Does a good cop really never get wet? The relationships between weather on stop and frisk

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Abstract

The study of discretionary police activity has largely focused on the demographic characteristics (particularly ethnicity) of the parties involved. This study proposes a police action model that facilitates a more-holistic analysis of individual and situational influences on police actions. This model is used to generate hypotheses about the relationship between police stop and search/frisk and weather (temperature and precipitation) in London and New York City. After controlling for other situational factors (such as public holidays and special events) and for the frequency of street crime, increasing temperatures are associated with small increases in police stops, while precipitation (rain and snow) is associated with substantial decreases. These relationships disappear, however, when stops conducted indoors (e.g. in shopping malls) are modeled. This research suggests that analysis of discretionary police activity should consider the influence of the environment as well as other factors.

Keywords: police, stop and search, stop and frisk, weather

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Introduction

Policing has elements of craft, and like any craft it has its share of folk wisdom handed down from one generation of practitioners to the next. Among the somewhat clichéd advice likely to be given to new officers is the admonition that "a good cop never gets wet" (see, among many others, Baker, 1976; Codella & Bennett, 2011; Moskos, 2008; Niederhoffer, 1967; Wardhaugh, 1996). Any officer (but particularly one on foot patrol) would undoubtedly have good reasons for wanting to stay dry. At the same time, police officers pride themselves on being the public service of last resort (Reiner, 2010, p. 120), which never says 'no' to a call for assistance. Policing cannot simply stop whenever the weather turns bad.

An extensive literature has demonstrated that the behaviors of offenders and crime victims are influenced by the environment and circumstances in which they find themselves (for a review, see Eck & Madensen, 2015). This includes evidence (discussed further below) that the patterning of crime is influenced by the weather. There is similar evidence that the pro-active (i.e. discretionary) behavior of police officers is influenced by situational factors (Ashby & Tompson, 2017).

The present study extends existing evidence in this area by analyzing the association between the weather and discretionary police activity. Using data on stops of suspects in public places by police in London and New York City, this study demonstrates that there is a significant association between aspects of the weather and pro-active police activity, and that this relationship is not explained by weather-based variations in the availability of people to be searched.

The influence of weather on crime and policing

The relationship between the frequency of crime and both static and dynamic characteristics of the environment is well established (for a recent review, see Tompson & Coupe, 2018). An analytical framework for the relationship between crime and situation is proposed by the routine activities approach (Cohen & Felson, 1979), which posits that the frequency of *opportunities* for crime varies in space and time according to a wide range of situational characteristics that influence the behavior of both offenders and victims.

According to this approach, weather may influence crime by influencing the routines of people in ways that change opportunities for them to become a victim or an offender (Cohn & Rotton, 2000). For example, a warm sunny day may bring more people into public places, creating more potential targets for personal robbery. Higher temperatures may also encourage people to open windows at home, making it easier for burglars to enter. Conversely, heavy rain may drive people away from public places, reducing opportunities for street crime while increasing opportunities at indoor locations such as shopping malls.

Several studies have looked at the influence of weather on crime through this theoretical lens. An early literature review by Cohn (1990) found that many types of violent crime were more common on hot days. The frequency of rioting (Carlsmith & Anderson, 1979), assaults (Harries & Stadler, 1988; Rotton & Frey, 1985) and rape (Cohn, 1993; Perry & Simpson, 1987) have all been found to increase with temperature. However, these relationships may be more nuanced than the so-called “temperature–aggression hypothesis” (Anderson, 1987, p. 1163) suggests. Tyson and Turnbull (1990) found no association between riots and temperature in South Africa, while Ticku (2015) found that the incidence of inter-communal riots in India increased with temperature up to a tipping point, above which rioting decreased in periods of extreme heat, echoing the `inverted U’ relationship between temperature and assaults found by Baron (1972).

Mixed results have also been found for other types of relationships between crime and weather, although fewer studies have considered variables such as rain and wind speed than temperature. Field (1992) found no association between precipitation and violence, burglary, robbery or criminal damage. Jacob, Lefgren, and Moretti (2007) found greater precipitation was associated with decreases in violent crime but no changes in property crime. Cohn and Rotton (2000) found that whereas theft, burglary and robbery increased with temperature, no such relationship existed for precipitation, wind speed or humidity.

Researchers have also looked for associations between weather and calls for service made to the police. Both Brunsdon, Corcoran, Higgs, and Ware (2009) and Cohn (1996) found that higher temperatures were associated with more calls for service, but that there was no relationship between call frequency and precipitation. Their results differed on the effect of wind speed, with Cohn (1996) finding more calls during windy periods but Brunsdon et al. (2009) finding no relationship.

Studies of both crime and calls for service have typically found a stronger relationship with temperature than with other variables such as precipitation (in addition to studies already cited, see Michel et al., 2016). This contradicts the conventional wisdom that ‘Constable Rain’ (i.e. bad weather) will reduce crime by keeping potential offenders indoors and out of trouble (Lippert & Walby, 2013; Tilley, 2015).

Theorizing situational influences on police activity

Calls for service can be thought of as non-discretionary police activity, since they are initiated by citizens rather than by officers themselves. Although officers responding to calls retain the discretion to deal with them in different ways (e.g. by making an arrest or simply issuing a verbal warning), they have little choice about whether or not to attend the the incident in the first place (Feldberg, 1995).

Whilst answering emergency calls is a core part of police work, it typically takes up only a minority of officers' time (Famega, Frank, & Mazerolle, 2005). Police also undertake a variety of self-initiated activities, and in many cases have wide discretion about what activities to undertake (Smith & Visher, 1981). One common type of discretionary activity is carrying out body searches of members of the public who officers suspect of being involved in crime (Fallik & Novak, 2012). Such searches are known by different terms in different places, typically 'stop and search' in the United Kingdom and 'stop, question, frisk' (SQF) – or simply 'stop and frisk' – in the United States. The term 'stop and frisk' will be used in the remainder of this article.

Although officers spend a large proportion of their time on discretionary activities, there has been little research on the situational factors that influence their decisions about what activity to undertake. The extensive existing research on stop and frisk has focused heavily on the personal characteristics (particularly ethnicity) of people being searched, to the near exclusion of research on situational factors. This is in contrast to the study of non-discretionary police activity, into which there has been more research (see Riksheim, 1993; Sherman, 1980 for reviews).

