Leading Indicators and Spatial Interactions:
A Crime Forecasting Model for Proactive Police Deployment

by

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Abstract

Based on crime attractor and displacement theories of environmental criminology, we specify a leading indicator model for forecasting serious property and violent crimes. The model, intended for support of tactical deployment of police resources, is at the micro-level scale; namely, one-month-ahead forecasts over a grid system of 104 square grid cells 4,000 feet on a side (with approximately 100 blocks per grid cell). The leading indicators are selected lesser crimes and incivilities entering the model in two ways: 1) as time lags within grid cells and 2) time and space lags averaged over contiguous grid cells of observation grid cells. Our validation case study uses 1.3 million police records including 16 individual crime types from Pittsburgh, Pennsylvania aggregated over the grid system for a 96 month period ending in December 1998. The study uses the rolling-horizon forecast experimental design with forecasts made over the 36 month period ending in December 1998, yielding 3,774 forecast errors per forecast model. We estimated the leading indicator model using both an OLS linear regression model and a nonlinear neural network, plus included a proven univariate, extrapolative forecast method as a benchmark for a Granger causality assessment. The analytical approach to forecast validation is based on decision support requirements of police for crime prevention. Needed is information on large forecasted changes in crime. The leading indicator models have the comparative advantage over extrapolative methods of being able to forecast the largest changes in crime, those due to breaks in crime series data such as step jumps in the forecast period. Expectations for forecast results should be that they yield good if imperfect leads on where to deploy crime analysts, patrols and detectives;

for example, if 50 percent of forecasted large changes were "positives," that would be a success. The end results are that the leading indicator models provide acceptable forecasts and are significantly better than the extrapolative method in three out of four cases, and for the fourth there is a tie but poor forecast performance. The leading indicators find 38 to 54 percent of positives in the three successful cases. The resulting workload for police is quite acceptable, with on the average of 7 large change cases per month with two thirds of such cases being false positives.

Introduction

Geography has become increasingly important in law enforcement and crime prevention. Criminology has long focused on individual propensities toward crime, but it was only during the last few decades that the criminogenic features of *settings* began to take on importance in research and practice. Environmental criminology gained in development, empirical verification, and practical applications by police (Cohen and Felson 1977; Brantingham and Brantingham 1981, 1984; Cornish and Clarke 1986; Cohen and Clarke 1998, p. 2). Places, besides persons, became targets for allocation of police resources, and fields including crime mapping (Harries 1999), geographic profiling (Rossmo 2000), and (most recently) crime forecasting (Gorr and Harries 2003) arose in support of the new-found law enforcement opportunities.

This paper introduces a leading-indicator crime forecasting model for proactive policing and crime prevention, building on the work of Olligschlaeger (1997, 1998). Police, like other professionals delivering services, know the current locations and intensities of demand for services. Indeed, crime mapping based on near real-time input of police reports has made the current picture complete, integrating data from various officers, shifts, and neighborhoods. With the current situation in hand, the next step and most difficult new information to obtain is forecasts of large changes in crime. If it were possible to get such forecasts, in the short term of up to a month, then police could focus crime analysts' activities and build up intelligence on highlighted areas, target patrols, reallocate detective squads, and carry out other police interventions to prevent crimes.

Attempting to make accurate forecasts of the relatively rare, large changes in crime from month to month is an ambitious and difficult undertaking; however, the expectations of police can adapt to accepting good leads mixed in with false positives. For example, if 50 percent of forecasted large changes actually have large changes, then we claim that this would be an excellent result. Such forecasts would provide an entirely new kind of valuable information for police, and police are already used to following up on many leads before success.

It is not difficult to get accurate extrapolative forecasts of crime. Gorr, Olligschlaeger, and Thompson (2003), using the case study data of this paper, demonstrated that exponential smoothing methods and classical decomposition yield accurate one-month-ahead forecasts for areas that have average historical crime levels in excess of 25 to 35 crimes per month. Such "business-as-usual" forecasts; however, cannot foresee the largest changes in crime levels, which are breaks in time series patterns such as step jumps up or down. To forecast breaks, one needs the leading indicator model presented in this paper. If leading indicators experience a break in the last month of the estimation data set, they are capable of forecasting a similar break in the dependent crime variable for the next month. We develop and evaluate crime-based leading indicators and spatial interactions as a means to forecast breaks in serious crime levels. Another paper (Gorr and McKay 2004), applying tracking signals to identify breaks in crime trends, shows that there are roughly 2 breaks every 3 years in high crime volume, square grid cells (4000 feet on a side) in Pittsburgh.

Section 2 provides a literature review and model specification. We draw on crime theories and police requirements to build our model. Section 3 presents the case study of

Pittsburgh, Pennsylvania with 104 grid cell locations and 96 months of crime data. This section includes an experimental design for validation of the leading indicator model, drawing on the forecasting literature. Results are in Section 4, and Section 5 concludes the paper.

Model Specification

Our leading indicator forecasts for serious crimes are based on a lag model for panel data. This section specifies the dependent variables, time-lagged leading indicator variables, and spatial interactions in the form of spatial and time lags. While multiple lags are possible, our preliminary research indicated that a single time lag of independent variables was often the most accurate forecasting model. Hence, we limit attention to it in this paper.

The choice of dependent variables depends on police requirements and data limitations. Municipal police in the U.S. have widely implemented a management by objectives approach known as CompStat, first developed by the New York Police Department (Henry and Bratton 2002). CompStat focuses on reducing serious crimes, which in the U.S. are the index or part 1 uniform crime report (UCR) crimes: murder, aggravated assault, rape, robbery, burglary, larceny, and motor vehicle theft. Part 1 crimes are the dependent variables of our model; however, police requirements and data limitations both argue for using aggregates of part 1 crimes instead of individual crimes.

Police desire information on crime for the smallest geographic areas possible in order to precisely target patrols and investigative efforts. The smallest administrative unit of police departments is the patrol district or car beat, which is the territory of a single unit (car). Clearly, areas studied need to be the size of car beats or smaller. We use square grid cells 4,000 feet (approximately 10 city blocks) on a side in our case study of Pittsburgh Pennsylvania. Grid cells have the advantage easy visual interpretation on maps, given their uniform size and shape. During the time of study, Pittsburgh had 42 car beats, 175 census tracts, and 104 grid cells. We experimented with several grid cell sizes and found 4,000 feet to be the smallest possible for Pittsburgh while still yielding reasonable model estimates. A necessary concession to working at this level is to sum all part 1 property crimes (robbery, burglary, larceny, and motor vehicle theft) to a single dependent variable, P1P, and similarly all part 1 violent crimes (murder, aggravated assault, and rape) to P1V for forecasting. This aggregation is necessary to yield monthly crime time series with sufficient data volumes for accurate model estimation. For example, it is impossible to forecast murder at the grid cell level, with on the average 80 murders per year in Pittsburgh.

