Tompson and Bowers *Crime Science* (2015) 4:8
DOI 10.1186/s40163-015-0022-9

Crime Science
a SpringerOpen Journal

RESEARCH Open Access

Testing time-sensitive influences of weather on street robbery

Lisa A Tompson* and Kate J Bowers

Abstract

Although the relationship between weather and crime has been extensively investigated over the past century, little consensus has emerged on the directions of the relationships observed and the mechanisms through which weather might exert its influence. This paper advances an argument that the interpretation of weather, and subsequent activities based on that interpretation, leads to spatio-temporal variations in criminal opportunities, and hence crime.

Two hypotheses relating to unseasonal weather and effects of weather on discretionary activities are proposed. Negative binomial regression models are used to test these at the 6-hour shift unit of analysis on street robberies in the Strathclyde region of Scotland. In line with predictions, in this temperate microclimate, more favourable weather in winter (higher temperatures and low wind speeds) was associated with increases in robbery. Partial support was also found for the hypothesis regarding time delineated for discretionary activities. Here, temperature, wind speed and humidity were seen to be significant predictors of robbery during the night shift and weekends. Notably rain was shown to have a negative relationship with robbery at the weekends. This affirms that people are less likely to venture outdoors when it is raining when travel behaviour is optional. Counter to our hypothesised effects, fog was the only variable to significantly interact with public holidays. We conclude by discussing how these analyses might be extended and briefly discuss implications for crime prevention.

Keywords: Routine activity approach; Social contact; Discretionary activities; Thermal comfort; Robbery; Micro-temporal; Temperature; Wind speed

Background

The relationship between weather and crime holds an enduring fascination to criminology scholars (see Baumer & Wright 1996; Cohn 1990 for an overview of studies. Also, Anderson et al. 1997; Ceccato 2005; Cohn & Rotton 1997; Hipp et al. 2004; LeBeau 1994; Sorg & Taylor 2011; Van Koppen & Jansen 1999). Collectively, empirical findings suggest that climatological and meteorological variations are associated with patterns of crime, some of which are seasonal. However the relationships are far from clear cut; to date there is little consensus on the directions of the relationships observed and the mechanisms through which weather might exert its influence (Block 1984; Peng et al. 2011; Yan 2004). Ostensibly, the impact of weather across different locales and microclimates is not constant; a premise which underpins the current study.

Pre-eminently, Sutherland and Cressey (1978) underscore that weather conditions "provide the habitat for human life and consequently may facilitate or impede contacts among human beings and perhaps in that sense be related to opportunities for criminal behaviour". This social contact hypothesis is, presumably, an antecedent to the routine activity approach, which has been one of the principal theoretical explanations for the effect of weather on crime (Cohn 1990; Landau & Fridman 1993; Lab & Hirschel 1988). The routine activity approach asserts that there are three essential elements of a crime which converge in space and time; a motivated offender, suitable target and the absence of a capable guardian (Felson 1987). People's everyday routine activities explain how the paths of victims and offenders overlap to create a tapestry of criminal opportunities. The convergence of

* Correspondence: l.tompson@ucl.ac.uk
Department of Security and Crime Science, University College London, 35 Tavistock Square, London WC1H 9EZ, UK

these three elements is thus dependent on how modern social life is organised.

As human activities are the cornerstone of the routine activities approach, it is important to consider the patterning of activities over time, and how they relate to weather conditions. Previous research has neglected to consider this in detail, a point stressed by Rotton and Cohn (2000). Further to this, temperature and other weather conditions can vary considerably over the course of the day, as well as over the seasons. Prior research has often examined weather variables alongside concurrent crime patterns at the day level and coarser temporal resolutions, which fails to account for the (often very significant) intra-day variation (Cohn & Rotton 1997).

In this paper we integrate Criminological evidence with research findings from other disciplines concerned with weather and behaviour to obtain a fuller picture of the likely mechanisms driving the effect of weather on crime patterns. In doing so, we advance an argument that the interpretation of weather, and subsequent activities based on that interpretation, lead to spatio-temporal variations in criminal opportunities and hence crime. We begin to test these hypothesised effects by presenting initiatory analysis that adopts a finer temporal resolution than typically seen in weather and crime research.

The paper proceeds as follows: first, we develop our argument that weather exerts its influence differentially at different times and conditions. Next, we describe our study area, data and analytical approach. The results are presented and discussed in relation to the convergence of victims and offenders in space and time. We conclude by discussing how these analyses might be extended and briefly discuss implications for crime prevention.

The adverse-favourable weather hypothesis

Weather conditions shape the types of activities that people take part in (LeBeau & Langworthy 1986; Ceccato 2005). Numerous scholars have postulated that people are more likely to stay indoors in adverse weather and be outdoors when weather is pleasant (Brunsdon et al. 2009; Hipp et al. 2004; Lab & Hirschel 1988; LeBeau & Corcoran 1990; Rotton & Cohn 2000), and this is borne out by empirical findings in transport studies and public health (Böcker et al. 2013; Horanont et al. 2013; Tucker & Gilliland 2007). Outdoor activities usually peak in the summer months in temperate climates when the days are longer, whereas regions with harsh weather conditions in winter have a population used to staying at home for prolonged periods. Weather can also be more severe at certain times of the day, such as early morning fog. Social contact between people in public settings is thus reduced when weather is perceived to be unpleasant. This inevitably affects the availability of guardians present in a particular setting, as well as the likelihood of convergence of victims and offenders.