This single exception to this (of which the authors are aware) is a study by Ashby and Tompson (2017), who used the routine activities approach to understand the relationships between variations in city-wide patterns of routine activities and the frequency of stop and frisk. Just as the routine activities approach seeks to explain the occurrence of crime events, they proposed an analogous police action model. This explains the occurrence of a police stop as the product of an officer who is motivated to search a person meeting a person who the officer believes is suitable to be searched, in the absence of other parties or situational characteristics that make the search less likely to occur.

Figure 1 shows this police action model in a format similar to the problem analysis triangle commonly used to represent the elements of the routine activities approach (for which, see Eck & Madensen, 2015). In the innermost triangle, the officer and the person to be searched (referred to as the subject) must come together in a specific place that is conducive for a search to occur. The middle triangle shows those actors (referred to as controllers) who influence the likelihood of the officer and subject coming together, the motivation of the officer and the extent to which the subject appears to be officer to be a suitable person to search. The outermost triangle shows those actors (referred to as super controllers) who can influence the search event not by their direct influence on the officer, subject or place but indirectly via their ability to influence controllers.

The value of the police action model is that it allows researchers to consider not only the characteristics of police officers and those with whom they interact, but also the settings in which those interactions occur together with the actors who influence the decisions of both officers and subjects. This is analogous to the way in which the routine activities approach stimulated researchers to pay greater attention to the situations in which crimes happened, as well as the motivations of offenders and the characteristics of victims. In the field of policing, this allows researchers to go beyond the dominant discussions of the characteristics (particularly ethnicity) of subjects and the motivations (particularly biases) of police officers.

Hypothetically, many factors can influence each element in the model. For example, a police officer may be less likely to carry out searches on a particular day as a result of being pre-occupied with problems at home. Conversely, a subject may become more likely to attract the attention of an officer for a drugs search after switching from smoking outdoor-grown marijuana leaf to stronger (and stronger smelling) hydroponically grown cannabis (Gannoni & Goldsmid, 2015). Among controllers, a police sergeant might make officers more likely to carry out searches by setting informal targets for the number of people officers should search (Curtis, 2015). Meanwhile, potential subjects' parents might make them less likely to be searched by coaching them on how to avoid attention from the police (Lee, 1997). At the level of the super controller, a politician might influence the number of stops by encouraging senior officers to issue guidelines limiting the circumstances in which officers are permitted to search subjects (Shiner & Delsol, 2015).

The police action model can be used to make predictions about how changes in the routine activities of different actors might influence the likelihood of searches taking place. For example, Ashby and Tompson (2017) found that the number of stops carried out decreased sharply on Christmas Day, when many fewer potential subjects are likely to be on the streets. Conversely, major public events such as Halloween, during which more people may be available to be stopped and officers may have more reason to carry out searches, were associated with large increases in stops. However, they found the frequency of stops was not simply a function of the number of available subjects, since other events associated with increases in the number of people in public places (such as New Year's Eve) were associated with reductions in stops. Instead, it appeared to be the interaction between the different elements of the police action model that explained the observed variations.

The present study

The present study sought to extend existing knowledge of situational influences on discretionary police activity by examining the relationship between weather and stop and frisk.

The police action model suggests at least two mechanisms by which the weather could influence the frequency of stop and frisk. Firstly, bad weather might discourage people from spending time in public places where they might come into contact with police patrols, reducing the number of opportunities for officers to conduct searches. Secondly, bad weather might influence both the ability and motivation of officers to conduct searches when there was an opportunity to do so. For example, it is likely to be more difficult (and unpleasant) to write down the details of a suspect or complete a traffic ticket in heavy rain.

Six hypotheses related to these two mechanisms were tested to understand the relationship between proactive police activity and the weather. These will be discussed in turn.

H1: There will be fewer stops on days with lower temperatures. It seems likely that higher temperatures will increase outdoor activity that, in turn, leads to more people on the street. Low temperatures may discourage officers from carrying out searches or make it more difficult for officers to identify potential offenders to stop. For example, a person wearing a bulky jacket on a hot day may be using it to conceal stolen goods, but such a person would be more difficult to distinguish in cold weather when bulky jackets are commonplace.

H2: There will be fewer stops on the hottest/coldest days of the year. Although people may prefer warm weather to cooler days, extremes of either heat or cold can cause discomfort. Extreme heat may encourage people (police included) to remain in an air-conditioned office or car, whereas extreme cold may encourage the same behavior. This hypothesis therefore predicts that there will be fewer stops on days during which the maximum temperature is higher than the maximum temperature on 95% of days and (separately) on days during which the minimum temperature is lower than the minimum temperature on 95% of days.

H3: There will be fewer stops on days with unseasonably extreme temperatures. While extreme temperatures may be unpleasant, the impact of a particular temperature on human behavior may be different depending on the time of year. In winter people are likely to expect cold weather, and so may not be particularly affected by a given day being colder than most winter days. However, an unseasonably hot or cold day may have a greater impact if its unexpected nature catches people unawares (Tompson & Bowers, 2015). This hypothesis predicts that there will be fewer stops on days that have a maximum temperature that is greater than two standard deviations above the mean daily maximum temperature for the 28-day period centered on that day of the year over the six years for which data were available. Days were also treated as having unseasonably extreme temperatures if the minimum temperature was more than two standard deviations below the mean daily minimum temperature for the corresponding 28-day period.

H4: There will be a fewer stops on days with more hours of precipitation. As the name of this article suggests, it has long been a truism of policing that 'good' police officers ensure they do not – if possible – get caught in the rain. Officers may be both less motivated and less able to carry out pro-active activities when it is raining or snowing (for example if a snow storm causes an increase in calls for service), and potential subjects of a stop may spend less time on the street. It seems possible that both the duration and intensity of precipitation will influence behavior, such that the same volume of water (as measured by a rain gauge) falling either heavily over a few minutes or lightly over a few hours may have different effects. It was thus necessary to use both the intensity and duration of precipitation to test this hypothesis.

H5: Weather will influence stops conducted outside, but not inside. Weather patterns are correlated with other types of seasonal variation. As will be discussed below, the models used in this study included variables for variations in routine activities unrelated to weather in order to control for this. To distinguish between influences associated with weather and those derived from other patterns of activity, this hypothesis predicts that precipitation and temperature will be significantly associated with the frequency of stops taking place outdoors but not associated with the frequency of stops carried out indoors (for example in public buildings or on transit systems).

