Crime, Weather, and Climate Change

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Abstract

This paper estimates the impact of climate change on the prevalence of criminal activity in the United States. The analysis is based on a 50-year panel of monthly crime and weather data for 2,972 U.S. counties. I identify the effect of weather on monthly crime by using a semi-parametric bin estimator and controlling for county-by-month and county-by-year fixed effects. The results show that temperature has a strong positive effect on criminal behavior, with little evidence of lagged impacts. Between 2010 and 2099, climate change will cause an additional 30,000 murders, 200,000 cases of rape, 1.4 million aggravated assaults, 2.2 million simple assaults, 400,000 robberies, 3.2 million burglaries, 3.0 million cases of larceny, and 1.3 million cases of vehicle theft in the United States.

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1 Introduction

A small body of research has begun to explore how civil conflict and warfare are influenced by changes in climate (Burke et al, 2012; Hsiang, Meng, and Cane, 2011). However, little is known about the implications of climate change for more common categories of criminal behavior. Studies of the short-term relationship between crime and weather typically find that higher temperatures cause substantial increases in crime (Horrocks and Menclova, 2011; Brunsdon et al, 2009; Bushman, Wang, and Anderson, 2005; Cohn, 1990). However, because crime rates exhibit negative serial correlation over a span of days to weeks (Jacob, Lefgren, and Moretti, 2007), a naive extrapolation of the short-term relationship between weather and crime may substantially overestimate the actual impacts of long-term climate change on criminal activity.

To address this gap in the literature, in this paper I develop the first comprehensive estimates of the impact of climate change on U.S. crime rates. My analysis draws on historical data to estimate the causal relationship between weather and crime, and then uses this relationship to predict future crime levels under the weather conditions expected under the IPCC's A1B scenario.[1] To support the analysis, I have constructed a panel dataset that includes monthly crime and weather data for 2,972 U.S. counties for the period from 1960 to 2009. My data on criminal activity are drawn from the U.S. Federal Bureau of Investigation's

[1] All climate projections cited in this paper are based on the IPCC's A1B scenario. A1B is a "middle-of-the-road" scenario that tends to produce emissions and climate results that are intermediate between high emissions scenarios such as A1FI and low emissions scenarios such as B1. This scenario represents a future world with high rates of economic growth and substantial convergence between developing and developed economies, where rapid technological change is based on a balance of fossil-fuel intensive and non-fossil sources of energy (IPCC, 2000). Under this scenario, the IPCC predicts that global temperatures will rise by about 5 degrees Fahrenheit (2.8 degrees Celsius) by the year 2099, compared to baseline temperatures between 1980 and 1999 (IPCC, 2007).

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Uniform Crime Reporting (UCR) data. These data, which are based on monthly reports from 17,000 U.S. law enforcement agencies, tabulate offenses in nine major categories: murder, manslaughter, rape, aggravated assault, simple assault, robbery, burglary, larceny, and vehicle theft. I merge these data with temperature and precipitation records from weather stations in the U.S. National Climatic Data Center's Global Historical Climatology Network Daily (GHCN-Daily) dataset. After combining these two data sources, I generate a dataset with 1.46 million unique county-by-year-by-month observations.

To identify the effect of daily weather on monthly crime, I use a semi-parametric weather bin estimator (Deschenes and Greenstone, 2011) that includes variables that measure the number of days per month spent in each of eleven maximum daily temperature bins ($<$10 degrees F, 10-20 F, ..., 90-100 F, $\geq$100 F) and five daily precipitation bins (0 mm, 1-4 mm, 5-14 mm, 15-29 mm, and $\geq$30 mm). I regress monthly crime rates on these bin variables, controlling for extensive fixed effects that capture both average crime levels in each year-by-county set of observations and average monthly patterns of crime and weather within each county. Finally, I use the results from these regressions to predict crime rates under the weather patterns likely to be experienced in each decade between 2010 and 2099, based on projections of future U.S. climate drawn from two general circulation models.

My analysis makes two main contributions. First, I document a striking relationship between monthly weather patterns and crime rates. Across a variety of offenses, higher temperatures cause more crime. For most categories of violent crimes, this relationship appears approximately linear through the entire range of temperatures experienced in in-sample counties. However, for property crimes (such as burglary and larceny), the relationship between temperature and crime is highly non-linear, with a kink at approximately 40 degrees

F. Above this cutoff, changes in temperature have little effect on crime rates. These results improve on past research in several ways: in my use of a semi-parametric specification, which allows for a more flexible functional form than the linear or quadratic specifications imposed in previous work; in my use of extensive fixed effects to address data quality issues that plague the crime literature; and in my use of an unusually long and rich 50-year panel dataset on monthly crime and weather for the entire continental United States, rather than daily or weekly regional datasets that have been used in most previous analyses of the relationship between crime and weather.

Second, I develop the first detailed predictions of how climate change will affect patterns of criminal activity in the United States. My results suggest that in the year 2090, crime rates for most offense categories will be two to five percent higher because of climate change. Under the IPCC's A1B climate scenario, the United States will experience an additional 30,000 murders, 200,000 cases of rape, 1.4 million aggravated assaults, 2.2 million simple assaults, 400,000 robberies, 3.2 million burglaries, 3.0 million cases of larceny, and 1.3 million cases of vehicle theft, compared to the total number of offenses that would have occurred between 2010 and 2099 in the absence of climate change.[2] The present discounted value of the social costs of these climate-related crimes is between 19 and 59 billion dollars.

I am aware of only two previous empirical studies of the effects of climate change on crime in the United States: Anderson, Bushman, and Groom (1997) and Rotton and Cohn (2003). Due to methodological concerns, it is difficult to interpret the results from these

[2]For comparison, I assume that the total baseline number of crimes that will occur in the United States between 2010 and 2099 will be: 980,000 murders, 37,000 cases of manslaughter, 5.7 million cases of rape, 52 million aggravated assaults, 189 million simple assaults, 25 million robberies, 135 million burglaries, 429 million cases of larceny, and 72 million cases of vehicle theft. These totals are based on the assumption that crime rates during the next century will be similar to actual crime rates between 2000 and 2009.

studies. Both papers are based on annually-averaged data for large geographic units (e.g., Anderson, Bushman, and Groom regress average annual U.S. crime rates on average annual U.S. temperatures), and thus may face challenges with credibly identifying how weather affects crime rates. Furthermore, findings from these studies may be biased by the substantial year-to-year reporting inconsistencies in the FBI's UCR crime data. In contrast, by using monthly crime data and daily weather data for a panel that includes almost all U.S. counties, and by using a semi-parametric fixed-effects approach to analyze month-to-month changes in crime rates within each county and year, my analysis solves the potential methodological and measurement error issues with this previous work.

The remainder of this paper is organized as follows. Section 2 provides background on the relationship between weather and crime. Section 3 describes the primary data sources, and Section 4 discusses my empirical methodology. Section 5 presents my main findings on the relationship between climate change and crime. Section 6 discusses the results and Section 7 concludes.

2 Background on Weather and Crime

Researchers have proposed several hypotheses that explain why weather might affect crime (Cohn, 1990; Agnew, 2012). The first—that weather is a variable in the production function for crime—draws on Gary Becker's canonical model of crime, in which individuals make decisions about whether to commit criminal acts based on rational consideration of the costs and benefits (Becker, 1968). In this model, weather conditions are an input that affects both the probability of successfully completing a crime and the probability of escaping undetected afterward (Jacob, Lefgren, and Moretti, 2007).

A second explanation draws on a social interaction theory of crime, under which the frequency of criminal acts is driven in large part by social interactions that occur during day-to-day life (Glaeser, Sacerdote, and Scheinkman, 1996; Rotton and Cohn, 2003). Applied to weather, such a hypothesis implies that weather conditions that foster social interactions are likely to increase crime rates.

A third possible explanation draws on theories in which external conditions directly affect human judgment in ways that cause heightened aggression and loss of control (Card and Dahl, 2011; Baumeister and Heatherton, 1996). Experimental evidence strongly suggests that ambient temperatures affect aggression (Anderson, 1989; Baron and Bell, 1976). Such studies imply that weather may directly influence people's psychological propensity to commit violent criminal acts.

Although using empirical data to distinguish between these hypotheses is difficult, there is considerable evidence that weather does affect criminal behavior (Cohn, 1990). Previous research on this topic has typically taken one of two empirical approaches. First, some studies have focused on measuring the short-term relationship between weather and crime, using hourly, daily, or weekly microdata (Horrocks and Menclova, 2011; Bushman, Wang, and Anderson, 2005; Cohn and Rotton, 2000; Brunsdon et al, 2009). However, interpreting this research in the context of climate change is complicated by negative serial correlation in crime. In a large study using weekly data on crime and temperatures in 116 U.S. jurisdictions for the period 1996 to 2001, Jacob, Lefgren, and Moretti (2007) find that although rates of violent crime and property crime are elevated during weeks with hot weather, the effect is offset somewhat by lower than usual crime rates in the following weeks. This result suggests that understanding the cumulative impacts of climate change on crime may require working with data at a more aggregate time scale (e.g., months).[3]

The second empirical approach in the literature is to use aggregate annual data to measure how weather affects crime at the national or state levels. The two existing studies that use this approach examine the time series relationship between yearly average crime rates and yearly average temperatures, for the United States as a single unit (Anderson, Bushman, and Groom, 1997) or for a panel of states (Rotton and Cohn, 2003). These studies have found mixed results, possibly due to the lack of geographic and temporal resolution in their crime and weather data. Another issue with this work is that U.S. aggregate crime statistics suffer from known quality issues, with different data sources implying considerably different trends in crime rates in the 1970s and 1980s (Levitt, 2004). As a result, analyses based on such geographically-aggregate annual data may face serious econometric problems.

3 Data

3.1 Data Sources

The analysis for this paper is based on an unusually long and rich panel dataset of monthly crime rates and weather for 2,972 counties in the 49 continental states (including the District of Columbia). The dataset covers the 50-year period from 1960 to 2009, and contains 1.46 million unique county-by-year-by-month observations. It is based on two primary sources: Uniform Crime Reporting (UCR) data from the U.S. Federal Bureau of Investigation (FBI,

[3] I am aware of only three studies that have measured the relationship between monthly weather and crime data: Simister (2002), Simister and Cooper (2005), and Simister and Van de Vliert (2005). For example, Simister and Cooper (2005) estimate how monthly temperatures affect assault in Los Angeles.

2011a), and Global Historical Climatology Network Daily (GHCN-Daily) weather data from the National Climatic Data Center (NCDC Climate Services Branch, 2011).

The FBI's UCR data are the longest continuously-collected historical record of criminal activity in the United States. These data are based on monthly reports from approximately 17,000 local, county, city, university, state, and tribal law enforcement agencies. Although participation is voluntary and has increased over time, in 2010 the UCR data covered law enforcement agencies representing 97.4 percent of the U.S. population (FBI, 2011b). The data submitted by each agency each month include the number of reported offenses of murder, manslaughter, rape, aggravated assault, simple assault, robbery, burglary, larceny, and vehicle theft. In cases when a crime falls into more than one category, the FBI uses a "hierarchy rule" to assign the crime to the most serious offense category (FBI, 2004).

A central challenge in constructing monthly county-level crime rate time series is that the number of reported crimes in the UCR data increases dramatically through the 1960s and 1970s, due both to changes in the number of agencies reporting and to more comprehensive reporting by individual agencies. Thus, developing a county-level time series that is consistent across years would be difficult at best. Although previous research on criminal behavior has made use of annual aggregated UCR data (e.g., Levitt, 1996), in this paper I take a different approach in which I construct a time series that is consistent only across months within each county-by-year group of observations.

To build this time series, I first drop any agency-by-year records in which an agency reported less than twelve months of data for that year.[4] I then sum the total number of

[4]I also drop agency-by-year records in which the agency reported data on a quarterly, bi-yearly, or yearly basis, rather than monthly. Most of these cases are agencies located in Florida or Alabama.

reported crimes by all remaining agencies in each county, by category of crime, to generate a county total for each month and year. Finally, using county population data from the U.S. Census (U.S. Census Bureau, 1978, 2004, 2011), I calculate the monthly crime rate per 100,000 persons, for each county-by-month observation. As I discuss below in the Methodology section, the fact that the number of reporting agencies differs across years within each county does not affect my regressions results, since I identify the effect of weather on crime using only variation in month-to-month weather and crime within a particular county and year (for which the set of reporting agencies is identical).