Nevertheless, use of P1P and P1V the dependent variables is compatible with the top-down analysis process used in CompStat where participants need to make monthly, jurisdiction-wide scans for crime problems to allocate limited analytical, investigative, and patrol resources. Leading indicator forecasts help make such a scan, with areas having a large forecasted increase in crime getting priority and perhaps those areas with the opposite getting resources withdrawn. With such decisions made, crime analysts can "drill down" into selected areas for diagnosis and tactical-level planning of targeted patrols, assignment of detectives, etc. It is in the second stage of crime analysis that information on individual part 1 and leading indicator crimes is needed.

Lesser crimes and incivilities, represented by selected part 2 crimes and citizen complaint call codes, are the leading indicators in our model. In general, these variables are suggested by two crime theories on spatial interactions: crime attractors and crime displacement, which we discuss below. It is fortunate for police (and perhaps unique) that they collect their own transactional data on leading indicators, thus enabling corresponding forecasts. Other, well-known economic indicators (Klein and Moore 1983) that are related to crime at the country or regional levels (Deadman, 2003; Harries 2003) change too slowly and are not available at the micro-geographic levels and time frames needed for tactical law enforcement within municipalities. Today police have real-time information systems and can process and aggregate individual crime incidents to any desired variables to support forecasting.

Lesser crimes, like serious crimes, also receive intense enforcement because they too are costly to the public and because it is believed that they are precursors to serious crimes. Proponents of the Broken Windows theory of crime (Wilson and Kelling 1982; Kelling and Coles 1996) believe that tolerance of minor incivilities and infractions of the law in neighborhoods are attractors to criminals, signaling settings conducive to crime. In addition, certain land uses and other conditions serve as attractors – bars, parking lots, sporting events, concerts, etc. A major law of geography, that on distance decay of attractions, suggests that criminals generally do not travel far to crime (Capone and Nichols 1975) and hence would be attracted from nearby areas to a “broken windows” neighborhood. This law has been incorporated into the pattern theory of crime (Brantingham and Brantingham 1984) and is the basis of geographic profiling (Rossmo 2000). Broken Windows proponents believe that tolerated “soft crimes” harden later to serious crimes. This belief has led to "zero tolerance" enforcement of lesser crimes as a means of ridding neighborhoods of crime, both lesser and serious. A reduction of lesser crimes should lead to the opposite effect on serious crimes, also a reduction.

Even if the attractor theory is not at cause, an additional argument holds for serious violent crimes, P1V. Only ten percent of all part 1 crimes are violent, with the remainder being property crimes. P1P crimes are as numerous as leading indicator crimes, but P1V crimes are much less prevalent as the leading indicators. (See Table 1 below which includes descriptive statistics for the dependent and independent variables of our model.) If a new criminal element moves into a neighborhood for reasons other than being attracted by broken windows, those individuals still bring with them all of their bad habits and multiple law-breaking practices for both lesser and serious crimes. Hence by chance alone, because of differences in levels, we would expect to see large volume lesser crimes committed first, and then later serious violent crimes.

An opposing effect to crime attractors is crime displacement. Police have long believed that increased enforcement in one simply displaces criminal activity to other nearby locations (Eck 1993, Ratcliffe 2002) or to other kinds of displacement. For example, a belief in crime displacement was the basis for the large drug market analysis program (DMAP) of the U.S. National Institute of Justice in the early 1990s, which supported development of crime mapping in the U.S. and in which the authors participated. In that program, we witnessed much drug dealing displacement first-hand through the Pittsburgh Police Bureau's DMAP GIS. Subsequent empirical research on crime displacement suggests, however, that crime displacement is less prevalent than thought. Twenty-two out of 55 studies where crime displacement has been studied found there to be no evidence of it at all (Hessling 1994). Our own recent work; however, including study of crime displacement in response to police raids of "nuisance bars" in Pittsburgh found a displacement effect (Cohen, Gorr, and Singh 2003).

Without much more theory to draw on for crime leading indicators, we decided to use an expert judgment for selecting particular lesser crimes as leading indicators. Our first step was to compile a list of all part 2 crimes and computer aided dispatch citizen complaint codes for Pittsburgh. We then asked police crime analysts in two cities to select leading indicators from this list. With that task done and the initial selection complied, we then asked two criminologists to further refine and classify the list. The result is in Table 1 which is the final list of leading indicators classified by P1P and P1V. Offense data is taken whenever a police officer believes that a crime has been committed. Hence, under-reported crimes (like sex crimes and assaults) or victimless crimes (like illegal drug use or prostitution) are biased low, reflecting police policies and limitations rather than the total amount of crime in a community. Citizen calls for service, on the other hand, are more representative of wide areas and victimless crimes, but are flawed because the observers are untrained citizens or citizens attempting to manipulate the system (e.g., claiming a more serious problem than existing in order to get quick response). Table 1 includes descriptive statistics for all variables. Note that five out of 14 of the leading indicators have low means (C_TRUAN, C_VICE, LIQUOR, PROST, PUBDRUN, and TRESPAS), less than one, but also have high standard deviations and maximums. We therefore retained these variables under the assumption that relatively high values for them are concentrated in a few areas and would be discriminating for those areas.

Application of the theories discussed above and expert-based efforts on our part thus led to a leading indicator forecast model with P1P or P1V as dependent variables and two sets of independent variables as seen in Table 1. The first set of variables have a single time lag, one month, for each leading indicator. In addition, are averages of each leading indicator in contiguous grid cells (queens case) to the observation cell, lagged one month. We expect the signs of coefficients for time-lagged independent variables in the same grid cell as the dependent variable to be positive, reflecting their assumed direct effect on serious crime. If the attractor theory is correct, then we expect the coefficient signs of the spatial lags to be negative, with nearby grid cells drawing criminals away from an observation grid cell. In contrast, if displacement is the operant mechanism and police actively enforce lesser crimes, then we expect the coefficient signs of the spatial lags to be positive for the observation grid cell. Criminals will react to enforcement by moving, but not far away. Displacement could have an immediate effect on violent crimes if displaced criminals invade the turf of other established criminals in displacement areas. The latter will protect their turf.

Note that 4,000 foot grid cells are large enough to have much internal attraction and displacement, which net out. For attractors, Cohen () makes the point that opportunity is a cause of crime, increasing crime levels. Thus an increase in attractive crime conditions in an area will increase crime overall. Our grid cells are also small enough to have spatial interactions with other grid cells.

