aggression levels. Some support for this assertion can be drawn from a recent literature on the relationship between violence and unexpected sports outcomes. For instance, Rees and Schnepel (2009) show that several categories of criminal activity are especially high in U.S. college towns in the event of unexpected football outcomes. Card and Dahl (2011) also find that expectations are important in determining the level of domestic violence on NFL game days. Given that unexpected sports outcomes seem to affect one's tendency towards violence, it is not unreasonable to suppose that unexpected temperature shocks could have a similar effect. Incidentally, this mechanism fits in well with the model presented in Section 1.2.

The results of this paper give some weight to the emotional cue argument, but there are also findings that seem to discredit it. On the supporting side, forecast errors appear to affect violent crime without affecting property theft, which is consistent with the underlying mechanism being connected to aggression. Also, the findings of Figure 1.9 provide marginal evidence that unexpectedly cool temperatures reduce violence on days with expected temperatures at or above 80 F.[36] On the other hand, forecast errors appear to affect violent crime most in the moderate temperature range, where even large errors in expectation would not be associated temperatures that one would think of as upsetting.

Finally, it is possible that forecast errors affect crime via some form of unobserved selection. This is a compelling possibility, but also untestable due to data limitations. For example, if forecast errors have heterogeneous effects on the plans that people of different ages and/or genders make, then they could affect the incidence of crime. Even if there is no selection along these lines, unexpectedly hot or cold weather might induce selection in the activities that people partake in. Since some activities are more likely to result in crime, this form of selection would impact criminal activity.

1.7 The Effect of Observed/Expected Precipitation

In principle, the concepts employed in this paper to examine the effect of temperature on crime could be extended to any weather variable, with the most obvious candidate being precipitation. After all, if expectations about temperature are presumed to affect the plans that people make, then people's beliefs about precipitation are likely to be just as important. There are, unfortunately, significant obstacles to investigating this possibility.

The incorporation of expectations into the study of temperature and crime is very straight-forward: on any given day, there is an expected temperature and an observed

[36] This is consistent with cooler temperatures having a calming effect that serves to reduce aggression.

temperature, both of which are measured in the same units. In such a context, the difference between expectation and observation (i.e. the forecast error) has an unambiguous magnitude and direction, and consequently all errors are easy to calculate, interpret, and compare. In contrast, precipitation forecasts almost always[37] take the form of percent chances of precipitation, whereas observed precipitation data is measured as a quantity (e.g. in millimeters or inches). As a result, the concept of a forecast error is not well-defined, making it difficult or impossible to establish (and thus compare) error magnitudes.[38] Furthermore, my precipitation forecasts match up poorly with my observed precipitation data because the forecasts refer specifically to the *daytime* (i.e. 6:00am-6:00pm) chance of precipitation, whereas the observed precipitation data record the amount of precipitation accumulated during the entire day (12:00am-11:59pm). Thus, the daily time period my precipitation forecast data cover do not match the time period during which the daily precipitation totals are calculated.

While the limitations of my forecast data hamper my ability to examine the effect of observed and expected precipitation on crime, I do include a rich set of controls for day t observed precipitation, expected chance of precipitation, and the future expected chance of precipitation in all of the regression models discussed in this paper. Reviewing the coefficients associated with these controls is important, as it allows one to check if observed and expected precipitation affect crime in the manner one would expect. To that end, Tables 1.C.6, 1.C.7, and 1.C.8 report the coefficient values for the semiparametric bin

[37] Precipitation quantity forecasts certainly exist, but they are comparatively rare, and are not available in my data.

[38] For example, suppose that on two days (A and B) the observed rainfall totals are 0.5” and 1”, respectively. On day A, the forecast chance of precipitation is 30%; on day B, the same probability is 60%. There is no unambiguous way to measure forecast error on either day, and thus one cannot compare errors across days.

estimators used to represent all of these channels in the regression model given by (14). It should be noted that these results come from the same regressions used to produce Figures 1.2, 1.3, and 1.4.

The results of Table 1.C.6 largely agree with what one would expect: when observed daily precipitation is higher, there is less criminal activity. In fact, I find that a day with at least 1" of precipitation experiences about 6.9% less violent crime, all else equal. The effect of property theft is much more muted in magnitude, but still mostly significant. This is especially true in the case of larceny, where observed precipitation reduces crime by as much as 2.2%.

The coefficients associated with current day chance of precipitation (reported in Table 1.C.7) suggest that violent crime falls when the forecast chance of precipitation is higher. These declines exceed 5% in some cases, but the coefficient values are only significant for the two highest bins (71%-90% and ≥ 90%). The results for property theft are more mixed. Overall, property theft is not significantly impacted by the current day chance of precipitation; however, the subcategory of larceny declines significantly as precipitation becomes more likely. Finally, Table 1.C.8 makes clear that, unlike temperature, expectations about the chance of precipitation in the future (relative to the current day) have no consistent effect on any of the crime categories studied.

The results discussed in this section are rough at best, and much better data will be needed to make significant progress in the study of precipitation and crime. In the meantime, however, it is comforting to note that crime appears to fall of days that experience precipitation, as well as on days where the chance of precipitation is high. Both findings are consistent with the story that individuals incorporate weather expectations into their planning decisions.

1.8 Conclusion

On a basic level, the purpose of this study is to better understand the relationship between temperature and crime through the incorporation of expectations. I have shown that current day temperature expectations can largely account for the effect of observed maximum temperature on crime; however, I also find evidence that forecast errors and future temperature differences impact current day criminal activity in certain contexts. Furthermore, these effects vary considerably according to the level of expected temperature, and the time of week.

These findings are of central importance for the literature on temperature and crime, but also contribute to our understanding of criminal labor supply. By showing that warmer expected future temperatures reduce crime on the current day, I provide evidence that criminals may be forward-looking in their labor supply decisions (at least over a very short time horizon). This is a unique finding, and contrasts with past studies that show criminals to be either extremely impatient or completely myopic. It also highlights the importance that environmental conditions play in determining the productivity of crime, and suggests many new avenues for future research.

Main Table and Figures

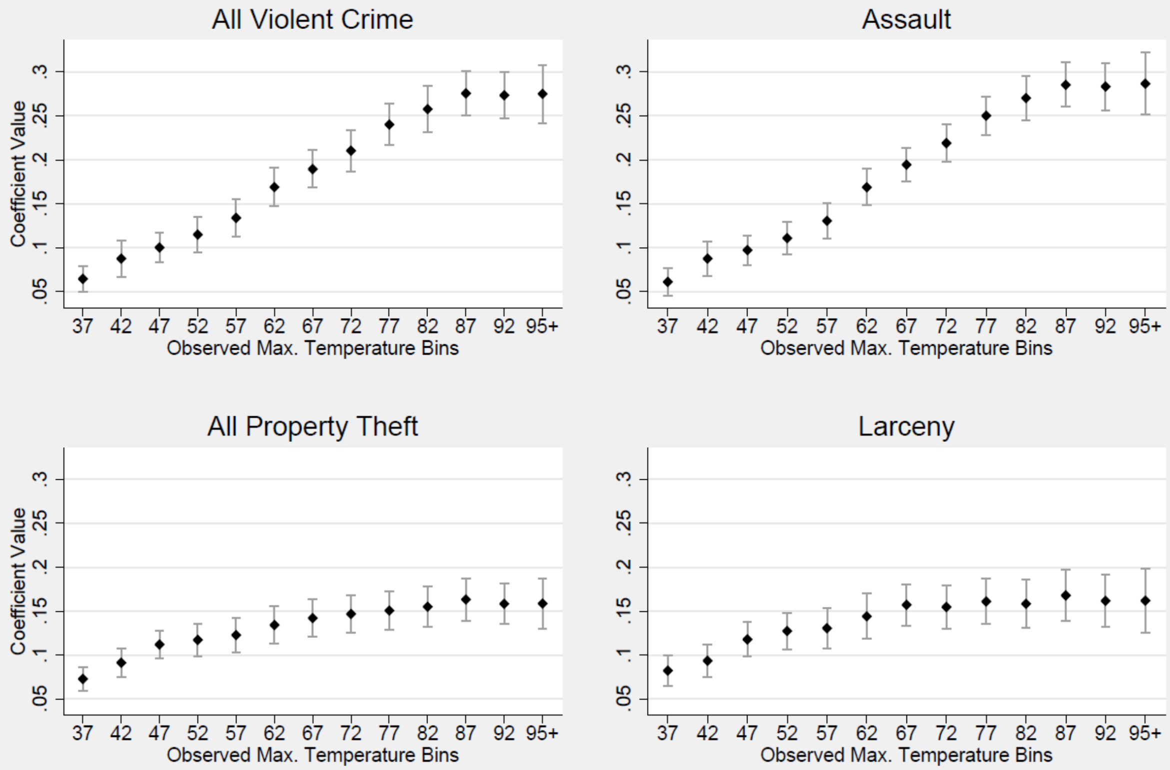
Table 1.1 - Crime, Obs. Weather, and Forecast Weather Summary Statistics

Panel 1 - Daily Crime	Basic Summary Stats.				Percentiles				
Crime (All Locations)	Mean	S.D.	Min	Max	5th	25th	50th	75th	95th
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
All Offenses	73.13	79.38	0	529	13	28	44	74	270
Violent Crime	19.65	24.79	0	169	2	6	11	20	80
Assault	15.76	19.84	0	140	1	5	9	16	65
Property Theft	32.84	36.32	0	253	5	12	19	35	120
Larceny	21.04	20.97	0	164	3	8	13	25	70
Panel 2 - Daily Crime Counts (Outside of Residences Only)									
All Offenses	41.95	44.03	0	322	7	16	26	45	151
Violent Crime	9.09	11.53	0	103	0	2	5	10	36
Assault	6.37	7.84	0	90	0	2	4	7	25
Property Theft	19.75	21.73	0	173	3	7	12	22	72
Larceny	14.89	15.39	0	131	2	5	9	18	51
Panel 3 - Observed and Forecast Weather									
Total Precip. (mm)	2.58	8.1	0	250.2	0	0	0	0.51	15.75
Max. Temp. (F)	65.96	19.9	-12	115	31	51	69	82	93
Forecast Max. Temp. (F)	65.79	20.01	-13	113	31	51	68	82	94
Forecast Error (F)	0.18	3.49	-15	15	-5	-2	0	2	6
Forecast Time (hrs.)	17.37	2.39	12	23.98	14.93	15.7	16.4	17.43	22.17

Notes: This table contains basic summary statistics and percentile values for crime counts, observed weather, and forecast weather. All data values are at the daily level, and statistics are calculated using the full 2004-2012 sample of 141,359 city-days. The weather variables summarized include observed daily maximum temperature, observed daily total precipitation, forecast daytime (6:00am-6:00pm) maximum temperature, forecast error, and forecast publication time represented in hours (i.e. 16=4:00pm).

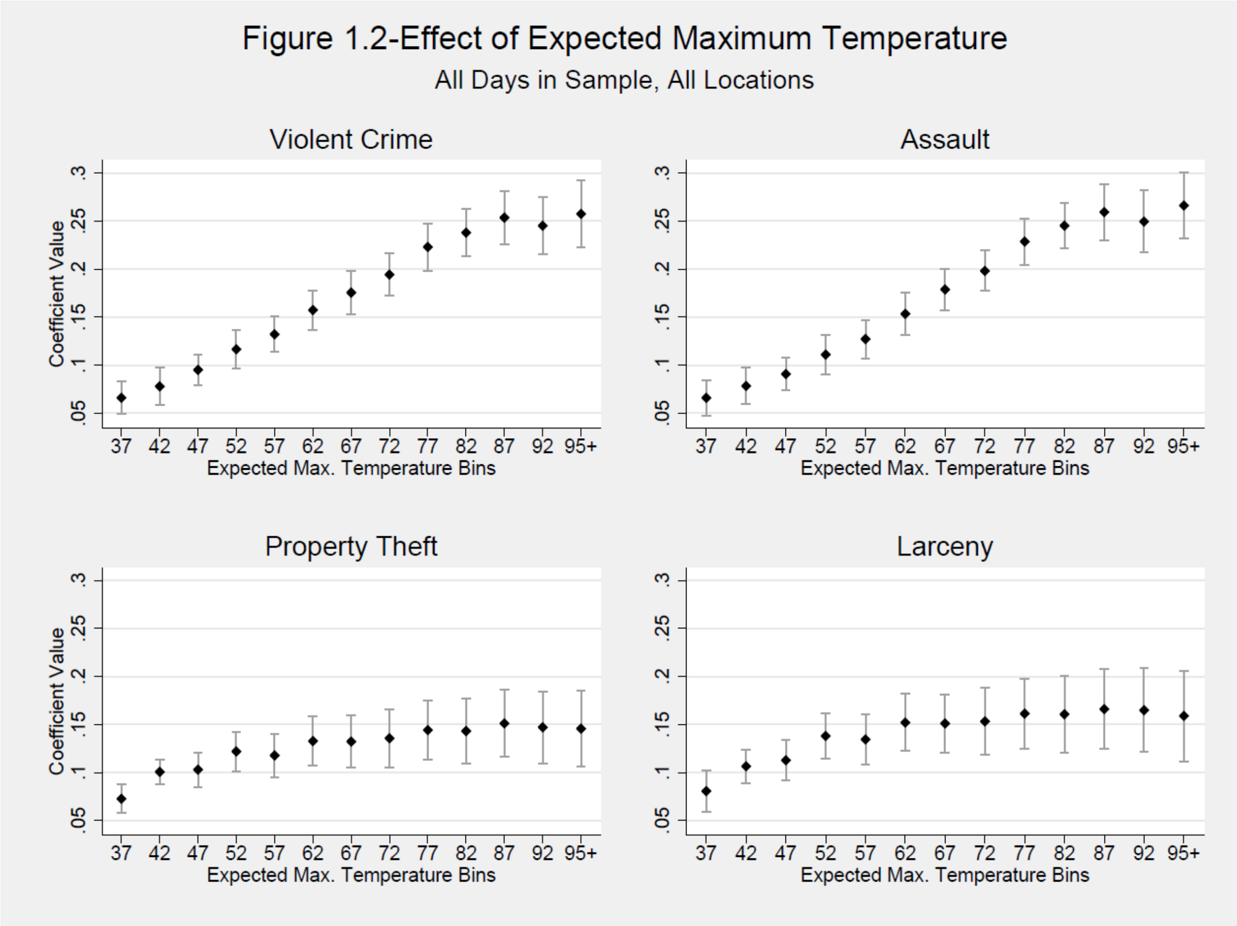
Figure 1.1-Effect of Observed Maximum Temperature on Crime

All Days in Sample, All Locations



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	141359	141359	141359	141359
F-Statistic	67.03	67.05	21.49	17.23
P-Value	0	0	0	0

Notes: The plots in this figure display the observed maximum temperature coefficient values and 95% confidence intervals obtained by estimating a regression of the following form: $\theta_{i,t} = \rho_0 + \tau X_{i,t} + \sum_{j\neq 1} a_j T_{i,j,t} + \eta_{i,t}$. In this regression, $\theta_{i,t}$ is the log of daily criminal activity in all locations, and the right-hand-side variables include a set of controls ($X_{i,t}$) and a semi-parametric bin estimator capturing observed daily maximum temperature ($\sum_{j\neq 1} a_j T_{i,j,t}$). The set of controls includes year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, and controls for current day total precipitation. The semi-parametric bin estimator for observed maximum temperature on the current day captures 14 temperature ranges, with < 35 F being the omitted category. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1+y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 52 is the midpoint of the bin [50,55). Figure 1.C.1 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.

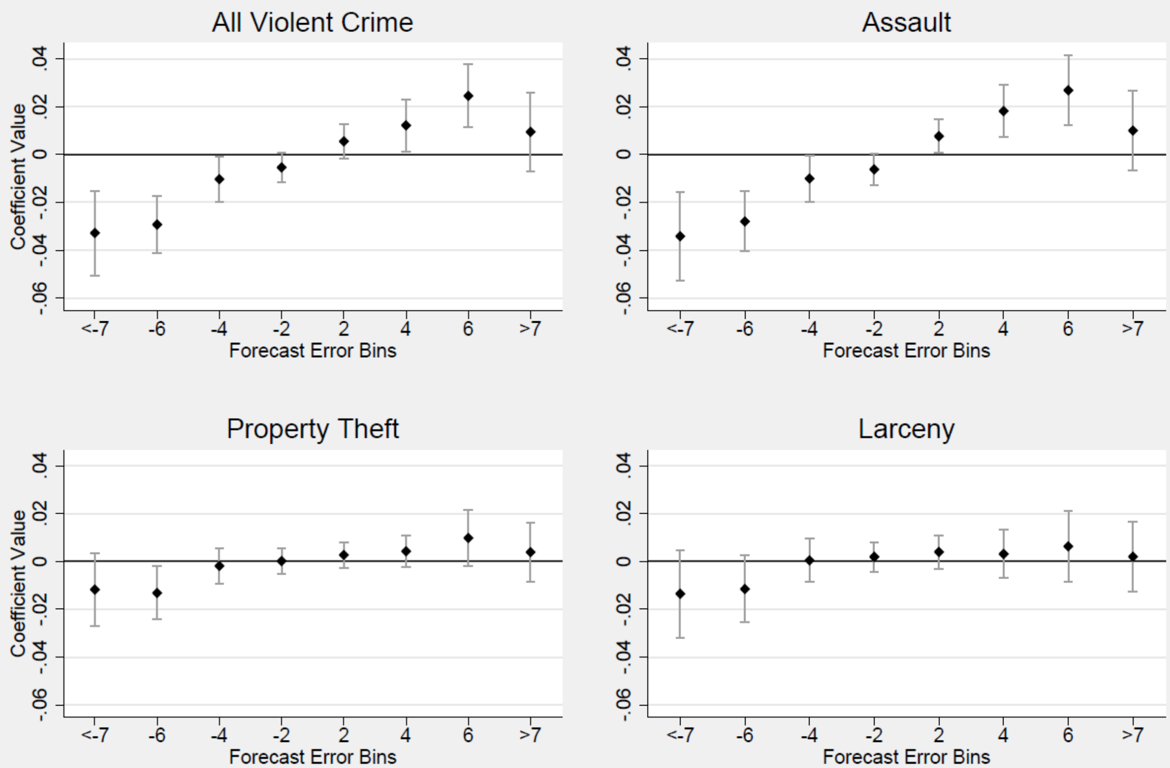


	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	141359	141359	141359	141359
F-Statistic	38.12	49.63	24.7	17.77
P-Value	0	0	0	0

Notes: The plots in this figure display the expected maximum temperature coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1+y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 52 is the midpoint of the bin [50,55). Figure 1.C.2 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.

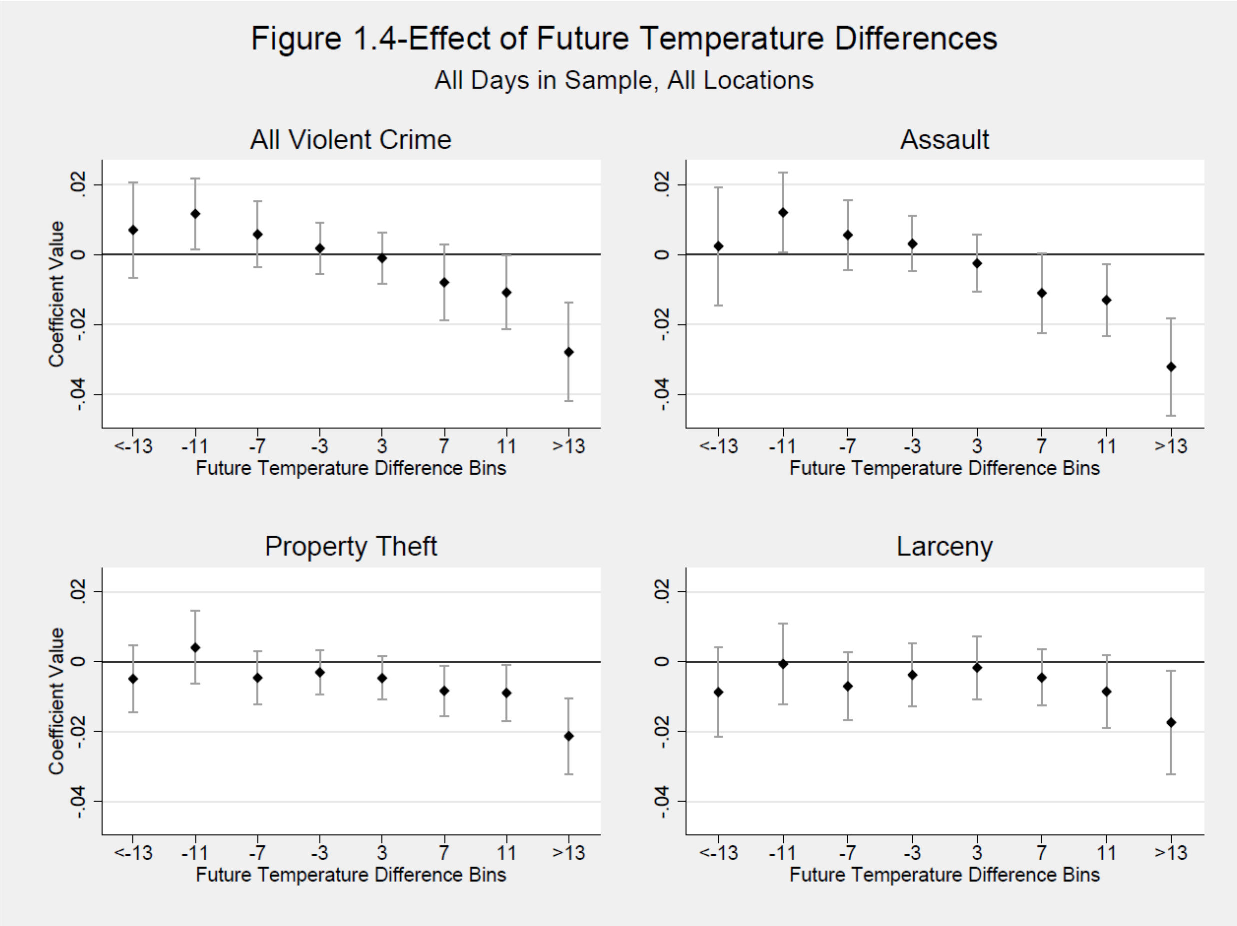
Figure 1.3-Effect of Forecast Errors

All Days in Sample, All Locations



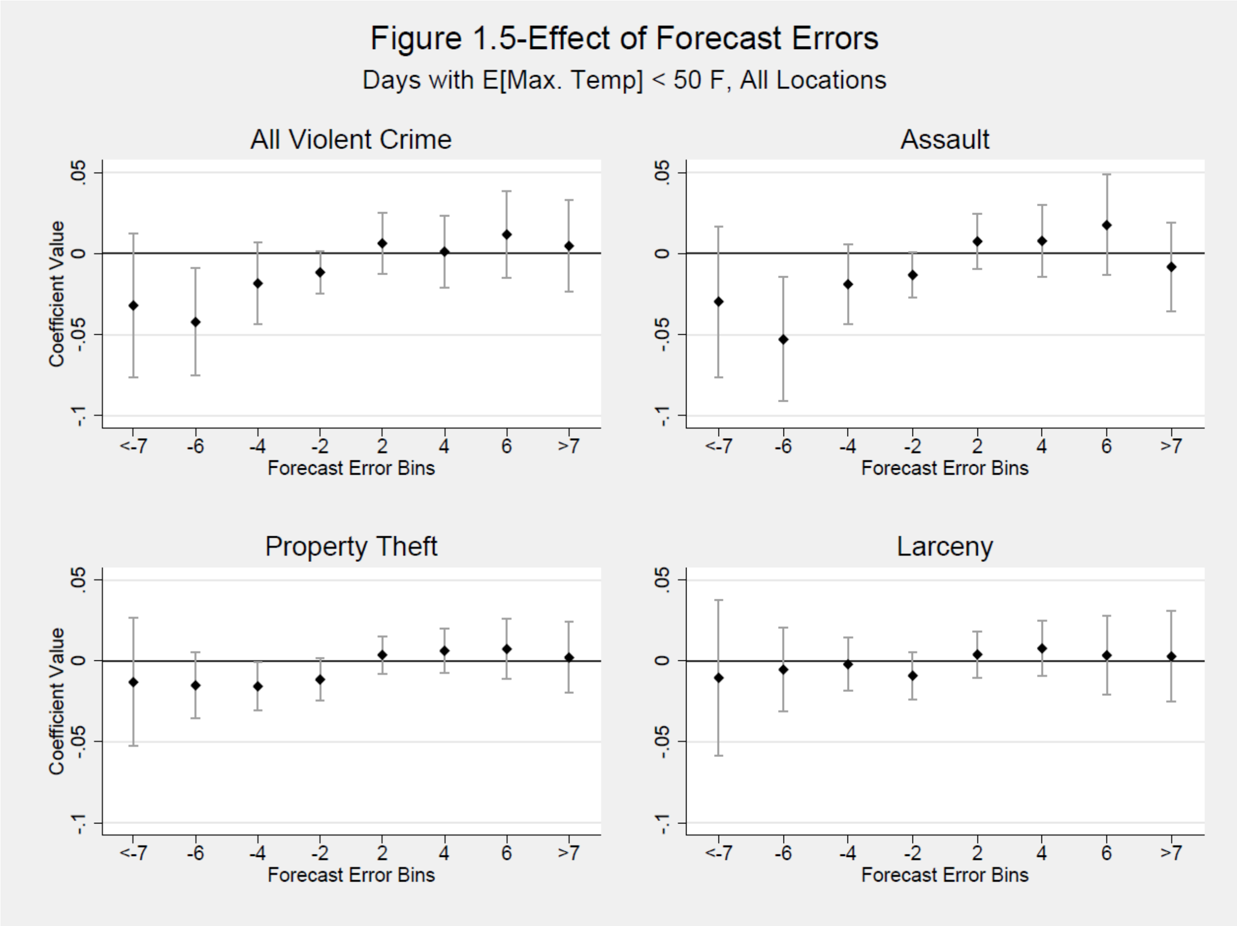
	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	141359	141359	141359	141359
F-Statistic	9.57	11.85	2.61	1.54
P-Value	0	0	0.02	0.17

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin [1,3). Figure 1.C.3 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.