H6: The frequency of crime will partly, but not fully, explain the association between stops and weather. As mentioned above, an association between weather and stop and frisk could be explained either by variations in the number of subjects available to be searched (if people stayed indoors during inclement weather) or variations in the ability and motivation of officers to carry out searches. If any relationship between stops and weather were explained wholly by the availability of subjects to be searched, this would have different implications for understanding policing than if any relationship were explained wholly by variations in the ability and motivations of officers. It is therefore important to control for the availability of subjects in order to distinguish between these types of relationship.

Measuring the number of people in public places is notoriously difficult (Malleson & Andresen, 2016), but it may be possible here to use the frequency of street crime (e.g. assault, robbery) as a proxy for on-street population. Since these crimes require (at a minimum) the presence of an offender and a suitable target for crime (Cohen & Felson, 1979), we might expect the number of street crimes being committed to be correlated with the number of potential offenders on the street. Indirectly controlling for the availability of people involved in street crime in this way is particularly appropriate because officers carrying out stops are typically searching for potential offenders, rather than stopping people at random.

If weather conditions influenced the behavior of members of the public but not of police officers, we would expect the frequency of street crime (as proxy for the presence of offenders) to wholly explain any weather-related variations in police activity. Conversely, if offenders were unaffected by the weather but police officers were, we would expect crime not to explain any weather-related variations in police activity. Neither of these scenarios seems likely: police are only human and so we may expect that if offenders are influenced by the weather, so are officers. As such, H6 predicts that the frequency of crime will explain some, but not all, of any association between police activity and the weather.

Data

The relationship between weather and crime has been found to vary between cities. Cohn and Rotton (2000) noted that there are cross-national variations in the seasonality of crime, while

Andresen and Malleson (2013) and McDowall, Loftin, and Pate (2012) found variations at more local levels. To account for potential variations between places, the six hypotheses were tested using data from two cities: London and New York City. These cities were chosen because data were available on stop and frisk and because police searches were (until recently) common in both cities, giving a large sample size. The public availability of all the data required for this study (search data, crime data, weather data, public event data, etc) over a sufficient time period is unusual, and so it was not possible to extend the analysis to other cities.

Six years of daily counts of stop and frisk in London and stop, question frisk encounters in New York City were used for the present study, covering 2006–2011 in New York City and 2008–2013 in London. These are the same data used by Ashby and Tompson (2017), allowing this study to build directly on those results. In both cities, officers conducting searches of citizens while on patrol are required to complete a short form recording details of the person stopped and the circumstances. Anonymized records for stops conducted in London were obtained via a request under the Freedom of Information Act 1998, while similar data for New York City were publicly available as a result of litigation brought by the American Civil Liberties Union against the City of New York.

Like any administrative data, it is likely that the stop data used in this study contain various errors. For example, officers in London are allowed to omit some information from the search record if they are required to immediately respond to another incident while completing the form. Police officers completing records on the street, sometimes in the middle of the night or after long and stressful tours of duty, are also likely to make mistakes when completing search records. However, these errors are unlikely to have influenced the results of the current study for at least two reasons. Firstly, only the fact that a search had occurred (and whether it had occurred indoors or outdoors), rather than the detailed information as to the reasons for the search and the circumstances, were used in this study. Secondly, officer mistakes are likely to be pseudo-random (particularly when aggregated to daily stop counts), and can be captured by the white-noise error term in the models used.

Recording searches is a legal requirement in both cities, but it is possible that the data may be affected by individual cases of misconduct by officers in failing to record searches or otherwise falsifying records. However, there does not appear to be any strong reason to believe that such incidents would influence the use to which the data were put in the current study, since to do so any misconduct would have to systematically vary by day of the year. In any case, administrative data from police agencies appear to be the only way to test the present hypotheses, since there is no other source of information on how-often police carry out searches. For this reason, police search data have been used extensively by researchers (see, for example, Gelman, Fagan, & Kiss, 2007; Goel, Rao, & Shroff, 2016; Ridgeway, 2007). For a more-detailed discussion of the data used here, see Ashby and Tompson (2017).

Data for both cities were used to test H1–H4, but only the data for New York City specified whether stops were carried out indoors or outdoors and so could be used to test H5. Similarly, daily counts of street crime were unavailable for London, so only New York City data were used to test H6.

Crime data were obtained from the NYC OpenData website. Since the weather is unlikely to influence all types of crime, only street crime was used in testing H6. Street crime was defined as any arson, assault, criminal damage, fraud, kidnapping, theft or robbery that was shown in police crime records as having occurred on a street or in a park, playground or open area.

In order to produce comparable results across the two cities, a source of weather data was required that contained cross-national observations in a consistent format[1]. One source of consistent international weather data comes from the observations made by airport control towers for the benefit of arriving and departing flight crews. To facilitate international flights, such observations are recorded in a common format known as a METAR report. METAR reports are issued by airports every 30 minutes and include information on precipitation intensity, temperature and wind-speed together with warnings about any temporary hazards such as smoke or fog that may reduce visibility (OFCM, 2005).

The closest airport to the center of London is London City Airport, approximately 10 kilometers east of the city center. In New York City, an automatic weather station situated in Central Park in Manhattan produces METAR reports for the benefit of the various airports and heliports in and around the city. Although there may be intra-city variations in weather, particularly since both cities are coastal, it was felt that the reliability provided by the consistent

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[1] This meant that observations recorded by the National Weather Service in the United States or the Meteorological Office in the United Kingdom were unsuitable, since those agencies record data in incompatible ways. The National Oceanic and Atmospheric Administration (NOAA) Global Historical Climate Network (GHCN) provides harmonized weather data from different countries, but was not useful for this study for two reasons. First, the only GHCN weather station in London without missing data for the relevant years is at Heathrow Airport, on the very edge of the city and about 25 kilometers from central London. Secondly, GHCN data include only the volume of precipitation, not the intensity or duration.

recording of METAR data was more important than any local variation that could be captured by combining multiple (but inconsistent) local sources of weather information.

Figure 2 shows the distribution of each of the weather variables along with the distribution of stops. The coldest 5% of days had a minimum temperature at or below 0ºC in London and at or below –2ºC in New York City; the hottest 5% of days had a maximum temperature at or above 25ºC in London and at or above 31ºC in New York City.

