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

Justin Ladner*†
Updated: 1/17/2015

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 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 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

---

\(^1\) 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.
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.\textsuperscript{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 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 2 presents the theoretical model and its predictions, Section 3 discusses the empirical methodology, Section 4 provides an overview of the data used, Section 5 presents results, Section 6 discusses potential mechanisms, and Section 7 concludes.

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

\textsuperscript{3} See, for example, Lee and McCrary (2005).
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.

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 ($T^e_1$), and the expected temperature in period 2 ($T^e_2$). Player $i$ can expect to receive $b_1 = b(T^e_1)$ units of utility from leaving her residence in period 1, and $b_2 = b(T^e_2)$ units of utility from doing so in period 2. Furthermore, player $i$ is assumed to have a player-specific discount factor $\delta_i$. 

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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 $\delta_1 b_2$.

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. 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 $\pi$, $\omega$ 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 $\pi_0$ 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:

$$\max \{b_1 - N^B_1 \pi_0 L, \delta_i [b_2 - N^B_2 \pi_0 L] \}$$

where $\delta_i \sim U[0,1]$ and $N^B_1 = \lambda p^B \rho^c, N^B_2 = \lambda p^B (1 - \rho^c)$

(1)

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

---

4 For instance, during the period in which she has left home her residence may be burglarized.

5 The value $\rho^c$ represents the critical value of the discount factor for type B players.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
leave their residence. Each of these 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 \(\pi_0\) in their maximization problem. Player \(j\) has a player-specific discount factor given by \(\rho_j\), 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:

\[
\max\{N_1^A\pi_0G, \rho_jN_2^A\pi_0G\}
\]

where \(\rho_j \sim U[0,1]\)

and \(N_1^A = \lambda P^A\delta^c\), \(N_2^A = \lambda P^A(1 - \delta^c)\)

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 \(\delta\) and \(\rho\).

**Solving for Critical Values**

For type A and type B players, the critical values of \(\delta^c\) (for type A) and \(\rho^c\) (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 \(\delta\) is given by the following condition:

\[
b_1 - N_1^B\pi_0L = \delta\left[ b_2 - N_2^B\pi_0L \right]
\]

\[
\Rightarrow \delta^c = \frac{b_1 - N_1^B\pi_0L}{b_2 - N_2^B\pi_0L}
\]

Define \(\phi = \lambda P^B\pi_0L\)

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

For type B players, one can solve for the critical value of \(\rho\) in a similar fashion:

\[
N_1^A\pi_0G = \rho_jN_2^A\pi_0G
\]

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
\[ \Rightarrow \rho^c = \frac{N_A \pi_0 G}{N_B \pi_0 G} \]

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

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

\[ \rho^c = \begin{cases} 
\frac{\delta^c}{1 - \delta^c} & \text{if } \delta^c < 0.5 \\
1 & \text{if } \delta^c \geq 0.5 
\end{cases} \quad (4) \]

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. Instead, we are interested in how these critical values change with \( b_1 \) and \( b_2 \):\(^7\)

\[ \frac{\partial \delta^c}{\partial b_1} = \frac{(1 - \delta^c)^2 K_2}{K_2^2 (1 - \delta^c)^2 + K_2 \phi + K_1 \phi} \quad (5) \]

\[ \frac{\partial \delta^c}{\partial b_2} = \frac{-(1 - \delta^c)^2 K_1}{K_2^2 (1 - \delta^c)^2 + K_2 \phi + K_1 \phi} \quad (6) \]

\[ \frac{\partial \rho^c}{\partial b_1} = \frac{\partial \delta^c}{\partial b_1} \quad (7) \]

\[ \frac{\partial \rho^c}{\partial b_2} = \frac{\partial \delta^c}{\partial b_2} \quad (8) \]

\[ \text{Where} \quad K_1 = b_1 - \rho^c \phi \]

\[ K_2 = b_2 - (1 - \rho^c) \phi \]

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 \( T_1 \).\(^6\)

---

\(^{6}\) I derive this solution in Appendix I.

\(^{7}\) See Appendix I for the derivation of these derivatives.

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
and $T^e_2$. 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.