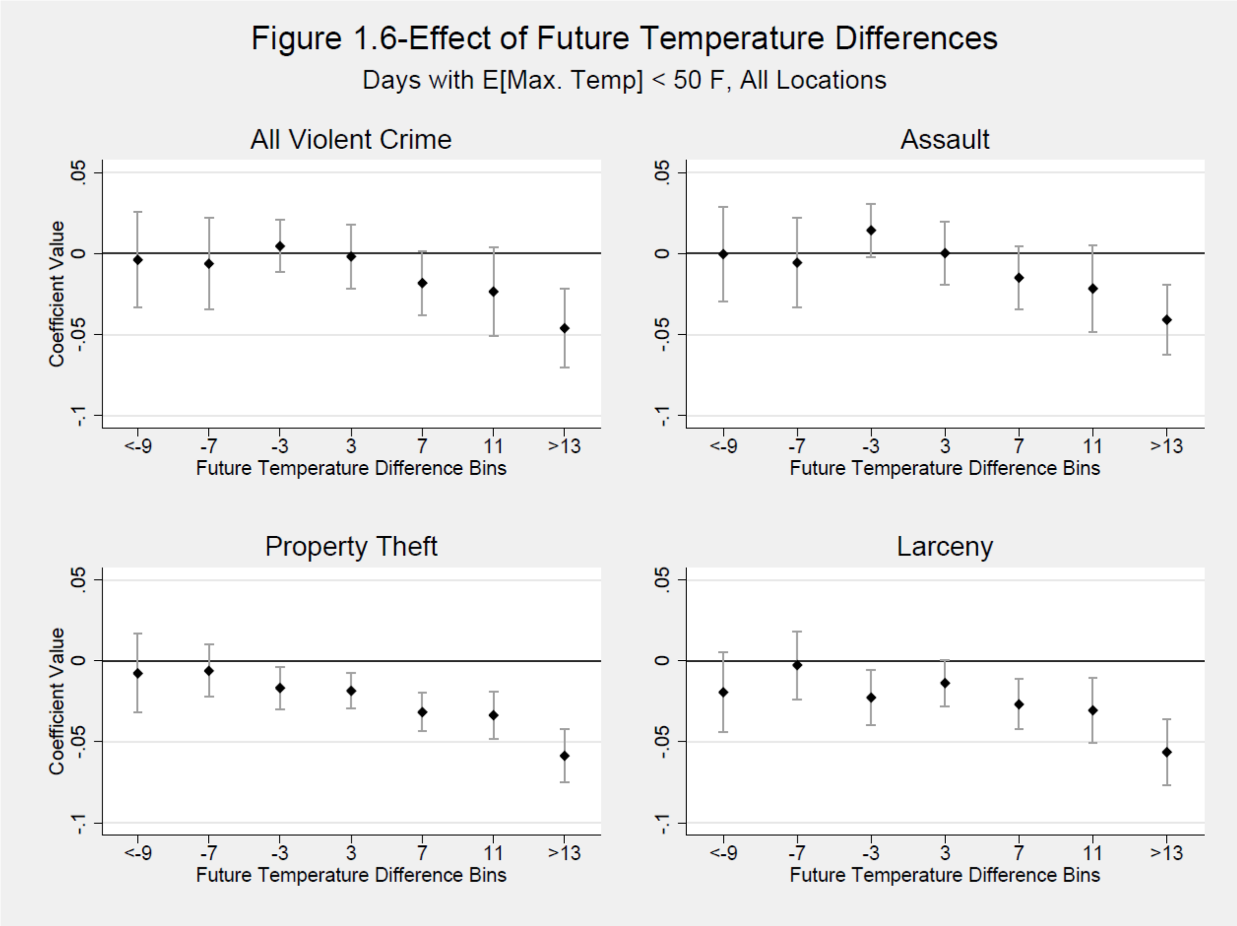
	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	141359	141359	141359	141359
F-Statistic	3.34	4.53	2.79	1.26
P-Value	0	0	0.01	0.28

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin [1, 5). Figure 1.C.4 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.84	0.81	0.87	0.81
Obs.	32892	32892	32892	32892
F-Statistic	1.96	2.46	1.59	0.42
P-Value	0.07	0.03	0.15	0.91

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days with an expected maximum temperature below 50 F. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin (1,3].



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.84	0.81	0.87	0.81
Obs.	32892	32892	32892	32892
F-Statistic	4.9	4.89	10.72	7.24
P-Value	0	0	0	0

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days with an expected maximum temperature below 50 F. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1+y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin (1,5].

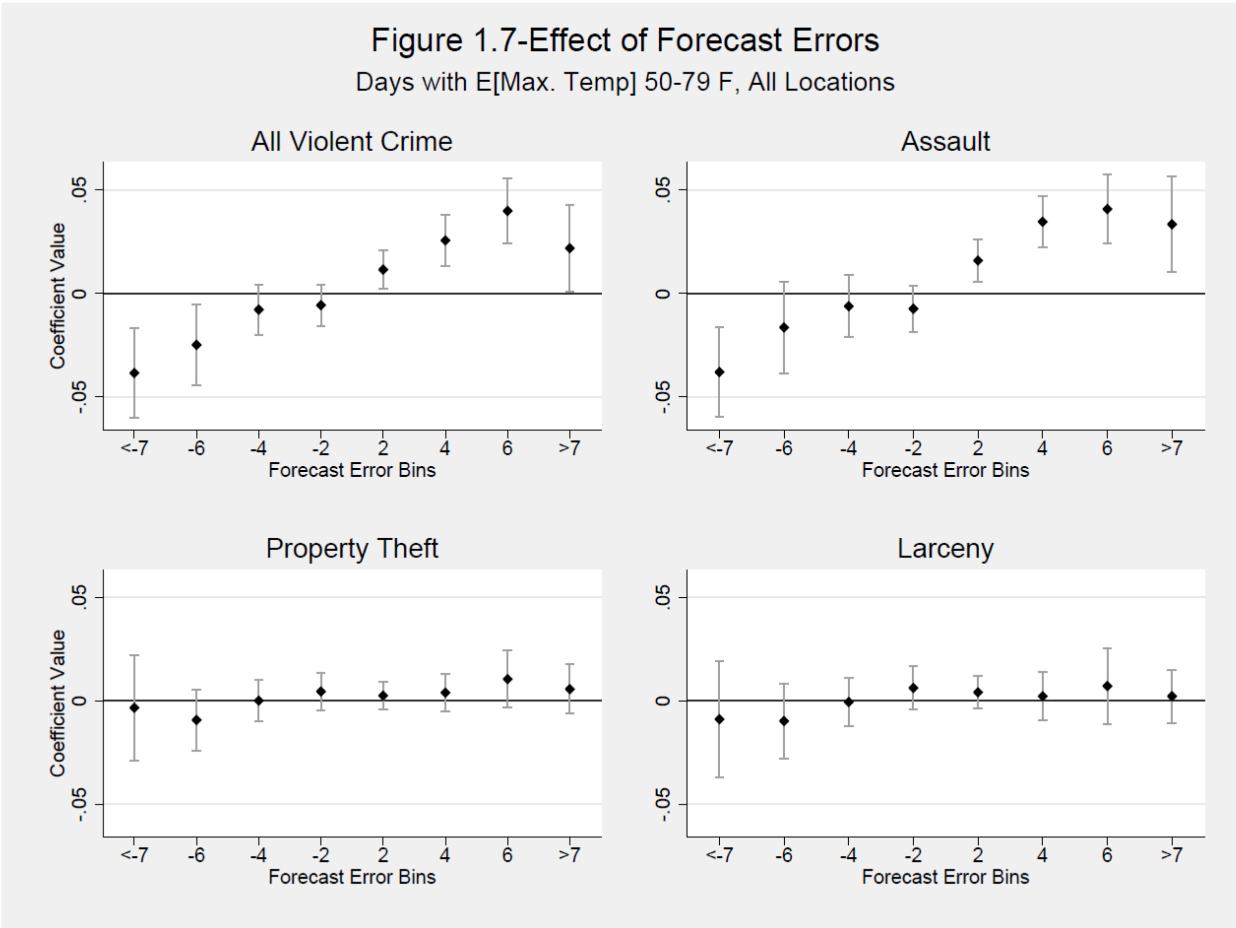


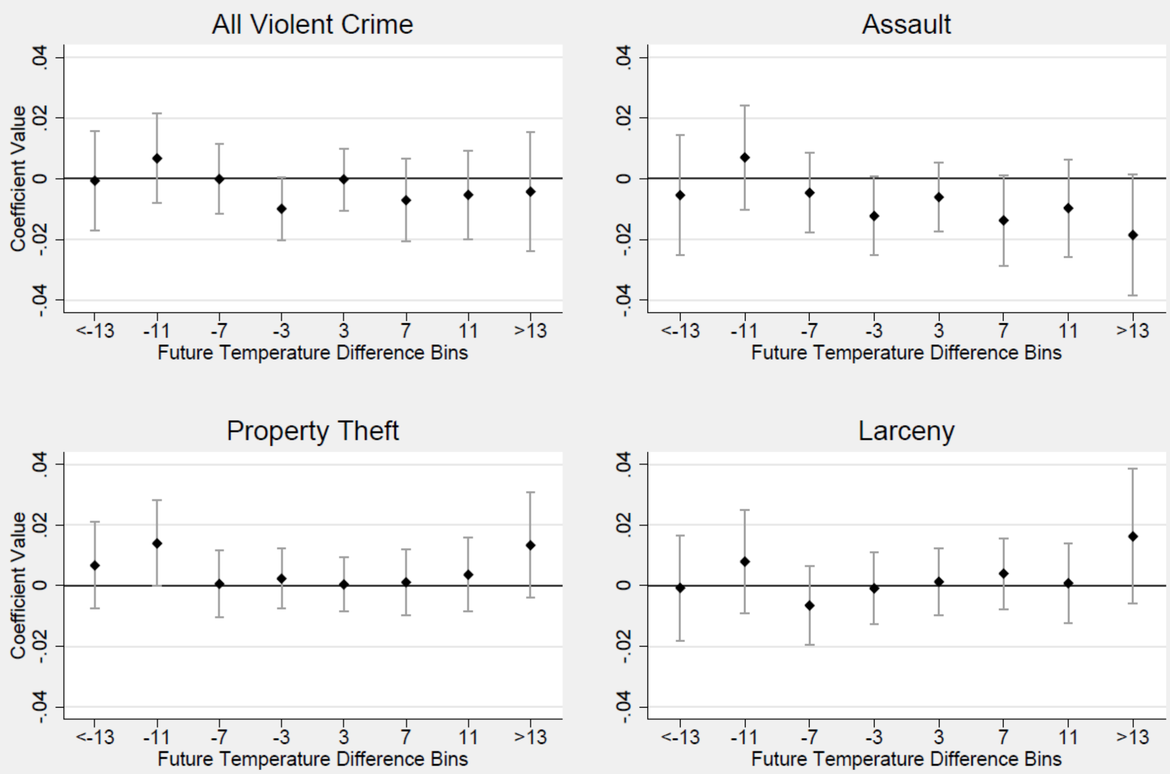
Figure 1.7-Effect of Forecast Errors
Days with E[Max. Temp] 50-79 F, All Locations

	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	64682	64682	64682	64682
F-Statistic	8.51	10.64	1.41	1.24
P-Value	0	0	0.22	0.3

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days with an expected maximum temperature in the range 50-79 F. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin [1,3].

Figure 1.8-Effect of Future Temperature Differences

Days with E[Max. Temp] 50-79 F, All Locations



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	64682	64682	64682	64682
F-Statistic	1.05	1.85	1.11	1.08
P-Value	0.41	0.09	0.37	0.39

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days with an expected maximum temperature in the range 50-79 F. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1+y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin (1,5].

	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.87	0.84	0.89	0.84
Obs.	43785	43785	43785	43785
F-Statistic	2.68	1.8	1.46	1.05
P-Value	0.02	0.1	0.2	0.42

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days with an expected maximum temperature at or above 80 F. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin (1,3].

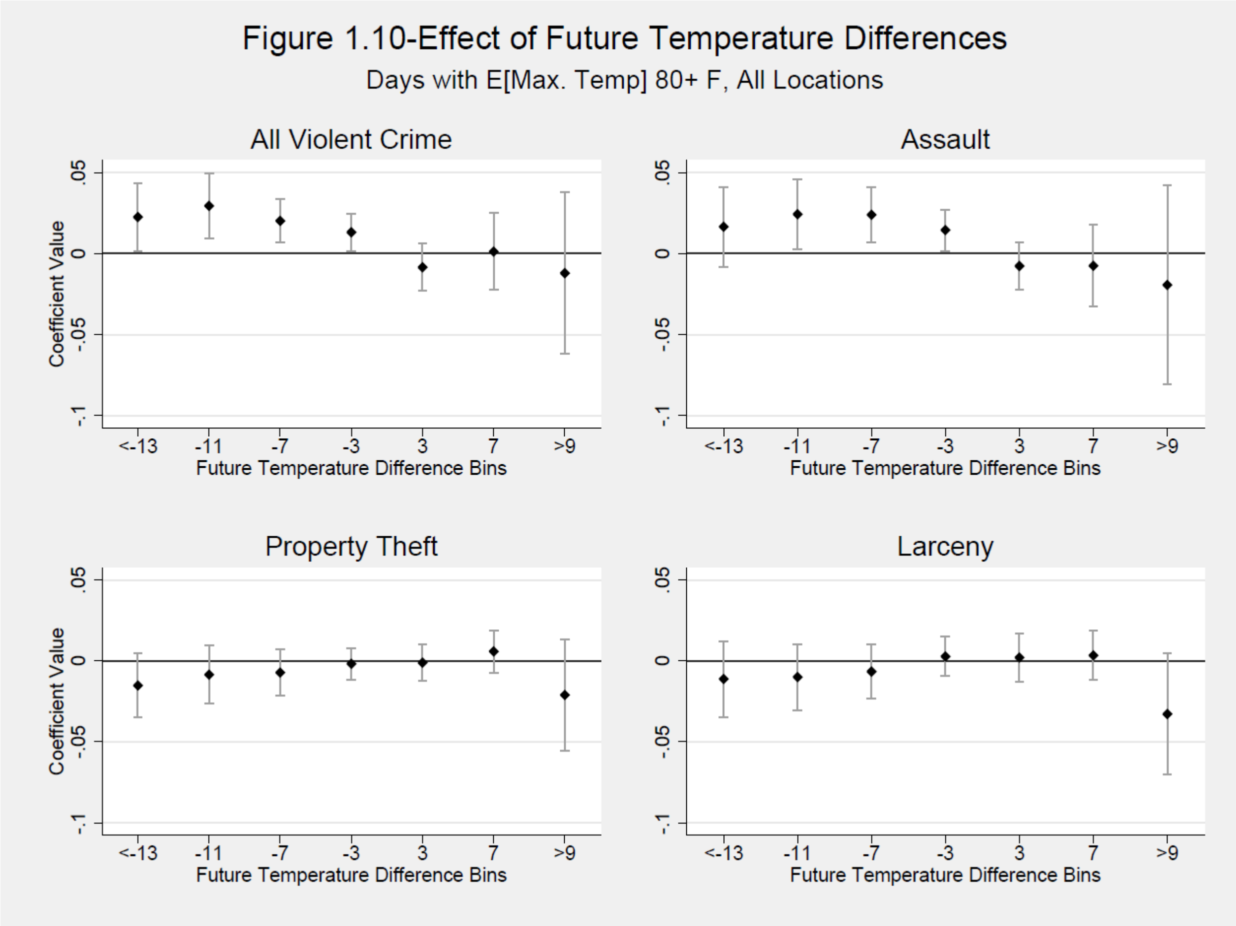
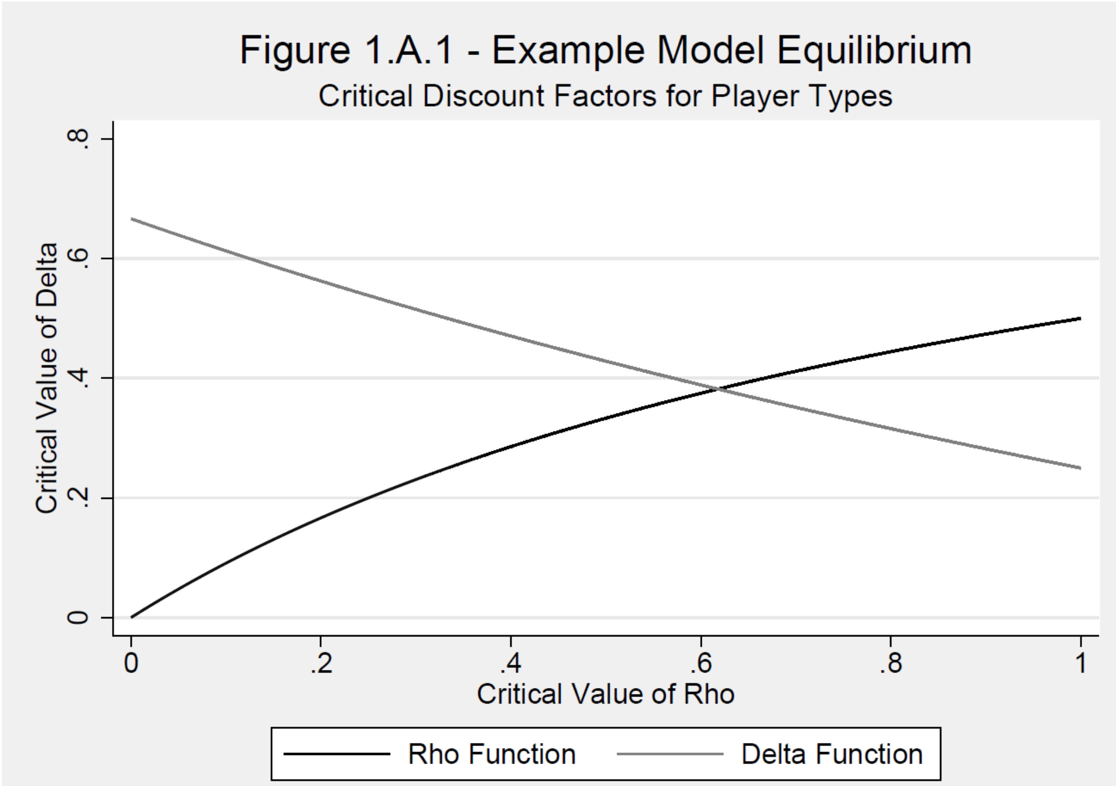


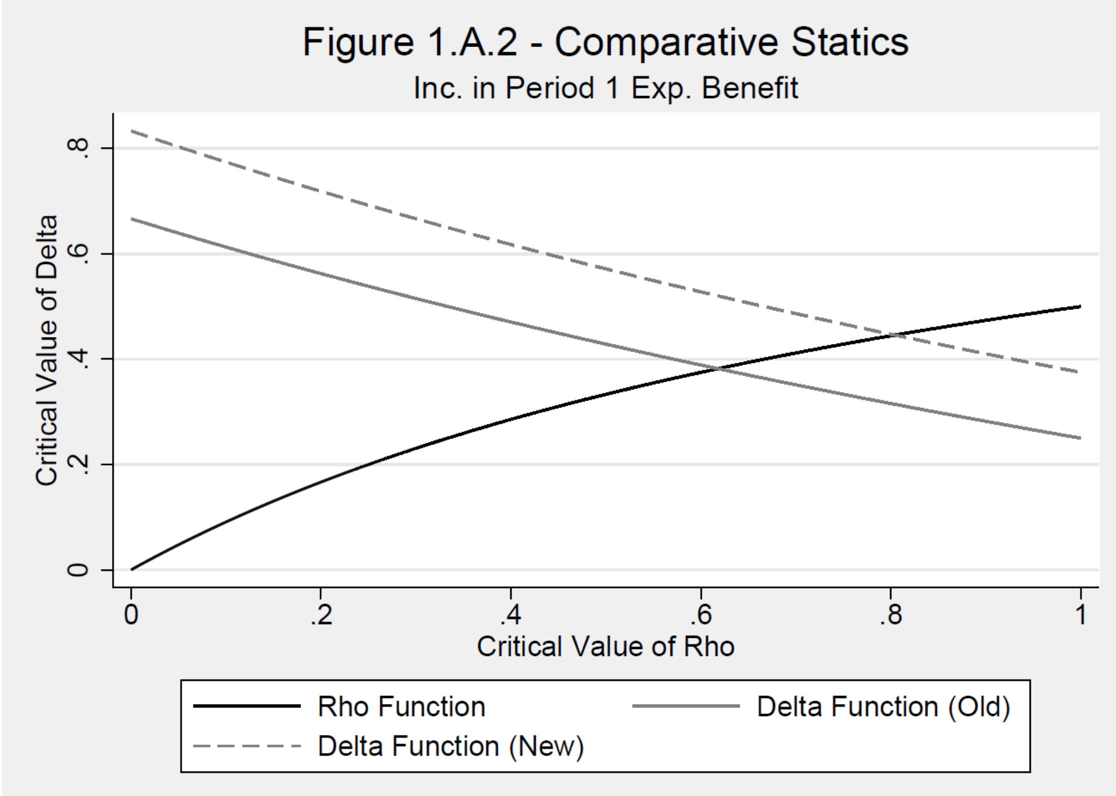
Figure 1.10-Effect of Future Temperature Differences
Days with E[Max. Temp] 80+ F, All Locations

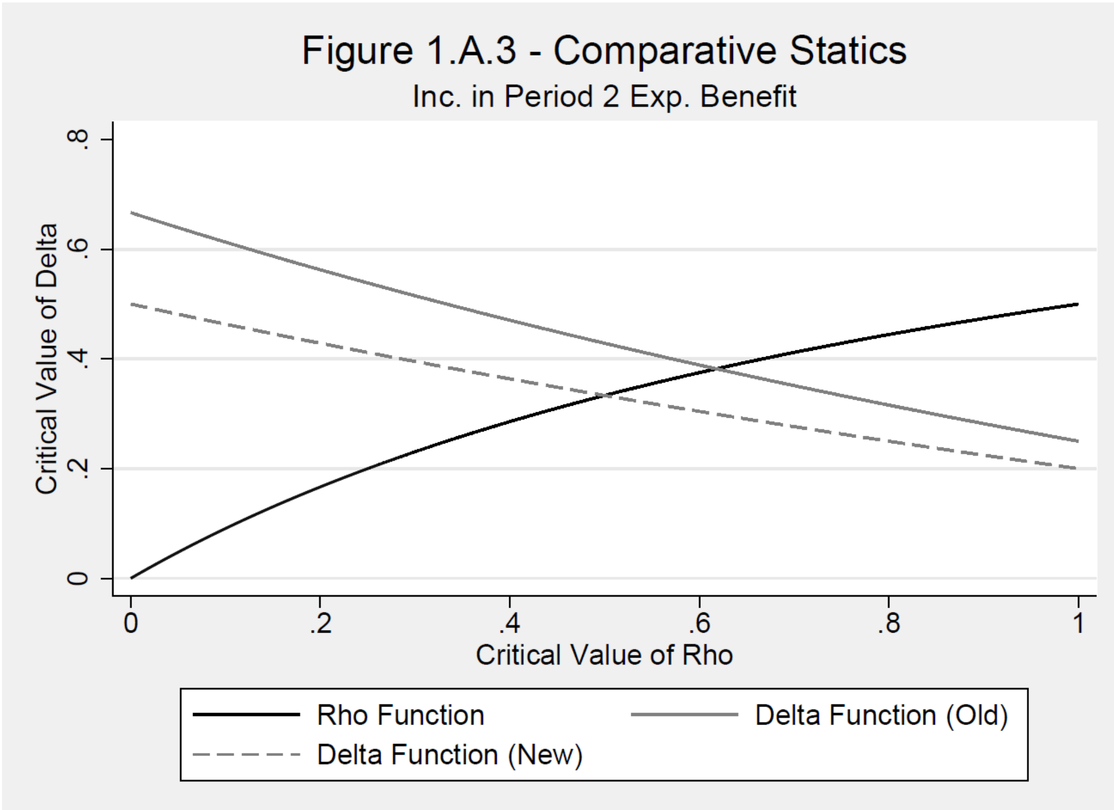
	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.87	0.84	0.89	0.84
Obs.	43785	43785	43785	43785
F-Statistic	2.38	1.88	0.81	1.29
P-Value	0.04	0.09	0.58	0.27

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days with an expected maximum temperature at or above 80 F. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin (1,5].

1.A Model Appendix







Notes: The three figures shown above provide an example equilibrium of the model discussed in Section 1.2 (Figure 1.A.1), along with two comparative statics reflecting the effect of an increase in Period 1 benefit (Figure 1.A.2) and Period 2 benefit (Figure 1.A.3). Every equilibrium consists of critical discount factors for each player type.

Model Solution

In Section 1.2, the maximization problems yielded a system of two non-linear equations:

$$\delta^c = \frac{b_1 - \rho^c\phi}{b_2 - (1-\rho^c)\phi}$$

$$\rho^c = \begin{cases} \dfrac{\delta^c}{1-\delta^c} & if\ \delta^c < 0.5 \\ 1 & if\ \delta^c \geq 0.5 \end{cases}$$

Let us assume an interior solution, so that the second equation simplifies to $\rho^c = \frac{\delta^c}{1-\delta^c}$. This system of two equations has two unknowns, and can be solved as follows:

$$\delta^c = \frac{b_1 - \rho^c\phi}{b_2 - (1-\rho^c)\phi} = \frac{b_1 - \left(\frac{\delta^c}{1-\delta^c}\right)\phi}{b_2 - \left(1 - \left[\frac{\delta^c}{1-\delta^c}\right]\right)\phi}$$

$$\Rightarrow \delta^c = \frac{b_1 - \left(\frac{\delta^c}{1-\delta^c}\right)\phi}{b_2 - \left(\frac{1-2\delta^c}{1-\delta^c}\right)\phi}$$

$$\Rightarrow \delta^c b_2 - \delta^c\phi\left(\frac{1-2\delta^c}{1-\delta^c}\right) = b_1 - \phi\left(\frac{\delta^c}{1-\delta^c}\right)$$

$$\Rightarrow \delta^c b_2(1-\delta^c) - \delta^c\phi(1-2\delta^c) = b_1(1-\delta^c) - \delta^c\phi$$

$$\Rightarrow (\delta^c b_2 - b_1)(1-\delta^c) - \delta^c\phi(-2\delta^c) = 0$$

$$\Rightarrow \delta^c b_2 - (\delta^c)^2 b_2 - b_1 + \delta^c b_1 + 2\phi(\delta^c)^2 = 0$$

$$\Rightarrow (2\phi - b_2)(\delta^c)^2 + (b_1 + b_2)\delta^c - b_1 = 0$$

$$\Rightarrow \delta^c = \frac{-(b_1+b_2) \pm \sqrt{b_1^2 + b_2^2 + 8\phi b_1 - 2b_1b_2}}{4\phi - 2b_2}$$

$$\Rightarrow \rho^c = \frac{-(b_1+b_2) \pm \sqrt{b_1^2 + b_2^2 + 8\phi b_1 - 2b_1b_2}}{4\phi - b_2 + b_1 \mp \sqrt{b_1^2 + b_2^2 + 8\phi b_1 - 2b_1b_2}}$$

For δ^c to be a real number, we must have $b_1^2 + b_2^2 + 8\phi b_1 - 2b_1 b_2 > 0$. With this assumption, reasonable values for the model constants dictate that the positive root be used.[39]

<u>Derivation of Important Derivatives</u>

In Section 1.2, formulas for $\frac{\partial \delta^c}{\partial b_1}$, $\frac{\partial \delta^c}{\partial b_2}$, $\frac{\partial \rho^c}{\partial b_1}$, and $\frac{\partial \rho^c}{\partial b_1}$ are given. In the following lines, those expressions are derived formally:

$\frac{\partial \rho^c}{\partial b_1}$

$$\rho^c = \frac{\delta^c}{1 - \delta^c}$$

$$Define \begin{array}{c} f = \delta^c \\ g = 1 - \delta^c \end{array}$$

$$\frac{\partial \rho^c}{\partial b_1} = \frac{gf' - fg'}{g^2} = \frac{(1 - \delta^c)\frac{\partial \delta^c}{\partial b_1} - \delta^c\left(-\frac{\partial \delta^c}{\partial b_1}\right)}{(1 - \delta^c)^2} = \frac{\frac{\partial \delta^c}{\partial b_1}}{(1 - \delta^c)^2}$$

$\frac{\partial \rho^c}{\partial b_2}$

$$\rho^c = \frac{\delta^c}{1 - \delta^c}$$

$$Define \begin{array}{c} f = \delta^c \\ g = 1 - \delta^c \end{array}$$

$$\frac{\partial \rho^c}{\partial b_1} = \frac{gf' - fg'}{g^2} = \frac{(1 - \delta^c)\frac{\partial \delta^c}{\partial b_2} - \delta^c\left(-\frac{\partial \delta^c}{\partial b_2}\right)}{(1 - \delta^c)^2} = \frac{\frac{\partial \delta^c}{\partial b_2}}{(1 - \delta^c)^2}$$

[39] Given that the constants λ and π_0 are intuitively very small numbers, the constant $\phi = \lambda P^B \pi_0 L$ should also be very small.