Estimation of our model includes a linear multiple regression model, and a non-linear neural network. Early in our research we compared results from Poisson regressions, for the count data of crime levels, and found coefficient estimates to be similar to those of OLS; hence, we have used OLS for forecasting. The nonlinear neural network model (Olligschlaeger 1998), with a single middle layer and standard feed forward estimation, provides an exploratory, self-adjusting mechanism to find additional patterns in the independent variables beyond the linear OLS specification.

Case Study and Validation Approach

We collected approximately 1.3 million individual crime incident data records (crime offense reports and computer aided dispatch, citizen complaints calls) for Pittsburgh, Pennsylvania over the period 1991 through 1998. We used a geographic information system to geocode the points, with overall address match rates of 90 percent for offense records and 80 percent for computer aided dispatch records. Overall, these rates are at national averages for police data, which is on the order of 85 percent. With data points and grid cells on a GIS map, we used spatial joins to assign grid cell identifiers to crime points, and then used database queries to create crime grid cell and monthly series data.

Our forecast validation study uses the rolling-horizon experimental design (e.g., Swanson and White 1997), which maximizes the number of forecasts for a given time series at different times and under different conditions. This design includes two or more forecast models yielding alternative forecasts made in parallel. For each forecast model included in an experiment, we estimate models on training data, forecast one month ahead to new data not previously seen by the model, and then calculate and save the forecast errors. Next we roll forward one month, adding the observed value of the previously forecasted data point to the training data, dropping the oldest historical data point, and forecasting ahead with all models to the next month. This process repeats until all data are exhausted.

The regression model estimates used a three year estimation window, extrapolative methods, to be explained below, required a five year estimation window, and neural network estimation started with the earliest five years of data available and retained all historic data as the horizon rolled forward. The rolling three-year window for regression estimation allows estimated parameters to vary over time, thus capturing effects of unmeasured factors such as changes in police policies or innovations in crime. The univariate method needs at least five years of data to estimate seasonal effects. For the data sample available, thus the earliest forecast origin was December 1995, retaining January 1991 through December 1995 for estimation. One-month-ahead forecasts were made for January 1996 through December 1998 for a total of 36 months times 104 grid cells and 3,744 forecast errors per forecast method.

We used our own form of Granger causality testing (Granger 1969) to determine the relative value of leading indicators for serious crimes. Granger causality is simply as follows: A variable X Granger-causes Y if Y can be better predicted using the histories of both X and Y than it can using the history of Y alone. Our use of this concept for leading indicators determines whether they forecast serious crimes significantly better than the best univariate, extrapolative method, especially for large crime changes. To develop benchmark accuracy measures, we first optimized over univariate methods to get the most accurate extrapolative forecasts (Gorr, Thompson, and Olligschlaeger 2003).

The forecast literature generally uses central tendency of forecast error measures as the criterion for comparing alternative forecast models or assessing the value of forecasts. For a rolling-horizon experiment employing panel data, let

Y_{it} = crime count in grid cell i at time t (i=1, …, m and t=1, …T), the dependent variable of estimation data panel

$T = T_1, \ldots T_n$ forecast origins (last estimation data points)

$F_{i,T+k}$ = forecasted crime, k steps ahead (we restrict k=1)

$e_{i,T+k} = F_{i,T+k} - Y_{i,T+k}$ = forecast error

Then example criteria are:

$MSE(k) = \sum\sum (e_{i,T+k})^2/(mn)$ = mean squared error

$MAPE(k) = \sum\sum abs(e_{i,T+k}/Y_{i,T+k})/(mn)$ = mean absolute percentage error

We determined however, that such measures are inappropriate for the police application at hand; namely, detecting large changes in crime. Measures such as the MSE and MAPE assess forecast accuracy across all crime levels and do not directly assess change. In contrast, the decision requirement of police is on forecasted change versus actual change:

$$F\Delta_{i,T+k} = F_{i,T+k} - Y_T = \text{forecasted change} \quad (1)$$

$$A\Delta_{i,T+k} = Y_{i,T+k} - Y_T = \text{actual change} \quad (2)$$

A common practice of crime analysts, and basis of our forecast performance measure, is the use threshold crime levels as triggers or exception reports for possible action. An example rule using a threshold level might be as follows: if part 1 violent (P1V) crimes are forecasted to increase by more than 5 in any given grid cell, then that cell merits attention. (Gorr and McKay, 2004 present additional threshold-based rules.) Hence, rather than assessing accuracy based on the performance of individual point forecasts for each grid cell, we examined forecast performance within ranges of changes for both decreases and increases. Using contingency tables, based on measures (1) and (2), we contrast forecasts and actual outcomes within each range and designate correctly trigger decisions as true positives and true negatives, and incorrect decisions as false negatives and false positives. We apply pair-wise comparison t-tests within classes to determine if leading indicator forecasts are significantly better than univariate forecasts.

Results

Tables 2 and 3 present sample regression estimates for P1P and P1V leading indicator models for the first three-year data window (January 1993 through December 1995) and last such window (January 1996 through December 1998) out of 36 sets of such regressions used for forecasting[1]. All models displayed have relatively high

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[1] Note to referees: we have not yet estimated robust regression models for these two tables. Hence the significance tests are likely overly optimistic due to temporal and spatial autocorrelation. Nevertheless, the

adjusted R-Square values, in the range 0.68 to 0.79, and many significant coefficients. Out of the 42 estimated coefficients for time-lagged leading variables (not the time and space lagged variables) in Tables 2 and 3, only 8 are not significant at traditional levels and only 2 have the wrong (negative) sign. Thirty-two are positive and significant, and all but 2 are strongly significant. Thus there is some evidence that the proposed leading indicators in fact lead serious crimes, although comparisons below with extrapolative models have stronger evidence of this.

Figures 1 and 2 provide time series plots of OLS estimated parameters for space and time lags of both crime variables for the purpose of examining attractor (negative coefficients) versus displacement (positive coefficients) behavior. Figure 1 has all such parameter paths except that for truancy which has the lowest data magnitudes of all leading indicators, too low for reliable estimation and thus having an erratic time path. Figure 2 has only parameter paths for such variables that were significant at any level in Table 3, in order to cut down on clutter in the graph. We plotted each estimate at the center of its data window, thus providing estimates of conditions at correct times on the horizontal scale

In Figure 1 for P1P, positive coefficients had time parameter paths that remained positive and roughly stable, except for weapons offenses and trespassing. Weapons violations markedly increased, more than doubling starting in the latter months of 1995. This corresponds to a period in which the Pittsburgh Bureau of Police started aggressively enforcing gun laws, so perhaps this explains the increasing spillover effect. Trespassing increased to a peak in the first half of 1995 and then decreased. The negative

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coefficients denoted with *** (.0001 or better significance) will certainly remain significant for the robust estimates.

coefficients in Figure 1 also had mostly stable time paths. The split between positive (displacement) and negative (attractor) coefficients has twice as many displacement than attractor leading indicators.

