Crimes of Opportunity or Crimes of Emotion? Testing Two Explanations of Seasonal Change in Crime*

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Abstract

While past research has suggested possible seasonal trends in crime rates, this study employs a novel methodology that directly models these changes and predicts them with explanatory variables. Using a nonlinear latent curve model, seasonal fluctuations in crime rates are modeled for a large number of communities in the U.S. over a three-year period with a focus on testing the theoretical predictions of two key explanations for seasonal changes in crime rates: the temperature/aggression and routine activities theories. Using data from 8,460 police units in the U.S. over the 1990 to 1992 period, we found that property crime rates are primarily driven by pleasant weather, consistent with the routine activities theory. Violent crime exhibited evidence in support of both theories.

Sociologists have long had an interest in how seasonal climatic changes may interact with social structures to influence the behavior patterns of individuals. Early work in this area includes Durkheim's classic studies of seasonal differences in suicide rates (Durkheim 1952:107-18), a topic that has seen renewed attention in recent decades (Bollen 1983; Warren 1983). Seasonality in birth and death rates has also been investigated (Land & Cantor 1983), as has the linkage between seasonal changes in testosterone production and sexual activity, with mixed success (Smolensky et al. 1981; Udry & Morris 1967). This

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article focuses on one of the most robust and socially problematic seasonal trends in behavior, namely seasonal changes in crime rates. The notion that seasonal weather patterns affect crime rates was suggested at least as early as the nineteenth century, when Adolph Quetelet observed such a relationship with data from France (Quetelet [1842] 1969). More recent descriptive evidence from the U.S. also suggests that there are seasonal differences for at least some types of crime (Dodge 1980, 1988). This article addresses the question of *why* such a relationship should exist. While various explanations for seasonal changes in crime have been offered, rarely have these theories been empirically contrasted using methodological tools that directly and dynamically model seasonal changes in crime.

Two dominant theories for explaining seasonal oscillations in crime rates are the temperature/aggression theory and the routine activities theory. While both theories suggest that temperature is related to crime rates, they propose different causal mechanisms for bringing about this relationship. In the more psychologically based temperature/aggression theory first proposed by Quetelet, uncomfortably hot temperatures increase the frustration of individuals, leading to aggressive behavior (Quetelet [1842] 1969). Thus one would expect *violent* crime to reach its highest levels during the hot days of summer, while the more calculating nature of *property* crime should be unaffected by heat and thus show no seasonal oscillations. In fact, in his own analyses, Quetelet noted that property crime in France in the late 1820s actually peaked during the *winter*, which he explained as a response by individuals to a shortage of basic needs. The more recent routine activities theory employs a social explanation, focusing explicitly on the changing activity patterns of individuals to explain seasonal oscillations in *all* types of crime (Cohen & Felson 1979). In this theory, pleasant temperatures encourage individuals to spend more time outside the home, increasing opportunities for criminal victimization.

While much empirical work has looked at each of these theories separately, rarely have studies been conducted with the express purpose of comparing the two. As a result, advocates of both approaches often simply demonstrate a linear relationship between temperature and crime. Such a relationship is consistent with both theories and thus does not provide a basis for comparison. Our approach to comparing these two theories is both theoretical and methodological. By exploring the mechanisms proposed by each theory, we determine how they make subtly different seasonal crime predictions. This allows us to form hypotheses from each of the theories that differ in their implications. While we do not suggest that these theories are necessarily mutually exclusive — and indeed it is possible that both are at work in some instances — our approach allows us to evaluate the predictions of each theory with empirically observed seasonal crime patterns.

Testing these hypotheses requires a methodological approach that will allow us to directly model seasonal fluctuations in crime rates, something that is notably lacking in previous research on this topic. The model we propose is a variant of the latent curve model (LCM) of Meredith and Tisak (1990) (see also McArdle 1988; McArdle & Epstein 1987; Muthen 1991). The LCM involves the estimation of trajectories of change that may vary over the units of study. While these trajectories are typically modeled with linear, quadratic, or higher-order polynomial functions, recent extensions of the LCM permit the estimation of trajectories that are nonlinear functions of time (Browne 1993; Browne & du Toit 1991; Cudeck 1996; du Toit & Cudeck 2001). While these extensions to the LCM allow the possibility of modeling oscillating functions over time, this strategy has rarely been exploited in applied research. Using the LCM framework allows us to explicitly model the nonlinear cycle in crime that takes place over the seasons. One important result is that we can also predict variation in these seasonal changes over communities, allowing us to test the predictions of these two theories. Further, while many past studies have focused on only one or two communities, our approach facilitates comparisons over many communities — in our case a sample of 8,460 police units in the U.S.

Thus, our article makes four contributions. First, while past work has only viewed seasonal crime patterns in a descriptive manner, using structural equation modeling allows us to statistically test for the presence of seasonal crime patterns. Second, we construct a unique data set that combines crime rates in cities with nearby climate data. Third, we explicitly compare the two theories, and by specifying the implications of the causal mechanisms for each are able to derive testable hypotheses. Finally, we meld these theoretical derivations with a methodology uniquely suited to testing the hypotheses, allowing us to compare crime rates *between* cities at the same time that we model seasonal crime patterns *within* cities.

The article takes the following course. We first provide an overview of the two theories and then deduce a set of hypotheses on seasonal crime trends that differ between the two theories. Following that, we discuss the limitations of the methodological strategies used in past research on this topic and show how our approach addresses these limitations. We also note that, over any evaluation period, seasonal fluctuations in crime may be overlaid on both stable intercommunity differences and longer-term increases or decreases in crime rates, and we use the social disorganization perspective to help explain these differences. After describing our data and measures, we present our analytical model for capturing seasonal oscillations in crime rates and show how it allows us to evaluate the role of key predictors. In addition to the statistically powerful results obtained by analyzing a nationally representative sample of police units, we also explore specific case studies of crime rates for communities in particular states. We conclude with a summary of the results and their implications for future research.

Temperature Aggression Theory

The earliest explanation for the observed regularity of seasonal crime oscillations was the temperature/aggression (T/A) theory. As initially formulated by Quetelet ([1842] 1969], this theory suggests that hot temperatures lead to greater discomfort, which in turn gives rise to more aggressive behavior. Because the focus is on the psychological level of discomfort, some investigators have suggested that both hot *and* cold temperatures should lead to greater discomfort and hence aggression (for a nice review, see Anderson 1989). This has been generalized to other forms of discomfort, such as crowding (Calhoun 1962), and laboratory studies have even looked at the relationship between noxious smells and aggressive behavior (Berkowitz 2000).

However, incontrovertible empirical evidence for the T/A theory has been hard to come by. For instance, laboratory experiments have not fared particularly well. Scholars have attributed these null results to the possibility that entering a laboratory with an inordinately warm temperature might alert participants to the focus of the study and lead them to alter their behavior (Anderson 1989; Anderson & Bushman 1997). These subjects might then attribute provocative behavior by a confederate "to the heat" and therefore show an even more restrained response than would otherwise be the case.

As a result, much of the evidence for the temperature/aggression theory consists simply of studies showing correlations between temperature and crime rates (Anderson 1989, 2001). For instance, in support of the T/A theory, studies using daily data from Chicago and Houston (Anderson & Anderson 1984) and Des Moines and Indianapolis (Cotton 1986) found evidence of a linear trend between temperature and violent crime but no relationship between temperature and property crime. However, focusing on particular cities limits the generalizability of the results of such studies; in addition, Cohn (1990a) points to other studies that have found contradictory evidence regarding the relationship between temperature and homicide rates. Fewer studies have looked at a large number of communities at a given time, also showing inconsistent findings. DeFronzo (1984) looked at 142 standard metropolitan statistical areas (SMSAs) in the U.S. with populations greater than 200,000 in 1970. Most notable about this study was that it found that after adding demographic controls, the number of hot days (temperature greater than 90 degrees Fahrenheit) experienced by an SMSA had a positive effect only on homicide and burglary rates. While the finding for homicide is consistent with the T/A theory, the lack of findings for other types of violent crime, along with the finding for burglary, are at odds with the theory's predictions. Proponents of the T/A approach have countered that the large number of control variables employed by Cohn's study may have introduced collinearity problems, making the estimates unstable. Additionally, the focus on only large SMSAs limits the generalizability of the study and raises possible selection issues (Berk 1983;

Heckman 1979). A second study looking at 260 SMSAs in the U.S. in 1980 also found that the number of hot days had a positive effect on homicide, even with other controls in the model (Rotton 1993). In sum, while the results of these studies are sometimes consistent with T/A theory, they are too often based on simple tests of a linear relationship between violent crime and temperature.

Rountine Activities Theory

In contrast to T/A theory, routine activities (RA) theory suggests that seasonal oscillations in crime rates are not due to increased aggression on the part of individuals, but rather to altered behavioral patterns (Cohen & Felson 1979). For a crime to occur in this model, there must be a concurrence in space and time of three elements: (1) an offender, (2) a suitable target, and (3) the absence of guardians (Cohen & Felson 1979). Temperature can play an important role in determining whether these conditions are met. For instance, when it is very cold, individuals are more likely to stay at home, reducing the number of suitable targets, and as a result burglary becomes much more difficult (since people are in the home) as do such crimes as assault and robbery (as individuals are not out and about providing potential targets). However, it is important to note that RA theory does not focus exclusively on temperature, viewing it as only one of many factors that change the normal behavior patterns of individuals in a community.

In part for this reason, studies attempting to evaluate RA theory often do not explicitly address temperature effects. In their initial test of the theory, Cohen and Felson (1979) noted how structural changes in female labor force participation affected opportunities for crime, asserting that more women entering the labor force moved them outside the home and increased the risk of criminal victimization. Their model then used changes in the percentage of women in the labor force to explain changes in crime rates in the entire U.S. (Cohen, Felson & Land 1980).

Nonetheless, RA theory has strong implications for the seasonal oscillations observed in crime rates due to the hypothesized change in social patterns. For instance, Cohn (1990a) points out that vacations occur more often during warmer weather, leaving homes exposed to burglary and putting individuals out and about in environments and hence at risk of criminal victimization. In general, a greater amount of time spent outside the home during nicer weather should lead to more opportunities for criminal activity. This implies the opposite effect for cold weather, and evidence of this comes from a study of SMSAs finding that the number of cold days in a month has a significant negative effect on various crime types (DeFronzo 1984).

