

**Estimation of Crime Seasonality:
A Cross-Sectional Extension to Time Series Classical Decomposition¹**

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Abstract

Reliable estimates of crime seasonality are valuable for law enforcement and crime prevention. Seasonality affects many police decisions from long-term reallocation of uniformed officers across precincts to short-term targeting of patrols for hot spots and serial criminals. This paper shows that crime seasonality is a small-scale, neighborhood-level phenomenon. In contrast, the vast literature on crime seasonality has almost exclusively examined crime data aggregations at the city or even larger scales. Spatial heterogeneity of crime seasonality, however, often gives rise to opposing seasonal patterns in different kinds of neighborhoods, canceling out seasonality at the city-wide level. Thus past estimates of crime seasonality have vastly underestimated the magnitude and impact of the phenomenon. We present a model for crime seasonality that extends classical decomposition of time series based on a multivariate, cross-sectional, fixed-effects model. The crux of the model is an interaction of monthly seasonal dummy variables with five factor scores representing the urban ecology as viewed from the perspective of major crime theories. The urban ecology factors, interacted with monthly seasonal dummy variables, provide neighborhood-level seasonality estimates. A polynomial in time and fixed effects dummy variables for spatial units control for large temporal and spatial variations in crime data. Our results require crime mapping for implementation by police including thematic mapping of next month's forecasted crime levels (which are dominated by seasonal variations) by grid cell or neighborhood, thematic mapping of the urban ecology for developing an understanding of underlying causes of crime, and ability to zoom into neighborhoods to study recent crime points.

Key Words: Crime Seasonality, Urban Ecology, Multivariate Modeling, Crime Mapping

Introduction

Researchers have studied the seasonality of crime for more than 100 years with sometimes-contradictory results (Block, 1984; Baumer and Wright, 1996). Despite variation in the findings of this literature, researchers often point out two conclusions; namely, that property crimes peak in the fall and winter and violent crimes peak in the summer months (Baumer and Wright, 1996; Gorr et al., 2001). While these conclusions likely stand in many settings, there is a serious shortcoming in this literature because studies that use large spatial units of aggregation at the city, regional, and national levels dominate the literature (Farrell and Pease, 1994; Feldman and Jarmon, 1979). Research at such scales can mask variation at smaller areas (Sherman et al., 1989). For example, seasonality could vary across neighborhoods of a city but examining the seasonality at the citywide level would mask this variation. Suppose larcenies show no increase during the holiday season for the entire city, but there is a large increase in one part of the city while the rest of the city experiences a moderate decline in larcenies. These two opposing sub-patterns cancel each other out at the city level. While the part of the city with the large seasonal increase is a potential target for police interventions during the holidays, its seasonal peak would be missed. This is exactly the case that we find in Pittsburgh, Pennsylvania for several crime types, including larceny as we show below.

With the widespread use of geographic information systems (GIS) in crime mapping and increased attention given by criminologists to the role of places in crime and the criminology of place (Eck and Weisburd, 1995; Weisburd, 1997; Taylor, 1998; Sherman, 1995), studies such as those on topics like hot spots (Sherman et al., 1989; Sherman 1995; Weisburd et al., 1993; Braga, 2001), are using ever-smaller spatial units of analysis. We continue this trend by attempting to model crime seasonality at small-scales. In order to determine the extent to which

seasonality varies across a city, this study develops multivariate models of crime seasonality for several crime types within the city of Pittsburgh, Pennsylvania, from 1990 to 1998.

There are many motivations for undertaking this research. Among the most important are the practical implications that a sub-city model of crime seasonality has for policing. First, Lebeau and Langworthy (1986) indicated more than a decade ago that police administrators were primarily interested in the “daily and seasonal fluctuations of calls-for-service” for making personnel decisions. In addition, good estimates of seasonality are critical for evaluating the impacts of police interventions. We discuss each of these needs in turn next.

A long-term horizon police personnel decision is the number of police to assign to each precinct to meet response time standards for high priority calls for service. Many planning models require estimates of both average and peak seasonal demand. In the middle term are decisions such as when to schedule vacations and training (during low seasonal demand periods). In the short term are tactical decisions on targeted patrol and special interventions aimed to impact hot spots or serial criminals.

There are three major time series components that can impact such decisions: 1) time trend or the steady increase or decrease of crime from month to month over a sustained period of months or years, 2) an innovation or shock such as the start of a neighborhood gang war or release of a serial criminal from jail, and 3) seasonality. For short-term tactical allocation of police or targeting patrol, seasonality has the most reliable information on potential large changes in crime. Time trends generally consist of a series of small, relatively steady changes that accumulate. Innovations or shocks are somewhat rare but can produce the largest crime increases. Intelligence information or leading indicator forecast models are needed for short-term forecasting of innovations. Seasonality, as revealed by our models developed in this paper,

can account for 15 percent to nearly as much 50 percent increases in crime in one month faithfully every year. To find such increases, however, we show that crime analysts must estimate seasonality on small geographic scales and then map next month's seasonality for tactical support.

A model of small-scale crime seasonality would not only allow police to make more effective human resource decisions, but also to better design, implement, and evaluate neighborhood-level intervention activities. A hypothetical example, motivated by our results below, is useful. Suppose that the crime analysis unit in a certain city estimates and tracks seasonality at the neighborhood level, producing thematic maps of neighborhood seasonality, which display next month's forecasted crime which is dominated by seasonality. Furthermore, in September suppose the map of October seasonality predicts that a certain neighborhood of the city has a large October increase of 12 burglaries above the mean. Based on this, the police department sends an alert to persons living in the neighborhood to close and lock their garages, windows, and doors during that month. Following the end of October, the crime statistics reveal that the October spike in burglaries was only four above the mean, thus providing evidence that the intervention was successful. In contrast, just examining month-to-month variations in burglary data, without considering seasonality, would indicate an increase for October, signaling a failure of the intervention, when in fact there was a relative decrease in seasonality. This simple hypothetical example suggests that a reliable model of sub-city seasonality would have clear benefits for policing and crime prevention.