The hypothesis that inclement weather leads to reduced social contact, and thus reduced opportunities for crime to occur, was first advanced by Rotton and Cohn (2000). They aimed to extend the negative affect escape (NAE) model proposed by psychologists to explain the relationship between temperature and aggression (Baron 1972). Succinctly put, the NAE purports that up to a certain limit increases in heat will covary with increases in the likelihood of aggressive behaviour. However, once a 'critical' threshold of temperature is reached an individual is more likely to feel lethargic or want to escape that situation, which reduces the likelihood of aggression. Rotton and Cohn (2000) approximated social contact by including disorderly conduct calls for service in their time-series analysis, testing the relationship between weather variables and assault over different intervals in the day. Their results were consistent with a model of mediated moderation; that is, the inverted U-shaped relationship between temperature and assault purported by proponents of the NAE model was reduced when social contact was controlled for. This led the authors to postulate that inclement weather (especially extremes in temperature) could be considered a factor that increased social avoidance – the opposite of social contact – and kept people in their 'primary territories' (homes). Later work by these scholars suggested that the shape of the relationship between temperature and aggression varied according to time of the day (Cohn & Rotton 2005).

Wider support for this inverted NAE model can be found in research on how weather affects peoples' non-crime related activities (Zacharias et al. 2001). Systematic review findings reveal that in many countries an increase in temperature – particularly when accompanied by calm conditions - is positively associated with increased use of public space, up to certain heat-thresholds (Böcker et al. 2013). Thermal comfort is though influenced by many factors in addition to the temperature measured in the NAE model. Other weather conditions (including precipitation, humidity and wind speed), exposure times, cultural clothing, urban design, socio-demographic characteristics and individual traits combine to determine how people perceive their outdoor environment (Yahia & Johansson 2013; Stathopoulos et al. 2004).

We all become accustomed to seasonal norms in weather (of course, depending on the regional microclimate), and these shape our expectations and behaviour in relation to our travel patterns, activities and clothing. Cross-cultural comparisons of people's thermal comfort levels in urban climatology and biometeorology have revealed that the upper limits of thermal comfort vary across different populations (Chen & Ng 2012; Yahia & Johansson 2013).

Furthermore, Böcker et al. (2013) argue that climatological differences might become culturally embedded so that they affect attitudes to certain weather – temperature in particular.

In light of this, we argue that Rotton and Cohn's hypothesis needs to be extended to truly capture people's responses to adverse weather, which encompasses a wider set of meteorological variables than temperature. What is considered to be adverse weather is likely to be interpreted differently by people in different places, and this in itself can vary over time. Leaving aside demographic and individual traits for the purposes of this exposition[a], we reason that interpretation of weather conditions is grounded in a person's *expectations* of that weather at a point in space-time. Such expectations are, plausibly, the mechanism through which weather influences outdoor activities. Expectations are hence likely to be relative to the expected weather for the season (which is intimately related to the microclimate). Empirical findings lend credence to this proposition: Datla and Sharma (2010) demonstrated that snow has a stronger negative influence on car traffic volumes in Alberta, Canada in autumn and early spring compared with the same conditions in winter. Perhaps Albertans are better prepared for the presence of snow in winter, when it is more probable. From a more recreational viewpoint, in Chicago Dwyer (1988) found that the relationship between urban forest attendance and warm sunny weather was much stronger in spring compared with the same weather conditions in summer.

For the purposes of this paper we are calling this the 'adverse-favourable weather hypothesis' (hypothesis 1). Adverse-favourable represents the range of weather conditions that we seek to test. In keeping with our rationalization above we posit that reductions in robbery will be associated with adverse unseasonal weather, and increases in robbery will be associated with favourable unseasonal weather.

The discretionary activities hypothesis

When considering influences on people's routine activities it is useful to differentiate between obligatory activities and discretionary activities (LeBeau 1994). Discretionary activities are pursued by choice, whereas obligatory activities have to be performed in all but extreme weather conditions. For this reason weather exerts a stronger influence on discretionary trips for leisure reasons, compared to utilitarian trips such as commuting (LeBeau & Corcoran 1990; Böcker et al. 2013). As Field (1992) states, people may be willing to postpone discretionary activities until the weather is more pleasant (also see Cools et al. 2010). We should though note that obligatory and discretionary activities lie on a continuum, rather than being dichotomous. For example, certain discretionary activities, such as shopping, are more utilitarian than leisure pursuits, and therefore these might not be put-off indefinitely in sustained adverse weather. Instead it might be the case that they are pursued in a constrained way.

People, then, can plan their discretionary activities according to their expectations of future weather as well as the current conditions. It is plausible to assume that weather forecasts influence activities planned in advance, or with a long duration (Böcker et al. 2013), however to the author's knowledge this has not been empirically tested hitherto. Spontaneous discretionary activities, such as those in pursuit of recreation or entertainment, may be more influenced by what weather is expected over the scale of hours, rather than days, and thus decision-making is done at different temporal scales.

