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Crime Hot Spot Forecasting: Modeling and Comparative Evaluation

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1. Introduction

The success of crime mapping in identifying hot spots and other location-based crime patterns is well established (e.g., Sherman et al. 1989, Sherman 1995, Spellman 1995, Dussault 1999). Crime maps portray valuable information to the extent that criminals are creatures of habit, repeatedly using the same locales for committing crimes, or are attracted to certain high crime risk areas. Then, targeted patrol, undercover operations, problem-solving policing, and other police tactics can be brought to bear on identified areas of concentrated offending with good effects. There are situations, however, in which crime patterns change over time. For example, enforcement may cause crime to displace in location, the arrival of college students to an urban campus in late August may lead to an increase in robberies near and on campus because of the availability of good targets for criminals, and a rivalry between neighboring gangs may reach the boiling point causing a gang war and violent crimes. These are situations in which it would be desirable to have crime forecasts.

Many police resources are mobile and easily focused on or transferred to different locations immediately. Consequently, short-term, one-month-ahead forecasts are sufficient for many law enforcement and crime prevention purposes. For example, police review and planning meetings, such as Compstat, use a one-month horizon (Dodenhoff 1996). Perhaps the most critical requirement for crime forecasts is that they be for areas as small as possible. Police need to know where to target patrols, carry out surveillance, and other enforcement activities within individual patrol districts or car beats. Hot spots are on the order of only a few blocks in area (Sherman, L.W. and D.A. Weisburg, 1995).

Nevertheless, we shall see crime series data need to have approximately 30 or more crimes per month to permit reliable estimation of forecasting models so that only crime areas on the order of 10 blocks on a side can be forecasted one month ahead with sufficient accuracy for use. A third issue is on the selection of crimes for forecasting. While we are free to forecast any crimes, we limit attention primarily to major crimes; for example, our more complex models forecast part 1 violent and property crime aggregates.

In summary, we investigate alternative methods of forecasting major crimes one month ahead for fixed area units (precincts and square grid cells) that comprise a jurisdiction. Our research program addresses these requirements, taking benefit of research results from the field of forecasting. Publications in the *International Journal of Forecasting* and *Journal of Forecasting*, the annual International Symposium on Forecasting, and textbooks in the forecasting field over the past 25 years have provided a wealth of knowledge on forecast models and experimental designs for comparing and assessing forecast accuracy. Our theoretical work - including specification of forecast models, forecast performance measures, and experimental designs for evaluating crime forecasts - yields a *crime forecasting system* of value to practitioners and researchers. The empirical findings, drawn from a case study of Pittsburgh, Pennsylvania, are encouraging.

The next section of this report reviews the forecasting methods and models that we used and the third section reviews our experimental design. The fourth section addresses data issues and provides model specifications. The fifth section describes data processing steps. The sixth section provides detailed empirical findings. Finally, the sixth section

provides recommendations for police practitioners and researchers. A glossary of terms used in forecasting is also included.

2. Crime Forecasting Models

Certain non-model methods, provide benchmarks for forecasting. Models, if they are to be useful, need to forecast more accurately than the simple, non-model approaches. These non-model approaches include; for example, the random walk (also called the naïve method), which uses the most recent month's data as the forecast for next month. In fields where there is a great deal of volatility, such as forecasting stock market prices, the random walk is often the most accurate method because it has no memory and thus reacts immediately to changes. A non-model method commonly used by police uses data from July last year to forecast July of this year. We call this the Naïve Lag 12 method, because it is a variation on the random walk or naïve method. Most CompStat processes use a naïve lag 12 forecast as the basis for comparison to evaluate a recent month's performance, following practices originating with the New York City Police Department (http://www.nyc.gov/html/nypd/html/chfdept/process.html).

The most common short-term forecasting approach is to extrapolate or extend established time-based patterns into the future. Note that extrapolative methods are also called "univariate methods" because they include only one substantive variable, which for crime forecasting is crime count, plus a time index (e.g., month serial number with the oldest month having the index 1). Generally included are time trend (steady increase or

decrease of crime level with advancing time) and seasonal adjustments. For example, if robberies have a trend decreasing on average four per month but next month is July, a peak month on average having a seasonal increase of 10 robberies, the forecast for July would include a net change over June of plus six robberies.

An extrapolation constitutes a "business as usual" forecast, merely continuing the established time patterns with no "surprises." Besides often yielding the most accurate short-term forecasts, extrapolations also make a good basis of comparison, "counterfactual cases", for evaluating enforcement activities because of their business-as-usual nature. One compares the extrapolative (counterfactual) forecast with the actual crime level of the same month. If the actual crime level is much different than the forecast, then there is evidence of a change in crime patterns.

The comparative forecasting literature has found that simple univariate methods often forecast the most accurately in the short term. More complex models tend to have too many parameters to estimate and run afoul in many ways. See Makridakis, et al. (1982) and Makridakis and Hibon (2000). Hence, we use two simple models that have many useful properties: simple exponential smoothing (Brown 1963) and Holt exponential smoothing (Holt 1957). Smoothing models place more weight on recent data points with weights falling off exponentially (quickly) with the age of the data. This feature makes smoothing models self-adaptive to changing time patterns in the data, albeit with a time lag. Thus if a crime series of data had been steadily increasing until July, at which time the data have a turning point and start to decrease, Holt exponential smoothing will

eventually start estimating a decreasing trend on its own. Simple exponential smoothing merely estimates the average of the data for the end of the data set, with no trend component. Hence it adapts to changing levels in data, increasing or decreasing as needed, but its forecast is a constant for all future months; namely, the smoothed estimate for the last historical month. The benefit of the smoothing methods, like all model-based methods, is that they average out the random errors in the data and thus provide a more reliable basis for making forecasts.

We also use the simplest method for estimating seasonality; namely, classical decomposition. Classical decomposition uses a moving average approach to estimate seasonal factors and can easily be implemented in a spreadsheet. More complex methods, such as Census X11, just provide more complex adjustments to the basic approach. Multiplicative seasonal adjustments, as opposed to the additive adjustment example that we gave above for robberies, have the advantage of being dimensionless and thus are useful in settings such as crime forecasting, applying to low as well as high crime areas. For example, a seasonal factor of 1.0 is on the time trend line, 1.20 is 20 percent higher than the time trend, 0.70 is 30 percent below the time trend, etc. While we found over 100 papers on the seasonality of crime, none included estimation of seasonality at the sub-city level nor testing of the value of seasonality estimation for increasing crime forecasting accuracy. Gorr, Olligschlaeger, and Thompson (2000) provides a review of this literature. To learn about the mechanics and details of exponential smoothing methods and classical decomposition, see any standard

forecasting text book; for example, Makridakis and Wheelwright (1987), Yaffee, R. (2000), and Bowerman and O'Connell (1993).

A more sophisticated approach to short-term forecasting uses leading indicators, if they are available (Klein and Moore 1983; Moore, Boehm, and Anirvan 1994; LeSage 1989, 1990; LeSage and Pan 1995). For example, a sharp increase in certain minor crimes and disturbances in an area this month may indicate the presence and building of a criminal element and therefore forecast an increase in serious crimes in the area next month. The minor crimes and disturbances are the leading indicators. Enforcement and spatial crime displacement may yield another leading indicator. For example, a crackdown on drugs at a hot spot this month may lead to drug dealing in a nearby area next month. In this case, drug offenses in a locale is a leading indicator.

These sorts of changes in crime patterns do not fall into the "business-as-usual category," and are unforeseeable as simple extrapolations. Successful leading indicators can forecast what otherwise would be surprises - departures from past patterns that one cannot foresee with univariate forecasts. If a leading indicator undergoes a large step jump or trend reversal, then the corresponding forecast can also make the same break from the historical pattern. The trick is to be fortunate enough to have leading indicator variables – not every field of application does. We are fortunate and find promising evidence that selected part 2 crimes and computer aided dispatch (CAD) calls lead part 1 violent and property crimes and CAD drug calls.

Leading indicator forecasting, such as done in macroeconomic and other advanced forecasting problems, requires multivariate statistical models. We used two multivariate model formulations: 1) linear with estimates by ordinary least squares and 2) nonlinear using a neural network formulation with a single middle layer and standard feed forward estimation (Olligschlaeger 1997). Very often, linear models are best (Dawes 1974). On the other hand, because ours are among the first leading indicator models for crime forecasting it is desirable to include neural network models because they have automatic pattern recognition capabilities that can find nonlinear and other complex behavior.

3. Crime Forecast Experimental Designs

We collected all offense reports and 911 CAD calls from the Pittsburgh, Pennsylvania Bureau of Police for the years 1990 through 1998. After extensive data processing to provide aggregate crime space and time series data (see Section 5 below), we conducted two major sets of forecast experiments with these data: 1) a study based on precincts to determine the best univariate forecast method for crime and 2) a study based on 4,000 foot, uniform grid cells to evaluate the value of leading indicator forecast models with the best univariate forecast model as the benchmark of comparison. The philosophy of this design is that to be a candidate for use, a leading indicator model must forecast more accurately than the simpler, but best univariate model.

We used 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. In this design, we use several forecast models and make alternative forecasts 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 calculate and save the forecast error. Then 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 to the next month. This process continues over a number of months.

For univariate forecast methods, we used a five-year rolling horizon. One conservative rule-of-thumb states that five years (60 months) of data are needed to accurately estimate trends and seasonality; however, data older than five years become irrelevant as trends change over that length of time. The simple and Holt exponential smoothing methods that we use are self-adaptive and yield time-varying parameter estimates that adjust with some lag to changing time trends. The moving window allows seasonality estimates from classical decomposition, which are not self-adaptive, to slowly adjust over time as well.