The picture in Figure 2 for part 1 violent crimes is quite different. Three coefficients, for simple assaults, prostitution, and weapons violation, that were significantly negative or positive in the beginning, deteriorated over time with parameter paths approaching zero. Some parameter paths crossed the zero axis; including citizen calls on vice (which became significant at the 0.1 level). Two parameter paths remained stable, criminal mischief and public disorder citizen call. More analysis is needed to determine assignable causes for these trends. Overall, there is again evidence of a mixture of attractor and displacement spatial interactions for violent crimes.

Figures 3 and 4 provide another assessment of the leading indicators, their practical significance in predicting level of serious crimes. In this case, we estimated the model by least squares regression over the entire study period for regression analysis of 1993-1998. Each of the bar charts in these figures was obtained by averaging the leading indicators across "active" grid cells, defined to be cells with average dependent variable crime counts of 10 or more for property crimes and 5 or more for violent crimes. Then we multiplied the averaged leading indicators by estimated regression coefficients, with the results displayed as bar charts indicating the average contribution of each term. For example, Figure 3 shows that criminal mischief typically is correlated with about 13 part 1 property crimes and in Figure 4 that simple assaults is correlated with nearly 3 part 1 violent crimes.

There are relatively few practical leading indicators for part 1 property crimes (Figure 3). Criminal mischief has the largest impact, with disorderly conduct next, followed by criminal mischief in neighboring grid cells, and then trespassing. For part 1 violent crimes (Figure 4), simple assaults in the same grid cell dominate other leading indicators; however, a number of other leading indicators contribute practically as well including citizen call shots fired, criminal mischief, simple assaults in neighboring grid cells, citizen drug calls, disorderly conduct, and citizen weapons calls. On the negative, attractor side, public disorder citizen calls has the largest impact.

Tables 4 through 10 present results comparing linear OLS, nonlinear neural network models, and the univariate forecasting method. The univariate method is the best as determined by Gorr, Olligschlaeger, and Thompson (2003): Holt exponential smoothing including a time trend with seasonality estimated using classical decomposition applied to pooled, city-wide data for seasonality.

First are forecast error comparisons for part 1 property crimes, using change and error measures (1) and (2). Table 4 displays relative frequencies for cases in which the true change from the last historical data point to the forecast period was large: 15 or more decrease in the top panel and 15 or more increase in the lower panel. Rows labeled "Positive" are percentages of correct forecasts; for example, the percentage of forecasts of a decrease of 15 or more part 1 property crimes that were the actually in that range. The regression model was most accurate for large decreases, finding 54% of actual such cases. The univariate and neural network ran a distance second and third at 25 percent and 17 percent respectively. For large increases, the more important case, all three models failed, with the highest percentage of such cases found being 9 percent.

Table 5 has additional information and significance tests for differences by forecasted change category. The first two columns under crime level indicate the average crime levels in the last month of the estimation data set and in the month in the forecast period, so the reader can see the magnitudes of changes. The third through fifth columns under Mean Forecast for Time T+1 are average forecasts corresponding to the average actuals in T+1. All forecast methods are biased to the mean, as expected, with forecasts for decreases too high on the average and the opposite for increases. The remaining columns display the MAPE within each forecasted change category, and include results of a pair-wise comparison of the best method with the remaining methods in each row. The tests show that regression is significantly the best model for large decreases, as is the univariate method for smaller decreases, and the neural network for all increases. The last column has the number of data points in each category.

Finally, for part 1 property crimes, Table 6 provides information on the number of positives and false positives. The top panel has information for cases in which the forecast was for a decrease of 15 or more part 1 property crimes. The best method, the regression model, signaled a total of 121 possible such increases, of which 35 (29 percent) were correct and 56 more were actually smaller increases. So the total number of increases forecasted was 91 (75 percent). On the more serious problem side, 30 were decreases (25 percent). The neural network was never wrong, all 11 of the cases that it predicted were actually large decreases. The univariate method had a low number of cases triggered also, with 16 (64 percent) out of 25 correct and 23 (92 percent) being increases. The positives in the lower panel are unremarkable.

Next are forecast error comparisons for part 1 violent crimes. Table 7 displays relative frequencies for cases in which the true change from the last historical data point to the one-month-ahead forecast was large: 5 or more decrease in the top panel and five or more increase in the lower panel. For large decreases, the regression model was again the best, finding 41 percent of the positives compared to 24 percent for the univariate method and 22 percent for the neural network. In the second panel, for large increases of 5 or more, the neural network is by far the best, finding 38 percent of such actual cases, whereas the univariate and regression methods both found only 7 percent.

In Table 8, skipping to the significance tests, the regression model was significantly the best for large decreases, and the univariate test was so for smaller decreases, and the neural network for all increases. Lastly, in Table 9 for numbers of positives and false positives, The regression model signals 64 large decrease cases, with 38 correct and another 19 being smaller decreases and only 7 small increases. Again the neural network signals fewer cases, only 28, but has greater relative success with 28 being decreases and 20 correct. The univariate method is similar. In the lower panel, the neural network now has the most forecasted large changes, 74, of which 22 are correct and another 37 are smaller increases. So the neural network signals have 59 increases (80 percent).

In summary of the results, the leading indicator models are significantly better than the univariate method in three out of four large change cases: large decreases for P1P and P1V and large increases for P1V. The neural network and univariate methods tie as best for P1P large increases, but performance in identifying large increases is unacceptably low in that case.

Discussion and Conclusion

This paper has yielded theoretical, empirical, and practical results on leading indicator forecast models for serious crimes. At the theoretical level, we were able to draw on environmental crime theories to determine leading indicators for serious crimes and interpret signs of estimated coefficients. If coefficients for space and time-lagged independent variables (selected lesser crimes and incivilities) are negative, the variables correspond to attractors, drawing crimes away from an observation area. Otherwise, positive coefficients correspond to crime displacement from nearby areas to the observation area. Coefficients of time-lagged independent variables are all expected to be positive reflecting crime attraction and leading behaviors.

The design of the leading indicator forecast model and its empirical tests are intended to provide information needed by police for deploying resources to prevent crime increases (or to retract resources from areas forecasted to have large crime decreases). The empirical tests use a state-of-art, rolling-horizon forecast experimental design with the innovation that forecasts are evaluated in the context of threshold decision rules. An example rule is: if the forecasted change from current crime level is 15 or higher, then assign crime analysis, patrol, and detective resources to the area. Corresponding tests use a contingency table analysis where multiple ranges of forecasted changes are examined and tested using paired comparisons.