It is also the case that there will be temporal, spatial and social trends in people's discretionary activities. During the working week, for much of the daytime period, the employed will be conducting obligatory activities. This will tie them to a particular place and commute pattern. More choice may be available later on back in their area of residence, where they can choose whether to leave the house or not. The non-working population will have more discretion for when and for how long they leave their residence. Recent research has demonstrated that offenders make shorter trips to commit residential burglary at night-time than during the day, presumably because they choose not to venture as far later on (Bowers & Johnson 2015). Such travel patterns affect the availability of guardians, targets and offenders and we hypothesise that weather will have a stronger influence when travel is (in general) more likely to be optional (hypothesis 2).

Explaining the influence weather has on human activities in public space permits us to make hypotheses as to how this affects the constellation of motivated offenders, suitable targets and capable guardians in the context of the routine activity approach. Outdoor crimes with human victims require the presence of both offender and target but, pressingly, guardianship needs to be absent for a crime event to be more likely. Of all the people present in public space, those who are not offenders can be either targets or guardians depending on their vulnerability to be a victim of crime. Weather can therefore be considered a situational influence on crime (Cohn 1993) as it can alter the opportunity structure for crime to occur.

The present study

Recent developments in weather data availability and advances in statistical modelling mean that we can now begin to test the conditional factors for weather interpretation outlined above. The objective of the present study is to test the two stated hypotheses – the influence of unseasonal weather and the influence of weather on discretionary and obligatory activities. We do so using police recorded street robbery data, which is defined as stealing property from a person by means of violence or threats of violence. Street robbery happens in outdoor environments affected by the weather, and has social contact between victim and offender as a prerequisite condition. The other advantage of using street robbery as an example of criminal behaviour is that it is (usually) recorded with good temporal precision (personal communication with data provider).

People's weekly and daily patterns of obligatory and discretionary activities are highly individualised. However the biological need for sleep can be considered a universal temporal constraint on people's activity patterns (Ratcliffe 2006). At a societal level (in a UK context), we can reasonably assume that the majority of people will have their obligatory activities in daytime hours in the working week (that is, Monday to Friday). This does not, of course, include people without any formal educational or professional obligations, or people with working patterns outside of these hours, but for the purposes of our study on aggregate patterns we think this a reasonable position to take.

Investigating patterns at a fine-grain temporal resolution has been uncommon in weather and crime research to date (see Tompson & Bowers 2013), however it mirrors a wider trend in Criminological research to progress down the cone of resolution to investigate robbery at a micro-level (Haberman & Ratcliffe in press; Irvin-Erickson et al. in press). The present study employs a unit of analysis of a *6-hour shift*, effectively segmenting each day in the data period into four. We wanted to capture the core of the day when it could be considered most people (young people and adults) would be involved in obligatory activities. In addition, we thought it important to aim for the greatest homogeneity of weather conditions in each shift, and as temperature is closely related to the sun's trajectory, considered sunrise and sunset times when selecting temporal boundaries for these shifts. We consolidated these aims by defining shifts as 4 am - 9.59 am; 10 am - 3.59 pm; 4 pm - 9.59 pm; and 10 pm - 3.59 am[b].

Methods

Recorded street robbery data were provided by (at the time) Strathclyde Police[c] for 2002–2011. As temporal precision was important to the analysis, robbery events that were recorded to span more than four hours were removed. This resulted in an overall loss of 83 records (0.6% of the overall dataset). The mean timespan for the remaining robbery events was 5.4 minutes, with 95 per cent of events occurring within a 30 minute period.

Robberies that fell in shifts not completely covered by the data period (night shifts on 31 December 2001 and 2011) were also removed from the data (n = 4); leaving 14,857 street robbery events available for the analysis. These events were aggregated to each complete temporal shift for every day in the ten-year data period[d]. Table 1 presents the distribution of robberies over these shifts and clearly shows that they are concentrated in the late and night shifts, when most people are free from their obligatory activities.

It is worth briefly describing the distinctive microclimate of the study area, which is just less than 14,000 km^2. The Strathclyde Policing area covers the Inner Hebrides all the way down to the metropolis of Glasgow, with some 2.3 million people living within its boundaries. Consonant with established empirical trends, the majority of recorded street robbery occurs in the predominantly urban Glasgow area (Flatley et al. 2010). This falls in a temperate oceanic climate zone. However, Glasgow is warmer than other areas on similar latitudes due to the Gulf Stream coming in from the Atlantic Ocean. The weather tends to be very unsettled, although Glasgow experiences milder temperatures than elsewhere in Scotland and snowfall is infrequent. The weather in summer months can be changeable and varies from cool and wet to warm, with occasional hot days. Autumn months can sometimes bring more settled and pleasant weather. Generally speaking, Glasgow sees many overcast days with high humidity. Table 2 provides information on the mean weather values for the period 1981–2010 (metoffice.gov.uk).