Contrasting the Theories

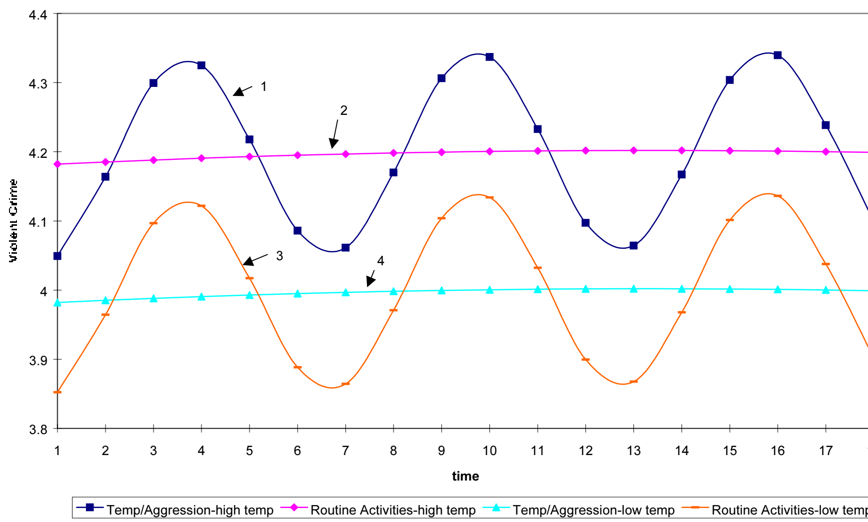
It is notable that while some studies attribute seasonal changes in crime to increased aggression (e.g., Anderson & Anderson 1984), a study of monthly crime data for England and Wales attributed a similar finding to more time spent outside the home during nicer weather (Field 1992). These different conclusions suggest that the climatic patterns in a community may be important for distinguishing which of these two theories is at work: the fact that a seasonal effect is found in Britain where the summers are fairly mild lends support to RA theory, while the presence of a seasonal effect in an area with hot summers might suggest the T/A theory. This difference points out a possible way to compare these two theories, especially when evaluated using a large sample of communities with considerable variation in climate patterns.

While each of these theories suggests a positive relationship between seasonal temperature changes and oscillations in crime rates, a close inspection of the two approaches reveals that they have subtle, but key, differences in their predictions. First, while the T/A approach suggests that hotter temperatures in the summer will lead to greater aggression and hence an increase in violent crime rates, this aggression is *not* hypothesized to affect rates of property crime. To the extent that property crime involves calculating behavior and not aggression, it should not be affected by seasonal temperature fluctuations. In contrast, routine activities theory suggests that altered behavior patterns will result in seasonal relationships for both property and violent crime. In particular, favorable weather makes individuals more likely to leave home. This may provide additional tempting targets that will particularly affect property crime rates. This yields a key distinction between these two theories:

> *Hypothesis 1:* The routine activities theory predicts that there will be a positive seasonal effect for the property crime rate, while the temperature/aggression theory predicts that there will not be a seasonal effect for *property* crime rates.

And while each of these theories predicts a seasonal effect for *violent* crime rates, the mechanisms they propose for the effect of temperature on violent crime suggest subtle distinctions in this relationship. We illustrate these hypothesized relationships in Figure 1. Because the T/A theory focuses on higher temperature bringing about the psychological causal mechanism of greater frustration/aggression, there is little reason to expect that increases at the low end — or even the midrange — of the temperature scale will increase violent crime rates. That is, a community that experiences temperatures around 40 degrees Fahrenheit in the winter and 75 degrees Fahrenheit in the summer should see no seasonal change in crime since there is little reason to expect that this temperature range leads to greater discomfort, and this is represented by line 4 in Figure 1. Arguably, the level of discomfort *decreases* for increasing middle-range temperatures and only starts becoming uncomfortable at higher temperatures. The precise point at which temperature becomes uncomfortable

FIGURE 1: Theoretical Model: Comparing Seasonal Violent Crime Predictions for Temperature/Aggression and Routine Activities Theories



is not clear: while some studies have used 90 degrees Fahrenheit (Anderson, Bushman & Groom 1997; DeFronzo 1984; Rotton 1993), this has been criticized as arbitrary (Cohn 1990a). We sidestep this issue by focusing on the climatic patterns of communities and suggest that looking at the typical range of temperatures within a community can yield a clue to which of these theoretical mechanisms is at work. The crucial point is that the T/A theory predicts areas with hotter climates will experience the greatest seasonal crime oscillations, as shown by line 1 in Figure 1.

On the other hand, the routine activities theory suggests that the relationship between temperature and crime rates will be most pronounced in the midrange of temperatures. That is, fewer crimes will be committed during colder temperatures as individuals spend more time inside their homes to avoid the inclement weather, thus reducing the risk of victimization. But as the temperature begins to warm, people venture outside their homes, increasing the possibility of criminal acts, as shown by line 3 in Figure 1. At some point increasing temperature ceases to become more pleasant and no longer induces increasing numbers outdoors (Rotton & Cohn 2000), and thus line 2 in Figure 1 shows that variations in already hot temperatures will have little effect on crime rates. Thus, this model implies that seasonal fluctuations in crime will be greatest for communities with midrange temperatures. Specifically, an area with cold winters and mild summers will see greater seasonal oscillations in violent crime rates than will an area with moderate winters but hotter summers.

Note that this suggests distinguishing temperature differences *within* a community from temperature differences *between* communities. The amount the temperature varies *within* a city over the course of the year is important for seasonal oscillations in crime rates. A city experiencing little variation in temperature from month to month would see little seasonal change in crime rates, according to both theories, while increasing the variation in monthly temperatures may increase seasonal oscillations in crime rates, depending on the particular temperature range. On the other hand, differences in temperature *between* cities can show the effect of heat but say little about seasonal oscillations in crime rates. Thus, examining the interaction between the average temperature in an area and the amount of variation in monthly temperatures may help in distinguishing between these two theories. These observations lead to our second hypothesis:

> *Hypothesis 2:* The effect of seasonal variability in temperature on crime rates will depend on the average climate of the community. The temperature/aggression theory predicts that temperature variability will induce the greatest seasonal changes in violent crime rates in areas with hotter climate, while the routine activities theory predicts that temperature variability will induce the greatest seasonal variability in both property- and violent-crime rates in areas with moderate climates.

We also attempt to directly model some of the causal mechanisms proposed in the two theories. Unfortunately, this is quite difficult for the T/A theory, as it ideally requires collecting survey data on the psychological state of individuals to determine both whether frustration increases in the hotter summer months and whether this leads to aggression and violent criminal acts. However, we might posit that close proximity of individuals, when combined with hotter temperatures, would lead to increased aggression. That is, since a key feature of the T/A approach suggests that unpleasant conditions can evoke *either* fight or flight tendencies based on the individual's background (Berkowitz 2000), areas with high population density may inhibit the ability for flight. Moreover, a high population density may increase discomfort and hence promote aggression.[1] Supporting this view, Calhoun's (1962) classic study of the effects of overcrowding on rats demonstrated a complete breakdown in normal social behavior. However, others, such as de Waal, Aurali, and Judge (2000), have noted that primates (and especially humans) may circumvent this process by using coping mechanisms (such as gaze aversion and minimizing movements) that diminish the psychological impact of crowding. It remains an open question whether the added stressor of hot temperatures could break down these coping mechanisms and lead to higher rates of violent crime in cities. Past research in human populations has in fact shown population density to be positively related to overall crime rates. Alone, this effect may be explained by more opportunities provided by "agglomeration effects" (Glaeser & Sacerdote 1999). However T/A theory suggests that high-density areas might also show particularly pronounced *seasonal* oscillations for violent crime. This observation leads to our third hypothesis:

> *Hypothesis 3:* The temperature/aggression theory suggests that areas with high population density may experience greater seasonal fluctuations in violent crime rates.

In contrast, modeling the causal mechanisms proposed by RA theory is not as daunting a task. Since the routine activities theory posits that more outdoor behavior by individuals results in more criminal opportunities, areas with a large number of eating and drinking establishments as well as amusement and recreational services establishments should provide more opportunities for criminal acts (Miethe, Hughes & McDowell 1991). The presence of a greater number of such establishments should increase crime opportunities in general and thus lead to a positive effect on overall levels of crime. Additionally, to the extent that such establishments are frequented more often during better weather, providing more potential targets, their presence may also result in particularly pronounced seasonal changes in crime, particularly for property crime. We may thus formulate our fourth hypothesis:

> *Hypothesis 4:* The routine activities theory predicts that areas with a larger number of entertainment establishments will have higher annual rates of crime and will have greater seasonal fluctuations in crime rates.

Stable Intercommunity Differences

Up to this point our discussion has focused mostly on short-term seasonal changes in crime rates. However, we also need to take into account relatively stable intercommunity differences in crime rates. We examine this issue from the perspective of social disorganization theory (Shaw & McKay 1942). Social disorganization refers to "the inability of a community structure to realize the common values of its residents and maintain effective social controls" (Sampson & Groves 1989:777). The cohesion of a community minimizes the negative social externality of criminal activity. Ecological characteristics of communities are posited to reduce the networks of ties among residents in the community, leading to greater disorganization and hence an inability to combat crime when it appears (Sampson 1985; Sampson & Groves 1989; Veysey & Messner 1999). For instance, residential instability is postulated to reduce the interaction among citizens in a community, thus reducing the ability for a community to police the behavior of individuals (Krivo & Peterson 1996; Skogan 1990). Similarly, areas with high levels of ethnic heterogeneity often have little crossrace interaction which will reduce the cohesion of a community (Warner & Rountree 1997). In addition to the network of ties within the community, family ties are also hypothesized to help in fostering cohesion. In particular, areas with many divorced families lack the social oversight and role models that would inhibit crime. Finally, while areas with high rates of poverty might still have reasonable levels of social interaction, limited economic and political resources may inhibit their ability to effectively combat crime (Krivo & Peterson 1996, Sampson & Groves 1989). Following Bursik (1988) and Dahlback (1998), we combine the social disorganization theory with the routine activities theory in a dynamic model to test whether these measures of disorganization are also related to seasonal changes in crime.

Dynamic Models of Crime

While we have theoretically framed the climate/crime relationship dynamically in relation to the observed seasonal oscillations, most empirical studies have not used longitudinal methodology that would be conducive to testing hypotheses of this nature. Instead, much research has involved simple linear regressions of crime with temperature. The most common approach is to use daily data from one or two cities to test for a linear relationship between temperature and crime rates (Anderson & Anderson 1984; Cheatwood 1995; Cotton 1986; Farrell & Pease 1994; Harries & Stadler 1984; Suttles 1968). An advantage of these studies is that the daily crime and temperature data allow for a closer inspection of the temperature/crime relationship. One drawback is that such studies rarely explicitly model the nonlinear effects of climate patterns over time. By focusing on a linear relationship between temperature and crime rates, the causal mechanisms proposed by the routine activities and temperature/aggression theories cannot be distinguished. A second drawback is that it is uncommon to study a large number of communities (exceptions are DeFronzo 1984, Rotton 1993), and so the results may have little generalizability: Does the community studied represent all communities in the U.S., or does it have idiosyncratic weather/crime patterns?

Among the studies that have modeled dynamic changes in crime, a common approach is to examine a single time series of data pooled over the entire U.S. (Landau & Fridman 1993; Tennenbaum & Fink 1994; Warren 1983). The advantage of a time series approach is that it can be used to test for evidence of seasonal changes on crime and how these might change over time. The key disadvantage of a times-series approach is that with a single time series there is no opportunity to model variation in seasonal change over communities. As noted earlier, predicting such variation may help to determine why seasonal oscillations occur.