The second major component of my dataset is daily weather data taken from the U.S. National Climatic Data Center's GHCN-Daily database. The GHCN-Daily database is a compilation of weather station records drawn from a variety of sources, and includes about 75,000 weather stations worldwide (NCDC Climate Service Branch, 2011). The weather variables that I extract for each of the 1,200 land-based U.S. weather stations are daily maximum temperature and daily precipitation. Unlike some other sources of weather data (e.g., the NCDC's Global Summary of the Day), the GHCN-Daily data are subjected a set of quality assurance reviews that include checking for weather data that are duplicated, weather data that exceed physical or climatological limits, consecutive data points that show excessive persistence or gaps, and data with inconsistencies internally or across neighboring stations.

Because the GHCN-Daily data report weather at a set of weather stations that are spaced irregularly across the United States, I use the station data to generate county weather as follows. First, I create a set of grid points covering the entire United States, spaced approximately 5 miles apart, and calculate the distance from each grid point to each weather station. Next, I estimate a county-level temperature signal using all stations within 50 miles of any grid point within a county. Finally, I adjust the absolute value of this signal so that it is equal to the average temperature reported at the stations closest to each county grid point. I calculate county-level precipitation using a similar procedure.

After combining the county-level crime and weather data, I take several final steps to clean the dataset. First, I drop all county-by-year records in which U.S. Census estimates indicate that the county had a population of fewer than 1,000 persons. Second, I drop all county-by-year records in which zero crimes were reported in all months, or in which weather data are missing for at least one month. Third, I eliminate outliers (almost all of which appear to be reporting errors) by dropping county-by-year observations in which the crime rate in any month is greater than twice the value of the 99th percentile crime rate for the entire sample. Finally, to minimize problems with heteroskedasticity in the data, I drop counties in which the mean crime rate is above the 99th percentile or below the 1st percentile for the entire sample. The resulting dataset includes 2,972 in-sample counties (out of the universe of 3,143 counties), with a total of 1.46 million unique county-by-year-by-month observations.

3.2 Summary Statistics

This section of the paper presents summary statistics on crime and weather patterns in the United States. To illustrate how these patterns vary geographically, I divide the United States into four climate zones and then assign each county to a climate zone based on its long-term mean annual maximum daily temperature. The zones are <55 degrees F, 55 to

64 degrees F, 65 to 74 degrees F, and ≥75 degrees F. Panel (a) of Figure 1 shows a map of the climate zones. As expected, northern areas of the United States are more likely to have cooler climates. For comparison, Panel (b) of the figure shows a map of county-level annual crime rates per 100,000 persons, for all crimes. The panel shows that crime rates are highest along the Eastern Seaboard, in the West, and in areas bordering the Great Lakes. However, there is no obvious cross-sectional relationship between the temperature zones and crime rates.[5]

Table 1 summarizes basic characteristics of the crime and weather datasets, by climate zone. The first panel presents mean annual crime rates per 100,000 persons, by type of offense. The panel shows that some categories of crime, such as murder, manslaughter, rape, and robbery, are relatively uncommon. The three categories with the highest rates are larceny, burglary, and simple assault.

The second panel in Table 1 describes the annual distribution of daily temperatures and precipitation for in-sample counties. Unlike crime rates, these data show substantial variation across climate zones. For example, although counties in the coolest climate zone (<55 degrees F) have an average of only six days per year in which the maximum temperature exceeds 90 degrees F, counties in the warmest climate zone (≥75 degrees F) typically have 86 days per year with temperatures above 90 degrees F.

The final panel in Table 1 describes county socioeconomic characteristics. The panel shows that counties in cooler climate zones have fewer minorities and are more likely to be rural.

[5]Given the many socioeconomic variables that influence crime, the absence of a strong visual cross-sectional relationship between temperatures and crime does not necessarily indicate the lack of a causal relationship. A cross-sectional analysis in the spirit of Mendelsohn, Nordhaus, and Shaw (1994) would have to control for other first-order determinants of crime (e.g., population density).

Figures 2 and 3 present initial evidence on the influence of seasonality on weather and crime patterns. Figure 2 shows the mean value of daily maximum temperature and daily precipitation, by climate zone and month. The figure shows strong seasonal patterns in all climate zones, for all variables. Seasonal variation is largest in the coolest climate zone (<55 degrees F), where the mean temperature difference between January and July is 60 degrees. For comparison, the January-July temperature difference in the warmest climate zone (≥75 degrees F) is about 35 degrees.

Figure 3 presents similar graphs illustrating how crime rates vary by climate zone and month. The figure shows that all categories of crime display evidence of seasonality, although the degree of seasonal variation varies widely across crimes. A few categories of crime, particularly murder, manslaughter, and robbery, show only modest seasonal variation. Other categories, such as rape, assault, and non-violent property crimes, exhibit strong seasonality. Additionally, the relationship between seasonality and crime rates varies across climate zones and type of crimes. For example, larceny and burglary show more pronounced seasonal variation in cooler climate zones, whereas robbery shows somewhat more seasonality in warmer climates.

4 Methodology

The summary statistics from the previous section suggest a strong correlation between monthly weather and crime rates. In this section I develop a causal econometric model of this relationship. Specifically, I model crime in month m of year y in county i as follows:

$$\begin{aligned} C_{iym} = & \sum_{j=1}^{11} \alpha_0^j T_{iym}^j + \sum_{k=1}^{5} \beta_0^k P_{iym}^k \\ & + \sum_{j=1}^{11} \alpha_1^j T_{iym-1}^j + \sum_{k=1}^{5} \beta_1^k P_{iym-1}^k \\ & + \phi_{im} + \theta_{iy} + \epsilon_{iym} \end{aligned} \tag{1}$$

In this equation, C_{iym} represents the monthly crime rate per 100,000 residents, ϕ_{im} is a county-by-month fixed effect, θ_{iy} is a county-by-year fixed effect, and ϵ_{iym} is a zero-mean error term. Following Deschenes and Greenstone (2011), I model the daily distribution of temperatures within a month using eleven bin variables: <10 F, 10-19 F, 20-29 F, 30-39 F, 40-49 F, 50-59 F, 60-69 F, 70-79 F, 80-89 F, 90-99 F, and ≥100 F. For example, the variable T_{iym}^j represents the number of days in month m of year y in county i in which the temperature fell into temperature bin j. I use a similar convention for the precipitation variables P_{iym}^k, with five bins: 0 mm, 1-4 mm, 5-14 mm, 15-29 mm, and ≥30 mm. Because of the possibility that changes in crime rates due to weather shocks may exhibit negative serial correlation (Jacob, Lefgren, and Moretti, 2007), I also include a one month lag of each temperature and precipitation bin variable. Furthermore, because weather patterns in a particular month are highly correlated between adjacent geographic areas, I cluster all standard errors at the year-by-month level. I also weight each county-by-month-by-year observation by the county population in that year.

Equation (1) includes several features designed to address issues that have been problematic in previous analysis of the effect of weather on criminal behavior. First, by using a semi-parametric specification for weather, I avoid imposing structural assumptions on the relationship between weather and crime. Previous analyses have used as independent variables mean weekly temperature and precipitation (Jacob, Lefgren, and Moretti, 2007) or mean yearly temperature and temperature squared (Rotton and Cohn, 2003). These specifications assume that weather has a linear or quadratic effect on crime—which, as the results from this paper show, may fail to capture important features of the relationship.

Second, Equation (1) includes an extraordinarily comprehensive set of fixed effects. In addition to including dummy variables for typical monthly patterns in weather and crime with each county, I include dummy variables that capture the average crime rate and weather conditions in each county-by-year set of observations. In other words, my identification strategy is based on only the residual variation in crime and weather remaining between months within a particular county and year, after controlling for average monthly patterns in that county.

The motivation for this extensive set of fixed effects is related to the quality of the FBI's crime data. The UCR crime data exhibit strong interannual trends that appear to be driven at least partially by differences in reporting. Examination of the microdata shows that at the level of individual counties, these trends are exacerbated, with crime rates in many counties jumping substantially from year to year as the set of reporting agencies changes over time. In the two previous national studies of crime and climate change (Anderson, Bushman, and Groom, 1997; Rotton and Cohn, 2003), the authors addressed this problem by modeling annual changes in aggregate national or state crime rates as an autoregressive process. Because this approach is not a satisfactory method for dealing with measurement error in the dependent variable, I choose an alternative methodology that requires no consistency in reporting between years. Instead, as discussed in the data section, I construct monthly crime rates within each county-by-year by aggregating the total number of reported crimes each month only for agencies that reported twelve complete months of data for that year. Thus, although the set of reporting agencies within each county changes between years, making interannual comparisons invalid except under very strong assumptions, an identical set of agencies report for each month within a particular year. The identifying assumption for my analysis is that after controlling for county-by-year and county-by-month fixed effects, differences in weather and crime between months within a county represent the true effect of weather on crime.

5 Results

This section presents the main results from the analysis.

5.1 Weather and Crime Rates

I begin by presenting the regression results from estimating Equation (1). Because of the large number of coefficients, the results are easiest to understand using a graphical approach. For example, Figure 4 plots the regression coefficients on the temperature and lagged temperature bin variables. In each subfigure, the horizontal axis represents the daily maximum temperature bins, and the vertical axis represents the coefficient, with units of number of crimes per 100,000 persons per month. The figure shows that across all types of crime, higher temperatures cause statistically significant increases in crime rates. As an illustration, compared to a day in the 60-69 degrees F bin, an extra day in the 30-39 degrees F bin leads to 0.002 fewer murders, 0.08 fewer aggravated assaults, and 1.1 fewer larcenies, per 100,000 persons per month. In comparison, the mean monthly crime rates for these three offenses are .35 cases of murder, 14 cases of aggravated assault, and 114 cases of larceny. Although the estimated coefficients appear small relative to mean crime rates, the coefficients represent the effect of only a single day of weather per month, and in aggregate imply substantial effects. For example, in a spring month with 10 unusually warm days (in the 60-69 degrees F bin), crime rates for these three offenses would be approximately seven to ten percent higher than crime rates in a spring month with 10 unusually cold days (in the 30-39 degrees F bin).

Figure 4 also shows significant nonlinearities in the effect of temperatures on crime. These nonlinear effects are most apparent for property crimes such as burglary and larceny. For bins below 40 degrees F, increases in temperature have a strong positive effect on the number of burglaries and larcenies reported. However, above 40 degrees F, increases in temperature have little or no effect on these crimes. The degree of nonlinearity varies by offense, with violent crimes tending to have a much more linear relationship through the entire range of temperatures.

In addition to showing the effect of current monthly temperatures on current monthly crime, Figure 4 also presents coefficients and confidence intervals for the effect of lagged temperature from the previous month. For most offenses, the coefficients on lagged temperatures are close to zero and not statistically significant. Thus, unlike Jacob, Lefgren, and Moretti (2007), who find a significant and opposite coefficient on lagged weekly temperatures that dampens the effect of weather on weekly crime, I conclude that at the monthly level, there is little evidence that weather has a lagged effect on crime patterns.[6]

[6]The Appendix presents additional evidence that a one-month aggregation period is sufficient to account

Table 2 presents complete regression results from estimating Equation (1), including the results for the precipitation bin variables. The table shows that the effects of precipitation on crime rates vary by offense. Although precipitation causes statistically significant decreases in larceny, the opposite is true for vehicle theft: more vehicles are stolen in months with many rainy days.

In addition to the main specifications presented in Figure 4 and Table 2, I have run a variety of other sensitivity analyses in which I allow the coefficients on the weather bin variables to vary by climate zone, monthly mean temperature, and decade. The results from these analyses are qualitatively similar to the main specification presented here, and are presented in the Appendix.

5.2 Climate Change and Crime Rates

To assess how climate change is likely to affect crime rates in the United States, I combine the regression estimates from the previous section with data on simulated U.S. weather conditions for the time period from 2010 to 2099. These simulations are based on the IPCC's A1B scenario, a "middle-of-the-road" climate change scenario that assumes eventual stabilization of atmospheric CO2 levels at 720 ppm (IPCC, 2000, 2007). I use predictions from two general circulation models: the U.K. Hadley Centre's HadCM3 climate model, and the U.S. National Center for Atmospheric Research's CCSM3 climate model. The predictions, which are available from an archive maintained by the World Climate Research Programme's Coupled Model Intercomparison Project Phase 3 (CMIP3), have an interpolated resolution of two degrees of latitude by two degrees of longitude (WCRP, 2007; Maurer et al, 2007).

for any "harvesting" that might occur as a result of negative serial correlation in crime rates.

To use these data to estimate how climate change is likely to affect crime rates in each county in my analysis, I follow several steps. First, I use the HadCM3 and CCSM3 projections to calculate average predicted monthly temperature and precipitation for each decade between 2000 and 2099, for each two degree-by-two degree grid point. Taking the average monthly values for 2000-2009 as a baseline, I then calculate the absolute change in mean monthly temperature and the proportional change in mean monthly precipitation at each grid point for each subsequent decade, relative to 2000-2009. I then assign each U.S. county a predicted change in temperature and precipitation for each future decade and month, based on the changes predicted at the closest HadCM3 and CCSM3 grid point.