For multivariate, leading indicator models estimated by least squares regression, we used a three-year moving window. Whereas univariate models use only data from individual areal units (e.g., precinct or uniform grid cell) for time trend estimation, the multivariate methods use data from all areal units in estimation. Hence, while they have more parameters to estimate, on balance they generally need fewer data points over time. Least squares provides constant parameter estimates over time that are non-adaptive. Therefore

we chose the shorter time window of three years for least squares, which allows estimated parameters to adjust over time, as the data window moves forward. Neural network models are notorious for needing very large sample sizes, hence we kept all available historical data for estimation as the forecasts rolled forward for those models.

We made forecasts over a 36 month period (January 1996 through December 1998), in order to generate an adequate sample size of forecast errors for statistical testing purposes. This provided 36 forecast errors per univariate method and 5,076 (36 months x 141 grid cells) per multivariate method. To compare forecast accuracy of competing univariate methods, we used pair-wise (matched comparisons) t-tests of forecasts for significance testing. Paired-comparison tests properly account for the lack of independence between the alternative forecasts.

We used a form of Granger causality testing (Granger 1969) to determine the relative value of leading indicator models. This approach dictates that the test of leading indicators is whether they forecast significantly better than univariate methods, especially for large crime changes. To develop benchmark accuracy measures, we first carefully optimized over univariate methods to get the most accurate forecasts (Gorr, Thompson, and Olligschlaeger 2000). Using these best univariate results as benchmarks provides the most stringent test of leading indicator models.

It is desirable to evaluate crime forecasts in the context of their use in decision-making. We envision police using threshold crime levels to respond to forecasted changes in crime patterns as examined in a crime mapping system. An example rule using a threshold level might be as follows: if part 1 violent crimes are forecasted to increase by more than five in any given grid cell, then that cell merits attention; otherwise ignore the grid cell in regard to violent crimes. The corresponding crime mapping system would use choropleth maps that display forecasted changes in serious crime across the entire jurisdiction; for example, using cut points and intervals for color coding (e.g., a dichromatic scale, with increasingly darker blues for larger forecasted decreases, increasingly darker reds for larger forecasted increases, and white for small changes). 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 we contrasted forecasts and actual outcomes within each range and designated correct forecasts as true positives and true negatives, and incorrect forecasts as false negatives and false positives. We applied pair-wise comparison t-tests within classes to determine if leading indicator forecasts were significantly better than univariate forecasts.

Evaluation within crime count classes has two benefits. First, the approach follows the appropriate decision-making strategy that police action should be triggered by exceeding threshold changes in crime counts (corresponding to the extreme categories in the choropleth, forecasted-change maps). Second, we do not expect leading indicators to be superior to univariate forecasts in all cases. Rather they will have a comparative

advantage when crime changes are large. Our evaluation strategy thus provides an essential segmentation of forecasts – into classes such as low (take no action), medium (be vigilant), and high (take action) increases – that may expose significant differences in performance relevant for practice.

Within an actual change category, say an observed decrease of between 10 and 15 crimes from the previous data point to the forecast period, we identify the corresponding set of actual and forecasted values. For each point, we have a univariate and a multivariate-leading-indicator forecast. We can thus compute the difference of squared or absolute forecast errors for each matched pair in the same change category. To evaluate the relative performance of the multivariate method within a change category, we ask whether the mean error over all matched pairs in the category is significantly different from zero. If we subtract the univariate absolute error from the multivariate absolute error, then a mean error that is significantly different from zero in a negative direction indicates that the multivariate forecast is more accurate (i.e., has smaller forecast errors). By performing separate tests within different change categories, the tests also use more information and have more power than comparisons of the overall mean squared error or other summary error measures derived from alternative forecasts.

4. Data Issues and Model Specification

There are two related data issues that distinguish crime forecasting from much of the existing literature on forecasting. These are that 1) short-term crime forecasting concerns

small-scale phenomena and this makes it difficult to obtain reliable model parameter estimates (Duncan, Gorr, and Szczypula 2001) and 2) police can generate their own dependent and leading indicator variables as aggregates of incident point data and this enables configuration and real-time operation of a leading-indicator forecasting system. Thus automated systems can produce a space and time series of crime data with any spatial unit, time interval, and crime type aggregate as needed to best forecast crime. Furthermore, spatial econometrics data approaches are valuable for such a setting, especially the construction of spatially-lagged variables (Anselin 1986, Anselin et al. 2000).

There is a great range of areal unit sizes of interest to police. For administrative purposes, crime trends by precinct and patrol district (car beat) are useful; for example, in monthly Compstat meetings. For hot spot analysis, much smaller areal units are desired. Some authors have studied hot spots at the extremely-small, city block level (Roncek and Maier 1991, Sherman 1995). Two opposing forces are at work as the analyst decreases areal unit size: 1) areal units become more homogeneous in population and land use characteristics, benefiting modeling and 2) monthly crime counts become small resulting in high levels of randomness and ultimately unreliable parameter estimates. Our empirical work addresses the tradeoff between these two forces.

Pittsburgh, Pennsylvania, our study area, is a city of approximately 370,000 population and 55 square miles. It has six precincts and 46 car beats. Through experimentation starting with 1,500 foot grid cells and working up to larger grid sizes, we found that the

smallest areal unit for which we could reliably forecast crime was square grid cells, 4,000 feet on a side (approximately 10 blocks on a side). Pittsburgh has 141 4,000 foot grid cells, so there are approximately 3 grid cells per car beat. While large compared to individual hot spots, such grid cells are valuable in drawing attention to areas forecasted to be "heating up" or "cooling down." Then the crime analyst can zoom in using a GIS to examine detailed leading indicator and crime points within hot areas to pin point blocks for police actions. Figure 1 is a map showing the 4,000 foot grid system with robberies and 911 drug calls points for a single month, July 1991. As can be seen, the grid cells, while large, reasonably isolate individual hot areas within cells.

We used two sets of areal units for forecasting. For our initial study we decided to forecast a representative set individual crime types by precinct: simple assault, aggravated assault, robbery, burglary, and 911 drug calls. The resulting data cover a large range of crime counts per observation, including quite large counts. The dependent variables for the grid cell data include two crime aggregates, part 1 violent crimes (aggravated assaults, robbery, rape, and homicide) and part 1 property crimes (burglary, larceny, motor vehicle theft, arson, and robbery), and 911 drug calls. Note that we included robbery in both part 1 crime categories, because robbery has elements of both property and violent crimes.

The model parameters most sensitive to small scale are the monthly seasonality factors of the univariate forecast models (Bunn and Vassilopoulos 1993, 1999; Gorr, Olligschlaeger, and Thompson 2000). An observation for the seasonal effect of a given

month only occurs once per year, thus severely restricting observations on the corresponding seasonal factor. In five year's data, for example, there are only five observations for each month's seasonal factor. We therefore compared univariate forecasts with seasonal estimates made using crime data within precinct versus seasonal estimates made city-wide. The former has the advantage of tailoring seasonal estimates to particular land uses (e.g., residential versus up-scale commercial), while the latter adds reliability through increased volume of crimes in each month.

All independent variables in our leading indicator models are lagged one month. Future research should include longer lags, but quite often it is the first lag that has the most predictive power. Furthermore, our models also include spatial lags: independent variables lagged one month and averaged over all immediate neighbors of a grid cell that touch along a line or at a point (the so-called, "queens case" contiguity, with a maximum of eight neighbors for non-boundary grid cells). The spatial lags allow for interactions over space, including effects of crime displacement, spillover effects (e.g., of nearby drug dealing on robberies or burglaries), and crime magnet effects such as holiday shopping, etc.).

5. Data Processing Steps

All data processing and analysis were accomplished in the PC computer environment using the Oracle database management system, PC SAS 7, ArcView GIS 3.2, and

Microsoft Office packages. Accompanying files provide documentation of data sets, code tables, and programs; namely:

- *Codebook.doc* – includes a) a file dictionary listing the names and descriptions of all documentation files, input data files, code tables, SAS programs, and output files; b) a data dictionary for key data sets, with definitions for variables; and c) listings and definitions for codes. Several input and output data sets have identical structures and differ only by dependent variable, crime type. For such data sets, only a single example data set has detailed documentation.

- *DataListings.doc* – includes the first and last five records for key data sets. Again, a single example data set has a listing for data sets that are identical in structure.

- *DataStatistics.doc* – provides descriptive statistics for each variable of key data sets.

All SAS programs have detailed comments for documentation. If the accompanying data files are installed as c:\CrimeForecast*.*, then all SAS programs will run with correct pointers to input SAS data sets.

We obtained electronic records for offense reports from the Pittsburgh Police's PSMS records management system for 1990 through 1998. We obtained these data in trade for building a crime mapping GIS for use by uniformed police in the downtown precinct (zone 2). (This GIS has been in daily use since January 1, 1999 and was rolled out for all precincts in the summer of 2001.) We also obtained electronic records for CAD calls for

1993 through 1998, and already had CAD data from 1990 through 1992 from our previous DMAP grant. By agreement with the Pittsburgh Police, we are not able to provide the raw data to others; however, we can share aggregate crime counts by crime type, area, and time period such as created by us for our research on forecasting. It is the aggregate-level data that we are submitting with our final report.

While PSMS is a hierarchical database, it contains sufficient data to allow the construction of a modern relational database. In all, we obtained 19 data sets from PSMS and imported needed data sets into an Oracle database for conversion to relational tables and subsequent processing. This was a large undertaking. Fortunately, experience gained from the DMAP grant carried over to this task.

The first data processing task undertaken was to address match all offense and CAD incident locations. We purchased a street centerline map for this purpose from a premier vendor, GDT. We cannot transfer this file with our submitted data sets by licensing agreement. We obtained approximately a 90 percent address match rate for offense data and 85 percent rate for CAD data. These are significantly better rates than obtained with the street centerlines available from Pittsburgh's GIS department. A check plotting all CAD and offense data as points on the GDT street map showed very few blocks with no points; hence, we conclude that non-matches are mostly randomly located or in a few well-known areas that have address irregularities.