Interestingly, one study we are aware of did attempt to directly model the nonlinear seasonal changes in crime rates over multiple locations. In their model, Michael and Zumpe (1983) used a cosine function to capture the wave-like changes in crime that take place over the course of a year. This allowed them to determine the peak time point of the waves, which generally occurred in the summertime. While interesting, this study has limitations. First, most of the units of analysis were states — a unit arguably far too large to consider as a community. Considering how crime rates can vary from city to city, it is not clear that the state is an adequately homogeneous unit of analysis for measuring crime rates. Using smaller units of analysis allows other social determinants of crime to be appropriately controlled. Second, while the modeling strategy employed by Michael and Zumpe detected considerable differences in the amplitude of seasonal change in crime rates across locations, it could not be used to explore the source of those differences. As we have noted, these differences *between* communities may be important for differentiating the T/A and RA theories.

The approach we advocate embeds Michael and Zumpe's (1983) analytic approach within a latent curve model that can be used to both estimate *and* predict community-level variation in the amplitude of seasonal changes in crime rates. This novel methodological approach allows us to test the T/A and RA theories on a large sample of U.S. communities by explicitly modeling the phenomenon of interest.

Data

Crime Data

The data set used here uniquely combines information from a variety of sources. The crime data were obtained from the Uniform Crime Reports (UCR) covering the years 1990–92 and were downloaded from the National Archive of Criminal Justice Data Web site (U.S. Dept. of Justice 2000).[2] The Federal Bureau of Investigation collects these data from police units in the U.S., with a coverage rate of about 96% of the population (U.S. Dept. of Justice 1995).[3] The UCR include monthly data on frequency of occurrences of the major types of crime as defined by the FBI. We then combined murder, robbery, and assault into a measure of violent crime and combined burglary, larceny, and motor vehicle theft into a measure of property crime.[4] This scheme follows the coding by the UCR for these crime types, and for five of the six crimes used is quite uncontroversial. The one exception is robbery, as this crime entails both force and the acquisition of something of value from the victim. Some have focused on the fact that robbery involves the transfer of something of value between individuals and have classified it as a property crime (Anderson & Anderson

1984; Cohen, Felson & Land 1980). However, we follow the standard established by the UCR and focus on the fact that robbery entails the use of force and categorize it as a violent crime.[5]

While there are 12,000 to 14,000 potential reporting units in a given year, many of these units represent small reporting areas, such as university police. As a result, these small units do not represent "populations," for their constituency lives in a local area that is served by another reporting police department. As well, they tend to report very little crime. We combine the units with zero population with the nearest reporting unit, yielding 8,460 police reporting units for our sample period.[6] Since our study population is all cities, townships, and county sheriffs in the U.S., we can have considerable confidence in the representativeness of the results.

We then combined the crime data from adjacent months into bimonthly values. This decision was motivated by two considerations. First, there can be a measurement/interval problem when using a time series variable measured with error (Boker & Nesselroade 2002). The intuition is straightforward: as time points between observations move closer together the actual difference in the true values of two observations will generally become smaller; however, since the magnitude of the error term remains relatively constant, the ratio of the error to the true difference in the two observations becomes larger. This larger relative effect of the error term can introduce enough noise to obscure a naturally occurring process, making it more difficult to detect. A second issue is that there may be fluctuations in monthly crime data if crime is more likely to occur on weekends (Anderson & Anderson 1984; Rotton & Frey 1985). One study found that 55% of the total assaults occurred during just the three days of Friday-Sunday (Harries & Stadler 1984). As a result, monthly data can have excessive systematic fluctuation that corresponds to the number of weekends in a given month: collapsing data over two months helps to smooth out this effect (Cohn 1990b). To calculate bimonthly figures, the mean of the crime totals for the two months was obtained, then divided by the mean of the population for the two months, and finally multiplied by 100,000 to give a crime rate expressed per 100,000 population (mirroring common representation). Because these figures generally showed considerable skewness, log transformations were taken to obtain more normal distributions. Log transformations are also appealing because results can be intuitively interpreted in terms of the percentage change in the dependent variable.

Climate Data

The temperature data come from the National Climatic Data Center. We used the TD 3220 Summary of the Month cooperative data set for the average monthly temperatures, and then geospatially linked up communities with crime data to the closest reporting weather station. In general, these matches are very close: the average station is about 14 miles from the geocoded center of the city. Given the typical circumference of a city, it is likely that these reporting stations are indeed in the city. One weather station was 380 miles from the city of interest, the next furthest distance was 63 miles, and the rest were within 40 miles.[7] The climate of each community was captured by three variables: (1) the average temperature for the area over the entire three-year study period to capture temperature variation *between* cities (what we refer to as the "climate" of the community); (2) the standard deviation in the monthly temperatures over this three-year period to capture temperature variability *within* a city; (3) an interaction of these two variables.

Demographic Data

The demographic data we used come from the 1990 U.S. census. We included four measures of the level of disorganization within a community. First, we used a measure of the percentage of the population at or below 125% of the poverty rate. Second, we calculated a measure of ethnic heterogeneity in an area. This was constructed as a Herfindahl index (Gibbs & Martin 1962) of four racial/ethnic groups,[8] and takes the following form:

$$1-\sum_{1}^{j=k} G_j^{\,2} \tag{1}$$

where G_j represents the proportion of the population of ethnic group j out of k ethnic groups. Subtracting from 1 makes this a measure of heterogeneity, rather than homogeneity. Third, we measured residential instability by the average length of tenure at the current residence for the community.[9] Fourth, we include a measure of the percentage of the families that are divorced. Finally, we measured the population density of the city per kilometer.

Entertainment Establishments Data

Our measure of the number of eating and drinking establishments and the number of amusement and recreational services establishments per 100,000 population comes from the 1992 Economic Census conducted by the U.S. Census Bureau (Miethe, Hughes & McDowall 1991). Since our crime data is from 1990 to 1992, temporal precedence issues arise from using 1992 establishment data as a predictor of earlier changes. However, given the stable nature of the number of such establishments, and their rank order over communities, we suggest that this figure is likely a better proxy for the number of establishments present in a city during 1990–92 than the measure collected in 1987 because 1992 is at least within the time period of the study.

Treatment of Missing Data

While 75% of our cases had full data coverage, we used multiple imputation for cases with missing data (Rubin 1987; Schafer 1997). Multiple imputation requires weaker assumptions than less preferable means of handling missing data such as listwise deletion, pairwise deletion, or mean imputation (Allison 2001; Schafer & Graham 2002).[10] Multiple imputation owes its name to the fact that a range of values (rather than a single value) are imputed for each missing data point. The actual number of imputed data sets that is optimal depends on the amount of missing data present. In our case, the missing information was only 3% for any given variable on average, and using ten imputed data sets gives us a relative efficiency for our parameters ranging from 98% to 99.97% — compared to 100% if no data were missing (Rubin 1987). Since the imputed data is "complete," the standard errors for the parameters will be too small for any given data set. The standard errors are corrected using an algorithm that combines the results from the multiple imputed data sets. In SAS 8.2, this algorithm is implemented in the Proc MIANALYZE procedure. We calculate the chi-square and various fit statistics by taking the mean value over the 10 imputed data sets.[11] Table 1 shows the summary statistics for the imputed data used in the study. Note that the predictor variables were all centered on their grand means in the analyses.

Data Analysis

While past studies of seasonal crime patterns have often focused on just one or two cities, or looked at a time series for the entire U.S., the Latent Curve Model (LCM) allows us to model seasonal oscillations in crime for a large number of cities. Although latent curve models are often used to model monotonic trajectories of change over time, our approach implements a nonlinear cosine function to capture the oscillatory patterns observed in crime rates over seasons. The strength of the LCM approach is that it (1) employs a highly structured confirmatory factor analysis model for repeated measures where each "factor" represents a trajectory parameter that can vary over communities and then (2) allows us to predict these latent factors as a function of exogenous explanatory variables. These capabilities are crucial since our hypotheses predict that not all communities will experience the same magnitude of seasonal crime oscillations.

In matrix form, the LCM may be expressed as

$$y = \Lambda\eta + \varepsilon \tag{2}$$

where y is a $t \times 1$ vector of values for the property (or violent) crime rate in each city at each time point (where t is the number of time points), ε is a $t \times 1$ vector of disturbance terms for each individual case at each time point, η is a

TABLE 1: Summary Statistics for 10 Imputed Data Sets

	Property Crime		Violent Crime	
	Mean	Std. Dev.	Mean	Std. Dev.
January–February 1990	5.31	.98	3.28	1.69
March–April 1990	5.38	.93	3.38	1.71
May–June 1990	5.43	.95	3.54	1.69
July–August 1990	5.54	.94	3.55	1.71
September–October 1990	5.45	.96	3.45	1.71
November–December 1990	5.38	.98	3.30	1.70
January–February 1991	5.32	.98	3.25	1.70
March–April 1991	5.42	.94	3.40	1.70
May–June 1991	5.48	.95	3.57	1.71
July–August 1991	5.60	.94	3.64	1.69
September–October 1991	5.47	.95	3.51	1.71
November–December 1991	5.36	1.00	3.37	1.70
January–February 1992	5.34	.95	3.41	1.68
March–April 1992	5.36	.97	3.53	1.69
May–June 1992	5.43	.95	3.59	1.71
July–August 1992	5.54	.95	3.63	1.69
September–October 1992	5.43	.96	3.59	1.70
November–December 1992	5.32	1.01	3.45	1.69
	Mean	Std. Dev.	Min	Max
Average bimonthly temperatures, 1990–92	65.67	8.25	19.42	89.00
Standard deviation of bimonthly temperatures, 1990–92	14.72	3.18	2.51	32.71
Population density, 1990	.69	.86	.00	17.69
Percentage at 125% of poverty level and below, 1990	17.72	10.83	.00	73.46
Ethnic heterogeneity, 1990	19.99	17.80	.00	75.12
Residential instability, 1990	3.93	.39	2.55	5.52
Percentage of families divorced, 1990	18.87	7.54	.00	76.87
Entertainment venues, per 100k population, 1992	32.40	32.22	.00	1489.70

(N = 8,460)

$m \times 1$ vector for the latent variables measuring the level of crime and its change over time (where m is the number of latent variables), and Λ is a $t \times m$ matrix that specifies the functional relationship between these latent variables and observed crime rates. In our model, the η vector contains latent variables that capture the overall level of crime in the community as well as short-term (seasonal) and long-term (annual) crime trends.