$\frac{\partial \delta^c}{\partial b_1}$

$$\delta^c = \frac{b_1 - \rho^c \phi}{b_2 - (1 - \rho^c)\phi}$$

$$Define \quad \begin{aligned} f &= b_1 - \rho^c \phi \\ g &= b_2 - (1 - \rho^c)\phi \end{aligned}$$

$$\Longrightarrow \frac{\partial \delta^c}{\partial b_1} = \frac{gf' - fg'}{g^2} = \frac{[b_2 - (1 - \rho^c)\phi]\left(1 - \phi \frac{\partial \rho^c}{\partial b_1}\right) - (b_1 - \rho^c \phi)\left(\phi \frac{\partial \rho^c}{\partial b_1}\right)}{[b_2 - (1 - \rho^c)\phi]^2}$$

$$Define \quad \begin{aligned} \mathrm{K}_1 &= b_1 - \rho^c \phi \\ \mathrm{K}_2 &= b_2 - (1 - \rho^c)\phi \end{aligned}$$

$$\Longrightarrow \frac{\partial \delta^c}{\partial b_1} = \frac{\mathrm{K}_2\left(1 - \phi \frac{\frac{\partial \delta^c}{\partial b_1}}{(1 - \delta^c)^2}\right) - \mathrm{K}_1\left(\phi \frac{\frac{\partial \delta^c}{\partial b_1}}{(1 - \delta^c)^2}\right)}{\mathrm{K}_2^2}$$

$$\Longrightarrow \frac{\partial \delta^c}{\partial b_1} \mathrm{K}_2^2 (1 - \delta^c)^2 = \mathrm{K}_2 (1 - \delta^c)^2 - \phi \mathrm{K}_2 \frac{\partial \delta^c}{\partial b_1} - \phi \mathrm{K}_1 \frac{\partial \delta^c}{\partial b_1}$$

$$\Longrightarrow \frac{\partial \delta^c}{\partial b_1} [\mathrm{K}_2^2 (1 - \delta^c)^2 + \phi \mathrm{K}_2 + \phi \mathrm{K}_1] = \mathrm{K}_2 (1 - \delta^c)^2$$

$$\Longrightarrow \frac{\partial \delta^c}{\partial b_1} = \frac{(1 - \delta^c)^2 \mathrm{K}_2}{\mathrm{K}_2^2 (1 - \delta^c)^2 + \mathrm{K}_2 \phi + \mathrm{K}_1 \phi}$$

$\frac{\partial \delta^c}{\partial b_2}$

$$\delta^c = \frac{b_1 - \rho^c \phi}{b_2 - (1 - \rho^c)\phi}$$

$$Define \begin{array}{c} f = b_1 - \rho^c \phi \\ g = b_2 - (1-\rho^c)\phi \end{array}$$

$$\Rightarrow \frac{\partial \delta^c}{\partial b_2} = \frac{gf' - fg'}{g^2} = \frac{[b_2 - (1-\rho^c)\phi]\left(-\phi \frac{\partial \rho^c}{\partial b_2}\right) - (b_1 - \rho^c \phi)\left(1 + \phi \frac{\partial \rho^c}{\partial b_2}\right)}{[b_2 - (1-\rho^c)\phi]^2}$$

$$Define \begin{array}{c} \mathrm{K}_1 = b_1 - \rho^c \phi \\ \mathrm{K}_2 = b_2 - (1-\rho^c)\phi \end{array}$$

$$\Rightarrow \frac{\partial \delta^c}{\partial b_2} = \frac{\mathrm{K}_2\left(-\phi \frac{\frac{\partial \delta^c}{\partial b_2}}{(1-\delta^c)^2}\right) - \mathrm{K}_1\left(1 + \phi \frac{\frac{\partial \delta^c}{\partial b_2}}{(1-\delta^c)^2}\right)}{\mathrm{K}_2^2}$$

$$\Rightarrow \frac{\partial \delta^c}{\partial b_2} \mathrm{K}_2^2 (1-\delta^c)^2 = -\phi \mathrm{K}_2 \frac{\partial \delta^c}{\partial b_2} - \mathrm{K}_1 (1-\delta^c)^2 - \mathrm{K}_1 \phi \frac{\partial \delta^c}{\partial b_2}$$

$$\Rightarrow \frac{\partial \delta^c}{\partial b_1} = \frac{-(1-\delta^c)^2 \mathrm{K}_1}{\mathrm{K}_2^2 (1-\delta^c)^2 + \mathrm{K}_2 \phi + \mathrm{K}_1 \phi}$$

1.B Data Appendix

NIBRS Data

The National Incident Based Reporting System (NIBRS) is a database of incident level crime data that law enforcement agencies of various types contribute to. The majority of these agencies are city police departments, though county, state, and university agencies are also present. In this paper, I focus exclusively on city police departments. Unlike the FBI's Uniform Crime Reports (UCR) system, law enforcement agencies are not required to report to NIBRS; in fact, an agency must apply to do so, since the reporting requirements are much more stringent. As the name suggests, the data contained in NIBRS includes information about individual criminal incidents. Used in this sense, an "incident" is a set of criminal offenses, offenders, victims, and other circumstances that are connected in time and space. In the full NIBRS database, a single incident may include up to 10 offenses, 99 offenders, 99 victims, and 99 arrestees.

Of course, in practice criminal incidents are rarely so complex. Since the complete NIBRS database is notoriously difficult to manage, the Inter-university Consortium for Political and Social Research (ICPSR) produces annual NIBRS extracts, which limit the information available for each incident. For instance, NIBRS extracts only allow for 3 offenses, victims, offenders, and arrestees in each incident. These simplifications reduce the (still very large) size of the dataset, but in practice less than 1% of NIBRS incidents are affected.

All offenses in the NIBRS database are identified by one of over 40 possible crime codes. These codes are based on those used in the UCR system. Two crime categories are studied in this paper: violent crime and property theft. Violent crime is defined as the sum of homicide, assault, sexual assault, robbery, and weapons violations.[40] Property theft is defined at the sum of larceny, burglary, motor vehicle theft, and stolen property offenses (i.e. possession or distribution of stolen property). These categories are defined again (along with the relevant UCR crime codes) in Table 1.C.1. Collectively, violent crime and property theft account for about 70% of criminal activity on any given day, with most of the remainder being accounted for by vice crimes (especially drug offenses), property damage offenses, and offenses related to disorderly conduct.

Forecast Accuracy

A central issue in this paper is forecast accuracy, including actual accuracy and people's perceptions of accuracy. Tables 1.C.2 and 1.C.3 address realized forecast accuracy in two separate senses. First, one might be concerned that forecast accuracy changes in the very near term; for example, is a forecast published at 12:00pm on day $t-1$ a less accurate prediction of the weather on day t, compared to a forecast published at 9:00pm on the same day? If this were the case, then the practice (adopted in this paper) of taking the latest available forecast from day $t-1$ to predict the weather on days t through $t+6$ could be problematic. In fact, there is no evidence to support such a conclusion. Table 1.C.2 reports the results of splitting the forecast data into four groups, and then measuring the accuracy of each forecast group by regressing observed outcomes from day t on forecast values from $t-1$. Each group represents a 3-hour block in which a forecast might be published during the afternoon of day $t-1$ (12:00pm-2:59pm, 3:00pm-5:59pm, 6:00pm-8:59pm, and

[40] These terms are themselves aggregates of more specific offenses. For example, "assault" is defined as the sum of simple assault, aggravated assault, and intimidation.

9:00pm-11:59pm). For daily maximum temperature (Panel 1), the dependent variable in each regression is observed maximum temperature on day t, while the independent variable is forecast maximum temperature on day $t-1$. Regardless of when the forecast is published, the coefficient values for temperature are between 0.97 and 0.98, with R-squared values hovering in the 0.97 range. Daytime precipitation forecasts are less accurate overall (as demonstrated in Panel 2), but once again that accuracy does not appear to depend on the time of publication on day $t-1$.

Table 1.C.2 establishes that any forecast published during the afternoon of day $t-1$ will accurately forecast the weather on day t. However, this paper also looks at expectations in the near future (i.e. beyond day t). Consequently, one would also like to know how accurate the $t-1$ predictions are for days $t+1$ to $t+6$ (the last day in the 7-day forecast). Table 1.C.3 addresses this question by regressing observed weather during each day on the $t-1$ forecast value pertaining to that day.[41] As one would expect, the explanatory power of weather forecasts appears to diminish steadily as one goes further into the future, especially in the case of precipitation (see Panel 2 of Table 1.C.3). However, maximum temperature forecasts continue to have remarkable explanatory power, even up to day $t+6$.

For the purposes of this paper it is not necessarily of paramount importance that forecasts are actually accurate; rather, it is necessary that people perceive them to be accurate (otherwise forecasts would not capture the expectations that people form about the near future). Lazo, Morss, and Demuth (2009) suggests that people perceive weather forecasts to be highly accurate, especially if the time being forecast is within 3 days of the

[41] The nature of these regressions is akin to Table 1.C.2.

prediction's publication.[42] For forecasts that apply to the more distant future, confidence declines; however, a significant minority of people continue to maintain confidence in forecasts that apply to time periods as far as one week into the future.

Matching Cities to Weather Stations and Forecast Locations

One of the most important parts of creating the dataset used in this paper is the matching of cities to weather stations and forecast locations. In this context, the weather station is the location from which observed weather data is drawn for a given city, and the forecast location is the official forecast city that each city in the sample is assigned to.[43] In all cases, I adopt the practice of using one weather station and one forecast location for each city.

This matching process proceeds in two stages, with the goal of maximizing the accuracy of observed and expected weather for each city. In the first stage, I match each city with the best possible weather station during 2004-2012 period. For a time series of this length, most cities only have one or two candidates for a complete or near-complete record of daily weather data. In almost every case, the weather stations that have the longest and most comprehensive records belong to local airports or military bases; in fact, every weather station used in this paper falls into one of those categories. Outside of requiring that the weather station chosen for each city has no more than a handful of missing values for the time period studied, I also require that a weather station be within 12 miles of the center of

[42] The authors find that 75% of survey respondents who use weather forecasts regularly (96.4% of the overall sample) place at least medium confidence in forecasts for a time 3 days into the future. Confidence is even higher, as one would expect, for forecast that are made for times in the nearer future.

[43] In most cases, the "forecast city" is the same as the city whose crime data is being used, so the term "forecast location" is usually synonymous with the name of the city the forecast is being assigned to in the data. However, there are exceptions to the rule. Stamford, CT is one such example, since the forecast applied to Stamford in my dataset actually comes from nearby White Plains, NY.

the city (or cities) to which it is assigned.[44] All observed weather data were downloaded from the online archive Wunderground.

Having made every effort to accurately represent each city's observed weather conditions in the first step, the second stage of the matching process involves matching a forecast location to each weather station. This process is made difficult by the fact that forecast locations for the Tabular State Forecast product are usually given as city names, as opposed to individual weather stations.[45] My approach to identifying forecasts that are appropriate for each weather station chosen is to require that forecasts meet certain accuracy conditions. Specifically, I consider a forecast location to be well-matched to a weather station if it satisfies two conditions:

1. The average daily maximum temperature forecast error is no more than 1 F in absolute value.
2. No more than 3% of all maximum temperature forecast errors are more than 10 F in magnitude.

As long as a weather station/forecast location pairing meets these conditions,[46] then it is accepted as a good pairing for the dataset used in this paper. These requirements (especially the first) are quite stringent.

[44] City center-to-station distances were calculated using coordinate data from the batch geocoder GPS Visualizer, which is a free online service that draws coordinate data from Bing Maps. Using the coordinates of each location, one is able to measure the distance between them using the Spherical Law of Cosines.
[45] According to a discussion I have had with an NWS forecaster familiar with the production of the TSF, all TSF forecasts literally apply to a specific weather station, even though they are given a broader heading that captures the city to which they should be applied. For a given city, the weather station that the TSF applies to is apparently usually the nearest airport or military base.
[46] Both conditions are calculated *after* excluding observed weather data that seems impossible or highly improbable. See the section "Sample Restrictions and Dropped Observations" for details.

Sample Restrictions and Dropped Observations

The main text of the paper identified some restrictions that I have placed on the sample, and the appendix above has gone into more detail. However, I summarize all of these conditions here for reference. First, I will highlight the restrictions which determined whether a given city was included in the dataset:

1. All included cities must appear in the NIBRS database during the entirety of the 2006-2012 period. If available, data from 2004 and 2005 are also used.
2. Cities are added according to population, as measured by the 2006-2012 average population of each city. Thus, the sample includes the largest 50 cities (according to this measure) in the NIBRS database that meet all other sample restriction conditions.
3. It must be possible to match each city with a weather station from the Wunderground archive that 1) covers the 2004-2012 period, 2) has very few (preferably no) missing weather observations, 3) is located no more than 12 miles from the city center, and 4) can be matched to a forecast location that meets the accuracy conditions cited earlier in this appendix.

All cities that satisfy these conditions are included in the final sample. However, additional observations are dropped in some special cases:

1. Highly improbable forecast errors – Any city-day with a maximum temperature forecast error larger than 15 F is dropped, since it is almost certain that such cases represent bad observations from the weather station assigned to the city. Errors of this size are very rare (about 0.2% of the possible study sample).
2. Highly improbably precipitation values – Any city-day reporting total precipitation in excess of 10” is dropped. This is also an extremely rare event.

Unusual crime trends – The NIBRS data includes a flag that identifies when each agency started reporting to NIBRS, as well as flags that identify any period of time in which the agency might not be reporting (for example, if a smaller agency has deferred to a larger local authority to report to NIBRS). To be considered for this study, a NIBRS agency must be self-reporting. Even so, as a check of the data, trends in daily crime counts were examined for each city. In three cases (Grand Rapids, MI; Newport News, RI; Lawrence, KS) highly irregular dips in the overall offense rate were observed in isolated periods of time. During these periods, there would be several consecutive days of little-or-no reported crime, which is incredible for cities of this size. Since these irregularities were very brief and did not persist over time, my approach was to drop any city-month in which such an irregular period occurred. A total of 6 city-months are dropped for this reason.

1.C Additional Tables and Figures

Table 1.C.1 - Description of Major Crime Categories
UCR Codes in Parentheses

Violent Crime	Includes all forms of homicide (91-3), all forms of assault (131-133), sexual assaults (111-114), robbery (120), and weapons violations (150).
Property Theft	Includes all forms of larceny (2331-238), burglary (220), motor vehicle theft (240), and stolen property offenses.

Notes: This table defines the major categories of crime studied in this paper. As is clear from the table, larceny and assault (which are also studied individually) are subcategories of property theft and violent crime (respectively). The components of each category are defined in the data using a standardized coding system adopted by the FBI's Uniform Crime Reports (UCR).

Table 1.C.2 - Relationship Between Forecast Time and Forecast Accuracy

Panel 1 - Temperature	All Times	12pm-3pm	3pm-6pm	6pm-9pm	9pm-12am
	[1]	[2]	[3]	[4]	[5]
Forecast Max. Temp.	0.979***	0.987***	0.978***	0.981***	0.978***
	(0.00168)	(0.00234)	(0.00193)	(0.00222)	(0.00254)
Observations	141,359	7,996	99,820	10,702	22,841
R-Squared	0.970	0.966	0.970	0.971	0.969
Panel 2 - Precipitation (Linear Probability Models)					
Forecast Chance Precip.	0.011***	0.013***	0.011***	0.012***	0.011***
	(0.00019)	(0.00029)	(0.00020)	(0.00030)	(0.00027)
Observations	141,359	7,996	99,820	10,702	22,841
R-Squared	0.390	0.451	0.387	0.385	0.383

Notes: Panel 1 of this table includes regressions of observed maximum temperature on forecast daytime (6:00am - 6:00pm) maximum temperature. Panel 2 contains linear probability models, where the left-hand side variable is an indicator for positive total daily precipitation, and the right-hand side variable is the daytime chance of precipitation. Column 1 regressions include all 141,359 city-days in the 2004-2012 sample of 50 NIBRS cities. In the remaining columns, the sample has been split according to when the forecast for each city-day was published. Column 2 includes all city-days with forecast times between 12:00pm and 2:59pm of the previous day, for example. Standard errors are clustered by city. Significance indicators: * - 0.10 , ** - 0.05 , *** - 0.01

Table 1.C.3 - Accuracy of Max. Temperature Forecasts for Future Days

	Future Days					
Panel 1 - Temperature	T + 1	T + 2	T + 3	T + 4	T + 5	T + 6
	[1]	[2]	[3]	[4]	[5]	[6]
Forecast Max. Temp.	0.977***	0.975***	0.975***	0.972***	0.968***	0.967***
	(0.00171)	(0.00154)	(0.00156)	(0.00180)	(0.00201)	(0.00212)
Observations	141,335	141,332	141,330	141,328	141,326	141,327
R-Squared	0.957	0.941	0.925	0.906	0.886	0.864
Panel 2 - Precipitation (Linear Probability Models)						
Forecast Chance Precip.	0.012***	0.014***	0.015***	0.015***	0.014***	0.012***
	(0.00023)	(0.00025)	(0.00028)	(0.00033)	(0.00039)	(0.00048)
Observations	141,225	141,221	141,213	141,214	141,211	141,213
R-Squared	0.347	0.294	0.236	0.171	0.118	0.067

Notes: Panel 1 of this table includes regressions of observed maximum temperature during future days (t+1, t+2, ... ,t+6) on forecast maximum temperature (where the forecast is published during the afternoon of day t-1). Panel 2 includes linear probability models in which the dependent variable is an indicator for observed precipitation on day t+j, and the only right hand side variable is the forecast chance of daytime precipitation for that day. Once again, the forecasts used were published on day t-1. Standard errors are clustered by city. Significance indicators: * - 0.10 , ** - 0.05 , *** - 0.01

Table 1.C.4 - Description of Regression Controls

Control	Description
Year-by-City Fixed Effects	Indicators for every city-year in the sample (e.g. there is an indicator for Detroit-2006).
Day-of-Week Fixed Effects	Indicators for every day-of-week in the sample (e.g. there is an indicator for Fridays).
Month-by-City Fixed Effects	Indicators for every city-month in the sample (e.g. there is an indicator for Detroit-January).
First of Month Indicator	An indicator for whether a given day is the first day of a month.
Holiday/Unique Day Indicators	A set of indicators capturing 17 major holidays and other days that have special significance. The list includes: New Year's Day, MLK Day, Presidents Day, Fat Tuesday, St. Patrick's Day, Easter, Memorial Day, July 4th, Labor Day, Columbus Day, Halloween, Veterans Day, Thanksgiving, Black Friday, Christmas Eve, Christmas Day, and New Year's Eve.
Daily Total Precipitation (Current Day)	This set of controls is a semi-parametric bin estimator that uses six bins to capture precipitation on the current day. The bins are: 0," (0," 0.25"), [0.25," 0.5"), [0.5," 0.75"), [0.75," 1"), and 1+." The first bin (0") is the omitted category.
Lagged Daily Precipitation	This set of controls is identical to what is described above for daily total precipitation on the current day, the precipitation value simply applies to the previous day (i.e. day $t-1$).
Lagged Daily Maximum Temperature	This set of controls is a semi-parametric bin estimator that uses fourteen bins to capture maximum temperature on the previous day. The bins are: < 35 F, 35-39 F, 40-44 F, 45-49 F, 50-54 F, 55-59 F, 60-64 F, 65-69 F, 70-74 F, 75-79 F, 80-84 F, 85-89 F, 90-94 F, 95 + F. the first bin (< 35 F) is the omitted category.
Daytime Chance of Precipitation (Current Day)	This set of controls is a semi-parametric bin estimator that uses six bins to capture the daytime chance of precipitation on the current day. The bins are: [0%, 10%], (10%, 30%], (30%, 50%], (50%, 70%], (70%, 90%], 90+%. The first bin ([0%, 10%]) is the omitted category.
Future Chance of Precipitation (Difference)	This set of controls is a semi-parametric bin estimator that uses seven bins to capture the difference between the daytime chance of precipitation on the current day and the average daytime chance of precipitation over the six days beyond the current day. The bins are: < - 70%, [-70%, -50%), [-50%, -30%), [-30%, -10%), [-10%, 10%], (10%, 30%], 30+%. [-10%, 10%] is the omitted category.

Table 1.C.5 - Effect of Temperature Expectations and Forecast Errors on Crime
Linear Models

	Violent Crime		Property Theft	
	All	Assault	All	Larceny
	[2]	[3]	[4]	[5]
Exp. Max. Temp. (EMT)	0.00468***	0.00473***	0.00292***	0.00335***
	(0.000294)	(0.000315)	(0.000312)	(0.000372)
Forecast Error (FE)	0.00294***	0.00327***	0.00118***	0.00104**
	(0.000390)	(0.000378)	(0.000290)	(0.000411)
Future Temp. Diff. (FTD)	-0.000169	-0.000390	0.000617**	0.00108***
	(0.000314)	(0.000383)	(0.000237)	(0.000303)
Observations	0.85	0.83	0.88	0.83
R-Squared	141359	141359	141359	141359
EMT = FE (P-Value)	0	0	0	0

Notes: The T_t^e, e_t, and D_f^e coefficients reported in Panel 1 of this table are produced by estimating equation (13) in Section 1.3 of the text. All regressions include the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, a control for current day total precipitation, a control for current day daytime chance of precipitation, and a control for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The p-value reported pertains to the hypothesis test that the T_t^e and e_t coefficients are equal. Standard errors are clustered by city.

Table 1.C.6 - Effect of Observed Precipitation on Crime

Omitted Category: 0" precipitation

	Violent Crime		Property Theft	
	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]
[0.01, 0.24]	-0.00576	-0.00673*	0.00225	-0.00190
	(0.00354)	(0.00340)	(0.00205)	(0.00272)
[0.25, 0.49]	-0.0254***	-0.0264***	-0.00861**	-0.0140**
	(0.00590)	(0.00569)	(0.00390)	(0.00554)
[0.5, 0.74]	-0.0531***	-0.0600***	-0.0158**	-0.0164*
	(0.00724)	(0.00790)	(0.00718)	(0.00845)
[0.75, 0.99]	-0.0404***	-0.0403***	-0.0129**	-0.0171**
	(0.0105)	(0.0119)	(0.00597)	(0.00815)
≥ 1	-0.0685***	-0.0647***	-0.0112	-0.0221**
	(0.00780)	(0.00887)	(0.00710)	(0.00840)
R-Squared	0.85	0.83	0.88	0.83
Observations	141359	141359	141359	141359
F-Stat	19.37	18.17	3.4	2.73
P-Value	0	0	0.01	0.03

Notes: The coefficients reported in this table are obtained by estimating the regression given by equation (14) in Section 1.3 of the text. Observed precipitation is one of the controls included in $X_{i,t}$, and is represented using a semiparametric bin estimator with six bins. City-days on which the recorded precipitation is 0" form the omitted category. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city.

Table 1.C.7 - Effect of Current Chance of Precipitation on Crime

Omitted Category: ≤ 10% Chance of Precipitation

	Violent Crime		Property Theft	
	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]
[11, 30]	0.000231	0.00313	0.00383	0.00204
	(0.00326)	(0.00391)	(0.00283)	(0.00385)
[31, 50]	-0.0136**	-0.0147**	0.00973*	0.00703
	(0.00659)	(0.00727)	(0.00556)	(0.00710)
[51, 70]	-0.0112	-0.0135	0.00394	-0.00300
	(0.0124)	(0.0133)	(0.00771)	(0.00936)
[71, 90]	-0.0399***	-0.0416***	-0.0118	-0.0230*
	(0.0146)	(0.0148)	(0.0108)	(0.0130)
> 90	-0.0506**	-0.0538***	-0.0249	-0.0414**
	(0.0201)	(0.0194)	(0.0159)	(0.0167)
R-Squared	0.85	0.83	0.88	0.83
Observations	141359	141359	141359	141359
F-Stat	3.79	4.02	2.36	2.04
P-Value	0.01	0	0.05	0.09

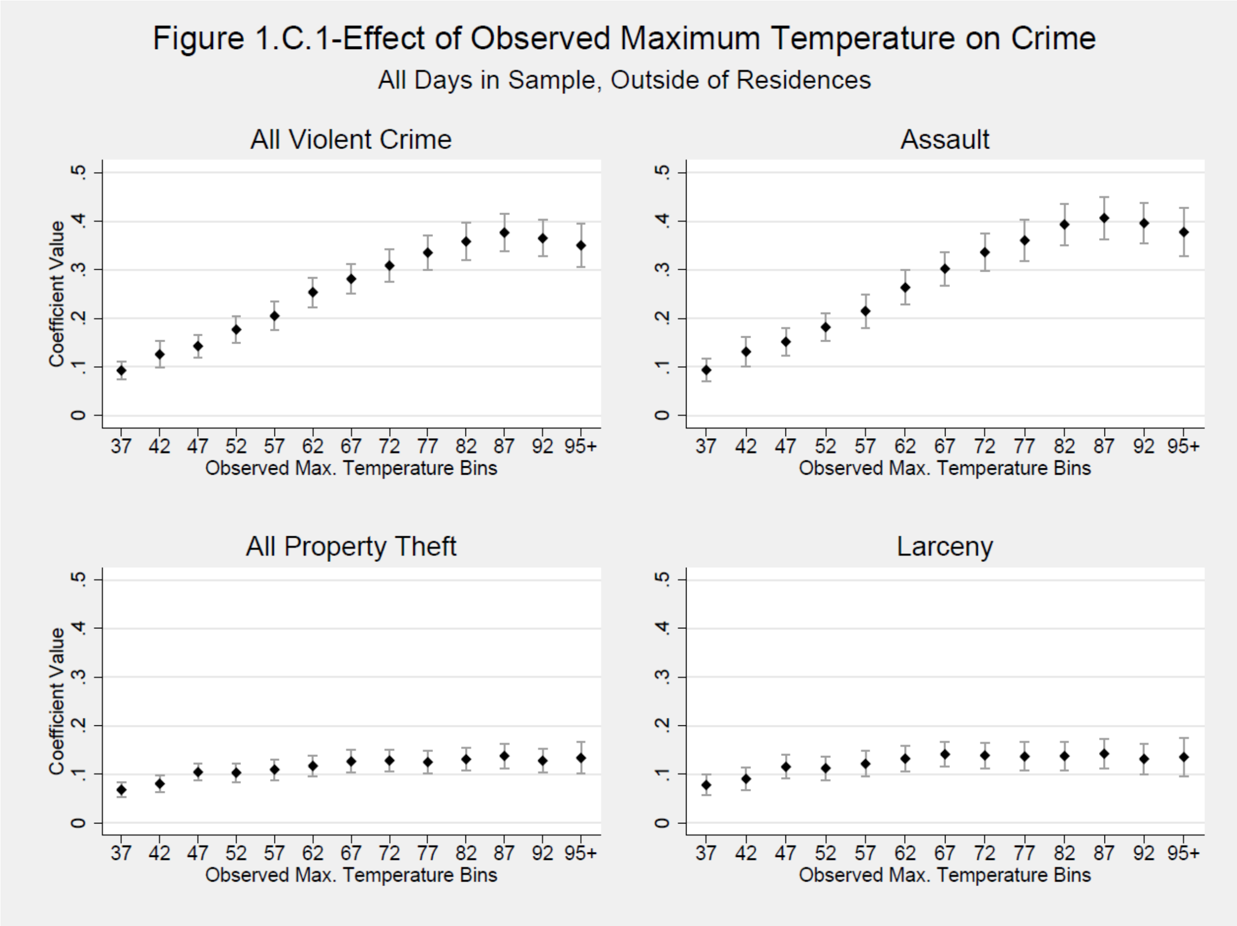
Notes: The coefficients reported in this table are obtained by estimating the regression given by equation (14) in Section 1.3 of the text. Current day daytime chance of precipitation is one of the controls included in $X_{i,t}$, and is represented using a semiparametric bin estimator with six bins. In this context, "daytime chance of precipitation" is defined as the probability of having positive precipitation between 6:00am and 6:00pm. City-days on which the forecast daytime chance of precipitation is no more than 10% form the omitted category. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city.