The most temporally fine-grained weather data were sourced for Glasgow Airport (weather station EGPF from wunderground.com[e]). A total of 164,270 weather readings over the ten year data period were available. These readings were typically at 30 minute intervals, although just over three per cent of the intervals were greater than this because of missing data. 18 readings occurred between 01:00–02:00 in March and were corrected (by adding one hour) so that they corresponded to the new daylight saving time. On 36 occasions the weather readings produced null values for temperature and humidity; these were excluded.

Weather readings were then aggregated to the shift unit of analysis. Mean values were calculated for temperature, humidity and wind speed. Frequencies of observations of fog, snow and thunder were generated before being

Table 1 Temporal concentration of street robberies into shifts

Shift	n	%
Early (4 AM – 9:59 AM)	1,219	8.2
Mid (10 AM – 3.59 PM)	3,416	23.0
Late (4 PM – 9.59 PM)	5,389	36.3
Night (10 PM – 3:59 AM)	4,833	32.5
Total	14,857	

Table 2 Mean weather values for the Met Office station Springburn (nearest station to Glasgow) for period 1981–2010

Month	Max. temp (°C)	Min. temp (°C)	Days of air frost	Sunshine (hours)	Rainfall (mm)	Days of rainfall
Jan	6.0	1.0	11.0	37.8	112.8	17.0
Feb	6.6	1.1	10.2	62.9	88.5	13.5
Mar	8.8	2.3	6.5	86.2	96.9	15.7
Apr	11.7	4.0	2.1	127.6	62.9	12.5
May	15.1	6.5	0.2	173.3	61.4	12.0
Jun	17.5	9.4	0.0	148.9	65.1	11.7
Jul	19.2	11.1	0.0	149.0	83.5	12.7
Aug	18.5	11.0	0.0	142.2	101.1	14.1
Sep	15.8	8.8	0.1	111.2	112.7	13.8
Oct	12.1	6.0	1.3	80.0	129.4	16.6
Nov	8.7	3.3	5.7	51.1	105.5	15.9
Dec	6.1	1.0	10.8	32.9	104.4	14.7
Annual	12.2	5.5	47.9	1203.1	1124.3	170.3

N.B. wind averages are not available for this station.

transformed into a proportion using the count of weather readings per shift. Following the aggregation process 18 shifts had no weather readings. These were assigned the mean values of weather readings from the nearest two corresponding shifts (i.e. one day before and after). This was considered to be superior to assigning the mean values from shifts on the same day due to the notable variation in temperature over the course of a day.

Lastly, the aggregated robbery data were appended to the aggregated weather data. A sequential variable was created to represent the days over the study period (n = 3,652) to control for the underlying trend of decreasing robbery. Binary temporal variables representing the seasons and weekend period[f] were then generated, based on the shift date and time. Public holidays and notable celebratory events (such as Burns Night and St Andrews Day) were also represented by a binary variable.

The dependent variable was the count of street robbery in each temporal shift for each day in the ten-year data period. Being highly clustered in time, these counts were overdispersed with the variance greater than the mean ($\mu = 1.08$, $\delta = 1.22$). Diagnostic tests revealed that a negative binomial regression model was more appropriate than a regular Poisson model or zero-inflated negative binomial model[g]. In comparison to regular Poisson regression models, negative binomial regression models have an extra parameter to model the overdispersion.

Two models were generated, the first testing the adverse-favourable weather hypothesis – where the effect of unseasonal weather could be estimated on the count of robbery in each shift. This model included all weather variables, spring, summer and autumn (winter was held as the reference category[h], and interactions between these. The interaction between summer and snow was excluded as the zeros in this variable produced perfectly collinear coefficients. The sequential variable described above was included as a control for temporal autocorrelation in the robberies.

The second model tested the effect of weather on discretionary activities. This model included the weather variables, the shift variables (night time was held as the reference category[h]), and the variables representing weekends and public holidays. Interactions between the weather and all temporal variables were included, along with the sequential variable. As both models compare a number of independent variables, the problem of multiplicity – that is, testing multiple hypotheses – might undermine the analysis by increasing the likelihood of type I error (Benjamini & Yekutieli 2001). We used the false discovery rate to correct for this[i].

Collinearity between the independent variables was assessed using variance inflation factors (VIF) scores prior to the modelling. The maximum and mean VIF scores were 1.9 and 1.3 respectively for the seasonal model (model 1) and 3.2 and 1.7 respectively for the discretionary activities model (model 2). These were considered acceptable[j].

Results

The negative binomial regression coefficients, along with their associated confidence interval values, were exponentiated to produce incidence rate ratios (IRR) – a ratio based on the incidence of counts. These provide a simple means of assessing the influence of each independent variable on the rate of change in robbery events, when the other variables are held constant in the model.

