J Quant Criminol (2012) 28:389–410
DOI 10.1007/s10940-011-9145-7

ORIGINAL PAPER

Seasonal Cycles in Crime, and Their Variability

David McDowall · Colin Loftin · Matthew Pate

Published online: 9 October 2011

Abstract Seasonal crime patterns have been a topic of sustained criminological research for more than a century. Results in the area are often conflicting, however, and no firm consensus exists on many points. The current study uses a long time series and a large areal sample to obtain more detailed seasonality estimates than have been available in the past. The findings show that all major crime rates exhibit seasonal behavior, and that most follow similar cycles. The existence of seasonal patterns is not explainable by monthly temperature differences between areas, but seasonality and temperature variations do interact with each other. These findings imply that seasonal fluctuations have both environmental and social components, which can combine to create different patterns from one location to another.

Keywords Seasonal patterns · Panel data · Spatial variability

Introduction

Crime seasonality is a source of predictable variation that can be helpful for developing theories and in forecasting the future. Largely because of these uses, seasonal patterns have been a topic of near-continuous criminological study since the mid-nineteenth century. The findings from this research are nevertheless inconsistent, and differing conclusions exist about even such basic questions as the months in which property crimes reach their peak.

The current paper seeks to add to knowledge about seasonal crime patterns in three ways. First, it presents an analysis of monthly panel data that covers more areas and a longer temporal dimension than previous efforts have considered. This is important because stochastic noise can obscure seasonality, and even a long time series will complete comparatively few cycles. Second, the paper examines mechanisms through which seasonal changes might influence crime rates, especially whether monthly temperatures are sufficient to account for their existence. Lack of evidence that this is so would support the

D. McDowall (✉) · C. Loftin · M. Pate
School of Criminal Justice, University at Albany, 135 Western Avenue, Albany, NY 12222, USA
e-mail: dmcdowall@albany.edu

notion that seasonality has a social component that goes beyond the physical environment. Third, the analysis considers if all United States cities exhibit the same cycles, or whether differences exist in major seasonal characteristics.

The remainder of the paper first selectively reviews the literature on crime seasonality, covering both theoretical mechanisms that could underlie the patterns and empirical findings about their properties. The following sections then discuss the research questions more thoroughly, describe the data and methods, and present the results. The analysis finds evidence of seasonal cycles in all of the crime rates that it examines. These patterns remain after controlling for monthly temperature differences, and for most offenses they vary considerably in form across areas. The final sections consider the implications of the results for understanding how seasonal fluctuations operate to generate crime.

Research on Seasonality in Crime Rates

Empirical Findings

The literature on crime seasonality is large in volume, and it includes a variety of only loosely connected topics. Existing work ranges from analyses of fluctuations in high-frequency data (hourly, daily, weekly) to studies of the criminological relevance of humidity, cloud cover, and other environmental conditions. Thorough reviews of this research are already available (e.g., Baumer and Wright 1996; Cohn 1990), and the present paper will consider only the part of it that focuses on recurring annual patterns.

The most elementary questions about seasonality are whether crime rates follow predictable cycles, and if so, in which months are they highest and lowest. Research generally concludes that offenses do differ with the seasons (homicide being a possible exception), but existing work disagrees about most other issues.

Quetelet (1969/1842) reported that peaks occurred in the winter for property crimes and in the summer for violent crimes, and his claims heavily influenced later thinking. Sutherland's (1947) classic textbook asserted the findings as facts, and contemporary discussions still occasionally use them as summaries (e.g., Baumer and Wright 1996).

Some current studies do find opposite cycles for violent and property crimes (e.g., Farrell and Pease 1994), but such outcomes are relatively rare. Lab and Hirschel (1988) note that most work since the early twentieth century instead shows either summer peaks for all offenses or complex patterns that resist easy summarization. Representative examples include Cohn and Rotton (2000), Dodge (1988), Dodge and Lentzner (1980), and Yan (2004), who reached similar conclusions from different geographical areas and data sources. The most sophisticated and comprehensive analysis, by Hipp et al. (2004), also concludes that both types of crime take place most often in the summer.

Yet even among recent studies, substantial differences appear when the discussion moves from broad classifications to individual offenses. Some research finds seasonal patterns in rape rates, for example, (e.g., Anderson 1989; Hird and Ruparel 2007; Michael and Zumpe 1983), but other research does not (e.g., Deutsch 1978). Robbery (conceived of variously as a property crime or a violent crime) has summer peaks in some studies (e.g., Cohn and Rotton 2000), and winter peaks in others (e.g., Field 1992; Landau and Fridman 1993).

Homicide has received the most attention among individual offenses, and it produces the most divergent results. Studies that do find seasonal patterns almost always conclude that the peak is in the summer (Anderson 1989; Hakko 2000; Tennenbaum and Fink 1994;

Warren et al. 1983). Many studies, however, find no evidence of any homicide seasonality at all (Deutsch 1978; Landau and Fridman 1993; Michael and Zumpe 1983).

Researchers have often attributed the negative findings to the fact that homicides occur less frequently than do other crimes (e.g., Rock et al. 2003; Tennenbaum and Fink 1994). One consequence of this rarity is that conclusions about seasonal patterns can more easily vary with analytical approaches. Rock et al. (2003), for example, used modern methods to study a homicide series originally collected by Brearley (1932). Brearley's rudimentary analysis had found that the series was not seasonal, but Rock et al. detected a clear cycle that peaked in the summer.

A closely related problem is that all existing homicide research has had a relatively short temporal component. The Brearley data covered only 6 years, and the time spans for other studies have been of similar length. Examples include Deutsch (1978), who analyzed 10 years of monthly data; Landau and Freedman (1993), who analyzed 9 years; Rock et al. (2008), who analyzed 5 years; and Tennenbaum and Fink (1994), who analyzed 14 years. Study periods this brief require a very strong pattern if an analysis is to detect it.

Homicide research has also generally studied only a few local areas or a single national aggregate. For the examples above, Deutsch (1978) analyzed time series from 10 U.S. cities; Landau and Freedman (1993) used a nationwide series from Israel; Rock et al. (2008) used a nationwide series from England and Wales; and Tennenbaum and Fink (1994) used a nationwide series from the United States. Results from a nation or a handful of subnational units may be misleading if seasonal cycles operate differently in some places than in others.

The concerns about short series and limited areal samples could apply to other individual offenses besides homicide, and also to broader property and violent crime aggregations. When one dimension, temporal or areal, has been large in seasonal research, the other dimension has been small. In the most thorough study, Hipp et al. (2004) analyzed a sample of more 8,000 local areas, but only over a three-year interval. The time dimension reduced their ability to study variation in the seasonal effects, and it raised the possibility that the choice of an atypical period might have influenced their results.

Theoretical Background

Contemporary research usually accounts for crime seasonality through use of temperature-aggression theories or routine activities theory. Temperature-aggression theories are the more limited of the two, and they stress the idea that humans become increasingly irritable as heat and humidity levels rise (e.g., Anderson 1989). Several variants of the theories exist, differing from each other in important respects (Bell and Baron 1976; Anderson et al. 1995; Cohn et al. 2004). All versions of the theories nevertheless predict that the summer months will experience higher rates of criminal violence due to the greater frequency of hot weather. Beyond this general claim, temperature-aggression theories otherwise have little to say about seasonal fluctuations in violence, and they lack any straightforward application to property crimes. Most empirical research involving the theories therefore focuses on temperature variations, and seasonal cycles ultimately have no analytical interest in themselves (Anderson et al. 1997; DeFronzo 1984; Harries and Stadler 1983).

