The Unspecified Temporal Criminal Event: What is Unknown is Known with Aoristic Analysis and Multinomial Logistic Regression[1]

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ABSTRACT

Environmental criminologists begin their study of crime by asking where and when crimes occur. Police databases contain information on the temporal nature of criminal events and some criminal events, such as burglary and automotive theft, are reported over an unspecified time period or time range/window—there is a start time and an end time but no actual time of occurrence. Recent work on this subject has manifested in a relatively new technique, aoristic analysis, which estimates the probability of a criminal offence occurring within a certain time span. This technique is a great step forward from previous temporal analysis techniques and has great utility for law enforcement personnel when analyzing range data. However, it is important that analysts use caution when databases contain abundances of extreme time ranges. In order to facilitate the comparative analyses of the temporal aspects of crime, an alternative technique is suggested, multinomial logistic regression, which incorporates the advantages of aoristic analysis and extends the analysis of the temporal criminal event into the realm of inferential statistics.

KEYWORDS: temporal analysis; aoristic analysis; logistic regression.

"Environmental criminologists begin their study of crime by asking where and when crimes occur" (Brantingham and Brantingham 1991: 2). Since criminal phenomena occur when a law, an offender, and a target coincide in time and space, capturing temporal information with precision and accuracy is crucial for analytical purposes. The availability of motivated offenders and suitable targets changes for many locations throughout the day and, therefore, crime is neither randomly nor uniformly distributed in time or space. Thus, understanding these patterns can assist criminal justice personnel in precision focused prevention efforts (Cohen and Felson, 1979; Brantingham and Brantingham 1984, 1991; Ratcliffe 2000; Rossmo 2001).

Criminal justice databases record temporal information on almost all criminal events. Sometimes, as with crimes against the person, a precise time is known. However for many criminal events, such as burglary and automotive theft, the exact time is not always known. Although some burglaries are committed in which the offender is apprehended at the scene (or caught by alarm or surveillance), most do not follow this pattern. What remains is a time range (or time window) in which the event took place. The temporal data of these time ranges record only a potential start and end time for when the event occurred. The problem becomes how to investigate when the criminal event occurred, having only a start and end time.

Traditional criminological techniques have attempted to get at a more precise estimate of these ranges using a variety of measures. These measures include choosing either the start or end time as the best indicator, using a form of rigid time analysis, or some type of averaging measure. Unfortunately the results of these traditional measures fail to meet any theoretical or evidentiary support and therefore cease to be a final solution to the problem.[2] This has led to the statement that "[the] temporal dimension of crime [has] lagg[ed] behind while advances in crime location geocoding, mapping technology and user competence have allowed the spatial element to flourish" (Ratcliffe 2002: 24).

Now at this point the critical thinker may ask: "If it is so difficult to deal with the time range issue, why not ignore the range data and focus the analysis on the events that have exact times?" Alternatively, one could use the average, mode, or median of the known times to predict the unknown times of other occurrences. These two possibilities are unsatisfactory for two reasons. First range data may contain information about the criminal event that exact data do not; therefore, the range data should be incorporated into the analysis, if possible. And second, using a measure of central tendency on the known cases for prediction is just as

arbitrary as using the same measure on ranges of the unknown cases.

An alternative to these traditional techniques in criminology, first pioneered by Ratcliffe and McCullagh (1998), is aoristic analysis. Aoristic analysis is a technique used when time windows exist that "can provide a temporal weight and give an indication of the probability that an event occurred within a defined period" (Ratcliffe 2000: 669). The advantage of the aoristic technique is that it does not have to exclude any temporal possibilities. All raw police data, including exact times and range times, are incorporated into the analysis. This prevents the researcher or investigator from throwing out a considerable amount of temporal range data gathered on crimes like burglary and automotive theft (Ratcliffe 2000). If this measure can solve the time range issue, it becomes a crucial advancement for dealing with the temporal criminal event. It is, therefore, prudent to investigate aoristic analysis to see if it can resolve the time range (window) problem.

After providing a brief example of how aoristic analysis is actually performed in section 2, the properties of aoristic analysis are shown in section 3. An alternative methodology, multinomial logistic regression, is presented in section 4 to deal with the limitations of aoristic analysis. An empirical application of both aoristic analysis and multinomial regression is performed in Section 5. Section 6 concludes.