The next step was to geocode address matched records by geographic area. While we experimented with several uniform grid sizes (from 1500 to 6000 foot grid cells) and we ultimately chose to use a 4,000 foot grid size. We also worked with police precincts (called zones in Pittsburgh). Hence we used ArcView and a spatial overlay operation to assign grid cell number from the 4,000 foot grid and zone number to each address-matched offense and CAD call.

Our specification of leading indicator variables took three major steps. First we created major crime codes by grouping offense codes and CAD calls. For example, two separate CAD weapons codes were both reclassified as weapons and 15 separate simple assault codes were all reclassified as simple assault (see CodeTables.xls). Second, we had crime analysts from the Pittsburgh and Rochester, NY Police Departments review all non-part 1 major crime codes and all CAD major crime codes to suggest potential leading indicators for part 1 crimes and drug CAD calls. As the third and last step, a noted criminologist, Jacqueline Cohen, refined the list provided by the crime analysts to leading indicators for part 1 property crimes, part 1 violent crimes, and CAD drug calls. The result is Table 4 of Codebook.doc and c:\CrimeForecast\CodeTables.xls. Tables 1-4 and Figures 4 – 6 below also contain information about these leading indicators.

As the final data preparation step, we used our Oracle database to aggregate data to create the aggregate crime, space, and time series data used in the forecast experiments. Two SAS datasets are the result:

- PghSect.sas7bdat – univariate forecast data set containing monthly data by police precinct for a representative set of crime types.

- G4000.sas7bdat – multivariate, leading indicator forecast data set containing monthly data by grid cell for part 1 property crimes, part 1 violent crimes, 911 Drug CAD calls, and corresponding three sets of leading indicators. Leading indicators are lagged one month behind the dependent variables (part 1 crimes and drug calls), plus are also included as averages over up to eight contiguous grid cells lagged one month (space and time lag).

6. Empirical Findings on Forecast Accuracy

Figure 2 contrasts the relative accuracy levels of alternative univariate forecast methods, based on the mean absolute percentage error (MAPE) criterion for one-month-ahead forecast errors. The smoothing methods, using pooled estimates for deseasonalizing data have the smallest forecast errors, while Naïve Lag12 is the worst, with 37 percent higher forecast errors on the average. Using pair-wise comparison t-tests, the smoothing methods are significantly more accurate than the naïve methods at conventional levels, and the pooled seasonality versions of smoothing methods are significantly more accurate than those with seasonality estimated by precinct. In the tradeoff between more homogeneous seasonality estimates (tailored by precinct) versus increased reliability through pooling, pooling wins.

Figure 3 shows the average relationship between MAPE forecast error obtained from the simple exponential smoothing method with pooled seasonality estimates versus average monthly crime count of precincts. There is a "knee of the curve" which indicates that below average crime counts of around 30 per month, forecast errors increase rapidly. At 30 or more, forecast MAPE's are approximately 20 percent, and this level of accuracy is quite acceptable. The curve in Figure 3 is the result of a model (see Gorr, Olligschlaeger, and Thompson 2000) which regressed forecast absolute percentage error on fixed effects for precinct and crime type plus time series characteristics of data (magnitude of time trend and seasonality) – in addition to the inverse of average crime count. Only the inverse of average crime count and the dummy variable for simple assaults were significant, providing evidence that scale is the largest factor in determining forecast error. We conclude that univariate forecasts provide adequate accuracy for sufficiently high average crime counts.

Tables 2 through 4 present regression estimates for our three leading indicator models for the first three-year data window (January 1993 through December 1995). These models have quite good adjusted R_Square values (0.76, 0.79, and 0.73 for part 1 violent crimes, part 1 property crimes, and drug calls respectively) and many significant coefficients that generally make sense. Over time, as the window moved forward, model fits became somewhat worse as crime trends changed. Leading indicator parameters also changed over time. Figures 7 – 9 are time series plots of selected parameter estimates for each model. On the horizontal axis of each graph, model 1 covers the period January 1, 1993 through December 1995, then for model 2 the graph advances these two dates by one

month, etc., through model 36 which covers the period January 1, 1996 through December 31, 1998. There are many interesting trends of indicator variables growing more or less important as crime patterns change. The approach of using moving windows for leading indicator models, to make them adaptive, appears to be quite valuable.

Figures 4 through 6 provide another summary of the leading indicator models, in this case estimated by least squares regression over the entire study period 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 five or more. Then we multiplied the averaged leading indicators by estimated regression coefficients, with the results displayed as bar charts.

While many leading indicators are significant, both statistically and in the practical sense of contributing to the magnitude of forecasts, some are more important. 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 significantly as well including CAD shots fired, criminal mischief, simple assaults in neighboring grid cells, CAD drug calls, disorderly conduct, and CAD weapons calls. There are fewer important leading indicators for part 1 property crimes (Figure 5). Criminal mischief has the largest impact, with disorderly conduct next, followed by criminal mischief in neighboring grid cells, and then trespassing. Finally, for CAD drug calls, drug offenses (which is the same as drug arrests) dominates (showing a persistence of drug dealing in place), followed by

CAD weapons calls, CAD public disorder calls, CAD vice calls, and CAD shots fired. The leading indicator models are all significant and make reasonable sense.

Tables 5 through 13 present results comparing linear multiple regression and nonlinear neural network leading indicators versus univariate forecasting methods. The univariate method is the best as determined from our first study: Holt smoothing with seasonality estimated using classical decomposition applied to pooled, city-wide data. Note that the order of presentation progresses from the best performing models (for violent crimes) to worst performing models in terms of forecast accuracy. Also note that the information in these tables is complex, but that this cannot be avoided. It is somewhat innovative to compare alternative models using contingency table analysis and there are many elements to consider.

We begin with forecast error comparisons for part 1 violent crimes. Table 5 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. Rows labeled "Positive" are correct ranges of forecasts; for example, a model forecasted a decrease of five or more part 1 violent crimes and that was also the actual case.

We see that the regression leading indicator was most accurate at forecasting large decreases with 41 percent of such cases forecasted correctly. Fifty-seven percent of actual large decreases (5 or more) were incorrectly forecast as small decreases and the

balance of 2 percent were forecast as small increases. In contrast, the univariate method only forecasted 24 percent and the neural network 22 percent as being large decreases. Table 6, row 1 shows that the regression model is statistically better than the other two methods with type 1 error less than 5 percent. The neural network model is far superior for large increases (bottom panel of Table 5), with 38 percent of such cases forecasted. Both the regression and univariate models only forecasted 7 percent of he large increases. Table 6 shows the neural network model to be significantly better than the other two models. Note in Table 6 that the univariate model is significantly the best for small decreases and the neural network is best for small increases.

Table 7 addresses false positives, cases where a forecast indicates a large change, but the actual change is small. The regression model makes 64 forecasts of large decreases, but only 38 (64 percent) actually are large. The other two methods make fewer forecasts of large decreases, and have slightly larger percentage of positives: univariate has 33 large change forecasts with 22 correct (67 percent) and neural networks have 28 large decrease forecasts with 20 correct (71 percent). Results for large increases shift attention to the neural network model which had 74 forecasts of large increases with 22 correct (30 percent). The other two methods had similar percentages of correct forecasts, but much fewer high increase forecasts (18 for univariate and 12 for regression) and only four correct each.

Thus, for part 1 violent crimes, the leading indicator models are far superior to the univariate method for large changes. A general question is whether such results are

practically useful. We think so. The leading indicators are from 17 to 31 percentage

points better than the univariate method (from Table 5), with roughly 40 percent of large

change cases identified one month ahead. The leading indicator forecasts are analogous

to high-quality leads on locations of large crime changes, probably worth focusing

resources on.

Tables 8 and 9 provide results for part 1 property crimes. We will not discuss these

results in detail, nor those for 911 drug calls in Tables 10 through 13. For property

crimes, the regression model is significantly better than then alternatives for forecasting

large crime decreases, but the neural network and univariate methods are best and not

significantly different for large increases. Similarly, the neural network and regression

models are tied as best for large drug call decreases, but all three methods tie for large

increases and do not perform well.

Needing improvement are leading indicator models for large increases in part 1 property

crimes and 911 drug calls. Results for all other cases are good for the leading indicator

models. We believe that future research, employing additional model components

including fixed effects for demographic and land uses that affect crime levels and

additional lag structure for leading indicator variables will make major improvements in

the performance of these models.

7. Recommendations

First are recommendations for police:

1. *Forecast major crimes one month ahead for precincts, car beats, and uniform grid cells as small as approximately 10 blocks on a side.* These are the requirements of crime forecasting for tactical deployment of police. Precincts and car beats are important for administrative purposes. Grid cells are the easiest areal units to interpret visually and provide the finest-grain results. Additional recommendations below provide details and caveats.

2. *Stop using the same month from last year as the basis for evaluating police performance in a month this year.* This method is by far the worst method that we evaluated for forecasting one month ahead. A better practice would be to use forecast prediction intervals or methods from quality control to determine if a recent month were unusual – significantly higher or lower than the established trend. Future work should provide empirical examples.

3. *Estimate seasonal factors for use in crime analysis.* Estimate seasonal factors using multiplicative, classical decomposition from jurisdiction-wide data. Study the seasonals and corresponding crime maps for peak crime seasons and patterns.

4. *Make univariate forecasts for crime types and areas that have average monthly crime counts of 30 or more.* Deseasonalize data. Use Holt exponential smoothing for time trend estimation and forecasting. With crime counts of 30 or more, the average forecast error is around 20 percent. With crime counts much

lower, forecast errors rise rapidly. The univariate methods provide business-as-usual forecasts, extrapolating established trends and seasonality.

5. *Develop and refine a set of leading indicator crimes and CAD calls.* Our research proposed sets of part 2 crimes and CAD call types as leading indicators of part 1 violent and property crimes, and CAD drug calls. Our experimental research demonstrated that leading indicators are significantly better than univariate forecast methods for cases with large crime count decreases and for violent crime increases in the forecast period.