Routine activities theory offers a more comprehensive approach to seasonality, and it can in principle explain patterns in both violent and property offenses. The theory calls attention to how temporal cycles help structure individual behaviors, most obviously through changes in the physical environment. Pleasant weather in the spring and summer encourages people to spend more time outdoors, for example, and away from their homes.

Absence from home then reduces the ability of these potential victims to guard their property, and it in addition places them in settings with higher risks of assaultive violence (see, e.g., Cohn 1990). Other physical factors that might influence contact between victims and offenders, such as the number of daylight hours, similarly vary with the seasons (Van Kopen and Jansen 1999).

Although existing applications of routine activities theory emphasize the weather and environmental phenomena, social activities may independently work to generate seasonal fluctuations. Miron (1996) argues that much of the seasonality in the economy is due to summer vacations and to Christmas-related production and consumption. It seems plausible that these and other socially-patterned cycles would also influence outcomes such as crime.

In its current state, routine activities theory is limited by its ability to fit almost any pattern of results. Cohn and Rotton (2000) used it to account for summer robbery peaks, for example, while Landau and Fridman (1993) used it to explain robbery peaks in the winter. Such contradictory predictions are due to the theory's flexibility, which makes it compatible with multiple outcomes. Most of the research that has relied on routine activities theory has therefore used it to organize findings, not as a source of testable hypotheses.

The work of Hipp et al. (2004) provides a notable exception to this lack of theoretical development. Hipp and colleagues tested predictions from routine activities and temperature-aggression theories, finding much more support for the former than the latter. Besides comparing routine activities theory with other explanations, another way to increase its relevance to seasonality would be to use it to understand how seasonal patterns might arise. As explained in more detail below, the present paper will attempt to move in this direction.

Current Study

The divergent findings of earlier research suggest that accurate seasonal estimates require data from many years and from multiple locations. To obtain such estimates, the current paper will use a monthly panel of 88 U.S. cities followed over a twenty-four-year period. Considering the temporal and spatial dimensions together, this is the most extensive set of data yet assembled to study crime seasonality. While any data set has limitations, the findings will be much less dependent on features unique to settings and times than has been true in the past.

The analysis will consider each of the major FBI Part I offenses, and it will estimate a separate seasonal coefficient for each month of the year. Past research has most often used general indices of property and violent crimes, and has concentrated on bimonthly or quarterly rates. These aggregations are useful with small data sets because they reduce the impact of random variations. They also risk diluting the strength of the seasonal differences, however, and they can conceal patterns specific to a particular offense. The larger number of observations in the present study eliminates the need for this loss of detail.[1]

Developing better estimates of crime seasonality is worthwhile by itself, and the results should help resolve questions about the size and nature of the annual cycles. Beyond improved estimates, however, the analysis will also address two theoretical questions about

[1] Consistent with the bulk of research in all areas of the social sciences, we define seasonality as any cyclical pattern that repeats itself at regular intervals. The finer variation in monthly data allow a more detailed study of seasonal patterns than do quarterly aggregations into spring, summer, autumn, and winter. The relatively course quarterly aggregations may in fact obscure information about how seasonality occurs.

how seasonal fluctuations might occur. The first of these involves the degree to which seasonality is the result of monthly temperature changes. As mentioned earlier, the activity patterns that accompany warmer or cooler weather may help generate seasonal variability in exposure to crime. In particular, comfortable temperatures encourage persons to engage in activities outside their homes, so increasing the risks to themselves and their property.

If routine activities operate this way, crime rates should always be higher in the summer, and temperature changes should substantially mediate the seasonal pattern. Including average monthly temperatures in a model with seasonal effects should accordingly reduce the size of the annual variations, and in the extreme make them disappear entirely. If appreciable differences remain after controlling for average temperatures, environmental conditions become a less compelling explanation for the existence of seasonality. The outcome would still be consistent with routine activities as a source of seasonal fluctuations, but it would suggest that social factors should receive more attention than has previously been true.

Past research has not directly considered the role of temperatures in generating seasonal crime cycles. A partial exception is Cohn and Rotton (1997, 2000), who analyzed violent and property crimes in Minneapolis. They found statistically significant monthly differences after controlling for temperatures and weather conditions, supporting the notion that these were not the only variables underlying the seasonal patterns. Still, their major interests lay elsewhere, and they did not report whether the seasonal effects were larger before they added the controls.

If monthly temperature changes do not fully explain seasonality, another issue is whether the seasonal variations interact with temperatures. Here temperatures would moderate the seasonal cycle, and the impact of seasonality would differ across cities. Conclusions about seasonal patterns, including about such basic matters as whether crime rates are highest or lowest in the summer, could then depend on the areas under study.

Hipp et al. (2004) have already presented evidence of variability in seasonal influences, showing that cities with larger temperature differences have more pronounced annual crime cycles. Hipp and his associates were primarily interested in time-constant climate features, however, and so did not examine month-to-month temperature changes. They assumed that areas differed only in the extremity of their oscillations, and that other characteristics of the cycles operated identically. In contrast, the analysis here allows the possibility that even the basic appearance of the seasonal patterns may vary across cities. Hipp et al. address an important question, and the current research in part complements their efforts. Still, the issues that Hipp et al. consider are different from those in the present paper.

Data

The study uses monthly data from the 88 U.S. cities that had 2000 Census populations of 200,000 persons or more. The analysis covers the years between 1977 and 2000, and separately considers the crimes of homicide, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft. Offense counts come from the FBI's Uniform Crime Reporting (UCR) program, and populations for the rates are interpolations of UCR estimates.

The UCR program devotes most of its efforts to producing annual crime counts. The program also collects and distributes monthly counts, but it does not attempt to insure their accuracy or consistency. Many agencies submit crime reports only intermittently through the year, or they provide quarterly or semiannual totals rather than monthly ones (Maltz 1999, 2007). Beyond the difficulties posed by these temporally aggregated submissions, zeros in the monthly counts may indicate either no offenses or an absent report.

To avoid these problems, the paper uses a unique data file assembled and distributed by Michael Maltz (2009). Maltz individually examined agency-level UCR submissions, flagging months with missing, aggregated, or questionable entries. His efforts make it possible to take advantage of the monthly UCR data without the errors that have reduced their value in the past.

The Maltz data set begins in 1960, and it includes more than seventeen thousand law enforcement agencies. The current study might therefore have extended itself in both the temporal and cross-sectional dimensions. Areas with small populations nevertheless have few serious crimes, and low frequencies make it more difficult to detect the existence of seasonal patterns. Monthly crime counts for offenses such as homicide are often low even for cities with populations exceeding 200,000, and less populous areas would make the problems worse. A longer time span would similarly result in some cities having unacceptably small populations in the earlier years of the analysis. In 1960, for example, Mesa, Arizona had only 34,000 residents, and Plano, Texas, had only 4,000. Although the study's selection criteria are somewhat arbitrary, they balance a reasonably long temporal dimension with a reasonably large cross-section.

Analytic Strategy

The paper's basic analytical model is a panel extension of the classical time series decomposition (see, e.g., Brockwell and Davis 2002; Mills 2003). The classical decomposition divides a series into trend, seasonal, and random components, and the paper's specification of it is:

$$Y_{it} = \alpha_i + \beta_1(\text{Time}_t) + \cdots + \beta_n\left(\text{Time}_t^n\right) + \gamma_1(\text{January}_t) + \cdots + \gamma_{11}(\text{November}_t) + v_{it}$$

Here the α_i are coefficients for fixed effects (dummy variables) that individually distinguish each city; β_1 through β_n are slopes for a linear time trend and its powers; γ_1 through γ_{11} are coefficients for a set of monthly dummy variables; and v_{it} is an error unique to a year and city.