METAR reports do not include the volume of precipitation but instead record whether or not – at the time of the report – rain or snow is falling. It is therefore possible to estimate the duration (in hours) of precipitation during a day. METAR data divide precipitation into drizzle, rain and snow. The distinction between drizzle and rain in these records is that drizzle consists of drops with a diameter less than 0.5 millimeters that "appear to float" while falling to the ground (OFCM, 2005, pp. 8–1). For the present study, the METAR data was aggregated into daily mean temperatures and daily counts of the number of hours in which drizzle, rain or snow was recorded.

Two variables were included in the models presented here to control for change over time. An index variable, with the value of 1 for the first day of the period under study, 2 for the second day and so on, was included (this variable was divided by 28 so that a one-unit change is equivalent to change over a 28-day period). A variable representing the day of the year was also included, with 1 January having a value of 1. These variables more-effectively capture change over time than a categorical variable representing the year, which erroneously treats 1 January and 31 December as being equivalent despite their being 365 days apart, while representing 31 December in one year and 1 January in the following year as being different when they are directly adjacent days. Month of the year was not included because months are defined arbitrarily (and are of different lengths). However, a categorical variable recording whether a day was the first or last day of a month, or neither, was included to capture any potential effect from officers incorrectly recording events as happening on the first or last days of a month when their exact date of occurrence was unknown.

Since both weather conditions and crime are known to vary seasonally, it was necessary to control for seasonal effects in order to isolate variations in stops associated with daily weather conditions and crime counts. To do this, the daily number of hours of daylight (i.e. the time between civil dawn and civil dusk) was incorporated into the models presented below. This variable was mean-centered so that the intercept of the model can be interpreted as the number of stops expected on a day with the average hours of daylight, rather than a (non-existent) day with zero hours of daylight.

One potential confounding variable was any seasonal variation in the number of police officers available to search subjects. Time-specific data on the number of officers on duty in either city were not available, so any variation could not be measured directly. However, neither the New York City Police Department nor the Metropolitan Police Service in London use seasonal officers (as some other agencies do, particularly in vacation resorts) so the number of officers available for deployment is likely to be approximately equal across the year. While officers may prefer to take vacation days at particular times of year, police agencies typically use a number of techniques to ensure that sufficient officers are available year-round (Buren & Stenzel, 1984). For example, in New York City the collective bargaining agreement between labor and management states that no more than 2% of officers may be on vacation at any one time (Patrolmen's Benevolent Association, 2016). As such, any seasonal variation in available officers is likely to be very small, and so will not be considered further.

Analytic approach

The daily count of stops was approximately normally distributed (Figure 2) but serially correlated. To account for this autocorrelation, generalized least squares (GLS) regression was used. Several GLS specifications were tested, with a first-order autoregressive – AR(1) – models found to have significantly lower residual deviance than GLS models with no correlation structure specified. Higher order models were also tested but performed no better.

Analysis was conducted in R version 3.4.3 (R Core Team, 2017) using the 'tidyverse' suite of packages (Wickham, 2017) for data manipulation and the 'nlme' package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2017) for GLS regression.

Several different modelling approaches are available to deal with autocorrelated count data. To test the robustness of the results to the choice of approach, the models were re-run using three alternative approaches: a seasonal first-order autoregressive model with a seasonal period of seven days, a negative binomial regression with standard errors adjusted for autocorrelation using the Newey-West estimator, and a generalized linear autoregressive moving average (GLARMA). The results of these models are presented in the online supplementary material accompanying this article. The direction and magnitude of the co-efficients in each model were almost identical across all four approaches, with 95% confidence intervals overlapping in all cases except Christmas Day and 26 December in the London model and Christmas Day and Thanksgiving in the New York City model. Even in these cases, the co-efficients were in the same direction and the differences in magnitude were relatively small. The results presented here do not therefore appear to be sensitive to the choice of modelling approach.

To test for significance, models were compared to a null model with no predictors using likelihood ratio tests. To test for differences in co-efficients across models, the equation suggested by Paternoster, Brame, Mazerolle, and Piquero (1998) was used:

$$Z = \frac{b_1 - b_2}{\sqrt{SEb_1{}^2 + SEb_2{}^2}}$$

where b_i is a model co-efficient and SEb_i is the standard error of that co-efficient. Absolute values of Z greater than 1.96 indicate that the two co-efficients are significantly different from one another at the $p < .05$ level.

Testing H5, and comparing models across the two cities, required comparison of models with different intercept terms, because the count of outdoor stops was greater than the count of indoor stops. In order to compare individual co-efficients across models, the daily count of stops in each model was scaled by dividing each value by the standard deviation of the variable, such that the co-efficients can be interpreted consistently across models. To aid interpretation, unscaled co-efficients are referred to in the text. Scaled co-efficients are provided in the Online Appendix.

Results

Since the frequency of police stops is likely to be influenced by situational factors other than the weather, it was necessary to incorporate other potential influences into the models used for this study. The models presented here are extensions of those reported by Ashby and

Tompson (2017), incorporating weather variables in addition to those previously studied. The models previously reported in Tables 3 (for London) and 4 (for New York City) in Ashby and Tompson (2017) are – for comparison purposes – referred to here as the 'activity' (A) models.

The activity models (reproduced in the Online Appendix) demonstrate significant associations between variations in macro-level routine activities and the frequency of police stops both in London and New York City. In both cities, day of the week and some public holidays were associated with significant changes in stops, with these being most substantial in the case of Fridays and Christmas Day. Some public events, such as Halloween in both cities and both Bonfire Night and the Notting Hill Carnival in London were also associated with large changes in the frequency of stops. Overall, the models demonstrated that variations in routine activities can account for a large proportion of the day-to-day variations in police stops – for more details, see Ashby and Tompson (2017).

Weather

H1 to H4 were tested by adding variables representing temperature, extreme temperature, unseasonal temperature and hours of precipitation (drizzle, rain and snow) to the existing activity models. These new models are referred to as the 'activity + weather' (AW) models. Figure 3 shows the model estimates and 95% confidence intervals for the weather variables included in the AW models for London and New York City. Co-efficients that are significantly different from zero are highlighted. For reasons of space, full results for each model are reported in the Online Appendix.

Likelihood ratio tests showed that, overall, the London and New York City AW models were significantly better than corresponding null models (i.e. models with no predictors) at predicting the number of stops each day: $\chi^2(41) = 2{,}323$, $p < .001$ for London and $\chi^2(43) = 2{,}791$, $p < .001$ for New York City. In both cities, the AW models were also significantly better predictors of stops than the A models: $\chi^2(41) = 286$, $p < .001$ for London and $\chi^2(43) = 451$, $p < .001$ for New York City.