6. *Use leading indicators in crime mapping.* Plot choropleth maps of crime forecasts as an early warning map. Allow the analyst to zoom into the individual leading indicator points and major crimes to diagnose a forecast.

Recommendations for researchers include:

1. *Evaluate crime forecasts using the rolling horizon experimental design.* Obtain sufficiently long data sets so that models can be reliably estimated and forecasted over a long enough series of forecast origins. We used eight years of data. We used a five-year rolling window for univariate forecasts, a three-year ahead rolling window for multiple regression leading indicator model estimation, and made a series of 36 one-month-ahead forecasts.

2. *Compare advanced to simple forecast methods.* Compare forecast accuracy of leading indicator models to the best univariate method. In order to recommend a leading indicator model, it needs to forecast more accurately than the simpler, business-as-usual univariate method. Expect the leading indicator models to

perform better than univariate methods for large changes in crime counts, large increases or decreases.

3. *Evaluate forecast accuracy in intervals corresponding to threshold decision rules.* Example decision rules might be: a. do nothing different (low change forecasted), b. be vigilant (medium change forecasted), and c. intervene (large change forecasted). Evaluate alternative models within forecasted change intervals using pair-wise comparisons to control for lack of independence of forecasts.

4. *Consider advanced leading indicator models for future work.* The list of potential extensions and improvements for leading indicator models is long: consider vector autoregressive models to identify lags longer than one month, include nonlinear terms in the model specification (based on neural network results), use census and land use features to add fixed effects components and better fit city-wide data, weight averages for spatial lags based on nature of relationship between neighboring cells, and build different models for crime increases versus decreases.

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Table 1.
Definition of Leading Indicators by
Dependent Variable Type

Data Type	Leading Indicator	Dependent Variable Type		Drug Calls
		Part 1 Crimes		
		Violent	Property	
911 CAD Call	CRIMINAL MISCHIEF	X	X	X
	DOMESTIC	X		
	DRUGS	X	X	
	PUBLIC DISORDER	X		X
	SHOTS	X		X
	VICE	X	X	
	WEAPONS	X	X	X
OFFENSE	ARSON	X	X	X
	CRIMINAL MISCHIEF	X	X	X
	DISORDERLY CONDUCT	X	X	X
	DOMESTIC	X		
	DRUGS	X	X	X
	LIQUOR	X	X	X
	PROSTITUTION	X		X
	PUBLIC DRUNKENESS	X		X
	SIMPLE ASSAULT	X		
	TRESPASS	X	X	X
	VICE	X	X	
	WEAPONS	X	X	X

Table 2
Regression Model for Part 1 Violent Crimes: 1993-1995.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	26	51481	1980	604	<.0001
Error	5049	16544	3.28		
Corrected Total	5075	68025			

Root MSE		1.81	R-Square	0.76
Dependent Mean		1.93	Adj R-Sq	0.76
Coeff Var		93.9		

Parameter Estimates

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
INTERCEPT	[illegible]	[illegible]	[illegible]	[illegible]
C_DOMESTIC	[illegible]	[illegible]	[illegible]	[illegible]
NC_DOMESTIC	0.00073	0.00816	0.09	0.9285
C_DRUGS	[illegible]	[illegible]	[illegible]	[illegible]
NC_DRUGS	-0.04740	0.02508	-1.89	0.0588
C_PUBLIC	-0.00298	0.00629	-0.47	0.6363
NC_PUBLIC	[illegible]	[illegible]	[illegible]	[illegible]
C_SHOTS	[illegible]	[illegible]	[illegible]	[illegible]
NC_SHOTS	0.00042	0.01637	0.03	0.9794
C_VICE	-0.00811	0.02356	-0.34	0.7307
NC_VICE	0.09459	0.06212	1.52	0.1279
C_WEAPONS	[illegible]	[illegible]	[illegible]	[illegible]
NC_WEAPONS	-0.04256	0.02444	-1.74	0.0816
CRIM_MISCHIEF	[illegible]	[illegible]	[illegible]	[illegible]
N_CRIM_MISCHIEF	[illegible]	[illegible]	[illegible]	[illegible]
DISORD_CONDUCT	[illegible]	[illegible]	[illegible]	[illegible]
N_DISORD. CONDUCT	0.00315	0.02471	0.13	0.8986
LIQUOR	0.00875	0.01912	0.46	0.6474
N_LIQUOR	-0.02362	0.05047	-0.47	0.6399
PROST	[illegible]	[illegible]	[illegible]	[illegible]
N_PROST	-0.11611	0.05850	-1.98	0.0472
PUBDRUN	[illegible]	[illegible]	[illegible]	[illegible]
N_PUBDRUN	-0.03453	0.03656	-0.94	0.3451
SIMPLE_ASSAULT	[illegible]	[illegible]	[illegible]	[illegible]
N_SIMPLE_ASSAULT	[illegible]	[illegible]	[illegible]	[illegible]
TRESPASSSING	0.04523	0.02585	1.75	0.0803
N_TRESPASSING	0.09618	0.06606	1.46	0.1455

Table 3
Regression Model for Part 1 Property Crimes: 1993-1995.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	1041288	65080	1158.20	<.0001
Error	5059	284270	56		
Corrected Total	5075	1			

Root MSE		7.49	R-Square	0.79	
Dependent Mean		11.65	Adj R-Sq	0.79	
Coeff Var		64.36			

Parameter Estimates

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-1.10487	0.17710	-6.24	<.0001
C_DRUGS	0.03421	0.03230	1.06	0.2895
NC_DRUGS	0.06626	0.08995	0.74	0.4613
C_TRUANCY	0.21061	1.22422	0.17	0.8634
NC_TRUANCY	-0.34338	2.86034	-0.12	0.9045
C_VICE	-0.99699	0.09445	-10.56	<.0001
NC_VICE	-0.45854	0.25383	-1.81	0.0709
CRIMINAL MISCHIEF	1.12121	0.06247	17.23	<.0001
N_CRIMINAL MISCHIEF	0.51911	0.02436	10.74	<.0001
DISORD. CONDUCT	-0.74664	0.03302	-22.46	<.0001
N_DISORD. CONDUCT	-0.13513	0.08337	-1.62	0.1051
LIQUOR	0.25393	0.07239	3.28	0.0001
N_LIQUOR	-0.01709	0.20480	-0.08	0.9335
TRESPASSING	1.37499	0.10249	13.24	<.0001
N_TRESPAS	0.53914	0.25097	2.15	0.0317
WEAPONS	0.69969	0.15531	4.48	<.0001
N_WEAPONS	1.72024	0.36135	4.91	<.0001

Table 4
Regression Model for 911 Drug Calls: 1993-1995.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	24	97766	4073	561	<.0001
Error	5051	36642	7.25		
Corrected Total	5075	134409			

Root MSE	2.69	R-Square	0.73	
Dependent Mean	2.08	Adj R-Sq	0.73	
Coeff Var	129.29			

Parameter Estimates

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.01673	0.06794	-0.25	0.8055
C_CRIMINAL MISCHIEF	0.00783	0.00972	0.81	0.4204
NC_CRIMINAL MISCHIEF	-0.04331	0.02148	-2.02	0.0438
C_PUBLIC	0.07222	0.00907	7.96	<.0001
NC_PUBLIC	0.01082	0.02104	0.51	0.6069
C_SHOTS	0.08526	0.00977	8.74	<.0001
NC_SHOTS	-0.04450	0.02276	-1.96	0.0502
C_TRUANCY	0.30641	0.44144	0.69	0.4876
NC_TRUANCY	-1.17982	1.03985	-1.13	0.2566
C_VICE	0.49126	0.03486	14.09	<.0001
NC_VICE	-0.25624	0.09072	-2.83	0.0046
C_WEAPONS	0.20223	0.01499	13.55	<.0001

Table 5
Percentage of Positives and False Negatives for
Large Change Actuals: Part 1 Violent Crimes.

Actual Change is 5+ Decrease (92 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 (58 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 6
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 7
Number of Positives and False Positives for
Large Change Forecasts: Part 1 Violent Crimes.

Forecasted Change is 5+ Decrease

	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

	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

Table 8
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 (47 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 9
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 10
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 (47 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 11
Percentage of Positives and False Negatives for
Large Change Actuals: 911 Drug Calls.

Actual Change is 5+ Decrease (96 cases)

	Forecasted Change	Univariate	Regression	Neural Network
Positive	5+ Decrease	21	43	39
False Negative	0 to 5 Decrease	70	46	46
False Negative	0 to 5 Increase	8	10	13
False Negative	5+ Increase	1	1	3
	Total	100	100	100

Actual Change Is 5+ Increase (76 cases)

	Forecasted Change	Univariate	Regression	Neural Network
False Negative	5+ Decrease	3	11	7
False Negative	0 to 5 Decrease	16	21	18
False Negative	0 to 5 Increase	64	51	55
Positive	5+ Increase	17	17	20
	Total	100	100	100

Table 12
911 Drug Calls:
Pair-wise Comparisons Test Results.

	Call 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	13.1	6.2	9.9*	7.5*	9.0*	4.0*	3.8*	3.9*	96
0 to 5 Decrease	1.2	0.7	1.1*	1.1	1.3	0.6*	0.7	0.8	3524
0 to 5 Increase	1.4	3.2	2.0*	2.4	2.3	1.5*	1.6	1.6	1098
5+ Increase	7.3	15.9	9.6*	7.8	9.4	6.8*	8.2	7.3	76

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

Table 13
Number of Positives and False Positives for
Large Change Forecasts: 911 Drug Calls.