The fixed effects allow for constant between-area differences in crime, and they control for factors that make a particular city's rate consistently higher or lower than the sample average. The time variables allow for linear and nonlinear trends that operate identically across all cities, and the monthly dummies measure the impact of seasonal variations. Classical decompositions usually consider seasonal patterns only within a single area. The present paper modestly extends the approach to panel data, but it is not the first analysis to do so (see, e.g., Cohen et al. 2003; Gorr et al. 2003).

The dummy variable specification imposes deterministic effects, and a stochastic model would allow variation in the seasonal influences across years (Ghysels and Osborn 2001). Miron (1996) points out that deterministic seasonality is usually theoretically plausible, however, and notes that models for it are straightforward to apply. He argues that these features make deterministic effects the most reasonable starting point for any study of seasonal fluctuations.

A seasonal ARIMA analysis (Brockwell and Davis 2002; McCleary et al. 1980), perhaps the major stochastic alternative to classical decomposition, would also not address the paper's central interests. An ARIMA model can easily incorporate seasonal correlation structures, but it will not provide coefficients for the individual months of the cycle. Without additional computations, one could not use ARIMA results to find the months in which crime rates were highest or lowest, or to estimate the sizes of monthly differences. The classical decomposition, in contrast, provides these quantities directly. An ARIMA model also would not easily combine data from multiple areas, and it would require all seasonal variation to follow a symmetrical curve. A panel model pools data by design, and a set of seasonal dummy variables allow a cycle that is asymmetrical around its peak and trough.

An important weakness of classical decomposition, especially compared with ARIMA modeling, is in its handling of trends and other forms of time series nonstationarity. Classical decomposition assumes that nonstationarity–any lasting departure of a series away from its mean–is due to deterministic trends that operate consistently over time. Series often display stochastic nonstationary features, however, which a deterministic model cannot remove (see, e.g., Enders 2010). To evaluate the dependence of the results on the deterministic trend assumption, the paper will therefore consider supplementary analyses that allow for stochastic nonstationary behavior.

A classical decomposition is not the only deterministic model that the paper might have used. Trigonometric analysis is a well-developed alternative approach, and several past studies have applied it (Michael and Zumpe 1983; Rock et al. 2003, 2008; Hipp et al. 2004). Dummy variable and trigonometric models are equivalent in their implications, however (Ghysels and Osborn 2001: 20–24), and the dummy variables are easier to interpret.

Many methods for studying seasonality exist, and all of them have advantages and limitations unique to themselves. Like any method, classical decomposition is not ideal in all respects. It considers questions about the size and pattern of month-to-month seasonal fluctuations, however, and this allows it to directly address the paper's major interests.

Besides the fixed effects, trends, and monthly dummy variables, the basic model also allows for two ways in which calendar variation might generate false evidence of seasonal patterns. First, shorter months have fewer opportunities for crime than do longer ones, and they might be low points for that reason only. Second, homicides occur most often on the weekends (Ceccato 2005; Wolfgang 1958), and other offenses may also have day-of-the-week patterns of their own. This complicates the analysis, because the frequency of specific weekdays within a month will differ from year to year.

To handle the first issue, the model includes a variable for the number of days within each month. To accommodate the second, the model includes variables for the number of Saturdays, Sundays, Mondays, Tuesdays, Wednesdays, and Thursdays in each month, minus the number of Fridays. Bell and Hillmer (1983) propose this specification to reduce collinearity between the weekday variables, and the present analysis adopts it even though it seeks only to control their joint influence.

The basic model will estimate the size and form of the seasonal fluctuations, and it addresses the first of the paper's three major concerns. The paper's second interest is in whether average monthly temperatures help account for the existence of any seasonal effects. To consider this, the analysis augments the basic model with a measure of mean month-to-month temperatures within each city.[2] If temperature variations explain seasonal patterns, the coefficients for the monthly dummy variables should decrease in size after controlling for them.

[2] The temperature data are monthly means as recorded by the U.S. Weather Service. They were retrieved from http://www.eachtown.com on the World Wide Web, and were current as of June 5, 2011.

Finally, the paper's third concern is with whether the relationship between temperatures and seasonal fluctuations is constant across areas. If this is not so, temperatures moderate the relationship between seasonality and crime, and cities can exhibit fundamentally different seasonal patterns. To evaluate this possibility, the analysis will add product variables to measure the interactions between the seasonal dummies and the city-level monthly temperatures.

Results

Basic Classical Decomposition Model

Estimates for the basic model appear in Table 1.[3] The dependent variable in each equation is the logarithm of the relevant crime rate. The log transformation helps equalize error variances, and simplifies comparisons by expressing all effects in a proportional (percentage) metric.[4] Standard errors for the coefficients are heteroscedasticity and autocorrelation consistent, allowing for serial dependence while also providing additional protection against non-constant variances.[5]

Table 1 shows broadly similar seasonal patterns for the crimes, with most rates descending to their low points in the winter and reaching their peaks in the summer. All crimes occur least frequently in December, January or February, and except robbery, all occur most frequently in July or August. Measured from peak to trough, the sizes of the seasonal oscillations are roughly equal across the offenses, ranging from .15 for burglary to .33 for rape.

Robbery stands out as a partial exception to the other crimes, since it has a peak that occurs in December rather than during the summer. Rates in December are not much higher than those in July or August, however, and robbery follows the other crimes in having its trough occur during the winter.[6] Homicide also modestly differs from the

[3] To streamline the presentation, all tables omit the eighty-seven city-specific fixed effects. Similarly to reduce clutter, the tables include only trend variables for time (grand mean centered) and its squared values. For some crimes, time polynomials up to the twelfth-order in fact significantly contributed to the models. This is unsurprising given the large sample size, and polynomials higher than the second-order did not substantively affect the other estimates.

[4] Collinearity does not pose significant problems for the analysis. A single collinearity index for the entire set of eleven dummy variables is more helpful than are individual measures for each month. The study therefore evaluated collinearity using condition indices instead of the more familiar variance inflation factors. For the Table 1 models, the largest condition indices were twenty-two or less, below the value of thirty that Belsley et al. (1980) suggest as a threshold for concern. Much of the collinearity that did exist was due to the day-of-week measures. Dropping these from the analysis did not appreciably change the conclusions about seasonality, but it decreased the condition indices to eight or less.

[5] These are Rogers robust standard errors, which allow for unspecified forms of within-city serial correlation. Newey-West robust standard errors resulted in inferences that were substantively similar but not absolutely identical. Both types of robust standard errors provide consistent estimates under very general assumptions about heteroscedasticity and autocorrelation structures. More detailed assumptions about the errors (as exist, for example, in an ARIMA model) would increase estimation efficiency if the assumptions were true. The large sample size makes efficiency a relatively unimportant consideration here, however. Peterson (2009) offers a thorough technical discussion of Rogers, Newey-West, and other robust standard errors for panel data. Stock and Watson (2007) consider the same material more intuitively and in a more general context.

[6] Several of the contemporary studies that claim to find a winter property crime peak actually analyze robbery rates (e.g., Landau and Fridman 1993; Michael and Zumpe 1983). The FBI classifies robbery as a violent crime, and the purely property-related offenses of burglary, larceny, and motor vehicle theft all peak in August.