Next, I use these predicted changes to generate a simulated distribution of days across temperature and precipitation bins for each of the nine decades starting with 2010-2019 and ending with 2090-2099, for each month and county. I begin with the actual record of temperatures for each day, month, and county between 2000 and 2009. For each decade, I then add the predicted absolute change in monthly temperature to each daily temperature, by month and county, yielding a new predicted record of daily temperatures. I generate simulated precipitation data by multiplying the daily precipitation values by the proportional change in predicted precipitation. I then use these counterfactual weather records to calculate the mean number of days that will fall into each temperature and precipitation bin in each county and month, in each future decade. I conduct this procedure separately for the HadCM3 and CCSM3 predictions.

Finally, to predict how the projected change in weather will affect crime rates in each county, month, and decade, I combine the daily climate projections with the regression coefficients estimated in the previous section. I estimate the change in crime rates ΔC_{idm} in county i, decade d, and month m using the following formula:

$$\Delta C_{idm} = 10 \cdot \Big[\sum_{j=1}^{11} \alpha_0^j (\bar{T}_{i,d,m}^j - \bar{T}_{i,2000,m}^j) + \sum_{k=1}^{5} \beta_0^k (\bar{P}_{i,d,m}^k - \bar{P}_{i,2000,m}^k) + \sum_{j=1}^{11} \alpha_1^j (\bar{T}_{i,d,m-1}^j - \bar{T}_{i,2000,m-1}^j) + \sum_{k=1}^{5} \beta_1^k (\bar{P}_{i,d,m-1}^k - \bar{P}_{i,2000,m-1}^k) \Big] \quad (2)$$

where $\bar{T}_{i,d,m}^j$ refers to the mean number of days per month in which the simulated temperature in month m in county c in decade falls into temperature bin j. The predicted precipitation variable $\bar{P}_{i,d,m-1}^k$ is defined similarly. The variables $\bar{T}_{i,2000,m}^j$ and $\bar{P}_{i,2000,m-1}^k$ refer to the actual distribution of days across temperature and precipitation bins during the decade from 2000 to 2009. I multiply the entire expression on the right-hand side of the equation by ten to account for the number of years in each decade.[7]

Before discussing the results of this analysis, I describe the changes in weather predicted by the CCSM3 and HadCM3 models. Figure 5 shows the distribution of temperature and precipitation across bins for three scenarios: the actual weather patterns observed between 2000 and 2009, the weather patterns predicted for 2090 to 2099 by the CCSM3 model, and the weather patterns predicted for 2090 to 2099 by the HadCM3 model. The figure shows that the baseline (2000-2009) maximum daily temperature distribution is heavily left-skewed. As a result, the increases in temperatures predicted by the CCSM3 and HadCM3 models lead to a sharp increase in the number of days that are predicted to fall into the highest daily maximum temperature bins (90-99 F and $\geq$100 F). The number of days in all other bins decreases under both sets of model predictions.

Table 3 shows the predicted impacts of climate change on crime in the United States.

[7]Note that I also adjust ΔC_{idm} to account for the actual county population.

The first two columns of the table present estimates of the additional number of crimes that will occur between 2010 and 2099, compared to the number that would have occurred in the absence of climate change. The table shows that under both climate models, climate change will cause a strikingly large number of crimes during the next century. For example, under the HadCM3 model, there will be an additional 30,000 murders, 200,000 cases of rape, 1.4 million aggravated assaults, 2.2 million simple assaults, 400,000 robberies, 3.2 million burglaries, 3.0 million cases of larceny, and 1.3 million cases of vehicle theft. Almost all of these changes are significant at a five percent threshold. The only category of crime that is expected to decrease is manslaughter, but the expected change is only 2,600 crimes and is not significantly different from zero. Compared to the baseline number of crimes expected to occur during this 90 year period in the absence of climate change, these figures represent a 3.1% increase in murder, a 7.0% decrease in manslaughter, a 3.5% increase in cases of rape, a 2.6% increase in aggravated assault, a 1.1% increase in simple assault, a 1.7% increase in robbery, a 2.4% increase in burglary, a 0.7% increase in cases of larceny, and a 1.7% increase in cases of vehicle theft.

Because these offenses occur over a 90 year time period and include a variety of types of crimes, it is useful to aggregate them into a social cost metric. I estimate the social costs of future changes in crime using the following valuations per offense: $5,000,000 for murder and manslaughter, $41,247 for rape, $19,537 for aggravated assault, $4,884 for simple assault, $21,398 for robbery, $6,170 for burglary, $3,523 for larceny, and $10,534 for motor vehicle theft. The social cost estimates for murder and manslaughter are based on the value of a statistical life (VSL) for workers in U.S. labor markets. Estimates of VSL typically range between $4 million and $9 million (Viscusi and Aldy, 2003), and I choose $5 million as a plausible value. Estimates of the social cost of the remaining offences are drawn from a review article by McCollister, French, and Fang (2010). These valuations represent the tangible costs of crime, including medical expenses, cash losses, property theft or damage, lost earnings because of injury, other victimization-related consequences, criminal justice system costs, and career crime costs.[8] Although McCollister, French, and Fang also report intangible costs of crime (such as pain and suffering), I exclude these estimates because they are based on jury awards that may not accurately reflect individuals' actual willingness to pay to avoid victimization. Exclusion of this category of costs may bias my estimates of the social cost downward.

The right-hand side of Table 3 shows estimates of the social cost of the climate-related crime that is likely to occur between 2010 and 2099. Including all offenses, the social costs of this crime are between $19 billion and $59 billion. Because of the high value of a statistical life, the costs of future murders are by far the largest component of total social cost. As the table demonstrates, the estimates are somewhat sensitive to the choice of climate model and discount rate. For example, based on the HadCM3 model and a three percent discount rate, the present discounted cost of climate-related murder over the next ninety years is $37 billion. Based on the CCSM3 model and a six percent discount rate, the social cost of murder is only $11 billion.

One fact that is not apparent from Table 3 is that the impacts of climate change on crime are not uniformly distributed across the United States. To investigate distributional effects, Figure 6 presents—for each U.S. county—the per capita present discounted value of the total

[8]McCollister, French, and Fang (2010) do not report estimates of the social cost of simple assault. For the purposes of this analysis, I value each case of simple assault at 25 percent of the cost of a case of aggravated assault.

social costs of future climate-related crime, by county. In other words, the figure shows the discounted value of the social cost of additional crimes expect to occur in each county over the next 90 years, divided by each county's current population. The table shows that the per capita cost of climate-related crime is highest in the West, where costs are greater than $110 per person, and lowest in the South and East, where costs are less than $70 per person. A few counties in the hottest parts of Texas and California are actually predicted to benefit, due to the slight drop-off in crime that occurs when temperatures exceed 100 degrees F (relative to 90-99 degree F).

6 Discussion

The previous sections highlight two main results. First, weather has a strong causal effect on the incidence of criminal activity. For all offenses except manslaughter, higher temperatures lead to higher crime rates. The functional form of the relationship varies across offenses, with some categories, particularly property crimes, showing largest marginal effects below 40 degrees F. This low-temperature dependency is in some ways surprising. Analyses of the impact of climate change on other economic outcomes, such as agriculture, have highlighted the role of extremely warm temperatures (Schlenker and Roberts, 2009). In contrast, my results suggest that the impact of climate change on property crime may operate largely through changes in the frequency of days with low to moderate temperatures.

Second, climate change will cause a substantial increase in crime in the United States. Relative to the total number of offenses that would occur between 2010 and 2099 in the absence of climate change, my calculations suggest that there will be an additional 30,000 murders, 200,000 cases of rape, 1.4 million aggravated assaults, 2.2 million simple assaults, 400,000 robberies, 3.2 million burglaries, 3.0 million cases of larceny, and 1.3 million cases of vehicle theft. The present discounted value of the social costs of these climate-related crimes is between 19 and 59 billion dollars.[9]

In interpreting these results, it is important to keep in mind that climate change will affect humans in a variety of ways (Tol, 2009; Deschenes and Greenstone, 2007, 2011; Hsiang, Meng, and Cane, 2011), and that a comprehensive cost-benefit analysis of climate change should consider all dimensions of costs and benefits. For example, given U.S. residents' high willingness to pay to live in areas with moderate climates (Cragg and Kahn, 1996), it is possible that the social costs of increased crime will be offset, at least in some regions, by the social benefits of more pleasant weather.

It is also worth emphasizing that the estimates presented here do not take into account longer-term adaptation mechanisms. If climate change does cause a permanent increase in the frequency of crime, people in affected areas will have the opportunity to modify their behavior to avoid being victimized. Furthermore, it is likely that law enforcement agencies will respond with increased policing activity. The potential for such actions suggests that the estimates in this paper should be viewed as an upper bound on the potential impacts of climate change on crime.

[9]To put these dollar values in context, consider that Deschenes and Greenstone (2011) estimate that climate-related changes in mortality and energy consumption will cause welfare losses of $892 billion over the next century, based on a 3% discount rate and the HadCM3 model's predictions for the A1FI scenario. Differencing out my estimate of the mortality-related costs of crime (murder and manslaughter together have a cost of approximately $34 billion) implies that crime-related costs ($59 billion) are likely to be about seven percent as large as the energy consumption and non-crime-related mortality costs of climate change in the United States ($858). Of course, this comparison ignores important differences between the A1FI and A1B emissions scenarios (the A1FI scenario assumes higher emissions and more warming than the A1B scenario used in this paper).

The estimates in this paper also assume a static baseline of criminal activity, based on average crime rates between 2000 and 2009. Given the challenges of accurately predicting long-term trends in crime rates (Levitt, 2004), such an assumption is a reasonable analytical strategy. However, if for reasons unrelated to climate change, crime rates were to increase or decrease substantially over the coming decades, then the estimates from this paper could significantly over- or underestimate climate's effects on future crime.

As a final caveat, I emphasize that this paper's estimates of the social cost of climate-related crime should be considered to be highly uncertain. Although I monetize the social costs of additional crimes using point estimates drawn from the VSL and crime literatures (Viscusi and Aldy, 2003; McCollister, French, and Fang, 2010), I make no attempt to characterize the range of uncertainties associated with these valuations. Furthermore, consistent with previous literature on the role of discounting in economic analysis of climate change (Weitzman, 2007), I find that the present value of the social costs of additional crime depends heavily on the choice of a discount rate. Thus, the costs presented here are best interpreted as "back-of-the-envelope" estimates, rather than as precise statements of the exact cost of climate-related crime.

7 Conclusion

In this paper, I document a robust statistical relationship between historical weather patterns and criminal activity, and use this relationship to predict how changes in U.S. climate will affect future patterns of criminal behavior. The results suggest that climate change will have substantial effects on the prevalence of crime in the United States. Although previous assessments of the costs and benefits of climate change have primarily focused on other economic endpoints, the magnitude of the estimated impacts from this paper suggests that changes in crime are an important component of the broader impacts of climate change.

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[10] I acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison, the WCRP's Working Group on Coupled Modeling, and the U.S. Department of Energy Office of Science for their roles in making available and supporting the WCRP CMIP3 multi-model dataset.

