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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 30-year panel of monthly crime and weather data for 2997 US counties. I identify the effect of weather on monthly crime by using a semi-parametric bin estimator and controlling for state-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 22,000 murders, 180,000 cases of rape, 1.2 million aggravated assaults, 2.3 million simple assaults, 260,000 robberies, 1.3 million burglaries, 2.2 million cases of larceny, and 580,000 cases of vehicle theft in the United States.

Introduction

A small body of research has begun to suggest that civil conflict and warfare are influenced by changes in climate (Burke et al., 2012; Hsiang et al., 2011). However, less 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 show that higher temperatures cause substantial increases in crime (Horrocks and Menclova, 2011; Brunsdon et al., 2009; Bushman et al., 2005; Cohn, 1990), implying that climate change could have important impacts on criminal activity. However, because crime rates exhibit negative serial correlation over a span of weeks (Jacob et al., 2007), the hour-to-hour or day-to-day relationship between weather and crime is unlikely to be informative about the long-term effects of climate change on criminal behavior.

To address this gap in the literature, this paper develops the first comprehensive estimates of the impact of climate change on US 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.[2] To support the analysis, I have constructed a panel dataset that includes monthly crime and weather data for 2997 US counties for the period from 1980 to 2009. My data on criminal activity are drawn from the US Federal Bureau of

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[2] 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 °F (2.8 °C) by the year 2099, compared to baseline temperatures between 1980 and 1999 (IPCC, 2007).

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Investigation's Uniform Crime Reporting (UCR) data. These data, which are based on monthly reports from 17,000 US 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 US National Climatic Data Center's Global Historical Climatology Network Daily (GHCN-Daily) dataset. After combining these two data sources, I generate a dataset with 891,000 unique county-by-year-by-month observations.

To identify the effect of daily weather on monthly crime, I use a Poisson regression approach with semi-parametric weather variables (Deschenes and Greenstone, 2011) that measure the number of days per month spent in each of 11 maximum daily temperature bins ($<10\,^{\circ}$F, 10–20 °F,…, 90–100 °F, $\geq 100\,^{\circ}$F) and five daily precipitation bins (0 mm, 1–4 mm, 5–14 mm, 15–29 mm, and ≥ 30 mm). I regress monthly crime on these bin variables, controlling for extensive fixed effects that capture average crime and weather conditions in each county-by-year and state-by-month group of observations. 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 US climate drawn from 15 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 crime, this relationship appears approximately linear through the entire range of temperatures experienced in the continental United States. However, for property crimes (such as burglary and larceny), the relationship between temperature and crime is highly non-linear, with a kink at approximately 50 °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 focus on within-year variation as a way to address the measurement error issues created by long-term inter-annual trends in the quality of crime reporting; and in my use of an unusually rich 30-year panel dataset on monthly crime and weather for the entire continental United States, rather than the 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 1.5–5.5% higher because of climate change. Under the IPCC's A1B climate scenario, the United States will experience an additional additional 22,000 murders, 180,000 cases of rape, 1.2 million aggravated assaults, 2.3 million simple assaults, 260,000 robberies, 1.3 million burglaries, 2.2 million cases of larceny, and 580,000 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.[3] The present discounted value of the social costs of these climate-related crimes is between 38 and 115 billion dollars.

To put these numbers in perspective, recent research suggests that a 1% increase in the size of a city's police force results in an approximate 0.3% decrease in violent crimes and a 0.2% decrease in property crimes, with some variation across types of offenses (Chalfin and McCrary, 2012). Based on these elasticities, an immediate and permanent 4% increase in the size of the US police force would be required to offset the aggregate climate-related increases in murder, manslaughter, robbery, burglary, and vehicle theft that are likely to occur over the next century.[4] However, even with this additional law enforcement activity, climate change would still cause an additional 120,000 cases of rape, 1.0 million aggravated assaults, 1.5 million simple assaults, and 760,000 larcenies. These rough calculations imply that the most obvious mechanism for adapting to climate-related crime—increasing the size of the police force—would require a substantial public investment in law enforcement activity.

I am aware of only two previous empirical studies of the effects of climate change on crime in the United States: Anderson et al. (1997) and Rotton and Cohn (2003). Both papers are based on annually-averaged data for large geographic units (e.g., Anderson et al. regress average annual US crime rates on average annual US temperatures), and thus may face challenges with empirical identification of 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 US 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 econometric issues with this previous work.

The remainder of this paper is organized as follows: the first section, "Background on weather and crime," provides background on the relationship between weather and crime; the second section, "Data," describes the primary data sources; the third section, "Methodology," discusses my empirical methodology; the fourth section, "Results," presents my main findings on the relationship between climate change and crime; the fifth section, "Discussion," discusses the results; and the last section, "Conclusion," concludes the paper.

[3] 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.

[4] Because different crimes have different elasticities with respect to policing, a 4% change in the size of the police force would—in addition to offsetting the climate-related increase in murder, manslaughter, robbery, burglary, and vehicle theft—prevent an additional 300,000 robberies and 400,000 cases of vehicle theft over the next 90 years.

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 et al., 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 et al., 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 et al., 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 US jurisdictions for the period 1996–2001, Jacob et al. (2007) found 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).[5]

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 et al., 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 US 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.

Data

Data sources

The analysis for this paper is based on an unusually long and rich panel dataset of monthly crime rates and weather for 2997 counties in the 49 continental states (including the District of Columbia). The dataset covers the 30-year period from 1980 to 2009, and contains 891,000 unique county-by-year-by-month observations. It is based on two primary sources: Uniform Crime Reporting (UCR) data from the US Federal Bureau of Investigation (FBI, 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% of the US 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, both due 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. I address this problem in two ways. First, I limit my analysis to the period between 1980 and 2009, during which reporting appears to have been somewhat more consistent. Second, although previous research on criminal behavior has made use of UCR data aggregated to the annual level (e.g., Levitt, 1996), in this paper I

[5] 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.

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 fewer than 12 months of data for that year.[6] I then sum the total number of crimes reported by all remaining agencies in each county, by category of crime, to generate a county total for each month and year. 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 month-to-month variation in 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 US 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 1200 land-based US 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 to 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 estimate county weather using a bias-corrected inverse-distance-weighted average. Specifically, I generate temperature and precipitation time series for each county based on the weighted average weather conditions at all weather stations within 50 miles of the county. To place more emphasis on stations closest to each county, the weights in this calculation are set equal to the inverse of the distance from each station to the county. Of course, one potential problem with using a weighted average is that the set of reporting stations changes across time periods. Since long-term average temperatures vary across weather stations, gaps in reporting at some stations could create artifacts in which the daily average county temperature would falsely appear to fluctuate over time as certain stations move in and out of the set of reporting stations. To address this problem, I use a bias correction procedure that adjusts the intercept of the temperature time series at each station to better reflect the average long-term weather conditions in each county. I then calculate the weighted average using these bias-adjusted time series. The Appendix provides specific details about this 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 US Census estimates indicate that the county had a population of fewer than 1000 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. Finally, 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. The resulting dataset includes 2997 in-sample counties (out of the universe of 3143 counties), with a total of 891,000 unique county-by-year-by-month observations.

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 °F, 55–64 °F, 65–74 °F, and ≥ 75 °F. Panel (a) of Fig. 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 Fig. 1 shows a map of county-level annual crime rates per 100,000 persons, for all crimes (normalized using county population data from the US Census Bureau, 2004, 2011). 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.[7]

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 °F) have an average of only 6 days per year in which the maximum temperature exceeds 90 °F, counties in the warmest climate zone (≥ 75 °F) typically have 87 days per year with temperatures above 90 °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.

[6] 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.

[7] 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 et al. (1994) would have to control for other first-order determinants of crime (e.g., population density).

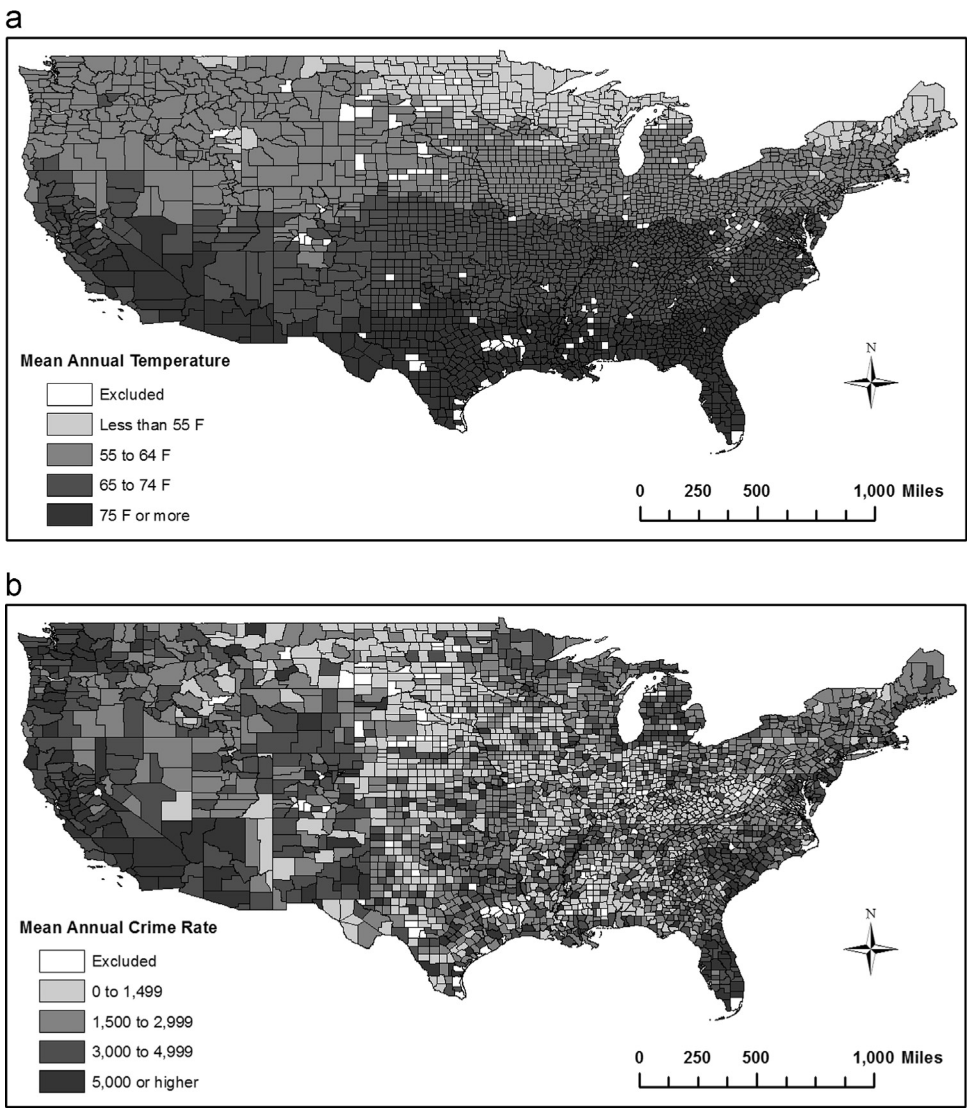

Fig. 1. Map of the study region: (a) mean annual maximum daily temperature (°F) and (b) Annual crime rate per 100,000 persons (all crimes). *Note*: The top panel depicts mean annual maximum daily temperature, by county. The bottom panel depicts the annual number of all crimes per 100,000 persons, by county. All statistics are based on data from 1960 to 2009.

Figs. 2 and 3 present initial evidence on the influence of seasonality on weather and crime. Fig. 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 weather variation is largest in the coolest climate zone (<55 °F), where the mean temperature difference between January and July is 60°. For comparison, the January–July temperature difference in the warmest climate zone (≥ 75 °F) is about 30°.

Fig. 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 and manslaughter, 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.

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.

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 (1.8)	0.6 (2.1)
Manslaughter	0.03 (0.51)	0.03 (0.50)	0.02 (0.45)	0.02 (0.42)
Rape	1.7 (4.3)	1.6 (3.7)	1.7 (3.6)	2.0 (3.5)
Aggravated assault	7 (15)	11 (17)	18 (22)	24 (25)
Simple assault	36 (46)	42 (43)	47 (54)	56 (59)
Robbery	1 (2)	3 (14)	4 (9)	5 (9)
Burglary	45 (48)	46 (45)	58 (47)	71 (53)
Larceny	132 (97)	136 (118)	131 (105)	155 (118)
Vehicle theft	10 (13)	12 (23)	14 (18)	16 (20)
Annual number of days in weather bin				
Max temp: < 10 °F	12 (10)	2 (4)	0 (1)	0 (0)
Max temp: 10–19 °F	19 (9)	6 (6)	1 (2)	0 (0)
Max temp: 20–29 °F	37 (9)	19 (11)	4 (5)	0 (1)
Max temp: 30–39 °F	52 (13)	43 (14)	17 (11)	3 (3)
Max temp: 40–49 °F	42 (10)	50 (13)	35 (12)	11 (7)
Max temp: 50–59 °F	41 (9)	51 (16)	51 (11)	32 (13)
Max temp: 60–69 °F	49 (12)	53 (13)	60 (13)	55 (13)
Max temp: 70–79 °F	65 (11)	64 (15)	69 (14)	78 (14)
Max temp: 80–89 °F	42 (15)	62 (18)	85 (19)	99 (26)
Max temp: 90–99 °F	6 (7)	14 (14)	40 (21)	78 (21)
Max temp: ≥ 100 °F	0 (1)	1 (2)	3 (7)	9 (17)
Precip: 0 mm	174 (46)	161 (44)	193 (40)	210 (45)
Precip: 1–4 mm	147 (37)	152 (34)	114 (29)	99 (30)
Precip: 5–14 mm	32 (11)	38 (14)	37 (12)	33 (13)
Precip: 15–29 mm	9 (5)	12 (6)	15 (6)	15 (7)
Precip: ≥ 30 mm	2 (2)	3 (3)	6 (4)	8 (5)
County characteristics				
Population	39,210 (56,471)	109,327 (273,217)	83,587 (346,614)	103,412 (285,195)
Pct white	96 (9)	95 (7)	86 (16)	77 (18)
Pct female	50 (1)	51 (1)	51 (2)	51 (2)
Pct ages 0–4	7 (1)	7 (1)	7 (1)	8 (1)
Pct ages 5–19	22 (3)	22 (3)	22 (3)	23 (3)
Pct ages 65-up	16 (4)	15 (4)	14 (4)	14 (5)
Pct metro center	2 (15)	8 (26)	7 (25)	4 (20)
Pct metropolitan	14 (35)	24 (42)	22 (42)	25 (43)
Pct urban	53 (50)	48 (50)	49 (50)	56 (50)
Pct rural	30 (46)	20 (40)	23 (42)	14 (35)
Counties	207	1112	1169	509
Complete county years	5364	29,316	28,567	10,984
County month obs.	64,368	351,792	342,804	131,808

Note: The table shows mean crime rates, weather conditions, and socioeconomic characteristics for all in-sample counties for the years 1980–2009. 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.