Table 1 Basic seasonal decomposition model

	Murder Coefficient (SE)	Rape Coefficient (SE)	Robbery Coefficient (SE)	Assault Coefficient (SE)	Burglary Coefficient (SE)	Larceny Coefficient (SE)	Motor vehicle theft Coefficient (SE)
January	−.07184* (.01836)	.03552* (.01494)	−.05669* (.00858)	−.01229 (.00717)	−.03292* (.00720)	−.03824* (.00667)	−.00753 (.00621)
February	−.25374* (.07019)	.17251* (.05466)	−.23198* (.03220)	−.01842 (.02488)	−.11972* (.01914)	−.07428* (.01392)	−.12112* (.02744)
March	−.08994* (.01813)	.09897* (.01359)	−.16227* (.00969)	.07462* (.00696)	−.08268* (.00787)	−.00219 (.00500)	−.02311* (.00809)
April	−.13084* (.02948)	.19597* (.02545)	−.21777* (.01529)	.12169* (.01155)	−.11164* (.00998)	−.02283* (.00746)	−.07190* (.01440)
May	−.05140* (.01595)	.20663* (.01504)	−.21467* (.00100)	.19129* (.00942)	−.07121* (.00695)	.00135 (.00679)	−.03351* (.00871)
June	−.09443* (.03031)	.31252* (.02512)	−.21778* (.01529)	.20764* (.01353)	−.06110* (.01259)	.03093* (.01086)	−.01518 (.01695)
July	.01951 (.01741)	.32322* (.01627)	−.10512* (.00852)	.25696* (.01081)	.02754* (.00946)	.07329* (.00956)	.07069* (.01283)
August	.03153 (.01974)	.33180* (.01661)	−.07932* (.00997)	.24162* (.01019)	.03492* (.00916)	.09837* (.00912)	.08794* (.01229)
September	−.06816* (.03136)	.30269* (.02324)	−.12701* (.01443)	.18031* (.01372)	−.00510 (.01191)	.02132* (.01022)	.01702 (.01681)
October	−.01381 (.01701)	.18075* (.01322)	−.05040* (.00918)	.13097* (.00729)	−.00669 (.00607)	.04799* (.00636)	.05188* (.00879)
November	−.10839* (.03152)	.15724* (.02151)	−.08978* (.01305)	.03551* (.01069)	−.03034* (.00856)	−.00434 (.00797)	−.01001 (.01320)
Time	.00076* (.00022)	−.00056* (.00020)	.00024 (.00023)	.00227* (.00022)	−.00260* (.00019)	−.00031 (.00016)	.00170* (.00024)
$Time^2$	−.00001* (.000002)	−.00002* (.000001)	−.00002* (.000001)	−.00002* (.000002)	−.00001* (.000001)	−.00001* (.000001)	−.00002* (.000002)

Table 1 continued

	Murder Coefficient (SE)	Rape Coefficient (SE)	Robbery Coefficient (SE)	Assault Coefficient (SE)	Burglary Coefficient (SE)	Larceny Coefficient (SE)	Motor vehicle theft Coefficient (SE)
Total days	−.03449 (.02454)	.07396* (.01898)	−.01591 (.01142)	.01669 (.00915)	.01454* (.00740)	.01235* (.00535)	−.00339 (.01041)
Saturdays	.00127 (.00960)	.00056 (.00662)	.01326* (.00437)	.00828* (.00296)	−.00370* (.00157)	−.00238* (.00136)	−.00293 (.00266)
Sundays	.00202 (.00877)	.00537 (.00693)	−.01568* (.00341)	−.00037 (.00264)	−.00853* (.00173)	−.01059* (.00121)	−.00405 (.00273)
Mondays	−.01609 (.00884)	−.00216 (.00693)	.00927* (.00330)	.00162 (.00281)	.00837* (.00172)	.00479* (.00135)	.00549* (.00252)
Tuesdays	.02706* (.00920)	.00677 (.00663)	−.00273 (.00279)	−.00013 (.00282)	.00167 (.00172)	.00356* (.00122)	−.00082 (.00235)
Wednesdays	−.02121* (.00930)	−.00327 (.00557)	.00007 (.00384)	−.00730* (.00292)	.00431* (.00170)	.00153 (.00107)	.00033 (.00253)
Thursdays	.00774 (.00797)	−.00001 (.00557)	.00028 (.00314)	.00095 (.00314)	.00197 (.00166)	.00396* (.00124)	−.00267 (.00286)
Constant	.38047* (.02298)	1.46026* (.01708)	3.2780* (.01468)	2.99108* (.01727)	5.27969* (.01026)	6.15575* (.16734)	4.35436* (.01929)

* $p < .05$, two-tailed test

remaining offenses, since its level during December is not significantly lower than its high point in August. Putting these comparatively modest exceptions aside, the unconditional results show that most crimes follow the same basic cycle.

Model Including Average Temperatures

Table 2 adds average monthly temperatures to the Table 1 model.[7] Because of the logarithmic transformation, the slopes multiplied by one hundred are the approximate percentage change in each offense expected from a 1° temperature increase. The temperature difference between the coldest and warmest months was on average about forty degrees, implying annual crime variations of between 7% (for homicide) and 27% (for assault). Except homicide, the effects of temperatures are statistically significant independent of the seasonal dummies. Monthly temperatures therefore have clear importance in generating seasonal crime cycles.

Several distinct patterns appear when comparing the estimates in Table 2 with their counterparts in Table 1. One should be cautious in interpreting the apparent differences across models, because some of them could be due to chance. The analysis nevertheless provides little support for the notion that temperature variations can fully explain the seasonal effects. If this were so, the coefficients for the seasonal dummy variables should decrease after controlling for temperatures, and this is substantially the case only for rape and assault. The maximum seasonal variation for rape drops more than 50% after adding temperatures to the models, while the maximum for assault decreases by 80%. Yet even for these crimes the seasonal variations remain statistically significant, so temperatures do not completely account for them.

The estimates for the remaining crimes vary in ways inconsistent with the idea that temperatures explain seasonality, and instead display a range of other outcomes. Among the most interesting of these are for burglary, larceny, and motor vehicle theft, which change in their basic seasonal structures. Without considering monthly temperatures, the three offenses reach their high points in August and are lowest in February. After removing the influence of temperatures, the crimes all show peaks in December or January, and their troughs occur in the spring and early summer.

These results are what one would expect if routine activity patterns had both environmental and social components. Presumably, the harsher weather conditions in winter make burglaries and other property crimes less attractive to potential offenders. Yet wintertime social activities–especially activities affecting property availability and guardianship around Christmas–may counterbalance the physical disincentives. The sources of the troughs in the spring and early summer are not as obvious, but they are much less prominent than are the Christmastime high points.

Monthly temperature variations do not much influence the seasonal patterns for the two remaining offenses, homicide and robbery. Although the peak and trough months are not identical in Tables 1 and 2, the differences in the coefficients are small. Homicide stands out from the other crimes in that it remains completely unaffected by temperature changes. This finding is somewhat puzzling, because the circumstances surrounding homicides and assaults are similar enough that one might expect the environment to have the same effects

[7] The analysis centered the monthly temperature variable about its grand mean to reduce collinearity with the other model components. Perhaps as a consequence, condition indices for the models including temperatures were only marginally higher than for their counterparts in Table 1.