Table 1.C.8 - Effect of Future Chance of Precipitation on Crime

Omitted Category: Future Chance Difference in [-10%, 10%]

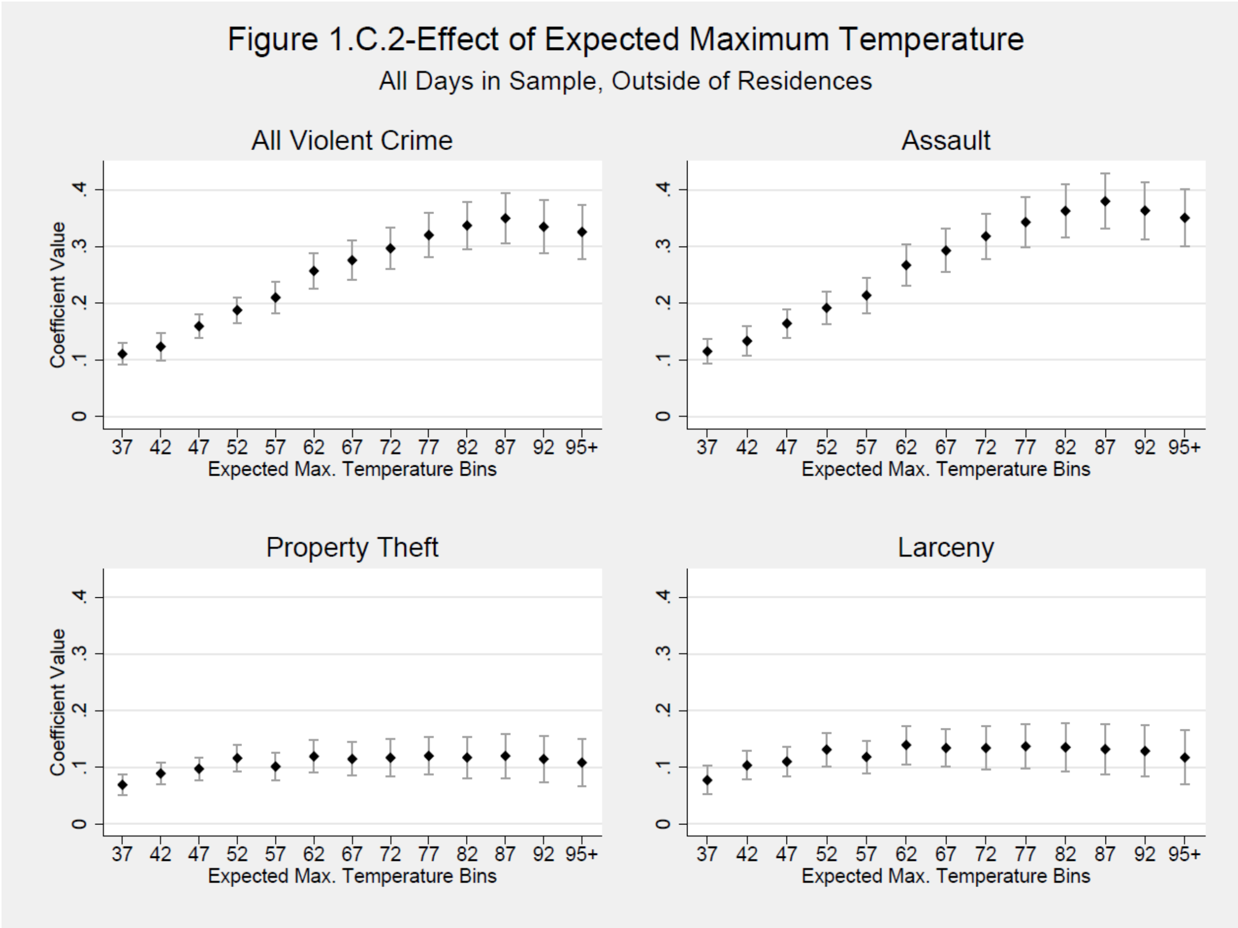
	Violent Crime		Property Theft	
	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]
< -70	0.00302	0.000949	-0.0182	-0.0117
	(0.0177)	(0.0173)	(0.0150)	(0.0172)
[-70, -51]	0.0122	0.00897	-0.0105	-0.00515
	(0.0118)	(0.0118)	(0.0114)	(0.0121)
[-50, -31]	-0.00306	-0.00134	-0.00714	-0.00271
	(0.00975)	(0.0100)	(0.00803)	(0.00909)
[-30, -11]	0.000348	-0.00373	-0.00514	-0.00395
	(0.00510)	(0.00521)	(0.00414)	(0.00521)
[11, 30]	-0.00174	-0.000666	-0.00554*	-0.00639*
	(0.00294)	(0.00353)	(0.00298)	(0.00353)
> 30	-0.0123	-0.0154	-0.00284	-0.00382
	(0.00762)	(0.0102)	(0.00713)	(0.0105)
R-Squared	0.85	0.83	0.88	0.83
Observations	141359	141359	141359	141359
F-Stat	1.44	0.9	1.15	0.89
P-Value	0.22	0.5	0.35	0.51

Notes: The coefficients reported in this table are obtained by estimating the regression given by equation (14) in Section 1.3 of the text. Future chance difference is one of the controls included in $X_{i,t}$, and is represented using a semiparametric bin estimator with seven bins. In this context, the "future chance difference" is defined as the difference between average forecast daytime chance of precipitation during the next six days and the current day daytime chance of precipitation. For example, if the chance of precipitation today is 30%, and the average chance of precipitation during the following six days is 50%, the future chance difference is +20%. City-days on which the future chance difference is no more than 10% from 0 form the omitted category. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city.



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.76	0.71	0.83	0.79
Obs.	141359	141359	141359	141359
F-Statistic	37.59	43.21	13.63	10.01
P-Value	0	0	0	0

Notes: The plots in this figure display the observed maximum temperature coefficient values and 95% confidence intervals obtained by estimating a regression of the following form: $\theta_{i,t} = \rho_0 + \tau X_{i,t} + \sum_{j\neq 1} a_j\, T_{i,j,t} + \eta_{i,t}$. In this regression, $\theta_{i,t}$ is the log of daily criminal activity outside of residences, and the right-hand-side variables include a set of controls ($X_{i,t}$) and a semi-parametric bin estimator capturing observed daily maximum temperature ($\sum_{j\neq 1} a_j\, T_{i,j,t}$). The set of controls includes year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, and controls for current day total precipitation. The semi-parametric bin estimator for observed maximum temperature on the current day captures 14 temperature ranges, with < 35 F being the omitted category. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1+y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 52 is the midpoint of the bin [50,55). This figure is the “outside of residences only” counterpart to Figure 1.1.

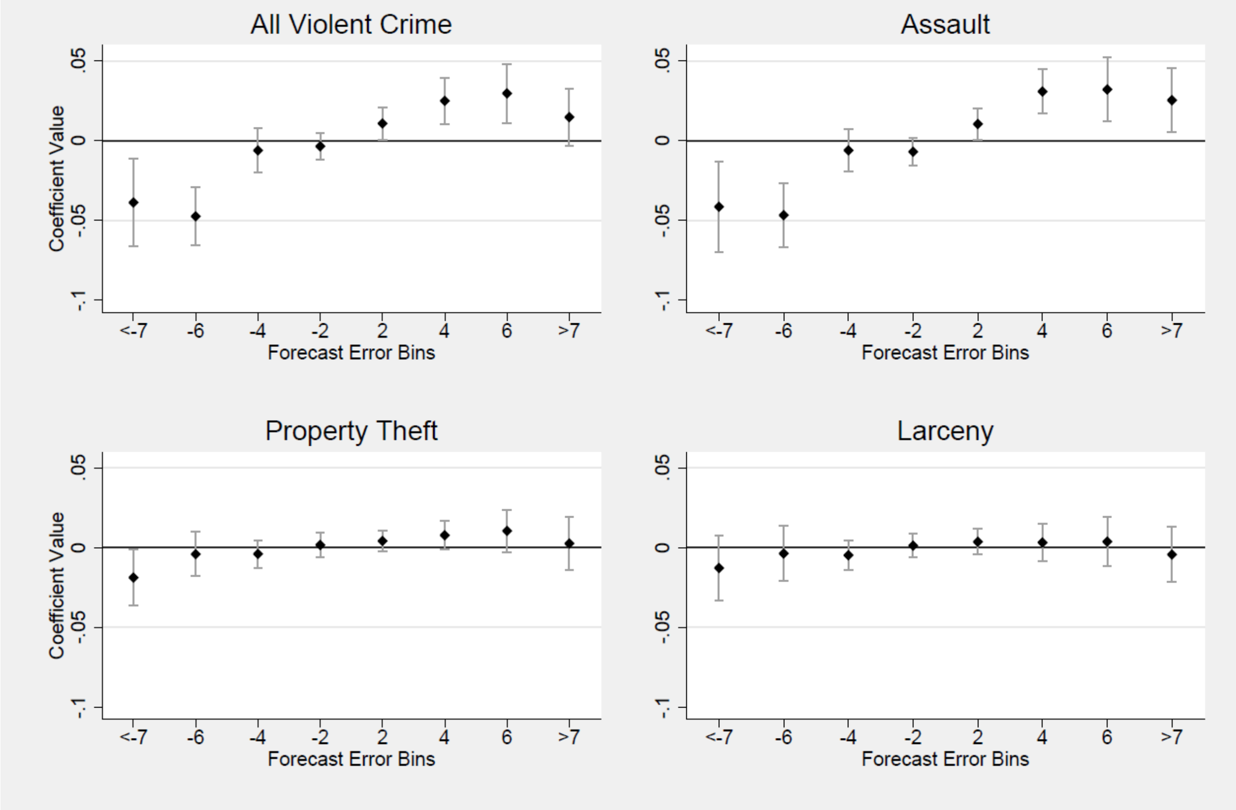


	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.76	0.71	0.83	0.79
Obs.	141359	141359	141359	141359
F-Statistic	34.97	25.59	10.91	8.18
P-Value	0	0	0	0

Notes: The plots in this figure display the expected maximum temperature coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, with the dependent variable limited to capturing criminal activity outside of residences. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 52 is the midpoint of the bin [50,55). This figure is the "outside of residences only" counterpart to Figure 1.2.

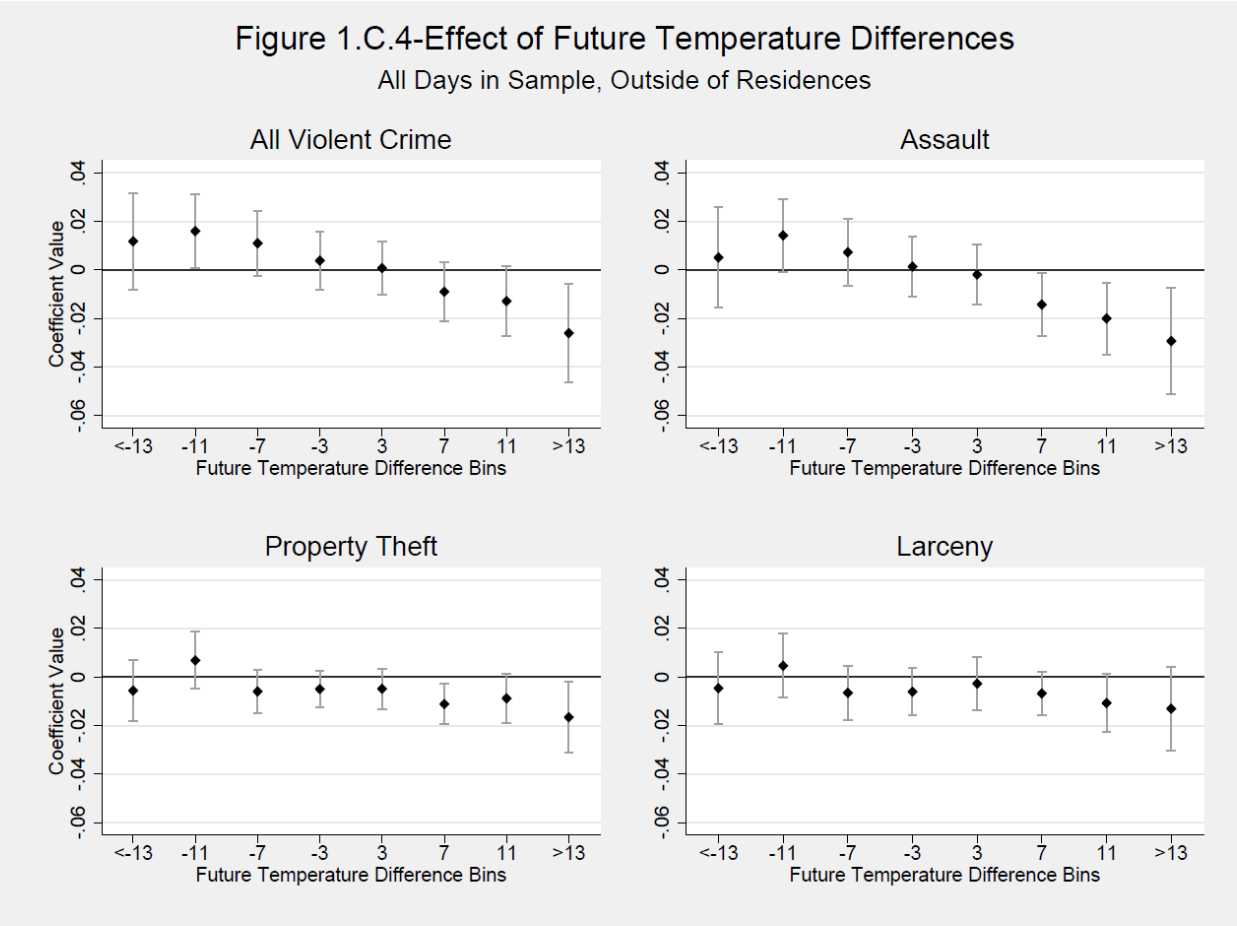
Figure 1.C.3-Effect of Forecast Errors

All Days in Sample, Outside of Residences



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.76	0.71	0.83	0.79
Obs.	141359	141359	141359	141359
F-Statistic	10.42	13.62	2.19	0.7
P-Value	0	0	0.05	0.69

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, with the dependent variable limited to capturing criminal activity outside of residences. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin [1,3). This figure is the "outside of residences only" counterpart to Figure 1.3.

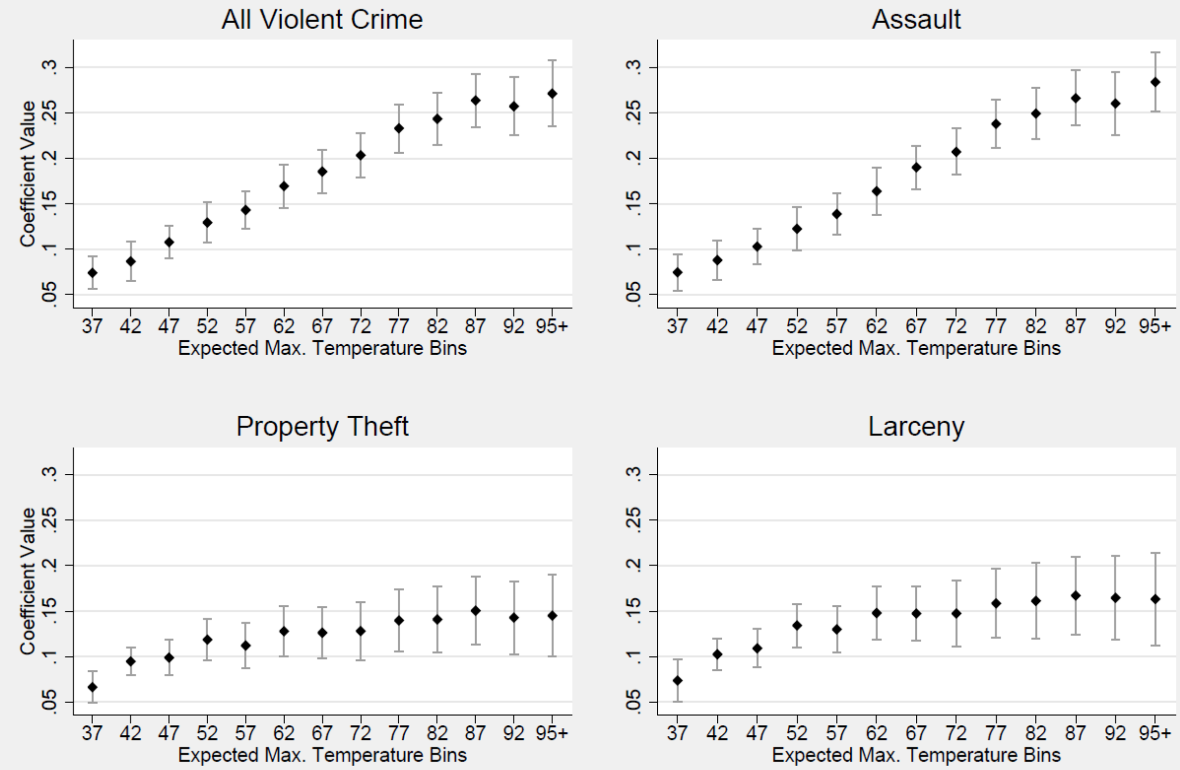


	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.76	0.71	0.83	0.79
Obs.	141359	141359	141359	141359
F-Statistic	2.84	3.33	1.68	0.98
P-Value	0.01	0	0.13	0.46

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, with the dependent variable limited to capturing criminal activity outside of residences. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin [1, 5). This figure is the "outside of residences only" counterpart to Figure 1.4.

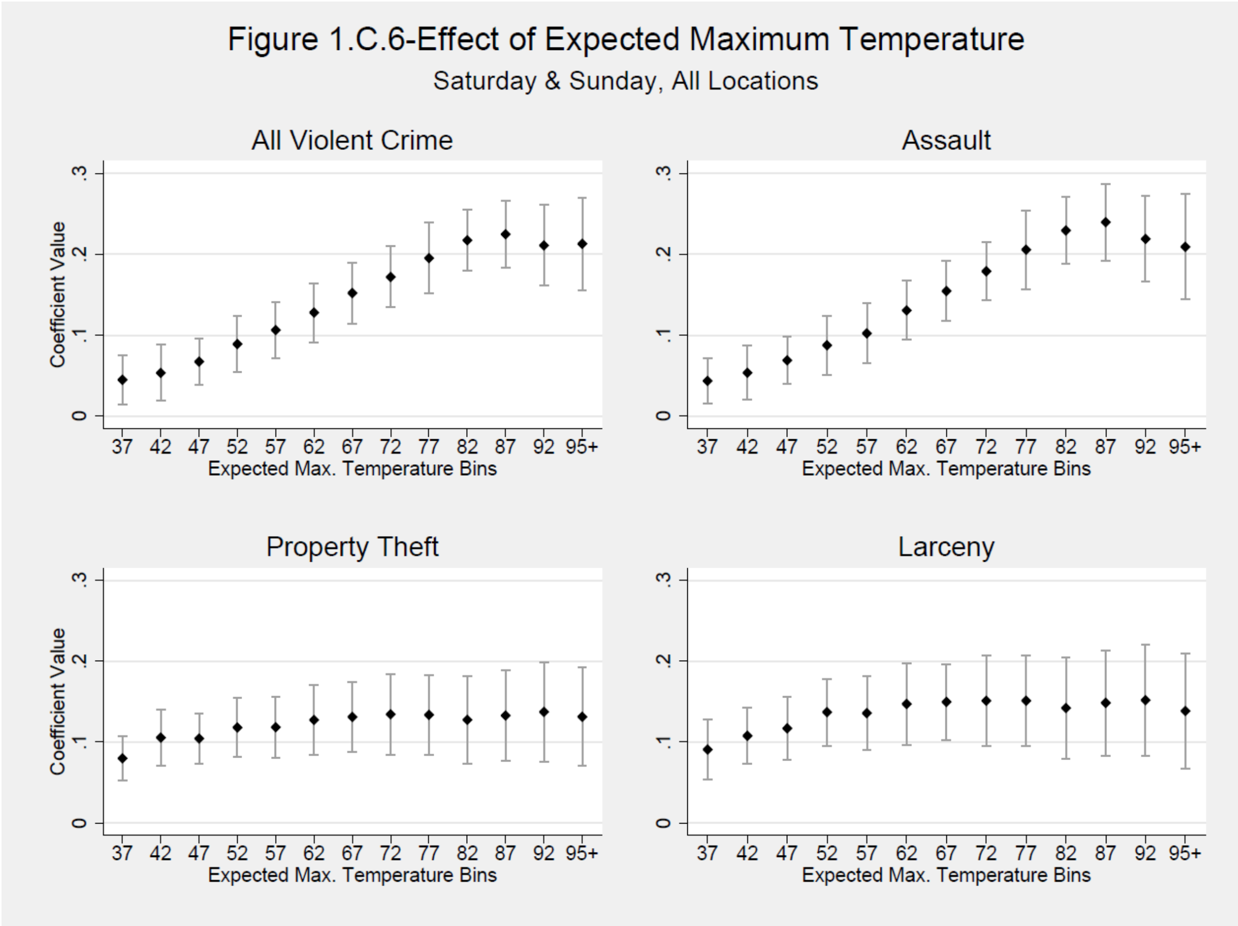
Figure 1.C.5-Effect of Expected Maximum Temperature

Monday-Friday, All Locations



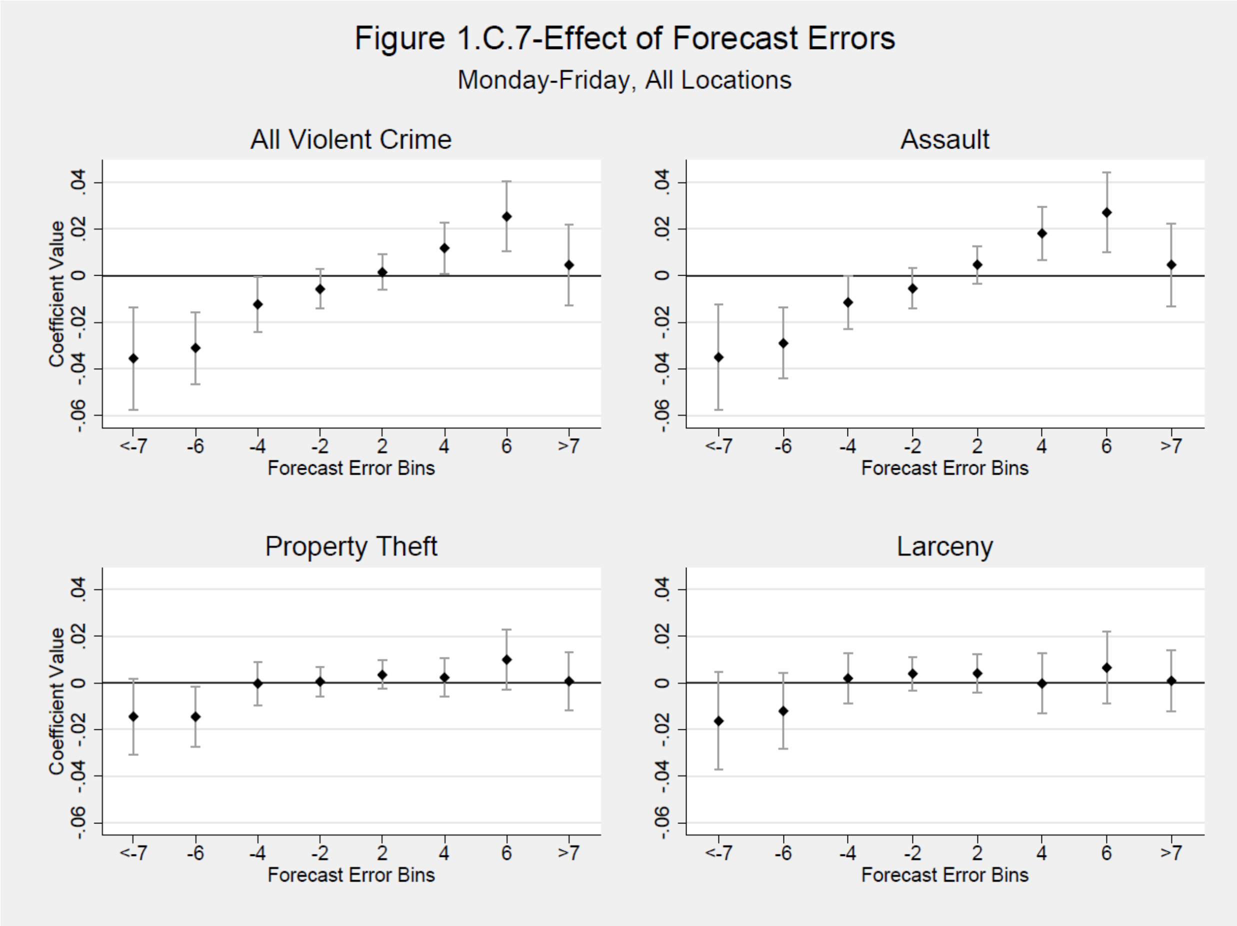
	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	101075	101075	101075	101075
F-Statistic	30.42	42.77	18.9	16.02
P-Value	0	0	0	0

Notes: The plots in this figure display the expected maximum temperature coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days from the workweek. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 52 is the midpoint of the bin [50,55).