AORISTIC ANALYSIS

Figure 1 allows the theoretical conceptualization of the aoristic technique to be shown. Across the top of Figure 1 is the overall timeline the events occur within. This timeline can be divided into different minute, hour, or day boundaries, with the important aspect being that the search block lengths, as illustrated by search blocks 1 - 4, are of equal duration (Ratcliffe 2000). Running vertically to the left of Figure 1 are the individual event time spans (*a, b, c, d*) that represent the recorded criminal events. Events *a* and *c* span the entire timeline, and therefore all four search blocks, having a 25 percent probability of occurring within each individual search block. Event *b* spans two of the search blocks, and thus has a 50 percent probability of occurring in each of those blocks. And event *d* falls entirely within one search block, so it occurs with certainty within search block three. The values in each cell are called the aoristic values.

Aoristic analysis uses this temporal information to calculate both an aoristic sum and an aoristic probability. The aoristic sum is simply the sum of all the probabilities (aoristic values) that occurred within each search block. For example, the aoristic sum for search block one would be $0.25 + 0.25 = 0.5$. The aoristic probability divides the aoristic sum by the number of criminal events to derive the probability distribution, $0.5/4 = 0.125$ for search block one. These two values are represented in the histogram in Figure 1 and the calculation is elaborated on below—for a complete theoretical account of aoristic analysis, see Ratcliffe (2000; 2002).

As with most theoretical representations it is useful to include a concrete example of how data actually fits into the analysis—Figure 2 illustrates in a pragmatic fashion how the analysis is done. The timeline represents a 24-hour day and four search blocks are

Figure 1. Aoristic Analysis

Source: Adapted from Ratcliffe (2000).

Figure 2. Aoristic Analysis, a Concrete Example.
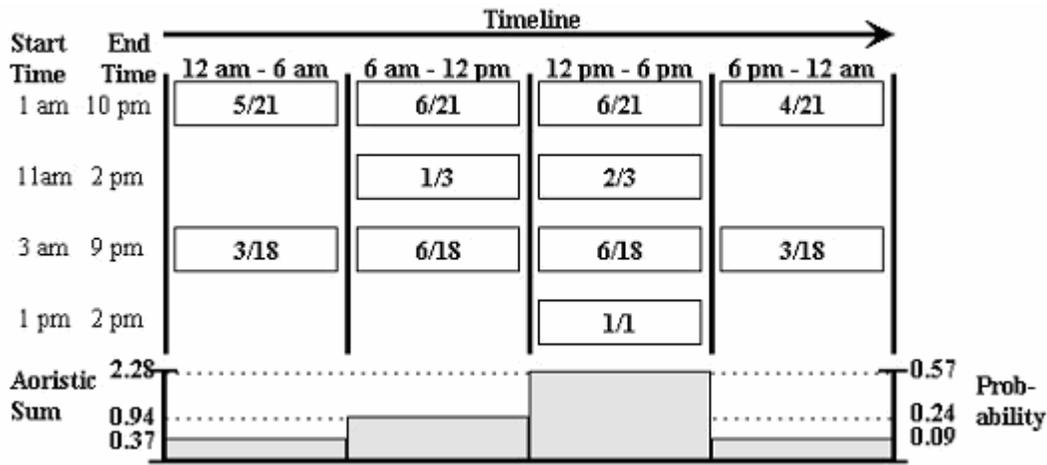
Source: Adapted from Ratcliffe (2000).

represents a 24-hour day and four search blocks are established, each with a duration of 6 hours (12 am - 6 am, 6 am - 12 pm, 12 pm - 6 pm, and 6 pm - 12 am). There are four events listed vertically on the left hand side of Figure 2, each with a start and end time.

The first event occurred between 1 am and 10 pm, a total duration of twenty-one hours. Since five of the twenty-one hours fall within the first search block, it is assigned a value of 5/21. The second and third search blocks are spanned completely, giving 6/21 for each. The four remaining hours in the event fall in the fourth search block, 4/21. This process is continued for the entire data set. At the conclusion of this process the cells are summed vertically in each of the search blocks to produce an aoristic sum and divided by the number of events to produce the aoristic probability. The use of this approach allows the researcher to incorporate all criminal event data whether they are specific times, or more often, range data.

PROPERTIES OF THE AORISTIC TECHNIQUE

For simplicity, we abstract from events such as *b* and only deal with criminal events that fall completely within one search block or cover all search blocks in the analysis. It should be noted, however, that the following results hold in a more complicated analysis; a simplified example is provided for a clearer exposition of the properties of aoristic analysis.[3] As stated above, each bar in the histogram of Figure 1 represents the sum of the aoristic values for all of the criminal events used in the analysis. In order to better illustrate the properties of aoristic analysis, the probability distribution, which shows the probability that the criminal event occurred in a particular search block, will be used---similar results hold for the aoristic sum histogram.