Table 2 Seasonal decomposition model, controlling for average monthly temperatures

	Murder Coefficient (SE)	Rape Coefficient (SE)	Robbery Coefficient (SE)	Assault Coefficient (SE)	Burglary Coefficient (SE)	Larceny Coefficient (SE)	Motor vehicle theft Coefficient (SE)
January	−.06694* (.01825)	.05256* (.01528)	−.05063* (.00835)	.00600 (.00686)	−.01767* (.00625)	−.02085* (.00549)	.00236 (.00608)
February	−.25416* (.07036)	.16000* (.05436)	−.23317* (.03221)	−.02218 (.02493)	−.12276* (.01934)	−.07766* (.01393)	−.12299* (.02762)
March	−.10318* (.02058)	.04904* (.01549)	−.17982* (.01234)	.02178* (.00798)	−.12682* (.01080)	−.05249* (.00807)	−.05171* (.01015)
April	−.15750* (.03456)	.09682* (.02812)	−.29065* (.02177)	.01643 (.01464)	−.19943* (.01405)	−.12289* (.01168)	−.12877* (.01746)
May	−.09163* (.03438)	.05751* (.02650)	−.26714* (.02339)	.03310* (.01513)	−.20318* (.01863)	−.14910* (.01553)	−.11906* (.01967)
June	−.14741* (.04751)	.11663* (.03732)	−.28676* (.03100)	−.00040 (.02126)	−.23463* (.02252)	−.16686* (.01904)	−.12763* (.02885)
July	−.04028 (.04637)	.10212* (.03339)	−.18296* (.02974)	.02253 (.02143)	−.16823* (.02538)	−.14988* (.02190)	−.05621 (.03045)
August	−.02656 (.04733)	.11664* (.03235)	−.15511* (.03017)	.01306 (.02148)	−.15571* (.02481)	−.11894* (.02108)	−.03563 (.02884)
September	−.11653* (.04591)	.12334* (.03422)	−.19013* (.02890)	−.01087 (.02077)	−.16386* (.02117)	−.15963* (.01712)	−.08585* (.02698)
October	−.04609 (.02706)	.06103* (.02148)	−.09324* (.01701)	.00395 (.01293)	−.11265* (.01485)	−.07280* (.01122)	−.01750 (.01640)
November	−.12349* (.03298)	.10123* (.02235)	−.10947* (.01567)	−.02382* (.01159)	−.07986* (.09166)	−.06076* (.00755)	−.04207* (.01437)
Time	.00076* (.000422)	−.00056* (.00020)	.00024 (.00023)	.00227* (.00022)	−.00260* (.00019)	−.00031 (.00016)	.00170* (.00024)
$Time^2$	−.00001* (.000002)	−.00002* (.000001)	−.00002* (.000001)	−.00002* (.000002)	−.00001* (.000001)	−.00001* (.000001)	−.00002* (.000002)

Table 2 continued

	Murder Coefficient (SE)	Rape Coefficient (SE)	Robbery Coefficient (SE)	Assault Coefficient (SE)	Burglary Coefficient (SE)	Larceny Coefficient (SE)	Motor vehicle theft Coefficient (SE)
Total days	−.03440 (.02456)	.07402* (.01890)	−.01588 (.01140)	.01670 (.00918)	.01458* (.00741)	.01242* (.00533)	.00359 (.00092)
Saturdays	.00123 (.00959)	.00044 (.00662)	.10321* (.00436)	.00818* (.00296)	−.00384* (.00516)	−.00253 (.00137)	−.00304 (.00267)
Sundays	.00208 (.00876)	.00551 (.00693)	−.01561* (.00341)	−.00029 (.00264)	−.00839* (.00173)	−.01044* (.00121)	−.00396 (.00274)
Mondays	−.01610 (.00884)	−.00225 (.00694)	.00925* (.00330)	.00166 (.00281)	.00830* (.00172)	.00472* (.00134)	.00545* (.00252)
Tuesdays	.02704* (.00929)	.00681 (.00662)	−.00274 (.00279)	−.00016 (.00282)	.00166 (.00172)	.00352* (.00122)	−.00083 (.00235)
Wednesdays	−.02119* (.00929)	−.00326 (.00557)	.00011 (.00384)	−.00723* (.00293)	.00439* (.00170)	.00163 (.00106)	.00038 (.00254)
Thursdays	.00762 (.00800)	−.00016 (.00614)	.00019 (.00314)	.00077 (.00316)	.00176 (.00166)	.00372* (.00123)	−.00280 (.00287)
Monthly Temperature	.00170 (.00116)	.00627* (.00089)	.00220* (.00076)	.00666* (.00061)	.00554* (.00068)	.00632* (.00059)	.00359* (.00092)
Constant	.39360* (.02515)	1.50955* (.01838)	3.29538* (.01624)	3.04336* (.01752)	5.32338* (.01099)	6.20553* (.00970)	4.38265* (.01913)

* $p < .05$, two-tailed test

on both. As Rock et al. (2008) note, however, much previous research has also found the two offenses to have different seasonal patterns.[8]

Overall, the results show interesting variations across the crimes. These differences are nevertheless secondary to the overall finding that temperature changes cannot explain the existence of seasonality. Annual temperature variations do have an impact on crime rates, but these effects operate along with other characteristics of the seasonal process. This outcome supports the notion that seasonal fluctuations are not due only to the physical environment, and that they also have a meaningful source in social activities.

Model Including Interaction Terms

The analysis has to this point assumed that the effects of temperatures and seasonality are geographically constant. Temperature differences and the seasonal dummy variables influence crime rates identically everywhere, and a single seasonal pattern characterizes all cities. The estimates in Table 3 consider the possibility that the monthly dummies instead interact with temperatures, so that seasonal changes operate differently in different locations.[9]

The sets of interaction terms made jointly insignificant contributions to the models for homicides and assault, and Table 3 therefore does not include these two offenses. This lack of significance is itself notable, because it means that homicide and assault rates do in fact follow the same seasonal patterns across the United States. Among the remaining crimes, the most consistently significant interaction coefficients are for the months in the winter (January, February, and March) and spring (April, May, and June). The offenses also generally display at least a few significant interactions at other times, and this is especially so for larcenies.

For robberies, burglaries, and vehicle thefts, the signs of the significant interactions are mostly opposite to those of their seasonal main effects. This pattern implies that seasonal fluctuations decrease as city temperatures rise. For rapes and larcenies, on the other hand, most of the interactions and main effects have the same signs, and temperatures amplify seasonality.

The interaction analysis allows for the possibility that cities differ in the extremity of their seasonal changes. For each crime, Table 4 lists the percentage difference between the peak and trough months for the three cities with the largest and smallest seasonal variations. The differences between the most and least seasonal cities are generally substantial. Larceny rates in Minneapolis are more than 42% higher at their peak than at their trough, for example, but the difference is only 12% in Tampa. For all crimes (and consistent with Hipp et al. 2004), the cities with flatter seasonal crime cycles have warmer climates, while seasonality is strongest in the colder climate cities.

8 In this connection, Kleck (1991) argues that assaults and homicides are less alike in their circumstances and motivations than criminologists often believe. He challenges especially the notion that weapon availability is often the only difference between the two crimes. Alternatively, Block (1984) argues that neither homicides nor assaults truly follow seasonal patterns. Instead, according to her explanation, assaults are more likely to come to police attention during the summer, so creating a false seasonality that depends on recording practices. Dodge (1988) found that aggravated assault reports by National Crime Survey respondents did have seasonal structure, however, and this is inconsistent with the operation of a recording artifact. More generally, the link between assaults and homicides has implications for many questions in criminology, and it deserves closer investigation than the current paper can give it.

9 The analysis used the centered monthly temperature variable to construct the interaction terms. The condition indices for the interaction models were all between 24 and 25. These are higher than for the other models, but still not large enough to suggest problematic collinearity levels.