Table 1: Summary Statistics, by Climate Zone

	Mean Annual Maximum Daily Temperature			
	<55 F	55-64 F	65-74 F	≥75 F
	Monthly Crime Rate (per 100,000 persons)			
Murder	0.1 (1.2)	0.2 (1.3)	0.4 (1.9)	0.6 (2.2)
Manslaughter	0.03 (0.53)	0.03 (0.50)	0.02 (0.45)	0.02 (0.42)
Rape	1.2 (3.5)	1.2 (3.2)	1.3 (3.3)	1.6 (3.5)
Aggravated Assault	6 (13)	9 (14)	15 (20)	20 (22)
Simple Assault	26 (40)	31 (39)	34 (48)	41 (52)
Robbery	1 (3)	2 (5)	3 (6)	4 (8)
Burglary	43 (48)	44 (45)	50 (46)	61 (53)
Larceny	111 (94)	117 (98)	107 (97)	125 (112)
Vehicle Theft	9 (12)	11 (15)	11 (15)	13 (18)
	Annual Number of Days in Weather Bin			
Max Temp: <10 F	13 (11)	3 (4)	0 (1)	0 (0)
Max Temp: 10-19 F	20 (8)	7 (6)	1 (2)	0 (0)
Max Temp: 20-29 F	37 (9)	20 (11)	5 (5)	0 (1)
Max Temp: 30-39 F	52 (12)	44 (14)	18 (11)	3 (4)
Max Temp: 40-49 F	41 (11)	49 (14)	35 (12)	12 (8)
Max Temp: 50-59 F	40 (9)	49 (16)	50 (11)	31 (13)
Max Temp: 60-69 F	49 (11)	52 (13)	59 (13)	54 (13)
Max Temp: 70-79 F	64 (11)	64 (14)	68 (14)	77 (14)
Max Temp: 80-89 F	43 (14)	63 (18)	86 (18)	101 (28)
Max Temp: 90-99 F	6 (7)	14 (13)	40 (21)	77 (22)
Max Temp: ≥100 F	0 (1)	1 (2)	3 (6)	9 (17)
Precip: 0 mm	179 (47)	165 (44)	196 (40)	215 (46)
Precip: 1-4 mm	143 (37)	149 (34)	111 (29)	95 (30)
Precip: 5-14 mm	32 (11)	37 (14)	36 (12)	33 (14)
Precip: 15-29 mm	9 (4)	11 (6)	15 (7)	15 (7)
Precip: ≥30 mm	2 (2)	3 (3)	6 (4)	8 (5)
	County Characteristics			
Population	36,289 (51,843)	96,286 (246,799)	71,616 (316,927)	86,742 (237,757)
Pct White	97 (8)	96 (6)	87 (16)	78 (18)
Pct Female	50 (1)	51 (1)	51 (2)	51 (2)
Pct Ages 0-4	7 (2)	7 (1)	7 (1)	8 (1)
Pct Ages 5-19	25 (5)	25 (4)	25 (4)	26 (5)
Pct Ages 65-up	15 (4)	14 (4)	13 (4)	13 (5)
Pct Metro Center	2 (15)	7 (26)	6 (24)	4 (20)
Pct Metropolitan	14 (35)	24 (43)	22 (41)	27 (44)
Pct Urban	54 (50)	50 (50)	50 (50)	56 (50)
Pct Rural	30 (46)	19 (40)	22 (41)	13 (33)
Counties	209	1,092	1,141	530
Complete County Years	9,183	48,288	45,544	18,954
County Month Obs.	110,196	579,456	546,528	227,448

Note: The table shows mean crime rates, weather conditions, and socioeconomic characteristics for all in-sample counties for the years 1960-2009. Numbers in parentheses indicate standard deviations. Results are presented separately for counties in each of four climate zones, based on mean annual maximum daily temperature.

Table 2: Maximum Daily Temperature and Monthly Crime

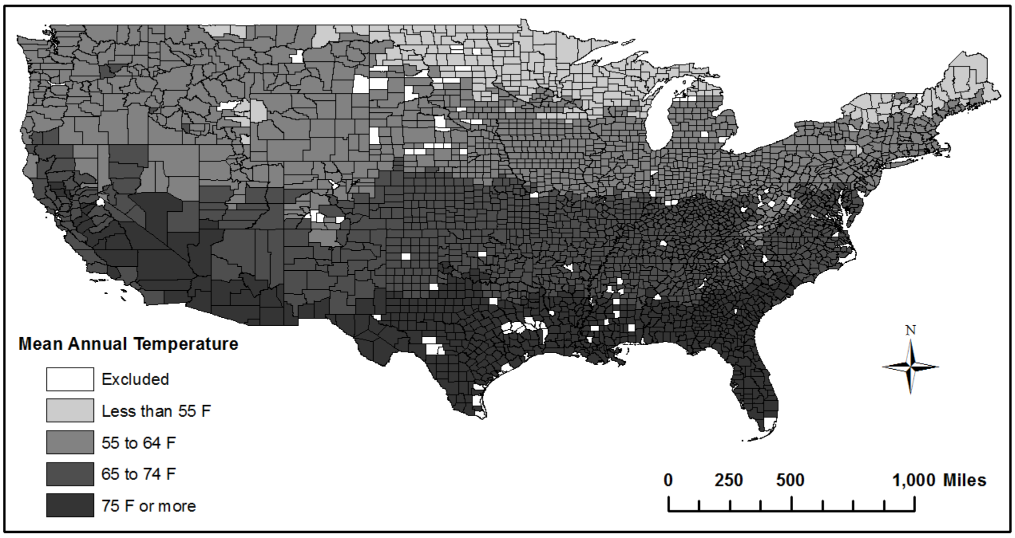
	Murder	Mansltr	Rape	Agg Asslt	Smp Asslt	Robbery	Burglary	Larceny	Veh Theft
Temp: < 10 F	-0.003***	-0.001**	-0.028***	-0.128***	-0.245***	-0.040***	-0.872***	-2.944***	-0.258***
	(0.001)	(0.000)	(0.003)	(0.019)	(0.061)	(0.012)	(0.057)	(0.169)	(0.025)
Temp: 10-19 F	-0.002**	-0.000	-0.026***	-0.058**	-0.249***	-0.051***	-0.843***	-2.596***	-0.308***
	(0.001)	(0.000)	(0.003)	(0.021)	(0.043)	(0.011)	(0.054)	(0.145)	(0.026)
Temp: 20-29 F	-0.002***	-0.000	-0.017***	-0.128***	-0.135***	-0.034***	-0.605***	-1.827***	-0.217***
	(0.000)	(0.000)	(0.002)	(0.013)	(0.031)	(0.009)	(0.040)	(0.094)	(0.020)
Temp: 30-39 F	-0.002**	-0.001**	-0.016***	-0.078***	-0.167***	-0.011	-0.267***	-1.080***	-0.156***
	(0.000)	(0.000)	(0.001)	(0.009)	(0.024)	(0.008)	(0.034)	(0.064)	(0.016)
Temp: 40-49 F	-0.001**	0.000	-0.010***	-0.035***	-0.054**	0.021**	0.038	-0.383***	-0.059***
	(0.000)	(0.000)	(0.001)	(0.008)	(0.021)	(0.007)	(0.031)	(0.058)	(0.013)
Temp: 50-59 F	-0.001**	-0.000	-0.005***	-0.024**	-0.023	0.002	0.021	-0.107*	-0.011
	(0.000)	(0.000)	(0.001)	(0.008)	(0.016)	(0.006)	(0.025)	(0.050)	(0.016)
Temp: 70-79 F	0.000	0.000	0.008***	0.091***	0.159***	0.009	0.006	-0.025	-0.020
	(0.000)	(0.000)	(0.001)	(0.009)	(0.018)	(0.006)	(0.030)	(0.058)	(0.015)
Temp: 80-89 F	0.001**	-0.000	0.012***	0.112***	0.223***	0.017*	0.072	-0.024	-0.010
	(0.000)	(0.000)	(0.002)	(0.012)	(0.031)	(0.008)	(0.044)	(0.096)	(0.018)
Temp: 90-99 F	0.002**	0.000	0.018***	0.178***	0.311***	0.026*	0.100	-0.104	0.049*
	(0.001)	(0.000)	(0.002)	(0.017)	(0.042)	(0.011)	(0.063)	(0.128)	(0.024)
Temp: ≥100 F	0.000	-0.000	0.020***	0.143***	0.294***	0.021	0.095	-0.351	0.003
	(0.001)	(0.000)	(0.005)	(0.032)	(0.059)	(0.017)	(0.107)	(0.207)	(0.051)
Precip: 1-4 mm	0.001**	0.000	0.002**	0.011*	-0.005	0.002	0.013	0.040	0.052***
	(0.000)	(0.000)	(0.001)	(0.006)	(0.013)	(0.004)	(0.020)	(0.046)	(0.009)
Precip: 5-14 mm	0.000	0.000	0.001	-0.020*	-0.009	-0.004	-0.040	-0.405***	0.026
	(0.000)	(0.000)	(0.001)	(0.009)	(0.021)	(0.007)	(0.037)	(0.086)	(0.019)
Precip: 15-29 mm	0.002*	0.001*	-0.001	-0.004	0.016	0.009	-0.059	-0.413***	0.136***
	(0.001)	(0.000)	(0.002)	(0.013)	(0.032)	(0.010)	(0.043)	(0.103)	(0.027)
Precip: ≥30 mm	-0.001	-0.000	-0.005	-0.070**	-0.029	0.046**	0.119	-0.921***	0.136**
	(0.001)	(0.000)	(0.003)	(0.023)	(0.041)	(0.015)	(0.067)	(0.163)	(0.047)
Lag T: < 10 F	0.001	0.001**	-0.002	0.008	-0.011	0.020	-0.001	-0.376**	0.046
	(0.001)	(0.000)	(0.003)	(0.020)	(0.042)	(0.012)	(0.047)	(0.119)	(0.028)
Lag T: 10-19 F	0.001	-0.001	0.001	-0.010	-0.051	0.010	-0.132**	-0.036	-0.046
	(0.001)	(0.000)	(0.003)	(0.028)	(0.061)	(0.014)	(0.050)	(0.135)	(0.025)
Lag T: 20-29 F	-0.001**	0.002***	0.003	0.014	0.037	-0.035***	-0.214***	-0.209*	0.003
	(0.000)	(0.000)	(0.002)	(0.013)	(0.030)	(0.009)	(0.039)	(0.092)	(0.018)
Lag T: 30-39 F	0.000	0.000**	0.001	0.033***	0.026	0.001	-0.034	-0.288***	-0.012
	(0.000)	(0.000)	(0.001)	(0.009)	(0.024)	(0.007)	(0.032)	(0.076)	(0.014)
Lag T: 40-49 F	0.000	0.000**	-0.000	-0.004	-0.026	-0.010	-0.046	-0.125	-0.004
	(0.000)	(0.000)	(0.001)	(0.008)	(0.022)	(0.006)	(0.029)	(0.068)	(0.014)
Lag T: 50-59 F	-0.000	0.000	0.003**	0.024**	-0.049***	-0.018**	-0.097***	-0.085	0.022
	(0.000)	(0.000)	(0.001)	(0.007)	(0.014)	(0.006)	(0.023)	(0.048)	(0.013)
Lag T: 70-79 F	0.001*	0.000	0.001	0.029***	0.018	-0.020***	-0.079*	-0.085	-0.024
	(0.000)	(0.000)	(0.001)	(0.008)	(0.019)	(0.006)	(0.031)	(0.063)	(0.016)
Lag T: 80-89 F	0.000	-0.000	-0.000	0.000	-0.045	-0.006	-0.043	-0.076	-0.014
	(0.000)	(0.000)	(0.002)	(0.012)	(0.031)	(0.008)	(0.041)	(0.103)	(0.018)
Lag T: 90-99 F	0.001	0.000	0.002	0.010	-0.050	0.001	0.026	-0.041	0.025
	(0.001)	(0.000)	(0.002)	(0.017)	(0.042)	(0.010)	(0.057)	(0.126)	(0.023)
Lag T: ≥100 F	0.001	-0.000	-0.006	-0.049	-0.140*	0.018	0.099	-0.117	-0.003
	(0.002)	(0.000)	(0.004)	(0.038)	(0.060)	(0.016)	(0.098)	(0.208)	(0.055)
Lag P: 1-4 mm	0.001***	0.000*	0.000	0.010	0.018	0.022***	0.052*	-0.013	0.027**
	(0.000)	(0.000)	(0.001)	(0.006)	(0.014)	(0.004)	(0.021)	(0.050)	(0.010)
Lag P: 5-14 mm	-0.000	-0.000*	-0.001	0.047***	0.061**	-0.003	-0.062	0.016	0.031
	(0.000)	(0.000)	(0.002)	(0.009)	(0.022)	(0.007)	(0.033)	(0.078)	(0.016)
Lag P: 15-29 mm	-0.001	-0.000	0.007***	0.023	0.081*	0.008	0.022	-0.036	0.047
	(0.001)	(0.000)	(0.002)	(0.014)	(0.032)	(0.011)	(0.047)	(0.108)	(0.025)
Lag P: ≥30 mm	0.003**	0.000	0.006	0.083***	0.167***	-0.004	-0.023	-0.273	0.054
	(0.001)	(0.000)	(0.003)	(0.019)	(0.044)	(0.017)	(0.068)	(0.141)	(0.042)
Observations	1,315,325	848,837	1,315,325	1,237,676	1,237,676	1,315,325	1,315,325	1,315,325	1,315,325
Clusters	539	341	539	506	506	539	539	539	539
R-squared	0.000	0.001	0.002	0.005	0.005	0.004	0.022	0.053	0.011

Note: Each observation represents a unique county-by-year-by-month. The dependent variable in all regressions is the monthly crime rate per 100,000 persons, with each column representing a different type of crime. The independent variables are the number of days per month that daily weather fell into the specified range, with 60-69 F as the omitted temperature bin and 0 mm as the omitted precipitation bin. All regressions control for county-by-year and county-by-month fixed effects. The county-by-year fixed effects are removed by long differencing relative to January of each county-by-year group of twelve months, and then dropping all (zeroed-out) January observations. County-by-month fixed effects are removed by de-meaning. All regressions are clustered by year-by-month, and weighted by county population.