Using only the criminal events that fall within one search block and the criminal events that span all the search blocks, the aoristic probability that a criminal event occurred during a particular search block can be represented by:

$$\text{Prob}(CE = SB_i) = \frac{u}{n}w + \frac{k_i}{n} \qquad (1)$$

where $CE \equiv$ criminal event; $SB_i \equiv$ search block i; $u \equiv$ the number of criminal offences that span all search blocks (unknown); $k_i \equiv$ the number of criminal offences that occur within search block i (known); $n \equiv$ the total number of criminal events analyzed; $w \equiv$ the aoristic value assigned to unknown events; $\sum_i k_i = k$ and $u + k = n$. The fractions u/n and k_i/n represent the proportions of unknown and known cases, respectively, such that $u/n + k_i/n = 1$. In the case of Figure 1, $i = 4$.

Suppose the number of unknown criminal events remains constant while the number of criminal events that occur within one search block increases. Beginning with one criminal event of each classification, we have $u/n = 1/2$ and $k/n = 1/2$. Then, add one known case in order to have a total number of cases of three, and $u/n = 1/3$ and $k/n = 2/3$. Continuing in this manner, we can see that the proportion of unknown cases approaches zero while the proportion of known cases approaches one.

Mathematically speaking, in the limit the effect of the unknown cases in the aoristic probability becomes zero:

$$\lim_{k_i, n \to \infty} \frac{u}{n} \to 0 \quad \text{and} \quad \lim_{k_i, n \to \infty} \frac{k_i}{n} \to 1 \quad (2)$$

Figure 3. Probability Distribution, No Unknown Events.
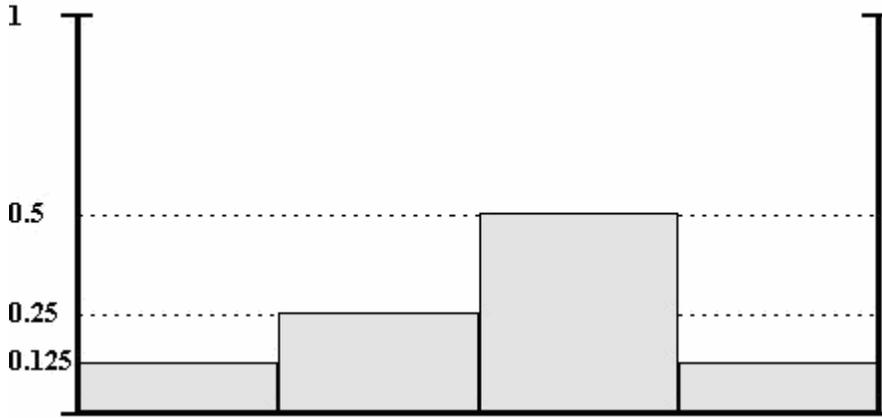
Therefore, the probability of a criminal event occurring in a particular search block is merely the proportion of total criminal offences that occur within that particular search block i:

$$\text{Prob}(CE = SB_i) = \frac{k_i}{n} \quad \forall \; i \qquad (3)$$

and in the example above, we have a probability distribution reflecting the proportion of criminal events within each search block.

Conversely, suppose the number of known criminal events remains constant, while the number of unknown criminal events increases. Beginning again with one criminal event of each classification, we would again have $u/n = 1/2$ and $k/n = 1/2$. However, if we add one unknown case, we would have $u/n = 2/3$ and $k/n = 1/3$. Invoking the concept of a limit again, the effect of the unknown events approaches one, while the effect of the known criminal events approaches zero:

$$\lim_{u,n \to \infty} \frac{u}{n} \to 1 \quad \text{and} \quad \lim_{u,n \to \infty} \frac{k_i}{n} \to 0 \quad \forall \; i$$

$$(4)$$

such that each search block will have the same probability, equal to w:

$$\text{Prob}(CE = SB_i) = w \quad \forall \; i \qquad (5)$$

This result gives the uniform distribution as the aoristic probability distribution.

This analysis has shown that the method of aoristic analysis needs to be used with caution when disproportional amounts of extreme time range data are held within the criminal justice database. Police need to be sensitive to this issue and take appropriate steps to ensure their findings are accurate. However, the utility for police to incorporate range data into their analysis—without discarding it—far outweighs any cautions that may or may not need to be employed. The technique is also a tremendous step forward from other techniques and continues to highlight academic relevance in dealing with real world police and community problems.