The results of model 1 can be seen in Table 3. This shows the IRR and accompanying confidence intervals, along with the original and adjusted p-values. We see from this that temperature, humidity and wind speed are

Table 3 Model 1: negative binomial model for seasonal influences on robbery

	IRR	2.5%	97.5%	p-value	Adjusted p-value
(Intercept)	4.359	2.762	6.862	<0.001	0.000
Sequential	1.000	1.000	1.000	<0.001	0.000
Mean temperature (°C)	1.038	1.025	1.052	<0.001	0.000
Mean humidity	0.988	0.983	0.993	<0.001	0.000
Mean wind speed (km per hour)	0.989	0.984	0.994	<0.001	0.000
Proportion of fog	1.002	0.999	1.004	0.196	0.305
Proportion of rain	1.001	1.000	1.003	0.104	0.171
Proportion of snow	0.996	0.987	1.004	0.345	0.508
Spring	0.591	0.336	1.042	0.069	0.138
Summer	0.533	0.271	1.047	0.067	0.138
Autumn	0.820	0.428	1.57	0.549	0.673
Int: mean temperature and spring	0.973	0.957	0.99	0.002	0.008
Int: mean temperature and summer	0.967	0.948	0.986	0.001	0.005
Int: mean temperature and autumn	0.975	0.96	0.992	0.003	0.011
Int: mean humidity and spring	1.006	0.999	1.012	0.076	0.142
Int: mean humidity and summer	1.006	1.000	1.013	0.063	0.138
Int: mean humidity and autumn	1.001	0.994	1.009	0.695	0.759
Int: mean wind speed and spring	1.011	1.003	1.018	0.004	0.012
Int: mean wind speed and summer	1.010	1.002	1.019	0.017	0.043
Int: mean wind speed and autumn	1.010	1.002	1.017	0.013	0.036
Int: proportion of fog and spring	0.994	0.988	1.001	0.084	0.147
Int: proportion of fog and summer	0.999	0.989	1.008	0.790	0.808
Int: proportion of fog and autumn	1.001	0.996	1.005	0.808	0.808
Int: proportion of rain and spring	0.999	0.997	1.001	0.504	0.673
Int: proportion of rain and summer	1.000	0.997	1.002	0.705	0.759
Int: proportion of rain and autumn	0.999	0.997	1.002	0.577	0.673
Int: proportion of snow and spring	1.005	0.988	1.02	0.562	0.673
Int: proportion of snow and autumn	1.008	0.981	1.03	0.540	0.673

N.B. Cragg and Uhler pseudo $R^2 = 0.068$, the 2x log likelihood = −39421.2.

the only weather variables that influence the (general) occurrence of robbery; with increases in temperature associated with an increase in robberies, and the opposite trend for humidity and wind speed. Interestingly, however, when the interactions with season are considered, the opposite effect is seen for these three weather conditions. This means that higher temperatures in winter (the reference category) increase robbery, whereas for the other seasons a (relative) decrease is seen with rises in temperature. Similarly, a higher wind speed in winter decreases robbery, whereas the reverse is seen for the other seasons. The same overall trend is apparent in humidity, but the coefficients (and therefore IRRs) do not reach the threshold of 95 per cent significance. The adjusted p-values were in some cases larger, but did not change the significant results.

The set of results in Table 3 can be interpreted as partial support for the adverse weather hypothesis. In winter the study area typically experiences low temperatures, and even a small increase in this can result in more robbery. Seemingly this supports the predictions made by Cohn and Rotton (2000) that extremely low temperatures lead to people using public space less, thus providing fewer opportunities for robbery to occur. Further, when wind speeds are higher in winter (presumably twinned with low temperatures), this decreases robbery occurrences. A cold winter wind appears to discourage outside activity. Indeed, wind has been found to be an important condition in perceptions of thermal comfort (Walton et al. 2007), and high wind speeds lead to people staying indoors more (Horanont et al. 2013). It is interesting that other weather variables do not show noteworthy associations, but this can be explained by the microclimate of the study area (i.e. regular precipitation and seldom snowfall). The null effect of rain mirrors findings by other UK research (Field 1992; Brunsdon et al. 2009).

Whilst the magnitudes of the effects of temperature and wind speed in model 1 appear small, it should be noted that these conditions have a considerable range – for example an increase of one km per hour in wind speed overall decreases robbery by 1.1 per cent. Hence if the wind speed increased by 20 km per hour this would translate to a 22 per cent decrease in robbery. It is worth stating that model 1 overall only explains 6.8 per cent of the variance in the count of robbery per shift over the data period (based on the pseudo R^2 value) – a rather limited amount, but in keeping with prior research (Cohn & Rotton 2000).

The results of model 2, which tested the influence of weather on time periods most likely to be used for discretionary activities, are presented in Table 4. A similar trend is evident in this model, whereby temperature, humidity and wind speed are seen as influential on robberies overall, with the IRRs for each weather condition in the same direction as model 1. Robbery is less likely in the early- and mid-shifts compared to the night shift (see Table 1) and less likely at the weekend according to this model (Chen & Ng 2012). Public holidays do not appear to exert an influence over robberies in general.

Examining the interaction variables in model 2 shows some subtle distinctions that provide evidence for the discretionary activities hypothesis (hypothesis 2). For temperature, the IRR direction for the early-, mid- and late-shifts contrasts with the overall temperature variable, indicating that higher temperatures in the night shift correspond with increased robberies. Considering that night-time temperatures are commonly the lowest in a day, the same logic applies to the interpretation of the seasonal effects; low temperatures at night-time dissuade people from being outdoors (because they don't have to be) – which in turn provides fewer opportunities for robbery to occur. The interaction of public holidays and temperature shows an increase in robberies for higher temperatures, but this is only significant at the 90 per cent threshold. Conceivably this reinforces that temperature affects people's choices to be outdoors when there is more discretion over what activities they pursue.