**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 ($T^e_t$) and forecast error ($\omega_t = T_t - T^e_t$) 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 $I_2$:

$$I_1 = \pi(\omega_1)\lambda P^A P^B \delta^c \rho^c$$
$$I_2 = \pi(\omega_2)\lambda P^A P^B (1 - \delta^c)(1 - \rho^c)$$ (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 $\delta^c$ and $\rho^c$. 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 $T^e_t$, but it is
reasonable to assume that \( \frac{db_t}{dT_t} \) is positive for most values of \( T_t^e \). 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 \( \omega_1 \) and \( \omega_2 \) 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 6.

A Graphical Representation

An example equilibrium for this model is depicted graphically in Figure M1,\(^9\) with comparative statics given in Figures M2 and M3. In Figure M1, 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 \( \delta^c \) as a function of \( \rho^c \), and (4) expresses \( \rho^c \) as a function of \( \delta^c \). Equilibrium requires that both expressions be satisfied simultaneously, which is graphically represented by the intersection of the two functions.

Figure M2 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 \( \rho \) is now associated with a

---

\(^8\) It is certainly not necessary to assume that \( \frac{db_t}{dT_t} > 0 \) 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.

\(^9\) The inclusion of an “M” before the number of any table or figure indicates that the table/figure is in Appendix I.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
higher value of \( \delta \). As our previous discussion would suggest, this shift results in higher values for \( \delta^c \) and \( \rho^c \), which leads to more crime in period 1. In a similar fashion, Figure M3 considers an increase in \( T^c_2 \), 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.

3 Empirical Methodology

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.\(^{10}\) 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).\(^{11}\) Furthermore, 74% of the

\(^{10}\) 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.

\(^{11}\) 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...
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.\textsuperscript{12}

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 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.\textsuperscript{13}

\textit{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:

$$\theta_t = \alpha + X_t'\gamma + f(T_t) + \epsilon_t \quad (11)$$

In (11), $\theta_t$ is a measure for some type of criminal activity pertaining to time period $t$ (e.g. a monthly assault rate), and $X_t$ is a set of fixed effects and other controls. There is considerable variation in the time scales studied; many researchers look at monthly crime data,\textsuperscript{14} but annual, weekly, and daily

\textsuperscript{12} Based on valuation questions in their survey, the authors report a median household value of weather forecasting of $286/year.

\textsuperscript{13} 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 5.

\textsuperscript{14} 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).

\textbf{Reading Note}: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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 $f(T_t)$, which represents some function of observed temperature for day $t$. Many different forms of $f(T_t)$ have been studied over the years, but the most basic option is to assume a linear relationship between temperature and crime (i.e. $f(T_t) = \beta T_t$). 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:

$$\theta_t = \beta_0 + X_t' \gamma + \beta_1 T_t + \varepsilon_t \tag{12}$$

In this model, $\beta_1$ 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 $X_t$. By accounting for expectations, one can increase the information contained in (12) in two distinct ways. First, it is possible to rewrite $T_t$ as $T_t = T_t^e + e_t$, where $T_t^e$ is the expected temperature on day $t$ and $e_t$ 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 $\overline{T_f^e}$). The forecasts used in this study cover seven days; as such, $\overline{T_f^e}$ is defined as the average expected temperature in the six days after the current day (i.e. $\overline{T_f^e} = \frac{1}{6} \sum_{j=1}^{6} T_{t+j}^e$). However, the theoretical model in Section 2 suggests that we are truly interested in how expected future temperature conditions differ from the current day; therefore, I define the variable $D_f^e = \overline{T_f^e} - T_t^e$, which I refer to as the “future temperature difference.” Using these new definitions and terms, one can estimate the regression model given in (13).

$$\theta_t = \alpha_0 + X_t' \tau + aT_t^e + b e_t + cD_f^e + \mu_t \tag{13}$$

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Note that the variables $T_t^e$ and $e_t$ decompose the variation that $T_t$ captured in (12), while the inclusion of $D_f^e$ 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.¹⁵ 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 ($T_t^e$, $e_t$, and $D_f^e$) were related to temperature in a linear manner. This simplification was convenient for expository purposes, but there is strong evidence in past research to suggest that the effect of temperature on crime may be non-linear.¹⁶ As such, in the analyses to follow 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:

---

¹⁵ 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).

¹⁶ See, for example, Cohn and Rotton (1997) and Cohn and Rotton (2000).
1. Expected Maximum Temperature ($T_{i,t}^e$) – 14 bins (indexed by $i$), 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 ($T_{1,t}^e$).

2. Forecast Error ($e_{j,t}$) – 9 bins (indexed by $j$), 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] ($e_{5,t}$).