Once patterns in range data for a particular place are known, the scholar may feel compelled to look for similarities, along with differences, with other places. In order to facilitate these comparisons, statistical inference may be used to test hypothetical relationships. We acknowledge that the purpose of aoristic analysis is not statistical inference, but a smoothing algorithm. Without statistical inference, however, the possible uses for the method are limited. Second, for computational ease, the method of calculating the aoristic value assumes a linear relationship between the probability of the criminal event and time. Previous research has shown that there is no reason to believe this relationship is linear, because criminal opportunities are unevenly distributed over time and space (Brantingham and Brantingham 1984).

Without a theoretical framework, and corresponding explanatory variables, standard hypothesis testing is precluded and the analysis can only give an indication of when the event is happening but cannot tell us why it is happening at that particular time. Therefore, a technique is needed that does not impose a randomly or uniformly distributed temporal aspect of crime and instead incorporates a nonlinear relationship that allows for hypothesis testing of those variables that are having the effect. An alternative technique is suggested, multinomial logistic regression, which incorporates the advantages of aoristic analysis and addresses the issues of theory and testing.

Figure 4. Probability Distribution, All Unknown Events
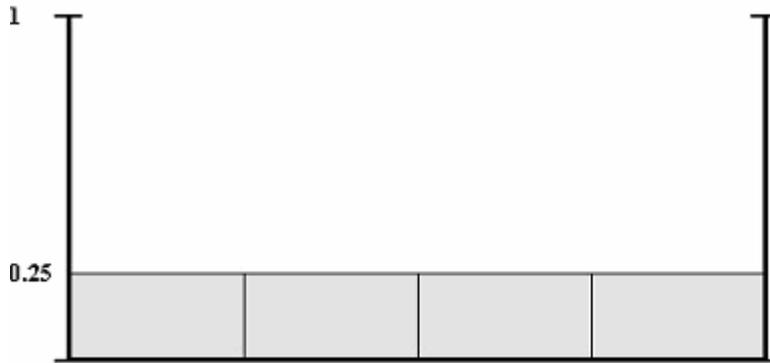
MULTINOMIAL LOGISTIC REGRESSION

The use of regression analysis can incorporate a nonlinear relationship between the criminal event and time through functional form and test the hypotheses of various theoretical models. The alternative technique put forth for analyzing the temporal aspect of criminal events is multinomial logistic regression (MLR). Multinomial logistic regression, developed by McFadden (1981), belongs to a class of statistical techniques called categorical data analysis that specify the dependent variable qualitatively (categories), such as the search blocks used in aoristic analysis, so the unspecified criminal event can be investigated. However, before we discuss the multinomial logistic regression model, it will be instructive to discuss the standard logistic model and its advantages over ordinary least squares regression.

The use of qualitative, or categorical, dependent variables causes problems with ordinary least squares (OLS) regression models. In the case of the binary choice model—2 categories—the dependent variable can be defined as a 0-1 dummy variable, with the variable equal to 1 if a particular choice is made. Upon estimation, the resulting predicted value of the dependent variable can be interpreted as the probability of that choice, such as the probability of a burglary occurring at a particular time (range). The main problem that arises using OLS—the linear probability model in this context—is that it is possible to produce predicted values outside the 0 - 1 range (Kennedy 1998). Categorical variables also produce heteroskedasticity, which invalidates statistical inference. However, the form of heteroskedasticity is known and can be modeled.[4] The predicted values outside the 0-1 range are not a desirable property of a probability since it implies deterministic behavior in the model. This difficulty can be avoided using the nonlinear logistic function—see Figure 5. The result of

estimation using the logistic function is a ``true'' probability because it is bounded by 0 and 1.

The probability that an event/choice occurs ($Y = 1$) and an event/choice does not occur ($Y = 0$) are given by:

$$\text{Prob}(Y = 1) = \frac{e^{X\beta}}{1 + e^{X\beta}} \quad \text{and} \quad \text{Prob}(Y = 0) = \frac{1}{1 + e^{X\beta}} \quad (6)$$

where e is the natural exponential function; X is the matrix of independent variables thought to affect the choice of search block, based on criminological theory; and β is the vector of estimated parameters. It should be noted that given the nonlinear nature of the probability function, β cannot have its OLS interpretation of the marginal effect of X on Y. If a marginal effect is desired, the difference in probabilities when changing a variable x_i should be calculated, but interpreted with caution as the probability difference will not remain constant with different starting values for x_i (Greene 2000).