Along these same lines, recent crime forecasting research offers further motivation for this study. Gorr et al. (2001) suggest that improved estimates of sub-city crime seasonality could improve the accuracy of one-month-ahead crime forecasts. In their paper, Gorr and colleagues

succeeded in using simple one-month-ahead rolling horizon univariate forecasting models to improve forecast accuracy by 20 to 40 percent over common police practices.² Their best forecasts, however, used city-wide estimates of seasonality and, furthermore, they indicated that forecast accuracy might improve by using sub-city level estimates of seasonality.

The next section of this paper critically reviews the relevant crime seasonality literature. A description of our model, the data, and our methodology follows the literature review. A section on the estimation results and some conclusions end the paper.

Literature Review

The oldest theory on seasonality is the “temperature aggression hypothesis,” stating that weather increases violent crime by means of ambient temperature and anger arousal (Guerry 1833; Ferri 1882; Baron 1972; Rotton and Frey 1985; Anderson 1987, 1989; Cohn, 2000; Baumer and Wright, 1996; Feldman and Jarmon, 1979; LeBeau and Langworthy, 1986; DeFronzo, 1984). Ambient temperature, humidity, and other weather variables, however, are not well suited for the purposes of explaining variation in sub-city seasonality because these measures do not vary over the space of a city. If the same weather has different effects on different people then the characteristics of the people and their neighborhood (i.e. local urban ecology) are the appropriate explanatory variables for small-scale crime seasonality.

The crime seasonality literature mostly fails to examine the phenomenon at small scales. A single study in the literature examines inter-neighborhood variation in the seasonality of assaults in Dallas (Harries et al., 1984). This study bases its conclusions on only eight months of data and therefore concentrates on exploratory analysis rather than modeling seasonality,

² Gorr and colleagues state that police commonly use crime data from the previous year alone to make their personnel allocation decisions.

attributing inter-neighborhood variation in seasonality to the differential affects of weather on the populations of different neighborhoods with varying socioeconomic status.³

Another area of theory building, predicated on a needs-based view of property crime suggests that seasonal unemployment and increased living expenses influence levels of criminal activity at different times of year (Falk, 1952). Census data on income, educational attainment, and other economic characteristics of the population are available at small scales within cities to represent this view on crime seasonality.

Routine activity theory (Cohen and Felson 1979) holds that crime opportunities are concentrated in time and place, with spatial-temporal differences affecting the probability of convergence of three conditions: 1) motivated offenders, 2) suitable targets and 3) the absence of a capable guardian. Recently, this theory of crime has had much application and success. Many demographic, socioeconomic, and land use variables are available at the neighborhood level for representation of these conditions.

We hypothesize that the varying ecological structures of small areas within a city are vital to understanding the variation in crime seasonality that exists within a city. The rhythms of life in such small areas or neighborhoods of a city might follow distinct patterns that fluctuate with the seasons. If the rhythms of neighborhood life determine the likelihood of crime, then they might also influence the seasonality of crime. There is a long tradition of using urban ecology to explain crime and other social phenomena (Shaw and McKay, 1969). For our purposes, the ecological structure of a place to consists of local businesses, land uses, and the socioeconomic status and demographic characteristics of visitors and residents. We develop a corresponding model of crime seasonality starting with the next section of this paper.

³ Harries et al., (1984) develop what they call an urban pathology index (UPI) to characterize the socio-economic status of Dallas neighborhoods.

Seasonality Model

This study uses principal component analysis, a method of data reduction closely related to factor analysis, to characterize the ecological structure of each spatial unit or place. Although used extensively in sociology (Heise, 1984; Marini et al., 1996) and other social sciences, factor analysis and principal component analysis originated in the field of psychology. Several latent factors result from the principal component analysis, and, in our case, describe the spatial units of analysis. We construct a factorial ecology (Janson, 1980) where we cluster similar spatial units into “reasonably homogeneous categories”. These categories (factors) help describe the characteristics of the spatial units and thereby describe their ecological structures. The scores for each of the spatial units on each of the factors provide a causal element in the model of seasonality.

Our model is analogous to classical decomposition, a common forecasting method for estimating seasonality of a single univariate time series (Makridakis et al., 1978). Like classical decomposition, we mechanically remove the temporal variation in our model. We extend the decomposition, however, by also mechanically removing or controlling for the spatial variation in the data through a fixed-effects model with dummy variables for grid cells. As a result, the variation accounted for by seasonality and random error is left and available for further modeling using causal variables, our factor scores, to explain seasonality.

The dependent variables in our models of seasonality for each crime type are the monthly crime counts. Recognizing that the spatial units in our analysis vary not only in their seasonality but also in their relative overall levels of crime, we add a dummy variable for each spatial unit. A time trend cubic (time, time², and time³) is also included in the model to account for the

overall time trend present in the data. Furthermore, the spatial unit dummies are interacted with the time trend variables to allow each spatial unit to have a unique time trend. It is important to note that the portion of the model described to this point does not account for seasonality, but attempts to thoroughly remove or control for time and space variations.

A common additive linear model for seasonality uses dummy variables. The model is of the form $y_t = \sum_{i=1}^s \gamma_i D_{it} + \varepsilon_t$: where s is the number of seasons (in our case $s=12$ months), and the γ_i represent coefficients for the different seasons. The seasonal component of our model, and the focus of our analysis, includes eleven seasonal dummy variables each one indicating a month with an intercept term corresponding to the suppressed month. As mentioned, we use ecological factor scores to account for the variation in seasonality within a city. These enter the model as interactions with the eleven monthly seasonal dummy variables and the factors that result from the principal components analysis. A summary of the model and its parts is as follows:

$Y = f(\text{Intercept, Place, Time, Place x Time Interactions, Seasonality, Seasonality x Factor}$

$\text{Interactions})$ where:

<i>Place</i>	=	dummy variables for every place but one,
<i>Time</i>	=	time trend variables for time, time ² , and time ³ ,
<i>Place x Time Interactions</i>	=	interactions between the PLACE dummy variables and each of the time trend variables,
<i>Seasonality</i>	=	11 monthly dummy variables,
<i>Seasonality x Factor Interactions</i>	=	Monthly dummy variables interacted with the factors that result from the principal components analysis.