3. Future Temperature Difference ($D_{k,f}^e$) – 9 bins (indexed by $k$), 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], (1 F, 5 F], ... , > 13 F). The omitted category is [-1 F, 1 F] ($D_{5,f}^e$).

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

$$\theta_t = \rho_0 + X_t'\tau + \sum_{i \neq 1} a_iT_{i,t}^e + \sum_{j \neq 5} b_j e_{j,t} + \sum_{k \neq 5} c_k D_{k,f}^e + \eta_t \quad (14)$$

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 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). The vector $X_t$ includes year-by-city fixed effects, month-by-city fixed effects, day-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 and one lag of observed precipitation, controls for

---

17 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.

18 Thus, if $y$ is the number of offenses of a particular type occurring on day $t$, then $\ln(y) = \ln\left(y + \sqrt{1 + y^2} \right)$.

19 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 $T_{t}^e$.

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
total precipitation\textsuperscript{20} on day $t$, controls for forecast daytime chance of precipitation on day $t$,\textsuperscript{21} and controls for the average forecast chance of daytime precipitation in the near future.\textsuperscript{22} The controls for precipitation expectations come from the same forecasts used for expected daily maximum temperature; a summary of the controls contained in $X_t$ is given in Table A4.\textsuperscript{23} For all regressions in this paper, standard errors are clustered by city.

The numerous controls contained in $X_t$ (especially the weather variables) are included in order to allow for a particular interpretation of the $a_i$, $b_j$, and $c_k$ coefficients. Specifically, the coefficient estimates discussed in Section 5 capture the effect of $T^c_t$, $e_t$, and $D^f_t$ \textit{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. Precipitation expectations (both for the current day and in the future) may also be important.\textsuperscript{24}

\textsuperscript{20} 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.

\textsuperscript{21} 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.

\textsuperscript{22} This variable is defined in a similar manner to $D^f_t$. 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%.

\textsuperscript{23} [0%, 10%] is the omitted category.

\textsuperscript{24} The inclusion of an “A” before the number of any table or figure indicates that the table/figure is in Appendix III.

\textsuperscript{24} Dropping some or all of these weather controls has little meaningful impact on the $a_i$, $b_j$, and $c_k$ coefficients (the magnitudes change in some cases, but the qualitative interpretation remains the same, and significance levels are not meaningfully altered).

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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 II.

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 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.

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. Instead, I group crimes into two major categories: violent crime and property theft. These two categories collectively

---

25 As measured by average population during the 2006-2012 period
26 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.
account for about 70% of all criminal activity\textsuperscript{27} 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.\textsuperscript{28} 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 A1, and sample summary statistics for daily crime counts are provided in Panels 1 and 2 of Table 1.

\textit{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 my analyses are daily maximum temperature and daily total precipitation. Panel 3 of Table 1 provides sample summary statistics for these two variables.

\textit{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.\textsuperscript{29} Given their ubiquity in day-to-day life,

---

\textsuperscript{27} The largest omitted category is vice crime (which is dominated by drug-related offenses), followed by property damage crimes (mostly vandalism).

\textsuperscript{28} Assaults account for the vast majority of violent crimes, and larcenies account for a majority of property theft.

\textsuperscript{29} For example, local news stations take NWS forecast data and use them in reporting their own forecasts.
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). 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, and include simple weather forecasts for a set of cities in a particular U.S. state. 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 chance of precipitation. A short 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 3. Panel 3 of Table 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

---

30 Go to [http://has.ncdc.noaa.gov/pls/plhas/has.dsselect](http://has.ncdc.noaa.gov/pls/plhas/has.dsselect).
31 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.
32 For larger states, a single TSF report will only cover a region of that state.
33 Nighttime is defined as 6:00pm-6:00am, while daytime is 6:00am-6:00pm.
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 II.

5 Results

The results discussed below are divided into several subsections. I begin with a simplified model in which all forecast information has been removed. This is followed by an examination of the regression model given by (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 III.

*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 3 for details). The results of this exercise are presented in Figure 1.
Figure 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 A1 demonstrates that the effect of observed maximum temperature on crimes occurring outside of residences is very similar.

Full Model

Figures 2 through 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 2 reports the effect of expected temperature on the current day, Figure 3 does the same for current day forecast errors, and Figure 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 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 2, Figure 2 is consistent with the prediction that crime rises when conditions on the current day are expected to be better. As Figure A2 demonstrates, the effect of expected maximum temperature on crimes outside of residences is very similar.