Figure 3 shows that mean daily temperature was not a significant predictor of police stops in London, contrary to H1. However, temperature was a significant predictor of stops in New York City, with higher temperatures associated with a (small) increase in stops. However, a Z-score test showed the co-efficients in the two cities to not be significantly different ($|Z| = 0.09$).

Regarding H2, the hottest 5% of days were associated with fewer stops by police in both cities, while the coldest 5% of days were a predictor of fewer stops only in New York City. However, due to the wide confidence intervals around these estimates, the Z-score test showed that the co-efficients for very-hot ($|Z| = 0.64$) and very-cold ($|Z| = 1.43$) days were not significantly different between the two cities. As such, the importance of the between-city difference should not be overstated. Unseasonably hot or cold days were not significant predictors of the number of police stops in either city, contrary to H3.

Figure 3 shows that all three of the precipitation variables are significant and the direction of the co-efficients is in line with the prediction of H4. Heavier precipitation appears to be associated with the greatest decrease in stops: every hour of snow in London, for example, is associated with 21 fewer stops, compared to 18 fewer stops for one of hour of rain and nine fewer stops for one hour of drizzle.

A better understanding of the relationships between weather and police stops can be obtained by using the AW model to predict the number of expected stops in different conditions.

Figure 4 shows the combined effect of the different weather variables on the estimated number of police stops in New York City on a nominal Friday in October 2006. With all other variables held constant, the AW model predicts 753 stops if the mean temperature is 13ºC and there is no rain, but only 483 stops if the mean temperature is –2ºC and there are 12 hours of rain – a 36% reduction in stops. It appears, therefore, that changes in weather can be associated with substantial changes in pro-active police activity even after controlling for other situational factors.

Indoor versus outdoor stops

To test H5, separate AW models were run for stops in New York City conducted indoors and outdoors. As expected, overall both models were significantly better than a null model in predicting daily counts of stops: $\chi^2(43) = 2{,}691, p < .001$ for stops conducted outdoors and $\chi^2(43) = 1{,}791, p < .001$ for those conducted indoors.

Figure 5 shows co-efficients and the corresponding confidence intervals for the weather variables in these models. As for the other models, complete results are presented in the Online Appendix.

There is a significant difference (i.e. $|Z| > 1.96$) between the scaled co-efficients for temperature increase ($|Z| = 11.7$), coldest days ($|Z| = 2.21$), and precipitation ($|Z| = 6.83$ for drizzle, $|Z| = 7.29$ for rain and $|Z| = 5.51$ for snow) between stops conducted indoors and those conducted outdoors. All of these variables are significantly different from zero for outdoor stops, while all (except for temperature increase and hours of snow) are not significant for indoor stops. For snow, the expected change in stops is reduced from 19 stops per hour in which it snowed for outdoor stops to 1 stop per hour for indoor stops (Figure 5). These results are consistent with H5.

Compared to outdoor stops, the relationship between temperature and police stops reverses direction when considering stops conducted indoors. Outdoors, increases in temperature are associated with more stops while indoors increases in (external) temperature are associated with fewer stops.

Incorporating offender availability into the model

To test H6, counts of street crime for New York City were added as a predictor to the AW model, with the new model being referred to as the 'activity + weather + crime' (AWC) model.

The AWC model was significantly better at predicting the number of stops each day in New York City when compared to both a null model ($\chi^2(44) = 2{,}818, p < .001$) and to the AW model ($\chi^2(44) = 27.7, p < .001$).

Table 1 shows the co-efficients for weather and crime variables in these two models, together with the results of the Z-score test comparing them. The co-efficient for street-crime count is significantly different from zero, with each additional offense being associated with 0.6 additional stops. The mean number of street crimes per day was 227 with a standard deviation of 38, so a one-standard-deviation increase in street crimes would be associated with an increase in 23 stops per day.

Although the addition of the count of street crimes increased the overall performance of the model, the Z score tests reported in Table 1 show that the addition of this variable did not cause a significant change in any of the co-efficients for weather variables. The only exception is the temperature-change variable, which changes from being associated with a significant (but small) increase in stops in the AW model to a non-significant increase in stops in the AWC model. These findings are contrary to H6, which predicted that the addition of street-crime counts to the model would lead to a partial, but not complete, reduction in the co-efficients of weather variables.

Discussion

The results presented in this study demonstrate that there are significant associations between the weather and the frequency of police searches in two large cities, London and New York (Figure 3). From this, it appears that the relationship between stops and weather conditions varies across different components of the weather. While precipitation is associated with a decrease in stops and more-intense precipitation with greater decreases (H4), the results for temperature (H1–3) are more mixed. Increases in temperature were associated with small increases in the frequency of stops, although the association was not significant in London. This trend reversed on the hottest days, with temperatures above the 95th percentile being associated with fewer stops. The Z-score test for equality of individual co-efficients demonstrated that these results were broadly consistent across the two cities.

As noted earlier, studies of weather and crime have generally found larger, more consistent effects for temperature than for measures of precipitation. The present analysis of stop and frisk found the opposite to be true: Figure 4 shows that over the range of typical values, precipitation is associated with larger changes in stops than temperature is.

The final two hypotheses (H5 and H6) attempted to account for two potential explanations for the observed associations between weather and stops. Since weather is known to influence many types of human behavior, it is possible that the associations found in the AW models could be due to the influence of other unmodeled variables that are correlated with weather. The results of testing H5 provided limited supporting evidence for the possibility that the observed variations in stops were in-fact caused by variations in weather. It appears that, in New York City at least, there are significant associations between, on the one hand, temperature and precipitation and, on the other, the frequency of stops conducted outdoors. Conversely, there is virtually no relationship between those weather variables and stops conducted indoors (Figure 5). This is consistent with the observed relationships being caused by variations in the weather, which are more likely to influence outdoor rather than indoor behavior.

While increasing our confidence in the relationships identified here, the results of the models used to test H5 leave open the question of whether those relationships are the result of weather-induced changes in the activities of potential search subjects, the activities of police officers, or a combination of both. H6 attempted to provide a partial answer to this question by incorporating a proxy measure of offender availability into the model. If weather led to fewer offenders spending time in (outdoor) public places, it would be expected that the associations between stops and weather would substantially weaken once street crime (as a proxy for offender availability) was introduced into the model. Conversely, if weather did not influence offenders but did influence police officers, it would be expected that adding crime to the model would not influence the frequency of stops. Contrary to expectations, this latter result was the one obtained (Table 1). Although it is not possible to conclusively exclude the observed variations being the result of one or more unmodeled confounding variables, these findings provide some insight into the potential mechanisms underlying relationships between weather and police stops. While undoubtedly limited, these findings may be valuable given the impracticability of experimental investigations of weather for identifying causal mechanisms.