The method of calculation used for obtaining the β-vector is not the same as OLS and, therefore, there is no R^2 to measure goodness of fit: rather than minimizing the squared errors (least squares) through the choice of β, the logistic regression maximizes a likelihood function by choosing β. There is, however, a variant of R^2 for logistic regression provided by McFadden (1974), the likelihood ratio index:

$$LRI = 1 - \frac{\ln L}{\ln L_0} \quad (7)$$

where ln L is the log-likelihood function with all the model parameters from the model and ln L_0 is the log-likelihood function only including a constant term. As with the measure of R^2, this index is bounded between 0 and 1. An alternative to measure the goodness of fit is to

Figure 5. Logistic versus Linear Probability Model
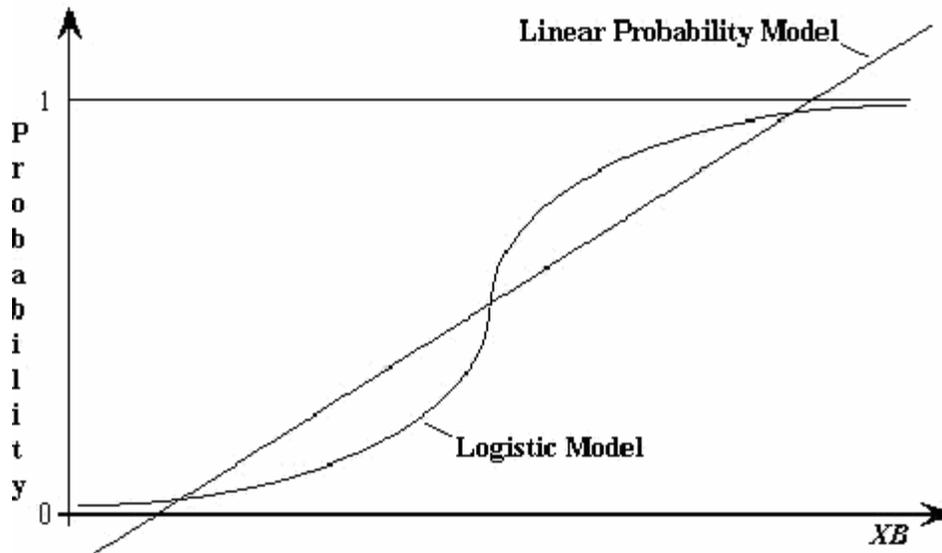
provide the percentage of successful predictions, which is bounded between 0 and 1.

The binary choice logistic model is easily extended to many choices/categories: the multinomial logistic regression (MLR) model. Similar to the binary choice logistic model, the estimation of the MLR model provides the probability of a given search block being chosen. Since there are multiple alternatives, estimation provides a β-vector for each alternative in order to calculate their respective probabilities:

$$\text{Prob}(Y = J) = \frac{e^{X\beta_i}}{1 + \sum_{i=1}^{J} e^{X\beta_i}} \quad \text{and} \quad \text{Prob}(Y = 0) = \frac{1}{1 + \sum_{i=1}^{J} e^{X\beta_i}}$$

(8)

where $J + 1 \equiv$ the number of alternatives. The end result of estimation is the ability to calculate the probability of each alternative occurring, with those probabilities changing depending on the values of the independent variables.

These resulting probabilities can be interpreted as representing the utility, or gain, from the choices. In other words, it is the probability that a particular choice will have the greatest gains over the other choices: maximizes the returns from the criminal event, or equivalently, minimizes being apprehended. This framework is usually referred to as the random utility model. In this type of model, the choices made by individuals will depend on the individual-specific attributes, choice- or category-specific attributes, or both. The selection of the model employed depends on theory and available data (Kennedy 1998).[5]

A COMPARISON OF THE TECHNIQUES

In order to facilitate a comparison of aoristic analysis and multinomial logistic regression, the crime of break and enter, hereafter referred to as burglary, in the City of Burnaby, British Columbia, Canada is investigated. Since these two methods of analysis are not directly comparable (aoristic analysis is descriptive and multinomial logistic regression is inferential) the resulting output from these techniques is of the greatest interest. The final output of aoristic analysis is a probability distribution, and a similar probability distribution can be calculated from the multinomial logistic regression results.[6]

Aoristic analysis uses the actual crime data and, therefore, is an appropriate representation of the time distribution of the criminal event under study. If multinomial logistic regression is to be proven useful, its resulting probability distribution should be similar to that of aoristic analysis. Its benefit over aoristic analysis is then judged by the underlying explanation of why the probabilities are changing.

Burglary and Aoristic Analysis

The distribution of time range data is shown in Table 1. Just over one-third (37.5 percent) of the burglaries occurred at a known time.[7] However, a large portion of the burglary data exhibit significant time ranges. A further 56.3 percent of the burglary data (totalling 93.8 percent of all burglaries in the range data set) have a time range of up to 10 hours. This should be no surprise since the majority of burglaries occur during the day when people are at work—an 8-hour workday

Table 1. Distribution of Time Ranges for Burglary.