Figure 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 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 A3.

Figure 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, 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 A4), the effect of future temperature differences is qualitatively similar, but the property theft coefficients generally lose a degree of statistical significance.

34 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 on 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.\textsuperscript{35}

\textit{Expected Temperature Ranges}

In Figures 3 and 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.

Figures 5 and 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 5, and those for future temperature differences are given in Figure 6. Since it is quite rare to have a future temperature differences that is less than -13 F in this

\textsuperscript{35} As the results discussed thus far suggest, the effects seen for crimes outside or residences are quite similar to those seen overall.

\textbf{Reading Note}: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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. On the other hand, Figure 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 7 (forecast errors) and Figure 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 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).

---

36 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.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure 9 (forecast errors) and Figure 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%).

The Workweek vs. the Weekend

To complement the results presented thus far, I re-estimate (14) separately for workweek and weekend subsamples. 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 markedly on these city-days. All of the figures associated with this exercise are located in Appendix III.

Figures A5 and A6 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 A7 and A8 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 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 A9 (workweek) and Figure A10 (weekend) complete the workweek-weekend comparison by reporting coefficient estimates for future temperature differences. Figure A9 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 A10 reveals a strong negative correlation between warmer expected future temperatures and property theft on weekend city-days.

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 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 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 (2014c) 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

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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 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 9 provide marginal evidence that unexpectedly cool temperatures reduce violence on days with expected temperatures at or above 80 F.\footnote{This is consistent with cooler temperatures having a calming effect that serves to reduce aggression.} 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.

7 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.

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
References


**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.


Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.


Main Tables and Figures

*Note: Any table/figure with an “A” in front of its numeric identifier is in Appendix III, while any figure with an “M” in front of its numeric identifier is in Appendix I.*

<table>
<thead>
<tr>
<th>Table 1 - Crime, Obs. Weather, and Forecast Weather Summary Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel 1 - Daily Crime</td>
</tr>
<tr>
<td>Crime (All Locations)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>All Offenses</td>
</tr>
<tr>
<td>Violent Crime</td>
</tr>
<tr>
<td>Assault</td>
</tr>
<tr>
<td>Property Theft</td>
</tr>
<tr>
<td>Larceny</td>
</tr>
<tr>
<td>Panel 2 - Daily Crime Counts (Outside of Residences Only)</td>
</tr>
<tr>
<td>All Offenses</td>
</tr>
<tr>
<td>Violent Crime</td>
</tr>
<tr>
<td>Assault</td>
</tr>
<tr>
<td>Property Theft</td>
</tr>
<tr>
<td>Larceny</td>
</tr>
<tr>
<td>Panel 3 - Observed and Forecast Weather</td>
</tr>
<tr>
<td>Total Precip. (mm)</td>
</tr>
<tr>
<td>Max. Temp. (F)</td>
</tr>
<tr>
<td>Forecast Max. Temp. (F)</td>
</tr>
<tr>
<td>Forecast Error (F)</td>
</tr>
<tr>
<td>Forecast Time (hrs.)</td>
</tr>
</tbody>
</table>

*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—Effect of Observed Maximum Temperature on Crime
All Days in Sample, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>67.03</td>
<td>67.05</td>
<td>21.49</td>
<td>17.23</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

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: \( \theta_t = \rho_0 + \tau X_t + \sum_{i=1} a_i T_{i,t} + \eta_t \). In this regression, \( \theta_t \) is the log of daily criminal activity in all locations, and the right-hand-side variables include a set of controls \( (X_t) \) and a semi-parametric bin estimator capturing observed daily maximum temperature \( (\sum_{i=1} a_i T_{i,t}) \).

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 A1 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
**Figure 2 - Effect of Expected Maximum Temperature**

All Days in Sample, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>38.12</td>
<td>49.63</td>
<td>24.7</td>
<td>17.77</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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 A2 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure 3-Effect of Forecast Errors
All Days in Sample, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>9.57</td>
<td>11.85</td>
<td>2.61</td>
<td>1.54</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.02</td>
<td>0.17</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 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 A3 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure 4-Effect of Future Temperature Differences
All Days in Sample, All Locations

All Violent Crime

Assault

Property Theft

Larceny

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>3.34</td>
<td>4.53</td>
<td>2.79</td>
<td>1.26</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
<td>0.28</td>
</tr>
</tbody>
</table>

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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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 A4 is essentially the same figure, except with the dependent variable limited to include only crimes outside of residences.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure 5—Effect of Forecast Errors  
Days with E[Max. Temp] < 50 F, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.84</td>
<td>0.81</td>
<td>0.87</td>
<td>0.81</td>
</tr>
<tr>
<td>Obs.</td>
<td>32892</td>
<td>32892</td>
<td>32892</td>
<td>32892</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>1.96</td>
<td>2.46</td>
<td>1.59</td>
<td>0.42</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.07</td>
<td>0.03</td>
<td>0.15</td>
<td>0.91</td>
</tr>
</tbody>
</table>

**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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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).