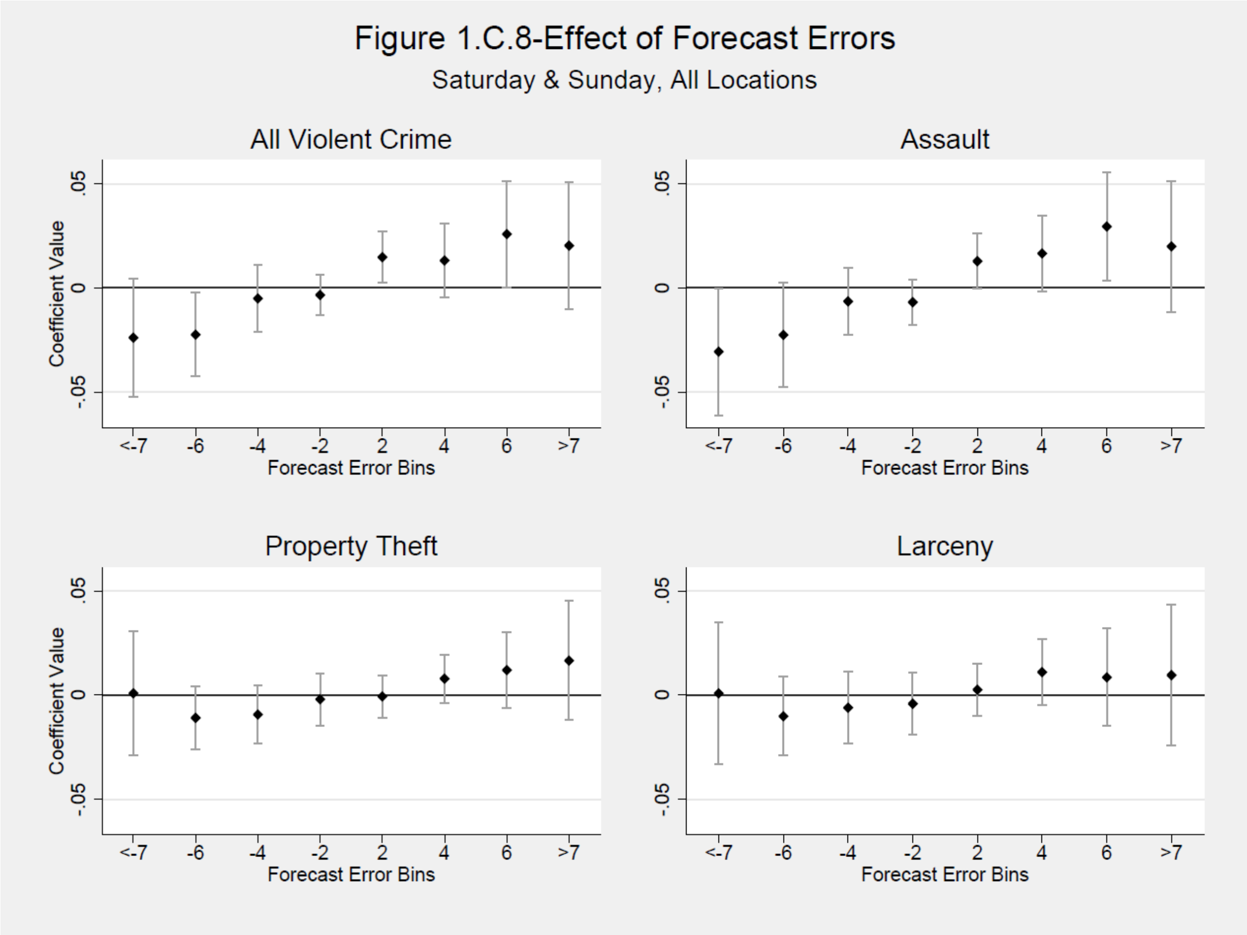
	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.86	0.84	0.87	0.82
Obs.	40284	40284	40284	40284
F-Statistic	19.06	19.17	4.55	7.04
P-Value	0	0	0	0

Notes: The plots in this figure display the expected maximum temperature coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days from the weekend. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 52 is the midpoint of the bin [50,55).



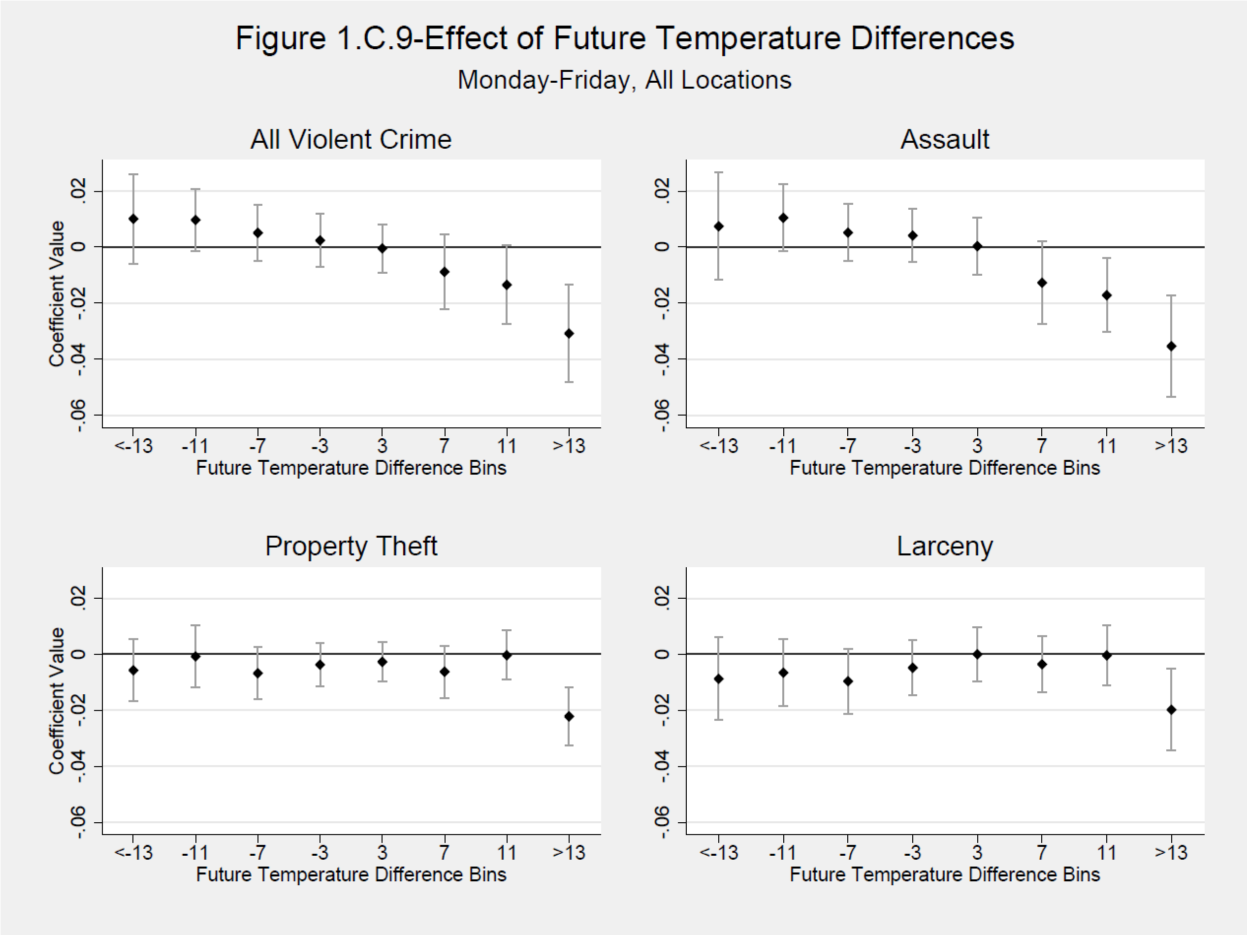
	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	101075	101075	101075	101075
F-Statistic	6.86	8.59	2.94	2.11
P-Value	0	0	0.01	0.05

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days from the workweek. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin (1,3].



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.86	0.84	0.87	0.82
Obs.	40284	40284	40284	40284
F-Statistic	2.88	3.12	1.7	0.96
P-Value	0.01	0.01	0.12	0.48

Notes: The plots in this figure display the forecast error coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days from the weekend. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 2 is the midpoint of the bin (1,3].

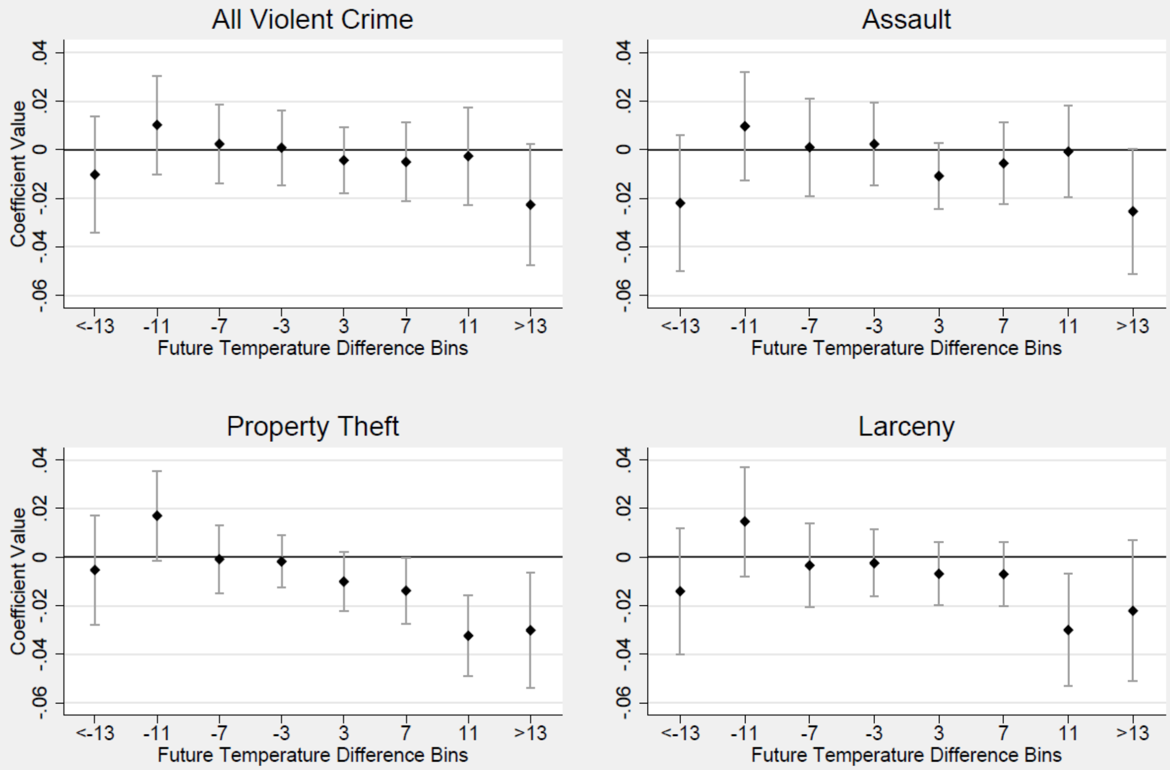


	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.85	0.83	0.88	0.83
Obs.	101075	101075	101075	101075
F-Statistic	2.23	3.07	3.5	2.08
P-Value	0.04	0.01	0	0.06

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days from the workweek. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin (1,5].

Figure 1.C.10-Effect of Future Temperature Differences

Saturday & Sunday, All Locations



	All Violent Crime	Assault	All Property Theft	Larceny
R-Squared	0.86	0.84	0.87	0.82
Obs.	40284	40284	40284	40284
F-Statistic	1.12	2.16	4.88	1.72
P-Value	0.37	0.05	0	0.12

Notes: The plots in this figure display the future temperature difference coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 1.3 of the text, using only sample city-days from the weekend. This regression includes the following controls: year-by-city fixed effects, month-by-city fixed effects, day-of-week fixed effects, an indicator for the first of the month, a set of holiday indicators, controls for one lag of observed daily maximum temperature and total precipitation, controls for current day total precipitation, controls for current day daytime chance of precipitation, and controls for future daytime chance of precipitation. To account for city-days in which there is no criminal activity in the category studied, the inverse hyperbolic sine transformation suggested by Burbidge et al. (1988) is used. Therefore, if y is the number of crimes of a particular type that occurred on a given day, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2}\right)$ is used as the dependent variable. The F-Statistic reported in the table pertains to the test that all coefficients are jointly equal to zero. Standard errors are clustered by city. In all plots, the x-axis labels represent bin midpoints; for example, 3 is the midpoint of the bin (1,5].

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CHAPTER 2

Danger in Numbers? : Crowd Size and Crime

Abstract

The number of people occupying a physical space (a value referred to here as "crowd size") is likely to be a significant determinant of criminal activity. However, the overall impact of this variable is ambiguous, as there are two likely effects that operate in different directions. On the one hand, larger crowds are associated with more person-to-person and person-to-property interactions, which should lead to more opportunities for crime. Conversely, big crowds may deter criminal activity via informal surveillance. In this paper, I use daily variation in public transit ridership to proxy for changes in the number of people inside and outside of residences in Chicago, IL. Using this proxy, I calculate the elasticity of criminal activity with respect to crowd size for violent crime and property theft. I find that a 1% increase in ridership is associated with a 0.74% increase in violent crime outside of residences, and a 0.23% increase in property theft outside of residences. The same increase in ridership is also associated with a 0.37% increase property theft inside of residences, and a 0.2% reduction in violent crime inside of residences. I re-estimate these elasticities for several subsamples of interest, and suggest an instrumental variables approach to estimation. Finally, I conclude my results by examining violent crime and property theft within the transit system itself, where ridership is a near-perfect measure of crowd size. In this context, a 1% increase in ridership is associated with a 0.73% increase in violent crime, and a 0.65% increase in property theft. The vast majority of these findings indicate that the relationship between crowd size and criminal activity is positive but inelastic, suggesting that more crowded areas are safer on a per-capita basis.

2.1 Introduction

All else equal, crowded spaces are often viewed as undesirable. They're noisy, disruptive, and uncomfortable. Having said that, there are other cases in which crowds are looked upon favorably, for example as a source of collective security. These competing forces are likely to affect many outcomes of interest, including the level of criminal activity. It is intuitive to believe that "crowd size" (defined here as the number of people in a fixed physical space at a point in time) is significantly related to criminal activity, but to date very little work has been done to directly address this subject in any academic discipline. Furthermore, authors in the economics of crime literature have ignored it entirely. The distribution of people in time and space is undoubtedly central to determining the costs and benefits associated with various criminal acts, which emphasizes the need for more research on this topic. In this paper, I use a novel data source to provide new insight into the relationship between crowd size and crime.

While the author is unaware of any extant study examining crowd size in the sense that it is defined and measured in this paper, there are numerous studies looking at closely related subjects. Most notably, a large criminology literature exists examining the effects of population size, population growth, and (especially) population density on crime.[47] Population density is most often posited to affect crime via two competing mechanisms: opportunity and informal surveillance. In the first case, one would expect criminal activity to increase with population density, simply because there are likely to be more person-to-person and person-to-property interactions (i.e. more opportunities for crime) when there

[47] Where "population density" is some measure of the number of people residing in a fixed area (e.g. the number of residents per square mile).

are more people per unit area. On the other hand, it also seems reasonable that high population density would deter crime via the informal surveillance that bystanders provide. Both mechanisms have strong intuitive appeal, but which channel dominates is an open question.

The empirical literature on population density and crime is decades old, with Watts (1931) being one of the earliest papers to identify the issue. Kvalseth (1977) reviews studies of population density and crime from that time period, and concludes that there is some evidence for a negative correlation between density and crime (though many of the estimates discussed are not statistically significant).[48] Shichor et al. (1979) look at property crimes and assaultive crimes, and find that property crimes involving direct offender-to-victim contact increase with density, while all other types of crime studied fall. More recently, Harries (2006) finds that property crime and violent crime both increase with census block population density in Baltimore County.

Aside from the literature on population density, several papers on closely related topics have informed this study. For example, a number of authors have attempted to directly examine the impact of bystanders on crime. To reflect the fact that crime and surveillance are codetermined, Bellair (2000) uses a simultaneous equation approach to investigate the effect of bystanders, and finds that robbery and stranger assault are inversely related to informal surveillance. There is also a social psychology literature on "bystander indifference," a phenomenon in which individuals do not respond to emergencies *because* there are other people around to witness the event. There are likely

[48] In fact, Kvalseth's own work using data from Atlanta, GA strong suggests a negative relationship between population density and crime.

to be several reasons for this observed behavior. Firstly, people may feel less inclined to aid others in a setting where many bystanders are around (since it is assumed that someone else will help). In addition, the reaction of other bystanders to an emergency may influence how serious an individual perceives that emergency to be. For example, Darley and Latane (1968b) find that subjects in an experiment were less likely to report smoke filling the room that they were in if indifferent bystanders were present. In the context of crowd size and crime, the issue of bystander indifference is central because its presence will diminish the effectiveness of informal surveillance.

The effect of "crowding" on crime is also a topic of independent interest to this study, though the difference between this measure and the traditional definition of population density is subtle (and sometimes ignored). Even so, the distinction is significant in that crowding refers to the specific condition of people being so closely congregated in a physical space that psychological stability and social order begin to break down.[49] Calhoun (1962) highlighted the importance of this issue by showing that rat populations degrade rapidly as a result of overcrowding. The effect of crowding on human behavior is studied in an experimental setting by Freedman et al. (1972), who show that all-male groups are more competitive and aggressive when placed in smaller rooms. In the context of criminal activity, this finding suggests that dense crowds will promote aggression, resulting in more violent crime.

[49] Nettler (1978) makes this point. Another way of distinguishing the two is to say that crowding is simply a specific measure of population density designed to capture living conditions that are very cramped. In the criminology literature, crowding is usually defined by the number of people per dwelling, or the number of dwellings per unit area.

Recall that the goal of this paper is to investigate how the number of people in a fixed space *at any point in time* affects criminal activity. While the literature discussed above does a great deal to inspire my research question, it provides limited insight into what the answer might be. For example, variables like population size and population density represent long-run characteristics of a given location, which is problematic for several reasons. First of all, neither variable captures the fact that crowd size in any space is a constantly changing parameter dependent on short-run conditions. In addition, population size and population density are likely to be endogenously determined. In the end, answering the question posed in this paper requires data that capture high frequency changes in crowd size that are less likely to be affected by unobserved factors.

In this study, I use ridership data published by the Chicago Transit Authority (CTA) to capture daily variation in the number of people inside and outside of residences. Unlike most American cities, Chicago has an extensive bus and rail network dedicated to public transportation, with an average daily ridership of about 1.3 million people during the study period. As I show in Section 2.3, a significant minority of Chicagoans use the CTA system on any given day, and the fraction who do does not appear to vary with observed weather conditions. In other words, public transit ridership is likely to be strongly correlated with the total number of Chicagoans who leave home during the day; consequently, it is a strong proxy for the average number of people inside and outside of residences. Furthermore, by including a rich set of controls, I significantly mitigate concerns about endogeneity. As a result, I am able to estimate the elasticity of crime with respect to crowd size for the first time.

My findings suggest that ridership is positively associated with criminal activity outside of residences, though in nearly every case the estimated elasticity is less than one. Specifically, I find that a 1% increase in ridership increases violent crime outside of residences by 0.74%, while property theft only increases by 0.23%. The major subcategories of assault and larceny are somewhat more responsive, with estimated elasticities of 0.93% and 0.32%, respectively. In almost every case (assault being the exception) one can reject the null hypotheses that a 1% increase in ridership leads to at least a 1% increase in criminal activity. In other words, larger crowds appear to produce more crime in an absolute sense, but on a per capita basis they are actually safer.

If one accepts that public transit ridership is a good proxy for crowd size outside of residences, it follows that ridership also proxies for crowd size *inside* of residences, though the relationship is more complex.[50] Therefore, I also investigate the effect of ridership on violent crime and property theft inside of residences. In doing so, I find that a 1% increase in ridership increases property theft inside of residences by 0.37%, while the same increase in ridership *reduces* violent crime by 0.2%. Understanding these results requires a careful consideration of the mechanisms that are likely to be involved, as I will discuss in the results section.

Having produced a series of estimates with the entire set of days available, I proceed to split the sample in a number of ways. For instance, one might wonder if crime responds more elastically to changes in ridership on weekends or workweeks In examining this question, I find that violent crime outside of residences is much more responsive to ridership during the workweek (i.e. Monday-Friday), with an estimated elasticity of 0.84

[50] I discuss this issue in more detail in Section 2.3.

(compared to a weekend estimate of 0.39). Violent crime inside of residences also declines more sharply with ridership during the workweek, with an estimated elasticity of -0.21 (compared to the statistically insignificant weekend estimate of -0.01). In contrast, the responsiveness of property theft outside of residences during the workweek (0.27) is quite similar to the weekend (0.25). However, as was the case with violent crime, property theft inside of residences responds more strongly to ridership during the workweek (0.41, vs. 0.27 during the weekend).

One might also wonder if seasonality mediates the effect of crowd size on crime, since seasonal conditions are likely to have a pronounced effect on the profitability of criminal activity and the manner in which people interact. To investigate this possibility, I split my data into a "cold season" and "warm season." The former sample includes all days from October to March, while the latter includes April through September. Whether inside or outside of residences, I find that violent crime responds to ridership similarly in both seasons. The same cannot be said for property theft, which appears to increase more with ridership during the cold season, both inside and outside of residences. Even so, the estimated elasticities for property theft remain low (relative to violent crime) throughout the year.

The results discussed above were generated by simple OLS models, where endogeneity is an ever-present concern. In this particular context, the most pressing threat to identification is that there may be numerous variables that affect public transit ridership and crime simultaneously. For instance, ridership and crime might both be driven by alcohol consumption, local sporting events, holidays, and similar factors. I go to great lengths to control for these variables when the data needed to do so are available,[51] but additional unobserved factors may exist. As such, I complete Section 2.5 by discussing a two stage least squares (2SLS) strategy which employs precipitation expectations as an instrument for ridership. In general, the estimates produced through this method have significantly greater magnitudes compared to their OLS counterparts, and in the case of violent crime the qualitative conclusions are quite different. While promising in some respects, this IV strategy is hampered by concerns about the exclusion restriction. After presenting the estimates, I discuss the seriousness of these concerns, and conclude that the exclusion restriction is unlikely to be satisfied in the case of property theft (but may be met for violent offenses).

The results summarized thus far rely heavily on the idea that public transit ridership is a good proxy for crowd size inside and outside of residences in Chicago. In Section 2.6, I limit my focus to crime within the CTA system itself, where daily ridership is near-perfect measure of average daily crowd size. In this setting, I find that a 1% increase in ridership is associated with a 0.73% increase in violent crime, and a 0.65% increase in property theft. Once again, the major subcategory of assault is somewhat more responsive to crowd size than violent crime overall (with an estimated elasticity of 0.89); in contrast, the estimate for larceny (0.64) is nearly identical to its parent category.[52] Since the absolute level of criminal activity in the CTA system on a daily basis is low compared to the city as a whole, I also examine the effect of crowd size on crime in this system using Poisson regression models.

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[51] For instance, I include controls for major holidays and professional sports game days.
[52] This is not surprising at all, since larceny accounts for almost all property theft crime in the CTA system.

The findings of this study have a number of important implications. On the most basic level, my OLS results suggest that more crowded areas have more violent crime and property theft in an absolute sense, but are safer on a per capita basis. This finding is not unreasonable, but also not necessarily something one would have expected ex ante. In addition, this paper makes a more general contribution to the economics of crime literature, which to date has focused primarily on how laws, regulations, and other policies encourage or deter criminal activity. This is understandable, but the lack of attention paid to environmental conditions is unfortunate, since the characteristics of a physical space often provide powerful incentives or disincentives for would-be criminals. Understanding these incentives is of central importance, especially from a policy perspective.[53] Crowd size is one such characteristic, and this study provides the first-ever direct examination of how this variable may serve to encourage or deter crime.

The remainder of this paper is organized as follows: Section 2.2 describes the various sources of data used in the paper, Section 2.3 discusses the value of ridership as a proxy, Section 2.4 describes my empirical methodology, Section 2.5 reports results for crime in the entire city, Section 2.6 reports results for crime in the CTA system specifically, and Section 2.7 concludes.

2.2 Data

The analyses conducted in this study require several types of data that must be drawn from a variety of sources. The sources most central to the study include crime data from the

[53] For example, understanding how environmental conditions such as crowd size affect crime is important because such conditions are often highly variable and *forecastable*. As such, this research may benefit crime forecasting techniques.

Chicago Police Department (CPD), ridership data from the CTA, observed weather data from the Global Historical Climatology Network (GHCN), and weather forecasts produced by the National Weather Service (NWS). In addition, I use extracts from the American Time Use Survey (ATUS) and CTA bus traffic data in my discussion of the ridership proxy in Section 2.3. All of these sources are described in more detail below.

The crime data used in this study include daily counts of different offense types, which were tabulated using a complete record of CPD crime reports. These report-level data are made publically available via Chicago's online data portal, and cover the 2001-2015 period.[54] In this paper, I focus on violent crime and property theft offenses, which collectively account for about 61% of all criminal incidents on a typical day.[55] These two crime types are defined in Table 2.A.2. In addition, I also examine the effect of crowd size on a catch-all category called "all offenses," which is a daily count of the number of crime reports (of all types) recorded by the CPD. Using a location description variable available in the data, I separately consider the effect of crowd size on crimes inside and outside of residences. I then supplement my main results with an examination of crimes that occur within the CTA system itself. Daily city-wide crime summary statistics are provided in Table 2.A.3, and daily summary statistics for crime in the CTA system are given in Table 2.A.4.

Like the crime data discussed above, the ridership data used in my analyses are made publically available via Chicago's online data portal. Daily ridership figures are

[54] Currently, the last day in the sample is 1/31/15.
[55] The remainder of criminal activity is dominated by drug crimes, as well as certain non-theft property offenses (e.g. vandalism and trespassing). I focus on property theft and violent crime because these major categories include all of the offense types that have received significant attention in the relevant literature.

calculated by aggregating daily ridership values for every bus route and train station in the CTA system. In all cases, "ridership" is measured by counting the number of people that access the CTA system via its various points of entry. For example, the daily ridership at an individual train station is calculated as the number of people who pass through that station's entry turnstiles. Daily ridership summary statistics are provided in Panel 4 of Table 2.A.4.

The instrumental variables strategy discussed in this paper requires the use of weather forecast data, which I retrieve from an online archive maintained by the National Oceanic and Atmospheric Association (NOAA). For most of the time period studied, I use the Tabular State Forecast (TSF) for O'Hare International Airport, which provides a seven-day forecast very similar to what one would see in a newspaper. Each forecast is published during the afternoon before the first forecast day, and includes predictions for daily maximum and minimum temperature, daytime chance of precipitation,[56] and a word or phrase describing the weather conditions (i.e. "partly cloudy"). The timing of the forecast is important, since it is meant to represent people's weather expectations immediately prior to the day in which crime and ridership are being measured. To produce the instruments used in this paper, I require the conditions word or phrase given for the first day of the forecast, as well as the daytime chance of precipitation given for the same day. Since the TSF was not produced until the middle of 2003, I use the Coded City Forecast product (CCF)

[56] "Daytime chance of precipitation" is defined as the probability (at the time of forecast) that at least 1/100th of an inch of rain will fall between 6am and 6pm on the day that the forecast applied to.

for the earlier years of the sample.[57] Except for the manner in which the reports are formatted,[58] the CCF and TSF reports provide identical information.