Forecasted Change is 5+ Decrease

	Actual Change	Univariate	Regression	Neural Network
Positive	5+ Decrease	20	41	37
False Positive	0 to 5 Decrease	14	41	23
False Positive	0 to 5 Increase	2	8	7
False Positive	5+ Increase	2	8	5
	Total	38	98	72

Forecasted Change is 5+ Increase

	Actual Change	Univariate	Regression	Neural Network
False Positive	5+ Decrease	1	1	3
False Positive	0 to 5 Decrease	3	20	30
False Positive	0 to 5 Increase	6	40	42
Positive	5+ Increase	13	13	15
	Total	23	74	90

Figure 1.
Map of Pittsburgh, Pennsylvania Showing 4,000 Foot Grid System with Robbery and 911 Drug Call Points for July 1991.
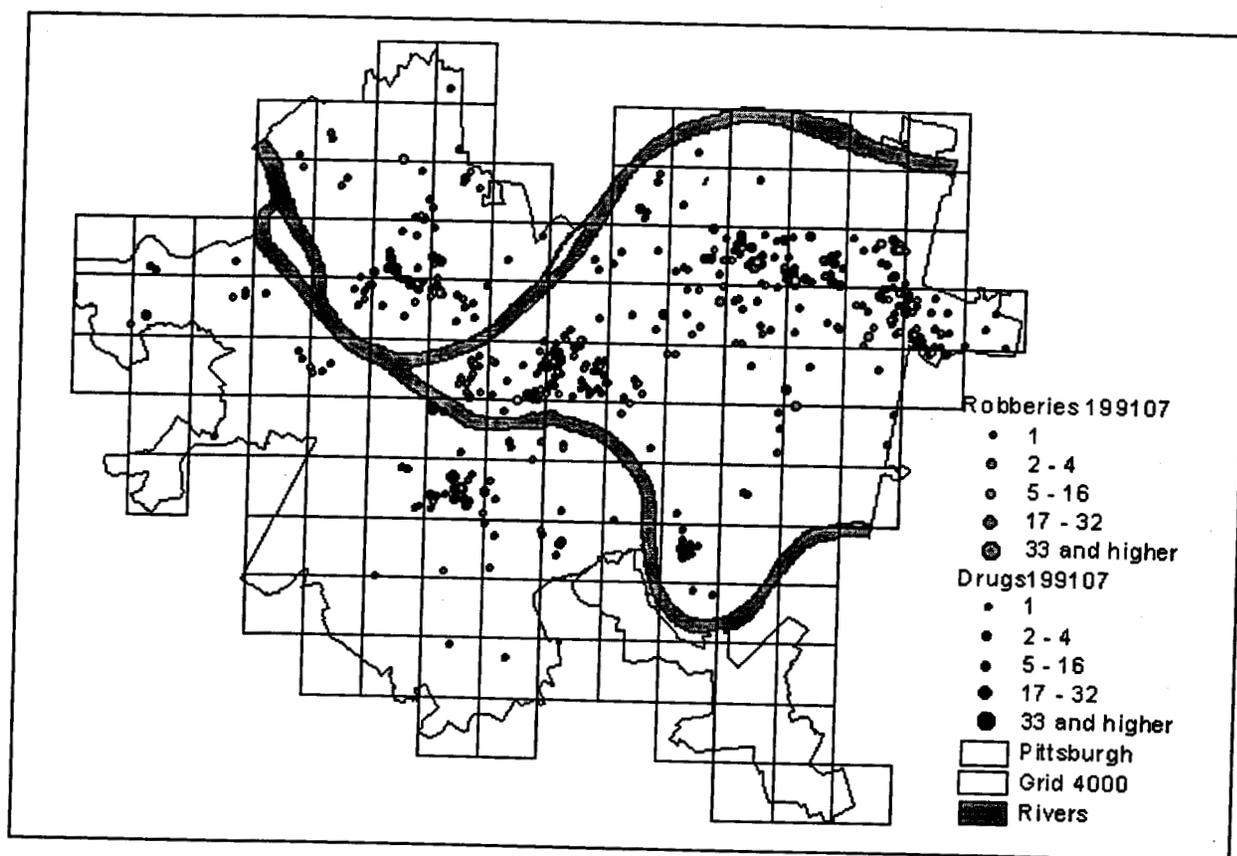
Figure 2.
Relative Forecast Accuracy of Univariate Forecast Methods.
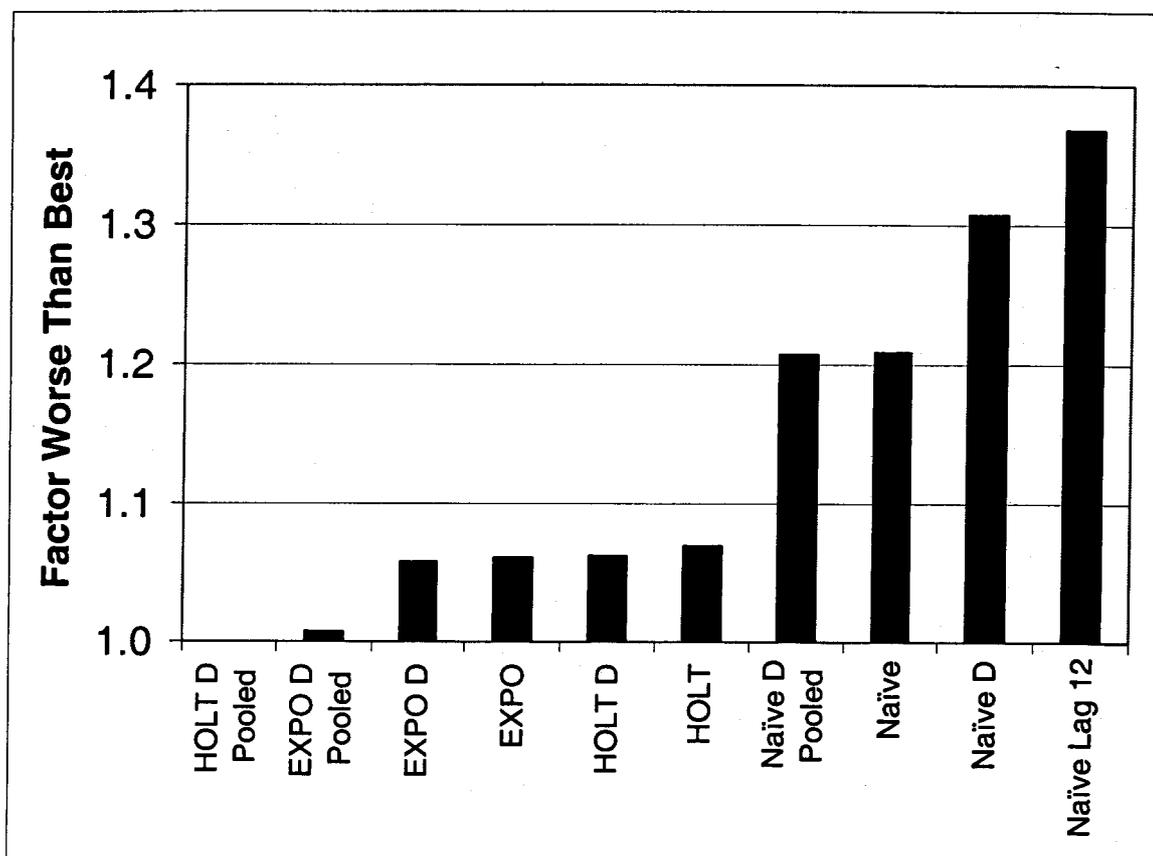
Legend:

EXPO	Simple exponential smoothing
HOLT	Holt linear trend exponential smoothing
Naïve	Random walk, most recent month is the forecast
Naïve Lag 12	Same month last year is the forecast
D	Forecast uses seasonal factors estimated by precinct
Pooled	Forecast uses seasonal factors estimated city-wide