Time span, Hours	Frequency	Percent	Valid Percent	Cumulative Percent
1	485	37.5	37.5	37.5
2	108	8.3	8.3	45.8
3	108	8.3	8.3	54.2
4	90	7	7	61.1
5	81	6.3	6.3	67.4
6	55	4.3	4.3	71.6
7	60	4.6	4.6	76.3
8	68	5.3	5.3	81.5
9	63	4.9	4.9	86.4
10	50	3.9	3.9	90.3
11	46	3.6	3.6	93.8
12	29	2.2	2.2	96.1
13	21	1.6	1.6	97.7
14	11	0.9	0.9	98.5
15	9	0.7	0.7	99.2
16	6	0.5	0.5	99.7
17	2	0.2	0.2	99.8
23	1	0.1	0.1	99.9
24	1	0.1	0.1	100
Total	1294	100	100	

Figure 6. Burglary and Aoristic Analysis
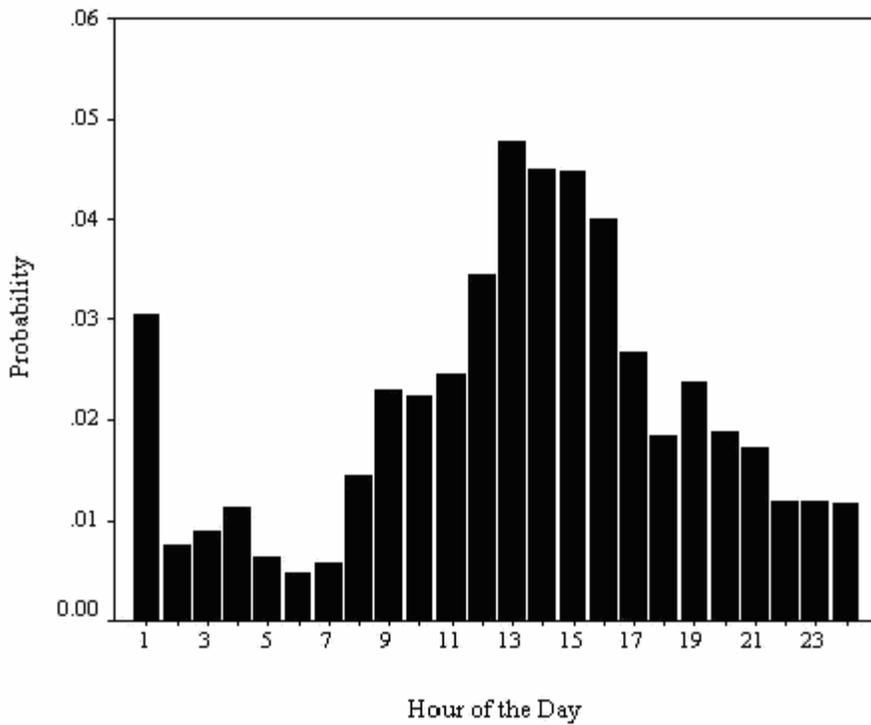
plus commuting time is generally between 9 and 10 hours. With such a large proportion of the burglary data represented by time ranges, the utility of aoristic analysis is quite apparent.

The aoristic probability output is presented in Figure 6. As expected according to routine activity theory (Cohen and Felson 1979), due to a lack of guardianship when people are at work, the highest probability of a burglary is during the early afternoon, with a spike in the probability occurring just after midnight. With one-third of the burglary data recorded with exact times, the probability distribution does not exhibit the tendency towards the uniform distribution, shown above. In fact, aside from the spike occurring after midnight, the probability distribution appears to be normally distributed, centered at 1 pm.

Burglary and Multinomial Logistic Regression

In order to ease estimation, two-hour time blocks are used for the multinomial logistic regression. The variables used for the inferential analysis are the unemployment rate, ethnic heterogeneity, the standard deviation of income, and the average dwelling value; all variables are measured at the census tract level in which each burglary occurred. These variables are chosen to represent social disorganization theory—see Sun et al. (2004) for a recent analysis employing this theory.