In Section 2.3 of this paper, I discuss the value of public transit ridership as a proxy for average crowd size inside and outside of residences in Chicago on a given day. As part of this discussion, I use survey data from 937 respondents of the ATUS during the 2004-2013 period to provide some information on the travel methods of Chicagoans. The ATUS is a complimentary part of the much larger Current Population Survey (CPS), and ATUS respondents typically complete their interview 2-5 months after their participation in the CPS has ended. Each ATUS respondent is asked a series of very detailed questions about their time use during a 24-hour "diary day,"[59] and this information is used to construct a minute-to-minute record of the respondent's activities during that period. For the purposes of this study, the ATUS data are used to identify whether a respondent left home, whether they used particular transportation methods, and how much time they spent using each method. These data were extracted from the ATUS Extract Builder (ATUS-X), an online service maintained by several partner organizations.[60] In order to identify respondents who lived within Chicago itself during the interview period, the ATUS data were merged with the original CPS base files, which are publicly available on the Bureau of Labor Statistics (BLS) website.

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[57] This forecast is also for O'Hare International Airport.
[58] The CCF forecast condenses a standard forecast into a string of letters and numbers (hence the term "coded"). This was very useful when computing power was limited in the 80s and 90s, but since the early 2000s the CCF has been discontinued by most Weather Forecast Offices.
[59] The diary day is not a traditional day; rather, it is a 24-hour period stretching from 4:00am to 4:00am.
[60] The organizations include the National Institutes of Health, the Economic Research Service, the Minnesota Population Center, and the Maryland Population Research Center.

As Section 2.3 will discuss in detail, most travel outside of residences in Chicago is done using automobiles, with buses and trains (i.e. public transportation) accounting for a much smaller fraction of total transportation. This is not necessarily a problem for the proxy used in this paper, as long as ridership levels and automobile traffic are highly positively correlated. To investigate this, I use another dataset provided by the CTA, which includes GPS speed data collected from buses in the CTA system. In its raw form, this resource includes very high-frequency[61] average speeds for 29 traffic regions in Chicago, where each average is based on a set of readings taken from the CTA buses in the region during that time period. Using this data, I calculate city-wide average daily bus speeds for a set of 447 days during the 2011-2013 period.[62] If one assumes that buses travel faster in light traffic conditions, and that automobile usage is positively correlated with public transit ridership, then one should expect high average bus speeds to be associated with low daily ridership. Conversely, low average bus speeds should be associated with high daily ridership.

The remaining data used in this study pertain to the set of control variables contained in my regression models. Many of these controls did not require any external data source,[63] or were defined via Google searches.[64] However, the weather variables used were gathered from the Global Historical Climatology Network (GHCN), which includes thousands of weather stations across the world. All observed weather data used in this study come from the weather station at O'Hare International Airport, from which I draw

[61] I limit the data to days in which there are 6 average speeds for each region every hour, for all 24 hours in the day (144 total average speeds per region per day).
[62] These daily averages are weighted by the amount of data collected in each region for every raw data point. In other words, regions that have more buses in them on average will receive more weight.
[63] Such as the fixed effects.
[64] The holiday indicators.

data on daily maximum temperature, daily minimum temperature, daily total precipitation, and daily average wind speed.

2.3 Ridership as a Proxy

In order to use public transit ridership data to assess the impact of crowd size on crime, one must be confident that this measure accurately captures changes in the average crowd size inside and outside of residences on a given day. In this section, I discuss how ridership relates to the unobserved measure of interest, and provide data which demonstrate its value as a proxy.

Over the course of a given day, the flow of people inside and outside of residences will be constantly changing and very complex. Some people will remain home all day, others will leave very briefly, others will spend almost all of their time away from home, and still others will leave and return to their residence many times as the day progresses. In addition, many people who leave home do so in order to go to another residence, and these individuals will have a relatively minor impact on the average crowd size outside of residences.[65]

Given all of these complications, it is important to understand what information public transit ridership can and cannot capture. Clearly, a daily ridership count does not tell one the number of total person-hours spent inside and outside of residences during the day;[66] instead, it is simply a signal for the total number of people who choose to leave home at any point during the day. Even so, this reveals important information about the average

[65] Relative to someone who leaves their home in order to go to a destination that is outside of a residence.
[66] This is the value one would need if one intended to calculate exact daily averages of crowd size inside and outside of residences.

crowd size inside and outside of residences. Simply put, when someone decides to travel away from home for any length of time, that decision will positively impact average crowd size outside of residences, and negatively impact the counterpart value inside of residences. The magnitude of these effects will obviously depend on how long the person in question remains outside of a residence,[67] but the direction of each effect is unambiguous. Therefore, as long as ridership accurately signals the number of people who choose to leave home on a given day, higher ridership levels imply a higher average crowd size outside of residences, and a lower average crowd inside of residences.

Does public transit ridership provide a reliable signal of the number of people who leave home during the day in Chicago? Obviously, one cannot say for certain how good a proxy ridership is without observing the true value of interest, but there are two datasets available that can shed light on this issue. The first of these is the American Time Use Survey (ATUS),[68] from which I have drawn a sample of 937 respondents who lived in Chicago at some point during the 2004-2013 period. Of these respondents, 794 reported leaving home during their diary day, and in Tables 2.A.5 and 2.A.6 I analyze the travel habits of this subset.

In Table 2.A.5, I divide the subset of 794 ATUS respondents who report leaving home according to whether their diary day falls on the weekend.[69] For these weekend and

[67] Consider three people: person A, person B, and Person C. Suppose that person A takes a train ride to a friend's house, stays there the entire day, and comes home on the same train in the evening. Person B, on the other hand, travels by train to Michigan Avenue and spends the day shopping (returning home in the evening by the same train). Person C stays home the entire day. Clearly, Person B makes the largest positive contribution to average density outside of residences and the largest negative contribution to average density inside of residences. However, relative to Person C, Person A affects both densities in the same manner as Person B (though the magnitudes are smaller).

[68] See Section 2.2 for a description of the ATUS sample used here.

[69] The ATUS is designed to over-represent weekends in the data; as a result, over half of the ATUS respondents used in my data (485 of 937) have a weekend diary day.

workweek groups, I compare the fraction of respondents who reported using any of three methods of transportation (automobile, biking/walking, and bus/train). I find that 74% of workweek respondents report travelling by automobile during their diary day, compared to 78% of weekend respondents. A smaller fraction of people report biking or walking, but once again the workweek and weekend fractions are similar (34% and 30%, respectively). In contrast, a significantly higher fraction of workweek respondents (23%) report travelling by a bus or train (i.e. public transit) compared to weekend respondents (14%).

In Table 2.A.6, I examine whether the probability of using each of the three transportation types examined above is affected by observed weather conditions during the diary day. This is an important question, since substitution in transportation types driven by environmental conditions could reduce the value of ridership as a proxy for the number of people outside.[70] The coefficients reported in this table were obtained by estimating simple linear probability models in which the left-hand side variable is an indicator for transportation usage, and the set of right-hand side variables includes measures of daily maximum temperature, daily minimum temperature, daily total precipitation, and daily average wind speed. Fortunately for my purposes, none of these variables appear to affect the probability of using any of the three transportation types.

The ATUS results above suggest a few basic conclusions: 1) a significantly smaller fraction of Chicagoans use the CTA system on the weekend, and 2) the fraction of people who use the CTA system on any given day is not a function of observed weather conditions. The latter finding is good for my purposes, and the former is not a problem so long as

[70] As an extreme case, suppose that people decide to leave home on a warm day, but remain in their local neighborhood instead of travelling a significant distance. In this case, CTA ridership may actually be low even though the number of people outside is high.

ridership is strongly and *positively* correlated with the unobserved value of interest (the number of people who leave home during the day).

To examine this point, I look at the correlation between daily CTA ridership and average daily traffic speed[71] for a set of 447 days during the 2011-2013 period. The logic behind this comparison is that average daily traffic speed is a good indication of how many cars use Chicago's road system over the course of a given day. When one combines this information with the fact that cars are the dominant form of transportation in Chicago, average daily traffic speed becomes an indirect measure of the number of people who leave home during the day. When these speeds are high, we can infer that relatively few people left their residence during the day; conversely, low average daily traffic speeds should be associated with many people leaving home. In other words, if CTA ridership is a good proxy for the number of people who leave home during the day, then average daily traffic speed and ridership should be negatively correlated.

Figure 2.A.1 displays a scatter plot and fitted trend line, where the dependent variable is the natural log of average daily traffic speed and the independent variable is public transit ridership. The negative correlation one would expect (based on the argument above) is clearly present, with a 100,000 person increase in ridership being associated with a highly significant 1% decline in average daily traffic speed. In fact, I find that CTA ridership accounts for about 21% of the variation in average daily traffic speed in the city of Chicago. Taken together, the findings reported in this section should bolster the reader's confidence in ridership's value as a proxy in the analyses to follow.

[71] As measured by GPS receivers on CTA buses; see Section 2.2 for details on this data.

2.4 Empirical Methodology

$$ln(crime_t) = \beta_0 + X_t'\gamma + \beta_1 ln(ridership_t) + \varepsilon_t \quad (1)$$

The majority of the results discussed in this paper are produced by estimating the OLS model given in (1), using a time series of 5,144 days spanning the 2001-2015 period (the final day in the series is January 31, 2015). In this model, $crime_t$ is a count of criminal activity for a particular crime type (e.g. violent crime outside of residences) on day t, and X_t is a set of controls including year-by-month fixed effects, day-of-week fixed effects, a first-of-month indicator, holiday controls, professional sports home and away game day controls, and current and lagged weather controls. Detailed definitions of these controls are given in Table 2.A.1. In this simple model, β_1 is interpreted as the percentage increase in $crime_t$ resulting from a 1% increase in $ridership_t$ (i.e. the elasticity of crime with respect to ridership on day t).

A central concern of estimating (1) is that ridership may be endogenous due to omitted variable bias. I attempt to lessen this concern by including a rich set of controls in my main findings; however, in Section 2.5.4 I introduce a two stage least squares (2SLS) approach as an alternative means of identification. Specifically, I instrument for the log of ridership using the forecast daytime chance of precipitation, and an indicator for the presence of a "rainy" warning in the weather forecast (see Section 2.2 for details on this forecast data). The idea of these two instruments is that people will be less likely to leave their home when they believe it is going to rain, and ridership will fall as a result. In fact, daily ridership is strongly negatively correlated with both variables, so that the first stage is quite strong. However, the value of these instruments hinges critically on whether precipitation expectations affect crime *only* by affecting ridership, an issue I will discuss fully during my analysis of the results.

Every regression model estimated in Section 2.5 uses heteroscedasticity autocorrelation robust (HAC) standard errors. These errors are estimated using the Barlett kernel, with the bandwidth selected according to the method proposed by Newey and West (1994).

In Section 2.6, I examine crime within the CTA system itself, where the absolute level of criminal activity is much lower on a daily basis (compared to the city as a whole). In fact, for a small percentage of the days in my sample, there are no violent crimes and/or property theft crimes on CTA property. As a result, the model given in (1) can only be estimated if one uses an approximation for $ln(crime_t)$ that is defined at zero. Burbidge et al. (1988) conclude that the inverse hyperbolic sine transformation is well-suited for this purpose; therefore, when estimating (1) for crime in the CTA system, I replace $ln(crime_t)$ with $ln\left(crime_t + \sqrt{1 + crime_t^2}\right)$.

The inverse hyperbolic sine transformation is a useful tool in this context, since it allows one to compare the CTA system results directly to the city-wide results in Section 2.5. However, the daily CTA system crime counts are small enough (on average) that the validity of such an approximation could be called into question.[72] To alleviate these concerns, I also estimate Poisson regression models for the crime categories of interest. In these models, the left-hand side variable is a daily crime count for a given offense category,

[72] The inverse hyperbolic sine transformation is an appropriate approximation for $ln(x)$ as long as x is "big enough" on average. However, what constitutes "big enough," is debatable, and the daily means for violent crime and property theft in the CTA system (about 4.5 incidents/day in in both cases) represent somewhat borderline cases.

and the right-hand side variable of interest is the level of daily ridership (measured in hundreds of thousands). All of the same controls in (1) are used in these Poisson models, and I report incident rate ratios.

As the results in Table 2.6 make clear, there is little evidence for first-order autocorrelation in the data[73], so the OLS and Poisson models I estimate for crime in Section 2.6 simply use heteroskedasticity-consistent (i.e. Eicker-Huber-White) standard errors.

2.5 City-Wide Results

The city-wide results of this study are reported in several distinct subsections. I begin by examining the effect of daily crowd size on crimes occurring inside or outside of residences for the entire 5,144 day sample. This is followed by a subsection which compares weekend days to workweek days, and a subsection which compares the fall and winter months to the spring and summer months. I then present my IV results, along with a discussion of the instrument's validity.

2.5.1 Main OLS Results

Table 2.1 reports the results obtained from estimating (1) for the full 5,144 day sample. Panel 1 reports estimated elasticities for crimes outside of residences, while Panel 2 does the same for crimes inside of residences.

The most basic conclusion one can draw from Panel 1 of Table 2.1 is that criminal activity outside of residences rises when public transit ridership rises, suggesting that the net effect of bigger crowds is more crime. This finding implies that, if larger crowds provide

[73] All reported Durbin-Watson statistics are close to 2.

any deterrent effect at all (via informal surveillance), then this effect is dominated by an increased opportunity for criminal activity. However, all of the estimated elasticities are less than 1 (i.e. inelastic), and in nearly every case (assault being the exception) I can formally reject the null hypothesis that the coefficient is greater than or equal to one. I find that a 1% increase in ridership increases property theft outside of residences by 0.23%, and larcenies outside of residences by 0.32%. In contrast, the same increase in ridership is associated with a 0.74% rise in violent crime outside of residences, and a 0.93% increase in assaults. As one would expect, the elasticity for "all offenses" (capturing all criminal activity) lies in between the two, at 0.35. Nearly all of these coefficients suggest that larger crowds are safer on a per-capita basis, since the response of criminal activity to crowd size is inelastic.

Why are violent crimes more responsive to changes in ridership? A plausible explanation is that violent crimes are often unplanned, spur-of the moment acts in which those involved are not rationally weighing the costs and benefits of their actions. If this is the case, then informal surveillance is unlikely to provide a strong deterrent effect; therefore larger crowds simply result in more opportunities for violent crime (and thus a larger number of incidents). In contrast, individuals committing property theft offenses are very likely to carefully consider the risks associated with each criminal act; in this case, informal surveillance may be a significant deterrent, even in an environment replete with opportunities for crime.

When considering the impact that ridership levels have on crimes occurring *inside* of residences, the reader should recall from Section 2.3 that high ridership levels imply a low average crowd size inside of residences. Furthermore, the absence of people inside of a residence may indicate fewer opportunities for person-to-person criminal acts, but not person-to-property criminal acts. This is because people typically leave behind almost all of their possessions when leaving their home; as a result, low crowd size inside of residences implies a lower level of informal surveillance within homes, but not necessarily a lower level of opportunity for property theft crimes.[74] Therefore, while low crowd size inside of residences may reduce violent crime by eliminating opportunity, the same cannot necessarily be said for property theft.

The mechanisms discussed above reveal themselves in Panel 2 of Table 2.1, as there is significant evidence that increases in ridership are associated with less violent crime and more property theft inside of residences. In fact, a 1% increase in ridership reduces violent crime inside of residences by 0.2%, while increasing property theft by about 0.37%. The estimated elasticity for assault is very similar to its parent category, but the same value for larceny (0.24) is somewhat less that what is found for property theft overall.[75] The drop in violent crime and increase in property theft roughly balance each other out, as the net effect of ridership on all criminal activity inside of residences is close to zero and insignificant.

2.5.2 Workweek vs. Weekend

The results discussed in Section 2.5.1 capture average effects over a 5,144 day time series, but there are reasons to believe that these elasticities may vary by the day of the week or time of the year. I explore both of these possibilities in Sections 2.5.2 and 2.5.3.

[74] Since the people committing the crimes will usually come from outside of the residence.
[75] This is not surprising, as most thefts inside of residences show up in the data as burglaries (since the theft typically occurs in conjunction with unlawful entry).

There are several reasons to believe that the effect of ridership on crime will be different across the workweek and weekend. First and foremost, ridership levels are much higher during the workweek (about 1.48 million riders/day compared to 0.93 million on Saturdays and 0.65 million on Sundays). This disparity will be important if the marginal effect of ridership on crime differs according to the absolute level of ridership. Furthermore, the activities that people engage in during the workweek and weekend are likely to differ, which will affect the manner in which people interact, their level of aggression, and perhaps even their willingness to commit crimes. Finally, factors such as alcohol consumption are likely to vary by the time of week, and these variables may play an important mediating role in the effect of crowd size on crime.

In fact, Panel 1 of Table 2.2 provides an interesting mix of results for crimes outside of residences. For example, the estimated elasticities for violent crime and assault during the workweek (0.83 and 1.1, respectively) are more than twice the size of their weekend counterparts. In stark contrast, the estimated elasticities for property theft and larceny outside of residences are broadly comparable across the workweek and weekend. In fact, the workweek estimates for property theft and larceny (0.27 and 0.36, respectively) are only slightly larger than their weekend counterparts (0.25 and 0.32).

My findings inside of residences are similarly mixed, as demonstrated in Panel 2 of Table 2.2. Once again, violent crimes appear to respond much more to ridership during the workweek, and the weekend estimates are close to zero and insignificant. Property theft and larceny inside of residences increases significantly with ridership during the workweek and weekend, but the differences are more pronounced than was the case outside of residences. Specifically, a 1% increase in ridership increase property theft by over 0.4% during the workweek and only 0.27% on the weekend. However, I also find that larceny is *more* responsive to ridership on the weekend, which adds an additional layer of complexity to these results.

2.5.3 Cold Season vs. Warm Season

Seasonality is another potential mediating factor when considering the effect of crowd size on crime, since it also is likely to influence the activities that people engage in and the manner in which they interact. For example, during warmer months people may spend more of their time away from home in outdoor areas (e.g. parks), and may be more willing to interact with other individuals when away from home. Changes such as these may reinforce or blunt the effect of crowd size on crime.

While the argument given above has some intuitive appeal, the results of Table 2.3 suggest that seasonality does not have a dramatic mediating role in the effect of crowd size on crime. This is especially true in the case of violent crime, where the estimated elasticities are quite similar across seasons, both inside and outside of residences. More evidence is present to suggest that seasonality matters for property theft and its subcategory of larceny, since during the cold season (i.e. October-March) elasticities are often markedly higher. For example, a 1% increase in ridership is associated with a 0.25% increase in property theft outside of residences during the cold season, but only a 0.11% increase during the remainder of the year. A similar gap exists for property theft inside of residences,[76] and the same pattern is found for larceny (though the gaps are, in percentage terms, slightly smaller).

[76] 0.37 for the cold season vs. 0.19 for the warm season

2.5.4 Instrumental Variables Approach

Even if one accepts that ridership is a good proxy for crowd size in the context studied here, it should be emphasized that all of the results discussed up to this point only serve as evidence for or against an *association* between crowd size and crime. In other words, one cannot make definitive causal statements based on these findings, which is naturally an undesirable limitation. The chief obstacle is that there are likely to be omitted variables that simultaneously affect CTA ridership and criminal activity, resulting in a correlation between ridership and the error term in (1). Broadly speaking, the omitted variables one should be worried about in this context capture the manner in which person-to-person and person-to-property interactions occur, and the frequency with which such events arise. For example, factors that affect the number and *type*[77] of people who leave home on a given day are also likely to affect the level of criminal activity. In addition, other variables (such as alcohol consumption) may determine the number of people who leave home and their psychological state (which could affect aggression levels and/or risk taking behavior). In the regressions discussed thus far, I include a rich set of controls in an attempt to capture as many of these characteristics as possible, but naturally some aspects of the atmosphere in which people interact cannot be observed.

A common solution to this problem is to employ instrumental variables, usually using two stage least squares (2SLS). In this context, the instrument used must significantly affect ridership, but cannot affect crime via any other channel, and must be uncorrelated with any potential omitted variables. In this section, I propose a set of two instruments for

[77] "Type" in this context refers to the demographic and/or socioeconomic characteristics of individuals.

this purpose, which capture current day[78] precipitation expectations. The first of these variables is simply the forecast daytime chance of precipitation on the current day, and the second is an indicator identifying days in the sample in which the weather forecast includes a specific written warning for "rainy" conditions. As one would expect, ridership falls significantly when the chance of precipitation is higher, and the presence of a written warning causes ridership to fall even more. Both of these effects are statistically significant, and the first stage F-statistic of 27.28 lies well above the most stringent threshold suggested by Stock and Yogo (2005). All first stage results are reported in Table 2.5.

The second stage results of this exercise are presented in Table 2.4. Due to missing forecast data, the sample size is reduced from 5,144 days to 4,659 days; therefore, Table 2.4 also includes OLS results for this limited set of days. For crimes outside of residences, the IV results are uniformly higher than their OLS counterparts, typically by about a factor of two. As a result, the elasticity estimates for violent crime (1.63) and assault (1.97) are both considerably above the unit elastic threshold. This finding represents a departure from the OLS results, as the IV estimates suggest that a 1% increase in ridership leads to a *more than* 1% increase in violent crime; in other words, larger crowds appear to have more violent crime on a per capita basis. The IV estimates for property theft (0.43) and larceny (0.70) are also significantly larger than their OLS counterparts, but one can still firmly reject the null hypothesis that the coefficient values are greater than or equal to 1; therefore, the IV results for property theft support the conclusion that larger crowds are associated with lower property theft on a per capita basis.

[78] The "current day" being the day on which crime and ridership are measured.

The findings for violent crime and property theft inside of residences are more blurry, mostly because the IV estimates have significantly larger standard errors (and are consequently statistically insignificant). In the case of violent crime, the IV approach eliminates the significant negative relationship that is present in the OLS results; instead, the estimates for violent crime and assault inside of residences are small, positive, and insignificant. Like their OLS counterparts, the IV estimates for property theft and larceny are positive, but measured with very low precision.

The results presented in Table 2.4 lead one to conclude that, at least outside of residences, criminal activity responds much more elastically to crowd size than OLS estimates would suggest. However, these results mean nothing if the exclusion restriction is not satisfied, and in some cases this seems likely. In particular, any type of criminal activity that involves forward planning (e.g. most, if not all forms of property theft) is likely to be affected by weather expectations, simply because these expectations impact the expected profitability of crime. For example, a pick pocket may decide not to work on days when he expects rain, and burglars may delay breaking into homes due to poor weather expectations. If this is true, then precipitation expectations do not affect crime *only* by affecting crowd size, and the IV estimates in Table 2.4 are meaningless. In contrast, the instruments used here may be much more promising for criminal acts that do not involve forward planning (i.e. most violent crimes), since in this case precipitation only affects the level of criminal activity by changing the distribution of people inside and outside of residences.

How should one view the IV results presented in Table 2.4? In the case of property theft and larceny, it is quite easy to imagine precipitation expectations violating the exclusion restriction, so the IV estimates should be taken with an ample grain of salt. For violent crime, this concern is smaller, and the IV results are correspondingly more valuable. Even so, one could argue that the need for an IV approach is not well-defined in this setting, since I have merely suggested a range of possible omitted variables without any indication of which factors might be the most significant. In the absence of an extremely compelling set of instruments, it may be better to accept the limitations of OLS, given that the relationships investigated in this study are novel and valuable in their own right.

2.6 Crimes in the CTA System

Recall that the purpose of this paper is to examine how the number of people in a physical space affects criminal activity in that space. When considering crime in the city of Chicago as a whole, one must be willing to assume that public transit ridership is an adequate proxy for the true variable of interest (the number of people who leave home on a given day). Section 2.3 provides considerable evidence to support this assumption, but the crime data available also allow me to investigate crime within the CTA system itself, where ridership is a near-perfect measure for average crowd size during the day.

The results of this exercise are reported in Tables 2.6 and 2.7. Table 2.6 considers the CTA system as a whole, and estimates the model given in (1). I find that a 1% increase in ridership increases the total level of criminal activity in the CTA system by 0.78%, with the estimated elasticity for violent crime being somewhat larger (0.73) than the equivalent value for property theft (0.65). Furthermore, the estimated elasticities for assault and larceny are 0.89 and 0.64,[79] respectively. These findings are all broadly consistent with the city-wide results for criminal activity outside of residences (see Panel 1 of Table 2.1), though the estimates for property theft and larceny are somewhat larger. Once again, for all categories except assault I am able to reject the null hypothesis that crime responds elastically to crowd size, suggesting that the CTA system is safer on a per capita basis when the average crowd size is larger.

There is a technical problem with estimating (1) for crime within the CTA system: the average number of criminal acts in the CTA system for a given type of crime is relatively small on a daily basis, and there are some days in which no violent crimes and/or property theft crimes occur. I solve this problem in Table 2.6 by using an inverse hyperbolic sine transformation for the left-hand side variable in (1),[80] but an alternative (and perhaps less controversial) solution is to estimate a Poisson regression model instead. Table 2.7 contains the results of estimating Poisson models for every crime category on interest in three specific contexts: the CTA system as a whole (Panel 1), the bus system (Panel 2), and the train system (Panel 3).[81] In all cases, the right-hand side variable of interest is ridership (measured in hundreds of thousands), and the coefficients reported are incident rate ratios.

As one would expect (given the results presented in Table 2.6), the estimated incident rate ratios in Panel 1 of Table 2.7 are all greater than one and highly significant, suggesting that the rate (per unit time) at which crimes occur in the CTA system is

[79] Larceny accounts for almost all property theft in the CTA system, which is why the estimated elasticities in columns [4] and [5] of Table 2.6 are so similar.
[80] See Burbidge et al. (19880 for details; this transformation is not used for the natural log of all offenses, since the daily count is always greater than 0.
[81] The reader will note from Table 2.A.4 that the latter two settings do not add to equal the first; this is because there are some areas that are part of the CTA system, but are not part of the bus system or train system (for example, CTA parking garages).

increasing in crowd size. Once again, this effect appears to be larger for violent crimes (1.08), especially assault (1.12).

Panels 2 and 3 separately consider the impact of crowd size and crime for the bus system and train system, respectively. It is important to note that, in each case, the ridership variable of interest captures the total daily ridership in the specific system being studied, not the level of ridership in the entire CTA system (as was the case in Panel 1). For example, the coefficients reported in Panel 2 capture the effect of a 100,000 person increase in bus ridership on crime within the bus system. In any case, these two panels clearly indicate that all types of criminal activity are more responsive to changes in crowd size in the bus system. This is especially true for property theft, where a 100,000-person increase in ridership increases the rate of offending in the bus system by a factor of 1.13, while the counterpart factor in the train system is only 1.04. This disparity is also present in the case of violent crime, where the incident rate ratio in the bus system is 1.11 (compared to a ratio of 1.06 in the train system).

Why does the level of criminal activity respond more to crowd size in the bus system? There are many possible explanations for this finding, a few of which are worth mentioning here. Of course, the population of people who use either system is not representative of the Chicago-area population in general, and the selected set of people who use the CTA bus system may serve to positively mediate the impact of crowd size on crime. In addition, buses are smaller than train cars, and consequently the same ridership levels in each system may imply a much greater number of people per unit area in the bus system. Such a setting may simultaneously serve to increase opportunities for crime (by moving people close together) and reduce the effectiveness of informal surveillance (by reducing the ability of bystanders to observe their surroundings). Naturally, one can think of other explanations, but without further data this question must be relegated to future research.