I assume that the number of crimes C_{iym} in month m of year y in county i of state s has a Poisson distribution with probability density function given by

$$f(C_{iym}|\mathbf{X}_{iym}) = \exp(-\mu(\mathbf{X}_{iym}))\mu(\mathbf{X}_{iym})^{C_{iym}}/C_{iym}! \tag{1}$$

where $\mathbf{X}_{iym}$ is the set of all observed covariates and $\mu(\mathbf{X}_{iym}) \equiv E[C_{iym}|\mathbf{X}_{iym}]$ is a link function that provides a parametric form for the conditional mean of C_{iym} given $\mathbf{X}_{iym}$. Following standard practice, I assume that $\mu(\mathbf{X}_{iym})$ takes an exponential form:

$$\mu(\mathbf{X}_{iym}) = \exp\left(\sum_{j=1}^{11} \alpha_0^j T_{iym}^j + \sum_{k=1}^{5} \beta_0^k P_{iym}^k + \sum_{j=1}^{11} \alpha_0^j T_{i,y,m-1}^j + \sum_{k=1}^{5} \beta_0^k P_{i,y,m-1}^k + \Phi_{sm} + \theta_{iy}\right) \tag{2}$$

In this equation, Φ_{sm} is a state-by-month fixed effect and θ_{iy} is a county-by-year fixed effect. Following Deschenes and Greenstone (2011), I model the daily distribution of temperatures within a month using 11 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 et al., 2007), I also include a one month lag of each temperature and precipitation bin variable.

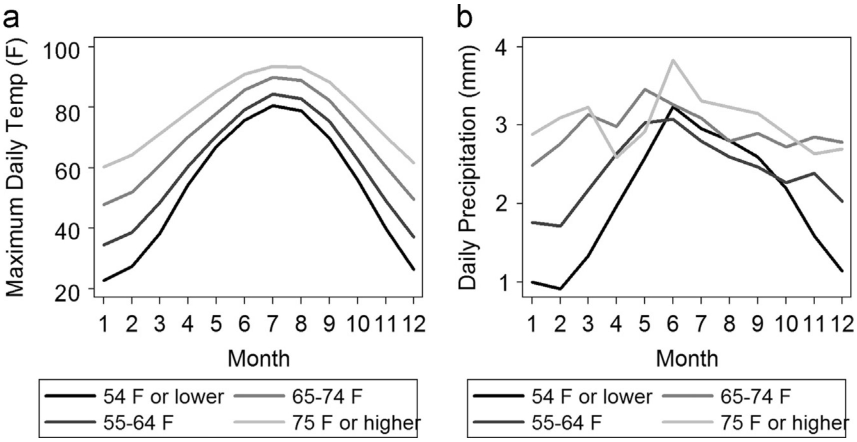

Fig. 2. Seasonal weather patterns, by climate zones: (a) maximum daily temperature (°F) and (b) daily precipitation (mm). *Note*: Each panel shows mean weather across counties within each climate zone, by month, for the period from 1980 to 2009.

I estimate the parameters in this fixed-effects Poisson regression model via maximum likelihood (Hausman et al., 1984; Wooldridge, 1999). Because weather patterns are highly correlated both between adjacent geographic areas and over subsequent months, I cluster all standard errors at the year level, using block boostrapping by year.

My choice of a Poisson regression approach is based on three considerations. First, because the dependent variable in my regressions is the number of crimes in each county–month–year combination, there are some types of uncommon crimes (e.g., manslaughter, murder) that take value zero for most observations. Compared to a log-linear OLS approach, the Poisson model easily accommodates these zero values. Second, although the Poisson distribution is not a perfect match for the empirical distribution of the UCR crime data, maximum likelihood estimation produces unbiased estimates of the coefficients in Poisson regression models, even if the Poisson distributional assumption is incorrect (Wooldridge, 1997, 1999). Of course, this robustness result does not extend to estimated covariance matrices. However, since I generate standard errors via bootstrapping, this lack of robustness is not an issue for my analysis. Third, Poisson regression does not suffer from an incidental parameters problem (Cameron and Trivedi, 1998). Thus, even though my model includes a large number of multiplicative fixed effects, the weather coefficients and fixed effects are both identified and can be estimated jointly.

Eq. (2) also 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 et al., 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, Eq. (2) includes an extraordinarily comprehensive set of fixed effects. In addition to including dummy variables that capture typical monthly patterns in weather and crime within each state, 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 state.

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 et al., 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 completely satisfactory 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 estimates within each county-by-year by aggregating the total number of reported crimes each month only for agencies that reported 12 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 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 state-by-month fixed effects, differences in weather and crime between months within a county represent the true effect of weather on crime.

Results

This section presents the main results from the analysis.

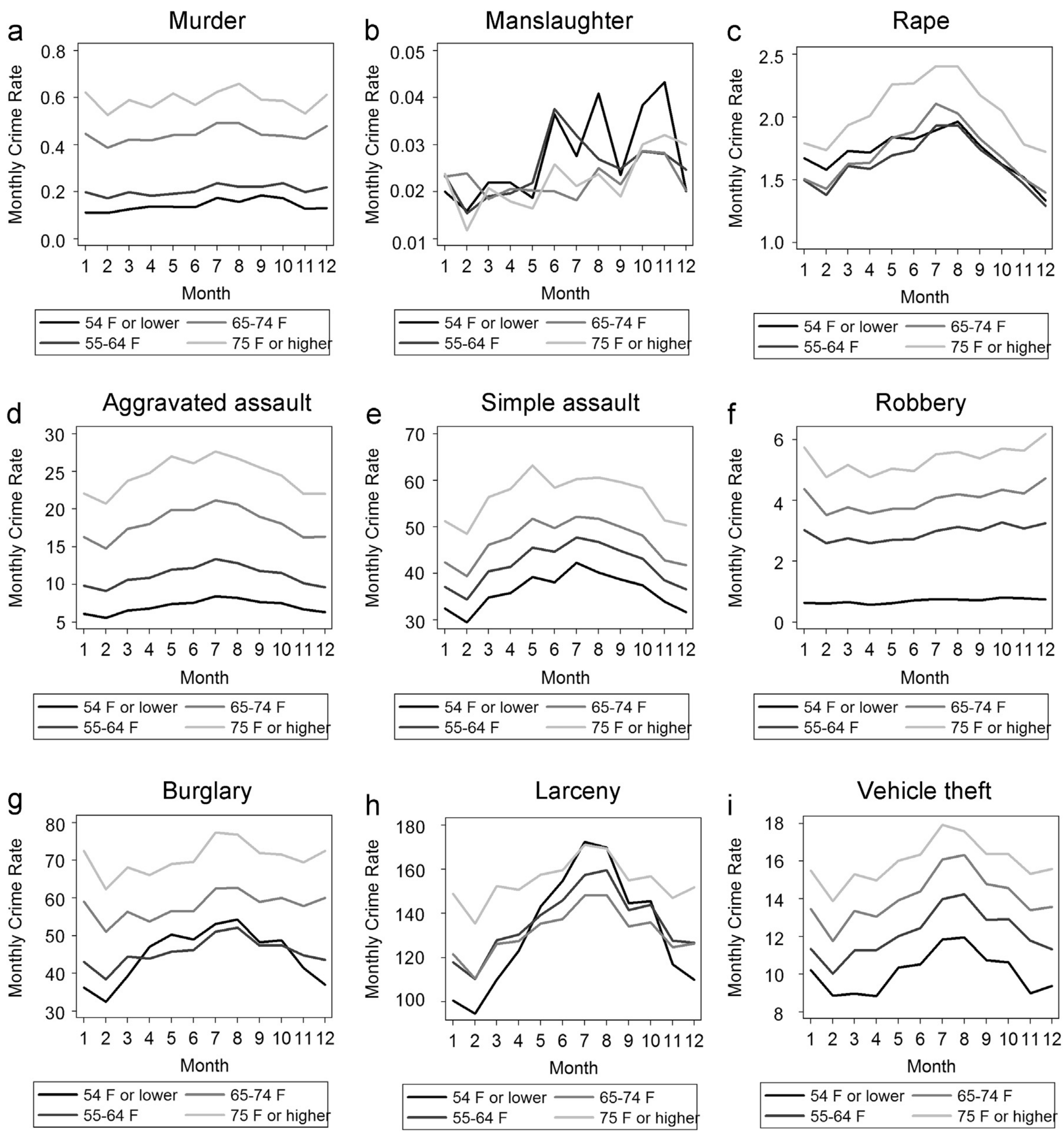

Fig. 3. Seasonal crime rate trends, by climate zone: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each panel shows the mean crime rate across counties within each climate zone, by month, for the period from 1980 to 2009. The crime rate variables represent the monthly number of crimes per 100,000 persons.

Weather and crime rates

I begin by presenting the regression results from estimating Eq. (2). Because of the large number of coefficients, the results are easiest to understand using a graphical approach. For example, Fig. 4 plots the regression coefficients on the temperature bin variables. In each subfigure, the horizontal axis represents the daily maximum temperature bin, and the vertical axis represents the coefficient, which can be interpreted as the percentage change in crime per month caused by one extra day in that weather bin relative to a day in the 60–69 °F bin.[8] The figure shows that across all types of crime,

[8] The Poisson regression model allows the state-by-month fixed effects to be correlated with the weather bin variables. Although the estimated state-by-month fixed effects are not shown here, they strongly reflect the seasonal pattern evident in Fig. 3, in which crime peaks in summer months. Due to the multiplicative form of the Poisson model, the correlation between the fixed effects and weather bins implies that the absolute magnitude of the marginal impact of a day of weather is greater in the summer than in the winter. Since most hot days occur during the summer, it also implies that a comparison of the raw coefficients in Fig. 4 understates the difference between the average absolute effect of hot days (which mostly occur in the summer) and cold days

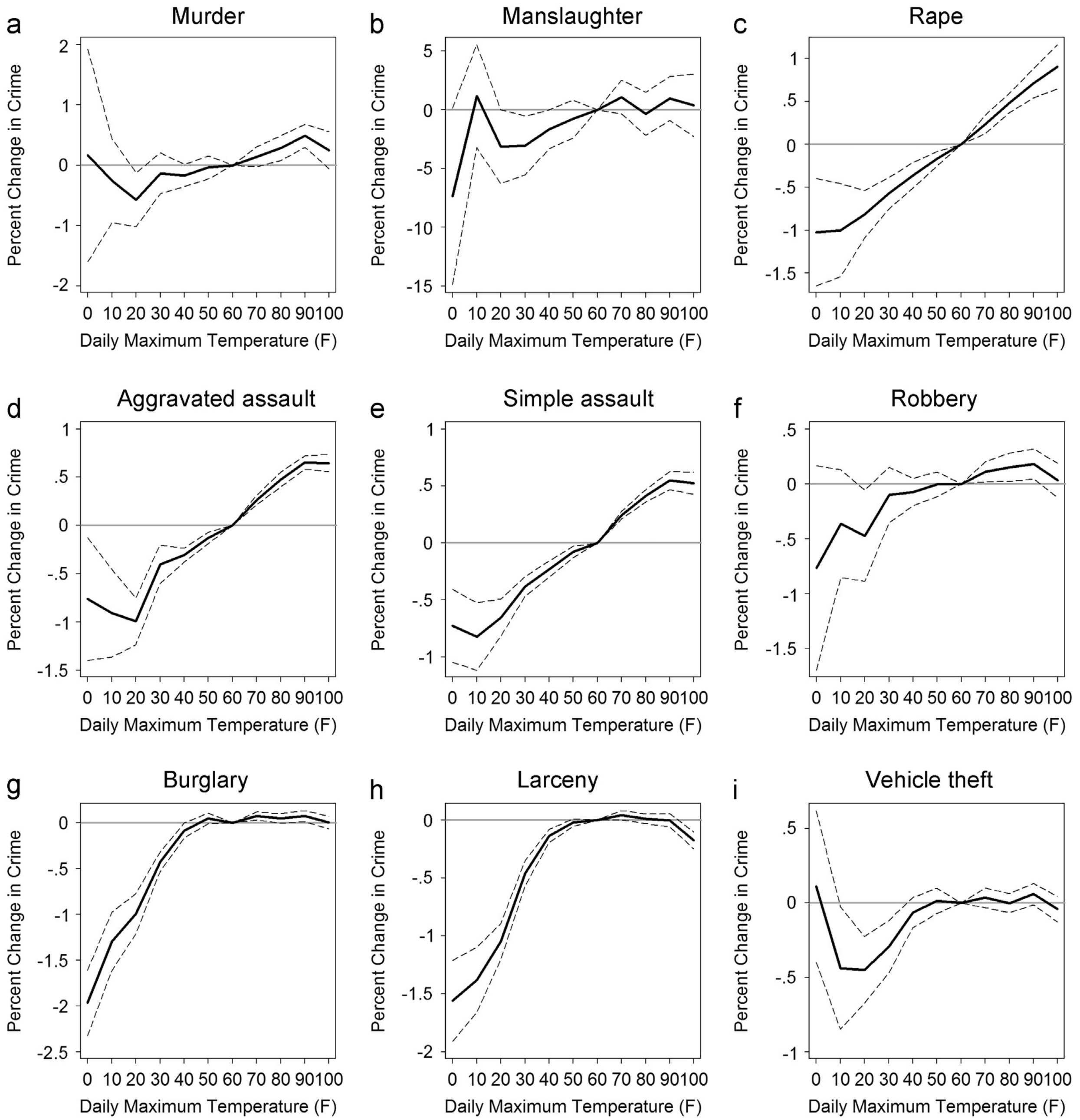

Fig. 4. The effect of daily maximum temperature on monthly crime: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows coefficients from a Poisson regression of the monthly number of crimes per county on a semi-parametric set of weather bin variables. The solid black lines represent the effect of current weather. Dashed lines represent 95% confidence intervals for the estimated coefficients. All coefficients are relative to 1 day in the 60–70 °F bin.

higher temperatures cause statistically significant increases in crime rates. As an illustration, compared to a day in the 60–69 °F bin, an extra day in the 30–39 °F bin leads to 0.6% fewer cases of rape, 0.4% fewer aggravated assaults, and 0.5% fewer larcenies. Although these coefficients are small, they 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 °F bin),

(*footnote continued*)
(which mostly occur in the winter). Thus, the coefficients in Fig. 4 should be interpreted as marginal effects that are conditional on the baseline crime rate for a particular month, county, and year.