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
Figure 6-Effect of Future Temperature Differences
Days with E[Max. Temp] < 50 F, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.84</td>
<td>0.81</td>
<td>0.87</td>
<td>0.81</td>
</tr>
<tr>
<td>Obs.</td>
<td>32892</td>
<td>32892</td>
<td>32892</td>
<td>32892</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>4.9</td>
<td>4.89</td>
<td>10.72</td>
<td>7.24</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

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 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].

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
Figure 7 - Effect of Forecast Errors
Days with E[Max. Temp] 50-79 F, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>64682</td>
<td>64682</td>
<td>64682</td>
<td>64682</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>8.51</td>
<td>10.64</td>
<td>1.41</td>
<td>1.24</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0.22</td>
<td>0.3</td>
</tr>
</tbody>
</table>

**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 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).

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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 9-Effect of Forecast Errors**

Days with E[Max. Temp] 80+ F, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.87</td>
<td>0.84</td>
<td>0.89</td>
<td>0.84</td>
</tr>
<tr>
<td>Obs.</td>
<td>43785</td>
<td>43785</td>
<td>43785</td>
<td>43785</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>2.68</td>
<td>1.8</td>
<td>1.46</td>
<td>1.05</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.02</td>
<td>0.1</td>
<td>0.2</td>
<td>0.42</td>
</tr>
</tbody>
</table>

**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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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].

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure 10-Effect of Future Temperature Differences
Days with E[Max. Temp] 80+ F, All Locations

<table>
<thead>
<tr>
<th></th>
<th>R-Squared</th>
<th>Obs.</th>
<th>F-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Violent Crime</td>
<td>0.87</td>
<td>43785</td>
<td>2.38</td>
<td>0.04</td>
</tr>
<tr>
<td>Assault</td>
<td>0.84</td>
<td>43785</td>
<td>1.88</td>
<td>0.09</td>
</tr>
<tr>
<td>All Property Theft</td>
<td>0.89</td>
<td>43785</td>
<td>0.81</td>
<td>0.58</td>
</tr>
<tr>
<td>Larceny</td>
<td>0.84</td>
<td>43785</td>
<td>1.29</td>
<td>0.27</td>
</tr>
</tbody>
</table>

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 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).
Appendix I: Model Appendix

Model Solution

In Section 2, the maximization problems yielded a system of two non-linear equations:

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

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

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:

Notes: The three figures shown here provide an example equilibrium of the model discussed in Section 2 (Figure 1), along with two comparative statics reflecting the effect of an increase in Period 1 benefit (Figure 2) and Period 2 benefit (Figure 3). Every equilibrium consists of critical discount factors for each player type.
\[
\delta^c = \frac{b_1 - \rho^c \phi}{b_2 - (1 - \rho^c) \phi} = \frac{b_1 - \left(\frac{\delta^c}{1 - \delta^c}\right) \phi}{b_2 - \left(1 - \frac{\delta^c}{1 - \delta^c}\right) \phi}
\]
\[
\Rightarrow \delta^c = \frac{b_1 - \left(\frac{\delta^c}{1 - \delta^c}\right) \phi}{b_2 - \left(1 - \frac{2\delta^c}{1 - \delta^c}\right) \phi}
\]
\[
\Rightarrow \delta^c b_2 - \delta^c \phi \left(\frac{1 - 2\delta^c}{1 - \delta^c}\right) = b_1 - \phi \left(\frac{\delta^c}{1 - \delta^c}\right)
\]
\[
\Rightarrow \delta^c b_2 (1 - \delta^c) - \delta^c \phi (1 - 2\delta^c) = b_1 (1 - \delta^c) - \delta^c \phi
\]
\[
\Rightarrow (\delta^c b_2 - b_1)(1 - \delta^c) - \delta^c \phi (-2\delta^c) = 0
\]
\[
\Rightarrow \delta^c b_2 - (\delta^c)^2 b_2 - b_1 + \delta^c b_1 + 2\phi (\delta^c)^2 = 0
\]
\[
\Rightarrow (2\phi - b_2)(\delta^c)^2 + (b_1 + b_2)\delta^c - b_1 = 0
\]
\[
\Rightarrow \delta^c = \frac{-(b_1 + b_2) \pm \sqrt{b_1^2 + b_2^2 + 8\phi b_1 - 2b_1 b_2}}{4\phi - 2b_2}
\]
\[
\Rightarrow \rho^c = \frac{-(b_1 + b_2) \pm \sqrt{b_1^2 + b_2^2 + 8\phi b_1 - 2b_1 b_2}}{4\phi - b_2 + b_1 \mp \sqrt{b_1^2 + b_2^2 + 8\phi b_1 - 2b_1 b_2}}
\]