Data

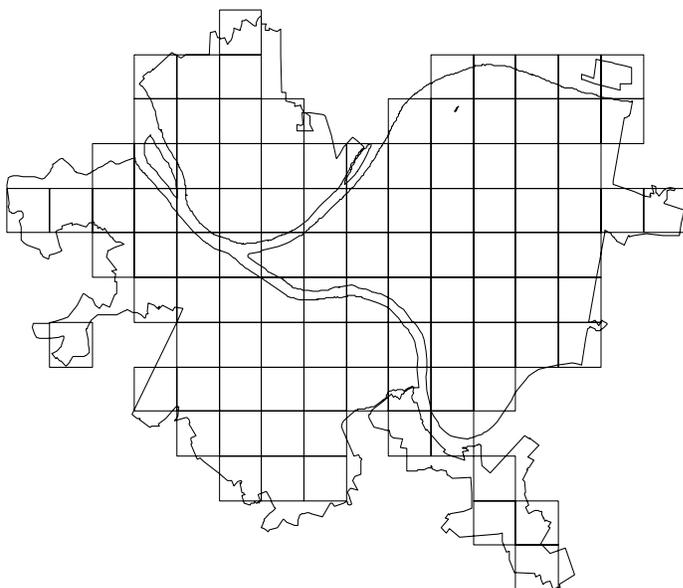
Our spatial units of analysis consist of a grid system containing 103 square grid cells 4000 feet (or roughly 10 city blocks) to a side overlaid on a map of Pittsburgh, Pennsylvania (see Figure 1). These spatial units of analysis provide us with several useful features. Instead of neighborhoods or police precincts, which have varying shapes and sizes, our grid cells hold these features constant. This simplification makes grid cells ideal for visual interpretation.

Furthermore, researchers can control grid cell size to match the scale of the phenomenon under study. In this case, the grid cells are large enough to offer sufficient monthly observations of crime to estimate our models, while they are also small enough for small-scale analysis and application. For example, Pittsburgh has 6 police precincts or districts and 43 car beats. Hence, our grid cells are generally half as small as the smallest police administrative area in Pittsburgh. Crime-mapping analysts can always overlay precinct or car beat boundaries on top of thematic maps made from the grid cells and easily relate both sets of boundaries. Furthermore, they can drill down to individual crime points in areas of interest identified by the thematic maps.

Our crime data consist of nine years of data (1990 to 1998) for selected 911 computer-aided dispatch (CAD) calls and offense reports as provided by the Pittsburgh Bureau of Police.⁵ CAD data, because they represent citizen calls for police emergency services, represent citizen perceptions of crime. We use CAD data for shots fired and drug calls. Our analysis uses offense report data for robbery, larceny, motor vehicle theft, simple assault, and aggravated assault. We mapped the offense records and CAD calls by address matching using a geographic information system (GIS), which yielded points on a street map. Spatial aggregations of these points provided the monthly time series of crime counts for each grid cell.

⁵ See Sherman et al. (1989) for a clear and concise description of the limitations and strengths of using police call data. They indicate that data on calls for service are subject to both underreporting and overreporting.

Figure 1: Map of Pittsburgh with 4000 Foot Grid Cells as Spatial Units



In addition to the crime data, we utilized several data sources to represent the ecological characteristics of our grid cells. Demographic and socioeconomic characteristics of each grid cell are based on block group data from the 1990 U.S. Census apportioned to our grid cells.⁷ Street address data from the 1997 PhoneDisc™ CD provided counts of crime-prone business types located in the grid cells. We used the data from both the census and the counts of certain business types by grid cell as inputs in the principal component analysis. Our belief that the grid cells used in this study possess relatively constant ecological characteristics during the study period is the basis for using the census data and the 1997 PhoneDisc data, which do not change over the course of the study period. We believe our results are robust without including the

⁶ See Sherman et al. (1989) for a clear and concise description of the limitations and strengths of using police call data. They indicate that data on calls for service are subject to both underreporting and overreporting.

⁷ The block group census data were apportioned to grid cells using a weighting scheme based 2000 block population assigned to block centroids. This is a reasonably accurate method of estimating the grid cell variables.

changing characteristics over time, but our future work in this area should improve on the results of this study by using data that change over time.

Before discussing the methodology used in the estimation of our models, some descriptive information about Pittsburgh is worth mentioning. Pittsburgh is a medium-sized city located in southwestern Pennsylvania. The city's weather is temperate with four seasons. Pittsburgh is typical of post-industrial American central cities in the northeast and Midwest as it experienced steady population loss over the last fifty years. During the most recent decade (1990 to 2000), which includes the study period, Pittsburgh lost 9.5 percent of its population going from 369,879 to 334,563.

In sum, we have nine years of crime data with 12 observations for each year in each of 103 grid cells yielding 11,124 data points for each crime type. We adjusted the monthly data by the number of days in the month. Table 1 gives descriptive statistics for each crime type. It is important to note that the crime types with the highest mean monthly crime counts are larceny, motor vehicle theft, and simple assault.