Table 2
Maximum daily temperature and monthly crime.

	Murder	Mansltr	Rape	Agg Asslt	Smp Asslt	Robbery	Burglary	Larceny	Veh theft
Temp: < 10 °F	0.002	−0.074	−0.010**	−0.008*	−0.007***	−0.008	−0.020***	−0.016***	0.001
	(0.009)	(0.038)	(0.003)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)
Temp: 10–19 °F	−0.003	0.012	−0.010***	−0.009***	−0.008***	−0.004	−0.013***	−0.014***	−0.004*
	(0.004)	(0.022)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Temp: 20–29 °F	−0.006*	−0.031*	−0.008***	−0.010***	−0.007***	−0.005*	−0.010***	−0.010***	−0.004***
	(0.002)	(0.016)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Temp: 30–39 °F	−0.001	−0.030*	−0.006***	−0.004***	−0.004***	−0.001	−0.004***	−0.005***	−0.003**
	(0.002)	(0.013)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Temp: 40–49 °F	−0.002	−0.017*	−0.004***	−0.003***	−0.002***	−0.001	−0.001*	−0.001***	−0.001
	(0.001)	(0.008)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Temp: 50–59 °F	−0.000	−0.008	−0.002***	−0.001***	−0.001**	−0.000	0.000	−0.000	0.000
	(0.001)	(0.008)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Temp: 70–79 °F	0.001	0.011	0.002***	0.003***	0.002***	0.001*	0.001***	0.000*	0.000
	(0.001)	(0.007)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp: 80–89 °F	0.003**	−0.003	0.005***	0.005***	0.004***	0.002**	0.000	0.000	−0.000
	(0.001)	(0.009)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Temp: 90–99 °F	0.005***	0.010	0.007***	0.007***	0.005***	0.002**	0.001*	−0.000	0.001
	(0.001)	(0.010)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Temp: ≥ 100 °F	0.002	0.004	0.009***	0.006***	0.005***	0.000	0.000	−0.002***	−0.000
	(0.002)	(0.014)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Precip: 1–4 mm	0.000	0.002	0.001	0.000	−0.000	−0.000	0.001**	0.000	0.001**
	(0.001)	(0.006)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Precip: 5–14 mm	0.001	−0.002	0.001**	−0.000	−0.001*	0.001	0.001***	−0.000	0.002*
	(0.001)	(0.009)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Precip: 15–29 mm	−0.001	0.006	0.001	−0.001	−0.001	0.000	0.001	−0.001	0.004***
	(0.002)	(0.019)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Precip: ≥ 30 mm	0.003	0.044*	0.000	−0.002*	−0.001*	0.003	0.003***	−0.001	0.003**
	(0.003)	(0.021)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Lag *T*: < 10 °F	−0.007	0.005	0.002	0.000	0.001	0.002	−0.001	−0.001	−0.000
	(0.007)	(0.053)	(0.004)	(0.003)	(0.002)	(0.006)	(0.002)	(0.001)	(0.002)
Lag *T*: 10–19 °F	0.009*	−0.047*	0.003	0.002	0.001	0.004	0.001	−0.000	−0.000
	(0.004)	(0.023)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Lag *T*: 20–29 °F	−0.001	0.038**	−0.000	0.001	0.000	0.001	−0.001	−0.001*	−0.000
	(0.002)	(0.014)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Lag *T*: 30–39 °F	−0.000	0.008	0.000	0.001	0.001	0.001	0.001	−0.000	−0.001*
	(0.001)	(0.010)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Lag *T*: 40–49 °F	−0.000	−0.001	−0.001	0.000	0.000	0.001	0.001*	0.000	−0.001
	(0.001)	(0.009)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Lag *T*: 50–59 °F	0.001	−0.002	0.000	0.001	0.000	0.000	0.000	−0.000	−0.000
	(0.001)	(0.008)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Lag *T*: 70–79 °F	−0.000	−0.008	0.001	0.000	0.000	0.001	0.000	0.000	0.000
	(0.001)	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag *T*: 80–89 °F	−0.000	−0.011	0.001	−0.001	−0.001*	0.000	0.000	−0.000	0.000
	(0.001)	(0.010)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Lag *T*: 90–99 °F	0.001	−0.011	0.002**	−0.000	−0.001*	0.001	0.000	0.000	0.001*
	(0.001)	(0.011)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Lag *T*: ≥ 100 °F	0.001	−0.014	0.000	−0.000	−0.001*	0.001	−0.000	−0.001*	−0.000
	(0.001)	(0.013)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Lag *P*: 1–4 mm	−0.000	0.001	0.000	0.000	−0.000	0.001	0.000	−0.000	0.001*
	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag *P*: 5–14 mm	0.000	−−0.010	0.000	0.001	0.001**	0.002	0.001	0.001	0.001*
	(0.001)	(0.007)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Lag *P*: 15–29 mm	0.003*	−0.024	0.001	0.002*	0.001**	0.001	0.000	0.000	0.003***
	(0.001)	(0.016)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Lag *P*: ≥ 30 mm	0.004	0.011	0.003*	0.001	0.001	0.002	0.002*	0.001	0.003*
	(0.003)	(0.020)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	474,180	25,920	683,184	847,632	843,780	665,532	883,044	884,472	854,316
Clusters	30	30	30	30	30	30	30	30	30

Note: Each column shows coefficients and standard errors from a fixed-effects Poisson regression of the monthly number of crimes per county on a semi-parametric set of weather bin variables. Each observation included in the regressions represents a unique county-by-year-by-month. The dependent variable in all regressions is the monthly number of crimes, which is modeled as an exponential function of a set of weather variables. The weather variables represent 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 state-by-month fixed effects. The county-by-year fixed effects are removed by conditioning on a sufficient statistic. State-by-month fixed effects are included as dummy variables. All regressions are clustered by year, with standard errors calculated by bootstrapping.

* denotes $p < .05$;

** denotes $p < .01$;

*** denotes $p < .001$.

crime rates for these three offenses would be approximately 4–6% higher than crime rates in a spring month with 10 unusually cold days (in the 30–39 °F bin).

Fig. 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 50 °F, increases in temperature have a strong positive effect on the number of burglaries and larcenies reported. However, at or above 50 °F, increases in temperature have little effect on these crimes. The degree of nonlinearity varies by offense, with violent crimes tending to have a more linear relationship through the entire range of temperatures.

Table 2 presents complete regression results from estimating Eq. (2), including the results for the precipitation bin variables. The table shows that precipitation does not have a statistically significant effect on most types of crimes. The only exceptions are burglary and vehicle theft, both of which appear to increase somewhat in months with many rainy or snowy days.

Table 2 also presents coefficients and standard errors 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 et al. (2007), who found 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.

One natural concern about these results is that the extensive set of state-by-month fixed effects may absorb too much of the relevant variation in the weather variables (Fisher et al., 2012). To address this concern, the Appendix presents alternative specifications based on climate zone-by-month fixed effects and month fixed effects (both sets of regressions still include county-by-year fixed effects). The results are similar to the main results, suggesting that the state-by-month fixed effects leave sufficient variation for identification of the coefficients on the main weather variables. Intuitively, this makes sense: monthly weather in a particular location can be quite unpredictable, even after controlling for typical monthly conditions in that location and for average conditions in that year.

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 Eq. (2) with data on simulated US 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 CO_2 levels at 720 ppm (IPCC, 2000, 2007). Because recent work has shown that analyses of the economic effects of climate change can be sensitive to the choice of climate model (Burke et al., 2011), I use predictions from 15 different general circulation models.[9] These predictions are available from an archive maintained by the World Climate Research Programme's Coupled Model Intercomparison Project Phase 3 (CMIP3), and have an interpolated resolution of two degrees of latitude by two degrees of longitude (WCRP, 2007; Maurer et al., 2007).

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 each model projection 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 decade, relative to 2000–2009. I then assign each US county a predicted change in temperature and precipitation for each future decade and month, based on the changes predicted at the closest grid point.

Next, I use each model's predicted changes to generate a simulated distribution of days across temperature and precipitation bins for each of the 9 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 subsequent decade, I then add the predicted absolute change in monthly temperature to each daily temperature observation in the 2000–2009 data, 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 each of the 15 climate model predictions.

Finally, to predict how the projected change in weather will affect crime rates in each county, month, and decade, I combine the climate projections with the regression coefficients estimated in the previous section. For each climate model, I calculate the

[9] The models are: BCCR-BCM2.0 (Bjerknes Centre for Climate Research), CGCM3.1 (Canadian Centre for Climate Modeling and Analysis), CNRM-CM3 (Meteo-France, Centre National de Recherches Meteorologiques, France), CSIRO-Mk3.0 (CSIRO Atmospheric Research, Australia), GFDL-CM2.0 (NOAA, Geophysical Fluid Dynamics Laboratory, USA), GISS-ER (NASA, Goddard Institute for Space Studies, USA), INM-CM3.0 (Institute for Numerical Mathematics, Russia), IPSL-CM4 (Institut Pierre Simon Laplace, France), MIROC3.2 (Center for Climate System Research, The University of Tokyo, National Institute for Environmental Studies, and Frontier Research Center for Global Change, Japan), ECHO-G (Meteorological Institute of the University of Bonn, Germany, and Meteorological Research Institute of KMA, Korea), ECHAM5/MPI-OM (Max Planck Institute for Meteorology, Germany), MRI-CGCM2.3.2 (Meteorological Research Institute, Japan), CCSM3 (National Center for Atmospheric Research, USA), PCM (National Center for Atmospheric Research, USA), and UKMO-HadCM3 (Hadley Centre for Climate Prediction and Research, Met Office, UK).

decade-long change ΔC_{idm} in the number of crimes in county i, decade d, and month m using the following formula:

$$\Delta C_{idm} \equiv \hat{C}^{p}_{idm} - \hat{C}^{b}_{idm} \tag{3}$$

where $\hat{C}^{p}_{idm}$ is the predicted number of crimes if climate change occurs, and $\hat{C}^{b}_{idm}$ is the baseline number of crimes if climate change does not occur. I estimate $\hat{C}^{p}_{idm}$ as

$$\hat{C}^{p}_{idm} = 10\exp\left(\sum_{j=1}^{11} \alpha_0^j \, \overline{T}^j_{i,d,m} + \sum_{k=1}^{5} \beta_0^k \, \overline{P}^k_{i,d,m} + \sum_{j=1}^{11} \alpha_1^j \, \overline{T}^j_{i,d,m-1} + \sum_{k=1}^{5} \beta_1^k \, \overline{P}^k_{i,d,m-1} + \phi_{sm} + \theta_{iy} \right) \tag{4}$$

and $\hat{C}^{b}_{idm}$ as

$$\hat{C}^{b}_{idm} = 10\exp\left(\sum_{j=1}^{11} \alpha_0^j \, \overline{P}^j_{i,2000,m} + \sum_{k=1}^{5} \beta_0^k \, \overline{P}^k_{i,2000,m} + \sum_{j=1}^{11} \alpha_1^j \, \overline{T}^j_{i,2000,m-1} + \sum_{k=1}^{5} \beta_1^k \, \overline{P}^k_{i,2000,m-1} + \phi_{sm} + \theta_{iy} \right) \tag{5}$$

where $\overline{T}^j_{i,d,m}$ refers to the mean number of days per month in which the simulated temperature in month m in county c in decade d falls into temperature bin j. The predicted precipitation variable $\overline{P}^k_{i,d,m}$ is defined similarly. The variables $\overline{T}^j_{i,2000,m}$ and $\overline{P}^k_{i,2000,m}$ 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 each equation by 10 to account for the number of years in each decade.[10] Following Burke et al. (2011), I generate point estimates and confidence intervals by bootstrapping the predicted impacts across different models and coefficient draws.

Before discussing the results of this analysis, I describe the changes in weather predicted by the suite of 15 climate models. Fig. 5 shows the distribution of temperature and precipitation across bins for two scenarios: the actual weather patterns observed between 2000 and 2009, and the weather patterns predicted for 2090–2099 by the mean of the 15-climate model ensemble. 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 climate 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), and a decrease in the number of days in all other bins. In contrast, the figure shows that the models predict little change in aggregate precipitation.

Table 3 presents the predicted impacts of climate change on crime in the United States. 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 climate change will cause a very large number of crimes during the next century. Between 2010 and 2099, there will be an additional 22,000 murders, 180,000 cases of rape, 1.2 million aggravated assaults, 2.3 million simple assaults, 260,000 robberies, 1.3 million burglaries, 2.2 million cases of larceny, and 580,000 cases of vehicle theft, as a result of climate change. Almost all of these changes are significant at a 5% threshold. The only category of crime that is not expected to increase is manslaughter, for which a 95% confidence interval ranges from a decrease of 6000 cases to an increase of 12,000 cases. 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 2.2% increase in murder, an insignificant 6.6% increase in manslaughter, a 3.1% increase in cases of rape, a 2.3% increase in aggravated assault, a 1.2% increase in simple assault, a 1.0% increase in robbery, a 0.9% increase in burglary, a 0.5% increase in cases of larceny, and a 0.8% 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 characterize the potential range of social costs using the following per-offense costs: $5 million for murder and manslaughter; $237,000 for rape; $70,000 for aggravated assault; $17,500 for simple assault; $21,000 for robbery; $25,000 for burglary, $3500 for larceny; and $11,000 for motor vehicle theft. These valuations are drawn from Cohen et al. (2004), McCollister et al. (2010) and Viscusi and Aldy (2003).[11] Given the considerably uncertainty about how to value criminal offenses, I emphasize that the calculations presented here are intended to provide only a "back-of-the-envelope" estimate of the rough magnitude of the social costs of future climate-related crime.

Based on these per-offense valuations, 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 climate-related crime are between $38 billion and $115 billion (based on a 3% discount rate). Most of these costs are driven by increases in violent crimes, particularly murder and aggravated assault. Consistent with previous research (Weitzman, 2007), the costs are sensitive to the choice of a discount rate, with point estimates of $78 billion based on a 3% discount rate and $29 billion based on a 6% discount rate.