For \(\delta^c\) 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.\(^{39}\)

**Derivation of Important Derivatives**

In Section 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:

\(^{39}\)Given that the constants \(\lambda\) and \(\pi_0\) are intuitively very small numbers, the constant \(\phi = \lambda \rho^c \pi_0 L\) should also be very small.
\[
\frac{\partial \rho^c}{\partial b_1} = \frac{\delta^c}{1 - \delta^c}
\]

Define \( f = \delta^c \)
\( g = 1 - \delta^c \)

\[
\frac{\partial \rho^c}{\partial b_1} = \frac{g f' - f g'}{g^2} = \frac{(1 - \delta^c) \frac{\partial \delta^c}{\partial b_1} - \delta^c \left( - \frac{\partial \delta^c}{\partial b_1} \right)}{(1 - \delta^c)^2} = \frac{\partial \delta^c}{\partial b_1} \frac{1 - \delta^c}{(1 - \delta^c)^2}
\]

\[
\frac{\partial \rho^c}{\partial b_2} = \frac{\delta^c}{1 - \delta^c}
\]

Define \( f = \delta^c \)
\( g = 1 - \delta^c \)

\[
\frac{\partial \rho^c}{\partial b_2} = \frac{g f' - f g'}{g^2} = \frac{(1 - \delta^c) \frac{\partial \delta^c}{\partial b_2} - \delta^c \left( - \frac{\partial \delta^c}{\partial b_2} \right)}{(1 - \delta^c)^2} = \frac{\partial \delta^c}{\partial b_2} \frac{1 - \delta^c}{(1 - \delta^c)^2}
\]

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

Define \( f = b_1 - \rho^c \phi \)
\( g = b_2 - (1 - \rho^c) \phi \)

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

Define \( K_1 = b_1 - \rho^c \phi \)
\( K_2 = b_2 - (1 - \rho^c) \phi \)

---

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
Appendix II: 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. Property theft is defined at the sum of larceny, burglary, motor vehicle theft, and stolen property offenses (i.e. possession or distribution of stolen

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.
property). These categories are defined again (along with the relevant UCR crime codes) in Table A1. 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 A2 and A3 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 A2 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 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 A2 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 A3 addresses this question by regressing observed weather during each day on the $t - 1$ forecast value pertaining to that day. 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 A3). 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 prediction’s publication. 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. In all cases, I adopt the practice of using one weather station and one forecast location for each city.

---

41 The nature of these regressions is akin to Table A2.
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

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
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 the city (or cities) to which it is assigned. 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. 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.

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.

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.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
As long as a weather station/forecast location pairing meets these conditions,\textsuperscript{46} then it is accepted as a good pairing for the dataset used in this paper. These requirements (especially the first) are quite stringent.

\textit{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

\textsuperscript{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.

\textbf{Reading Note:} When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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.

3. 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.
Appendix III: Additional Tables and Figures

Table A1 - Description of Major Crime Categories
UCR Codes in Parenthesis

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violent Crime</td>
<td>Includes all forms of homicide (91-93), all forms of assault (131-133), sexual assault (111-114), robbery (120), and weapons violations (520)</td>
</tr>
<tr>
<td>Property Theft</td>
<td>Includes all forms of larceny (231-238), burglary (220), motor vehicle theft (240), and stolen property crimes (280).</td>
</tr>
</tbody>
</table>

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 A2 - Relationship Between Forecast Time and Forecast Accuracy