Limitations

While this study has provided some insight into the relationship between police searches and weather, the analysis presented here is undoubtedly limited. Although this study prioritized the production of comparable results from London and New York City, the analysis is limited to these two very-large, very-dense global cities. It may well be that the results are not generalizable to smaller cities, suburbs or rural areas. However, it is possible that analysis of different environments will become easier as more agencies release open data on crime and policing as part of efforts to increase transparency (Tompson, Johnson, Ashby, Perkins, & Edwards, 2014). We encourage others to replicate the present study in other settings, and have released our analytical R code on the Open Science Framework at https://osf.io/rn9yj/ for that purpose.

Limitations of the available data meant that it was not possible to analyze variations in the relationships between stops and weather either within each city or within each day. This meant that this study would not have been able to detect, for example, differences in the relationships between stops and weather in the daytime and at night (as were found in the crime–weather relationships studied by Cohn & Rotton, 2005). The present study could not consider variations in weather–stop relationships associated with the circumstances of each stop, beyond the situational factors described above and whether or not each stop occurred indoors or outdoors. All of these unanswered questions could be explored by further research. Such research could use data that were similar in form to those used here but with more variables, which may require data to be collected specifically for that purpose. Alternatively, further studies could use different approaches such as systematic observations of police officers conducting stops or interviews with patrol officers.

Using the police action model

The hypotheses tested in this study were generated using the police action model outlined above. By conceptualizing police activity in terms of interactions between police officers, the subjects of police action and the places in which they come together, it is possible to consider each of these elements (and the influences upon them) separately. Using the routine activities approach to disaggregate the "almost-always" elements of a crime (Felson & Boba, 2010, p. 28) has allowed researchers to identify, for example, the importance of place managers in preventing crime (see Madensen & Eck, 2008). The authors believe there is potential for equivalent use of the police action model to be useful in extending our understanding of the drivers of police activity. The model is not a fully-fledged theory of police activity, but rather a predictive and analytical tool.

The police action model can be used to analyze police activity beyond stop and frisk. There are many circumstances in which police officers interact with other people that are of interest to policing scholars. Traffic stops, for example, can be an important factor in police–community relations (Ridgeway, Schell, Riley, Turner, & Dixon, 2006), but study of them has (with a few exceptions, such as the work by Bayley, 1986) been limited to exploring the (racial) biases of police officers (see, for example Engel & Calnon, 2004; Lundman & Kaufman, 2003; Rojek, Rosenfeld, & Decker, 2012; Smith & Petrocelli, 2001). While undoubtedly important, these are unlikely to be the only factors determining the occurrence of these encounters or their outcomes. Similar points could be made about research into, for example, police arrest decisions, although the focus on racial characteristics in research on arrests is somewhat less pronounced than for research on traffic stops (Riksheim, 1993).

The existing research on police interactions with the public could also be fruitfully incorporated into the police action model by conceptualizing officers' biases as one element that influence their perception of the suitability of different subjects to be searched. This would allow, for example, consideration of (racial) biases together with situational and other factors that influence police officers' decision making.

Conclusion

This study has demonstrated that weather conditions are significantly associated with the frequency of police stop and frisk. This has potential implications for policing practice, for example in the area of performance monitoring. Given that police in New York City made an average of 81 arrests per day following SQF encounters in 2006–2011, the variations in stops with weather conditions shown in Figure 4 indicate that officers would make about 29 fewer SQF-derived arrests on a cold day with 12 hours of rain than on a warm, dry day. If weather and other environmental factors are not factored into the processes – such as CompStat in New York City – by which local police commanders are held to account, senior officers may make sub-optimal judgments about performance.

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Declaration of interests

No potential conflict of interest is known to the authors.

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Tables

Table 1: Comparison of co-efficients for weather variables for the AW and AWC models for New York City

	activity + weather			activity + weather + crime			
	b	SE	p	b	SE	p	Z
1 hour of drizzle	-9.8	1.3	<.001	-9.3	1.3	<.001	-0.28
1 hour of rain	-14.0	1.6	<.001	-12.5	1.6	<.001	-0.65
1 hour of snow	-18.2	1.6	<.001	-17.5	1.6	<.001	-0.32
1ºC temperature increase	2.6	0.8	.002	1.0	0.9	.238	1.25
coldest 5% of days	-69.3	15.0	<.001	-65.1	14.9	<.001	-0.20
hottest 5% of days	-47.6	14.1	<.001	-45.9	14.1	.001	-0.08
unseasonably hot	-14.7	20.3	.470	-10.7	20.3	.596	-0.14
unseasonably cold	-0.1	29.9	.998	3.4	29.8	.909	-0.08
hours of daylight	-26.3	4.1	<.001	-26.0	4.0	<.001	-0.05
1 additional crime				0.6	0.1	<.001	

Figures

Figure 1: Police action model

Figure 2: Distribution of weather variables

Figure 3: Confidence intervals for weather variables in the AW models. For full model results, see Online Appendix

Figure 4: Combined effect of different weather conditions on the estimated number of police stops in New York City on a nominal Friday in October 2006

Figure 5: Confidence intervals for weather variables in the AW models for stops taking place indoors and outdoors in New York City. For full model results, see Online Appendix