The results are promising. Estimated models have coefficients with expected positive signs for time lagged independent variables and a mixture of positive and negative coefficients for time and space lagged independent variables, reflecting crime attractor and displacement crime theories. The end results of forecast validations are that the leading indicator models produce useful forecasts that are significantly better than the extrapolative method in three out of four cases, and for the fourth there is a tie but overall poor performance. Hence the leading indicator model passes our form of Granger causality test. The regression model is best for forecasting large crime decreases, but the neural network is best at forecasting large increases, all by wide margins.

In summary of Tables 4 – 9 above, the leading indicators find 38 to 54 percent of positives in the three successful cases. This corresponds to a workload of an average of only 7.1 forecasts of large changes per month of which 2.4 are positives and 4.7 are false positives, spread over 104 grid cells and 42 patrol units in Pittsburgh. Of the 4.7 false positives per month; however, 2.3 have actual changes in the forecasted direction (increase or decrease) but not in the large crime change range, and thus are not totally without merit. Thus the workload seems acceptable and potential net benefit positive.

Our future work in this area is focusing on a replication in a second city, Rochester, New York in which we are reexamining many assumptions and results of the current paper.

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Table 1.
Crime Leading Indicator and Dependent Variables.

Data Type	Crime Code	Variable Name	Leading Indicators Property	Leading Indicators Violent	Mean	Standard Deviation	Maximum
Citizen 911 Call Codes	DOMESTIC	C_DOMES		X	10.7	15.8	132
	DRUGS	C_DRUGS	X	X	1.9	4.6	95
	PUBLIC DISORDER	C_PUBLIC		X	6.2	8.3	75
	SHOTS FIRED	C_SHOTS		X	2.5	5.4	66
	TRUANCY	C_TRUAN	X		0.0	0.2	4
	VICE	C_VICE	X	X	0.3	1.5	41
	WEAPONS	C_WEAPO	X	X	2.5	4.4	53
Offense Crime Codes	CRIMINAL MISCHIEF	CRIMIS	X	X	5.1	6.5	50
	DISORDERLY CONDUCT	DISORD	X	X	2.7	5.1	97
	LIQUOR LAW VIOLATION	LIQUOR	X	X	0.4	1.5	34
	PROSTITUTION	PROST		X	0.4	2.1	54
	PUBLIC DRUNKENESS	PUBDRUN		X	0.4	1.6	46
	SIMPLE ASSAULT	SIMPASS		X	6.5	9.6	82
	TRESPASS	TRESPAS	X	X	0.7	1.4	17
Dependent Variables	PART 1 PROPERTY	P1P			10.3	14.6	115
	PART 1 VIOLENT	P1V			1.7	3.3	31

Table 2.
Estimated Coefficients for Leading Indicator Forecast Model: Part 1 Property Crimes

Variable	Estimated Coefficients 1993-1995		1996-1998	
Intercept	-1.10487	***	-0.63315	***
C_DRUGS	0.03421		-0.08362	**
NC_DRUGS	0.06626		0.13656	
C_TRUAN	0.21061		1.62792	***
NC_TRUAN	-0.34338		-0.59283	
C_VICE	-0.99699	***	0.12639	
NC_VICE	-0.45854	*	-0.46786	**
CRIMIS	1.12172	***	0.74551	***
NCRIMIS	0.50151	***	0.44472	***
DISORD	0.74668	***	1.04442	***
NDISORD	-0.13513		-0.25105	***
LIQUOR	0.25334	**	0.82613	**
NLIQUOR	-0.01709		0.26481	
TRESPASS	1.37588	***	1.05194	***
NTRESPAS	0.53914	**	0.57485	**
WEAPO	0.69690	***	0.94968	***
NWEAPO	0.72023	*	2.18272	***

N = 3,744
Adjusted R-Square = 0.79 for 1993-1995
= 0.76 for 1996-1998
Significance levels: * is .10, ** is.05, *** is .0001 or better
Variable names starting with N and in shading are space and time lags; others are time lags.

Table 3.
Estimated Coefficients for Leading Indicator Forecast Model: Part 1 Violent Crimes

	Estimated Coefficients			
Variable	1993-1995		1996-1998	
Intercept	-0.24545	***	-0.23292	***
C_DOMES	0.00973	**	0.01672	***
NC_DOMES	0.00073		0.01346	
C_DRUGS	0.08572	***	0.05347	***
NC_DRUGS	-0.04740		0.00549	*
C_PUBLIC	-0.00298		0.00239	
NC_PUBLIC	-0.07115	***	-0.03823	**
C_SHOTS	0.06798	***	0.08168	***
NC_SHOTS	0.00042		-0.01492	
C_VICE	-0.00811		0.02605	
NC_VICE	0.09459		-0.10392	*
C_WEAPO	0.03947	**	0.05960	***
NC_WEAPO	-0.04256	*	0.00860	
CRIMIS	0.04894	***	0.04291	***
NCRIMIS	0.02641	**	0.01478	
DISORD	0.04835	***	0.09128	***
NDISORD	0.00315		0.01797	
LIQUOR	0.00875		0.08745	***
NLIQUOR	-0.02362		0.02496	
PROST	0.10139	***	0.12945	***
NPROST	-0.11611	**	0.01516	
PUBDRUN	0.20295	***	0.06443	*
NPUBDRUN	-0.03453		0.08649	
SIMPASS	0.12191	***	0.07472	***
NSIMPASS	0.07719	***	0.01037	
TRESPAS	0.04523	*	0.10623	***
NTRESPAS	0.09618		-0.02356	

N = 3,744
Adjusted R-Square = 0.76 for 1993-1995
= 0.68 for 1996-1998
Significance levels: * is .10, ** is.05, *** is .0001 or better
Variable names starting with N and in shading are space and time lags; others are time lags.

Table 4.
Percentage of Positives and False Negatives for Large Change Actuals: Part 1 Property Crimes.

Actual Change is 15+ Decrease (65 cases)

	Forecasted Change	Univariate	Regression	Neural Network
Positive	15+ Decrease	25	**54**	17
False Negative	0 to 15 Decrease	68	37	75
False Negative	0 to 15 Increase	8	8	8
False Negative	15+ Increase	0	2	0
	Total	100	100	100

Actual Change Is 15+ Increase (57 cases)

	Forecasted Change	Univariate	Regression	Neural Network
False Negative	15+ Decrease	0	6	0
False Negative	0 to 15 Decrease	19	32	19
False Negative	0 to 15 Increase	72	55	77
Positive	15+ Increase	**9**	6	4
	Total	100	100	100

Table 5
Part 1 Property Crimes: Pair-wise Comparisons Test Results.