We first discuss how we model the level of crime and the short-term seasonal oscillations. We define the "level" (η_1) and "amplitude" (η_2) factors by setting the first and second columns of L to

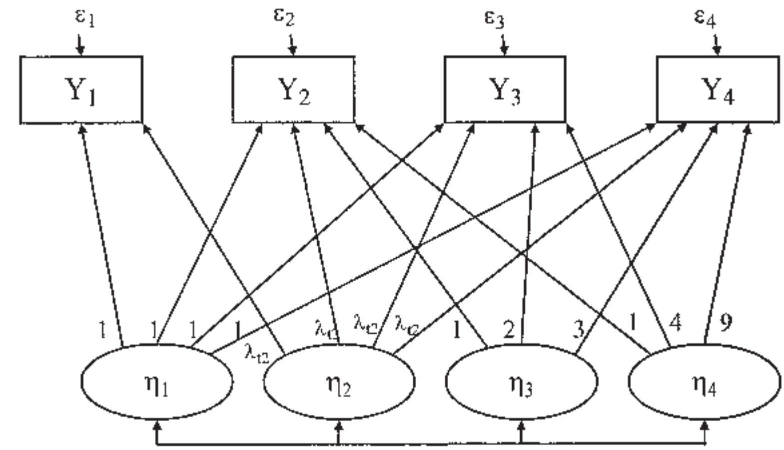
$$\lambda_{t1} = 1$$

$$\lambda_{t2} = \cos(2\pi * freq * (t + p))$$

where t represents time and is coded –8.5,–7.5 . . . 7.5,8.5 for the 18 bimonths (to be equal to 0 at the midpoint of our study period — summer of 1991). Note that the loadings for the "level" factor (η_1) are a constant value for all time points. Since we have centered time in our models, the level term represents approximately the midpoint of the long-term time trend about which the wave cycles. And because we have centered our predictors, the conditional mean of the level term represents the average amount of crime for an average community. In contrast, the loadings for the "amplitude" factor (η_2), which captures the height of the wave, are expressed as a nonlinear function of time and two new parameters, *freq* and *p*. The *freq* parameter represents the frequency of the wave, which is defined as the number of complete wave cycles per unit of time. For the present application we gave this parameter a starting value of 1/6, since there is one cycle per six bi-months — or one per year.[12] To capture the location of the peak point of crime during the year, we include the phase term *p,* which allows the peak of the wave to shift to any time point. Freely estimating this parameter allows us to test whether the peak occurs in the summertime for violent crime and whether Quetelet's ([1842] 1969) finding of a peak for property crime in the winter is present in these data. Since the level and amplitude terms are random, they can take on different values for various communities that depend on annual level of crime and the amplitude of the seasonal changes in crime. For instance, communities that experience large seasonal oscillations in crime rates between the winter and summer months will have larger positive values for the amplitude term than will communities with less seasonal change in crime rates. Note that it is possible for the amplitude term to vanish from the model if seasonal oscillations are not present (i.e., if it takes on a nonsignificant estimated mean and variance). As a result, the amplitude term is crucial for testing hypothesis 1: the prediction of T/A theory that *property* crime will not exhibit a seasonal effect would be supported if the mean and variance of the amplitude factor were not significantly different from zero.

While our main theoretical focus is on seasonal oscillations in crime, we must simultaneously account for longer-term time trends in crime over the three-year period of the study. We accomplish this by also including λ_{t3} to capture the linear increase in crime over the sample period for the latent "linear" factor (η_3), and λ_{t4} to capture the quadratic effect of crime over the sample period (the acceleration or deceleration rate) for the latent quadratic factor (η_4), defined as

FIGURE 2: Sample Latent Curve Model for Four Bi-months



$$\lambda_{t2} = \cos\left(2 \times \pi \times freq \times (t + p)\right)$$

$$\lambda_{t3} = t$$

$$\lambda_{t4} = t^2$$

The linear and quadratic factors represent the change in crime rates over the entire three-year period. For instance, a positive coefficient for the linear term would indicate that crime is generally increasing over this period, while a negative coefficient for the quadratic term would suggest that the rate of increase is decelerating over time — perhaps even reversing and heading downward at some point. Figure 2 is a path diagram of the model for just four bi-months (for clarity), showing that the latent variables directly predict the crime rate at each time point.

Since the latent variables in η can vary over cities, we are able to explore why some cities have greater values for these latent variables than others. In matrix form, the latent variable model is

$$\eta = \mu_\eta + \Gamma X + \zeta_\eta \tag{3}$$

where μ_η represents the $m \times 1$ vector of the intercepts for the latent variables, X is an $n \times 1$ matrix of exogenous variables of interest (where n is the number of exogenous variables), Γ is an $m \times n$ matrix showing the effect of these exogenous variables on the latent variable, and z is an $m \times 1$ vector of the disturbance terms for the equations. The estimation of these coefficients affecting the amplitude factor is crucial for testing hypotheses 2, 3, and 4. Positive values of these coefficients indicate that the variable of interest increases the community's observed amount of seasonal oscillation in crime, while negative values indicate less seasonal change in crime.[13]

TABLE 2: Model Fit Summary

	Unconditional Models		
	Level and Amplitude	Adding Linear Term	Adding Quadratic Term
Property-crime models			
χ^2	5669.535	3137.537	2098.201
χ^2 DF	164	160	155
Pr > χ^2	< .0001	< .0001	< .0001
1 – RMSEA Estimate	.937	.953	.961
1 – RMSEA 90% upper confidence limit	.938	.955	.963
1 – RMSEA 90% lower confidence limit	.936	.952	.960
Incremental fit index (IFI)	.992	.996	.997
Goodness-of-fit index (GFI)	.919	.958	.974
Violent-crime models			
χ^2	4942.018	1927.452	1266.46
χ^2 DF	164	160	155
Pr > χ^2	< .0001	< .0001	< .0001
1 – RMSEA estimate	.941	.964	.971
1 – RMSEA 90% upper confidence limit	.943	.965	.972
1 – RMSEA 90% lower confidence limit	.940	.962	.969
Incremental fit index (IFI)	.988	.996	.997
Goodness-of-fit index (GFI)	.922	.974	.983

In the following section we test our model on both violent and property crime. We first develop an unconditional model that does not include predictors of the latent factors in order to determine whether our model adequately captures seasonal oscillations in crime over this time period. We then augment the model with our predictor variables. Our analyses are first carried out on the entire sample of 8,460 communities. We then supplement these findings with "case studies" of the seasonal/crime patterns of communities in various states.

Results

Unconditional Model

Our first task is to determine the adequacy of our model for seasonal changes in property and violent crime over the 1990–92 period. We begin with a basic model that includes the level and amplitude factors and does not account for long-term change in crime over this three-year period. As expected, this model

FIGURE 3: Estimates of Property Crime, 1990–92

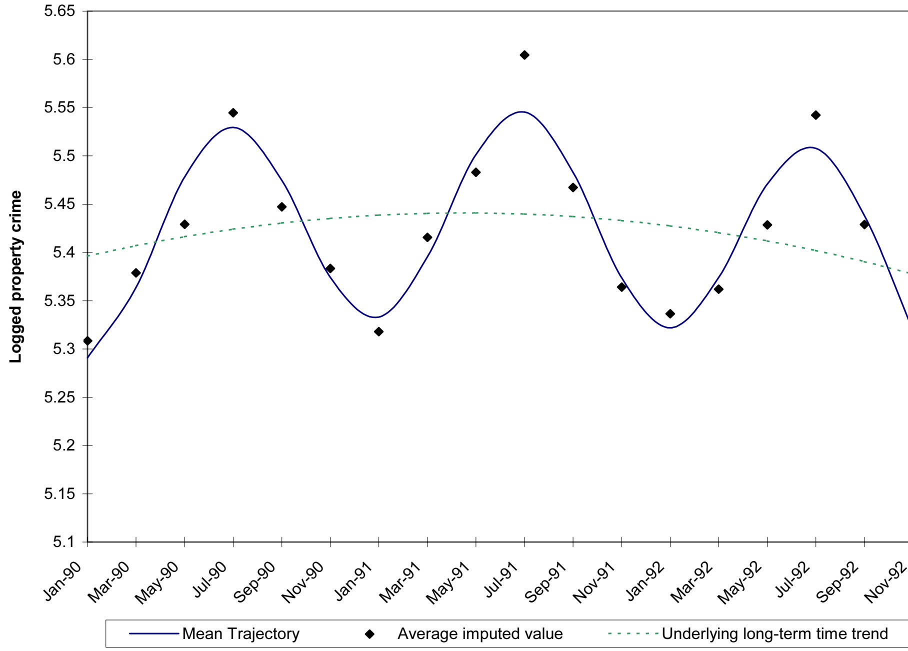
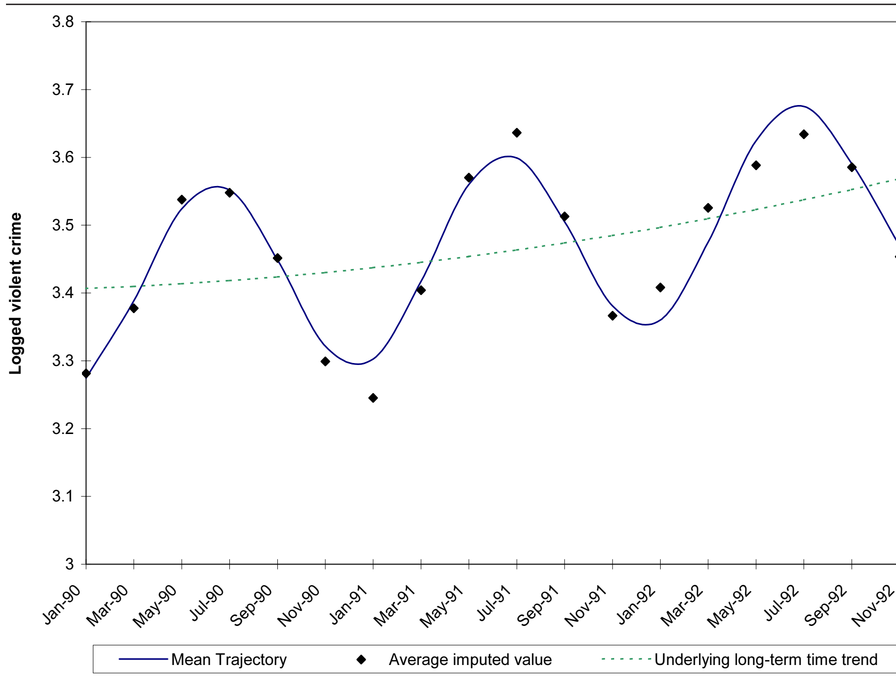


FIGURE 4: Estimates of Violent Crime, 1990–92



does not have a particularly good fit for either property or violent crime rates, as can be seen in the first column of Table 2. The very high chi-square ($\chi^2[164] = 5{,}670$) for property crime suggests that the time trends in the data are not solely a function of seasonal oscillations. Because it is reasonable to expect that there are also underlying annual changes in crime, we extend the model by adding a linear term. This second model results in a large improvement in fit, nearly halving the chi-square for the property crime model ($\chi^2[160] = 3{,}138$) and reducing it almost threefold for the violent crime model ($\chi^2[160] = 1{,}927$). The IFI of .99 and the 1 – RMSEA of .96 for the property-crime model suggest that this model is approaching satisfactory overall fit. Nonetheless, the addition of a quadratic term to capture curvature in the underlying trajectory results in a significant improvement in model fit: the reduction in chi-square of over 1,000 for the property-crime model ($\chi^2[155] = 2{,}098$) and over 600 for the violent-crime model ($\chi^2[155] = 1{,}266$) on just five degrees of freedom are highly significant improvements over the linear model. While the chi-squares of these final models are still significant, the large sample size and the large number of time points estimated give the test considerable power to detect trivial differences between the sample and model implied covariance matrices (Matsueda & Bielby 1986). The other fit indices show a very good fit to the data: The IFI is nearly 1 in the two models, and the 1 – RMSEA is .96 for the property-crime model and .97 for the violent crime model. The model thus shows good approximate fit to the data (Cudeck & Browne 1992; MacCallum, Browne & Sugawara 1996).