The interaction between mean humidity and weekends is statistically significant, meaning that higher humidity is associated with increased robberies during this period. This should however be interpreted with caution; the study area is known to have consistently high humidity[j] and this is not necessarily related to high temperatures as in other microclimates.

In a similar way to temperature, wind speed also exhibits a different influence on the night shift than for the other times of the day. In particular, higher wind in the early- and late- shifts increase robberies relative to the night-shift. Once more, this seems to indicate that during the night-time, where the number of discretionary activities is likely to be higher, increased wind discourages people from using public outdoor space.

One intriguing result seen in Table 4 is that an increased proportion of fog (in terms of time within the shift) on public holidays increases the likelihood of robbery. This runs counter to the effect we hypothesised, but could potentially be explained by the fog affording offenders an environment with decreased visibility, which would reduce the ability of capable guardians. Decreased visibility in terms of darker conditions has been shown to increase the likelihood of robbery (Tompson & Bowers 2013).

Viewing rain at the interaction level with temporal variables also reveals an interesting pattern. Whilst not significant at the general level, rain shows a significant relationship with the mid-shift and weekend. For the mid-shift increased rain is associated with small increases in robbery; for weekends this effect is reversed. As we previously mentioned, robberies predominantly occur in the late and night shifts at weekends, so it would seem that rain's effect on the mid-shift is more likely to relate to weekdays. One possible reason for this is that the profile of victims is different in the week (i.e. could comprise of school-children and workers) than at the weekend. So whereas rain might not deter offenders from operating in the middle of the day, people involved in obligatory activities are also in public space as potential victims. In contrast rain at the weekend can discourage the use of public space.

It is apparent from the adjusted p-values in Table 4 that several of the variables discussed fall below the conventional 95 per cent threshold when this correction method is applied. Namely these are the overall humidity; the mid-shift; and the interactions involving wind speed, fog and rain. Hence the more reliable results are those that remain significant after correcting for the multiplicity in the regression model. Clearly, more studies are needed to corroborate the other relationships found by this study.

Model 2 has a greater explanatory power for the variation in robbery at the shift level (pseudo $R^2 = 0.23$) than is customarily seen in studies examining weather. The inclusion of temporal variables that represent periods when people are free to pursue discretionary activities thus appears to offer greater prospects for predicting robbery.

Discussion and conclusions

Whilst weather and crime has been extensively studied over the past century by criminologists, the relationship

Table 4 Model 2: negative binomial model for discretionary activity influences on robbery

	IRR	2.5%	97.5%	p-value	Adjusted p-value
(Intercept)	3.438	2.048	5.751	<0.001	0.000
Sequential	1.000	1.000	1.000	<0.001	0.000
Mean temperature (°C)	1.013	1.005	1.020	0.001	0.006
Mean humidity	0.993	0.988	0.999	0.023	0.076
Mean wind speed (km per hour)	0.992	0.987	0.997	0.003	0.016
Proportion of fog	1.000	0.997	1.003	0.954	0.954
Proportion of rain	1.000	0.998	1.001	0.699	0.884
Proportion of snow	1.001	0.986	1.014	0.938	0.954
Early shift (4 am-10 am)	0.240	0.089	0.638	0.004	0.019
Mid shift (10 am-4 pm)	0.537	0.290	0.998	0.049	0.124
Late shift (4 pm-10 pm)	1.175	0.678	2.042	0.567	0.811
Weekend	0.467	0.328	0.664	<0.001	0.000
Public holidays	0.951	0.394	2.269	0.910	0.954
Int: mean temperature and early shift	0.974	0.961	0.988	<0.001	0.000
Int: mean temperature and mid shift	0.987	0.977	0.997	0.010	0.043
Int: mean temperature and late shift	0.977	0.968	0.986	<0.001	0.000
Int: mean temperature and weekend	1.000	0.993	1.008	0.942	0.954
Int: mean temperature and public holidays	1.021	0.999	1.043	0.063	0.151
Int: mean humidity and early shift	1.001	0.991	1.012	0.804	0.943
Int: mean humidity and mid shift	1.004	0.997	1.011	0.309	0.531
Int: mean humidity and late shift	1.001	0.995	1.007	0.833	0.943
Int: mean humidity and weekend	1.011	1.007	1.015	<0.001	0.000
Int: mean humidity and public holidays	0.996	0.987	1.005	0.412	0.681
Int: mean wind speed and early shift	1.011	1.002	1.020	0.021	0.076
Int: mean wind speed and mid shift	1.005	0.998	1.012	0.144	0.283
Int: mean wind speed and late shift	1.006	1.000	1.012	0.042	0.120
Int: mean wind speed and weekend	1.001	0.996	1.006	0.662	0.863
Int: mean wind speed and public holidays	1.004	0.992	1.016	0.523	0.803
Int: proportion of fog and early shift	0.996	0.990	1.001	0.141	0.283
Int: proportion of fog and mid shift	0.997	0.992	1.002	0.247	0.462
Int: proportion of fog and late shift	1.001	0.996	1.006	0.662	0.863
Int: proportion of fog and weekend	1.000	0.997	1.004	0.877	0.954
Int: proportion of fog and public holidays	1.007	1.000	1.014	0.032	0.098
Int: proportion of rain and early shift	1.001	0.998	1.004	0.462	0.736
Int: proportion of rain and mid shift	1.002	1.000	1.004	0.048	0.124
Int: proportion of rain and late shift	1.001	1.000	1.003	0.120	0.272
Int: proportion of rain and weekend	0.998	0.997	1.000	0.023	0.076
Int: proportion of rain and public holidays	1.002	0.998	1.006	0.300	0.531
Int: proportion of snow and early shift	0.997	0.977	1.016	0.780	0.943
Int: proportion of snow and mid shift	0.982	0.957	1.004	0.145	0.283
Int: proportion of snow and late shift	0.995	0.979	1.011	0.554	0.811
Int: proportion of snow and weekend	0.998	0.985	1.012	0.828	0.943
Int: proportion of snow and public holidays	0.991	0.952	1.021	0.585	0.811