Figure 3.
Mean Absolute Forecast Error from Simple
Exponential Smoothing with Pooled Seasonality Estimates versus
**Average Monthly Crime Level.**
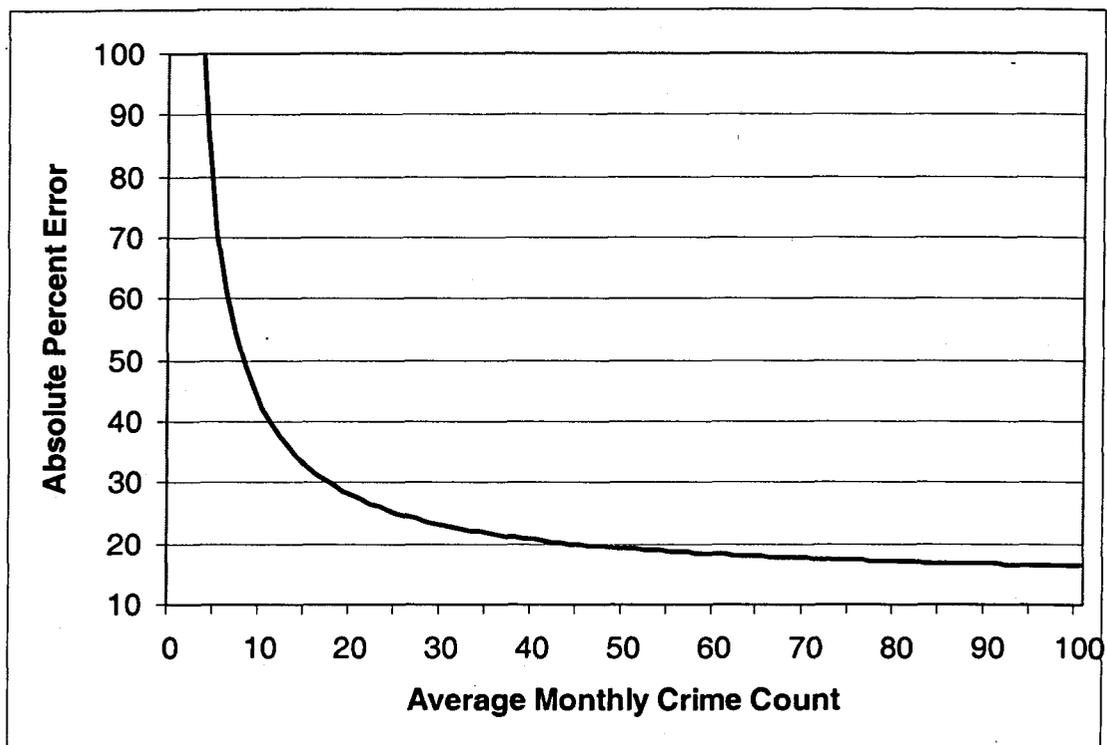
Figure 4.
Average Term Contributions: Violent Crime Leading Indicator Regression Model (based on average indicators for grid months with 5 or more violent crimes)
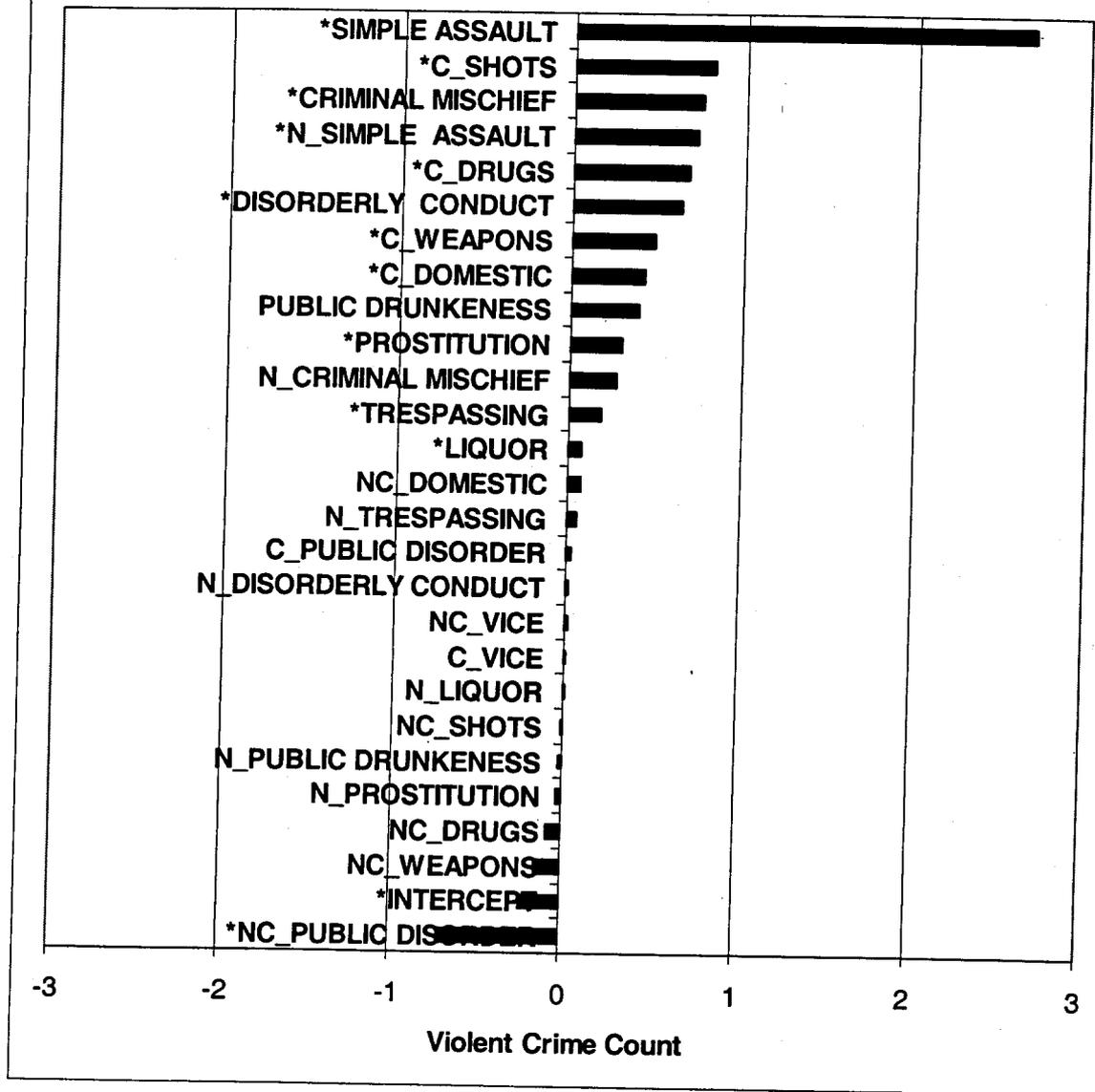
Legend:

C_	= 911 drug call
N_	= average of neighboring cells
NC_	= combination of C and N
*	= coefficient significant at 5% or better level

Figure 5.
Average Term Contributions: Property Crime Leading Indicator Regression Model (based on average indicators for grid months with 10 or more property crimes)
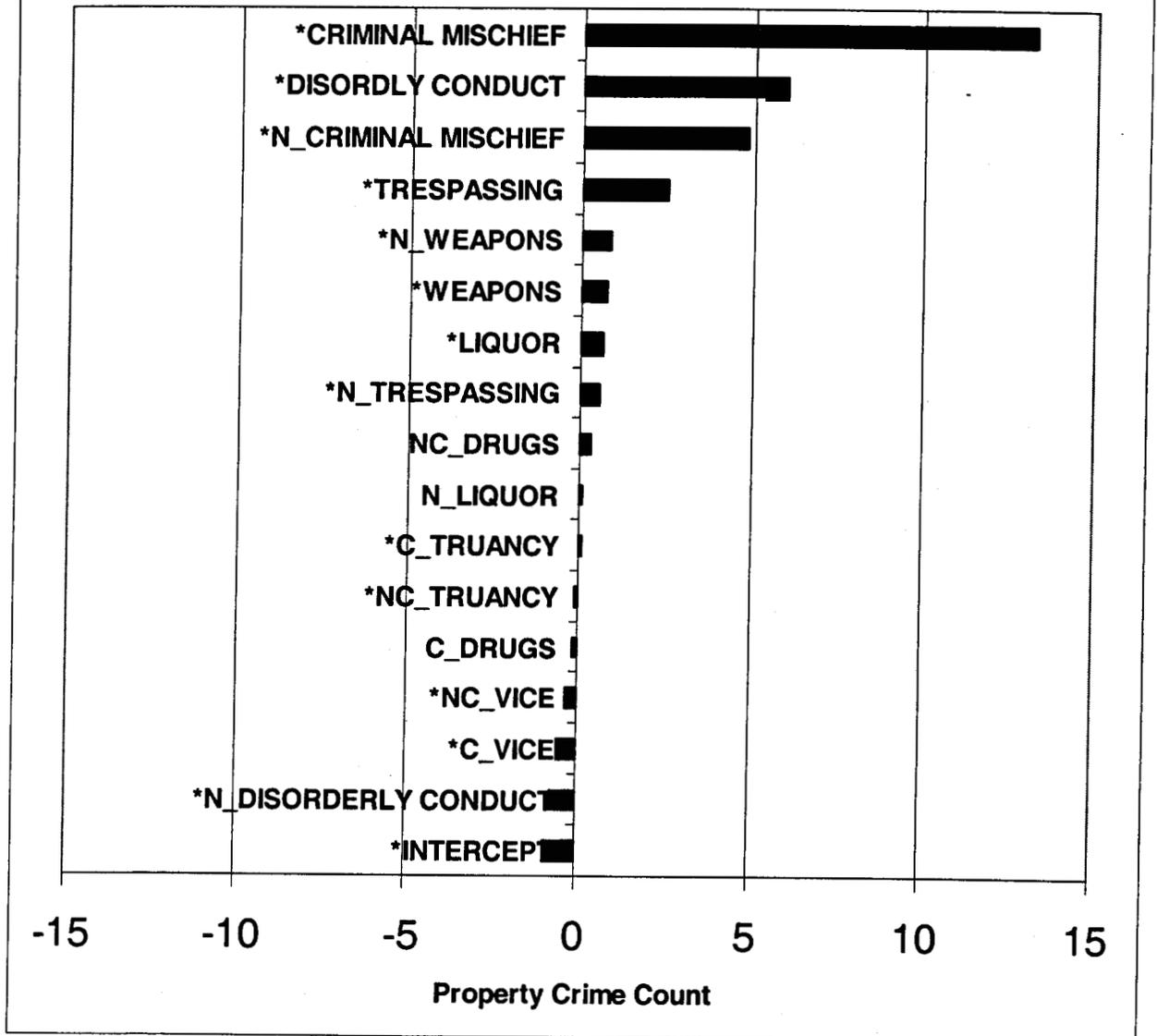
Property Crime Count

Legend:
C_   = 911 drug call
N_   = average of neighboring cells
NC_   = combination of C and N
*   = coefficient significant at 5% or better level