	Crime Level		Mean Forecast for Time T+1			Mean Absolute Forecast Error			N
	Time T	Time T+1	Univariate	Regression	Neural Net	Univariate	Regression	Neural Net	
15+ Decrease	46.9	26.4	35.1	**30.4**	37.6	10.5	**8.4***	11.9	65
0 to 15 Decrease	7.8	5.8	**7.0**	7.4	8.0	**1.8***	3.0	2.6	3011
0 to 15 Increase	9.0	12.9	10.1	10.7	**10.7**	3.4	4.5	**3.1***	1671
15+ Increase	27.6	50.0	**33.6**	29.4	**32.5**	**16.5***	20.6	**17.4***	47

* Most accurate forecast or not significantly worse than most accurate forecast, 5% or better significance test

Table 6
Number of Positives and False Positives for Large Change Forecasts: Part 1 Property Crimes.

Forecasted Change is 15+ Decrease (65 actual cases)

	Actual Change	Univariate	Regression	Neural Network
Positive	15+ Decrease	**16**	**35**	**11**
False Positive	0 to 15 Decrease	7	56	0
False Positive	0 to 15 Increase	2	27	0
False Positive	15+ Increase	0	3	0
	Total	25	121	11

Forecasted Change is 15+ Increase (57 actual cases)

	Actual Change	Univariate	Regression	Neural Network
False Positive	15+ Decrease	0	1	0
False Positive	0 to 15 Decrease	2	15	0
False Positive	0 to 15 Increase	4	26	1
Positive	15+ Increase	4	3	2
	Total	10	45	3

Table 7
Percentage of Positives and False Negatives for Large Change Actuals: Part 1 Violent Crimes.

Actual Change is 5+ Decrease (91 cases)

	Forecasted Change	Univariate	Regression	Neural Network
Positive	5+ Decrease	24	**41**	22
False Negative	0 to 5 Decrease	70	57	71
False Negative	0 to 5 Increase	7	2	8
False Negative	5+ Increase	0	0	0
	Total	100	100	100

Actual Change Is 5+ Increase (94 cases)

	Forecasted Change	Univariate	Regression	Neural Network
False Negative	5+ Decrease	0	0	0
False Negative	0 to 5 Decrease	16	22	9
False Negative	0 to 5 Increase	78	71	53
Positive	5+ Increase	7	7	**38**
	Total	100	100	100

Table 8
Part 1 Violent Crimes:
Pair-wise Comparisons of Forecast Errors.

Actual Change	Mean Crime Level		Mean Forecast for Time T+1			Mean Absolute Forecast Error			N
	Time T	Time T+1	Univariate	Regression	Neural Net	Univariate	Regression	Neural Net	
5+ Decrease	11.1	4.2	7.3	**6.3**	7.9	3.3	**2.6***	3.8	92
0 to 5 Decrease	1.1	0.6	**0.9**	1.0	1.2	**0.5***	0.6	0.8	3570
0 to 5 Increase	1.5	3.2	2.0	2.2	**2.6**	1.5	1.4	**1.3***	1074
5+ Increase	5.0	12.6	6.8	6.5	**9.1**	5.9	6.2	**4.0***	58

* Most accurate forecast based on paired difference test that contrasts each forecast method to the most accurate method at p<= .05 significance level.

Table 9
Number of Positives and False Positives for Large Change Forecasts: Part 1 Violent Crimes.

Forecasted Change is 5+ Decrease (91 cases)

	Actual Change	Univariate	Regression	Neural Network
Positive	5+ Decrease	22	**38**	20
False Positive	0 to 5 Decrease	10	19	8
False Positive	0 to 5 Increase	1	7	0
False Positive	5+ Increase	0	0	0
	Total	33	64	28

Forecasted Change is 5+ Increase (94 cases)

	Actual Change	Univariate	Regression	Neural Network
False Positive	5+ Decrease	0	0	0
False Positive	0 to 5 Decrease	4	1	15
False Positive	0 to 5 Increase	10	7	37
Positive	5+ Increase	4	4	**22**
	Total	18	12	74