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, Fig. 6 presents—for each US county—the per capita present

[10] I avoid estimating county-by-year fixed effects in my main regressions by conditioning them out using a sufficient statistic. To recover them for the purposes of prediction, I follow Guimaraes and Portugal (2009), relying on the fact that the Poisson model is one of the few nonlinear models that does not suffer from an incidental parameters problem.

[11] Neither Cohen et al. (2004) nor McCollister et al. (2010) report estimates of the social cost of simple assault. For the purposes of this analysis, I value each case of simple assault at 25% of the cost of a case of aggravated assault from Cohen et al. (2004).

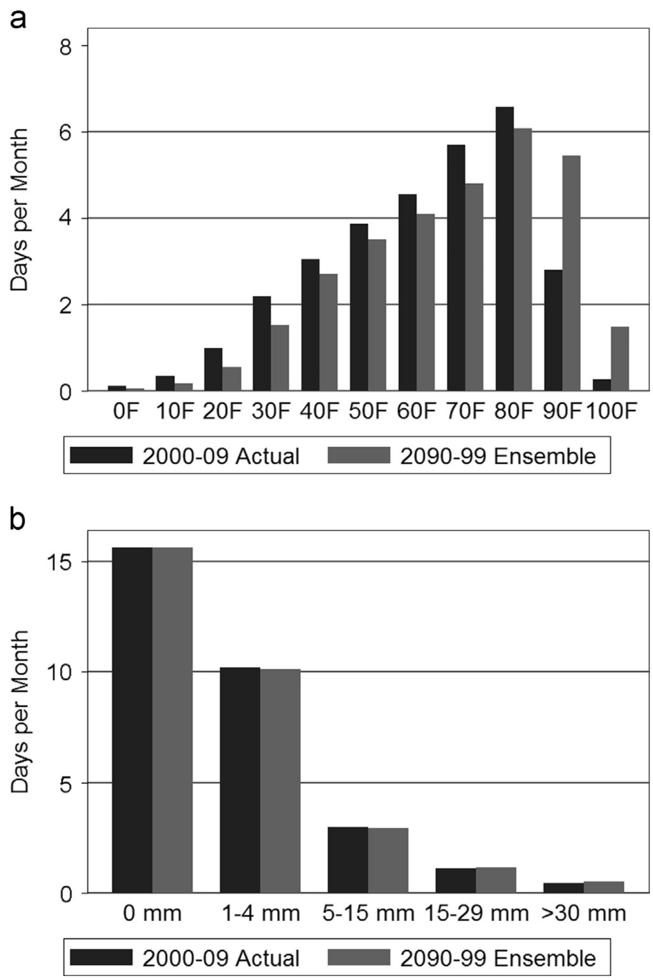

Fig. 5. Distribution of daily weather, by scenario: (a) maximum daily temperature (°F) and (b) daily precipitation (mm). *Note*: Each panel shows the number of days per month that fall into the specified weather bin. The "2000–09 Actual" category represents the average actual number of days per month in each weather bin for the period 2000–2009. The "2090–99 Ensemble" category represents the average predicted number of days per month in each weather bin for the period 2090–2099, averaged across the ensemble of 15 climate models.

Table 3
The predicted impact of climate change on crime.

	Number of additional crimes		Social costs, by discount rate			
			3%		6%	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
Murder	21,977	(12,349 – 33,368)	25.4	(13.7–38.7)	9.5	(4.8–14.8)
Manslaughter	2443	(−5938 to 11,911)	3.1	(−8.2 to 16.3)	1.3	(−3.8 to 7.2)
Rape	178,630	(102,472–263,451)	9.5	(4.8 – 14.4)	3.5	(1.3 – 5.6)
Aggr assault	1,220,537	(691,375–1,776,363)	19.2	(9.0 – 29.3)	6.9	(2.1 – 11.4)
Simple assault	2,276,755	(1,187,944–3,523,298)	9.0	(3.9 – 14.3)	3.2	(0.8 – 5.5)
Robbery	258,005	(3766–547,000)	1.2	(0.0–2.7)	0.5	(0.0–1.0)
Burglary	1,279,686	(502,866–2,113,597)	7.3	(0.8–13.2)	2.6	(−0.9 to 5.4)
Larceny	2,184,289	(400,215–4,348,172)	1.7	(−0.4 to 3.9)	0.6	(−0.6 to 1.6)
Vehicle theft	583,581	(258,021–948,395)	1.5	(0.6–2.5)	0.6	(0.2–1.0)
Total	8,005,904	(3,698,137–12,462,293)	78.1	(37.9–115.1)	28.7	(10.7–44.9)

Note: The "number of additional crimes" columns represent the total number of additional crimes that will occur due to climate change between 2010 and 2099, relative to the number that would occur if temperatures and precipitation stayed at the 2000–2009 averages. The "social cost" columns display the present value of the social cost of the additional crimes that will occur due to climate change, in billions of dollars. Future costs are discounted using two alternative discount rates: 3% and 6%. Numbers in parentheses are 95% confidence intervals calculated via bootstrapping.

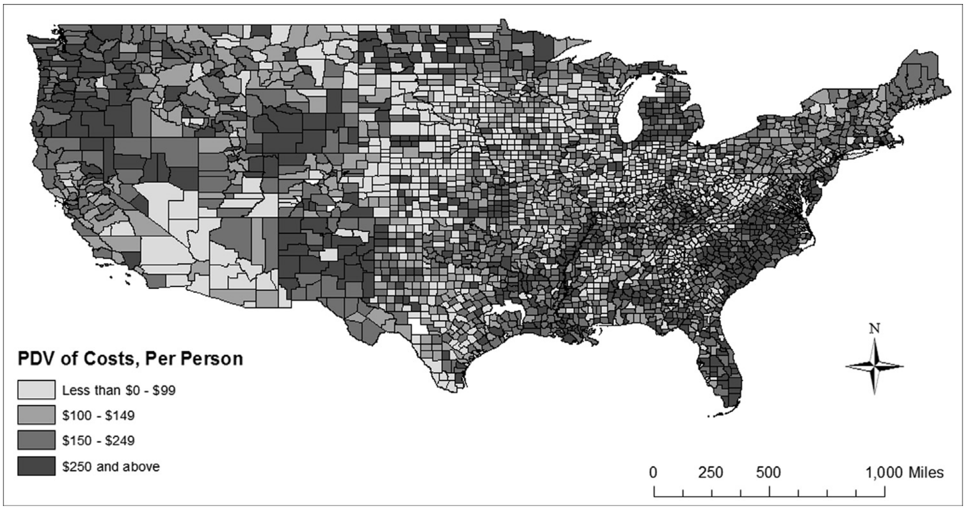

Fig. 6. Present discounted social cost of climate-related crime, per person. *Note*: The map shows the per capita present discounted value of the social costs of the additional crimes estimated to be caused by climate change between 2010 and 2099. Costs are presented per person, for each county, based on a 3% discount rate.

discounted value of the total social costs of future climate-related crime in that 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 figure shows that the per capita cost of climate-related crime is generally highest in the Northwest, Mid-Atlantic, and Mississippi River Basin, where costs are greater than $250/person, and lowest in the Midwest and Southwest, where costs are less than $100/person. However, there is considerable heterogeneity across counties, with highest future costs of climate-related crime in counties that currently experience high crime rates.

Discussion

The previous section highlights two main results. First, weather has a strong causal effect on the incidence of criminal activity. Across all categories of offenses, higher temperatures lead to higher crime rates. The functional form of the relationship varies by offense, with some categories, particularly property crimes, showing largest marginal effects below 50 °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.

Interpreting these coefficient patterns in light of existing hypotheses about weather and crime is challenging. The results for property crimes generally support the Becker hypothesis, in the sense that the obstacles created by cold weather (e.g., closed windows, snow) could easily explain why burglary and larceny are only sensitive to low temperatures.[12] However, for violent crimes, the Becker hypothesis seems less relevant, given that it is more difficult to provide plausible reasons why warmer temperatures would improve the odds of successfully committing murder or assault. Instead, the linear effect of temperatures on violent crime is more consistent with the hypothesis that warmer temperatures increase the frequency of social interactions, some small percentage of which result in violence. It is also consistent with the direct aggression hypothesis (e.g., Kenrick and MacFarlane, 1986; Vrij et al., 1994), although most violent crimes do level off at the highest temperatures (the only exception being rape). Overall, I conclude that the observed patterns of coefficients are unlikely to be attributable to a single causal mechanism.

The second major result from this paper is that 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 22,000 murders, 180,000 cases of rape, 1.2 million aggravated assaults, 2.3 million simple assaults, 260,000 robberies, 1.3 million burglaries, 2.2 million cases of larceny, and 580,000 cases of vehicle theft. The present discounted value of the social costs of these climate-related crimes is between 38 and 115 billion dollars.

It is important to note 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, it is likely that law enforcement agencies will respond with increased policing activity. Furthermore, people in affected areas will have the opportunity to modify their

[12] I speculate that the suggestive uptick in auto thefts that occurs at very cold temperatures could be caused by the common practice in cold climates of letting cars "warm up" by leaving them unattended with the engine running.

behavior to avoid being victimized. 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.

To characterize at least part of the scope for longer-term adaptation to climate-related crime, I conduct a simple analysis of the most obvious adaptation mechanism: increasing law enforcement. In particular, I estimate how large of a change in the police force would be required to offset the predicted changes in climate-related crime. Recent research suggests that the elasticity of crime with respect to the size of the local police force is roughly −0.67 for murder and manslaughter, −0.26 for rape, −0.10 for assault, −0.56 for robbery, −0.23 for burglary, −0.08 for larceny, and −0.34 for vehicle theft (Chalfin and McCrary, 2012). In other words, for example, a 1% increase in the size of the police force causes a 0.67% decrease in the number of murders committed. I use these point estimates to calculate the percentage by which the US police force would have to increase in order to offset the additional climate-related crime that is likely to occur between 2010 and 2099.

The results suggest that the required increases in the size of the police force to offset different types of climate-related crime are: 3.4% (murder), 12% (rape), 24% (aggravated assault), 12% (simple assault), 1.8% (robbery), 4.2% (burglary), 6.1% (larceny), and 2.4% (vehicle theft). These admittedly rough numbers suggest that adapting to increased crime rates by ramping up law enforcement would require a substantial public investment in police resources. Furthermore, since these numbers reflect a simple policy of immediately and permanently increasing the US police force, they understate (by roughly a factor of two) the actual increase in police presence that a ramping-up policy would require by the year 2099.

Of course, in interpreting the results from this paper, 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 et al., 2011), and that a comprehensive cost–benefit analysis of climate change should consider all dimensions of costs and benefits. For example, given US residents' high willingness to pay to live in areas with moderate climates (Cragg and Kahn, 1997), 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.

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 under-estimate climate's effects on future crime.

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 US 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.

Appendix

This appendix presents supporting material relevant to the main analysis. In Section A.1, I discuss issues related to construction of the combined crime and weather dataset. Then, in Section A.2, I present a variety of sensitivity analyses

Table A1
Uniform crime reporting offense definitions.
Source: FBI (2004).

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

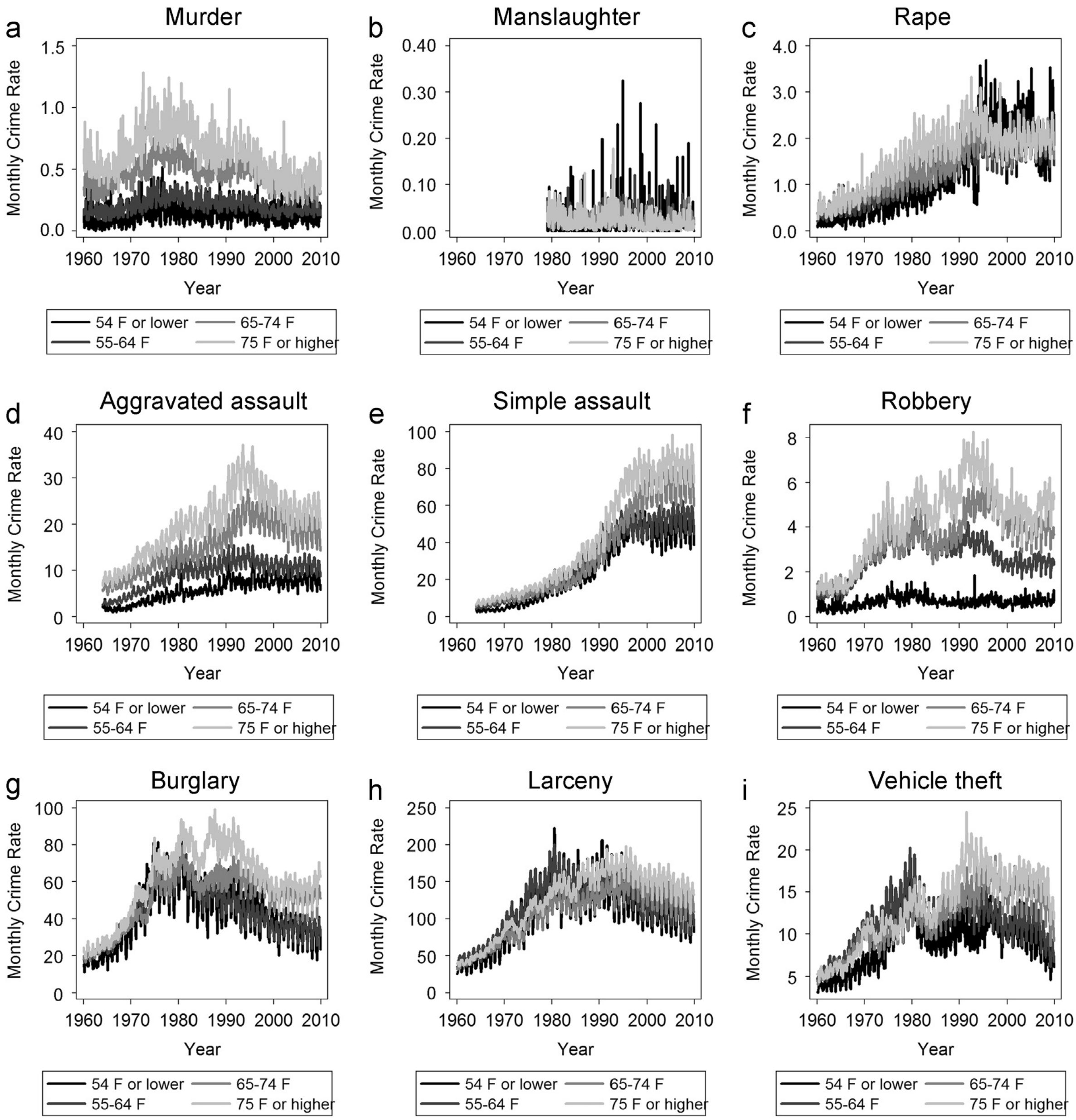

Fig. A1. Crime rate trends, by climate zone: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each panel shows the mean crime rate across counties within each climate zone, by year and month. The crime rate variables represent the monthly number of crimes per 100,000 persons.

designed to explore the robustness of the main regression results. Finally, in Section A.3, I discuss the challenges of evaluating the potential for long-term adaptation.