Methodology

There are some common problems encountered in the estimation of time-series, cross-sectional data including serial correlation and heteroscedasticity, which can result in inconsistent estimation and standard error estimates that are biased low. Simply using ordinary least squares (OLS) to estimate the model, without correcting for these problems, leads to overly optimistic results from significance testing. The methodology we used for the estimation to correct for this problem, OLS with panel-corrected standard errors (PCSEs), was introduced by Beck and Katz (1995) in a study they did criticizing the Parks Method, a commonly used method for estimating time-series cross-sectional data. Our data includes 108 months (time periods) from 1990 to 1998

and 103 grid cells (cross-sections). Thus, our data fit the description of what Stimson (1985) calls “time-serially dominated time-series cross-sectional data,” which simply refers to the case

Table 1: Descriptive Statistics for Dependent Variables

(Number of observations = 11,124; Minimum = 0)

	Mean	Standard Deviation	75% Quartile
CAD Drugs	3.09	7.91	2.82
CAD Shots Fired	2.20	5.18	1.96
Motor Vehicle Theft	5.73	7.10	7.85
Robbery	1.48	2.74	1.96
Burglary	3.19	4.19	4.05
Larceny	5.58	8.19	7.09
Simple Assault	8.51	10.30	11.14
Aggravated Assault	0.81	1.54	1.01

where the number of times is greater than the number of cross-sections. Beck and Katz (1995) designed their estimation method for this time-serially dominated case; hence, we use it.

Results

This section begins with a discussion of the results from the principal components analysis and then moves on to a description of the results from the estimation of our models for seasonality. Rather than use all of the many demographic, socioeconomic, and land use variables from our data sets to describe the ecological structure of the grid cells, we used principal components analysis as a data reduction tool. This is a practical consideration for estimation of our seasonality model, because we intend to interact ecological variables with the seasonal dummies. It is much easier to estimate and interpret a model with five factor scores instead of 20 original variables (see Table 2). Research in the criminology and public health

literatures offer compelling reasons for the inclusion of many of these variables. The input variables, listed in Table 2, in general relate to seasonal fluctuations in human behavior, or fluctuations in the rhythms of life in a grid cell.

Five factors result from running the principal components analysis with the varimax rotation technique, as shown in Table 3. Several of the factors echo major themes in the criminology literature. The low human capital factor is the first factor listed in Table 3. Highly weighted input variables on this factor include the rental proportion of housing, the dropout rate among young adults, the unemployment rate, the proportion of households that are female headed, the poverty rate, and the black proportion of the population. The social control literature and the public health literature indicate that socioeconomic status and human capital hold some importance in determining health of residents and social control in the neighborhood (Sampson and Raudenbush, 1999; Sampson et al., 1997; Bursik, 1988; Velez, 2001). High proportions of female-headed households in a neighborhood, for instance, might contribute to a lack of social control over the children of these mothers. The sections of Pittsburgh that score high on this low human capital factor are the solid fill shaded grid cells shown in the first map in Figure 2.

Table 2: Input Variables for the Principal Components Analysis:

Demographic and Socioeconomic Variables:

POPDENS	Population Density
RENRAT	Rental Proportion of grid cell population
DROPRAT	Dropout rate of young adults
PCAPINC	Per Capita Income
PUNEMP	Unemployment Rate of Grid Cell
PFHH	Percent of grid cell households that are female-headed
POVRAT	Poverty rate
PAYAD	Young adult percent of grid cell population
PHPIN1Y	Percent of all households in the grid cell that moved to the grid cell in the last year (1989-1990)
PCTBLK	Percent of total population that is African-American

Count Variables Related to Land Usage:

NUMSCHLS	Number of schools in the grid cell
SIC5311	Department stores
SIC5471	Convenience stores
SIC5812	Eating places
SIC5813	Drinking places
SIC6099	Check cashing establishments
SIC7011	Hotels and motels
SIC7021	Rooming and boarding houses
SIC7251	Parking Lots

Table 3: Five Factors Resulting from the Principal Components Analysis

<u>Factor:</u>	<u>Definition:</u>
Factor 1	Low human capital
Factor 2	Young adults/ Transient populations
Factor 3	Population density
Factor 4	Retail establishments (i.e. department stores, check cashing, etc.)
Factor 5	Convenience stores & drinking places

The number of young adults in the population weighs heavily in the creation of the second factor resulting from the principal component analysis. High scoring grid cells on this factor contain the colleges and universities located in Pittsburgh. These grid cells therefore possess clear seasonal patterns of behavior associated with them that follow the college calendar. Grid cells with numerous hotels and motels also score high on this young adult/transient population factor. Hotels and motels also have seasonal trends related to holidays, conventions, and local tourism.

Our third factor is the population density factor, but another input variable, the number of schools in the grid cell is also highly weighted in the composition of this factor. High population densities likely influence the routine activities of place by increasing the likelihood that potential offenders are in close proximity to potential targets in the absence of guardianship (Cohen and Felson, 1979). Furthermore, the presence of neighborhood schools in a grid cell suggests

seasonal behavior patterns related to the school calendar. Some researchers have found a relationship between the presence of a high school and nearby crime rates (Roncek and Faggiani, 1985). For the most part high scoring grid cells on the population density factor are located in the eastern portion of Pittsburgh, a highly residential portion of the city (see Figure 2).

The close relationship between factors four and five (both represent commercial activities and are often located in proximity to each other) merits discussing them together. First of all department stores and retail establishments along with check cashing businesses score high on the fourth factor, the retail establishment factor. These areas have distinct seasonal patterns of behavior associated with shopping. One expects areas scoring high on these factors to exhibit extraordinary seasonal peaks in larceny during the months of the holiday shopping season.