The resulting probabilities are divided by two and shown at one-hour intervals in Figure 7. It should be quite apparent that the probability distribution is very similar to that of aoristic analysis, with the highest probability being in the early afternoon and the presence of a spike in probability shortly after midnight—the spike is not as pronounced as aoristic analysis, however. The most notable difference between the two probability distributions is that the multinomial logistic regression probability distribution gives much less weight to the time ranges outside of the early afternoon; from 1 pm to 5 pm, the aoristic total probability of a burglary is 17.7 percent, whereas the multinomial logistic regression probability for the same time period is 38.2 percent—a significant difference that is likely

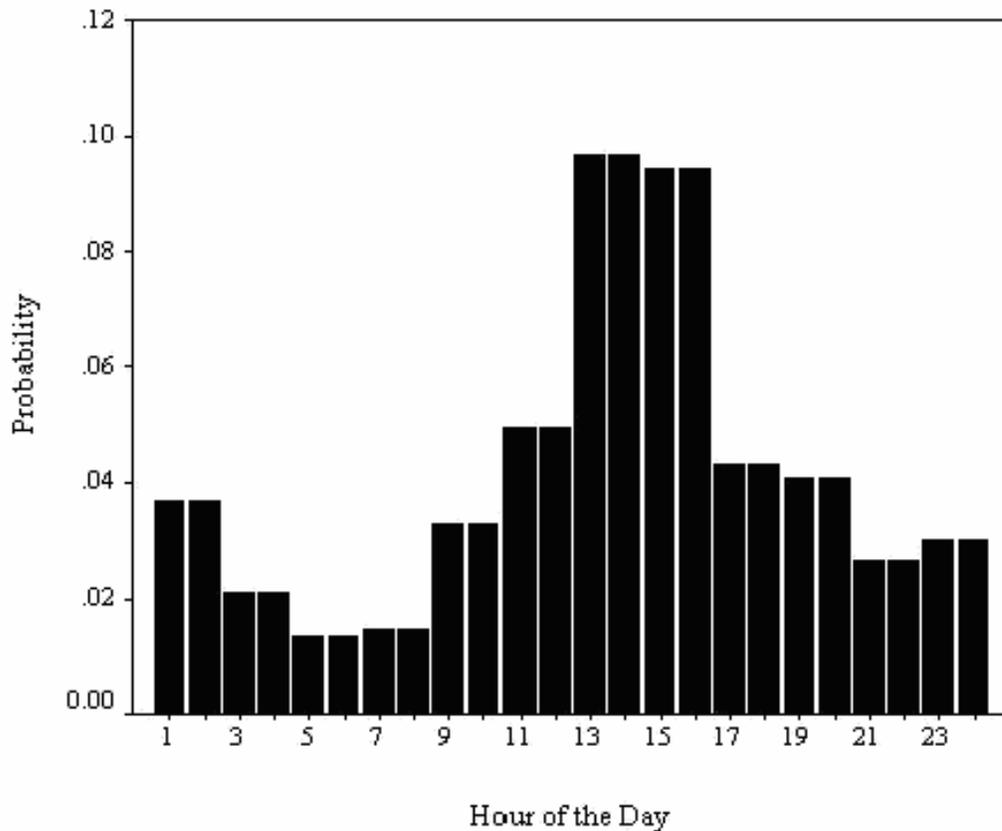*Figure 7. Burglary and Multinomial Logistic Regression*

Table 2. Multinomial Regression Results

	Coefficient	S.E.	P-Value		Coefficient	S.E.	P-Value
Hour = 3 - 4				Hour = 15 - 16			
Unemployment Rate	-0.108	0.165	0.513	Unemployment Rate	-0.006	0.120	0.961
Ethnic Heterogeneity	-0.066	0.065	0.312	Ethnic Heterogeneity	-0.094	0.046	0.043
S.D. Income	0.083	0.271	0.758	S.D. Income	0.262	0.170	0.123
Dwelling Value	-0.007	0.004	0.100	Dwelling Value	-0.006	0.003	0.055
Hour = 5 - 6				Hour = 17 - 18			
Unemployment Rate	-0.006	0.206	0.978	Unemployment Rate	0.224	0.134	0.094
Ethnic Heterogeneity	-0.178	0.077	0.020	Ethnic Heterogeneity	-0.180	0.052	0.000
S.D. Income	0.342	0.199	0.086	S.D. Income	0.362	0.182	0.046
Dwelling Value	-0.008	0.005	0.136	Dwelling Value	-0.009	0.004	0.014
Hour = 7 - 8				Hour = 19 - 20			
Unemployment Rate	-0.123	0.193	0.523	Unemployment Rate	-0.010	0.139	0.941
Ethnic Heterogeneity	-0.040	0.074	0.587	Ethnic Heterogeneity	-0.098	0.054	0.069
S.D. Income	0.203	0.225	0.366	S.D. Income	0.212	0.196	0.277
Dwelling Value	-0.008	0.005	0.131	Dwelling Value	-0.008	0.004	0.029
Hour = 9 - 10				Hour = 21 - 22			
Unemployment Rate	-0.099	0.145	0.493	Unemployment Rate	0.128	0.146	0.380
Ethnic Heterogeneity	-0.082	0.057	0.148	Ethnic Heterogeneity	-0.111	0.056	0.047
S.D. Income	0.067	0.252	0.790	S.D. Income	0.111	0.286	0.697
Dwelling Value	-0.008	0.004	0.041	Dwelling Value	-0.008	0.004	0.040
Hour = 11 - 12				Hour = 23 - 24			
Unemployment Rate	-0.075	0.138	0.585	Unemployment Rate	-0.131	0.155	0.398
Ethnic Heterogeneity	-0.138	0.053	0.010	Ethnic Heterogeneity	-0.085	0.059	0.149
S.D. Income	0.294	0.174	0.091	S.D. Income	0.374	0.178	0.035
Dwelling Value	-0.007	0.004	0.051	Dwelling Value	-0.012	0.004	0.003
Hour = 13 - 14							
Unemployment Rate	-0.048	0.120	0.691				
Ethnic Heterogeneity	-0.125	0.047	0.007				
S.D. Income	0.275	0.170	0.105				
Dwelling Value	-0.008	0.003	0.017				