A.1. Data notes

A.1.1. Reporting issues in the UCR crime data

The first main component of my dataset is monthly crime data taken from the US FBI's Uniform Crime Reporting (UCR) database (FBI, 2011a). Table A1 summarizes the definitions of the nine major categories of criminal offenses contained the UCR data (FBI, 2004).

As discussed in the main part of the paper, the UCR data suffer from important quality issues related to the consistency of crime reporting over time. To illustrate these problems, Fig. A1 presents the time trend in crime rates for the nine offense categories, by climate zone, over the period from 1960 to 2009. 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 this increase, it seems likely that it is driven by increased reporting of crimes, rather than by changes in underlying criminal behavior. Second, long-term trends across climate zones appear broadly similar, although there is some heterogeneity in absolute levels. Finally, there is a strong evidence of high frequency variation in crime rates due to seasonality.

As discussed in "Methodology" section, these features of the UCR data are what motivate my empirical focus on monthly variation within county-by-year groups of observations (for which set of contributing law enforcement agencies are identical). The data quality issues also motivate my decision to limit the analysis to the period from 1980 to 2009. By dropping observations from the 1960s and 1970s, I strike a balance between eliminating data with known quality issues and still including a sufficiently long time series for robust inference. Additionally, by focusing on the more recent 1980–2009 time period, my regressions are likely to have greater external validity for predicting future impacts over the next century.

A.1.2. Constructing county-level weather data

The second main component of my dataset is daily weather data for each US county, constructed from the NCDC's GHCN-Daily dataset (NCDC, 2011). The GHCN-Daily data provide daily weather at a set of approximately 1200 weather stations in the continental United States. The challenge of using these data to develop a consistent county-level daily weather dataset is twofold. First, the spatial locations of the weather stations in the GHCN-Daily data do not have a one-to-one correspondence with the locations of US counties. Second, many weather stations do not report in some time periods.

To address these problems, I construct maximum temperature and precipitation time series for each county based on a weighted average of bias-corrected weather data for weather stations within 50 miles of each county. In these calculations, I use inverse-distance weights that capture the intuition that a station near or within a county is more likely to reflect local county weather. Additionally, in order to avoid bias from the changing composition of reporting stations over time, I use a bias correction procedure to adjust the absolute value of the temperature signal from each weather station before I calculate the county-level averages.

The following paragraphs describe three main steps of the weather construction process in more detail:

Step 1: Generating weather station weights for each county

The GHCN-Daily dataset includes data from approximately 1200 weather stations in the continental United States. To generate station weights for each county, I begin by identifying all weather stations within 50 miles of the county. These are the stations that I use to construct the temperature time series for the county. I then calculate station weights that assign the highest priority to weather stations that are centrally located with each county.

To generate these weights, I first create a set of grid points tiled across the entire United States, spaced approximately 5 miles apart. I then calculate the inverse of the distance (i.e., $1/distance$) from each weather station to each grid point within the county. Finally, for each weather station, I calculate the average of the inverse distances (averaging across grid points within the county). The resulting weight can be envisioned as the "area-weighted" inverse distance from the station to the county. This procedure is particularly useful for counties that are irregularly shaped, for which the county centroid would not be a good reference point.

Step 2: Estimating bias-corrected temperature time series at each station

Because long-term average temperatures vary across weather stations, using a simple weighted average to calculate daily temperature in each county would create inconsistencies for time periods in which some stations have missing weather data. Fig. A2 shows an example of this problem based on data from two weather stations in San Bernardino County, California. The figure shows that Station 26250 consistently reports temperatures that are 5–10° higher than Station 42941. If the county

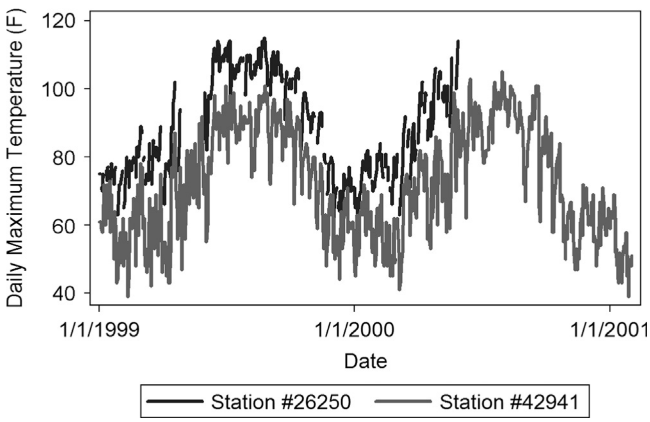

Fig. A2. Illustration of temperature data from two weather stations. *Note*: The figure shows examples of maximum daily temperature data from two weather stations located in San Bernardino County, California. The GHCN-Daily station IDs are USC00042941 and USC00026250.

temperature for each time period were calculated based on the average of all stations that reported in that time period, then in time periods when Station 26250 (the high-temperature station) did not report any data, the county average would skip down artificially, reflecting the changing composition of the set of reporting stations that period.

To avoid these kind of reporting-based artifacts, I generate bias-corrected temperature time series at each weather station, for each county. Overall, the bias correction procedure has two parts.

Part A: Calculate station intercepts to minimize absolute differences between stations

First, I calculate individual weather station intercepts that eliminate—as much as possible—the differences in the temperature times series between weather stations. In the context of Fig. A2, this would involve adding a constant to the temperature time series at Station 42941 so that the absolute values of the temperatures at Station 42941 are as similar as possible to the temperatures at Station 26250. (Equivalently, it could involve subtracting a constant from the time series at Station 26250, or adding constants at both stations. The only requirement for this part of the procedure is that the combination of constants must minimize the sum of absolute deviations between the two stations.)

More generally, in a county with S stations, I use an iterative process to compute a station-specific intercept term μ_s that I add to the temperatures T_{st} for each station s in all time periods t (where t refers to calendar time). For convenience, I initialize the intercepts all to zero prior to round one of the procedure (so that $\mu_{sr}=0, \ \forall\, r=0, \ \ s \in S$). The iterative process for each round r then proceeds as follows:

I calculate an adjusted temperature $T_{st}+\mu_{s,r-1}$ for each station and time period (based on the intercept terms from the previous round). I then randomly select one station i within the county to be the reference station. For each remaining station j, I calculate the difference between average adjusted temperatures at that station and the reference station, for all time periods for which both report. I use this difference to estimate the new value of the intercept term for each station:

$$\mu_{jr}=\mu_{j,r-1}+\frac{1}{n_{ij}}\sum_{t \in \kappa_{ij}}[(T_{it}+\mu_{i,r-1})-(T_{jt}+\mu_{j,r-1})] \tag{A1}$$

where n_{ij} represents the number of periods in which stations i and j both report, and κ_{ij} represents the set of time periods in which both stations report.

I repeat this procedure until each intercept term converges.

Part B: Adjust all intercepts to reflect typical county weather conditions

When the final intercept terms are added to the temperatures for each station, the resulting adjusted temperatures overlap (in the sense of minimized least absolute deviations) across all stations. However, because I choose the reference stations at random in each round of the iterative procedure, the adjusted temperature series based on these

Table A2
Distribution of crime by time of day, in NIBRS.

Time of day	Murder	Mansltr	Rape	Aggr assault	Simple assault	Robbery	Burglary	Larceny	Vehicle theft
12 AM	8.9	3.4	13.3	7.3	6.8	7.0	7.5	8.0	7.7
1 AM	5.6	6.0	5.6	5.6	4.6	5.7	2.7	2.2	3.8
2 AM	5.9	3.4	5.4	4.9	3.8	4.9	2.4	1.7	3.0
3 AM	3.5	5.2	4.7	3.1	2.5	3.7	2.0	1.2	2.3
4 AM	2.9	0.9	3.4	2.0	1.5	2.8	1.7	0.8	1.7
5 AM	2.7	2.6	2.2	1.2	1.0	2.0	1.7	0.8	1.8
6 AM	1.4	1.7	1.7	1.1	1.0	1.7	2.8	1.4	2.6
7 AM	2.3	2.6	1.9	1.5	1.8	1.4	4.8	2.7	3.6
8 AM	3.2	6.0	3.0	1.8	2.3	1.5	5.8	4.5	4.2
9 AM	2.5	3.4	2.5	2.0	2.3	2.2	4.1	3.7	3.5
10 AM	2.2	5.2	3.1	2.3	2.8	2.5	4.0	4.1	3.4
11 AM	2.9	1.7	3.0	2.8	3.3	2.6	3.5	4.1	3.2
12 PM	3.2	4.3	4.5	3.3	3.8	2.7	5.2	5.9	4.1
1 PM	3.6	1.7	3.1	3.3	3.7	2.9	3.6	4.7	3.1
2 PM	2.9	4.3	3.4	3.8	4.3	3.3	4.0	5.2	3.2
3 PM	3.6	1.7	3.8	4.5	5.3	3.7	4.7	5.9	3.7
4 PM	4.3	4.3	3.6	5.0	5.2	3.8	5.2	6.2	4.0
5 PM	3.4	3.4	3.5	5.2	5.6	3.8	6.7	6.7	5.2
6 PM	3.5	4.3	3.6	5.9	6.0	4.8	6.4	6.4	5.9
7 PM	3.7	5.2	3.9	6.2	6.3	5.8	4.4	5.3	5.0
8 PM	5.4	6.0	4.4	6.6	6.6	7.0	4.3	5.2	5.6
9 PM	8.5	5.2	4.7	7.0	6.8	7.9	4.3	4.7	6.1
10 PM	5.6	6.9	5.3	6.9	6.6	8.2	4.3	4.6	6.9
11 PM	8.2	10.3	6.3	6.7	6.0	8.0	3.9	4.1	6.5
8 AM–8 PM	39.0	45.7	41.0	46.1	51.0	39.7	57.6	62.6	48.5
8 PM–8 AM	61.0	54.3	59.0	53.9	49.0	60.3	42.4	37.4	51.5

Note: The table presents the percentage of reported incidents from the National Incident-Based Reporting System (NIBRS) that occurred at each time of day, by type of offense. The data on which the table is based include all incidents in the year 2000 for which a time of day was reported.

intercepts will be consistently higher or lower than actual county temperatures. Thus, the second step in my bias-correction procedure is to subtract a constant county-wide intercept term from all of the temperature time series. The goal of this adjustment is for the absolute temperature at each station to reflect the typical weather conditions at the stations that are most representative of the county. Thus, I choose a county-wide constant equal to the weighted average of all of the individual station intercept terms. The weights are based on the inverse distances calculated above. After subtracting this constant from all of the adjusted temperatures, the result is a set of “bias-corrected” temperature time series that overlap (in the sense of minimized least-absolute-deviations) and that represent typical conditions in each county.

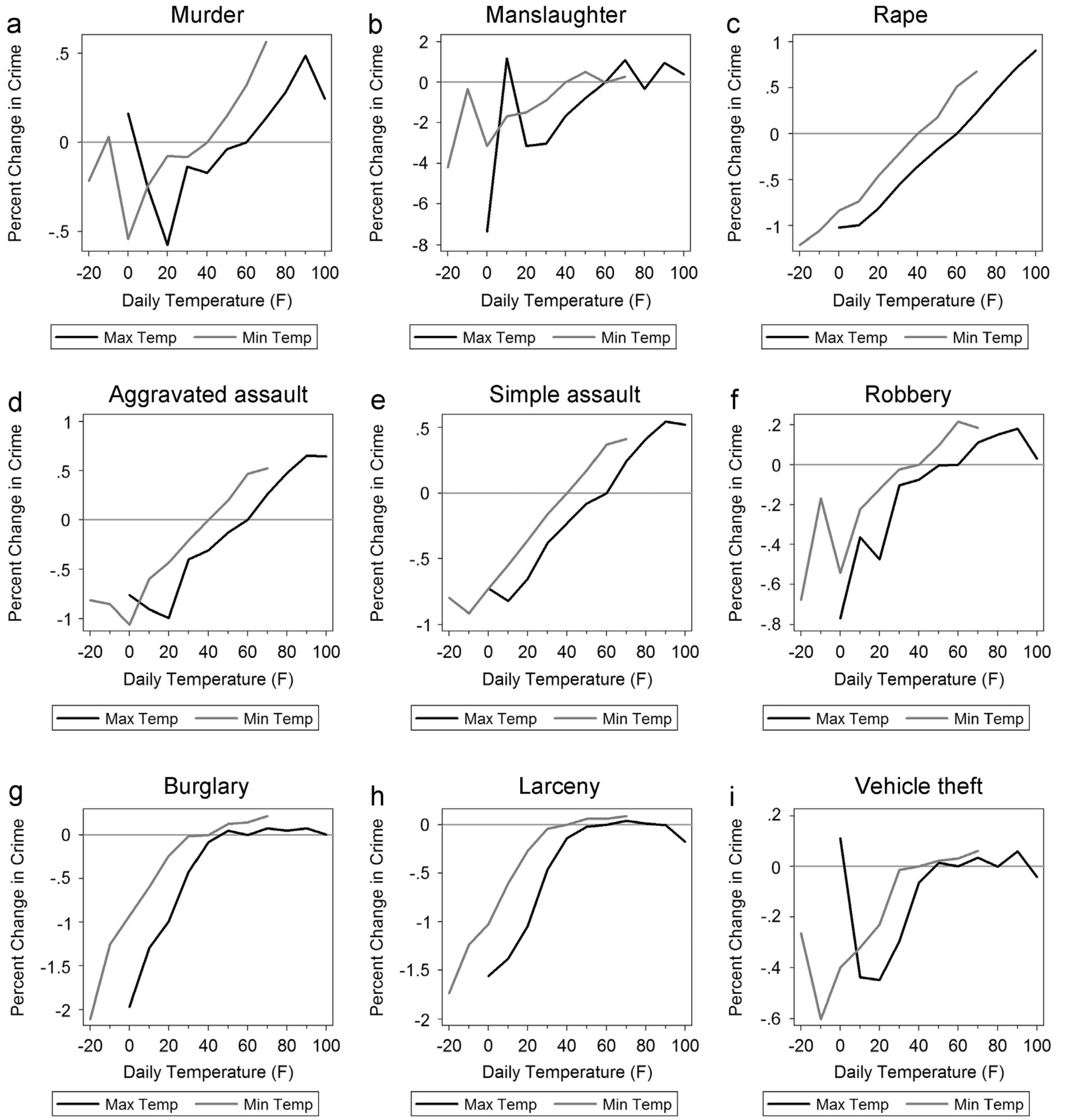

Fig. A3. Monthly crime and minimum daily temperature: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows coefficients from Poisson regressions of the number of crimes in each county, month, and year, on a semi-parametric set of weather bin variables representing minimum daily temperature and daily precipitation. All regressions include state-by-month and county-by-year fixed effects. All coefficients in the minimum temperature regressions are relative to 1 day in the 40–50 °F bin. For comparison, the figure also shows the coefficients from the main regressions based on maximum temperature, for which the coefficients are relative to 1 day in the 60–70 °F bin.