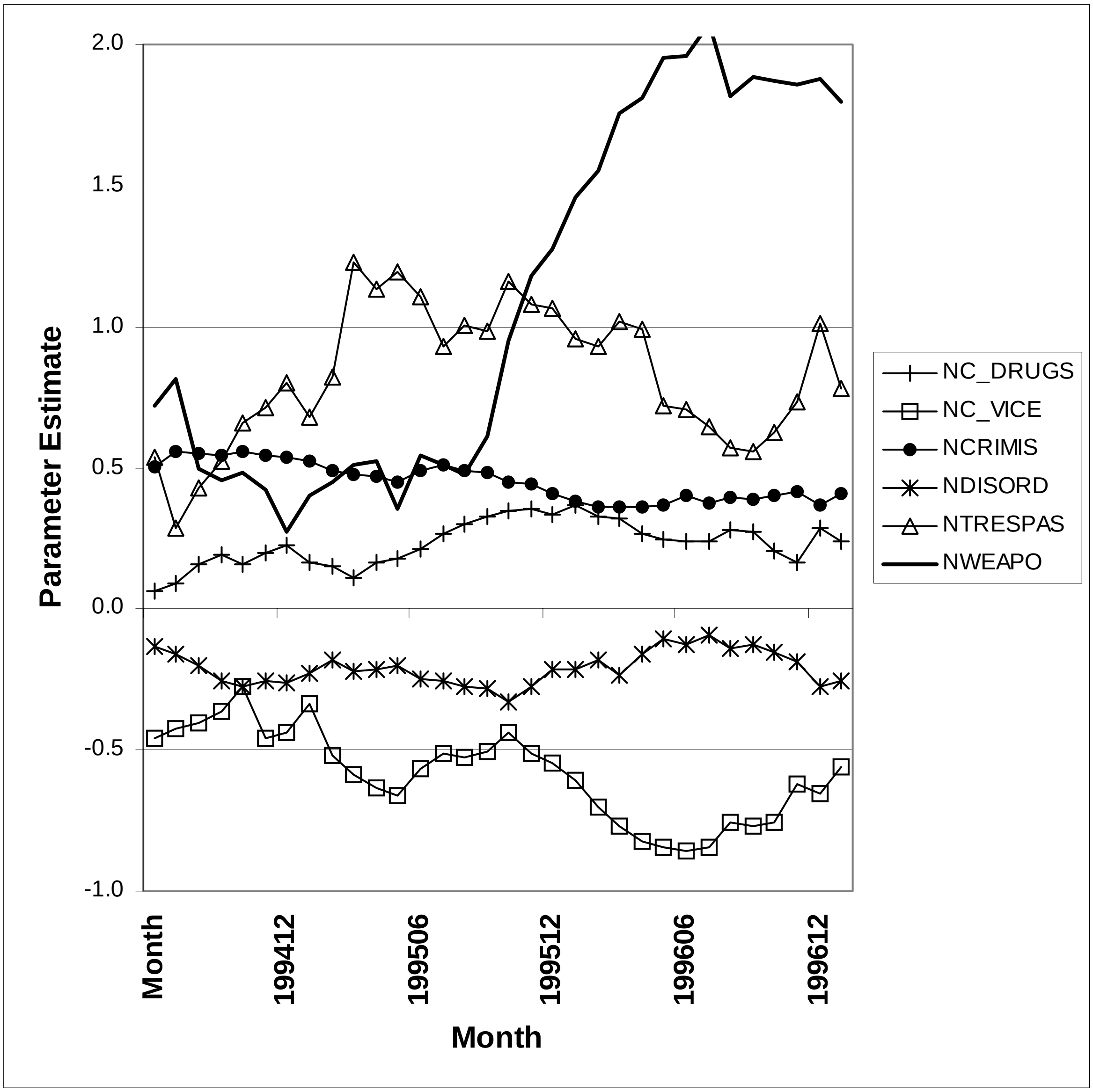

Figure 1. Estimated Parameter Paths from Moving Three-Year Data Window: Space and Time Lagged Variables, Part 1 Property Crime (P1P).

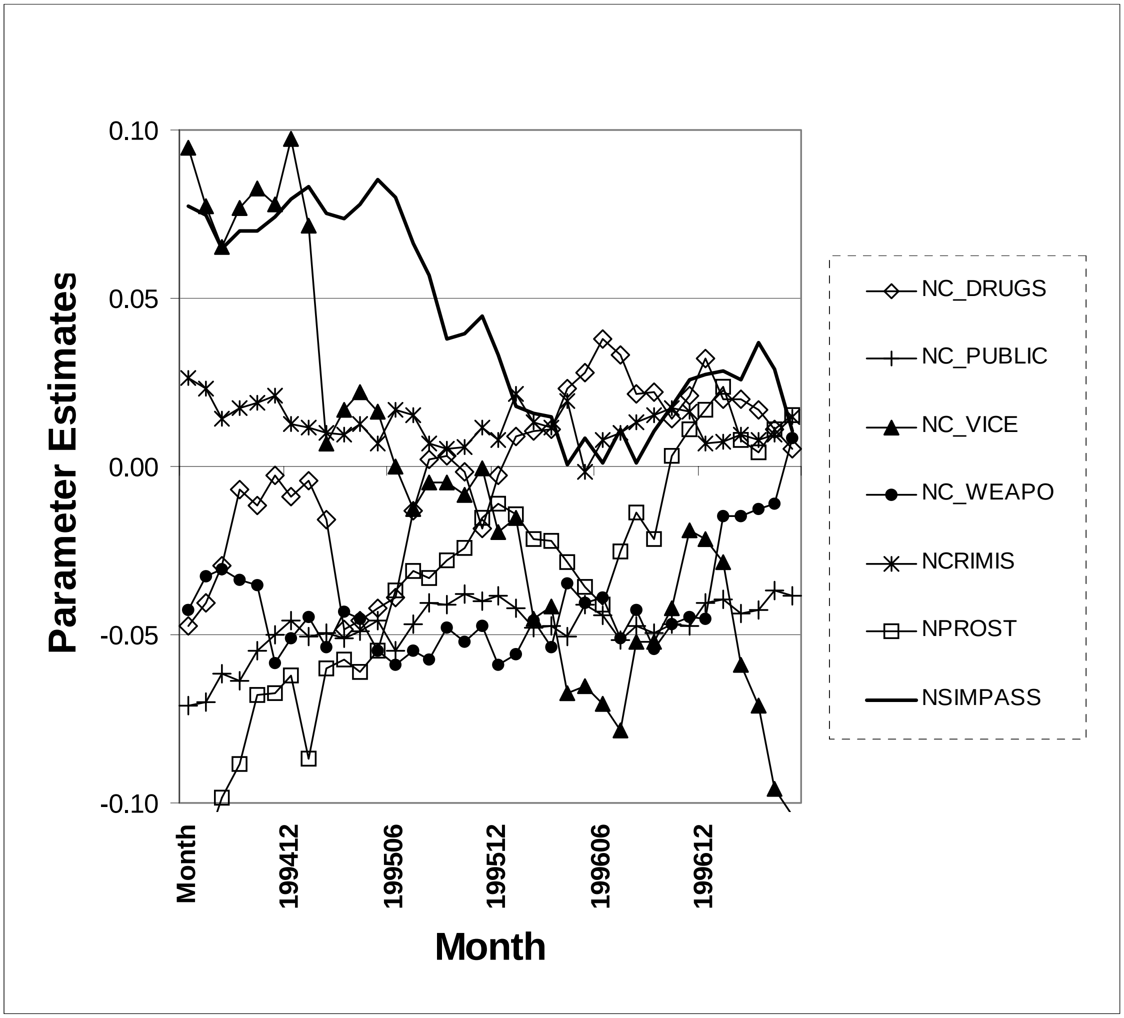

Figure 2. Estimated Parameter Paths from Moving Three-Year Data Window: Space and Time Lagged Variables, Part 1 Violent Crime (P1V).