N.B. Cragg and Uhler pseudo $R^2 = 0.23$, the 2x log likelihood = −36774.6.

between the two has eluded universal theorising. This paper contributes to this scientific debate by advancing an argument that it is people's subjective interpretation of weather that is the mechanism that influences their subsequent outdoor activity. Not accounting for the fact that different people use space differently at various times could be an explanation for why prior research has failed to establish a clear relationship between weather and crime. For crimes like street robbery, which require both victim and offender to interact, weather can determine whether people are present in an outdoor environment to provide the opportunity for robbery to occur.

Two hypotheses are tested in this study; the first relates to people's seasonal expectations of weather. This adverse-favourable weather hypothesis posits that when weather is markedly different than the seasonal norm people are either less or more willing to venture outdoors, depending on whether it makes conditions less or more favourable than expected. Thus, extremes in weather - excess heat in summer and extreme cold in winter – might limit people's (legitimate and illegal) contact with others in public space. Likewise, unexpectedly mild or favourable conditions might encourage increased use of public space.

The results in Table 3 appear to support this hypothesis. Both wind speed and temperature had statistically significant effects, both at the general level on robbery counts per shift, and when they interacted with seasonal variables. The winter period exhibited the most notable results in support of the adverse-favourable weather hypothesis; showing that an increase in temperature in these months resulted in greater robbery frequencies, but an increase in wind speed in these months resulted in a decrease in robberies. These two sets of results are interrelated; they both contribute to a person's sense of thermal comfort. Wind speed accompanied by cold temperatures considerably increases the 'wind chill factor'. Therefore adverse weather in winter is more influential in this particular study area. In other microclimates it is likely to be the case that extremes in temperature, humidity or stormy weather has a similar effect – a finding echoed throughout the weather and crime research (Cohn & Rotton 1997). Importantly, our findings support Rotton and Cohn's (2000) social contact/avoidance hypothesis, which postulates that extremes in temperature (both hot and cold) reduces social contact through people retreating to their primary territories (such as homes). However, our analysis extends their model by considering what might influence a person's interpretation of 'bad' or 'good' weather.

The second hypothesis tested in this study relates to discretionary activities. Here, we postulated that variation in weather would have a stronger effect on time periods that were demarcated for discretionary - or recreational - activities. The results presented in Table 4 support this hypothesis, but show that weather conditions exert differential effects on different periods of discretionary time. In these results, wind speed, temperature and humidity were again seen to be significant to robbery levels – particularly in periods when people are free from obligatory activities (night shifts and weekends). Notably rain was shown to have a negative relationship with robbery at the weekends. This affirms that people are less likely to venture outdoors when it is raining when travel behaviour is optional. Interestingly fog was the only variable to significantly interact with public holidays and did so in the opposite direction to the other variables- with more fog at weekends increasing robbery levels. We speculate that this exception could be related to guardianship levels - fog in particular considerably reduces the range of people's visibility.

Collectively these results produced greater explanatory power for the variation in robbery at the shift level than has been seen in prior research, which we think is related to the important influence of discretionary activity time on a crime type such as robbery, and the fine-grain unit of analysis chosen to study weather and robbery (the 6-hour shift). Such a micro-temporal level approach is critical to observing the variation of weather over the course of the day, and over other temporal scales.

Naturally our study has some limitations. Using data from one weather station only approximates the weather across the study area, and as weather is known to vary enormously at the localised level (see Brunsdon et al. 2009) it is certainly the case that there is some error in our measurements of weather. Further to this, relying on police-recorded data necessarily excludes unreported crimes; however this is true of all research using police data. We also recognise that there are other ways of estimating unseasonal effects, such as statistical variation of weather across seasons. Finally, without spatio-temporally accurate population data, we cannot directly estimate the influence of weather on levels of usage of public space (see Malleson & Andresen 2015). This can be seen as an intermediate outcome in the hypothesised chain of events between certain weather conditions and changes in robbery levels. However, the general agreement of the results shown above suggests that this explanation has substantial support.