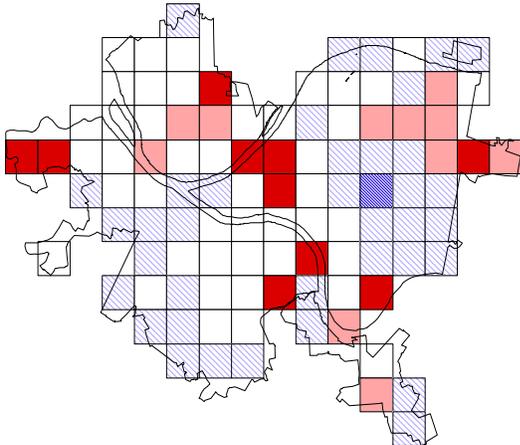
The fifth factor indicates the presence of drinking places (pubs, taverns, and bars) and convenience stores in high scoring grid cells. An extensive literature exists examining the relationship between crime and drinking places like bars and pubs (Roncek and Maier, 1991; Roncek and Pravatiner, 1989; Sherman, 1995). This factor will help us determine whether there is a distinct seasonal crime pattern related to the presence of drinking places or convenience stores. If heat increases the violence associated with alcohol consumption then we might expect distinct summer peaks in violent crimes in places that score high on this convenience stores and drinking places factor.

The principal component analysis scores each grid cell on each of the five factors described above. The maps in Figure 2, which map these scores in terms of standard deviations, reveal the heterogeneous ecologies of the 103 grid cells. The interaction of these factor scores for each grid cell with the monthly dummy variables creates the seasonal interactions, described

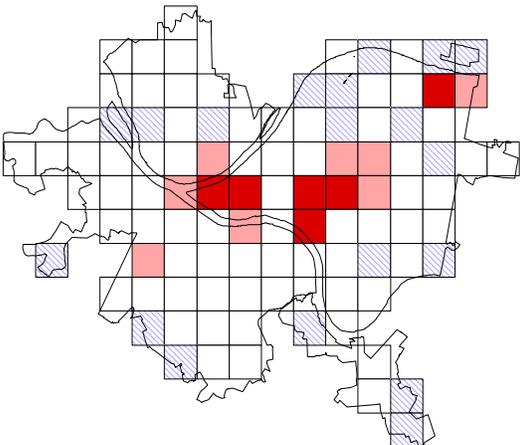
earlier in the model section of the paper. Hence, we integrate the results from the principal components analysis into our models for estimation in the form of the seasonal interactions.

Figure 2: Maps of Principal Components Analysis Results—Five Factors

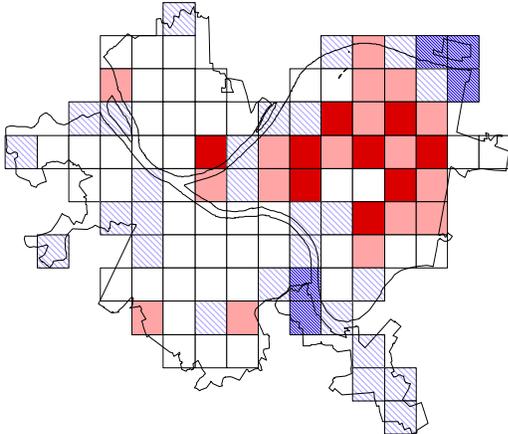
Factor 1—Low Human Capital



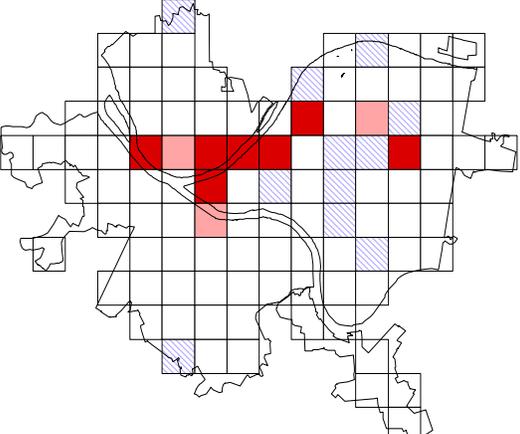
Factor 2—Young Adults/Transient Population



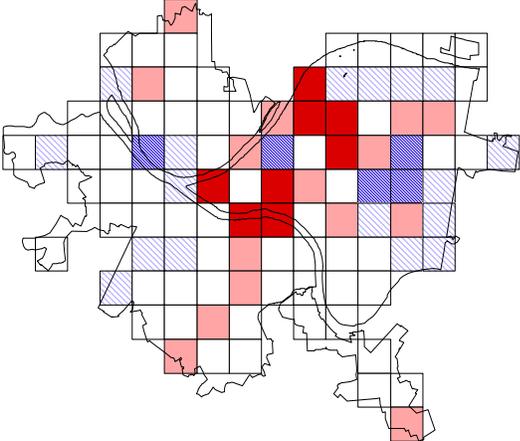
Factor 3—Population Density



Factor 4—Retail Establishments



Factor 5—Convenience Stores & Drinking Places



LEGEND:
[Blue hatched box] <-2 Std. Dev.
[Light blue hatched box] -2.0 - -0.51 Std. Dev.
[White box] -0.5 - 0.5 Std. Dev.
[Light red box] 0.51- 2.0Std. Dev.
[Dark red box] > 2 Std. Dev.

This paper’s primary hypothesis is that crime seasonality varies across the space of a city. The results from our model estimations for the eight crime types provide evidence to support this claim. The discussion of the estimation results in this section centers around the spatial heterogeneity of seasonality that is shown with our model results.

The overall regressions results for each crime type (shown in Table 4) indicate that the most successful models were those for larceny, simple assaults, robbery, and motor vehicle theft, though all had excellent explanatory power by most standards. The high R-square values in Table 4 are due mostly to the vary large space and time trends extracted by our polynomial time trend, fixed effects grid cell dummies, and interactions of those components. Nevertheless, there remains many significant seasonal dummies and seasonal - urban ecology factor interactions. Figures 3 through ten were designed to illustrate spatial heterogeneity of crime seasonality. Each chart displays the estimated seasonality for the two grid cells which have the highest scores for the two neighborhood types that have the most opposing seasonality patterns. These grid cells represent the extreme cases but, of course, police desire information on hot spots for targeting interventions and extreme seasonality yields a form of hot spot.