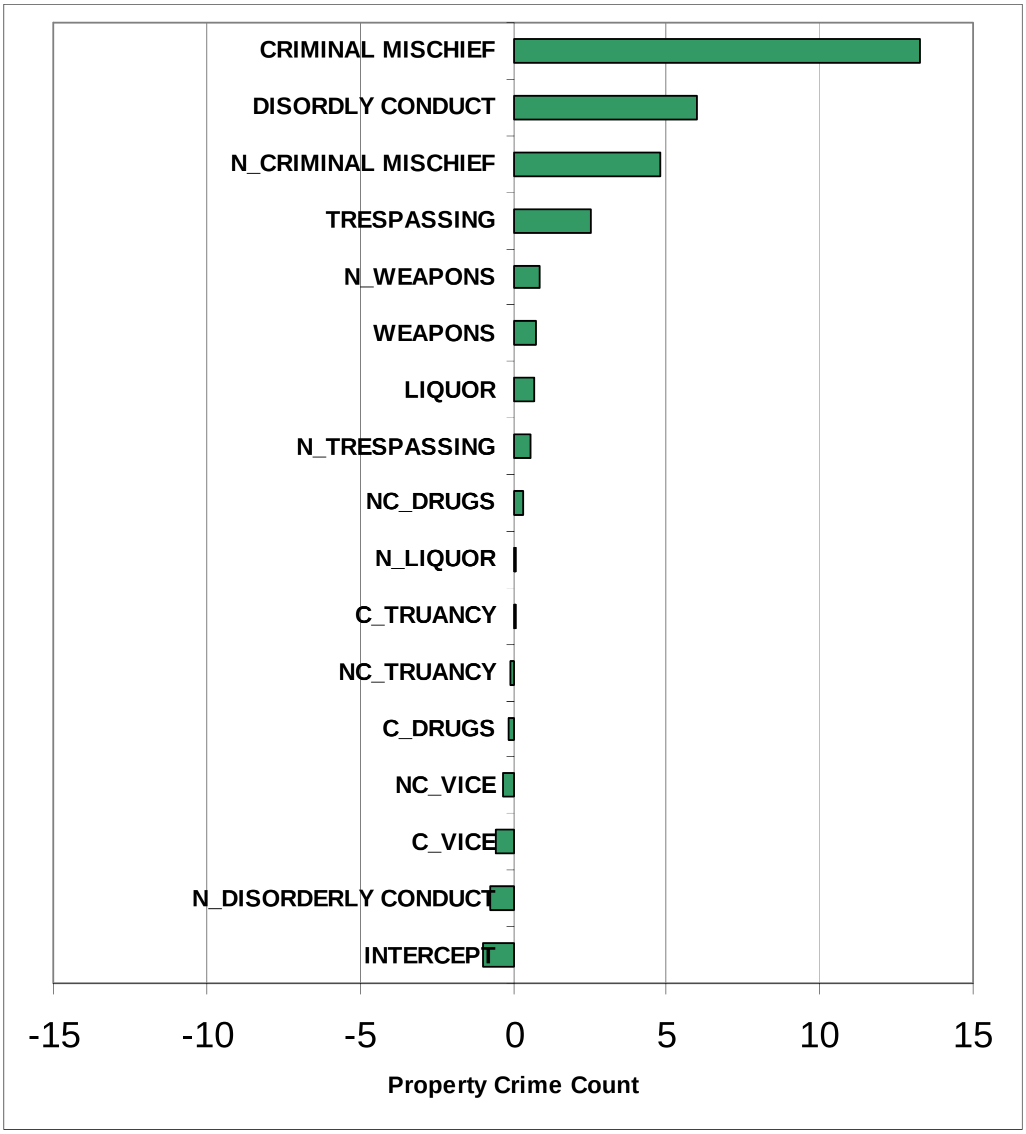

Figure 3. Average Term Contributions: Part 1 Property Crime Leading Indicator Regression Model (based on average indicators for grid months with 10 or more property crimes)

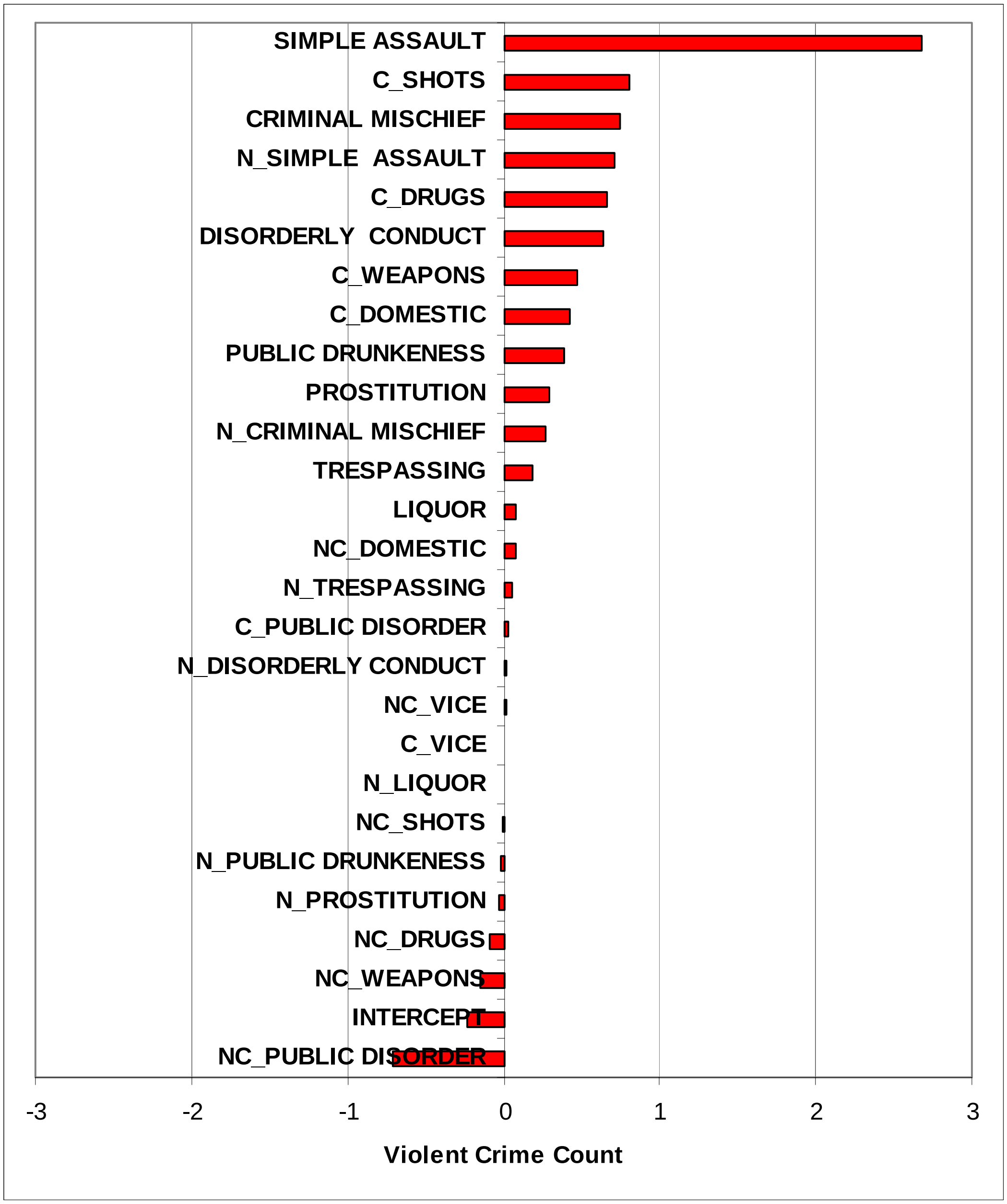

Figure 4. Average Term Contributions: Part 1 Violent Crime Leading Indicator Regression Model (based on average indicators for grid months with 5 or more violent crimes)