The mean trajectories implied by the models for property crime and violent crime are plotted in Figures 3 and 4, respectively. For comparison, the average imputed bimonthly means values are also displayed, as is the model-implied long-term time trend underlying the seasonal changes. Note that one parameter estimate of these trajectories that is important for evaluating the predictions of the two theories is the mean of the amplitude factor. Consistent with the prediction of the RA theory (hypothesis 1), this parameter is significantly greater than zero for both types of crime, indicating that seasonal oscillations take place for both violent and property crime. The magnitude of these changes is apparent in Figures 3 and 4. Note the considerable seasonal effect for *violent* crime, as predicted by both theories: the average summertime peak is about 35% higher than the number of violent crimes in the winter.[14] Of importance, while the T/A theory in hypothesis 1 predicts that no seasonal effect for *property* crime will be observed, in Figure 4 we in fact see considerable seasonal oscillations for property crime, with an average peak summertime crime rate almost 24% higher than during the winter.[15] This is strong support for the RA perspective that seasonal oscillations in *both* types of crime can be jointly explained by the changing behavioral patterns of individuals. Also of note in Figures 3 and 4 are the longer-term changes in crime over the study

TABLE 3: Using 1990 Demographic and Temperature Variables to Predict Violent- and Property-Crime Rates, 1990–1992

	Violent Crime		Property Crime	
	Level	Amplitude	Level	Amplitude
	(1)		(2)	
Intercept	3.42841**	.14492**	5.39247**	.09731**
	(.01536)	(.00437)	(.00868)	(.00266)
Average high temperature, 1990–92 (AHT)	–.00364	.00237**	.00445**	–.00266**
	(.00267)	(.00078)	(.00151)	(.00048)
Standard deviation of monthly high temperature, 1990–92 (SDHT)	.02171**	.00705**	.00761*	.00649**
	(.00625)	(.00182)	(.00357)	(.00112)
AHT × SDHT	–.00272**	.00020	–.00184**	–.00044**
	(.00041)	(.00012)	(.00023)	(.00007)
Population density per square kilometer, 1990	.17028**	–.01445**	.09243**	–.00920**
	(.01613)	(.00469)	(.00910)	(.00289)
Entertainment venues per 100k population, 1992	.00146**	.00031*	.00643**	.00034**
	(.00043)	(.00014)	(.00025)	(.00007)
Percentage below 125% of poverty rate	–.01824**	–.00008	–.01520**	–.00106**
	(.00159)	(.00047)	(.00090)	(.00029)
Ethnic heterogenity	.01606**	–.00013	.00634**	.00013
	(.00099)	(.00029)	(.00056)	(.00018)
Residential instability	1.00116**	–.02129*	.60506**	–.02162**
	(.03361)	(.00978)	(.01909)	(.00602)
Percentage of families divorced, 1990	.07027**	.00017	.03581**	-.00104*
	(.00240)	(.00071)	(.00136)	(.00043)
N	8,460		8,460	

Note: Standard error are in parentheses.

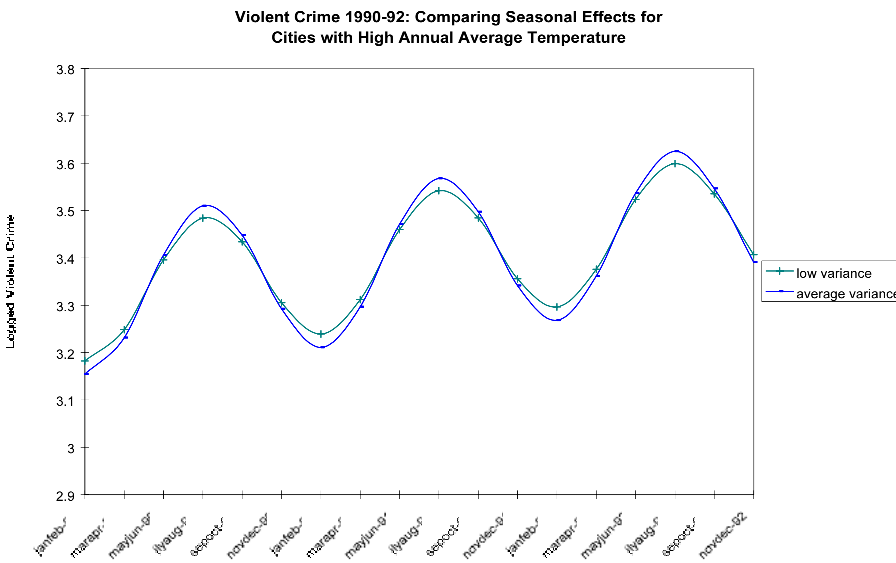
† $p < .10$ * $p < .05$ ** $p < .01$ (for two-tailed tests)

period. While property crime slowly rises and then falls, violent crime shows an accelerating increase.

Effects of Climate on Crime Rates

We next explore why some cities experience greater seasonal oscillations in crime rates, and whether climate patterns help to explain this variation. We first examine the effects of climate patterns on violent crime. Consistent with both the T/A and RA theories, cities with greater temperature variation have greater seasonal oscillations in violent crime. Table 3 illustrates that a one-degree increase in temperature variation increases the amplitude of violent crime 4.9%.[16] Also consistent with both theories, increasing the average annual

FIGURE 5: Violent Crime 1990–92 — Comparing Seasonal Effects for Cities with High, Average, and Low Annual Temperature



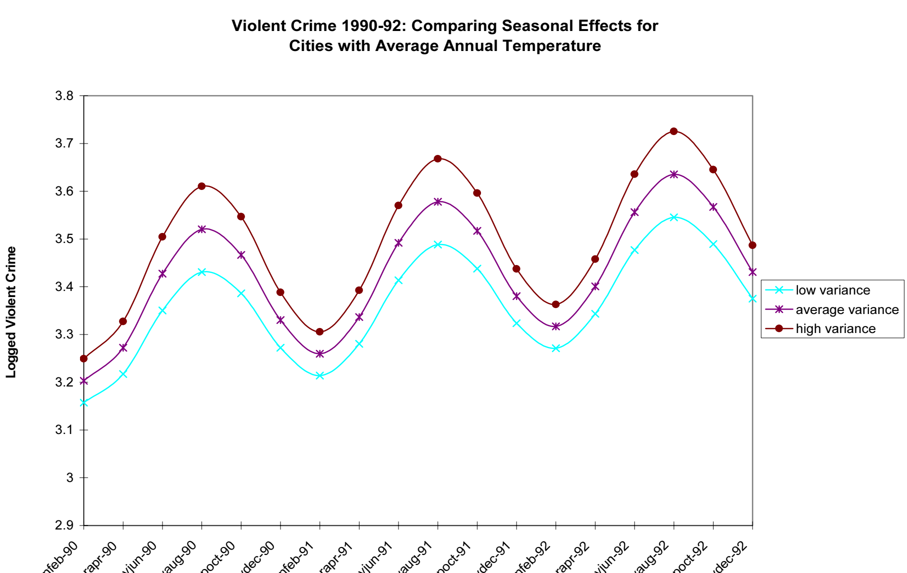
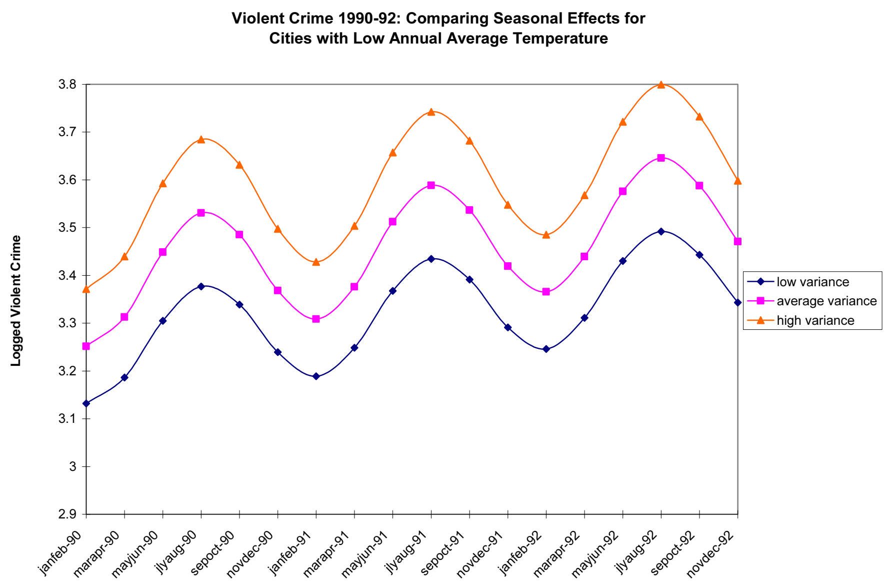


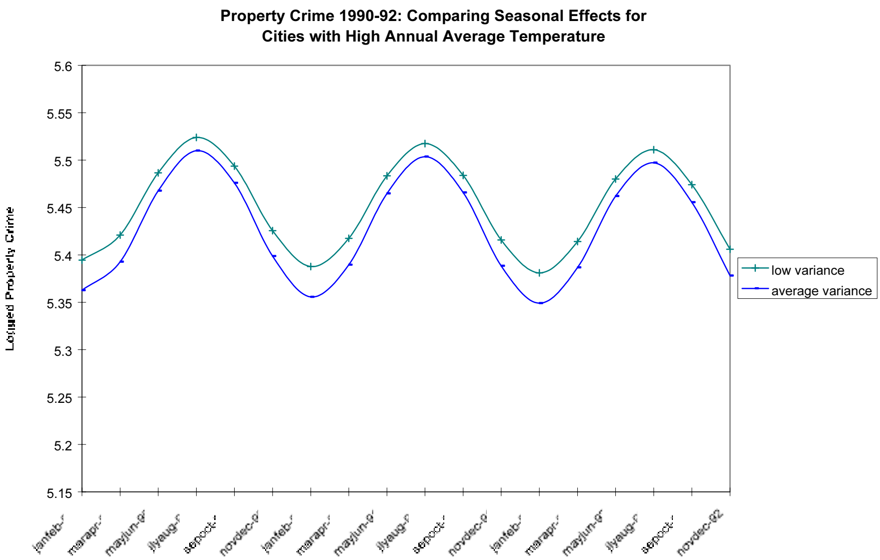
FIGURE 5: Violent Crime 1990–92 — Comparing Seasonal Effects for Cities with High, Average, and Low Annual Temperature (Cont'd)



temperature increases the amplitude 1.6% for each degree Fahrenheit increase in temperature.