Table 3 Seasonal decomposition model, with interactions between months and average monthly temperatures

	Rape Coefficient (SE)	Robbery Coefficient (SE)	Burglary Coefficient (SE)	Larceny Coefficient (SE)	Motor vehicle theft Coefficient (SE)
January	.04754 (.02710)	−.01252 (.01537)	.04191* (.01540)	.03362 (.00987)	.02609* (.01074)
February	.17377* (.05562)	−.17524* (.03367)	−.05094* (.02231)	−.02083 (.01631)	−.07338* (.02869)
March	.06769* (.01960)	−.12592* (.01481)	−.06589* (.01458)	−.01617 (.01192)	−.00776 (.01224)
April	.10401* (.03104)	−.25382* (.02262)	−.15059* (.01420)	−.09062* (.01192)	−.10037* (.01774)
May	.02785 (.03002)	−.23559* (.02679)	−.15526* (.01716)	−.09023* (.01295)	−.08817* (.01705)
June	.05268 (.04178)	−.24367* (.03847)	−.16032* (.02160)	−.06943* (.01778)	−.10255* (.02278)
July	.10470* (.04302)	−.13312* (.04261)	−.08773* (.02688)	−.02607 (.02415)	−.07638* (.02742)
August	.07366 (.03836)	−.07908 (.04528)	−.08075* (.02663)	.00296 (.02235)	−.05689* (.02339)
September	.07084* (.03844)	−.14325* (.03589)	−.09647* (.02133)	−.07164* (.01844)	−.07552* (.02286)
October	.05830* (.02407)	−.04915* (.01986)	−.06033* (.01692)	−.02918* (.01215)	.01515 (.01667)
November	.10919* (.02457)	−.09439* (.01722)	−.05267* (.01237)	−.05519* (.00919)	−.03216* (.01547)
Time	−.00056* (.00020)	.00024 (.00023)	−.00260* (.00019)	−.00031* (.00017)	.00170* (.00024)
Time^2	−.00002* (.000001)	.00002* (.000002)	−.00001* (.000001)	−.00001* (.000001)	−.00002* (.000002)
Total days	.07377* (.01887)	−.05617 (.01134)	.01489* (.00744)	.01297* (.00528)	.00313 (.01031)
Saturdays	.00041 (.00662)	.01322* (.00437)	−.00383* (.00157)	−.00258 (.00136)	−.00304 (.00267)
Sundays	.00547 (.00693)	−.01571* (.00340)	−.00842* (.00173)	−.01045* (.00121)	−.00404 (.00274)
Mondays	−.00226 (.00694)	.00935* (.00329)	.00837* (.00172)	.00479* (.00134)	.00553* (.00251)
Tuesdays	.00685 (.00661)	−.00280 (.00279)	.00165 (.00172)	.00349* (.00122)	−.00083 (.00234)
Wednesdays	−.00320 (.00557)	.00013 (.00383)	.00436* (.00170)	.00160 (.00107)	.00033 (.00253)
Thursdays	−.00020 (.00614)	.00025 (.00314)	.00182 (.00167)	.00374* (.00122)	−.00270 (.00287)
Temperature	.00609* (.00107)	.00013 (.00091)	.00278* (.00079)	.00431* (.00059)	.00193* (.00095)
January* temperature	−.00022 (.00112)	.00221* (.00068)	.00339* (.00071)	.00303* (.00044)	.00143* (.00048)
February* temperature	.00033 (.00104)	.00340* (.00080)	.00421* (.00072)	.00329* (.00044)	.00292* (.00054)

Table 3 continued

	Rape Coefficient (SE)	Robbery Coefficient (SE)	Burglary Coefficient (SE)	Larceny Coefficient (SE)	Motor vehicle theft Coefficient (SE)
March* temperature	.00190 (.00102)	.00411* (.00080)	.00482* (.00084)	.00224* (.00053)	.00338* (.00077)
April* temperature	.00378* (.00136)	.00305* (.00102)	.00394* (.00096)	−.00004 (.00061)	.00153 (.00109)
May* temperature	.00505* (.00170)	.00264* (.00124)	.00264* (.00090)	−.00165* (.00075)	.00129 (.00118)
June* temperature	.00489* (.00169)	.00155 (.00120)	.00087 (.00099)	−.00239* (.00094)	.00191 (.00128)
July* temperature	.00021 (.00200)	.00128 (.00125)	.00093 (.00125)	−.00290* (.00116)	.00432* (.00137)
August* temperature	.00285 (.00170)	−.00028 (.00145)	.00115 (.00112)	−.00305* (.00102)	.00453* (.00123)
September* temperature	.00497* (.00157)	.00110 (.00101)	.00103 (.00083)	−.00259* (.00069)	.00324* (.00113)
October* Temperature	.00303* (.00117)	−.00185* (.00075)	.00021 (.00063)	−.00257* (.00060)	−.00042 (.00114)
November* temperature	.00082 (.00101)	−.00045 (.00076)	.00028 (.00055)	−.00159* (.00053)	−.00063 (.00074)
Constant	1.48749* (.02365)	3.26846* (.01823)	5.28257* (.01312)	6.19363* (.01128)	4.35192* (.02058)

* $p < .05$, two-tailed test

The paper has several times noted the importance of social factors by pointing to the seasonal variation in crime that temperatures cannot explain. The interaction analysis highlights the impact of temperatures and calls attention to the fact that they also have a very substantial role in generating the annual cycles.

Related to the variable sizes of the seasonal effects, the interactions also imply that cities can follow altogether different patterns. A somewhat crude method of summarizing the differences is to consider how frequently high-crime months in some cities are low-crime months in others. According to Table 3, for example, burglary rates are overall lower in February than in December. Monthly temperature differences have positive effects on burglaries, however, and temperatures also interact positively with the February dummy variable. As a result, all cities above some threshold temperature should have higher burglary rates in February. February temperatures in three cities in fact exceed this threshold, and in contrast to the rest of the nation, February is for them a comparatively high-burglary month.

Similar considerations apply to other crimes and other months, and for each month Table 5 lists the number of cities that differ from the average pattern.[10] For robberies, most cities consistently follow the pattern, but deviations occur often for the other offenses. Deviations are also frequent for all months except May and June. Overall, these results

[10] A complication in evaluating the directional changes is that the coefficients in Table 3 use a mean-centered temperature variable for both the main and interaction effects. Many cities therefore have negative average temperatures in the early months of the year, and directional changes can occur even when the main and interaction effects have the same signs.

Table 4 Cities with strongest and weakest seasonal crime variations

Rape, strongest	% difference, peak and trough	Rape, weakest	% difference, peak and trough
Minneapolis	52.91	San Francisco	23.70
Madison	47.15	Oakland	24.02
Omaha	46.93	Honolulu	25.78
Robbery, strongest	% difference, peak and trough	Robbery, weakest	% difference, peak and trough
Anchorage	34.87	Miami	23.71
Minneapolis	32.97	Corpus Christi	23.79
Milwaukee	32.24	Honolulu	24.11
Burglary, strongest	% difference, peak and trough	Burglary, weakest	% difference, peak and trough
Minneapolis	37.34	Tampa	12.93
Madison	34.97	Corpus Christi	14.35
Milwaukee	33.20	San Jose	15.37
Larceny, strongest	% difference, peak and trough	Larceny, weakest	% difference, peak and trough
Minneapolis	42.21	Tampa	11.08
Madison	39.35	Miami	11.16
Anchorage	39.85	St. Petersburg	12.12
Motor vehicle theft, strongest	% difference, peak and trough	Motor vehicle theft, weakest	% difference, peak and trough
Minneapolis	32.15	San Diego	14.93
Madison	30.24	Anaheim	15.11
Omaha	30.11	Honolulu	15.27

Table 5 Number of cities in which seasonal change differs in direction from main effect prediction, by month

	Rape	Robbery	Burglary	Larceny	Motor vehicle theft
January	72	4	75	77	72
February	22	0	3	3	0
March	45	0	4	9	14
April	15	0	0	0	0
May	0	0	0	0	0
June	1	0	0	0	3
July	0	0	17	43	74
August	0	0	38	1	82
September	1	0	3	0	30
October	16	0	0	4	2
November	21	0	1	0	3

December is the comparison month for all effects indicate that seasonal cycles exhibit considerable geographic variation, and that general statements about seasonality will not adequately characterize all areas.

Supplementary Analyses

In addition to the main models, the paper also undertook two supplementary analyses to assess the sensitivity of the findings to changes in underlying assumptions. The first analysis examined whether stochastic nonstationarity might have affected the results. Classical decomposition is a straightforward method for separating seasonality from other time series components, and it can allow for the presence of deterministic trends. Still, as noted earlier, the method does not consider the possibility of stochastic nonstationarity. Stochastic nonstationarity would impart time-varying trends or drifts on the series, and a classical decomposition cannot control for these features.