Table 4: Results from Models for the Eight Crime Types

Crime Type	Adjusted R²
Motor Vehicle Theft	.75
Larceny	.87
Simple Assault	.80
Robbery	.79
CAD Shots Fired	.36
Burglary	.64
CAD Drug Calls	.70
Aggravated Assault	.53

First, note in Figures 3 through 10 that the citywide estimate of seasonality, obtained from our model with seasonal-factor interaction terms deleted, in every instance is much closer to zero than for the reported individual grid cells. The muted citywide seasonality results from the spatial heterogeneity of seasonality, a canceling-out effect, and from the combined effect of many low crime cells with relatively few high crime cells. Very likely then from these results, past studies on crime seasonality, most of which have been at the city or even larger scales, have vastly underestimated the magnitude and impact of seasonality. Law enforcement takes place in neighborhoods or car beats and thus small-scale variation in seasonality matters to police, not overall citywide seasonality. Grid cells or neighborhoods with large seasonal fluctuations can make good targets for interventions. Thus mapping seasonality for small areas across a city is important in making our results useful for policing purposes.

Another feature of Figures 3 through 10 for many of the crime types and grid cells displayed is that seasonality is a relatively large portion of total crime variation. Reported in these figures is the nine-year average crime count for each grid cell with seasonal estimates plotted. The averages include full annual cycles of seasonality and thus have seasonality removed through cancellation. These means thus provide a good basis for judging the relative magnitude of seasonality. In Figure 3, the peak of 3.2 seasonality for the retail establishment grid cell is 28 percent of the mean of 11.4. For larceny in Figure 4, the peak of 3.3 seasonality for the high population density grid is 17 percent of the mean of 13.4. For simple assaults in Figure 5, the peak of 3.8 seasonality is 47 percent of the mean of 8.07 for the low human capital grid cell. For shots fired, the peak of 1.9 seasonality in the high density grid cell is 32 percent of the mean of 5.9. In the remaining cases, seasonality is not as large a portion of total variation.

It is clear in several of the charts shown in Figures 3 through 10 that the ecological characteristics of place often contribute to opposing seasonality results. This results in the canceling-out effect mentioned above. Several noteworthy examples have both of the opposing coefficients are significant. For motor vehicle thefts in Figure 3, the highest scoring retail grid cell has April as the minimum seasonal effect while August is the peak month. In contrast, the highest scoring young adults grid cell, which has a high college student population, has a peak in April and a negative seasonal factor in August – the opposite of the retail area. A pronounced case of is that of larceny (Figure 4) in November and December. In those holiday shopping months, larcenies peak in the grid cell scoring highest on the retail establishment factor. In contrast, the grid cell scoring highest on the population density factor, located in a largely residential section of the city, has a seasonal trough for larcenies in November and December. Robberies (Figure 6) have a peak in December in the young adult grid cell while the low capital grid cell is positive but near zero. Shots fired (Figure 7) have a peak in June for the grid cell with highest population density, but a negative value for young adults (who are for the large part away in June). Burglaries (Figure 8) have a peak in August for the high population density grid cell, while a near-zero positive value for the low human capital grid cell. Aggravated assaults (Figure 10) has several opposing months for the high population density and young adults grid cells.

The evidence for simple assaults (Figure 1) supports the seasonality literature, that violent crimes peak during the summer. Our model for simple assaults reveals a very similar seasonal pattern in grid cells scoring high on the low human capital factor, the population density factor, and citywide. Throughout the city, therefore, simple assaults exhibit a summer peak and a winter trough and only the magnitude of the seasonal pattern varies. Drug calls (Figure 9) also

do not exhibit spatial heterogeneity, but have an unusual seasonal pattern with peaks in spring and fall, trough in winter, but low values in the summer when we might expect peaks. One explanation is that so many people are on the streets in drug dealing areas in the summer that drug dealing does not stand out. Also, at the time period of the data, there were no cell phones and low-income people are often in public places, away from their home phones, in the summer.

Our results indicate that property crimes tend to have seasonal fluctuations, and even opposing seasonal patterns when compared with other parts of the city, heavily influenced by variations in urban ecology. Urban ecology also plays a role in the seasonality of violent crimes. In this case ecological variations helps determine the magnitude of the seasonality; as violent crimes in all grid cells tends to increase with the heat of the summer months, and decrease in the cold of winter.

Conclusion

Using monthly crime data for 4000 feet square grid cells for Pittsburgh, Pennsylvania from 1990 to 1998, we were able to model crime seasonality at the sub-city level for eight crime types. The discussion in this final section of the paper will focus on detailing how this study fulfills much of the motivations for its undertaking by contributing to the crime seasonality literature, possessing practical policing and crime mapping-related implications, and providing a model for sub-city seasonality to be used in future crime forecasting efforts.

The results from the empirical models clearly reveal that crime seasonality varies considerably across the space of a city. This is most evident for several crime types. As mentioned, previous research on crime seasonality for the most part used large levels of data aggregation. Our results indicate that these large levels of data aggregation mask variation in

seasonality within the city. Hence, the models of sub-city crime seasonality created for this research fill a void in the crime seasonality literature.

In addition, there are clear practical implications of this research for policing, mostly related to the use of maps, created from the models of sub-city seasonality, to plan and evaluate monthly police interventions. With the results from the models, urban crime analysts could map each month's predicted seasonal pattern using color-coded grid cells. Grid cells with seasonal peaks might be represented in shades of red, while grid cells experiencing troughs might be colored with shades of blue. With the colored map in hand, police could target the "hot" grid cells for interventions and then evaluate the success or failure of the intervention based on its variation from the seasonality model's predictions. Finally, closely related to this topic of predictions, this study provides the basis for improving the forecast accuracy in the models presented by Gorr et al. (2001).