Figure 6.
Average Term Contributions: Drug Call Leading Indicator Regression Model (based on average indicators for grid months with 5 or more drug calls)
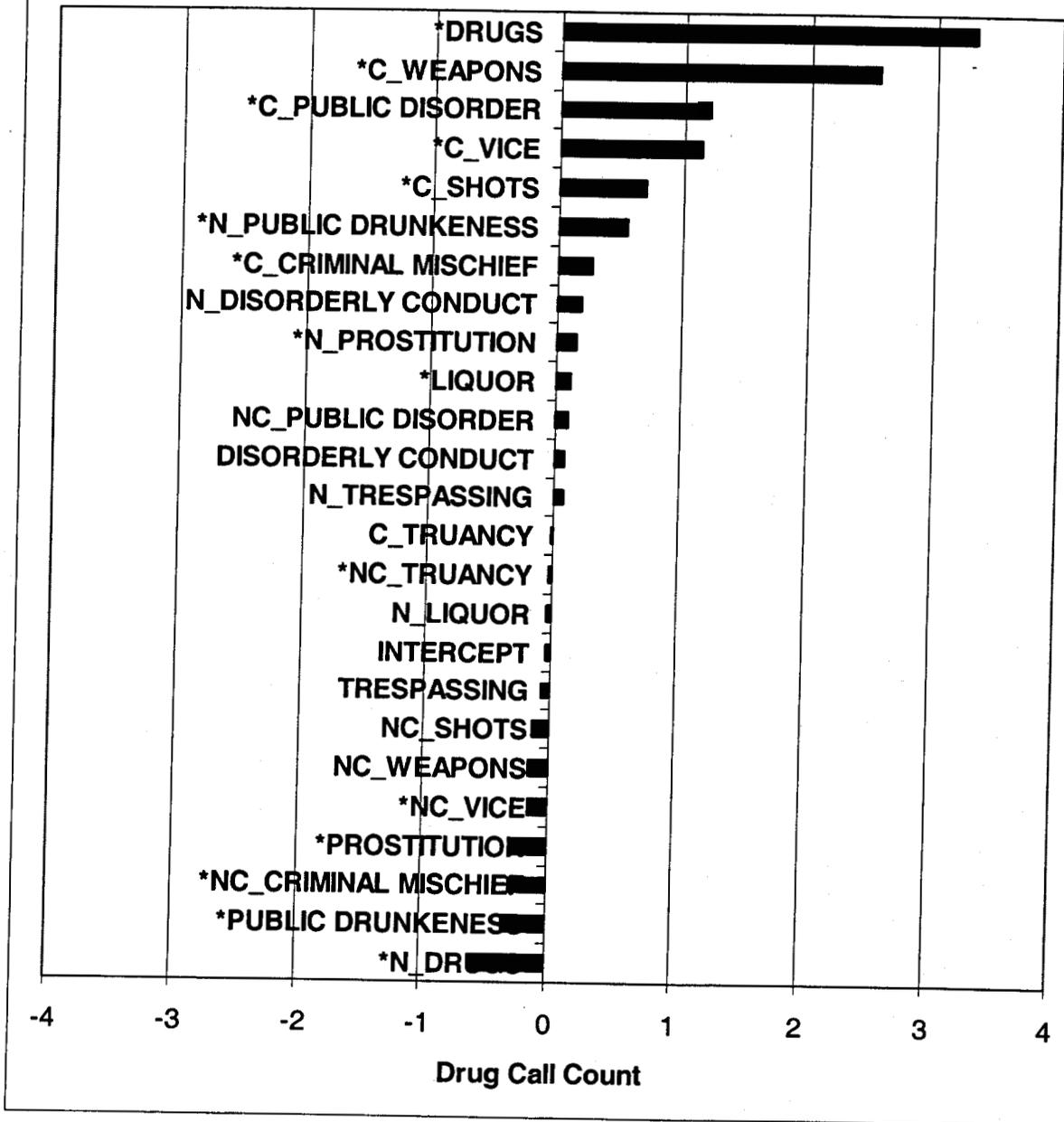
Legend:
C_ = 911 drug call
N_ = average of neighboring cells
NC_ = combination of C and N
• = coefficient significant at 5% or better level

Figure 7.
Sample Time-Varying Parameter
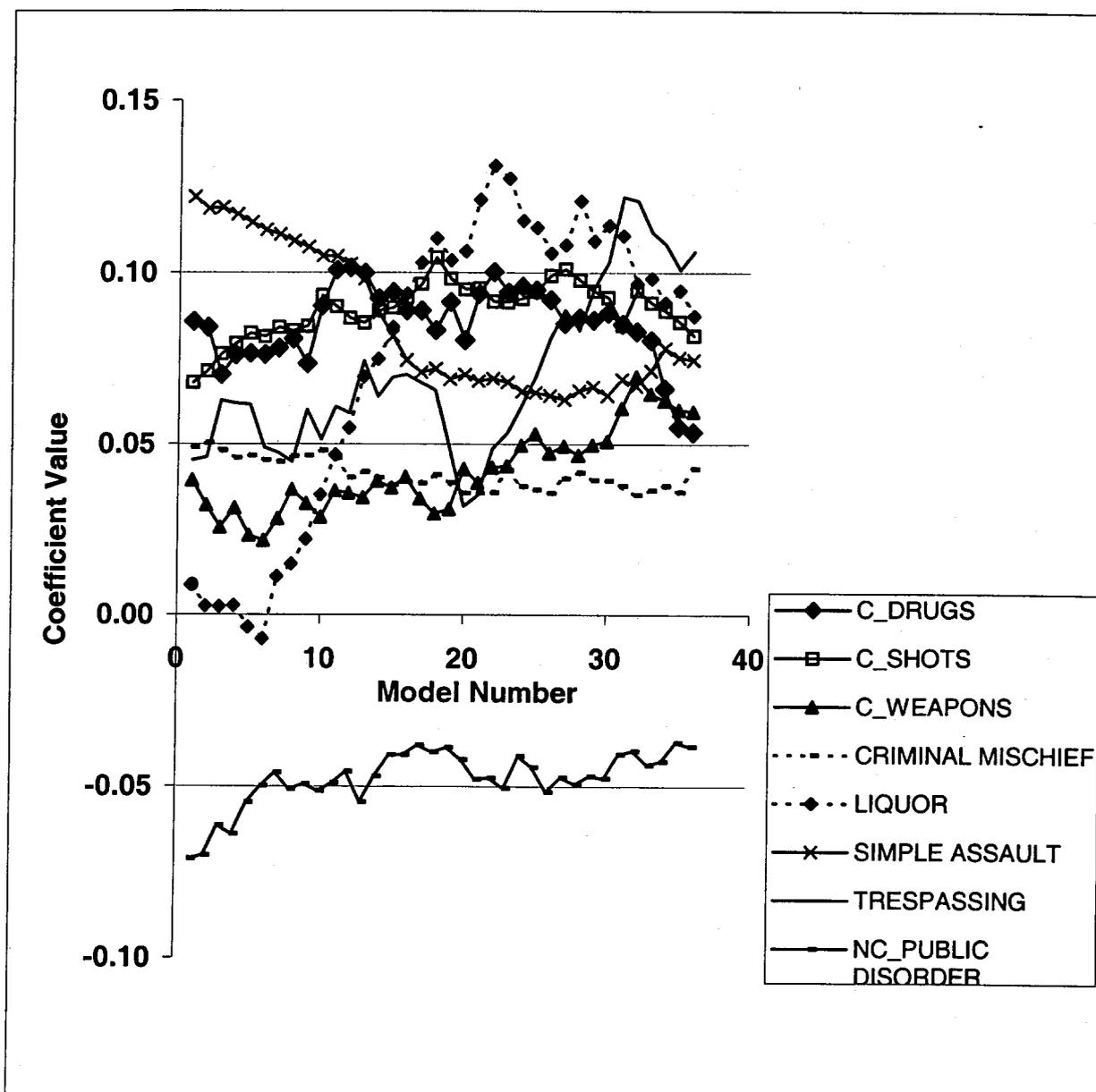**Paths for Violent Crimes Leading Indicator Model**