One could dispute the importance of stochastic nonstationarity for a study of seasonal variability. The goal of the analysis is to describe monthly crime rate patterns, and this description will hold over the study period even if the rates are stochastically non-stationary. Stochastic trends or drifts in the rates are clearly possible, however, and one would have more confidence in the findings if they did not depend on assumptions about the time series properties of the data.

Several panel unit root tests (see Baltagi 2008) rejected the possibility of stochastic trends or drifts for each crime. This outcome supports the original results, but it is of limited value. Most tests evaluate the null hypothesis that all series in a panel are non-stationary, and so would reject nonstationarity if even a single city followed a stationary process (Enders 2010: 246–247). Post-hoc testing showed that in fact only a handful of areas accounted for the rejections, and a conservative approach would be to proceed as if all series were nonstationary.

To allow for the possibility of stochastic trends and drifts, a supplementary analysis converted the variables from their original levels to first-differences. Differencing transforms a series into period-to-period changes, and it removes any nonstationarity that the original series contained. After reestimating the paper's models on the differenced data, the interaction coefficients for assaults became statistically significant. In all other major respects, the findings for the models and crimes were unchanged.

Besides nonstationarity, a second possible concern comes from the fact that the homicide counts often have values of zero, and so drop out of the analysis after the logarithmic transformation. No city recorded zero burglaries, larcenies, or vehicle thefts in any study month, and results for these crimes are clearly unproblematic. Zero assaults, robberies, or rapes occurred in less than 1% of the months, and here zeros are rare enough to ignore. Cities recorded no homicides in 13% of all months, however, and eliminating these observations might conceivably have affected the findings.

To evaluate the impact of the zero counts, a supplementary analysis estimated negative binomial panel models for the homicide series. These models had the same structure as did the original classical decomposition, but they used homicide counts, including the zero counts, as the dependent variable.[11] For all models, the negative binomial estimates were identical in substance to those from the main analysis, and so again supported the original conclusions.

[11] These models included city population as an exposure variable.

Discussion

This paper had three goals. The first was to use data with large cross-sectional and temporal dimensions to develop improved estimates of U.S. crime seasonality. To this end, the analysis found strong seasonal patterns in all seven of the offenses that it studied. Short time series and small areal samples have made it difficult to separate seasonality from random noise, especially for low-frequency crimes like homicide. Considered over a long time period and many areas, all major crimes appear to exhibit roughly similar degrees of seasonal variability.

The analysis also found that, except for robbery, all crimes peak in July or August and all fall to their low points in February. The robbery results differ only modestly from the other offenses, and they may not merit much stress. Several earlier studies also discovered a December robbery peak, however (e.g., Dodge 1988; Landau and Fridman 1993), and the finding continued to hold after controlling for temperatures. The Christmas holidays might account for more December robberies, but this would also suggest December peaks for larceny and other property-related crimes. However explained, the unique pattern for robbery shows the desirability of studying individual offenses rather than broader multi-crime aggregations.

The paper's second goal was to determine whether monthly temperature variations could explain the existence of the seasonal fluctuations. If this were true, it would mean that any influence of routine activities on crime seasonality would operate through the physical environment. To the extent that it was untrue, social activities must also play a role in the cycles.

The results went against the hypothesis that temperature differences can account for seasonality. Only two offenses (rape and assault) showed evidence consistent with this idea, and even for them the basic patterns remained after adding temperatures as a control. The results for the other offenses were generally complicated to interpret, but temperatures and seasonal variations had independent influences on all crimes except homicide. For property offenses (burglary, larceny, and vehicle theft), the seasonal and temperature effects differed enough that conclusions about seasonality changed after holding temperatures constant.

If seasonal variations are due to factors beyond temperature differences, the logical next step would be to learn more about the variables that generate the patterns. The presentation has stressed summer vacations and the Christmas holidays as likely sources for crime peaks, and this is consistent with seasonality in the economy (Miron 1996). The explanation is speculative, however, and it does not account for the low-crime periods in the late winter and early spring.

Future research might gain additional insight into crime seasonality from the American Time Use Survey (U.S. Bureau of Labor Statistics 2010) and similar studies of how people pattern their lives. Besides revealing cycles in crime-related activities, time use data could help identify the specific activities that underlie the existence of seasonal fluctuations. December is the highest shopping month, for example, but it is also second only to the summer for socializing (Time Use Institute 2010). Research on the relative frequency of other activities over the year could be similarly useful in understanding their influence on crime.

The third goal of the paper was to learn if seasonal fluctuations were identical across cities, or if instead they interacted with temperatures. If the areal patterns do not operate identically, general statements about seasonality can be misleading. Some cities may have more extreme seasonal oscillations than do others, and the high and low points of the cycles may be different in different places. The analysis found evidence of variable seasonality for all crimes except homicide and assault, and the differences were especially notable for property offenses.

Existing research has usually examined only one area, such as a single city or an entire nation, and the current study's findings raise doubts about the wisdom of this practice. For burglary and motor vehicle theft in particular, individual cities often departed substantially from the overall national averages. Researchers could therefore reach conflicting conclusions about cycles in these crimes depending on the areas that they considered. Cohn and Rotton's (2000) investigation of property offenses in Minneapolis, for example, used a city with one of the most unusual seasonal patterns in the nation (see Table 4). While their major findings were probably broad enough to avoid being site-specific, the generality of detailed results from the city would be questionable.

Most of the paper has stressed theoretical concerns, but seasonality also has important applications in forecasting. This is especially so for cities and smaller entities, where monthly forecasts can be helpful in allocating law enforcement resources. Although few suitable forecasting variables exist at low levels of aggregation, small areas often display substantial degrees of seasonal variability. Most current forecasting projects concentrate on neighborhoods or similar urban subareas (e.g., Berk and MacDonald 2009; Gorr et al. 2003), but forecasts for entire cities could also have reasonable policy uses. The current findings suggest that forecasting efforts will be more fruitful to the degree that researchers tailor them to individual cities and individual crimes.

Conclusions

This study has attempted to clarify the nature of seasonal crime rate fluctuations among U.S. cities. The analysis produced consistent evidence of seasonality in the offenses that it examined, with all crimes displaying winter troughs and most displaying summer peaks. Except for homicides, however, the seasonal patterns depended in part on month-to-month variations in city temperatures. Moreover, except for homicides and assaults, basic features of the patterns themselves differed across areas. Crime seasonality is not a unitary phenomenon, and differences in its operation over the nation may help account for the divergent results from past work.

The current study is bound by its own time span and cross-sectional sample, of course, and a larger and more diverse set of data might alter its findings. In addition, and perhaps of greater importance, variables besides average temperatures could act to moderate the seasonal influences. Seasonality may in fact vary with many area-specific attributes, and considering these features might affect major conclusions from the analysis.

More generally, seasonal patterns reflect the collective operation of omitted influences that vary in a cyclically predictable fashion. The most useful approach to understanding the patterns would obviously be to identify and measure the relevant influences, and to estimate their individual effects. Such a disaggregated analysis would allow a detailed explanation of how seasonality arises, and would avoid the necessity of speculating about the sources of the cycles. Equally obvious–and as in most other seasonal studies–the fine-grained micro data necessary for this type of investigation are simply unavailable in the present case.

These are limitations of the paper, but they also suggest the potential advantages of continued investigation of seasonal patterns. Crime seasonality contains two types of variation, one operating over time and one operating over space. Existing research has concentrated on the over-time fluctuations and largely ignored the spatial differences. Considering both dimensions together should allow criminologists to gain a deeper understanding of the nature of seasonality, and of how it influences crime across settings.