Figures 3 through 10: Results for Estimates of Seasonal Factors and Selected Seasonal Interactions for all Eight Crime Types

Note: Each bar represents the seasonality of the highest scoring grid cells for the respective factor.

The means reported are the 9-year mean for that crime type in the respective grid cell.

An asterisk above or below a bar indicates a significant seasonality coefficients at the 5% level or better significance level.

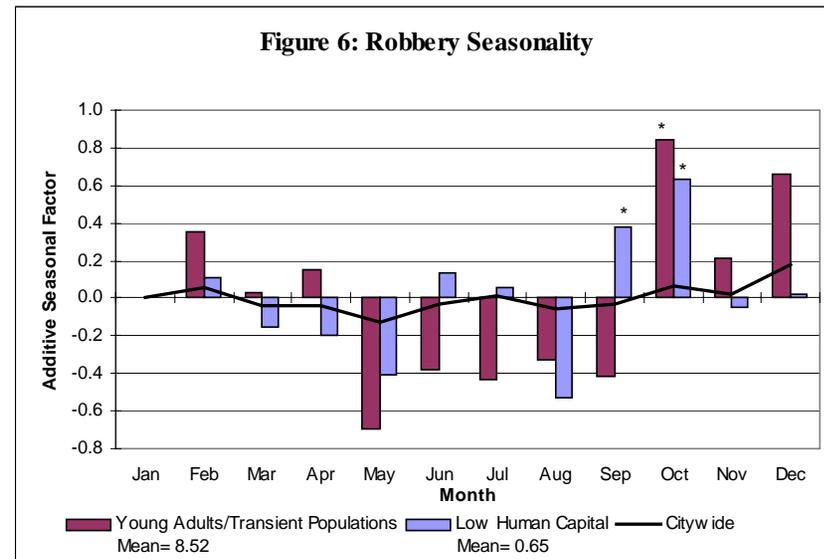
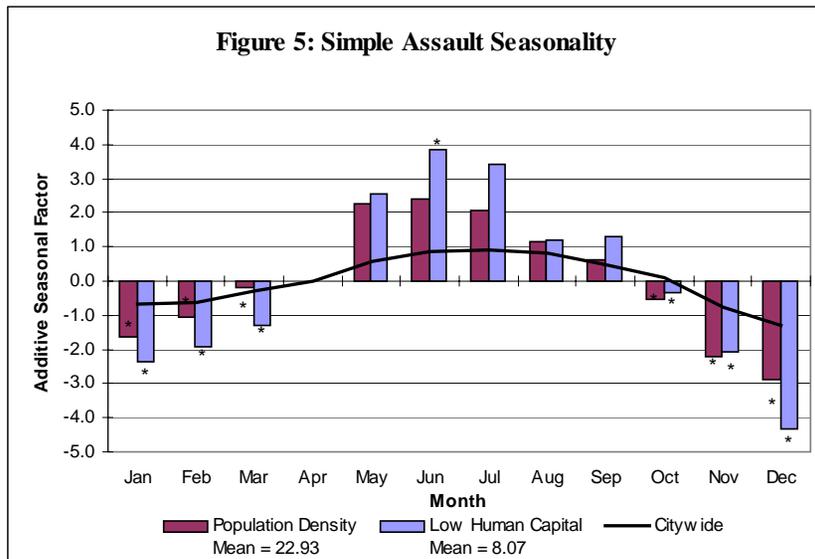
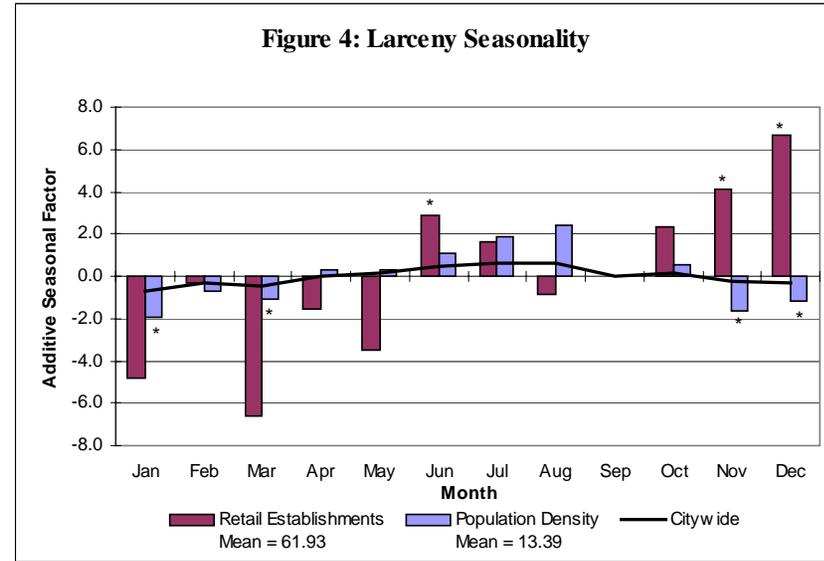
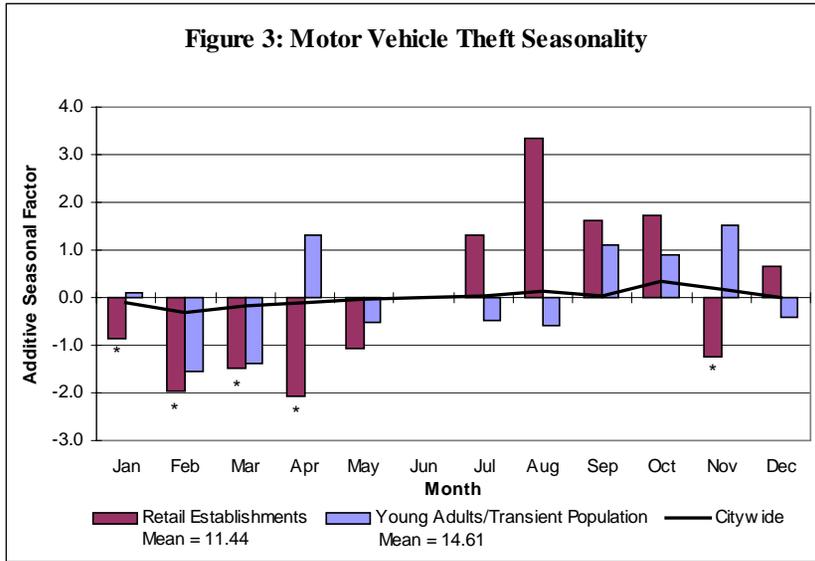