Scholars have suggested that the relationship between crime and weather is so complex that multiple theories are needed (Rotton & Cohn 1999). In our theorising we did not account for the fact that short-term transitory adverse weather may temporally displace routine activities (Field 1992). It may well be the case that there is a lagged effect for some weather conditions such as rain or excess heat (for example, see LeBeau 1994), where people delay their discretionary activities until a time when the weather is more pleasant. How weather and discretionary activities vary over spatial location (i.e. inter-neighbourhood, see Sorg & Taylor 2011) and different populations (i.e. stratifying victim populations by their routine activities) were also outside of the scope of this study. Future research may prosper by integrating this extra level of complexity into the investigation of weather on crime patterns and specifically testing the causal mechanisms we have proffered in this paper.

The strength of the hypotheses presented in this paper is that they do not focus *per se* on violent crime. Instead, they postulate what weather conditions will encourage people to leave their homes and interact in public space. For a different crime such as burglary, it might be the case that those same conditions create opportunities for vacant houses to be burgled. To test the generalizability of these findings they should be replicated in different microclimates, with different seasonal norms and routine activities shaped by discretionary activities.

Police crime prevention activity is already heavily shaped by known patterns of crime in space (in terms of well-established hotspot mapping). Temporal patterns in crime are less obvious, and require a greater infiltration of theory into standard crime analysis practices, complemented by advanced statistical modelling. The influence of weather on crime will always prove somewhat intangible due to the differential effects it has on different contexts. But by considering seasonal norms, discretionary time and the cultural expectations of people in given conditions it may be possible to appreciably understand how it might affect the interaction of victims and offenders in time and space. In turn this wisdom can help crime reduction agencies to advantageously position their resources to inhibit crime from occurring. We assert that weather should be considered alongside other situational variables, particularly during times of discretionary activity or noticeably favourable weather conditions in planning resource allocation.

Endnotes

[a]We do this firstly because it is outside our area of expertise, and secondly to construct a more parsimonious theoretical model. We do not doubt that demographic characteristics and individual traits will impact on a person's subjective interpretation of weather conditions. However we doubt that variation at this level of abstraction can be adequately tested by the analysis of crime data.

[b]We acknowledge that other scholars have selected different temporal boundaries when partitioning the day. For example, Rotton and Cohn (2000) used 21:00–2:59, 3:00–8:59, 9:00–14:59 and 15:00–20:59; Felson and Poulsen (2003) used 05:00–16:59 and 17:00–4:59 in their analysis. Our choice of temporal boundaries aimed to maximise homogeneity in each shift with respect to obligatory activities and temperature.

[c]Which became part of Police Scotland in April 2013.

[d]This equated to 14,607 shifts; 4 shifts per day multiplied by 3,652 days, minus the one incomplete shift.

[e]We also considered the differences between Glasgow Airport and nearby weather stations in other parts of the study area. The daily minimum, maximum and average temperature for the weather station closest to the majority of robberies (Drumalbin) exhibited good agreement with the Glasgow Airport readings (respective correlations: 0.93, 0.96 and 0.96). Other weather stations (Islay, Oban and Glen Ogle) exhibited similar levels of agreement and thus the differences were negligible. We therefore decided to use one central station for the weather data.

[f]We defined this as Friday 4 pm to Monday 4 am.

[g]A variety of tests were performed in the R statistical software: inspection of Pearson Chi-squared tests, Ord plots (Ord 1967), and the Vuong (Vuong 1989) test. These produced convergent results that a negative binomial test was the most appropriate for these data (Vuong statistic comparing Poisson against a negative binomial model was −8.23, p = <0.001).

[h]We selected the reference categories with a larger proportion of the robberies to protect against large VIF scores (Allison 1999).

[i]This was achieved using the 'fdr' parameter in the p.adjust command in R. We thank one of the anonymous reviewers for bringing this to our attention.

[j]The relationship between humidity and temperature was investigated through bivariate coefficient correlations. (LeBeau 1988) contends that the association between many weather variables is nonlinear, and therefore multicollinearity concerns between the variables cannot be ascertained through simple linear relationships explored in the VIF statistic. For example, the relationship between vapour pressure and temperature is logarithmic (Lowry 1969: 68). Thus, humidity relies heavily on temperature, and is not meaningfully interpreted on its own. The results of our investigation revealed no clear relationship, logarithmic or otherwise, which may be due to the consistently high humidity in the study area.

[k]The latter appears counter-intuitive as the 41.7 per cent of robbery in the study period happens during weekends (data not shown). However this can be explained by 80 per cent of weekend robbery being concentrated into the late and night shifts, which are accounted for by the other variables.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
LT conceived the study, conducted all data cleaning and analysis and drafted the manuscript. KB advised on the design of the study, provided

statistical guidance and helped to draft the manuscript. Both authors read and approved the final manuscript.

Received: 30 January 2015 Accepted: 16 April 2015
Published online: 28 April 2015

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