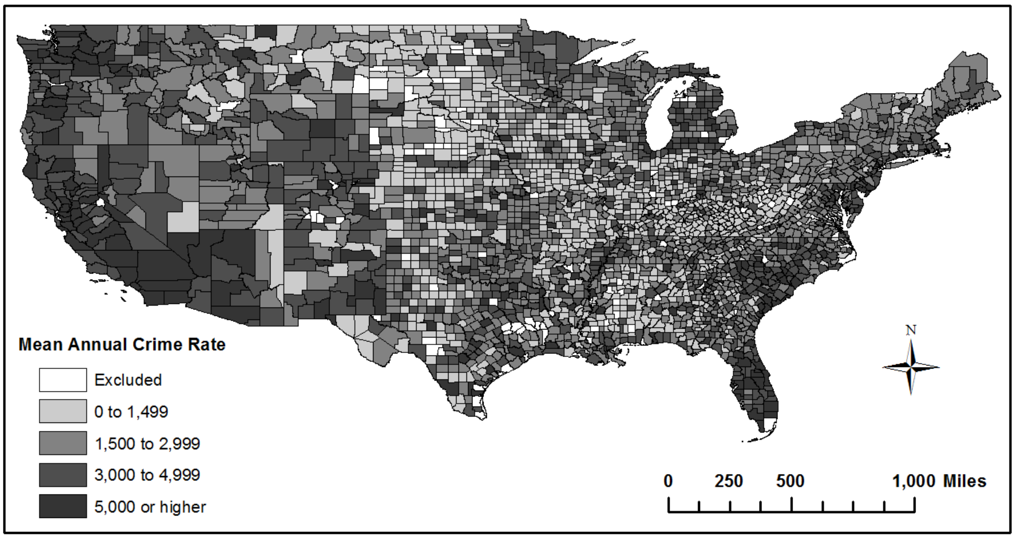
Table 3: The Predicted Impact of Climate Change on Crime

	Number of Additional Crimes		Social Cost (billions)			
			HadCM3		CCSM3	
Crime	HadCM3	CCSM3	3%	6%	3%	6%
Murder	29,894	23,855	37.4	15.5	29.3	11.4
	(9,160)	(5,338)	(10.7)	(4.2)	(6.3)	(2.4)
Manslaughter	-2,620	-2,042	-3.1	-1.3	-2.7	-1.1
	(2,098)	(1,473)	(2.6)	(1.1)	(1.8)	(0.7)
Rape	200,189	155,792	2.0	0.8	1.6	0.6
	(31,149)	(19,280)	(0.3)	(0.1)	(0.2)	(0.1)
Aggravated Assault	1,359,442	1,088,879	6.6	2.7	5.2	2.0
	(233,863)	(139,929)	(1.1)	(0.4)	(0.7)	(0.3)
Simple Assault	2,170,574	1,787,245	2.6	1.1	2.2	0.9
	(550,410)	(368,382)	(0.7)	(0.3)	(0.5)	(0.2)
Robbery	436,756	303,186	2.3	0.9	1.6	0.7
	(140,393)	(92,547)	(0.7)	(0.3)	(0.5)	(0.2)
Burglary	3,243,980	2,611,525	5.0	2.1	4.2	1.8
	(818,886)	(504,653)	(1.2)	(0.5)	(0.8)	(0.3)
Larceny	3,041,402	3,958,481	3.0	1.3	3.8	1.6
	(1,700,475)	(1,078,184)	(1.4)	(0.6)	(0.9)	(0.5)
Vehicle Theft	1,252,196	1,048,522	3.2	1.3	2.9	1.2
	(334,559)	(197,291)	(0.8)	(0.3)	(0.5)	(0.2)
Total	.	.	59.0	24.4	48.1	19.1

Note: The "Number of Additional Crimes" columns represent the number of additional crimes that will occur due to climate change, relative to the number that would occur if temperatures and precipitation stayed at the 2000-2009 averages. The "HadCM3" and "CCSM3" columns show results based on different climate models. The "Social Cost" columns present the present value of the social cost of the additional crimes that will occur due to climate change. Future costs are discounted using two alternative discount rates: 3% and 6%. Numbers in parentheses indicate standard errors.



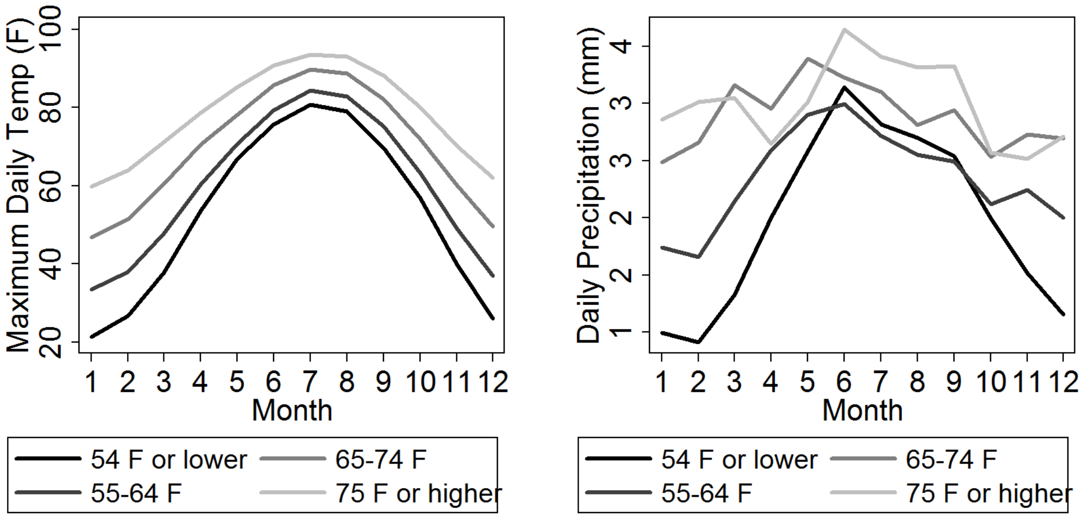
(a) Mean Annual Maximum Daily Temperature (F)



(b) Annual Crime Rate per 100,000 Persons (All Crimes)

Figure 1: Map of the Study Region

Note: Both panels show maps of all in-sample counties in the United States. The top panel depicts the mean annual maximum daily temperature, by county. The bottom panel depicts the annual number of all crimes per 100,000 persons, by county. All statistics are based on data from 1960-2009.

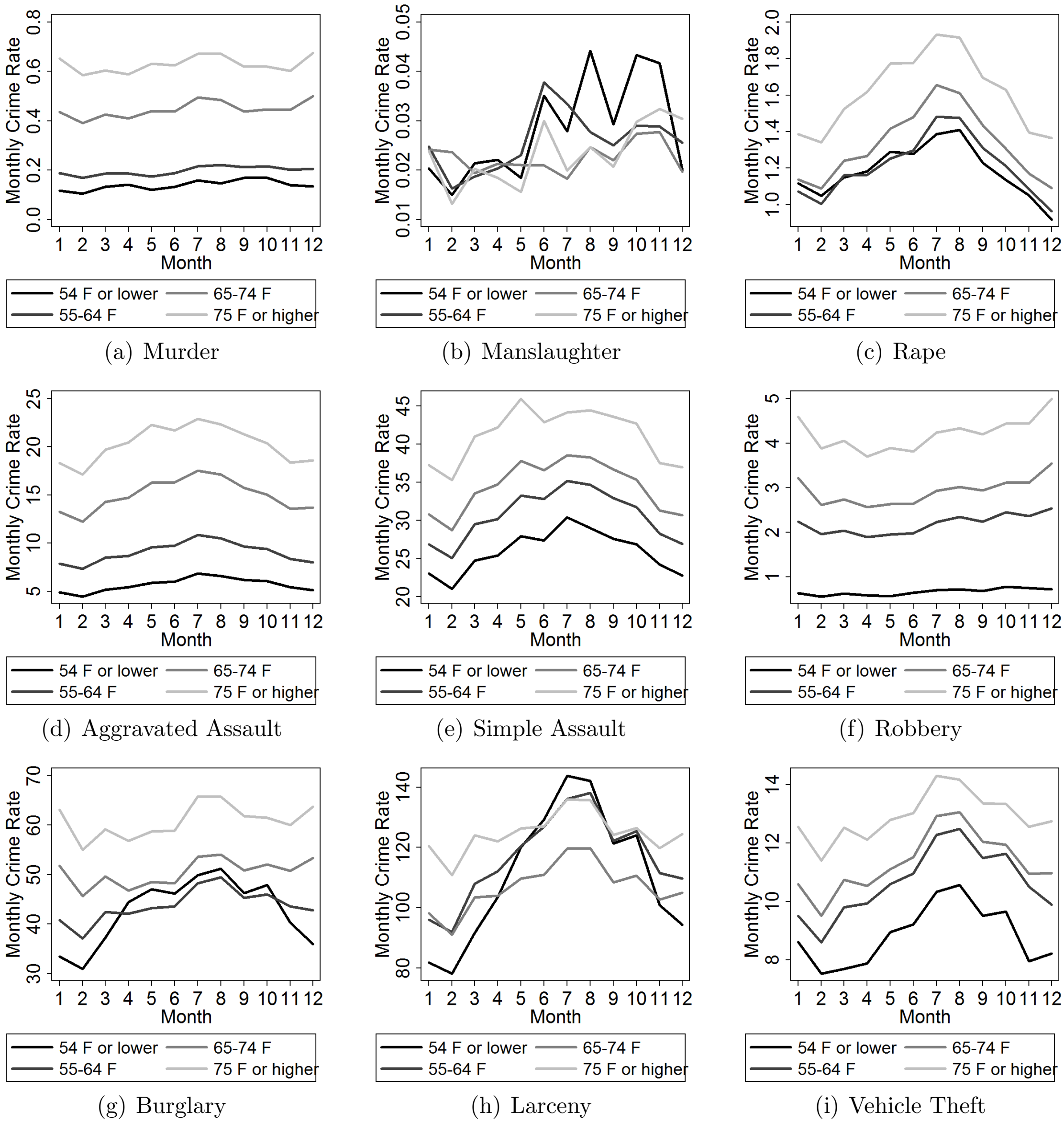


(a) Maximum Daily Temperature (F)

(b) Daily Precipitation (mm)

Figure 2: Seasonal Weather Patterns, by Climate Zone

Note: Each panel shows mean weather across counties within each climate zone, by month, for the period from 1960 to 2009.



(a) Murder
(b) Manslaughter
(c) Rape
(d) Aggravated Assault
(e) Simple Assault
(f) Robbery
(g) Burglary
(h) Larceny
(i) Vehicle Theft

Figure 3: Seasonal Crime Rate Trends, by Climate Zone

Note: Each panel shows the mean crime rate across counties within each climate zone, by month. The crime rate variables represent the monthly number of crimes per 100,000 persons.