Note: Hour 1 – 2 is the base category

due to some smoothing of the aoristic probabilities resulting from the use of time ranges.

Although the purpose of this comparison is not to test any particular theory, moderate support for social disorganization theory is found—the results of estimation are shown in Table 2. The magnitude and significance levels of each variable, not surprisingly, vary for different time periods, but are all significant for at least one of the time ranges. Therefore, social disorganization theory not only proves useful in a spatial analysis of crime, but a spatio-temporal analysis of crime as well.

CONCLUSIONS

Until recently, the temporal component of the criminal event had been neglected in criminological studies while the spatial component had burgeoned.

Since environmental criminologists study both *where* and *when* the criminal event occurs, the temporal component must advance along with the spatial component to further the understanding of crime. Aoristic analysis is such an advancement in the temporal component that attempts to resolve the time range (window) problem that previous criminological techniques could not deal with satisfactorily.

However, the current development of aoristic analysis is not the final resolution to the temporal component of the criminal event. The aoristic technique needs to be used with caution when a large proportion of the crime data are extreme time ranges. Unfortunately, this limits the extent to which the measure can be relied upon, but is a tremendous step forward from other techniques and continues to highlight academic relevance in dealing with real world

police and community problems. Also, although the technique, by definition, recognizes the importance of the temporal aspect of the criminal event, aoristic analysis does not incorporate a major component of environmental criminological understanding: crime is neither randomly nor uniformly distributed over time and space. Only when theoretical suppositions are successfully combined with robust statistical measures will the temporal analysis of crime thrive alongside the spatial component. A promising statistical measure is multinomial logistic regression.

The multinomial logistic regression technique has three advantages over aoristic analysis that allow the academic and the practitioner to both find greater depth in the empirical results. First, multinomial logistic regression does not impose a linear relationship on the criminal event and time. Second, multinomial logistic regression allows for the researcher to use theoretical suppositions, such as social disorganization and routine activity theories, to predict when the criminal event occurred. And finally, in order to learn which theoretical suppositions are having the greater affect on when the criminal event occurs, variables representing theory can be isolated and tested.

The multinomial logistic regression methodology outlined in this paper provides an alternative to aoristic analysis for investigating the temporal criminal event, which allows for statistical inference. An empirical application shows that both aoristic analysis and multinomial logistic regression produce similar probability distributions, but also that there are theoretical reasons (and corresponding statistical verification) for why crime happens at particular times—lending support for an inferential analysis of the spatio-temporal criminal event. Although we present an alternative methodology to aoristic analysis, we do not presume to replace this form of analysis in every instance. Practitioners in the field of criminal science need a pragmatic approach for analyzing crime. They do not have the luxury of waiting for data or techniques that are a perfect fit because investigations run in real time, not having the benefit of academic hindsight.

ENDNOTES
1. We would like to thank Patricia L. Brantingham, Paul J. Brantingham, and Seminar participants at the Western Society of Criminology, 30th Annual Conference for comments.

2. See Ratcliffe and McCullagh (1998) for a more detailed discussion.

3. In the examples below, the extremes of all exact times and all time ranges will be discussed. Clearly, if the researcher were only dealing with exact times, aoristic analysis would not be employed. These

extreme examples, however, are instructive to understanding the technique.

4. These problems are not associated with aoristic analysis.

5. The estimation of both binary and multinomial regression models is provided in most statistical packages.

6. Both analyses are performed at the city level.

7. A time is considered "known" if the start time and end time of the burglary are in the same hour: 5:00am – 5:59am, for example.

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