References

Anderson CA (1989) Temperature and aggression: ubiquitous effects of heat on occurrence of human violence. Psychol Bull 106:74–96

Anderson CA, Deuser WE, DeNeve K (1995) Hot temperatures, hostile affect, hostile cognition, and arousal: tests of a general model of affective aggression. Personal Soc Psychol Bull 21:434–448

Anderson CA, Bushman BJ, Groom RW (1997) Hot years and serious and deadly assault: empirical tests of the heat hypothesis. J Pers Soc Psychol 73:1213–1223

Baltagi BH (2008) Econometric analysis of panel data, fourth edn. Wiley, New York

Baumer E, Wright R (1996) Crime seasonality and serious scholarship: a comment on Farrell and Pease. Br J Criminol 36:579–581

Bell PA, Baron RA (1976) Aggression and heat: the mediating role of negative affect. J Appl Soc Psychol 6:18–30

Bell WR, Hillmer SC (1983) Modeling time series with calendar variation. J Am Stat Assoc 78: 526–534

Belsley DA, Kuh E, Welsch RE (1980) Regression diagnostics: identifying influential data and sources of collinearity. Wiley, New York

Berk R, MacDonald J (2009) The dynamics of crime regimes. Criminology 47:971–1008

Block CR (1984) Is crime seasonal? Illinois Criminal Justice Information Authority, Chicago

Brearley HC (1932) Homicide in the United States. University of North Carolina Press, Chapel Hill

Brockwell PJ, Davis RA (2002) Introduction to time series and forecasting, Second edn. Springer, New York

Ceccato V (2005) Homicide in São Paulo, Brazil: assessing spatial-temporal and weather variations. J Environ Psychol 25:307–321

Cohen J, Gorr W, Durso C (2003) Estimation of crime seasonality: a cross-sectional extension to time series classical decomposition. Working paper, H. John Heinz III School of Public Policy and Management, Carnegie Mellon University

Cohn EG (1990) Weather and crime. Br J Criminol 30:51–64

Cohn EG, Rotton J (1997) Assault as a function of time and temperature: a moderator- variable time-series analysis. J Pers Soc Psychol 72:1322–1334

Cohn EG, Rotton J (2000) Weather, seasonal trends and property crimes in Minneapolis, 1987–1988: a moderator-variable time series analysis of routine activities. J Environ Psychol 20:257–272

Cohn EM, Rotton J, Peterson AG, Tarr TD (2004) Temperature, city size, and southern subculture of violence: support for social escape/avoidance (sea) theory. J Appl Soc Psychol 34:1652–1674

DeFronzo J (1984) Climate and crime: tests of an FBI assumption. Environ Behav 16:185–210

Deutsch SJ (1978) Stochastic models of crime rates. Int J Compar Appl Crim Justice 2:128–151

Dodge RW (1988) The seasonality of crime victimization (NCJ-111033). U.S. Department of Justice, Bureau of Justice Statistics, Washington

Dodge RW, Lentzner HR (1980) Crime and seasonality (NCJ-64818). U.S. Department of Justice, Bureau of Justice Statistics, Washington

Enders W (2010) Applied econometric time series, third edn. Wiley, New York

Farrell G, Pease K (1994) Crime seasonality:domestic disputes and residential burglary in Merseyside 1988–90. Br J Criminol 34:487–498

Field S (1992) The effect of temperature on crime. Br J Criminol 32:340–351

Ghysels E, Osborn DR (2001) The econometric analysis of seasonal time series. Cambridge University Press, New York

Gorr W, Olligschlaeger A, Thompson Y (2003) Short-term forecasting of crime. Int J Forecast 19:579–594

Hakko H (2000) Seasonal variation of suicides and homicides in Finland: with special attention to statistical techniques used in seasonality studies. Dissertation, Department of Psychiatry, University of Oulo. Downloaded 6-5-2011 from http://herkules.oulu.fi/isbn9514256042/html/

Harries KD, Stadler SJ (1983) Determinism revisited: assault and heat stress in Dallas, 1980. Environ Behav 15:235–256

Hipp JR, Bauer DJ, Curran PJ, Bollen KA (2004) Crimes of opportunity or crimes of emotion? testing two explanations of seasonal change in crime. Soc Forces 82:1333–1372

Hird C, Ruparel C (2007) Seasonality in recorded crime: preliminary findings. Home Office Online Report 02/07. Downloaded 6-5-2011 from http://www.compassunit.com/docs/rdsolr0207.pdf

Kleck G (1991) Point blank: guns and violence in America. Aldine De Gruyter, New York

Lab SP, Hirschel JD (1988) Climatological conditions and crime: the forecast is? Justice Q 5:281–299

Landau SF, Fridman D (1993) The seasonality of violent crime: the case of robbery and homicide in Israel. J Res Crime Delinquency 30:163–191

Maltz MD (1999) Bridging gaps in police crime data (NCJ 176365). U.S. Department of Justice. Bureau of Justice Statistics, Washington

Maltz MD (2007) Missing UCR data and divergence of the NCVS and UCR trends. In: Lynch JP, Addington LA (eds) Understanding crime statistics: revisiting the divergence of the NCVS and UCR. Cambridge University Press, New York, pp 269–294

Maltz MD (2009) Monthly Uniform Crime Report (UCR) data from 1960 to 2004, for over 17,000 police departments, for 26 crime categories or subcategories [Computer data file]. Downloaded 6–5–2011 from http://sociology.osu.edu/mdm/UCR1960-2004.zip

McCleary R, Hay RA, with Meidinger EE, McDowall D (1980) Applied time series analysis for the social sciences. Sage, Beverly Hills

Michael RP, Zumpe D (1983) Annual rhythms in human violence and sexual aggression in the United States and the role of temperature. Soc Biol 30:263–277

Mills TC (2003) Modelling trends and cycles in economic time series. Palgrave, New York

Miron JA (1996) The economics of seasonal cycles. MIT Press, Cambridge

Peterson MA (2009) Estimating standard errors in finance panel data sets: comparing approaches. Rev Financ Stud 22:435–480

Quetelet A (1969/1842) A treatise on man and the development of his faculties. Scholars' Facsimiles and Reprints, Gainesville

Rock D, Greenberg DM, Hallmayer J (2003) Cyclical changes of homicide rates: a reanalysis of Brearley's 1932 data. J Interpersonal Violence 18:942–955

Rock D, Judd K, Hallmayer J (2008) The seasonal relationship between assault and homicide in England and Wales. Injury 39:1047–1053

Stock JH, Watson MW (2007) Introduction to econometrics, Second edn. Pearson-Addison Wesley, New York

Sutherland EH (1947) Principles of criminology, fourth edn. Lippincott, Phiadelphia

Tennenbaum AN, Fink EL (1994) Temporal regularities in homicide: cycles, seasons, and autoregression. J Quant Criminol 10:317–342

Time Use Institute (2010) How December is different. Downloaded 6-5-2011 from http://www.timeuseinstitute.org

U.S. Bureau of Labor Statistics (2010) American time use survey user's guide. Downloaded 6-5-2011 from http://www.bls.gov/tus/atususersguide.pdf

Van Kopen PJ, Jansen RWJ (1999) The time to rob: variation in time of number of commercial robberies. J Res Crime Delinquency 36:7–29

Warren CW, Smith JC, Tyler CW (1983) Seasonal variation in suicide and homicide: a question of consistency. J Biosoc Sci 15:349–356

Wolfgang ME (1958) Patterns in criminal homicide. University of Pennsylvania Press, Philadelphia

Yan YL (2004) Seasonality and property crime in Hong Kong. Br J Criminol 44:276–283