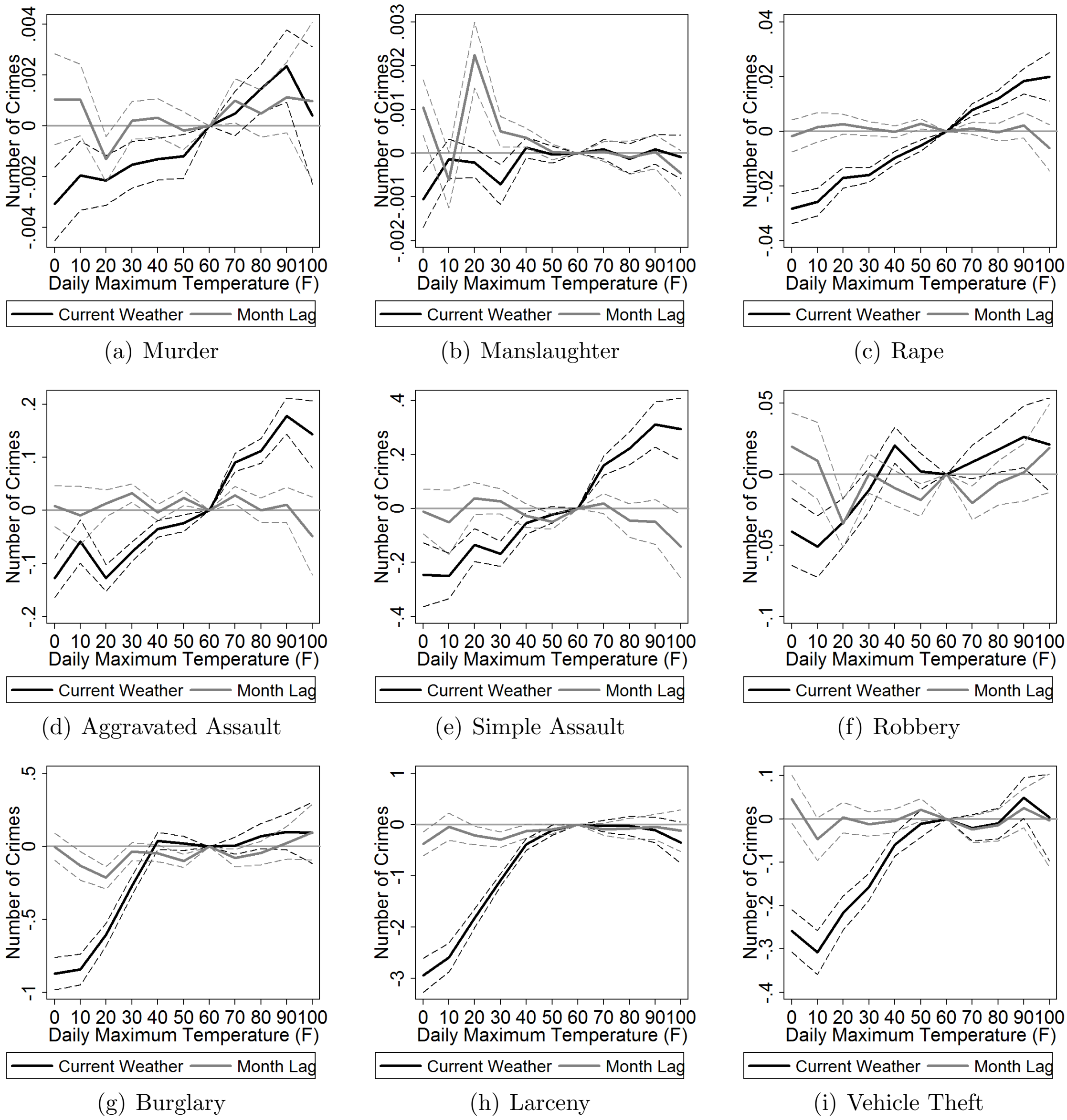
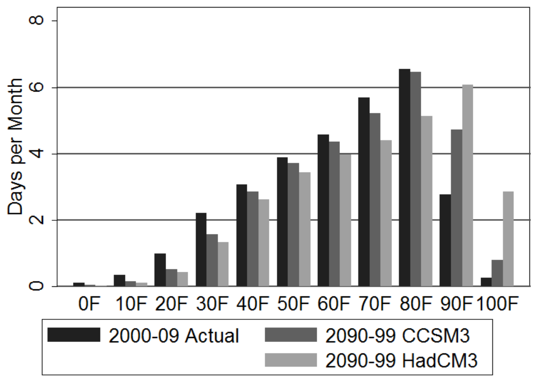
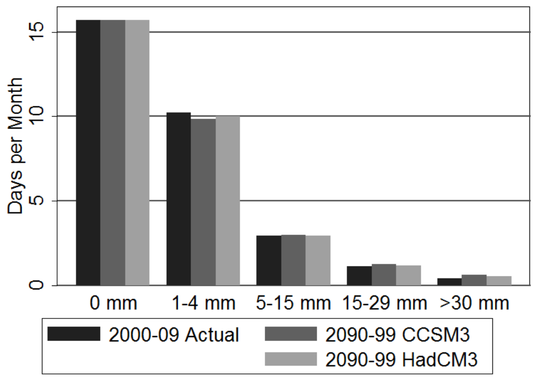


Figure 4: The Effect of Daily Maximum Temperature on Monthly Crime

Note: Each figure shows coefficients from a regression of the monthly crime rate per 100,000 persons on a semi-parametric set of weather bin variables. The solid black line represent the effect of current weather; the solid gray line represents the lagged effect of the previous month's weather. Dashed lines represent 95 percent confidence intervals for the estimated coefficients. All coefficients are relative to one day in the 60 to 70 degrees F bin.



(a) Maximum Daily Temperature (F)



(b) Daily Precipitation (mm)

Figure 5: Distribution of Daily Weather, by Scenario

Note: Each panel shows the number of days per month that fall into the specified weather bin.

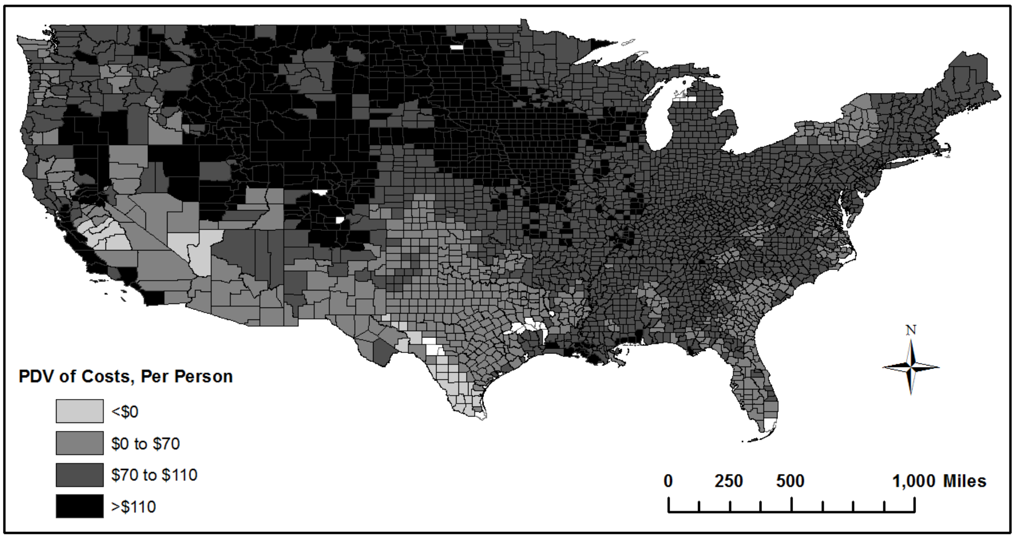


Figure 6: Present Discounted Social Cost of Climate-Related Crime, Per Person
Note: The map shows the per capita present discounted value of the social costs of the additional crimes estimated to be caused by climate change between 2010 and 2099. Costs are presented per person, for each county. The costs are based on climate predictions from the HadCM3 model, and are discounted using a discount rate of 6 percent.

Crime, Weather, and Climate Change
Appendix

November 10, 2012

UCR Data

As a reference, Table 1 of this Appendix summarizes the definitions of each type of criminal offense in the UCR data. Additionally, to illustrate the advantages and challenges of using the UCR crime reporting data, Figure 1 presents the time trend in crime rates for the nine major categories of offenses, by climate zone. Several main patterns are obvious from the data. First, crime rates increase dramatically between 1960 and 1980, in some cases by several hundred percent. Given the rapid and monotonic nature of the this increase, it seems likely that it is driven by increased reporting of crimes, rather than by changes in underlying criminal behavior. Second, trends across climate zones appear broadly similar, although there is some heterogeneity in absolute levels. Finally, there is strong evidence of high frequency variation in crime rates due to seasonality.

Sensitivity Analyses

As a supplement to results presented in the main part of the paper, this Appendix presents additional results from a variety of sensitivity analyses of the relationship between weather and crime.

One potential concern about the analysis is that the relationship between weather and crime may have changed over time. To address this concern, Figure 2 plots the coefficients from separate regressions based on each of the five decades covered by the data: 1960-1969, 1970-1979, 1980-1989, 1990-1999, and 2000-2009. The data show more noise than the main regression results, but the overall pattern of crime increasing with temperature remains similar across decades for almost all crimes.

A second potential question is related to long-term adaptation. In particular, if residents of warmer climates are better adapted to warmer temperatures, then the relationship between weather and crime may vary across geographic regions. To assess whether this is the case, Figure 3 shows the results from separate regressions for counties in each of the four climate zones (based on long-term mean annual maximum daily temperature): $<$55 degrees F, 55 to 64 degrees F, 65 to 74 degrees F, and $\geq$75 degrees F. The figure shows that the effects of moderate and warm temperatures on crime is strikingly similar across climate zones. For very cold temperatures, the coefficients show somewhat more divergence, but this imprecision is primarily due to the fact that there are few days in the dataset in which the warmest climate zones are exposed to very low temperatures.

Another possibility related to adaptation is that people adjust to seasonal conditions, so that crime rates are driven by weather conditions relative to local expectations for that time of year. Under this hypothesis, a 60 degree F day could have very different effects depending on whether it occurred in April or July. As a test of this supposition, Figure 4 presents the results of a regression that includes interactions of the weather bin coefficients with three county-month temperature category variables. These categorical dummy variables indicate whether the average temperature in each month-by-county, over the period from 1960 to 2009, fell into one of three bins: <45 degrees F, 45 to 69 degrees F, or ≥ 70 F. Although the regressions show a fair amount of noise, particularly for temperatures that are not typical of normal monthly conditions, there are no obvious differences in the effects of temperature on crime that can be attributed to seasonal adaptation.

One additional concern about the analysis is related to heteroskedasticity in the crime rate variables. There is a large degree of variation in absolute crime levels between counties, and plots of time trends for individual counties show that the degree of seasonal variation is roughly proportional to the magnitude of the crime rate. Unfortunately, because the data contain a large number of months in which no crimes were committed (particularly for violent offenses such as murder and manslaughter), using a log transformation would be an inappropriate way to deal with this heteroskedasticity. Instead, as a sensitivity analysis, I estimate separate regressions for counties in each of four crime quartiles. To construct the quartiles, I calculate the mean crime rate for total crimes for each in-sample county, averaging across months and years. I then order these mean crime rates from highest to lowest. Quartile 1 represents counties below the 25th percentile; Quartile 2 represents counties between the 25 and 49th percentiles; Quartile 3 represents counties between the 50 and 74th percentiles; and Quartile 4 represents counties at or above the 75th percentile.

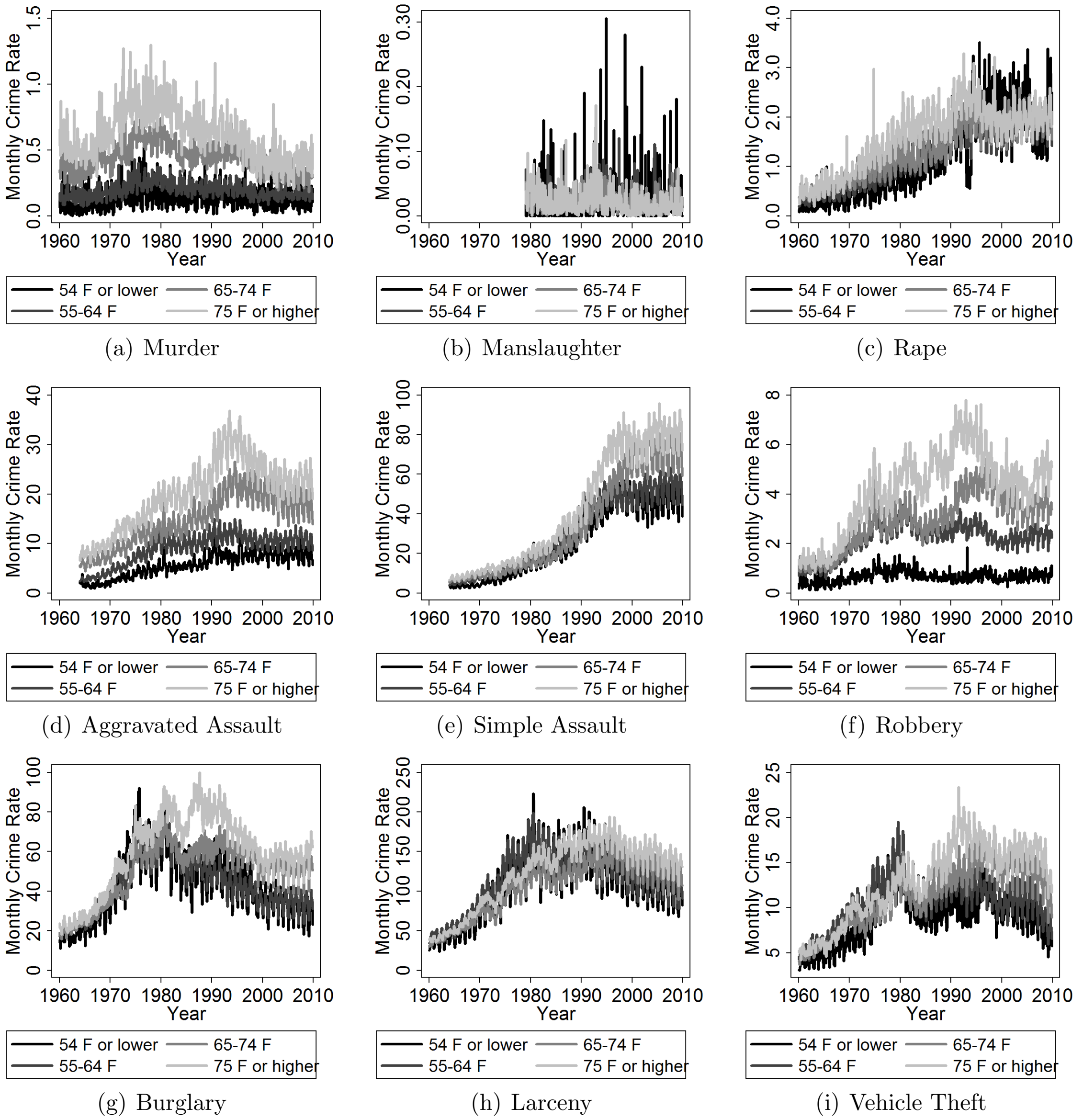
Figure 5 shows the results from this analysis. Generally speaking, the coefficients from Quartiles 1, 2, and 3 are of similar magnitude. As expected, the coefficients from regressions using data from Quartile 4 (counties with the highest average crime rate for all crimes) tend to be larger, although the exact degree of difference varies across types of crime.