These effects are consistent with the predictions of both theories. Where the two theories differ, however, is in their predictions of *when* crime should occur. To determine this, we first evaluate the interaction between average annual temperature and variation in monthly temperature, as hypothesis 2 of the T/A theory suggests that temperature variation will have the greatest effect on crime oscillations for communities in hotter climates. The results are inconclusive: the lack of significance for the interaction effect on the amplitude factor suggests that both theories may be at work. We can also view these results graphically to determine whether climate effects are more important in the summer or the winter. Holding average temperature within a city constant, increasing temperature variability has little effect on the seasonal oscillations in violent crime, as seen in Figure 5.[17] Only in the top panel are there differences based on temperature variability, and these differences suggest both theories are at work. For instance, a hot climate area with average annual temperature variability has an average July-August high temperature of 93.6°F, while this is 88.9°F degrees in a hot climate community with low temperature variability. Consistent with T/A theory, these hotter summers lead to slightly higher crime peaks (about 2.6% higher than a city with low temperature variability). On the other hand, increasing temperature variation in the winter for

FIGURE 6: Property Crime 1990–92 — Comparing Seasonal Effects for Cities with High, Average, and Low Annual Temperature



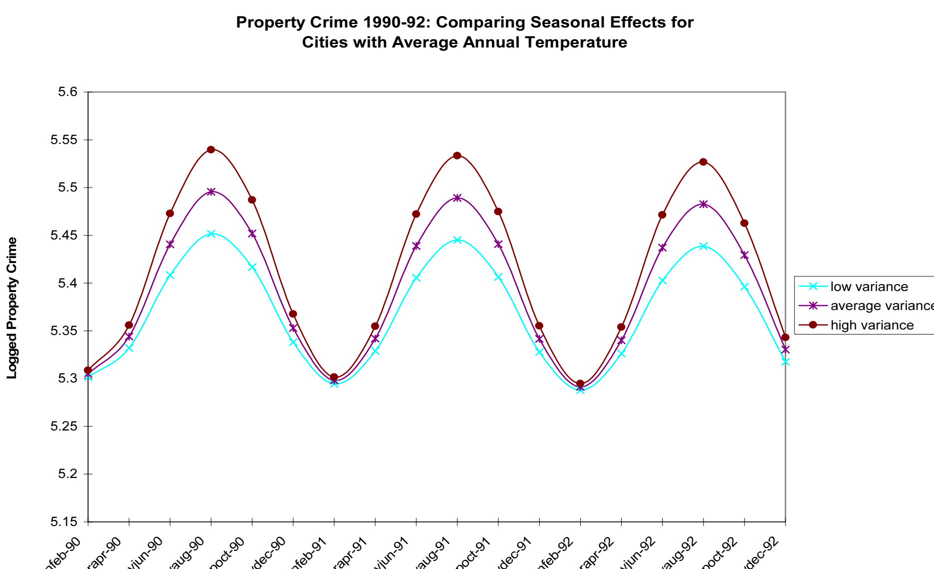
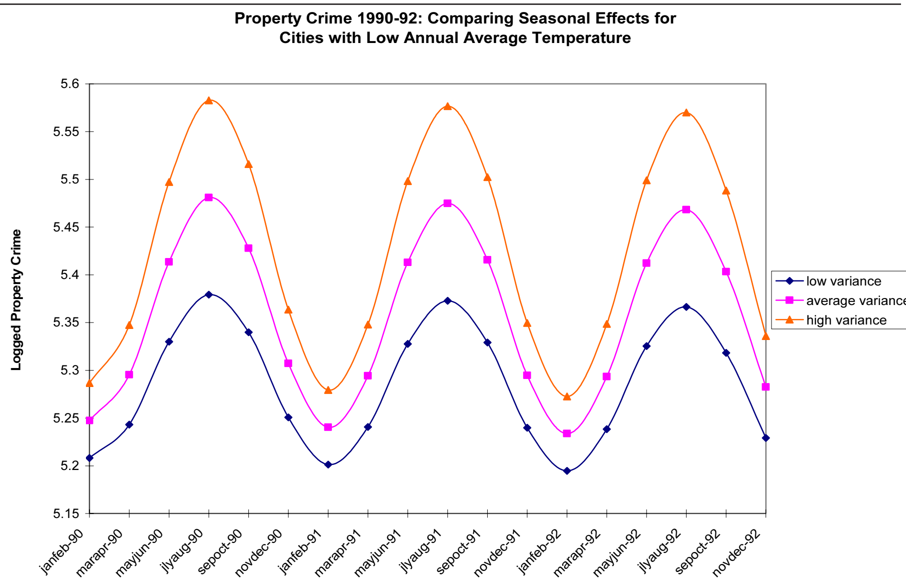


FIGURE 6: Property Crime 1990–92 — Comparing Seasonal Effects for Cities with High, Average, and Low Annual Temperature (Cont'd)



these hot climate areas results in lower temperatures in the more modest range of temperatures (60°F versus 56.4°F). Consistent with the RA theory, this results in a modest change in violent-crime rates at these moderate temperatures (about 2.8% lower than average variability), precisely the range where T/A theory would predict no crime variability.

Turning to property crime, the results show strong support for the RA theory. Here, the significant negative effect for the interaction term indicates that temperature variation within a city has a stronger effect on seasonal crime oscillations in cities with cooler climates than in those with hotter climates. We can see this effect graphically in Figure 6. Holding average temperature constant, we see in the middle and bottom panels that increasing temperature variation in average and cool climate areas has the strongest effect on seasonal oscillations in property crime during the summer. Since these cool-climate cities with high temperature variation have typical average July-August high temperatures of 81°F, this is consistent with the RA hypothesis that it is more pleasant temperatures that are most responsible for the observed seasonal crime oscillations for communities.

It is interesting to note that areas with hotter climates do not have higher overall levels of violent crime when controlling for demographic characteristics. This somewhat surprising finding contrasts with models run

TABLE 4: Intercept and Cosine Term Means for Models Run on Communities in Various States

	Violent Crime			Property Crime	
	Level	Amplitude		Level	Amplitude
Texas	3.652	.199	Maine	5.385	.237
Illinois	3.880	.194	Minnesota	5.335	.227
Maine	3.491	.194	New York	5.391	.153
Minnesota	3.351	.162	Illinois	5.217	.114
New York	3.155	.149	Washington	5.866	.090
Arkansas	2.640	.123	Texas	5.536	.071
Tennessee	3.263	.115	Arkansas	5.214	.071
North Carolina	3.326	.115	North Carolina	5.820	.065
Washington	4.433	.112	Florida	5.961	.034
Florida	4.391	.111	Tennessee	5.464	.024
California	4.513	.095	California	5.975	.008

Note: States are arranged in descending order by the magnitude of the amplitude factor.

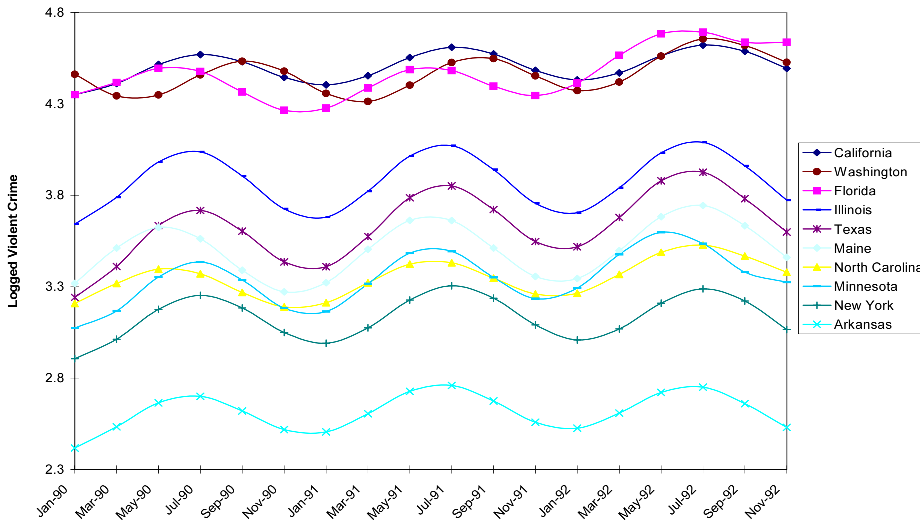
without our demographic controls (not shown here), where hotter temperature has a bivariate positive effect on violent crime and a much stronger positive effect on property crime.[18] This suggests that a simple comparison showing that hotter areas have higher crime rates is not telling the full story. Instead, when both variable sets are included, the demographic controls explain more of the variance in levels of violent crime *across* communities. Overall, these results of the climate variables have shown considerable support for the RA theory regarding property crime and mixed results for the two theories for violent crime. We next evaluate the role of the causal mechanisms proposed by these two theories.

Causal Mechanisms

Recall that in hypothesis 3, the T/A theory suggests that population density may exacerbate the frustration induced by hot, uncomfortable temperatures of summer. However, the results in Table 3 do not support this proposition. Instead, while population density increases the overall level of violent crime (consistent with past research) it has a surprisingly strong *negative* effect on the seasonal effect of violent crime. In fact, inconsistent with the T/A theory, increasing population density one person per kilometer proportionally decreases the seasonal effect of violent crime 10% (–.0144/.145 = .10).