<table>
<thead>
<tr>
<th>Panel 1 - Temperature</th>
<th>All Times</th>
<th>12pm-3pm</th>
<th>3pm-6pm</th>
<th>6pm-9pm</th>
<th>9pm-12am</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast Max. Temp.</td>
<td>0.979***</td>
<td>0.987***</td>
<td>0.978***</td>
<td>0.981***</td>
<td>0.978***</td>
</tr>
<tr>
<td></td>
<td>(0.00168)</td>
<td>(0.00234)</td>
<td>(0.00193)</td>
<td>(0.00222)</td>
<td>(0.00254)</td>
</tr>
<tr>
<td>Observations</td>
<td>141,359</td>
<td>7,996</td>
<td>99,820</td>
<td>10,702</td>
<td>22,841</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.970</td>
<td>0.966</td>
<td>0.970</td>
<td>0.971</td>
<td>0.969</td>
</tr>
</tbody>
</table>

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

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Panel 1 - Temperature

<table>
<thead>
<tr>
<th>Future Days</th>
<th>T + 1</th>
<th>T + 2</th>
<th>T + 3</th>
<th>T + 4</th>
<th>T + 5</th>
<th>T + 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast Max. Temp.</td>
<td>0.977***</td>
<td>0.975***</td>
<td>0.975***</td>
<td>0.972***</td>
<td>0.968***</td>
<td>0.967***</td>
</tr>
<tr>
<td>(0.00171)</td>
<td>(0.00154)</td>
<td>(0.00156)</td>
<td>(0.00180)</td>
<td>(0.00201)</td>
<td>(0.00212)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>141,335</td>
<td>141,332</td>
<td>141,330</td>
<td>141,328</td>
<td>141,326</td>
<td>141,327</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.957</td>
<td>0.941</td>
<td>0.925</td>
<td>0.906</td>
<td>0.886</td>
<td>0.864</td>
</tr>
</tbody>
</table>

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

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
<table>
<thead>
<tr>
<th>Control</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year-by-City Fixed Effects</td>
<td>Indicators for every city-year in the sample (e.g. there is an indicator for Detroit-2006).</td>
</tr>
<tr>
<td>Day-of-Week Fixed Effects</td>
<td>Indicators for every day-of-week in the sample (e.g. there is an indicator for Fridays).</td>
</tr>
<tr>
<td>Month-by-City Fixed Effects</td>
<td>Indicators for every city-month in the sample (e.g. there is an indicator for Detroit-January).</td>
</tr>
<tr>
<td>First of Month Indicator</td>
<td>An indicator for whether a given day is the first day of a month.</td>
</tr>
<tr>
<td>Daily Total Precipitation (Current Day)</td>
<td>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&quot;, (0&quot;, 0.25&quot;), (0.25&quot;,&quot; 0.5&quot;), (0.5&quot;,&quot; 0.75&quot;), (0.75&quot;,&quot; 1&quot;), and 1+.&quot; The first bin (0&quot;) is the omitted category.</td>
</tr>
<tr>
<td>Lagged Daily Precipitation</td>
<td>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).</td>
</tr>
<tr>
<td>Lagged Daily Maximum Temperature</td>
<td>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: &lt; 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 (&lt; 35 F) is the omitted category.</td>
</tr>
<tr>
<td>Daytime Chance of Precipitation (Current Day)</td>
<td>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.</td>
</tr>
<tr>
<td>Future Chance of Precipitation</td>
<td>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: &lt; - 70%, [- 70%, -50%], [-50%, -30%], [-30%, -10%], [-10%, 10%], (10%, 30%), 30+%. [-10%, 10%] is the omitted category.</td>
</tr>
</tbody>
</table>

Notes: This table defines in detail the full set of controls included in $X_t$ for the regressions underlying Figures 2 through 10 and A1 through A10. For the regression underlying Figure 1, all controls pertaining to weather expectations have been dropped.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
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: $\theta_t = \rho_0 + \tau X_t + \sum_{i=1} a_i T_{i,t} + \eta_t$. In this regression, $\theta_t$ is the log of daily criminal activity outside of residences, and the right-hand-side variables include a set of controls ($X_t$) and a semi-parametric bin estimator capturing observed daily maximum temperature ($\sum_{i=1} a_i T_{i,t}$). 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 $\ln(y) = \ln(y + \sqrt{1 + y^2})$ 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.