Step 3: Calculating weighted average weather for each county

The final step in constructing the weather series is to calculate the weighted average of the bias-corrected daily weather for each county. This procedure is straightforward. I simply use the inverse distance weights from Step 1 and the bias-corrected weather series from Step 2 to calculate weighted average weather conditions. The averages are taken across all weather stations that report on a particular day.

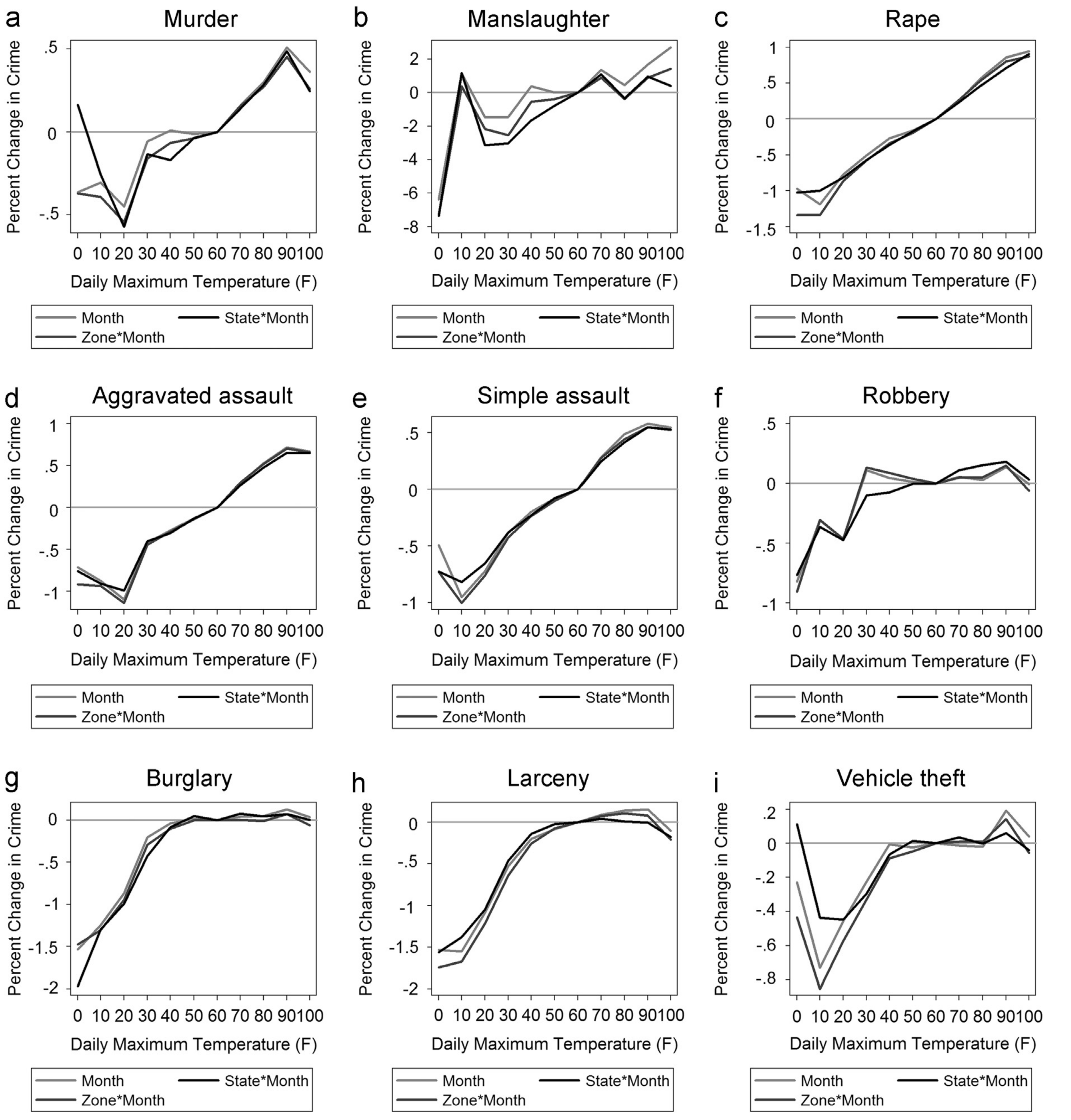

Fig. A4. Monthly crime and daily temperature, with relaxed fixed effects: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows coefficients from Poisson regressions of the number of crimes per county, month, and year, on a semi-parametric set of weather bin variables representing maximum daily temperature and daily precipitation. All regressions include county-by-year fixed effects and either state-by-month (the main specification), climate zone-by-month, or month fixed effects. 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: $<55\,^{\circ}$F, 55–64 °F, 65–74 °F, and $\geq 75\,^{\circ}$F. All coefficients are relative to 1 day in the 60–70 °F bin.

Table A3
Weather variation remaining after fixed effects.

	R-squared			Standard deviation of residuals			Fraction of residuals greater than 1 day		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Max temp: < 10 F	0.000	0.427	0.491	0.989	0.749	0.706	0.028	0.043	0.048
Max temp: 10–19 °F	0.000	0.525	0.580	1.374	0.947	0.890	0.071	0.096	0.102
Max temp: 20–29 °F	0.000	0.654	0.700	2.642	1.554	1.447	0.163	0.177	0.223
Max temp: 30–39 °F	0.000	0.724	0.761	4.246	2.230	2.077	0.934	0.298	0.380
Max temp: 40–49 °F	0.000	0.682	0.720	4.516	2.547	2.388	0.918	0.403	0.486
Max temp: 50–59 °F	0.000	0.670	0.709	4.732	2.718	2.552	0.902	0.494	0.554
Max temp: 60–69 °F	0.000	0.644	0.679	4.934	2.943	2.797	0.900	0.575	0.615
Max temp: 70–79 °F	0.000	0.640	0.672	5.857	3.516	3.353	0.916	0.619	0.672
Max temp: 80–89 °F	0.000	0.751	0.784	7.655	3.817	3.561	0.952	0.516	0.661
Max temp: 90–99 °F	0.000	0.709	0.765	5.913	3.187	2.867	0.945	0.321	0.539
Max temp: ≥ 100 °F	0.000	0.291	0.435	1.556	1.310	1.169	0.034	0.059	0.084
Precip: 0 mm	0.000	0.448	0.602	5.895	4.382	3.719	0.872	0.822	0.788
Precip: 1–4 mm	0.000	0.389	0.569	4.713	3.684	3.095	0.835	0.787	0.744
Precip: 5–14 mm	0.000	0.273	0.385	2.243	1.913	1.759	0.691	0.579	0.551
Precip: 15–29 mm	0.000	0.183	0.277	1.265	1.143	1.075	0.548	0.338	0.313
Precip: ≥ 30 mm	0.000	0.144	0.248	0.767	0.710	0.666	0.087	0.095	0.096
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-month FE		Yes	Yes		Yes	Yes		Yes	Yes
County-by-year FE			Yes			Yes			Yes

Note: Columns (1), (2), and (3) show the R^2 from an OLS regression of each weather bin variable on a constant (intercept) and selected fixed effects. Columns (4), (5), and (6) show the standard deviations of the residuals from those same regressions. The residuals are expressed in units of days per month. Columns (7), (8), and (9) show the proportion of the residuals that are greater than 1 day per month in absolute value. Note that for all columns, due to the large number of fixed effects, I avoid running explicit regressions and instead use demeaning to calculate residuals and then use the residuals to generate the R^2 statistics.

A.2. *Sensitivity analyses of the regression results*

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

A.2.1. *Minimum versus maximum temperature*

Anecdotal evidence that suggests that crimes are more likely to occur at night. Thus, it is reasonable to ask whether crime should be modeled as a function of maximum or minimum daily temperature.

To investigate this issue, I have tabulated time-of-day crime statistics from the National Incident Based-Reporting System (NIBRS) (FBI, 2013). Table A2 shows the results of this analysis, for all crimes reported in the year 2000 in the NIBRS data. The table shows that murder, manslaughter, rape, aggravated assault, and robbery are more likely to occur at night; burglary and larceny are more likely to occur during the day; and simple assault and vehicle theft are equally likely to occur at night or during the day. However, the table also shows that in each category of offense, crimes occur at all times of day. For example, the period between 8 am and 8 pm accounts for 39% of murders, 46% of manslaughter cases, 41% of rapes, 46% of aggravated assaults, and 40% of robberies.

Because the table suggests that some categories of crime are more likely to occur at night, I have run alternative regressions based on minimum daily temperatures, using the same Poisson fixed effects approach as the main regressions. Fig. A3 presents the results of this analysis. For each offense, the figure plots the coefficients on the minimum temperature bin variables. For comparison, the figure also shows the coefficients from the main regressions based on maximum temperature. Because minimum temperatures span a smaller range than maximum temperatures, I model minimum temperature using only 10 bins (compared to 11 bins for maximum temperature), with 40–49 °F as the omitted category (compared to the omitted category of 60–69 °F for maximum temperature). Since the average difference between maximum and minimum temperatures is 23°, the choice of 40–49 °F as the omitted minimum temperature bin provides a convenient visual way to contrast the minimum temperature coefficients against the maximum temperature coefficients.

Overall, Fig. A3 shows that the effects of minimum temperature and maximum temperature are remarkably similar. For every offense, the coefficients on maximum and minimum temperature show almost identical patterns, except for some very low or very high temperatures (for which the coefficients are imprecisely estimated). Based on these results, I conclude that maximum and minimum daily temperature operate on crime through similar mechanisms, and that using minimum temperature as the main independent variable would not materially change the results of my analysis.

A.2.2. *Less stringent fixed effects*

A second natural concern about the analysis is that the extensive set of state-by-month and county-by-year fixed effects may absorb too much of the relevant variation in the weather variables (Fisher et al., 2012). I address this concern in two ways.

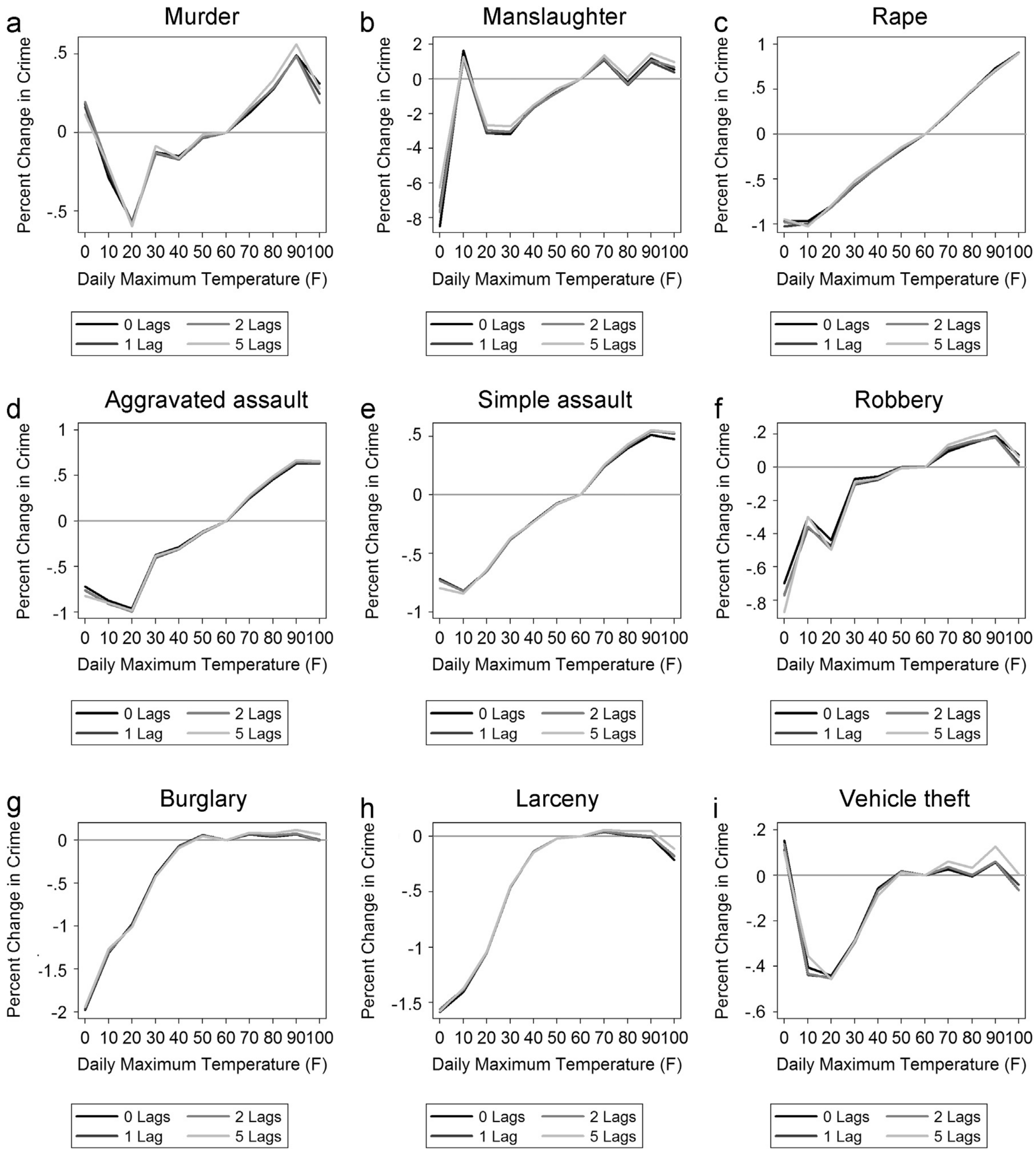

Fig. A5. Crime and daily temperature, by month lag: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows contemporaneous coefficients from Poisson regressions of the number of crimes per county, month, and year, on a semi-parametric set of weather bin variables representing maximum daily temperature and daily precipitation. The regressions include either zero, one, two, or five lags of the weather bin variables. All regressions include county-by-year fixed effects and either state-by-month. All coefficients are relative to 1 day in the 60–70 °F bin.