In hypothesis 4, the RA theory predicts that the number of drinking/entertainment establishments should work as a causal mechanism that both increases annual crime as well as interacting with more pleasant weather of

FIGURE 7: Estimated Violent Crime Rates by States



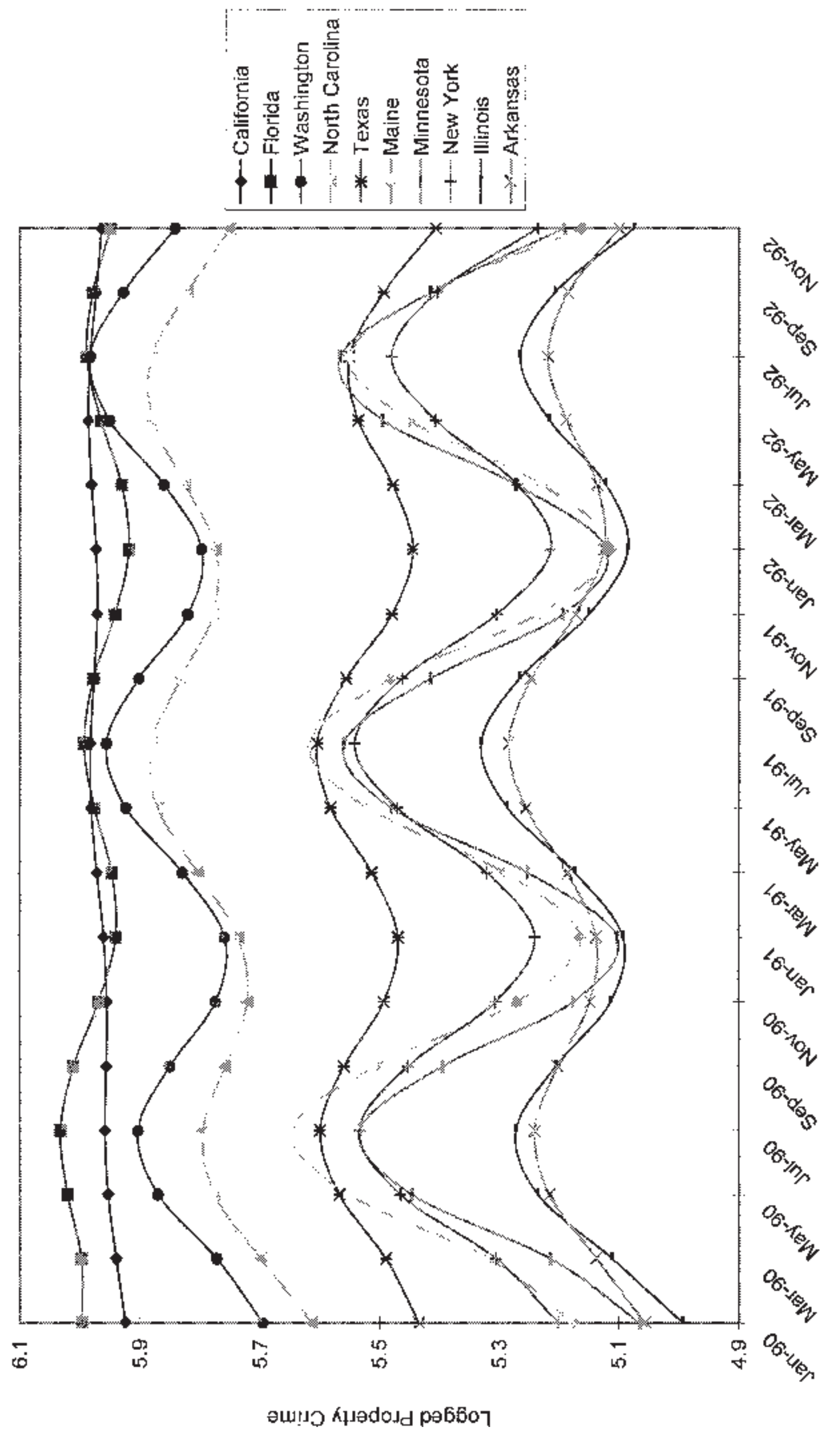
summer to increase the seasonal oscillations of crime rates. There is strong support for this proposition: entertainment establishments have a positive effect on both overall levels of crime and seasonal oscillations in crime. Adding 10 more drinking/entertainment establishments per 100,000 population increases the overall rate of violent crime 1.5% and property crime 6.6%.[19] This same increase proportionally increases the seasonal effect of violent crime 2.1% and property crime 3.5%. These results are consistent with the RA hypothesis that increased activity outside the home increases the possibility of property crimes, such as burglary, and violent crimes, such as robbery and assault.

Social Disorganization Variables

Finally, this same model also tests whether the measures of social disorganization have an effect on annual crime rates when controlling for climate variables, and whether measures of social disorganization help explain seasonal oscillations in crime rates. Regarding the first question, we see that increasing ethnic heterogeneity, residential instability, and percentage of divorces in cities all result in higher overall levels of violent and property crime, controlling for climate effects. For instance, a 1% increase in the percentage of divorces is associated with a 7% increase in the violent crime rate.

Regarding the second question of a positive impact of the social disorganization variables on the seasonal oscillations of crime rates, we see no support for this notion. Residential instability actually has a slightly negative effect on the seasonal oscillations of both violent and property crime, while

FIGURE 8: Estimated Property Crime Rates by Various States



increasing poverty and percentage of divorces both decrease the seasonal oscillations of property crime. Thus, we see a pattern where areas with greater social disorganization have somewhat higher overall rates of property crime (given the positive effects of ethnic heterogeneity, percentage of divorces, and residential instability), but fewer seasonal changes in crime. If it is the case that individuals in areas with high social disorganization are generally more cautious in their behavior in an effort to minimize the possibility of victimization (Anderson 1995), they may be less willing to alter their behavior in nicer weather. This is clearly speculative, but it suggests a direction for future research with individual-level data.

Additional Analysis: State-by-State Results

Our results using this large national data set demonstrate that the relationship between temperature and seasonal crime rates follows a distinct pattern largely consistent with the RA theory. Using the latent curve model also allows us to look more closely at the trajectories of individual communities rather than limiting ourselves to these larger overall patterns. Because our discussion of communities with high average temperature or high temperature variation is rather abstract, showing models of the communities within particular states can illustrate what seasonal crime patterns look like for communities in a relatively small geographic area with a somewhat homogeneous climate. That is, the temperate Mediterranean climate of California is very different from the climate of a northern state such as Maine. For this analysis, we select 10 states with at least 100 communities (for adequate sample size) representing different geographic regions of the U.S. We estimate models for property and violent crime containing the latent variables for the level, linear, quadratic, and amplitude terms on all the cities in the state of interest. There is considerable variation in the fit of these models: while some fit satisfactorily with 1 – RMSEA figures of .95 or above, a few have 1 – RMSEA figures less than .9. In particular, states with the least seasonal variation (such as California and Washington) show the worst fit.

For violent crime, T/A theory predicts that states experiencing the hottest summers should see the greatest seasonal variation in crime rates, while RA theory predicts that states with cooler climates will see greater variation. The results are mixed. Of the four states with the greatest seasonal oscillation in violent crime, two are states with relatively hot summers — Texas and Illinois — while the other two are the northern states of Maine and Minnesota, which have particularly mild summers and cold winters.[20] These results are seen in Table 4, which shows the mean values for the level factor (the average annual rate of crime for the communities within a state) and the amplitude factor (the average amplitude of crime oscillations for these cities).

However, there is support for the RA theory in that states with mild year-round climates — California, Florida, and Washington — tend to exhibit high overall rates of violent crime with relatively little seasonal variability. The mild winters and summers in these states probably lead to greater outdoor activity year round, leading to less seasonal crime variation. It is also notable that while the T/A theory predicts that the hottest states should have the highest overall rate of violent crime, Figure 7 graphing these crime trends by state shows that these three states with relatively mild year-round weather not only have the smallest seasonal oscillations, but also have the highest overall rates of violent crime.

Although the violent crime results show somewhat mixed support for the two theories, the results for property crime strongly support the RA theory. While the T/A theory predicts that we should see no seasonal oscillations here, they are quite dramatic and most pronounced in cooler climate areas. In support of the RA theory, property crime shows a strict ordering in Table 4 where the greatest seasonal oscillations occur for the two most northerly states (Minnesota and Maine), the southern states are further down the list, and two states with mild annual temperatures and little temperature variation (California and Florida) again show very high crime rates with small seasonal oscillations. In fact, the seasonal effect for California is essentially zero, as the parameter value for the amplitude term is smaller than its standard error. Similarly, the strong seasonal effect for cities in Minnesota and Maine is consistent with the explanation that cold winter temperatures in these regions lower the crime rate — indeed, Figure 8 shows that the average property crime in winter for cities in these two states are as low as those in all other states in this sample. This winter effect can be seen visually by viewing the plots in Figure 8 for Texas and Maine: while they have nearly identical levels of property crime in the summertime, Maine experiences a much deeper trough of property crime during the winter months.

Consistent with our results for the full sample of communities in all 50 states, these models run on communities within particular states generally support the RA theory. States with the coldest winter temperatures tend to have the greatest seasonal oscillations in crime, particularly for property crime. Likewise, areas with pleasant year-round temperatures have high overall rates of crime but see little seasonal change in crime. Consistent with past research, there is evidence here that the RA theory is particularly effective in predicting property crime (Bennett 1991).

Discussion

This study has detected significant seasonal oscillations for crime rates between 1990 and 1992, overlaid on more long-term changes in crime in a large sample of communities. By employing a latent curve model with a nonlinear component (an amplitude term), we were able to empirically test predictions from two distinct theories that offer different explanations for seasonal trends in crime rates. This contrasts with prior research in this area that has typically been descriptive, involved smaller samples, and therefore been unable to adequately model specific predictions derived from the T/A and RA theories. We now briefly summarize the results for our four hypotheses.

> *Hypothesis 1:* The routine activities theory predicts that there will be a positive seasonal effect for the property crime rate, while the temperature/aggression theory predicts that there will not be a seasonal effect for *property* crime rates.

The empirical results strongly supported the routine activities theory and strongly rejected the temperature/aggression theory. Figure 4 shows considerable evidence of a seasonal effect for property crime, suggesting a concurrence in space and time of potential offenders and targets and a lack of guardians. Our models of property crime showed a very satisfactory fit, had a significant amplitude term (with a 22% oscillation between property crime in the winter and in the summer), and had a peak around August 1. The particular strength of RA theory in predicting property crime has also been noted in past empirical work (Bennett 1991; Miethe & Meier 1994; Stahura & Sloan 1988). While some studies in the past have used robbery as a measure of property crime in testing the T/A theory (Anderson & Anderson 1984), we suggest that our measures of burglary, motor vehicle theft, and larceny are much cleaner measures of this concept. While the seasonal changes in violent crime were predicted by both T/A theory and RA theory, only RA theory predicted the seasonal effect observed for property crime. Given the very strong results for this hypothesis, claims that T/A theory alone explains all seasonal oscillations in rates of all types of crime are clearly untenable (Anderson 2001). In contrast, RA theory provides a parsimonious explanation of seasonal changes in both types of crime.

> *Hypothesis 2:* The effect of seasonal variability in temperature on crime rates will depend on the average climate of the community. The temperature/aggression theory predicts that temperature variability will induce the greatest seasonal changes in violent crime rates in areas with hotter climate, while the routine activities theory predicts that temperature variability will induce the greatest seasonal variability in both property- and violent-crime rates in areas with moderate climates.

There was modest support for the prediction of TA theory. We saw that increasing temperature variation had a positive effect on seasonal oscillations in our violent-crime model regardless of the climate of the community. In support of this hypothesis, temperature variation in hot climate communities had a positive effect on the oscillation in violent-crime rates. However, we also saw that temperature variation in moderate climate areas increased the oscillation of violent crime, in direct contradiction to this proposition. Similarly, the analysis of communities within individual states showed considerable seasonal variation in violent crime rates for cold climate areas.

Mixed support was also obtained for the prediction of RA theory. On the one hand, we did find contradictory evidence that temperature variation in hot climate areas increased violent crime rates. On the other, temperature variation in moderate climate areas increased the seasonal effect for both property- and violent-crime rates. Also, the particularly strong seasonal oscillations in violent and especially property crime for cities in northerly states such as Maine and Minnesota showed the effect of moderate summer temperatures on crime rates.