Online Appendix: regression co-efficients

London, all stops

	activity			activity + weather		
	b	SE	*p*	*b*	SE	*p*
intercept	1066.75	34.74	<.001	1075.24	39.20	<.001
28-day index	-6.40	0.64	<.001	-6.21	0.65	<.001
day of the year	-0.04	0.12	.740	-0.09	0.12	.459
first day of month	-33.26	19.19	.083	-34.38	17.88	.055
last day of month	-20.65	20.17	.306	-18.73	18.80	.319
Monday	171.57	16.18	<.001	175.64	15.17	<.001
Tuesday	361.34	17.95	<.001	363.34	16.82	<.001
Wednesday	486.00	18.77	<.001	483.94	17.60	<.001
Thursday	514.54	18.86	<.001	512.09	17.69	<.001
Friday	544.20	18.03	<.001	545.11	16.89	<.001
Saturday	351.70	10.34	<.001	353.23	9.63	<.001
New Year's Eve/Day	-298.51	56.70	<.001	-284.43	53.05	<.001
Good Friday	-472.73	57.80	<.001	-488.44	53.94	<.001
Easter Monday	-366.39	57.67	<.001	-350.66	53.85	<.001
Early May Holiday	-273.77	58.69	<.001	-290.35	54.59	<.001
Spring Holiday	-307.35	57.58	<.001	-306.16	53.51	<.001
Christmas Eve	-304.38	67.24	<.001	-298.80	62.81	<.001
Christmas Day	-563.45	76.59	<.001	-555.24	71.69	<.001
26 December	-358.71	67.23	<.001	-353.73	62.96	<.001
school day	86.19	16.31	<.001	84.05	15.35	<.001
marathon	-47.92	56.88	.400	-55.63	52.86	.293
Gay Pride parade	26.98	56.95	.636	-5.73	53.06	.914
Notting Hill Carnival	209.28	55.70	<.001	194.33	51.99	<.001
Halloween	987.61	58.99	<.001	976.42	54.94	<.001
Bonfire Night	444.39	56.32	<.001	433.40	52.32	<.001
election day	-8.82	69.39	.899	-12.02	64.67	.853
Olympics/Paralympics	46.31	78.14	.553	78.14	75.45	.300
stadium event	-57.36	18.17	.002	-60.50	16.90	<.001
terrorist attack	-88.36	47.66	.064	-60.90	46.24	.188
public disorder	-212.20	51.48	<.001	-180.18	48.20	<.001
DSEI arms fair	-123.82	74.84	.098	-90.26	70.43	.200

	activity			activity + weather		
	b	SE	*p*	*b*	SE	*p*
Opening of Parliament	-77.76	61.97	.210	-76.30	57.66	.186
1 hour of drizzle				-8.94	1.06	<.001
1 hour of rain				-17.73	2.16	<.001
1 hour of snow				-21.26	2.72	<.001
1ºC temperature increase				3.08	2.00	.123
coldest 5% of days				-37.76	31.17	.226
hottest 5% of days				-85.48	20.00	<.001
unseasonably hot				7.29	42.92	.865
unseasonably cold				-45.53	28.16	.106
hours of daylight				-14.60	5.47	.008

New York City, all stops

	activity			activity + weather		
	b	SE	*p*	*b*	SE	*p*
intercept	468.77	16.33	<.001	486.15	16.71	<.001
28-day index	6.85	0.28	<.001	6.93	0.26	<.001
day of the year	-0.58	0.06	<.001	-0.72	0.06	<.001
first day of month	-47.96	14.66	.001	-50.10	13.23	<.001
last day of month	-1.81	15.21	.905	0.80	13.71	.953
Monday	-117.18	10.91	<.001	-114.54	9.96	<.001
Tuesday	201.56	12.14	<.001	204.64	11.07	<.001
Wednesday	279.26	12.81	<.001	289.41	11.68	<.001
Thursday	276.72	12.61	<.001	278.39	11.49	<.001
Friday	342.18	12.10	<.001	350.31	11.01	<.001
Saturday	299.63	7.97	<.001	295.67	7.18	<.001
New Year’s Eve/Day	-119.26	42.09	.005	-119.04	38.12	.002
Christmas Eve	-336.39	50.40	<.001	-387.91	45.80	<.001
Christmas Day	-506.73	55.66	<.001	-538.81	50.59	<.001
school day	48.00	9.91	<.001	39.39	9.20	<.001
marathon	29.29	44.72	.513	16.13	40.19	.688
Gay Pride parade	0.19	44.52	.997	-3.01	40.00	.940
Halloween	242.32	46.63	<.001	231.80	41.94	<.001
election day	-161.79	41.45	<.001	-187.19	37.27	<.001
terrorist attack	46.95	37.09	.206	39.50	34.09	.247
Martin Luther King Day	63.65	45.34	.160	47.20	40.98	.249

	activity			activity + weather		
	b	SE	p	b	SE	p
Washington's Birthday	50.82	44.74	.256	59.75	40.38	.139
Memorial Day	-27.11	45.33	.550	-35.02	40.74	.390
Independence Day	-78.36	44.08	.075	-77.49	39.63	.051
Labor Day	46.95	45.02	.297	12.44	40.49	.759
Columbus Day	14.70	45.32	.746	5.68	40.90	.889
Veterans' Day	57.86	45.03	.199	34.01	40.58	.402
Thanksgiving	-474.38	45.44	<.001	-454.13	41.00	<.001
26 December	-144.82	50.21	.004	-116.57	45.53	.010
Superbowl	-61.10	108.11	.572	-112.02	97.14	.249
World Series	-106.42	58.96	.071	-96.28	53.17	.070
major disaster	-80.60	18.89	<.001	-38.21	17.56	.030
public disorder	101.67	37.56	.007	54.91	34.97	.116
UN General Assembly	-9.22	31.87	.772	-23.21	29.20	.427
1 hour of drizzle				-9.85	1.34	<.001
1 hour of rain				-13.97	1.55	<.001
1 hour of snow				-18.23	1.62	<.001
1ºC temperature increase				2.55	0.84	.002
coldest 5% of days				-69.27	14.96	<.001
hottest 5% of days				-47.60	14.14	<.001
unseasonably hot				-14.70	20.35	.470
unseasonably cold				-0.07	29.92	.998
hours of daylight				-26.34	4.07	<.001

New York City, outdoor and indoor stops

Note: to allow comparison of indoor and outdoor stops, daily counts of stops were centered and scaled by subtracting the mean value ($\overline{x} = 677$ for outdoor stops and $\overline{x} = 153$ for indoor stops) from each value then dividing the result by the standard deviation ($\sigma = 242$ for outdoor stops and $\sigma = 55$ for indoor stops).