2.7 Conclusion

The purpose of this study is to examine a simple question: "How does the number of people in a fixed physical space affect the level of criminal activity within that space?" Many authors have examined the effect of population size and population density on crime, but a variety of issues make these measures ill-suited for addressing the specific question in this paper. Instead, I use public transit ridership data as a proxy for the number of people inside and outside of residences in Chicago on any given day.

This approach is novel in the literature, and produces a number of interesting findings. In addition, I point out threats to identification when using OLS, suggest an instrumental variables solution, and discuss the merits of this approach for different types of criminal activity. I conclude my paper with an examination of crime within the CTA system itself, where ridership is a near-perfect measure of crowd size. In many ways, this final set of analyses provides the most direct answer to the original research question, and it suggests that violent crime has a positive and nearly unit-elastic response to changes in crowd size. In contrast, property theft has a more inelastic (though still positive and significant) response. These findings are consistent with three conclusions about the mechanisms discussed in the introduction: 1) the increased opportunity for crime created by higher crowd size appears to dominate the deterrent effect of heightened informal surveillance in an absolute sense, 2) for most categories of crime studied, my OLS resulst indicate that larger crowds are safer on a per capita basis, and 3) the uniformly smaller elasticity estimates for property theft may indicate that informal surveillance plays a more important role in crimes that have an obviously rational motivation.

This paper represents a valuable first step in the study of crowd size and crime, but much more needs to be done. In particular, solving the identification concerns raised in this paper should be a primary goal of future research.

Main Tables

Table 2.1 - Estimated Elasticities for Major Crime Categories
Daily OLS Models

		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
Panel 1 - Outside of Residences					
	[1]	[2]	[3]	[4]	[5]
ln(Ridership)	0.353***	0.735***	0.931***	0.227***	0.315***
	[0.0325]	[0.0565]	[0.0684]	[0.0324]	[0.0339]
R-Squared	0.94	0.88	0.87	0.88	0.85
Observations	5144	5144	5144	5144	5144
P-Value : Coef. ≥ 1	0	0	0.158	0	0
Panel 2 - Inside of Residences					
	[1]	[2]	[3]	[4]	[5]
ln(Ridership)	0.0314	-0.199***	-0.224***	0.367***	0.244***
	[0.0283]	[0.0312]	[0.0326]	[0.0309]	[0.0323]
R-Squared	0.87	0.83	0.82	0.78	0.67
Observations	5144	5144	5144	5144	5144
P-Value : Coef. ≥ 1	0	0	0	0	0

Notes: This tables reports the results of regressions in which the LHS variable is a log count of daily criminal activity, and the RHS variable of interest is a log count of daily total public transit ridership. As such, the reported coefficient values are interpreted as elasticities. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 2.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 2.2 - Estimated Elasticities for Major Crime Categories
OLS Models, Workweek vs. Weekend

Panel 1 - Outside of Residences

		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]	[5]
Workweek Estimate	0.417***	0.835***	1.061***	0.274***	0.357***
	[0.0431]	[0.0626]	[0.0827]	[0.0483]	[0.0512]
R-Squared	0.95	0.89	0.88	0.88	0.85
Observations	3675	3675	3675	3675	3675
P-Value : Coef. ≥ 1	0	0.004	0.77	0	0
Weekend Estimate	0.298***	0.393***	0.480***	0.248***	0.316***
	[0.0363]	[0.0509]	[0.0591]	[0.0431]	[0.0476]
R-Squared	0.95	0.93	0.93	0.89	0.85
Observations	1469	1469	1469	1469	1469
P-Value : Coef. ≥ 1	0	0	0	0	0

Panel 2 - Inside of Residences

	[1]	[2]	[3]	[4]	[5]
Workweek Estimate	0.0875**	-0.210***	-0.241***	0.406***	0.227***
	[0.0417]	[0.0470]	[0.0485]	[0.0347]	[0.0366]
R-Squared	0.87	0.79	0.78	0.74	0.65
Observations	3675	3675	3675	3675	3675
P-Value : Coef. ≥ 1	0	0	0	0	0
Weekend Estimate	0.0788**	-0.0125	-0.0156	0.266***	0.370***
	[0.0351]	[0.0469]	[0.0471]	[0.0579]	[0.0834]
R-Squared	0.9	0.81	0.81	0.79	0.72
Observations	1469	1469	1469	1469	1469
P-Value : Coef. ≥ 1	0	0	0	0	0

Notes: This tables re-estimates the models in Table 2.1 for workweek and weekend subsets. ”Workweek” estimates are generated by limiting the sample to include only days during the standard workweek (i.e. Monday-Friday), and “weekend” estimates are calculated by limiting the sample to Saturdays and Sundays. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 2.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 2.3 - Estimated Elasticities for Major Crime Categories
OLS Models, Cold Season vs. Warm Season

		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
Panel 1 - Outside of Residences					
	[1]	[2]	[3]	[4]	[5]
Oct. - Mar. Estimate	0.343***	0.683***	0.888***	0.252***	0.331***
	[0.0390]	[0.0558]	[0.0677]	[0.0391]	[0.0429]
R-Squared	0.94	0.88	0.87	0.88	0.85
Observations	2582	2582	2582	2582	2582
P-Value : Coef. ≥ 1	0	0	0.048	0	0
Apr. - Sep. Estimate	0.274***	0.644***	0.814***	0.111***	0.226***
	[0.0441]	[0.122]	[0.150]	[0.0312]	[0.0313]
R-Squared	0.93	0.84	0.83	0.87	0.82
Observations	2562	2562	2562	2562	2562
P-Value : Coef. ≥ 1	0	0.002	0.109	0	0
Panel 2 - Inside of Residences					
	[1]	[2]	[3]	[4]	[5]
Oct. - Mar. Estimate	0.0595*	-0.185***	-0.212***	0.384***	0.258***
	[0.0344]	[0.0406]	[0.0427]	[0.0393]	[0.0427]
R-Squared	0.87	0.82	0.81	0.78	0.65
Observations	2582	2582	2582	2582	2582
P-Value : Coef. ≥ 1	0	0	0	0	0
Apr. - Sep. Estimate	-0.0936***	-0.230***	-0.246***	0.191***	0.148***
	[0.0209]	[0.0404]	[0.0432]	[0.0417]	[0.0505]
R-Squared	0.85	0.81	0.81	0.75	0.61
Observations	2562	2562	2562	2562	2562
P-Value : Coef. ≥ 1	0	0	0	0	0

Notes: This tables re-estimates the models in Table 2.1 for cold season and warm season subsets. "Oct.-Mar." estimates are generated by limiting the sample to include only days falling in the October-March time frame, and "Apr.-Sep." estimates are calculated by limiting the sample to the April-September period. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 2.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 2.4 - Estimated Elasticities for Major Crime Categories
OLS vs. IV Models

Panel 1 - Outside of Residences		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]	[5]
OLS	0.353***	0.735***	0.930***	0.227***	0.314***
	[0.0349]	[0.0609]	[0.0740]	[0.0350]	[0.0364]
R-Squared	0.94	0.88	0.87	0.88	0.85
Observations	4659	4659	4659	4659	4659
P-Value : Coef. ≥ 1	0	0	0.171	0	0
IV	1.065***	1.634***	1.967***	0.428***	0.694***
	[0.142]	[0.220]	[0.256]	[0.151]	[0.170]
R-Squared	0.88	0.82	0.81	0.88	0.83
Observations	4659	4659	4659	4659	4659
P-Value : Coef. ≥ 1	0.677	0.998	1	0	0.036
Panel 2 - Inside of Residences					
	[1]	[2]	[3]	[4]	[5]
OLS	0.0334	-0.199***	-0.227***	0.375***	0.257***
	[0.0307]	[0.0347]	[0.0361]	[0.0319]	[0.0340]
R-Squared	0.87	0.82	0.82	0.78	0.66
Observations	4659	4659	4659	4659	4659
P-Value : Coef. ≥ 1	0	0	0	0	0
IV	0.177	0.0459	0.0302	0.107	0.441
	[0.116]	[0.171]	[0.176]	[0.212]	[0.331]
R-Squared	0.87	0.81	0.81	0.78	0.66
Observations	4659	4659	4659	4659	4659
P-Value : Coef. ≥ 1	0	0	0	0	0.045

Notes: This tables reports the second stage results obtained by estimating a 2SLS version of the model given in Equation (1). First stage results are reported in Table 2.5. OLS estimates are also reported in this table for comparative purporses. All controls are described in Appendix Table 2.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 2.5 - First Stage Results for IV Models

First Stage Coefficients

	Coefficient	Std. Error	Sig.
	[1]	[2]	[3]
"Rainy" Warning in Forecast	-0.014	0.006	**
% Chance of Precipitation	-0.0003	0.0001	***
Observations	4659		
First Stage F-Statistic	27.28		
Stock & Yogo (10% Max. Size)	19.93		

Notes: This table reports the first stage results obtained by estimating a 2SLS version of the model given in Equation (1). The variable being instrumented for is the natural log of total CTA ridership on day t. Two instruments are used: the daytime (i.e. 6:00am-6:00pm) chance of precipitation on day t, and an indicator for the presence of a "rainy" warning in the conditions section of the day t forecast. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 2.6 - Daily Estimates for Crime Within the CTA System
OLS Models

Panel 1 - OLS Models (Full CTA System)

		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]	[5]
ln(Ridership)	0.780***	0.726***	0.890***	0.645***	0.639***
	[0.0626]	[0.0962]	[0.0976]	[0.0968]	[0.0960]
R-Squared	0.51	0.2	0.14	0.33	0.33
Observations	5144	5144	5144	5144	5144
P-Value : Coef. ≥ 1	0	0.002	0.129	0	0
Durbin-Watson	1.94	2.05	2.07	2.05	2.05

Notes: This tables re-estimates the model given in equation (1), except that the dependent variable in this case is a log count of daily criminal activity for a given crime type *within the CTA system*. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 2.A.1. Eicker-Huber-White standard errors are used. Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 2.7 - Daily Estimates for Crime Within the CTA System
Poisson Models

Panel 1 - Poisson Models (Full CTA System)		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]	[5]
Ridership (100k)	1.063***	1.083***	1.115***	1.064***	1.064***
	[0.00465]	[0.00871]	[0.0116]	[0.00840]	[0.00839]
Pseudo R2	0.16	0.06	0.05	0.12	0.12
Observations	5144	5144	5144	5144	5144
Panel 2 - Poisson Models (Bus System Only)					
	[1]	[2]	[3]	[4]	[5]
Ridership (100k)	1.105***	1.113***	1.154***	1.128***	1.128***
	[0.00902]	[0.0137]	[0.0171]	[0.0164]	[0.0164]
Pseudo R2	0.13	0.08	0.06	0.14	0.14
Observations	5144	5144	5144	5144	5144
Panel 3 - Poisson Models (Train System Only)					
	[1]	[2]	[3]	[4]	[5]
Ridership (100k)	1.049***	1.059***	1.078***	1.043***	1.044***
	[0.00590]	[0.0116]	[0.0162]	[0.0103]	[0.0103]
Pseudo R2	0.11	0.03	0.03	0.07	0.07
Observations	5144	5144	5144	5144	5144

Notes: In this table, the OLS regression model in Equation (1) has been replaced by a Poisson regression model. The left hand side variable in all cases is a daily count for a given type of criminal activity *within the CTA system*. In Panel 1, "ridership" is total daily ridership in the entire CTA system. In contrast, the daily ridership total used in panels 2 and 3 are specific to the bus system and train system, respectively. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 2.A.1. Eicker-Huber-White standard errors are used. Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

2.A Additional Tables and Figures

Table 2.A.1 - Description of Regression Controls
Daily Regressions

Year-By-Month Fixed Effects	Indicators for every year-month combination in the sample (except for the omitted category). For example, there is an indicator for January 2007.
Weekday Fixed Effects	Indicators for every weekday in the sample (except for the omitted category). For example, there is an indicator for Friday.
First-of-Month Indicator	Indicator for whether a given day is the first day of the month.
Holiday Indicators	A set of indicators capturing 17 major holidays and other days that have special significance. The list includes: New Year's Day, MLK Day, Presidents Day, Fat Tuesday, St. Patrick's Day, Easter, Memorial Day, July 4th, Labor Day, Columbus Day, Halloween, Veterans Day, Thanksgiving, Black Friday, Christmas Eve, Christmas Day, and New Year's Eve.
Daily Max. Temperature	The observed maximum temperature on a given day, measured in degrees Fahrenheit.
Daily Min. Temperature	The observed minimum temperature on a given day, measured in degrees Fahrenheit.
Daily Wind Speed	The observed average wind speed on a given day, measured in tenths of meters per second.
Daily Total Precipitation	The observed total precipitation on a given day, measured in millimeters.
Lagged Weather Values	Seven lags of all the weather variables listed above are included in every daily regression.

Table 2.A.2 - Description of Major Crime Categories
UCR Codes in Parentheses

Violent Crime	Includes all forms of homicide (91-3), all forms of assault (131-133), sexual assaults (111-114), robbery (120), and weapons violations
Property Theft	Includes all forms of larceny (2331-238), burglary (220), motor vehicle theft (240), and stolen property offenses.

Notes: This tables defines the major crime categories studied in this paper. The large subcategories of assault and larceny are also examined, as they form the bulk of violent crime and property theft (respectively). The codes listed are used by the National Incident Based Reporting System (NIBRS) to classify individual offenses.

Table 2.A.3 - Daily Crime Summary Statistics
Entire City

Panel 1 - Crimes Outside of Residences				
	Mean	Std. Dev.	Min	Max
	[1]	[2]	[3]	[4]
All Offenses	753.83	174.57	169	1384
Violent Crime	206.1	61.01	39	389
Assault	156.48	52.51	30	321
Property Theft	246.92	55.61	58	429
Larceny	182.97	41.32	39	343
Panel 2 - Crimes Inside of Residences				
	[1]	[2]	[3]	[4]
All Offenses	359.98	69.23	149	1086
Violent Crime	123.1	30.76	54	396
Assault	114.33	28.76	49	278
Property Theft	102.53	26.8	35	394
Larceny	46.98	18.57	13	355

Notes: The statistics in this table are calculated using daily crime counts for the entire city of Chicago, IL over a 5,144 day time series (from 1/1/2001 to 1/31/2015). Panel 1 summarizes counts for crimes outside of residences, while Panel 2 does the same for crimes inside of residences.

Table 2.A.4 - Daily Summary Statistics
CTA System

Panel 1 - Crimes (Entire CTA System)				
	Mean	Std. Dev.	Min	Max
	[1]	[2]	[3]	[4]
All Offenses	16.19	5.9	2	38
Violent Crime	4.39	2.41	0	16
Assault	2.97	1.9	0	13
Property Theft	4.68	2.73	0	17
Larceny	4.61	2.72	0	17
Panel 2 - Crimes (Bus System Only)				
	[1]	[2]	[3]	[4]
All Offenses	4.3	2.68	0	18
Violent Crime	1.99	1.62	0	11
Assault	1.53	1.36	0	10
Property Theft	1.36	1.43	0	10
Larceny	1.36	1.43	0	10
Panel 3 - Crimes (Train System Only)				
	[1]	[2]	[3]	[4]
All Offenses	10.14	4.13	0	28
Violent Crime	2.13	1.54	0	11
Assault	1.25	1.15	0	7
Property Theft	2.81	1.88	0	12
Larceny	2.8	1.88	0	12
Panel 4 - Ridership (In Millions)				
	[1]	[2]	[3]	[4]
Total Ridership	1.28	0.37	0.28	1.89
Bus System	0.83	0.23	0.21	1.21
Rail System	0.46	0.14	0.07	0.75

Notes: The statistics in this the first three panels of this table are calculated using daily crime counts for crimes occurring within Chicago public transit system over a 5,144 day time series (from 1/1/2001 to 1/31/2015). Panel 1 summarizes counts for crimes in the entire system, Panel 2 does the same for crimes in the bus system, and Panel 3 does the same for the train system. Panel 4 reports summary statistics for daily ridership (measured in millions).

Table 2.A.5 - ATUS Transportation Usage Means

Workweek vs. Weekend

Panel 1 - Fraction Using Each Type of Transportation

	Automobile	Bicycle/Walk	Bus/Train
	[1]	[2]	[3]
Workweek	0.74	0.34	0.23
Weekend	0.78	0.3	0.14
Difference	-0.04	0.04	0.09
P-Value	0.22	0.23	0

Panel 2 - Ave. Time Spent Using Each Type of Trans. (Min.

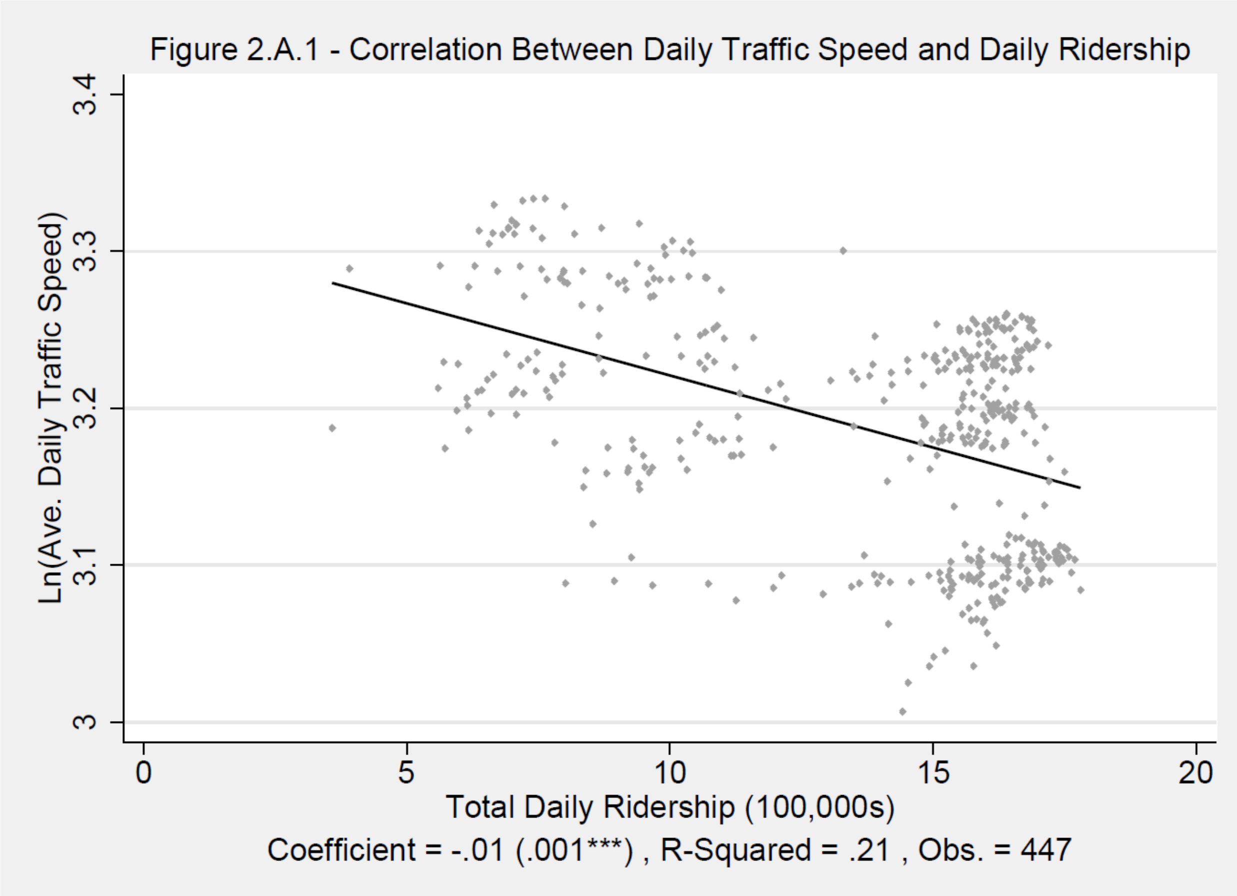
	[1]	[2]	[3]
Workweek	89.38	30.96	81.41
Weekend	85.78	27.48	77.61
Difference	3.61	3.49	3.8
P-Value	0.52	0.32	0.67

Notes: The statistics in this table were calculated using data from 794 ATUS respondents who completed their survey at some point during the 2004-2013 period, lived in Chicago at the time of the survey, and reported leaving home during their diary day. Panel 1 reports the percentage of respondents in the sample who reported using one of three types of transportation during their diary day. The sample in this panel is divided into workweek and weekend groups, and a T-test is conducted on the equality of the means. Panel 2 calculates the average time respondents spent (in minutes) using each transportation type. Once again, the sample is divided into workweek and weekend groups, and a T-test is conducted on the equality of the means.

Table 2.A.6 - Effect of Weather on Transportation Usage

	Automobile	Bicycle/Walk	Bus/Train
	[1]	[2]	[3]
Max. Temp.	-0.000225	0.00129	0.000624
	[0.00216]	[0.00236]	[0.00218]
Min. Temp.	0.000265	0.000236	-0.00124
	[0.00238]	[0.00263]	[0.00242]
Precip.	0.000807	-0.00168	-0.000826
	[0.000988]	[0.00115]	[0.000887]
Ave. Wind Speed	-0.00141	0.000324	0.000366
	[0.000991]	[0.00102]	[0.000913]
R-Squared	0	0	0
Observations	794	794	794

Notes: The regressions in this table were calculated using data from 794 ATUS respondents who completed their survey at some point during the 2004-2013 period, lived in Chicago at the time of the survey, and reported leaving home during their diary day. In these regressions, the left-hand side variable is an indicator for using a particular transportation type during the diary day, and the right-hand side variables include controls for daily maximum temperature, minimum temperature, total precipitation, and average wind speed. Eicker-Huber-White Standard errors are used. Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01



Notes: This figure displays a scatter plot and trend line to demonstrate the correlation between daily CTA ridership and daily average traffic speed in the city of Chicago. The sample includes 447 days during the 2011-2013 period. Daily average traffic speed is calculated using GPS bus speed data produced by the CTA and made publicly available through Chicago's online data portal. The details of this calculation are provided in Section 2.3. The coefficient and r-squared values come from an OLS regression in which the left-hand side variable is the natural log of daily average traffic speed, and the right-hand side variable is total daily ridership (measured in 100,000s). Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - $p < 0.10$, ** - $p < 0.05$, *** - $p < 0.01$

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CHAPTER 3

Weather Expectations, Time Use, and Criminal Activity

Abstract

Ladner (2015a) is the first study to investigate the effect of temperature on crime while incorporating a role for temperature expectations. That paper includes a model in which agents decide when to leave their residence based on these expectations; for example, more people will leave home in the present if the temperature in the future is expected to be less desirable. The location decisions of each agent collectively determine the level of criminal activity by altering the distribution of people inside and outside of residences. In this paper, I replicate many of the results from Ladner (2015a) for the city of Chicago, IL during the 2003-2014 period. In addition, I examine the impact of temperature expectations and forecast errors on public transit ridership, as a direct test of the underlying mechanisms in the model. I show that total ridership on day t is increasing in day t expected temperature, but is unaffected by the error in that expectation. I also show that ridership is lower when the future is expected to be warmer. The magnitude of these effects is very similar to what is seen for property theft, and the ratio of property theft offenses to ridership is not a function of temperature expectations or forecast errors. In contrast, violent crime on day t is much more responsive to day t expected temperature than public transit ridership, and is also significantly more affected by the forecast error. As a result, I conclude that the effect of temperature on violence cannot be entirely accounted for by changes in the distribution of people inside and outside of residences.

3.1 Introduction

The literature on temperature and crime dates to the 19th century,[82] and has been a frequent subject of discussion in recent years, both within academia and in the popular press. This renewed interest is in part due to concerns over climate change,[83] but also reflects a growing conviction amongst researchers and policy makers that one cannot fully understand patterns in criminal activity without understanding the role played by environmental conditions.

While an enormous amount of effort has gone into studying the temperature-crime relationship, until recently no research has incorporated a role for expectations, even though weather forecasts are ubiquitous in the modern world. Survey data strongly suggest that the average person has very well developed short-term expectations about the weather,[84] implying that any investigation of temperature's impact on crime must take these expectations into account. Ladner (2015a) is the first study to do so, and reveals many previously unknown details about the temperature-crime relationship. By studying a set of 50 U.S. cities during the 2004-2012 period, I show that violent crime and property theft on day t increase with expected temperature on day t, and fall when the weather is expected to be warmer in the future. Furthermore, I find that unexpectedly warm temperatures increase violent crime, while unexpectedly cool weather has the opposite effect. Interestingly, these errors in expectation (which I refer to as "forecast errors") have little to no significant effect on property theft.

[82] For a very early example, see Morrison (1891). While a handful of studies from this time period exist, the modern era on research on temperature and crime dates roughly to the late 1960s. Cohn (1990) provides an excellent review of the literature from these beginnings to the late 80s.
[83] For example, Ranson (2012) estimates that climate change may result in up to $68 billion dollars in additional social cost due to the effect of temperature on crime between 2009 and 2099.
[84] See Lazo, Morss, and Demuth (2009) for recent survey evidence on the subject.

How can these findings be rationalized? One of the most common explanations for the relationship between temperature and crime is that weather conditions influence the distribution of people inside and outside of residences at any point in time. For example, on a warm day many people will decide to leave home to enjoy the weather, which increases the number of opportunities for criminal activity. This explanation traces its roots to Cohen and Felson (1979), who proposed Routine Activity Theory (RAT) as a general model of criminal activity. The basic premise is that crimes are likely to occur when three factors coincide in time and space: 1) a suitable target, 2) a motivated offender, and 3) the absence of a capable guardian. The authors argue that the likelihood of these factors coming together is higher when more people are outside of their residence, for several reasons. For example, when many people are outside, there are more person-to-person interactions, and any one of these meetings has some chance of generating criminal activity. In addition, when more people are outside, there are more vulnerable targets for property theft (e.g. empty houses, cars parked in public places, etc.). According to this argument, any variable that changes the number of people inside and outside of residences (such as temperature) will affect crime.

Using a simple model of strategic interaction between criminals and non-criminals, Ladner (2015a) points out that individuals' location decisions in the present are likely to be derived from pre-made plans, and thus should depend on temperature *expectations* (rather than observed temperature conditions), both for the current period and the near future. People are more likely to leave home in the present if they expect the current period to have a relatively favorable temperature; conversely, when temperature conditions in the future are expected to be better, more individuals will delay leaving home (resulting in fewer opportunities for crime in the current period). The role of forecast errors is more mysterious; one possibility is that many people don't rely on forward planning when deciding whether to leave home, or that plans are reversible at low cost. In either case, forecast errors will affect crime in a manner similar to the expectations story outlined above.[85] Alternatively, it could be that forecast errors affect the probability that opportunities for crime actually result in criminal acts. For example, unexpectedly hot weather might agitate individuals and make them more prone to aggressive and/or risk-taking behavior.

Of course, a limitation of studying the impact of temperature on crime alone is that one cannot tell if the distribution of people inside and outside of residences is really responding to temperature expectations and forecast errors in the manner discussed above. The purpose of this paper is to produce a simplified version of the analyses conducted by Ladner (2015a), in a context where a strong proxy for the number of people outside of residences is available. Chicago, IL is the third largest city in the United States, and has an extensive public transit system used by about 1.3 million on a daily basis. The widespread usage of this bus and rail network makes daily total ridership an excellent signal for the number of people who decide to leave their home during the day. Furthermore, the city of Chicago makes daily crime and ridership data publically available dating back to 2001, providing a relatively long time series of data through which the effect of temperature on both variables can be studied.