> *Hypothesis 3:* The temperature/aggression theory suggests that areas with high population density may experience greater seasonal fluctuations in violent crime rates.

We found no support for this hypothesis. In fact, population density actually had a surprisingly negative effect on the seasonal oscillations of both violent- and property-crime rates.

> *Hypothesis 4:* The routine activities theory predicts that areas with a larger number of entertainment establishments will have higher annual rates of crime and will have greater seasonal fluctuations in crime rates.

There was considerable support for this hypothesis. Adding 32 of these establishments per 100,000 population (a one standard deviation increase) increases violent crime almost 5% and property crime nearly 23%. We also saw support for the second half of this hypothesis, in that adding 32 such establishments per 100,000 population proportionally increases the seasonal oscillation of violent crime 6.7% and property crime 11.1%.

Limitations

We point out that our model has taken the somewhat unusual approach of using contemporaneous data (our temperature measures) to predict a trajectory model, although it is more common to use temporally prior variables to predict the outcome of interest. In general, using contemporaneous data would preclude drawing causal inferences (Bollen 1989). However, we suggest our model represents a rare instance in which establishing a correlation between weather and crime patterns can be extended to a causal claim. The logic of this argument is simple: while we considered two theories that both predict that changes in temperature work through causal mechanisms to induce changes in crime patterns, we can think of no competing hypothesis that would suggest that changing crime patterns lead to changing temperature patterns. For this reason, we feel causal claims are provisionally justified in this case.

It is also interesting to note that the value of the phase term we used to locate the peak point of crime over the year showed some variation in the models run on individual states, particularly for violent crime in Figure 7. By implication, violent crime peaks at slightly different points in different states. For instance, while North Carolina shows a peak around May–June, violent crime in Illinois does not peak until July–August. This finding suggests that it might be possible to capture more of the intercommunity variability in crime trends by permitting the phase term to vary over communities. While Ware and Bowden (1977) noted the need for such an effect in oscillation models, the LCM framework cannot currently accommodate such an effect.

Conclusion

This study has illustrated the considerable fluctuation during the year in the amount of crime that occurs within a city. We also saw that while the social disorganization theory can explain much of the difference in crime rates between cities, it does not explain seasonal oscillations in crime rates. That is, our results suggest that while the demographic characteristics of a city determine *how much* crime occurs in an area over the course of a year, climate patterns affect *when* that crime occurs. Thus, individuals respond to their environment — either social or physical — in ways that can give rise to such emergent effects. Not only does this have important implications for research into the patterned behavior of individuals within communities that gives rise to crime rates, but it also suggests an important consideration for sociologists considering the patterned behavior leading to other social outcomes. Viewing how communities respond to different climate patterns can provide key insights into the mechanisms at work in such instances and suggests that our methodological strategy may be appropriate for addressing other research questions.

While we have shown considerable support for the routine activities theory, we do not suggest that the temperature/aggression theory has no merit. We saw some evidence that increasing summer temperatures in the hottest areas increase violent crime rates, and a hot climate state such as Texas showed considerable seasonal oscillations for violent crime. Additionally, past studies finding a seasonal pattern for family disturbances are consistent with the T/A theory and inconsistent with the RA approach (Michael & Zumpe 1986; Rotton & Frey 1985). That is, if colder weather confines individuals to the home more frequently, the social interaction perspective would imply that winter would be the peak time for family disturbances, when in fact the peak occurs in the summer. Our main conclusion is thus that the T/A theory may well have some use in explaining violent crime, but the bulk of our findings on seasonal changes in both violent *and* property crime can be attributed to RA theory and the fact that the changing behavior patterns of individuals during mild temperatures increases opportunities for criminal victimization. The claim of T/A proponents that the theory explains all seasonal crime patterns clearly does not hold in this study.

Future work will need to explore the mechanisms of these theories in more depth.[21] For instance, while the T/A theory suggests that frustration is simply a biological response to uncomfortable conditions, a reviewer suggested that inequality might be a necessary source of frustration for explaining when the temperature/aggression effect may occur. That is, introducing the sociological concept of social comparison theory suggests that individuals will be more frustrated when others near them have considerably more material objects; therefore, areas with greater inequality will have greater overall levels of frustration. In addition, this increased predisposition to frustration on the part of individuals may interact with hot weather to accentuate seasonal crime patterns. Of course, it is also possible that greater inequality is simply a proxy for greater numbers of possible offenders, and hence such a measure could also capture the effects of RA theory. While such a measure may not distinguish unambiguously between these two theories, it does suggest possible directions for integration of theories in viewing seasonal crime patterns.

Finally, we note that our findings in support of the routine activities theory do not call forth a policy response (we are not suggesting eliminating all entertainment establishments, nor suggesting a large population migration to North Dakota) but rather point out a natural tradeoff involved in lifestyle choices. That is, a hypothetical family that stays home all the time is at less risk for criminal victimization (as they by definition cannot be mugged on the street, and burglary is difficult when the home is always occupied), but at the cost of not enjoying the benefits of venturing outdoors. Our findings also do not necessarily imply a more unsafe environment for communities with greater numbers of entertainment establishments or more pleasant weather. While the patterns we have observed imply that these conditions are associated with higher crime rates, it does not follow that each individual who ventures out is more at risk of experiencing crime. To make such a conclusion with such data would be to commit an ecological fallacy. In fact, it is logically possible that the risk of crime when venturing outdoors is the same in either case, and the only variable being altered is the number of people who choose to go outdoors. In essence, we are observing overall rates here and simply arguing that these are driven by the behavioral patterns of individuals. To make the more nuanced claim that the actual risk of crime increases would require incorporating information on the actual behavior of individuals within a hierarchical model of communities. Such an approach might be a fruitful direction for future research.

Notes

1. Note that routine activities theory would have indeterminate predictions here: on the one hand, increasing density increases the number of possible victims and hence would increase crime. On the other, it would also increase the number of guardians, which would decrease crime. Hence, it does not make an unambiguous prediction in this instance.

2. The archive is housed at the Inter-university Consortium for Political and Social Research (ICPSR) (http://www.icpsr.umich.edu/NACJD/archive.html).

3. In census terminology, police units are places, minor civil divisions (townships), and counties (for county sheriffs).

4. We do not use the information on rape here since it may be subject to considerable reporting error; likewise, arson does not appear to be reported consistently.

5. We also ran models excluding robbery from violent crime, or adding it to property crime, and came to the same substantive conclusions in all models.

6. Some units report crime for very few months. These cases show troubling inconsistencies when performing diagnostics, with some showing relatively high crime rates for the only month they reported (December), suggesting that at least some of these may be reporting annual data for a single month. Because of these inconsistencies, and the relatively little information such cases would provide as a result of the limited response rate on the crime variables, we chose to drop these cases.

7. We have reason to suspect that a weather station within 40 miles of our city of interest is providing fairly accurate weather patterns. We also tested models dropping the two most extreme cases — yielding virtually identical results — and also tested a model that included a variable measuring the distance of the weather station from the city of interest, and this variable had no effect.

8. This uses the following mutually exclusive groups: Anglo, African American, Asian, and Latino.

9. We used the categorization scheme of the Census Bureau for length of residence; this has a similar effect to log transforming the average number of years in each category (correlated about –.98). A log transformation matches the theoretical expectation that residence within the community will increase attachment to the community at a slowing rate.

10. While full information maximum likelihood (FIML) is another viable strategy for missing data, the statistical programs implementing FIML at the time we performed our analyses were unable to handle the nonlinear parameters of our latent cosine model.

11. Taking the mean value of the multiply imputed chi-squares does not take into account the variance among the chi-square estimates. Meng and Rubin (1992) provide alternative strategies for obtaining a simultaneous F-test of the multiply imputed data sets. However, methods for combining various approximate fit indices, such as the RMSEA, are less developed at this point, and so we adopted the simpler strategy of taking the average value over these 10 imputations.

12. In these models we estimate the frequency parameter. Since we have strong theoretical reasons to expect this seasonal frequency to occur over one year, we could choose to fix this value. Indeed, the estimated value is almost always right at 1/6. However, freely estimating this parameter illustrates the generality of this methodological approach when applied to other problems where the frequency of the process may not be so well defined a priori.

13. While it is possible to also include predictors of the variables measuring the long-term changes in crime (the linear and quadratic factors), we do not include these here. Long-term change of crime over this three-year period is not of central interest to us here theoretically, and this is too short a period for viewing longer-term trends. But while we do not explain these longer trajectories for individual cities, our model nonetheless takes this variance into account.

14. This is obtained by substituting the values of the lambdas for a particular time point to estimate the amount of crime. We calculate values for January-February and July-August for each year and exponentiate to get the amount of raw crime at that time point. Subtracting the winter from the summer value and using the winter value as the denominator yields the annual fluctuation of 34.5%. A similar calculation for property crime yields a 23.6% difference between the highest and lowest points.

15. Recall that we are able to estimate where the peak of the amplitude term occurs from the phase (p) term in the amplitude expression, which was significantly different from zero in both models. In the models, we centered our time axis at July 1. Since the estimated phase term for the violent crime model was $p = -.17$, this suggests that we would need to shift our time-coding forward .17 bi-months. This is only about 10 days, suggesting a peak of July 10. For property crime, we estimated a phase term of $p = -.44$. This implies a shift of almost one month, and a peak of August 1.

16. This is computed by dividing the coefficient estimate for temperature variation by the mean amplitude (the intercept) (.00705/.14492 = .049). Interpreting individually the coefficient for the main effect of a variable involved in an interaction is justified here by the nonsignificance of the interaction term.

17. In Figures 5 and 6, "hot" and "high variability" are defined as one standard deviation above the mean. We do not include an estimate of hot cities with high temperature variability in these figures because no cases in our sample exhibited this extreme pattern.

18. We also tested models including a quadratic term for temperature to see whether there is a diminishing effect for increasing temperature. This variable showed little effect and does not change any of our general conclusions here.

19. When looking at a discrete change in a variable in a semi-log model, it makes more sense to view the compound percentage increase in the y-variable for a one-unit shift in the x-variable (Halvorsen & Palmquist 1980). Essentially, this implies using the equation $g = e^{\beta} - 1$, where g is the compound percentage growth rate and b is the estimated coefficient (for a complete derivation of this, see Lardaro 1993). For violent crime: $\exp(.00146 \times 10) - 1 = .015$.

20. For comparison, while Texas cities had an average daily high summer temperature (June through August) of 92 degrees Fahrenheit over this three-year period, the Minnesota cities' daily high temperature averaged a mild 78 degrees.

21. It should be noted that some of the mechanisms are not necessarily associated with one theory or the other. For instance, consider the possibility of taking into account the amount of air conditioning in an area. On the one hand, the T/A theory would suggest that areas with less air conditioning would show greater instances of aggression during hot weather (as the lack of air conditioning means individuals lack a respite from the hot weather). On the other hand, RA theory *also* suggests that areas lacking air conditioning will have higher crime rates: however, in this instance, this posited relationship is due to the fact that in areas with ample air conditioning individuals will remain at home to stay out of the heat.

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