	outdoor stops			indoor stops		
	b	SE	p	b	SE	p
intercept	-1.35	0.06	<.001	-0.28	0.06	<.001

	outdoor stops			indoor stops		
	b	SE	*p*	*b*	SE	*p*
28-day index	0.03	0.00	<.001	0.02	0.00	<.001
day of the year	0.00	0.00	<.001	0.00	0.00	<.001
first day of month	-0.20	0.05	<.001	-0.04	0.06	.482
last day of month	0.01	0.05	.827	-0.03	0.06	.621
Monday	-0.45	0.04	<.001	-0.12	0.04	.006
Tuesday	0.68	0.04	<.001	0.70	0.05	<.001
Wednesday	0.98	0.04	<.001	0.92	0.05	<.001
Thursday	0.93	0.04	<.001	0.92	0.05	<.001
Friday	1.20	0.04	<.001	1.05	0.05	<.001
Saturday	1.06	0.03	<.001	0.70	0.03	<.001
New Year's Eve/Day	-0.34	0.14	.016	-0.83	0.16	<.001
Christmas Eve	-1.30	0.17	<.001	-1.48	0.19	<.001
Christmas Day	-1.83	0.19	<.001	-1.89	0.21	<.001
school day	0.13	0.03	<.001	0.17	0.04	<.001
marathon	0.05	0.15	.748	0.13	0.18	.470
Gay Pride parade	-0.01	0.15	.968	-0.06	0.18	.731
Halloween	0.94	0.16	<.001	0.12	0.19	.528
election day	-0.71	0.14	<.001	-0.22	0.16	.182
terrorist attack	0.16	0.12	.202	0.16	0.12	.168
Martin Luther King Day	0.17	0.15	.262	0.12	0.18	.499
Washington's Birthday	0.21	0.15	.171	0.21	0.18	.244
Memorial Day	-0.10	0.15	.496	-0.15	0.18	.389
Independence Day	-0.21	0.15	.158	-0.46	0.18	.008
Labor Day	0.13	0.15	.400	-0.31	0.18	.084
Columbus Day	0.04	0.15	.791	0.02	0.18	.905
Veterans' Day	0.15	0.15	.324	0.08	0.18	.642
Thanksgiving	-1.45	0.15	<.001	-1.92	0.18	<.001
26 December	-0.40	0.17	.019	-0.49	0.19	.010
Superbowl	-0.39	0.37	.289	-0.37	0.43	.395
World Series	-0.28	0.20	.152	-0.43	0.22	.054
major disaster	-0.11	0.06	.074	-0.23	0.06	<.001
public disorder	0.26	0.12	.039	-0.13	0.11	.269
UN General Assembly	-0.06	0.11	.581	-0.03	0.11	.799
1 hour of drizzle	-0.04	0.01	<.001	0.01	0.01	.026
1 hour of rain	-0.06	0.01	<.001	0.00	0.01	.712

	outdoor stops			indoor stops		
	b	SE	*p*	*b*	SE	*p*
1 hour of snow	-0.07	0.01	<.001	-0.02	0.01	.006
1ºC temperature increase	0.02	0.00	<.001	-0.04	0.00	<.001
coldest 5% of days	-0.27	0.06	<.001	-0.08	0.06	.206
hottest 5% of days	-0.19	0.05	<.001	-0.08	0.06	.196
unseasonably hot	-0.05	0.08	.491	-0.05	0.09	.575
unseasonably cold	0.01	0.11	.934	0.06	0.13	.660
hours of daylight	-0.08	0.01	<.001	-0.11	0.01	<.001

New York City, models with and without crime

	activity + weather			activity + weather + crime		
	b	SE	*p*	*b*	SE	*p*
intercept	486.15	16.71	<.001	356.53	28.48	<.001
28-day index	6.93	0.26	<.001	6.99	0.26	<.001
day of the year	-0.72	0.06	<.001	-0.75	0.06	<.001
first day of month	-50.10	13.23	<.001	-53.89	13.18	<.001
last day of month	0.80	13.71	.953	2.79	13.64	.838
Monday	-114.54	9.96	<.001	-93.00	10.65	<.001
Tuesday	204.64	11.07	<.001	225.06	11.61	<.001
Wednesday	289.41	11.68	<.001	310.03	12.19	<.001
Thursday	278.39	11.49	<.001	299.54	12.04	<.001
Friday	350.31	11.01	<.001	365.16	11.27	<.001
Saturday	295.67	7.18	<.001	296.93	7.16	<.001
New Year’s Eve/Day	-119.04	38.12	.002	-131.73	37.93	<.001
Christmas Eve	-387.91	45.80	<.001	-383.04	45.54	<.001
Christmas Day	-538.81	50.59	<.001	-536.92	50.22	<.001
school day	39.39	9.20	<.001	36.48	9.15	<.001
marathon	16.13	40.19	.688	9.51	40.05	.812
Gay Pride parade	-3.01	40.00	.940	-6.65	39.85	.868
Halloween	231.80	41.94	<.001	213.25	41.91	<.001
election day	-187.19	37.27	<.001	-188.22	37.12	<.001
terrorist attack	39.50	34.09	.247	43.65	33.56	.193
Martin Luther King Day	47.20	40.98	.249	44.26	40.81	.278
Washington’s Birthday	59.75	40.38	.139	50.60	40.26	.209
Memorial Day	-35.02	40.74	.390	-44.28	40.60	.275
Independence Day	-77.49	39.63	.051	-85.41	39.49	.031

	activity + weather			**activity + weather + crime**		
	b	SE	*p*	*b*	SE	*p*
Labor Day	12.44	40.49	.759	-12.71	40.58	.754
Columbus Day	5.68	40.90	.889	-13.00	40.88	.750
Veterans' Day	34.01	40.58	.402	30.62	40.42	.449
Thanksgiving	-454.13	41.00	<.001	-462.18	40.85	<.001
26 December	-116.57	45.53	.010	-108.46	45.28	.017
Superbowl	-112.02	97.14	.249	-108.65	96.75	.261
World Series	-96.28	53.17	.070	-98.59	52.85	.062
major disaster	-38.21	17.56	.030	-33.68	17.32	.052
public disorder	54.91	34.97	.116	51.83	34.29	.131
UN General Assembly	-23.21	29.20	.427	-24.29	28.84	.400
1 hour of drizzle	-9.85	1.34	<.001	-9.31	1.34	<.001
1 hour of rain	-13.97	1.55	<.001	-12.54	1.57	<.001
1 hour of snow	-18.23	1.62	<.001	-17.49	1.62	<.001
1ºC temperature increase	2.55	0.84	.002	1.03	0.88	.238
coldest 5% of days	-69.27	14.96	<.001	-65.14	14.90	<.001
hottest 5% of days	-47.60	14.14	<.001	-45.95	14.06	.001
unseasonably hot	-14.70	20.35	.470	-10.74	20.27	.596
unseasonably cold	-0.07	29.92	.998	3.40	29.77	.909
hours of daylight	-26.34	4.07	<.001	-26.04	4.01	<.001
1 additional crime				0.61	0.11	<.001