First, I run regressions based on less stringent sets of fixed effects. In these regressions, I drop the state-by-month fixed effects, substituting instead climate zone-by-month fixed effects[13] or month fixed effects.[14] Fig. A4 shows the results of this analysis. Each panel of the figure presents three sets of regression results based on zone-by-month fixed effects, month fixed effects, and state-by-month fixed effects (the main results). The figure shows that across the three different specifications,

[13] Recall that I divide the United States into four climate zones based on average annual maximum daily temperature.

[14] All specifications still include the county-by-year fixed effects, which are necessary to control for changes in the set of agencies that report UCR data each year in each county. However, since weather varies more across months than across years in most locations, the county-by-year fixed effects are less of a concern.

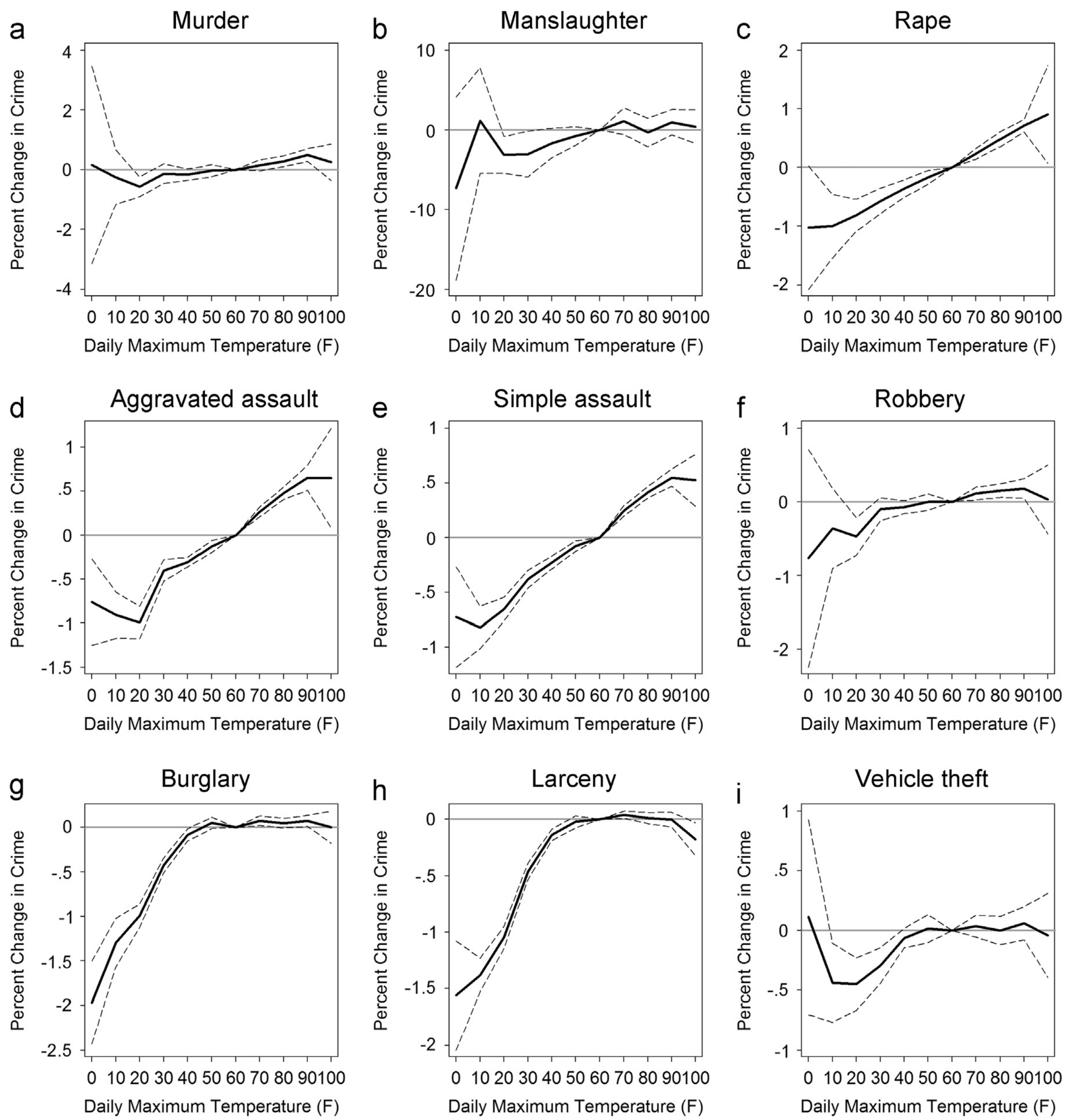

Fig. A6. Crime and daily temperature, with state clusters: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows contemporaneous coefficients from Poisson regressions of the number of crimes per county, month, and year, on a semi-parametric set of weather bin variables representing current and 1-month-lagged maximum daily temperature and daily precipitation. All regressions include county-by-year and state-by-month fixed effects, and are clustered by state. All coefficients are relative to 1 day in the 60–70 °F bin.

the estimated coefficients are extremely similar—which suggests that the use of extensive fixed effects is not likely to be a concern.

As a second way of addressing concerns about the extensive set of fixed effects, I follow Fisher et al. (2012) and estimate the amount of variation remaining in the data after controlling for fixed effects. Table A3 presents these results. The first three columns of the table show the R^2 for OLS regressions of each weather bin variable on (i) an intercept term, (ii) state-by-month fixed effects, and (iii) state-by-month and county-by-year fixed effects.[15] The R^2 values imply that the full set of county-by-year and state-by-month fixed effects account for between 44% and 78% of the variation in temperatures, depending on the specific weather bin. Columns (4–9) show the standard deviations of the residuals from the same sets of

[15] Note that due to the large number of state-by-month and county-by-year combinations, I calculate the R^2 values and residuals in Table A3 using demeaning.

regressions, as well as the fraction of residuals with absolute value greater than 1 day per month. Generally speaking, the results from these columns confirm what is shown in the R^2 columns: there is still a substantial amount of weather variation remaining after removing the fixed effects from the dataset. Intuitively, this makes sense: monthly weather in a particular location can be quite unpredictable, even after controlling for yearly conditions in that county and typical monthly conditions in that state.

A.2.3. Serial correlation

Both crime and weather exhibit autocorrelation. Thus, an additional question about the analytical approach used in this paper is whether 1 month is a sufficiently long time period to account for any lagged impacts of weather on crime. Although the insignificant coefficients on a 1-month lag of weather suggest this is the case, I also conduct sensitivity analyses in which I run regressions using data that include a larger number of lags.

Fig. A5 shows the results from regressions that include zero, one, two, and five lags of temperature. The results demonstrate that the inclusion of additional lags has no effect on the contemporaneous effects of weather. Additionally, although not shown here, the lagged temperature variables are statistically insignificant, suggesting that a 1-month aggregation period is sufficient to account for most “harvesting” that occurs as a result of negative serial correlation in crime rates.

Additionally, as an alternative check on the robustness of the results to serial correlation, I run regressions that are similar to my main specification, except with standard errors clustered by state, not by year. Fig. A6 presents the results from this analysis. The confidence intervals in these regressions are generally similar to the confidence intervals presented in the main body of the paper.

A.2.4. Linear functional form

The semi-parametric regressions presenting the main paper convey useful information about the effects of temperature on crime. However, for comparison with previous literature, I also present results in which I model crime as a linear function of temperature, while still using the Poisson fixed effects model to allow for multiplicative county-by-year and state-by-month fixed effects. Table A4 presents the estimated coefficients from these regressions. The table shows that all of the temperature coefficients are positive and statistically significant, and with the exception of manslaughter, the lagged temperature coefficients are generally small.

A.2.5. Regression results by decade

One last concern about the analysis is that the relationship between weather and crime may have changed over time. To address this concern, Fig. A7 plots the coefficients from separate regressions based on 5 different decades: 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.3. Adaptation

The overall objective of my analysis is to estimate how climate change is likely to affect crime. This section discusses the challenges of developing an econometric approach that could capture the potential for long-term adaptation through increases in policing or defensive expenditures by potential victims.

Table A4
Max daily temperature and monthly crime, linear specification.

	Murder	Mansltr	Rape	Agg asslt	Smp asslt	Robbery	Burglary	Larceny	Veh theft
Temp (°F)	0.003***	0.013*	0.007***	0.006***	0.005***	0.002***	0.003***	0.003***	0.001**
	(0.001)	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag temp	−0.000	−0.012*	0.000	−0.001**	−0.001**	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Precip (mm)	0.000	0.009	0.001	−0.002**	−0.001**	0.002	0.004***	0.001	0.004***
	(0.001)	(0.011)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Lag precip	0.003*	−0.011	0.002*	0.002**	0.001***	0.002	0.002**	0.001**	0.003***
	(0.001)	(0.014)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Obs.	474,176	25,920	683,182	847,627	843,775	665,530	883,039	884,467	854,311
Clusters	30	30	30	30	30	30	30	30	30

Note: Each column shows coefficients and standard errors from a fixed-effects Poisson regression of the monthly number of crimes per county on current and lagged temperature and precipitation. Each observation included in the regressions represents a unique county-by-year-by-month. The dependent variable in all regressions is the monthly number of crimes, which is modeled as an exponential function of a set of weather variables. All regressions control for county-by-year and state-by-month fixed effects. The county-by-year fixed effects are removed by conditioning on a sufficient statistic. State-by-month fixed effects are included as dummy variables. All regressions are clustered by year, with standard errors calculated by bootstrapping.

* denotes $p < .05$;

** denotes $p < .01$;

*** denotes $p < .001$.

A.3.1. Econometric strategies for measuring long-term effects

To illustrate the issues involved, consider a simple abstract model of a police department that must make a decision about policing effort. Suppose that crime $C \equiv C(T,E,X)$ is a function of temperature T, policing effort E, and some other variable X (e.g., geography). The police department will choose a level of effort $E = E^{*}(T_0, X_0)$ that maximizes a social welfare function that depends on the costs of crime, the costs of policing effort, the effectiveness of policing effort at reducing crime, and the initial values of the other variables $T = T_0$ and $X = X_0$.

Now, suppose that climate change causes temperature to increase by 1°, from T_0 to T_1. Given sufficient time to respond, the police department will choose a new level of effort $E = E^{*}(T_1, X_0)$. The goal of this paper is to estimate the resulting long-run change in crime:

$$\Delta C \equiv C(T_1, E^{*}(T_1,\ X_0), X_0) - C(T_0, E^{*}(T_0, X_0), X_0) \tag{A2}$$

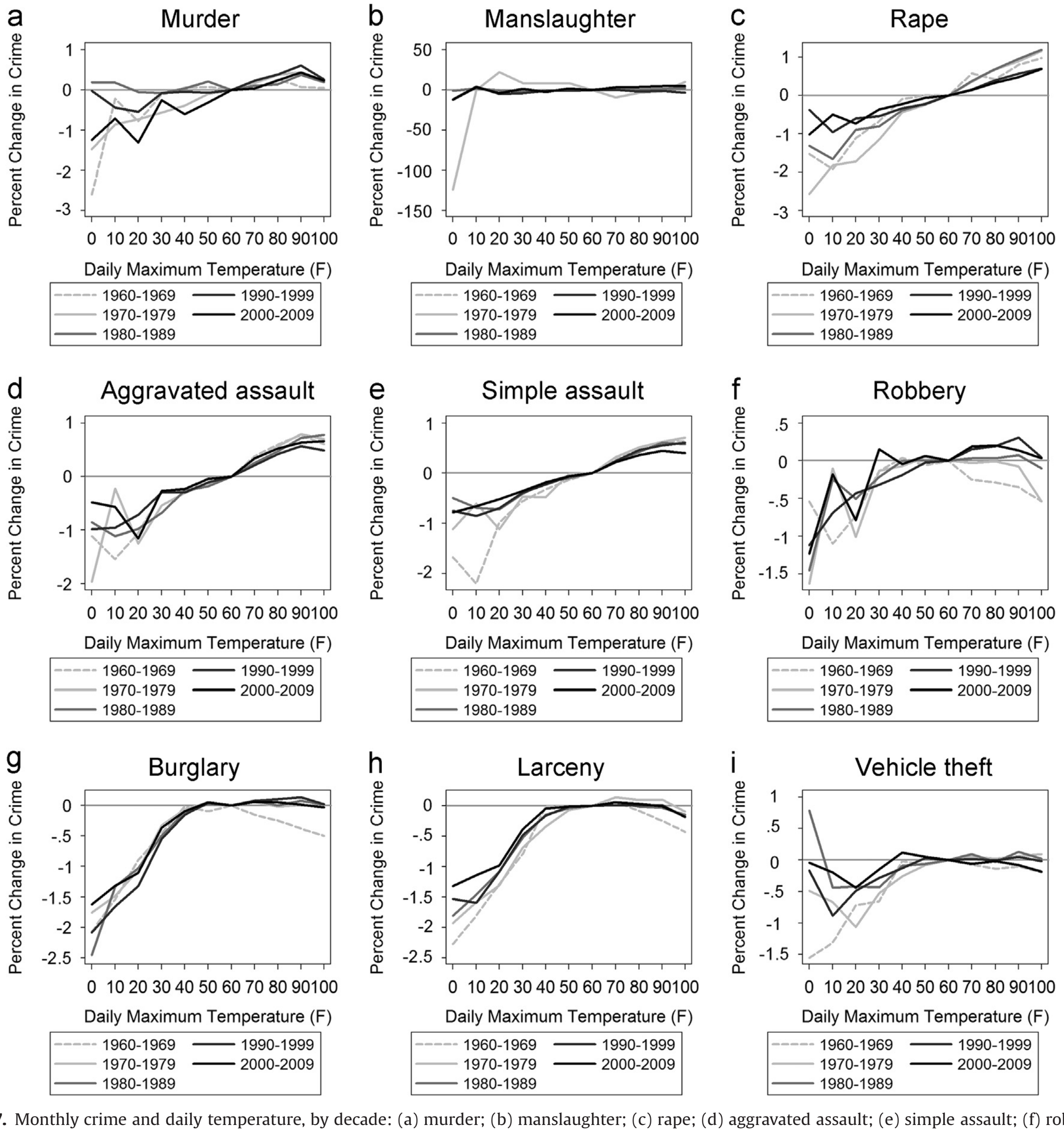

Fig. A7. Monthly crime and daily temperature, by decade: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows coefficients from Poisson regressions of the number of crimes in each county, month, and year, on a semi-parametric set of weather bin variables representing maximum daily temperature and daily precipitation. Estimates are shown for separate regression based on observations from five different decades: 1960–1969, 1970–1979, 1980–1989, 1990–1999, and 2000–2009. All regressions include state-by-month and county-by-year fixed effects, and all coefficients are relative to 1 day in the 60–70 °F bin.