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the "Notes" hyperlink at the beginning of the caption under the table or figure.
Figure A2-Effect of Expected Maximum Temperature
All Days in Sample, Outside of Residences

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.76</td>
<td>0.71</td>
<td>0.83</td>
<td>0.79</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>34.97</td>
<td>25.59</td>
<td>10.91</td>
<td>8.18</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**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 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 2.

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure A3-Effect of Forecast Errors
All Days in Sample, Outside of Residences

<table>
<thead>
<tr>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.76</td>
<td>0.71</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>10.42</td>
<td>13.62</td>
<td>2.19</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
</tbody>
</table>

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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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 3.
Figure A4—Effect of Future Temperature Differences
All Days in Sample, Outside of Residences

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.76</td>
<td>0.71</td>
<td>0.83</td>
<td>0.79</td>
</tr>
<tr>
<td>Obs.</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
<td>141359</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>2.84</td>
<td>3.33</td>
<td>1.68</td>
<td>0.98</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.01</td>
<td>0</td>
<td>0.13</td>
<td>0.46</td>
</tr>
</tbody>
</table>

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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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 4.
**Figure A5-Effect of Expected Maximum Temperature**

**Monday-Friday, All Locations**

### Table

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>R-Squared</strong></td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td><strong>Obs.</strong></td>
<td>101075</td>
<td>101075</td>
<td>101075</td>
<td>101075</td>
</tr>
<tr>
<td><strong>F-Statistic</strong></td>
<td>30.42</td>
<td>42.77</td>
<td>18.9</td>
<td>16.02</td>
</tr>
<tr>
<td><strong>P-Value</strong></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**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 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).

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
The plots in the figure display the expected maximum temperature coefficient values and 95% confidence intervals obtained by estimating the regression given by equation (14) in Section 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].
Figure A7 - Effect of Forecast Errors
Monday-Friday, All Locations

All Violent Crime

Assault

Property Theft

Larceny

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>101075</td>
<td>101075</td>
<td>101075</td>
<td>101075</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>6.86</td>
<td>8.59</td>
<td>2.94</td>
<td>2.11</td>
</tr>
<tr>
<td>P-Value</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
<td>0.05</td>
</tr>
</tbody>
</table>

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 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 $\ln(y) = \ln(y + \sqrt{1 + y^2})$ 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].

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Table A8: Effect of Forecast Errors

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.86</td>
<td>0.84</td>
<td>0.87</td>
<td>0.82</td>
</tr>
<tr>
<td>Obs.</td>
<td>40284</td>
<td>40284</td>
<td>40284</td>
<td>40284</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>2.88</td>
<td>3.12</td>
<td>1.7</td>
<td>0.96</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.01</td>
<td>0.01</td>
<td>0.12</td>
<td>0.48</td>
</tr>
</tbody>
</table>

**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 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 \( \ln(y) = \ln(y + \sqrt{1 + y^2}) \) 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].

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
**Figure A9—Effect of Future Temperature Differences**

Monday-Friday, All Locations

<table>
<thead>
<tr>
<th></th>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.85</td>
<td>0.83</td>
<td>0.88</td>
<td>0.83</td>
</tr>
<tr>
<td>Obs.</td>
<td>101075</td>
<td>101075</td>
<td>101075</td>
<td>101075</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>2.23</td>
<td>3.07</td>
<td>3.5</td>
<td>2.08</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.04</td>
<td>0.01</td>
<td>0</td>
<td>0.06</td>
</tr>
</tbody>
</table>

**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 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).

**Reading Note:** When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.
Figure A10-Effect of Future Temperature Differences
Saturday & Sunday, All Locations

<table>
<thead>
<tr>
<th>All Violent Crime</th>
<th>Assault</th>
<th>All Property Theft</th>
<th>Larceny</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.86</td>
<td>0.84</td>
<td>0.87</td>
</tr>
<tr>
<td>Obs.</td>
<td>40284</td>
<td>40284</td>
<td>40284</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>1.12</td>
<td>2.16</td>
<td>4.88</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.37</td>
<td>0.05</td>
<td>0</td>
</tr>
</tbody>
</table>

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 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 \( \ln(y) = \ln \left( \frac{y + \sqrt{1 + y^2}}{2} \right) \) 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).

Reading Note: When viewing this document in a PDF viewer, it is possible to move between the main text and figures or tables using underlined blue hyperlinks provided in the text. To return from a table or figure to the part of the main text pertaining to that object, click on the “Notes” hyperlink at the beginning of the caption under the table or figure.