A final question about the analytical approach used in this paper is whether one month is a sufficiently long time period to account for any lagged impacts of weather on crime. Although the insignificant coefficients on a one-month lag of weather suggest this is the case, I also conduct sensitivity analyses in which I run regressions using data that have been aggregated to quarterly and half-year time periods. Figure 6 shows the results of this analysis. Although regressions results based on more aggregate time periods are noisier than the results based on month-long time periods, the estimated coefficients from the three types of regressions are generally similar. The relationship between temperature and crime rates for aggravated and simple assault appears somewhat weaker based on the quarterly and half-year data. However, the effect of temperature on burglary and larceny is even stronger in the quarterly and half-year data. Overall, the figure suggests that a one-month aggregation period is sufficient to account for most "harvesting" that occurs as a result of negative serial correlation in crime rates.

Table 1: Uniform Crime Reporting Offense Definitions

Offense	Definition
Murder	The willful (nonnegligent) killing of one human being by another.
Manslaughter	The killing of another person through gross negligence.
Rape	The carnal knowledge of a female forcibly and against her will. [Includes attempted rape.]
Aggravated Assault	An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury.
Simple Assault	Assaults which do not involve the use of a firearm, knife, cutting instrument, or other dangerous weapon and in which the victim did not sustain serious or aggravated injuries.
Robbery	The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence or by putting the victim in fear.
Burglary	The unlawful entry of a structure to commit a felony or a theft. [Includes attempted burglary.]
Larceny	The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another.
Vehicle Theft	The theft or attempted theft of a motor vehicle.

Source: FBI (2004).



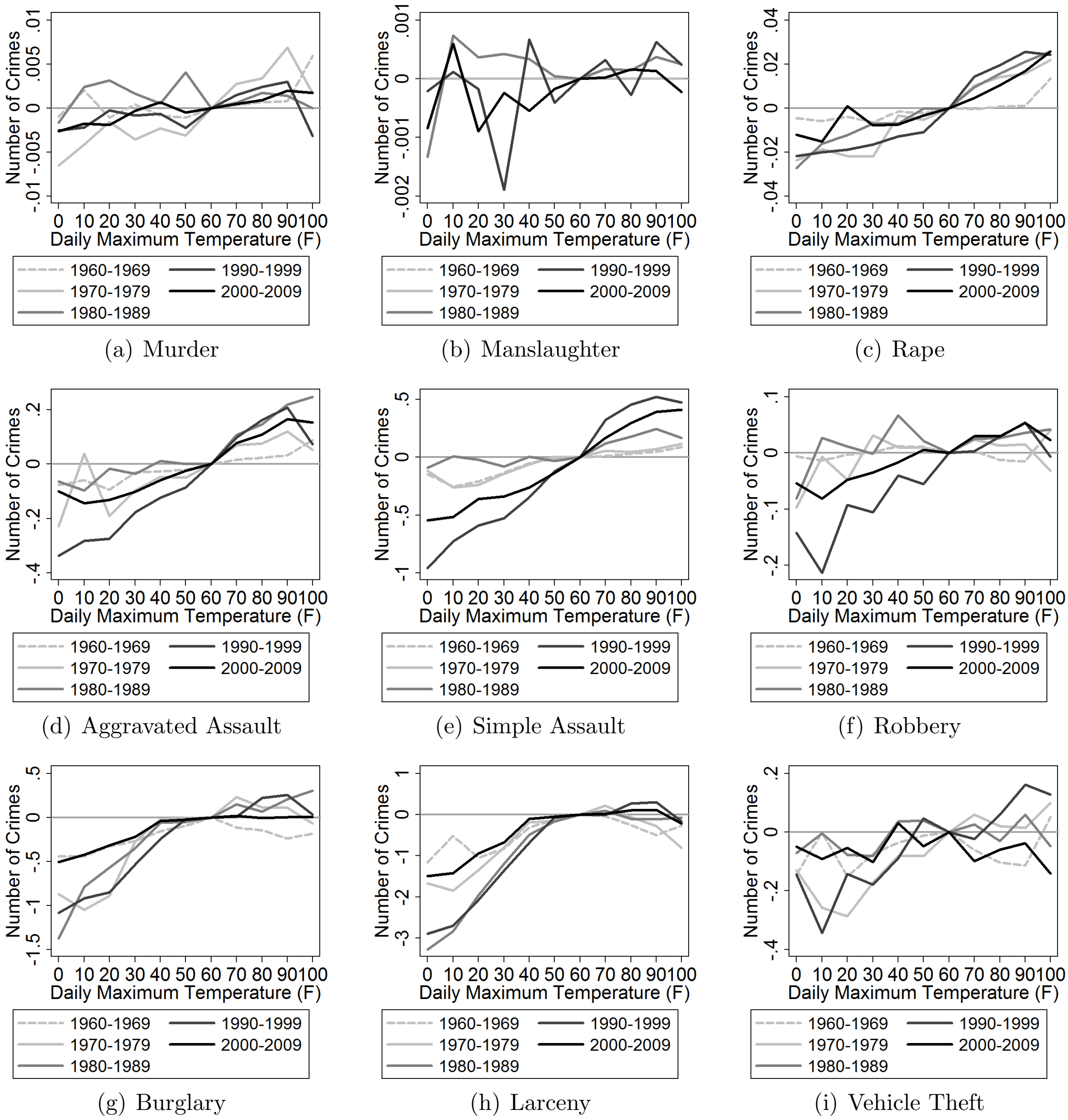
(a) Murder (b) Manslaughter (c) Rape

(d) Aggravated Assault (e) Simple Assault (f) Robbery

(g) Burglary (h) Larceny (i) Vehicle Theft

Figure 1: Crime Rate Trends, by Climate Zone

Note: Each panel shows the mean crime rate across counties within each climate zone, by year and month. The crime rate variables represent the monthly number of crimes per 100,000 persons.