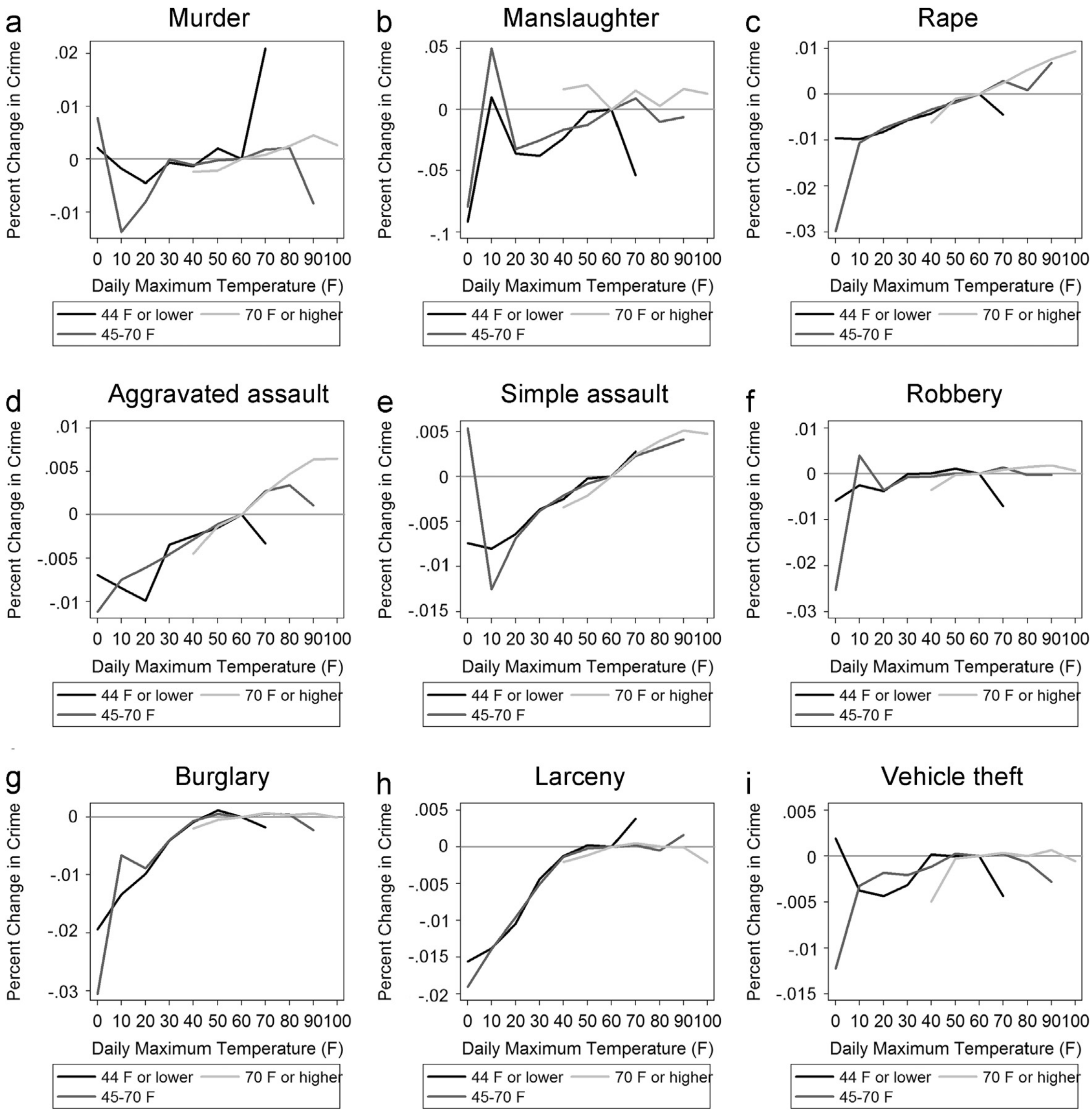

Fig. A8. Monthly crime and daily temperature, by mean monthly temperature: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows coefficients from Poisson regressions of the number of crimes per county, month, and year, on a semi-parametric set of weather bin variables (representing maximum daily temperature and daily precipitation) 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 °F, 45–69 °F, or ≥ 70 °F. All regressions include state-by-month and county-by-year fixed effects, and all coefficients are relative to 1 day in the 60–70 °F bin.

The second term in this definition (the level of crime under current temperature and policing effort) is easily observable. However, it is more difficult to develop an econometric methodology to estimate the first term (the level of crime after policing effort has adjusted to the 1° change in temperature). The approach that I use in the main part of this paper is to assume that the long-run police response to the change in temperatures has only a small impact on crime, so that ΔC can be estimated using panel data on short-term variation in temperatures within a particular geography and year:

$$\Delta C \approx \Delta C_{panel} \equiv C(T_1, E^*(T_0,\ X_0), X_0) - C(T_0, E^*(T_0, X_0), X_0) \tag{A3}$$

Econometric implementation of this panel approach requires both time and location fixed effects. Although this methodology has the advantage of being unlikely to be biased by omitted variables, its major weakness is the possibility that the short-term effects of temperature on crime may not be representative the longer-term relationship when adaptation is possible.

The primary alternative suggested by the literature is a Ricardian approach in the spirit of Mendelsohn et al. (1994). Such an approach would estimate the impacts of climate change on crime using cross-sectional variation in temperature across

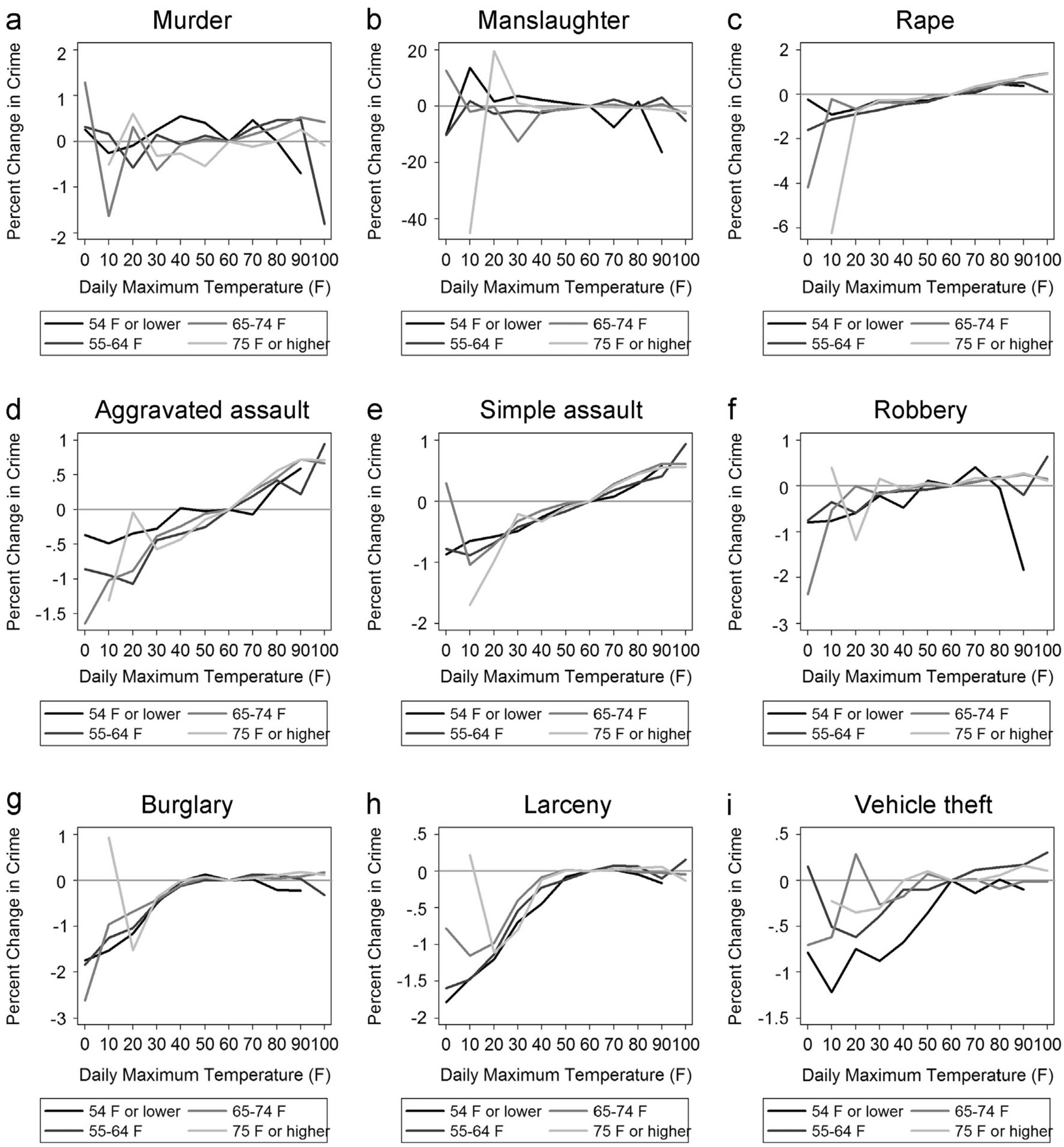

Fig. A9. Monthly crime and daily temperature, by climate zone: (a) murder; (b) manslaughter; (c) rape; (d) aggravated assault; (e) simple assault; (f) robbery; (g) burglary; (h) larceny; and (i) vehicle theft. *Note*: Each figure shows coefficients from Poisson regressions of the number of crimes in each county, month, and year, on a semi-parametric set of weather bin variables representing maximum daily temperature and daily precipitation. Each figure shows results from separate regressions baed on observation from counties in each of four climate zones. Counties are assigned to a climate zone based on whether their long-term mean annual maximum daily temperature falls into one of four ranges: <55 °F, 55–64 °F, 65–74 °F, and ≥ 75 °F. All regressions include state-by-month and county-by-year fixed effects, and all coefficients are relative to 1 day in the 60–70 °F bin.

geographies:

$$\Delta C \approx \Delta C_{ricardian} \equiv C(T_1, E^*(T_1,\ X_1), X_1) - C(T_0, E^*(T_0, X_0), X_0) \qquad (A4)$$

The drawback to this approach is that if geography X has a non-negligible impact on crime outside of the weather pathway (and if it is not possible to control for it using some econometric technique), then Eq. (A4) will produce biased estimates of the impact of climate change on crime. Because of the challenges of controlling for determinants of crime that are difficult to observe—e.g., culture—I do not pursue a Ricardian approach in this paper.

Other approaches are also possible. For example, some long-term adaptation strategies, such as hiring additional police officers, may be available on a seasonal basis. This suggests estimating the impacts of climate change on crime using variation in average weather conditions across seasons within a particular year and location (in practical terms, this would mean using month of the year as an instrumental variable for weather):

$$\Delta C \approx \Delta C_{seasonal} \equiv C(T_1, E^*(T_1,\ M_1), M_1) - C(T_0, E^*(T_0, M_0), M_0) \tag{A5}$$

In this equation, M_0 and M_1 denote different months of the year, and I suppress the X_0 in both terms for clarity. However, implementing this approach would require the assumption that seasonality affects crime only through weather. Unfortunately, given the many other seasonal factors that affect crime (e.g., school calendars, the holiday shopping season, day length), this identifying assumption is not likely to be valid.

A.3.2. Seasonal and geographic differences in marginal effects

The econometric strategies from the previous section involve looking for ways to estimate the long-term marginal effects of temperatures on crime. However, a slightly different set of approaches would involve looking for evidence of seasonal or geographic differences in the *relative* marginal effects of different temperatures on crime. For example, this methodology could test the hypothesis that due to adaptation, the marginal impact of hot days (relative to moderate days) is lower in months of the year or areas of the United States in which temperatures are usually hot. One drawback of this approach, however, is that there is no particular reason to expect adaptation to have any effect on marginal responses to temperature. Instead, it seems more (or at least equally) likely that adaptation would lead to shifts in the absolute crime level, with little impact on the marginal effects of temperature on crime. Furthermore, from an econometric standpoint, this approach would rely on the assumption that season or geography only affect crime rates (and the response of crime to temperature) via temperatures. As discussed in the previous section, this is unlikely to be a valid assumption. Nonetheless, as additional sensitivity analyses in support of the main results, I do present results from regressions in which I estimate the relationship between temperature and crime for different seasons and geographies.

First, I estimate the effect of temperatures on crime separately for months when it is usually cold, moderate, and hot, in each county. The cold–moderate–hot designations are based on dummy variables that indicate whether the long-term average maximum daily temperature in each county and month is less than 45 °F, between 45 °F and 70 °F, or greater than 70 °F. I modify the main regression specification to include interactions between each of these dummy variables and the weather bin variables. Fig. A8 presents the results of these regressions. Although the regressions show a fair amount of noise, particularly for temperatures that are not typical of normal monthly conditions, the general patterns are mostly similar across seasonal conditions, and it is difficult to identify anything that would be considered strong evidence of seasonal adaptation.

Second, I estimate the effect of temperature on crime separately for four different regions of the United States. Fig. A9 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 °F, 55–64 °F, 65–74 °F, and ≥ 75 °F. The figure shows that the effects of moderate and warm temperatures on crime is quite 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.

A.3.3. Summary

Overall, due to the challenges of developing an econometric approach that can generate unbiased estimates of long-term relationship between weather and crime, in this paper I choose rely on the panel approach described in Section A.3.1. Although this approach does not account for longer-term adaptation possibilities, I view it as the most credible way to provide useful information about the potential magnitude of the effects of climate change on future criminal activity in the United States.

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