Figure 7: CAD Shots Fired Seasonality

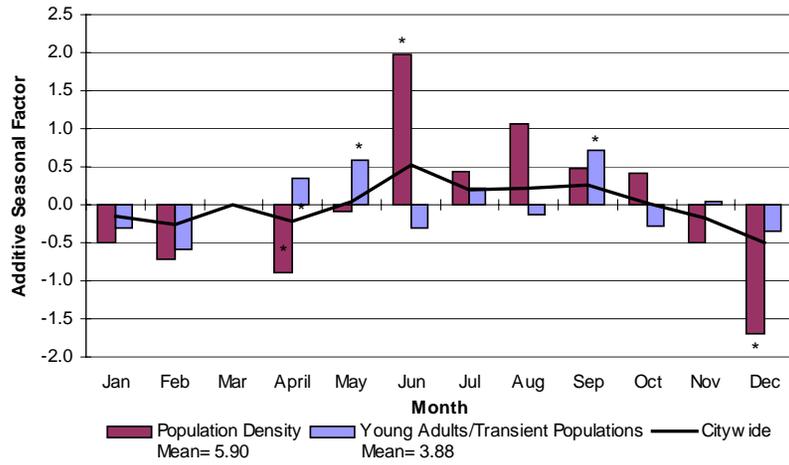


Figure 8: Burglary Seasonality

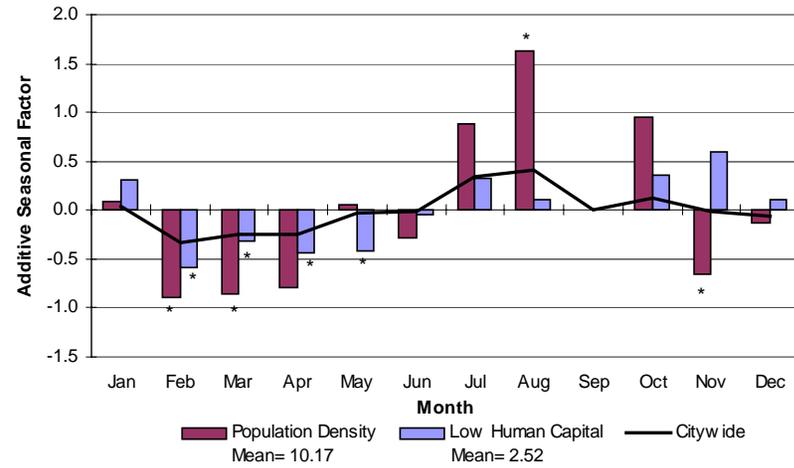


Figure 9: CAD Drug Call Seasonality

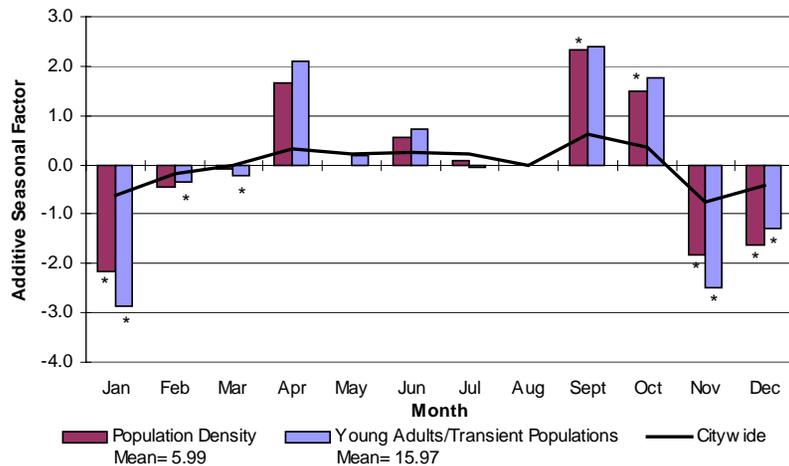
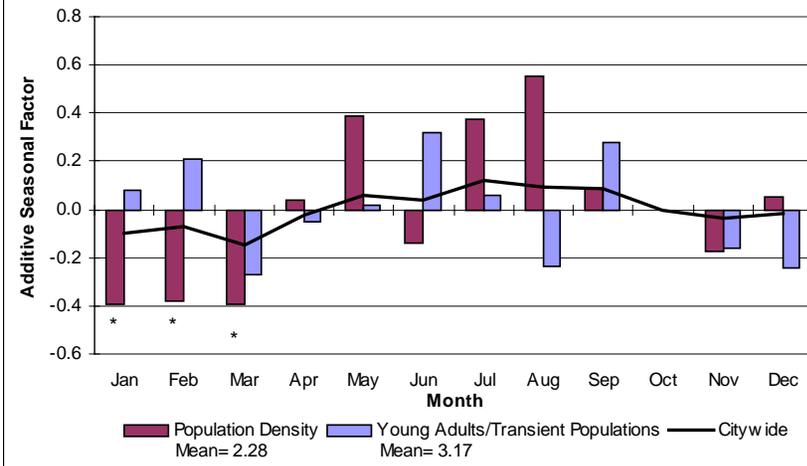


Figure 10: Aggravated Assault Seasonality



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