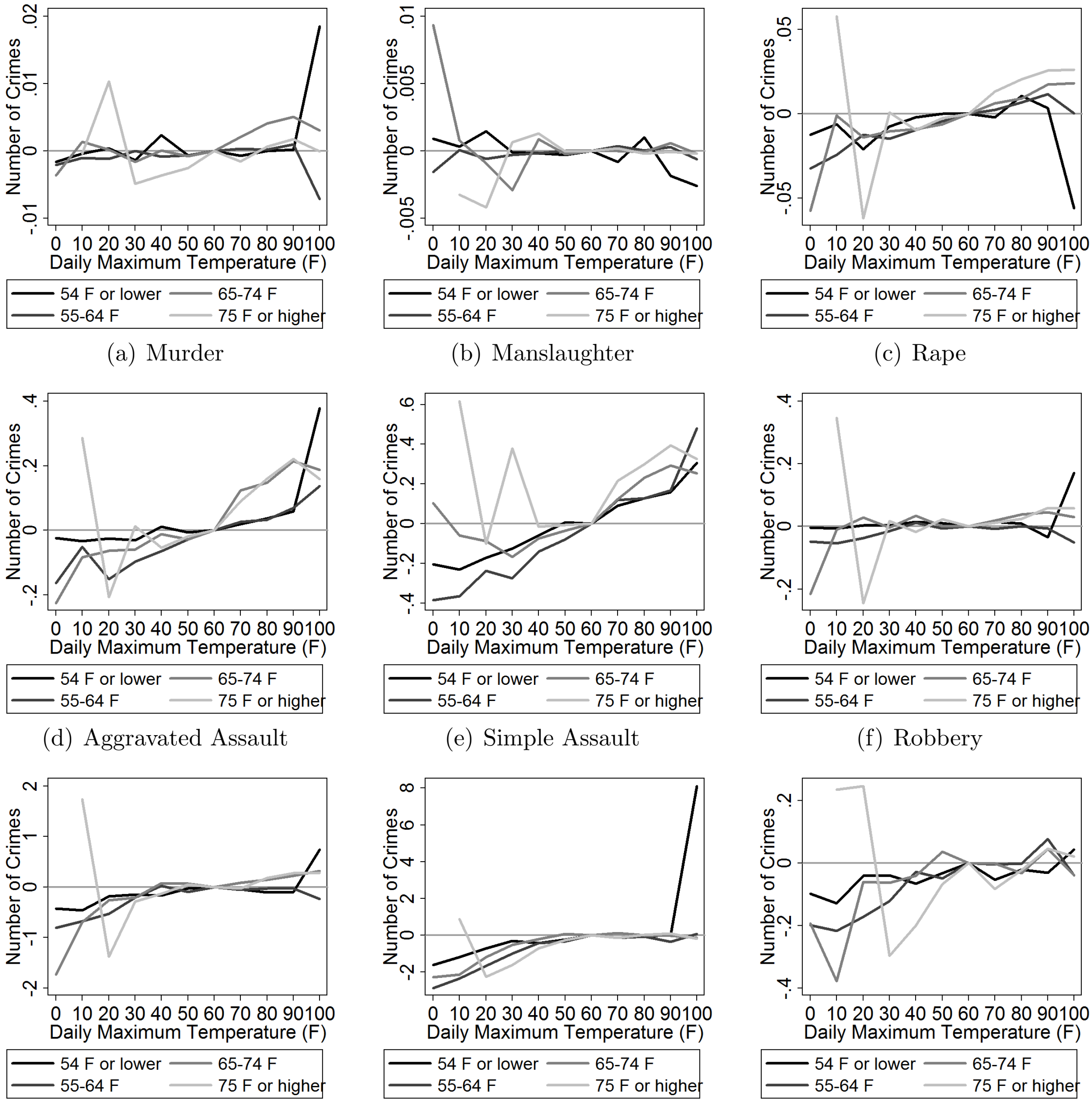
(a) Murder (b) Manslaughter (c) Rape

(d) Aggravated Assault (e) Simple Assault (f) Robbery

(g) Burglary (h) Larceny (i) Vehicle Theft

Figure 2: Monthly Crime and Daily Temperature, by Decade

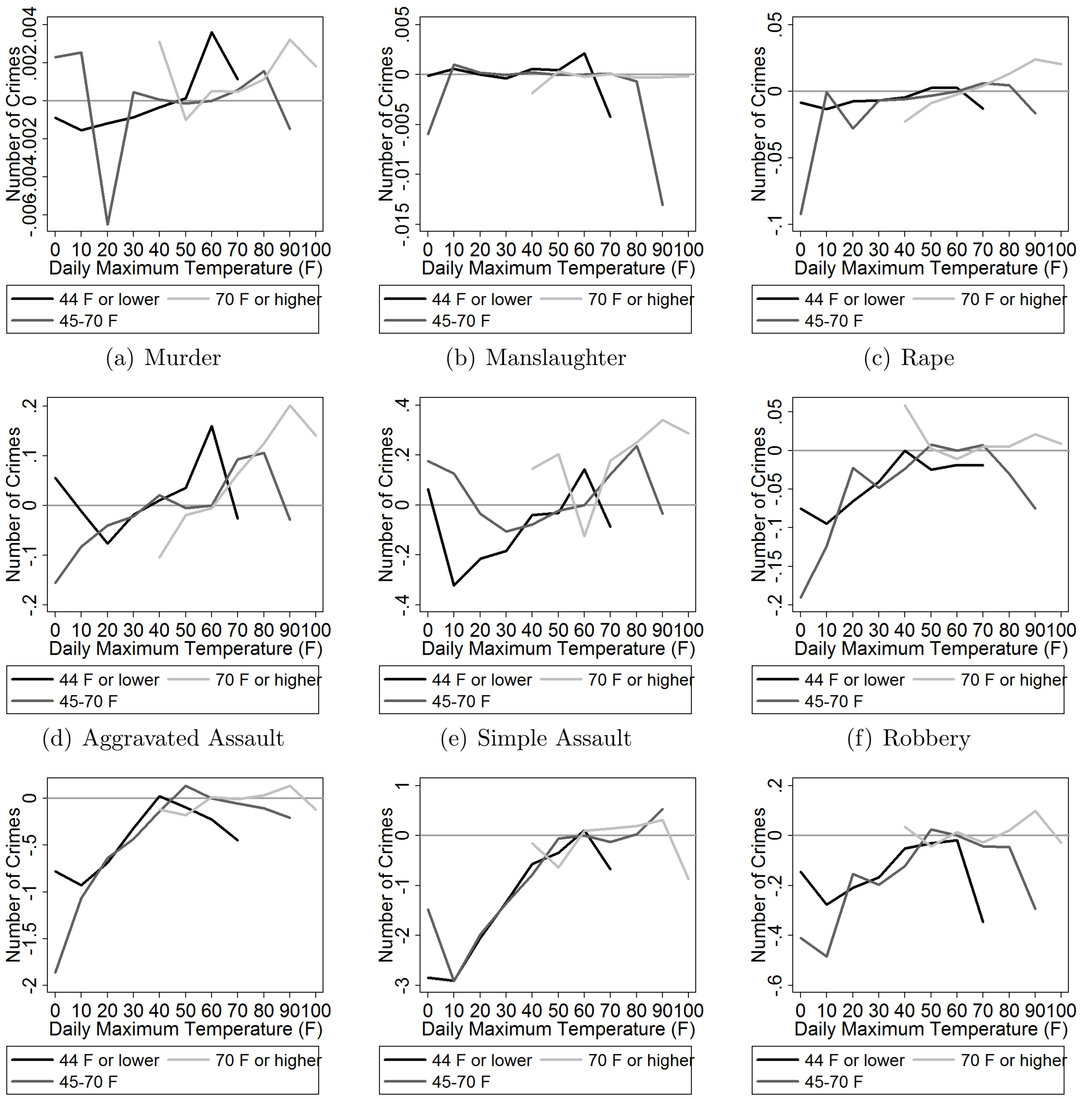
Note: Each figure shows coefficients from regressions of the monthly crime rate per 100,000 persons on a semi-parametric set of weather bin variables, for separate sets of observations from five different decades. These decades are: 1960-1969, 1970-1979, 1980-1989, 1990-1999, and 2000-2009. All coefficients are relative to one day in the 60 to 70 degrees F bin.



(a) Murder (b) Manslaughter (c) Rape
(d) Aggravated Assault (e) Simple Assault (f) Robbery
(g) Burglary (h) Larceny (i) Vehicle Theft

Figure 3: Monthly Crime and Daily Temperature, by Climate Zone

Note: Each figure shows coefficients from regressions of the monthly crime rate per 100,000 persons on a semi-parametric set of weather bin variables, for counties in each of four climate zones. Each in-sample county is assigned to a climate zone based on whether its long-term mean annual maximum daily temperature falls into one of four ranges: <55 degrees F, 55 to 64 degrees F, 65 to 74 degrees F, and ≥75 degrees F. All coefficients are relative to one day in the 60 to 70 degrees F bin.



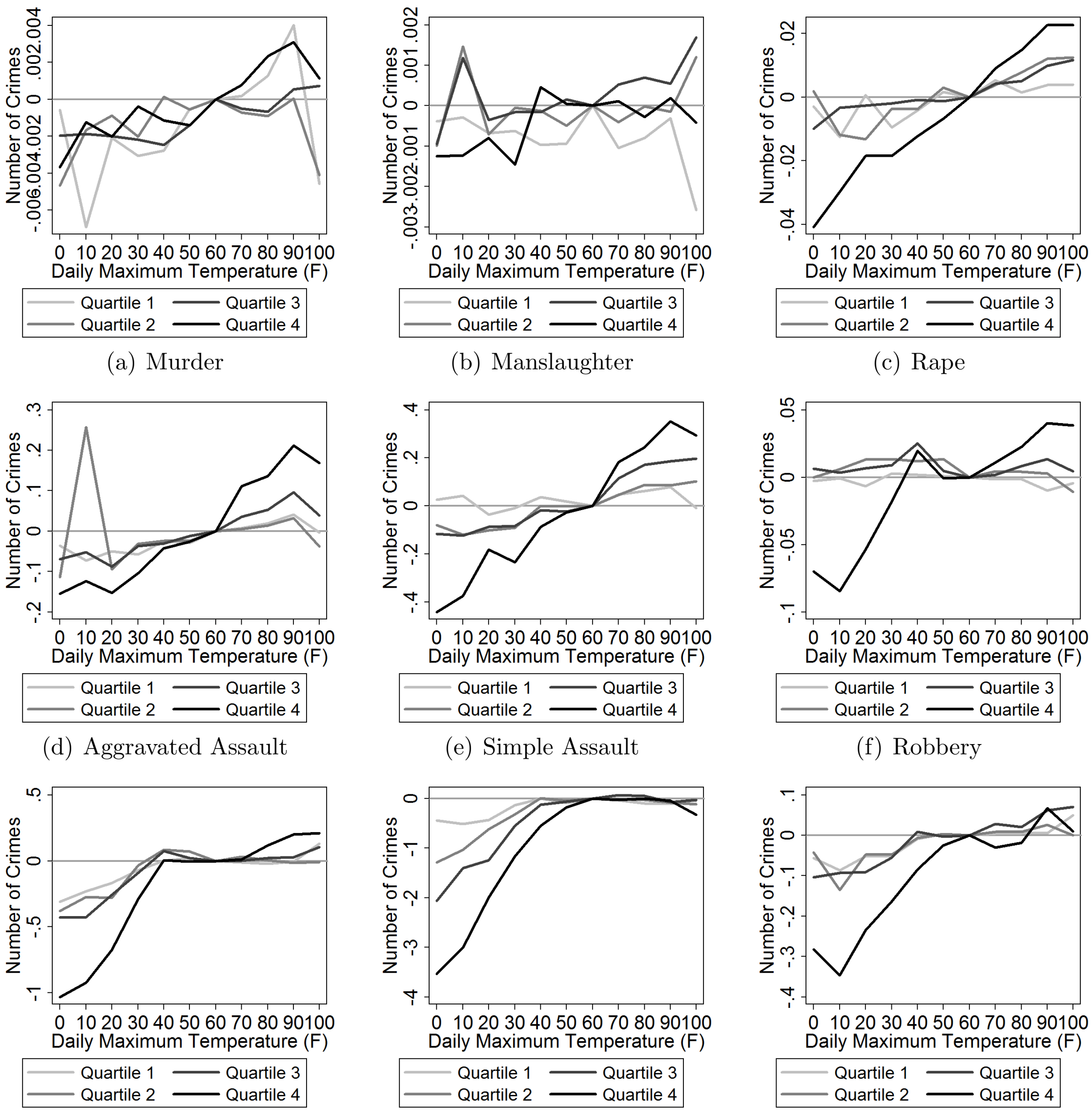
(a) Murder (b) Manslaughter (c) Rape

(d) Aggravated Assault (e) Simple Assault (f) Robbery

(g) Burglary (h) Larceny (i) Vehicle Theft

Figure 4: Monthly Crime and Daily Temperature, by Mean Monthly Temperature

Note: Each figure shows coefficients from a regression of the monthly crime rate per 100,000 persons on a semi-parametric set of weather bin variables, interacted with three county-month temperature category variables. These categorical dummy variables indicate whether the average temperature in each month-by-county, over the period from 1960 to 2009, fell into one of three bins: <45 degrees F, 45 to 69 degrees F, or ≥70 F. All coefficients are relative to one day in the 60 to 70 degrees F bin.



(a) Murder (b) Manslaughter (c) Rape

(d) Aggravated Assault (e) Simple Assault (f) Robbery

(g) Burglary (h) Larceny (i) Vehicle Theft

Figure 5: Monthly Crime and Daily Temperature, by Crime Rate Quartile

Note: Each figure shows coefficients from regressions of the monthly crime rate per 100,000 persons on a semi-parametric set of weather bin variables, for counties in each of four crime quartiles. To construct the quartiles, I calculate the mean crime rate for all crimes for each in-sample county, averaging across months and years. I then order these mean crime rates from highest to lowest. Quartile 1 represents counties below the 25th percentile; Quartile 2 represents counties between the 25 and 49th percentiles; Quartile 3 represents counties between the 50 and 74th percentiles; and Quartile 4 represents counties at or above the 75th percentile. All coefficients are relative to one day in the 60 to 70 degrees F bin.

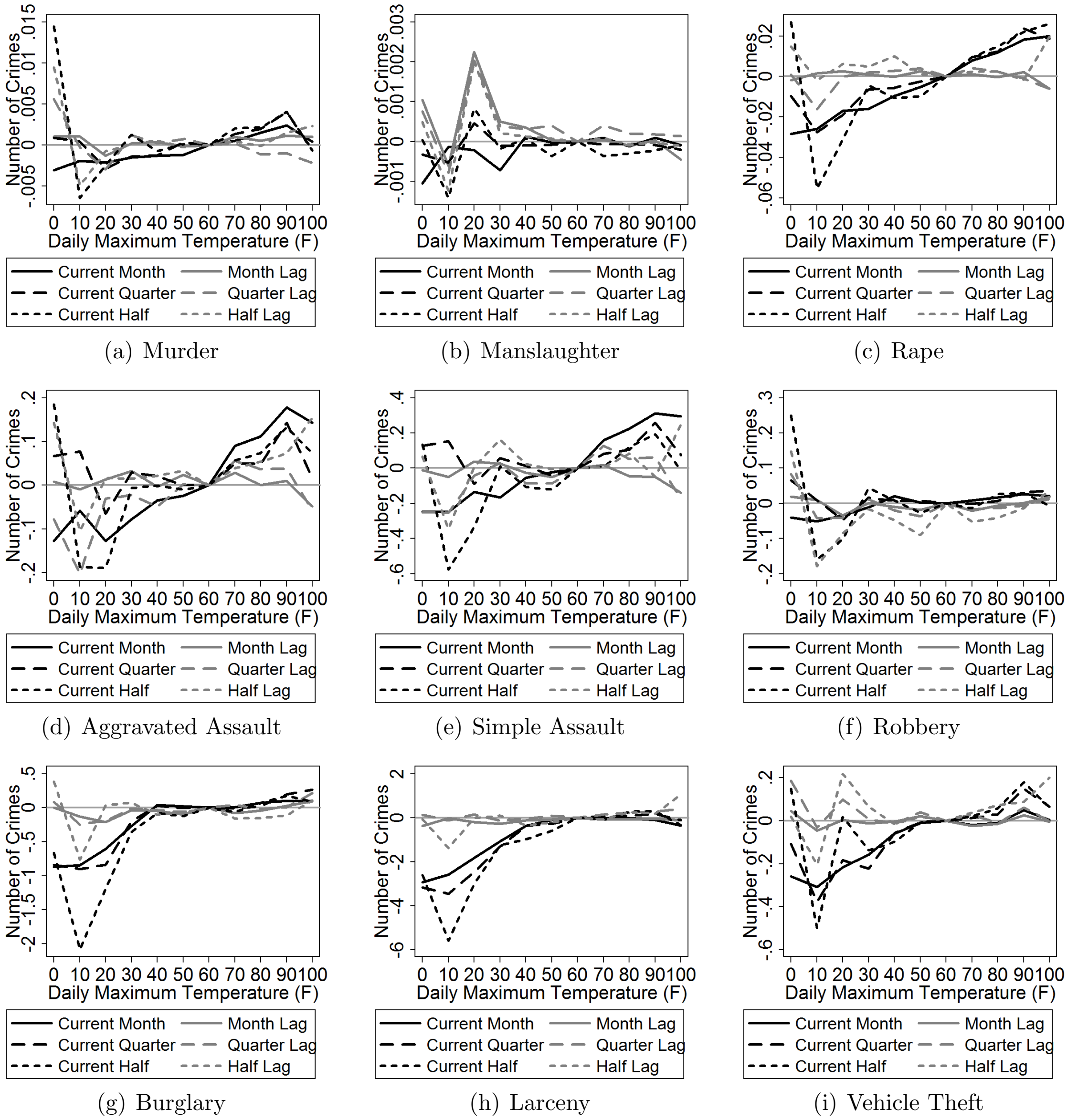


Figure 6: Crime and Daily Temperature, by Month, Quarter, and Half-year

Note: Each figure shows coefficients from regressions of the crime rate per 100,000 persons on a semi-parametric set of weather bin variables. Separate regression results are reported for crimes and weather aggregated by month, quarter, and half-year. All coefficients are relative to one day in the 60 to 70 degrees F bin.