[85] For example, an individual might decide to stay home on day t because she expects the temperature to be relatively cold, but then change her mind upon observing warmer than expected weather. In this case, forecast errors simply serve to determine the distribution of people inside and outside of residences, just as temperature expectations do.

By estimating a series of simple linear models, this paper examines the effect temperature expectations and forecast errors on criminal activity and public transit ridership in Chicago during the 2003-2014 period. I find that violent crime, property theft, and ridership on day t are all increasing in day t expected temperature, though the effect of a one degree increase in this variable is much greater for violent crime (0.58%) than it is for property theft (0.22%) or ridership (0.19%). In addition, I show that both criminal activity and ridership fall on days in which weather conditions in the future are expected to be warmer, especially if the current day is expected to be cold. Furthermore, I show that forecast errors have a significant effect on violent crime, but not on property theft or ridership. In nearly every respect, the effects I report for violent crime and property theft mirror the results of Ladner (2015a), and the results for ridership offer considerable support for the theoretical mechanisms briefly outlined above.

In addition to studying the effect of temperature expectations and forecast errors on criminal activity and ridership individually, I also look at how these variables affect the *ratio* of criminal activity to ridership. This ratio is of interest because it allows one to determine if crime and ridership respond similarly to the variables of interest, or if one of the two is more responsive. In the case of violent crime, I find that the ratio of violent crime to ridership is strongly increasing in day t expected temperature, forecast error, and future temperature difference. In stark contrast, the ratio of property theft to ridership is not significantly affected by any of the temperature variables studied, suggesting that property theft and ridership respond very similarly to changes in current day expected temperature, forecast errors, and future temperature expectations.

Without a doubt, the context considered in this paper is very specific, and the amount of data available is quite limited. For these reasons, this paper cannot hope to examine the effect of temperature expectations and forecast errors on criminal activity with the level of precision or generality that was possible in Ladner (2015a). However, by limiting my scope to this particular setting, this study capitalizes on a unique opportunity to investigate temperature's effect on crime and the distribution of people simultaneously. As a consequence, the results I present here are of exceptional complimentary value to my earlier work.

The remainder of this paper is organized as follows: Section 3.2 outlines my empirical methodology, Section 3.3 describes the data used, Section 3.4 reports all results, and Section 3.5 concludes.

3.2 Empirical Methodology

$$\ln(crime_t) = \alpha_0 + X_t'\gamma + \alpha_1 T_t + \varepsilon_t \quad (1)$$

The empirical methodology employed by this paper represents a simple extension of the regression model given in (1) above. In this model, $crime_t$ is the total number of criminal offenses of a particular type on day t, X_t is a set of controls, and T_t is the *observed* maximum temperature on day t. In this case, α_1 is interpreted at the effect of a one degree increase in T_t on $\ln(crime_t)$, conditional on all controls in X_t. As written, this model captures the simple positive correlation between observed temperature and crime that has been noted for years, but does nothing to account for people's temperature expectations.

Now suppose that one has access to data from a typical 7-day weather forecast. In this case, (1) can be augmented in two ways. First, T_t can be rewritten as the sum of the expected maximum temperature (T_t^e) and forecast error (e_t) on day t (i.e. $T_t = T_t^e + e_t$). In addition, one can define the variable $D_f^e = \left(\frac{1}{6}\sum_{j=1}^{6} T_{t+j}^e\right) - T_t^e$, which captures the average expected temperature in the next six days *relative* to the current day.[86] Throughout the remainder of the paper, I will refer to D_f^e as the "future temperature difference." Naturally, one can think of many alternative ways in which to capture future temperature expectations, but the definition used here represents an intuitive signal that uses all of the information available in the forecast.

Armed with these new variables, one can now estimate the model given in (2) below. The reader should note that (2) captures all of the variation in $\ln(crime_t)$ explained by (1), since the effect of T_t is completely captured by the inclusion of T_t^e and e_t; the only difference is that (2) allows for these two variables to have distinct effects on crime. The inclusion of D_f^e, on the other hand, captures an entirely new source of variation that was not accounted for in (1). The final two variables in (2) are interactions that are included to investigate the possibility that the effects of e_t and D_f^e depend on T_t^e, which seems intuitive.[87]

$$\ln(crime_t) = \beta_0 + X_t'\gamma + \beta_1 T_t^e + \beta_2 e_t + \beta_3 D_f^e + \beta_4 (T_t^e * e_t) + \beta_5 \left(T_t^e * D_f^e\right) + \epsilon_t \quad (2)$$

The model given in (2) represents a simplified version of the semi-parametric model estimated in Ladner (2015a). The principal value added in this paper is the ability to estimate the models given below in (3) and (4). The former is identical to (2), except that the dependent variable is now the natural log of public transit ridership on day t. Consequently,

[86] For example, $D_f^e = 5$ implies that the next six days are expected to be five degrees warmer than the current day, on average.
[87] For example, expecting it to be warmer in the future may strongly affect the plans that individuals make on days that are expected to be cold, but have little to no effect on days that are expected to be warm (since the net benefit gained from delaying one's activities away from home is presumably low in the latter case).

(3) can be used to determine if ridership responds to temperature expectations and forecast errors in the manner predicted by the mechanisms discussed above. Furthermore, since $\ln\left(\frac{crime_t}{ridership_t}\right) = ln(crime_t) - ln(ridership_t)$, we have that $\rho_i = \beta_i - \delta_i$ for any i. As such, testing the null hypothesis $H_0\colon \rho_i = 0$ is equivalent to testing whether β_i and δ_i are equal. In other words, estimating (4) allows one to determine whether or not $crime_t$ and $ridership_t$ respond in the same magnitude to any change in the variables of interest (i.e. T_t^e, e_t, D_f^e, or the interactions).

$$\ln(ridership_t) = \delta_0 + X_t'\gamma + \delta_1 T_t^e + \delta_2 e_t + \delta_3 D_f^e + \delta_4(T_t^e * e_t) + \delta_5\left(T_t^e * D_f^e\right) + \mu_t \quad (3)$$

$$\ln\left(\frac{crime_t}{ridership_t}\right) = \rho_0 + X_t'\gamma + \rho_1 T_t^e + \rho_2 e_t + \rho_3 D_f^e + \rho_4(T_t^e * e_t) + \rho_5\left(T_t^e * D_f^e\right) + \sigma_t \quad (4)$$

In all cases, these models are estimated using a time series of 3,859 days, beginning in the middle of 2003 and extending to the end of 2014 (all gaps arise due to missing weather forecast data). X_t includes year-by-month fixed effects, day-of-week fixed effects, a first-of-the-month indicator, holiday controls, professional sports game day controls, one lag of observed maximum temperature and precipitation, current day observed precipitation, and controls for current and future precipitation expectations. Detailed descriptions of these controls are given in Table 3.A.1. In all regressions, heteroscedasticity autocorrelation robust (HAC) standard errors are calculated according to the method proposed by Newey and West (1994).

3.3 Data

The analyses conducted in this study require several types of data that must be drawn from a variety of sources. The sources most central to the study include crime data from the CPD, ridership data from the CTA, observed weather data from the Global Historical Climatology Network (GHCN), and weather forecasts produced by the National Weather Service (NWS). All of these sources are described in more detail below.

The crime data used in this study include daily counts of different offense types, which were tabulated using a complete record of CPD crime reports. These report-level data are made publically available via Chicago's online data portal, and cover the 2001-2014 period. In this paper, I focus on violent crime and property theft offenses, which collectively account for about 61% of all criminal incidents on a typical day.[88] These two crime types are defined in Table 3.A.2. Daily city-wide crime summary statistics are provided in Table 3.A.3.

The ridership data used in my analyses are also made publically available via Chicago's online data portal. Daily ridership figures are calculated by aggregating ridership values for every bus route and train station in the CTA system. In all cases, "ridership" is measured by counting the number of people that access the CTA system via its various points of entry. For example, the daily ridership at an individual train station is calculated as the number of people who pass through that station's entry turnstiles. Daily ridership summary statistics are provided in Panel 1 of Table 3.A.4.

The ability of CTA ridership to proxy for the number of Chicagoans who choose to leave home on a given day is of central importance to this paper. Ladner (2015b) uses the same ridership data for the same purpose, and demonstrates ridership's value as a proxy via several different data sources. Firstly, I use survey data from the American Time Use

[88] The remainder of criminal activity is dominated by drug crimes, as well as certain non-theft property offenses (e.g. vandalism and trespassing). I focus on property theft and violent crime because these major categories include all of the offense types that have received significant attention in the relevant literature.

Survey (ATUS) to show that a significant minority (about 18%) of Chicagoans use buses and/or trains for transportation;[89] importantly, I also show that this fraction does not vary with observed weather conditions. Furthermore, I use CTA bus traffic speed data from the 2011-2013 period to demonstrate a strong negative correlation between CTA ridership and average daily bus speed. If traffic speed and the number of cars on the road are inversely related, then the negative correlation between CTA ridership and traffic speed suggests that public transit usage and car usage are positively correlated. If automobile usage is a strong signal for the number of people outside of residences,[90] then its strong correlation with CTA ridership provides significant evidence in support of the latter's usage in this paper.

Of course, all of the analyses I conduct below rely on having weather forecast and observed weather data. For weather forecasts, I use the Tabular State Forecast (TSF) product produced by the NWS for Chicago's O'Hare International Airport during the 2003-2014 period. This 7-day forecast looks very similar to the sort of forecast one would see in a newspaper, and includes predictions for daily maximum temperature, daytime chance of precipitation, and a word or phrase describing expected weather conditions (e.g. "partly cloudy"). In all cases, the forecasts I use were published on the afternoon of day $t - 1$, where the dependent variable in all of my regression is calculated on day t. Therefore, these forecasts capture people's weather expectations just before day t, when plans for that day are likely to be made.

[89] This fraction is significantly higher during the workweek (23%) than the weekend (14%).
[90] This is very likely to be true, since (according to the ATUS data), well over 70% of Chicagoans who report leaving home during their diary day use a car to travel.

The observed weather data used in this study come from the GHCN, and include daily values for maximum temperature and total precipitation. The specific station used here is located at Chicago's O'Hare International Airport (the same place that the weather forecast applies to). A number of summary statistics for observed and forecast weather data are provided in Panel 2 of Table 3.A.4.

3.4 Results

In this section, I present my results in a series of three tables, I begin by estimating the model given in (2) for violent crime and property theft in Chicago during the 3,859 day sample period. These regressions constitute a simplified replication of the main results from Ladner (2015a). I then use the same sample to estimate the effect of temperature expectations and forecast errors on public transit ridership. This is followed by estimating the regression model given in (4), along with a brief discussion of the implications of my findings.

Table 3.1 contains the results obtained from estimating (2) for the entire 3,859 day sample. In all cases, the dependent variable is a daily log count of total criminal activity for a given crime type. Violent crime and property theft are the main categories of interest, though I also examine the major subcategories of assault and larceny. In addition, I produce estimates for the all-encompassing category of "all offenses," which includes the total number of incidents (of all kinds) reported by the CPD on a given day.

The most basic finding in Table 3.1 is that all types of criminal activity studied respond positively to the expected maximum temperature in the current period. This effect is quite strong for violent crime, where a 1 degree increase in expected maximum temperature on day t increase violent crime on that day by 0.58%. This value is essentially the same for the major subcategory of assault (0.6%). Property theft (0.22%) and larceny (0.24%) respond much more modestly to the same increase in expected maximum temperature, though these effects are still highly statistically significant. Given that violent crime and property theft encompass the majority of all criminal activity, it should come as no surprise that the effect of a one degree increase in expected maximum temperature on the total level of criminal activity is in the middle (0.35%).

Table 3.1 also reveals strong evidence that increases in D_f^e are negatively correlated with criminal activity, especially property theft. In fact, a one degree increase in the future temperature difference is associated with a 0.35% fall in property theft, and a nearly 0.4% fall in larceny. The same increase only reduces violent crime by 0.2%, and has no significant impact on assault. For the catch-all category of all offenses, a one degree increase in D_f^e reduces criminal activity by 0.33%. In all of the significant cases discussed here, the coefficient on the interaction term $FTD * EMT$[91] reveals that the effect of future temperature differences on crime is more pronounced on days that are expected to be cold.

Table 3.1 further shows that forecast errors significantly affect violent crime, with a one degree increase in error being associated with a 0.31% increase in violent crime and a 0.3% increase in assault.[92] Furthermore, I am able to reject the null hypothesis that the expected maximum temperature and forecast error coefficients equal each other with 90% confidence. Therefore, a one degree increase in expected maximum temperature does not appear to have the same effect on violence as an equivalent increase in forecast error. As in Ladner (2015a), forecast errors do not affect property theft or larceny in any significant

[91] Here, FTD is short for "future temperature difference," and EMT is short for "expected maximum temperature."
[92] This estimate is only significant at the 90% level.

manner; furthermore, the estimated impact of forecast errors on the "all offenses" category is also insignificant.

Table 3.2 estimates three versions of the regression model given in (3), where the dependent variable is the log of total ridership, bus ridership, or train ridership (in columns 1, 2, and 3, respectively). The coefficient estimates are quite similar for each of the three, so I will focus on discussing total ridership here. I find that a one degree increase in expected maximum temperature on day t results in a 0.19% increase in total daily ridership, while a similar increase in the future temperature difference reduces ridership in the current period by 0.42%. In other words, there is strong evidence that individuals delay their out-of-residence activities if they expect it to be warmer in the future. As was the case with criminal activity, the coefficient on the $FTD * EMT$ interaction reveals that this effect is especially strong on days that are expected to be cold. Finally, forecast errors do not appear to have any effect on ridership.

In comparing the results of Table 3.1 and Table 3.2, the reader may have noted that the coefficient estimates for property theft and ridership are quite similar, while those for violent crime seem to differ from the other two significantly. One can examine this similarity formally by estimating the regression model given in (4), where the dependent variable is the log of the ratio of crime and ridership. If expected maximum temperature, forecast errors, and future temperature differences affect the numerator and denominator in in the same manner, then the ratio itself should not vary with any of the three channels (see Section 3.2 for a discussion of this point). Table 3.3 contains estimates for (4) for all of the major crime categories studied. As expected, the ratio of property theft to ridership is not a function of any of the variables of interest. In stark contrast, a one degree increase in the expected maximum temperature on day t increases the log ratio of violent crime to ridership by 0.39%, while a one degree increase if forecast error increases the same ratio by 0.51%. A similar increase in the future temperature difference also increases to ratio of violent crime to ridership, by 0.22%.

There are several important observations to take away from the results reported in Table 3.3. First of all, the fact that property theft and ridership respond nearly identically to the variables of interest strongly suggests that changes in the distribution of people inside and outside of residences can go a long way towards explaining the relationship between temperature and property theft. This finding represents a significant contribution to the literature, as it provides some of the most direct evidence to date in support of the Routine Activity Theory mechanism that has long been associated with the effect of temperature on property-based criminal activity.

An equally clear fact is that there must be some unobserved factor that makes the relationship between violent crime and temperature unique. Ultimately, the data available for this study do not allow me to identify the source of this uniqueness, but there a few things to consider going forward. One possibility is that higher temperatures are associated with aggression, and this mechanism has received significant attention in the in the fields of criminology and social psychology.[93] This could explain why a given increase in expected maximum temperature increases violent crime more than it increases ridership, and might even account for the effect of forecast errors on the same ratio. However, forecast errors may also constitute negative emotional cues that incite violent behavior. There is no direct

[93] See Anderson (1989) for a discussion of several different temperature-aggression models, along with a review of the empirical evidence.

evidence for such a mechanism in the literature on temperature and crime,[94] but some research on sports outcomes and crime suggests that deviations from expectations can trigger violence.[95] Furthermore, there is no intuitive reason that future temperature differences should affect aggression, so some other explanation for this finding must be sought.

3.5 Conclusion

Ladner (2015a) is the first study to incorporate a role for expectations in the investigation of temperature and crime. The model outlined in that paper suggests that temperature expectations affect crime by altering the distribution of people inside and outside of residences, and thus increasing or diminishing the number of opportunities for criminal activity. By incorporating weather forecast data, this paper seeks to test the basic elements of this model.

In principle, the methods used in this paper could be applied to any weather variable of interest. For example, understanding how people's expectations about precipitation affect planning (and therefore criminal activity) is of particular importance, since precipitation is intuitively one of the most important weather elements people consider when making plans. Unfortunately, most weather forecasts report an expected chance of precipitation rather than an expected quantity, which poses a number of obstacles.[96]

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[94] Since this paper and Ladner (2015a) are the only two papers to investigate the effect of forecast errors.
[95] See Card and Dahl (2011) and Reese and Schenpel (2009) for examples. In both cases, the authors find that unexpected losses are associated with increases in violence, over-and-above the effect of a loss in and of itself.
[96] Ladner (2015a) discusses this in more detail.

Even so, a first step in addressing this question is provided by Table 3.A.5, where the observed and forecast precipitation controls included in all of the regression models of this paper are reported. Note that the coefficients in columns [1] through [5] come from the same regressions used in in Table 3.1, and the coefficients from column [6] are drawn from the regression used to produce column [1] of Table 3.2. In all cases, it is clear that observed precipitation significantly reduces criminal activity, and column [6] indicates that precipitation has the same effect on ridership. However, there is no indication that ridership or criminal activity are affected by precipitation expectations, either for the current day or the future. This lack of significance may be due to a lack of data, or may be a byproduct of the fairly rigid regression specification;[97] in any case, I will relegate a comprehensive examination of the relationship between precipitation expectations and crime to future research.

This paper confirms the findings of Ladner (2015a) in the specific context of Chicago, IL during the 2003-2014 period; furthermore, I demonstrates that public transit ridership responds to temperature expectations in the manner predicted by the model. In fact, property theft and ridership respond in a near-identical manner to temperature expectations, and neither appears to respond to forecast errors. In contrast, violent crime responds significantly to forecast errors, displays a much larger response to expected maximum temperature (relative to ridership), and is significantly less responsive to future temperature differences. Through these results, I provide novel insight into the mechanisms underlying the temperature effect on crime.

[97] For example, Ladner (2015a) uses a more flexible semiparametric specification, and finds that the current day expected chance of precipitation reduces criminal activity.

Main Tables

Table 3.1 - Effect of Temperature Expectations and Forecast Errors on Crime
All Days in Sample, All Locations

		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]	[5]
Exp. Max. Temp. (EMT)	0.00347***	0.00580***	0.00600***	0.00217***	0.00242***
	[0.000343]	[0.000459]	[0.000508]	[0.000456]	[0.000490]
Forecast Error (FE)	0.00106	0.00311**	0.00299*	-0.000603	-0.000451
	[0.00113]	[0.00149]	[0.00157]	[0.00134]	[0.00148]
Future Temp. Diff. (FTD)	-0.00325***	-0.00200**	-0.00114	-0.00350***	-0.00397***
	[0.000584]	[0.000784]	[0.000856]	[0.000819]	[0.000814]
Interaction: FE*EMT	0.0000102	0.0000173	0.0000294	0.00000862	0.00000958
	[0.0000174]	[0.0000227]	[0.0000236]	[0.0000208]	[0.0000234]
Interaction: FTD*EMT	0.0000564***	0.0000236**	0.00000481	0.0000719***	0.0000812***
	[0.00000751]	[0.0000109]	[0.0000117]	[0.0000111]	[0.0000111]
R-Sqaured	0.93	0.87	0.87	0.87	0.84
Observations	3859	3859	3859	3859	3859
EMT = FE (P-Value)	0.043	0.074	0.061	0.063	0.092

Notes: This tables reports the results of regressions in which the LHS variable is a log count of daily criminal activity. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 3.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 3.2 - Effect of Temp. Exp. and Forecast Errors on Ridership
All Days in Sample

	Total	Bus	Rail
	[1]	[2]	[3]
Exp. Max. Temp. (EMT)	0.00193***	0.00204***	0.00174***
	[0.000428]	[0.000483]	[0.000406]
Forecast Error (FE)	-0.00197	-0.00174	-0.00233
	[0.00186]	[0.00188]	[0.00187]
Future Temp. Diff. (FTD)	-0.00415***	-0.00488***	-0.00294***
	[0.000990]	[0.000998]	[0.00108]
Interaction: FE*EMT	0.000044	0.0000421	0.000047
	[0.0000286]	[0.0000285]	[0.0000296]
Interaction: FTD*EMT	0.0000731***	0.0000854***	0.0000521***
	[0.0000156]	[0.0000158]	[0.0000169]
R-Sqaured	0.94	0.94	0.93
Observations	3859	3859	3859
EMT = FE (P-Value)	0.044	0.059	0.029

Notes: This tables reports the results of regressions in which the LHS variable is a log count of daily public transit ridership in the city of Chicago, either in total (column 1), for the bus system (column 2), or the train system (column 3). Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 3.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

Table 3.3 - Effect of Temperature Expectations and Forecast Errors on Crime-Ridership Ratios
All Days in Sample, All Locations

		Violent Crime		Property Theft	
	All Offenses	All	Assault	All	Larceny
	[1]	[2]	[3]	[4]	[5]
Exp. Max. Temp. (EMT)	0.00154***	0.00387***	0.00407***	0.000242	0.000486
	[0.000380]	[0.000441]	[0.000440]	[0.000530]	[0.000542]
Forecast Error (FE)	0.00303**	0.00507***	0.00495***	0.00136	0.00152
	[0.00148]	[0.00154]	[0.00167]	[0.00192]	[0.00213]
Future Temp. Diff. (FTD)	0.000901	0.00216***	0.00302***	0.000652	0.000182
	[0.000758]	[0.000738]	[0.000725]	[0.000775]	[0.000866]
Interaction: FE*EMT	-0.0000338	-0.0000267	-0.0000146	-0.0000353	-0.0000344
	[0.0000236]	[0.0000255]	[0.0000273]	[0.0000296]	[0.0000329]
Interaction: FTD*EMT	-0.0000167	-0.0000494***	-0.0000683***	-0.00000116	0.00000811
	[0.0000121]	[0.0000123]	[0.0000117]	[0.0000113]	[0.0000130]
R-Sqaured	0.95	0.95	0.95	0.92	0.9
Observations	3859	3859	3859	3859	3859
EMT = FE (P-Value)	0.364	0.48	0.619	0.595	0.655

Notes: This tables reports the results of regressions in which the LHS variable is a log ratio of daily criminal activity to daily total public transit ridership. See Section 3.2 and equation (4) for details. Numerous controls are present, including year-by-month fixed effects, day-of-week fixed effects, a first of month indicator, holiday indicators, professional sports game day indicators, and controls for current and lagged weather conditions. Detailed definitions for these controls are given in Appendix Table 3.A.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

3.A Additional Tables

Table 3.A.1 - Description of Regression Controls
Daily Regressions

Year-By-Month Fixed Effects	Indicators for every year-month combination in the sample (except for the omitted category). For example, there is an indicator for January 2007.
Weekday Fixed Effects	Indicators for every weekday in the sample (except for the omitted category). For example, there is an indicator for Friday.
First-of-Month Indicator	Indicator for whether a given day is the first day of the month.
Holiday Indicators	A set of indicators capturing 17 major holidays and other days that have special significance. The list includes: New Year's Day, MLK Day, Presidents Day, Fat Tuesday, St. Patrick's Day, Easter, Memorial Day, July 4th, Labor Day, Columbus Day, Halloween, Veterans Day, Thanksgiving, Black Friday, Christmas Eve, Christmas Day, and New Year's Eve.
Daily Max. Temperature	The observed maximum temperature on a given day, measured in degrees Fahrenheit.
Daily Total Precipitation	The observed total precipitation on a given day, measured in millimeters.
Lagged Weather Values	One lag of observed max. temperature and total precipitation are included in every daily regression.
Daytime Chance of Precip.	The percent chance of non-zero precipitation between 6:00am and 6:00pm on the current day.
Chance of Precip. (Future Diff.)	The difference between the current day chance of precipitation and the average future chance of precipitation (average based on remaining 6 days in forecast).

Table 3.A.2 - Description of Major Crime Categories UCR Codes in Parentheses	
Violent Crime	Includes all forms of homicide (91-3), all forms of assault (131-133), sexual assaults (111-114), robbery (120), and weapons violations (150).
Property Theft	Includes all forms of larceny (2331-238), burglary (220), motor vehicle theft (240), and stolen property offenses.

Notes: This tables defines the major crime categories studied in this paper. The large subcategories of assault and larceny are also examined, as they form the bulk of violent crime and property theft (respectively). The codes listed are used by the National Incident Based Reporting System (NIBRS) to classify individual offenses.

Table 3.A.3 - Crime Summary Statistics

	Mean [1]	Std. Dev. [2]	Min [3]	Max [4]
All Offenses	1068.61	217.98	318	1888
Violent Crime	311.89	74.2	93	644
Assault	255.77	65.38	79	470
Property Theft	336.45	68.88	103	661
Larceny	222.01	47.57	59	545

Notes: The statistics in this table are calculated using daily crime counts from Chicago, IL over a 3,859 day time series beginning in the middle of 2003 and ending on 12/31/2014 (with gaps).

Table 3.A.4 - Additional Summary Statistics

Panel 1 - Daily Ridership (In Millions)

	Mean	Std. Dev.	Min	Max
	[1]	[2]	[3]	[4]
Total Ridership	1.3	0.36	0.28	1.81
Bus	0.83	0.23	0.21	1.21
Rail	0.47	0.14	0.07	0.75

Panel 2 - Daily Observed and Forecast Weather Values

	[1]	[2]	[3]	[4]
Precip. (mm)	2.72	8.24	0	174.2
Max. Temp.	59.8	21.25	-1.84	102.92
E[Max. Temp.]	59.05	21.25	-11	104
Forecast Error	0.75	3.52	-13.08	14.92

Notes: The statistics in this table are calculated using daily crime counts from Chicago, IL over a 3,859 day time series beginning in the middle of 2003 and ending on 12/31/2014 (with gaps). Panel 1 summarizes daily public transit ridership values, while Panel 2 does the same for observed and forecast weather data.

Table 3.A.5 - Effect of Observed and Expected Precipitation on Crime
All Days in Sample, All Locations

		Violent Crime		Property Theft		
	All Offenses	All	Assault	All	Larceny	Ridership
	[1]	[2]	[3]	[4]	[5]	[6]
Obs. Precip. (mm)	-0.00132***	-0.00163***	-0.00176***	-0.000573***	-0.000832***	-0.00110***
	[0.000236]	[0.000295]	[0.000315]	[0.000162]	[0.000196]	[0.000259]
Current Chance (%)	-0.000265	-0.000191	-0.000216	0.000119	-0.000245	-0.000362
	[0.000180]	[0.000331]	[0.000362]	[0.000243]	[0.000291]	[0.000236]
Future Chance Diff. (%)	0.0000466	0.000259	0.000314	0.000185	-0.00000949	0.000113
	[0.000165]	[0.000307]	[0.000336]	[0.000228]	[0.000267]	[0.000217]
R-Sqaured	0.93	0.87	0.87	0.87	0.84	0.94
Observations	3859	3859	3859	3859	3859	3859

Notes: This table reports the coefficients from the precipitation variables included as controls in the vector X_t of the regression model given in (2). These estimates were obtained from the same regressions used to produce the results of Table 3.1. Heteroskedasticity autocorrelation robust (HAC) standard errors are calculated according to the method outlined in Newey and West (1994). Significance levels: * - p < 0.10 , ** - p < 0.05 , *** - p < 0.01

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