Figure 8.
Sample Time-Varying Parameter
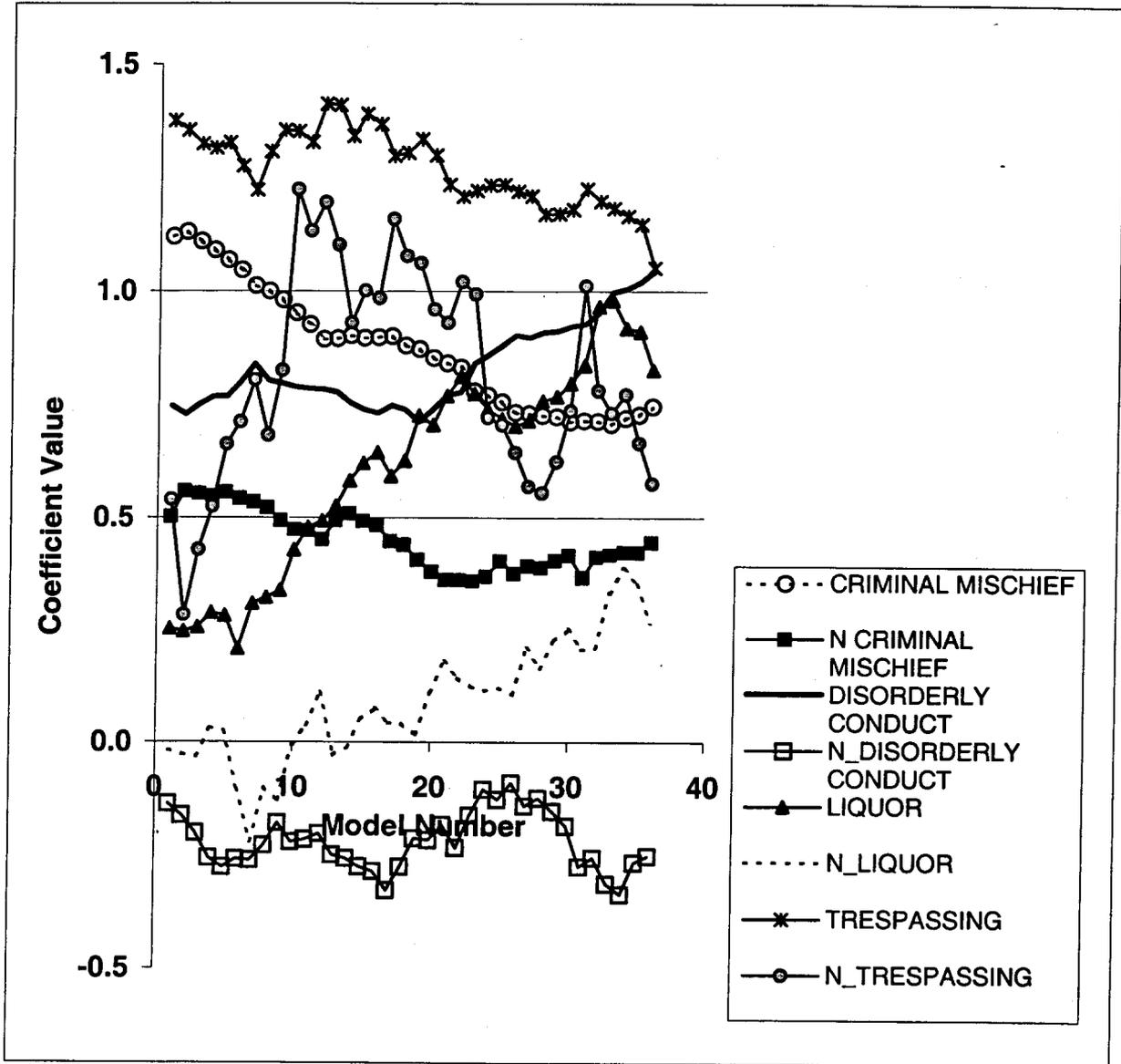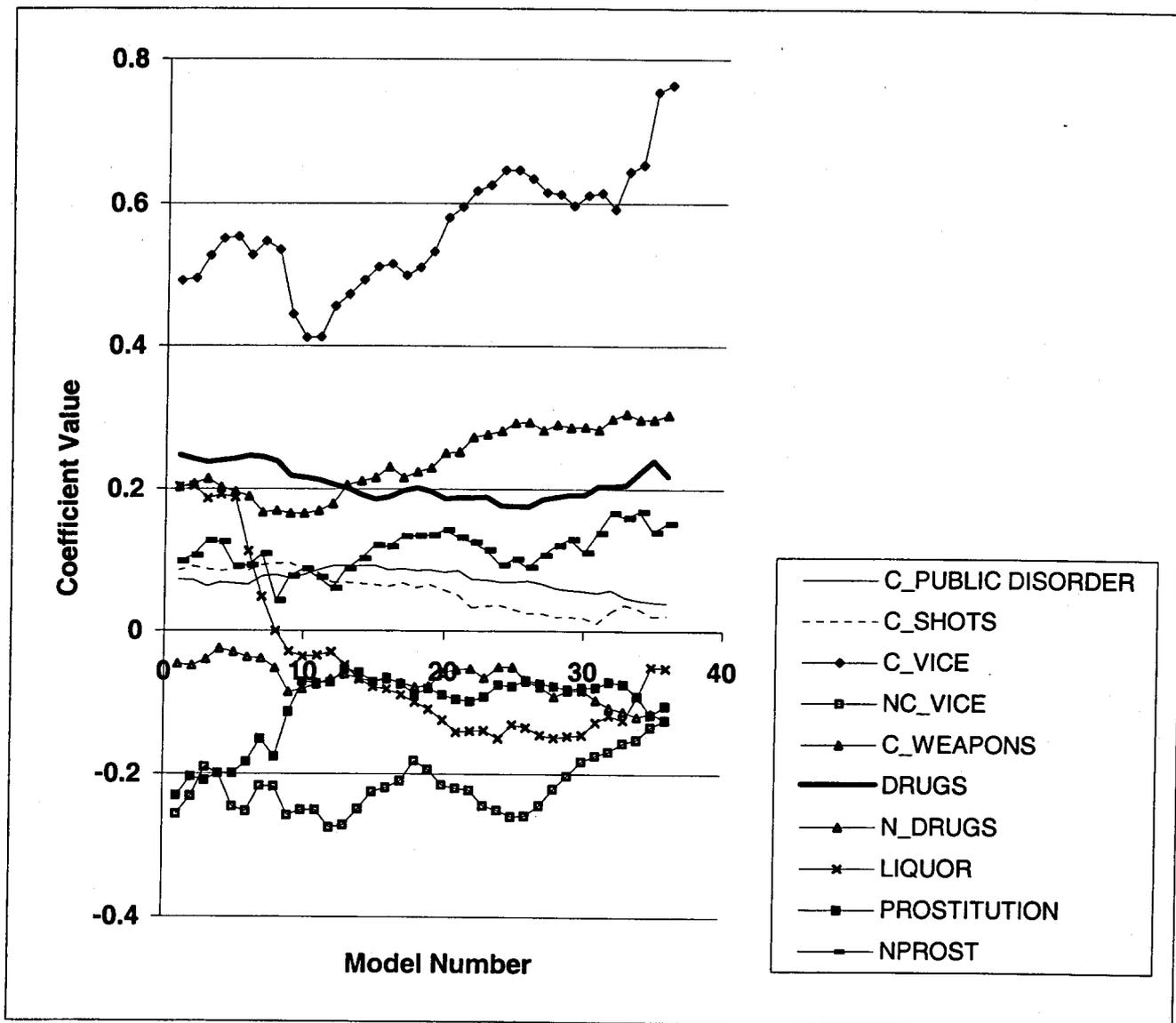## Paths for Property Crimes Leading Indicator Model

Figure 9.
Sample Time-Varying Parameter
Paths for Drug Calls Leading Indicator Model

Glossary

Areal Unit	Spatial area which is a unit of observation (e.g., precinct, census tract)
Autoregressive/Moving Average Models	Complex univariate forecast model popular in the 1970s and 1980s also known as Box/Jenkins forecast models
Classical Decomposition	Simple method used to estimate seasonal factors
Counterfactual Forecast	An extrapolative forecast used as the basis for comparison or evaluation
Dependeent Variable	Variable of interest for decision making (e.g., number of robberies in a precinct per month)
Deseasonalizing Data	Either subtracting additive seasonal estimates or dividing by multiplicative seasonal estimates to remove seasonal variations from time series data
Exponential Smoothing	An extrapolation procedure used for forecasting. It is a weighted moving average in which the weights are decreased exponentially as data becomes older.
Extrapolation	A forecast based only on earlier values of a time series
Forecast Horizon	The number of periods from the forecast origin to the end of the time period being forecast.
Hold-Out Sample	Data not used in constructing a forecast model but are forecasted using the model, providing the basis for validationof the model in forecast experiments.
Holt Exponential Smoothing	Exponential smoothing model estimating a time trend
Independent Variable	Variable used to explain or predict the dependent variable (e.g., a time index or number of leading indicator crimes)
Lag - Spatial	Often the average or sum of an independent variable in areal units surrounding the areal unit being considered as an observation
Lag - Time	A difference in time between an observation and a previous observation; sometimes used for independent variables that are leading indicators (e.g., last month's shots fired CAD calls may predict this months aggravated assaults)
Leading Indicator Forecast Models	A multivariate time series model in which the independent variables are leading indicators (e.g., this month's shots fired CAD calls and simple assaults may predict next month's part 1 violent crimes)
Least Squares Regression Model	The standard approach to regression analysis wherein the goal is to minimize the sum of squares of the deviations between actual and predicted values in the calibration data.
Mean	The average of a variable in a sample of data
Mean Absolute Percentage Error (MAPE)	=Sum of 100*Absolute Value (Actual Value - Forecast Value)/Actual Value over a set of forecasts; yields average percentage errors with signs removed (e.g., 20% MAPE means that on average a forecast is 20% too high or too low, off by 20%)

Multivariate Model	Model in which the dependent variables is explained by two ro more independent variables
Naïve Forecast	Forecast method that does not use any averaging of data to remove effects of noise
Neural Network Model	A complex multivariate model that is capable of self-learning intricate mathematical patterns in data
Noise	The random, irregular, or unexplained component in a measurement process.
Optimization Procedure	A mathematical set of steps that search for the best values for a model based on training datra
Pairwise Comparison t-Tests	A statistical test that compares pairs of alternative estimates or forecasts for the same quantity
Pooled Estimates	Estimates that use data from a group of areal units instead only the real unit being modeled (e.g., a univariate time series model for a precinct that uses seasonal factors estimated form all precincts in a jurisdiction)
Random Walk	A model in which the latest value in a time series is used as the forecast for all periods in the forecast horizon.
Rolling Horizon Forecast Experiment	An experimental design for evaluating alternative forecast models using training data and hold-out samples in which the forecaster makes several forecasts as if time is passing and new forecasts must be made when new data arrives; the design gets the most out of a time series data set by making many forecasts at different points in time, thus yielding many forecast errors for analysis and summary.
Seasonality	Systematic cycles within the year, typically caused by weather, culture, or holidays
Seasonality - Additive	Seasonal estimates that are added to a trend model to represent seasonality; generally not valid for use across areal units because of differences in magnitudes of the dependent variable (e.g., high versus low crime areas)
Seasonality - Multiplicative	Seasonal estimates that are mutiplied times a trend model to represent seasonality; are factors suc as 0.8 or 1.3 that are dimensionless and thus work well across areal units (e.g., high and low crime areas)
Short-term Forecasts	Generally forecasts with horizons less than a year
Simple Exponential Smoothing	Exponential smoothing model estimating only a moving average and is only capable of a horizontal forecast over time with no time trend
Smoothing Parameters	One to three parameters that control how quickly an exponential smoothing model can adapt to time series pattern changes, generally estimated using an optimization procedure
Standard Deviation	The square root of the variance. A summary statistic, usually denoted by s, that measures variation in the sample
Standarized Data	Data which have been transformed to have a mean of zero and standard deviation of one

Step Jump	A sudden and relatively large change in a time series pattern that moves the entire pattern up or down relative to the old pattern
Time Series	Data collected over time and aggregated to counts or sums by time period (e.g., weeks, months, quarters, years)
Time Series Patterns	Systematic changes in a quantity as a function of time such as linear trend, seasonality, or consistent under or over estimates
Time Trend	Part of a time series model in which an estimated amount is added to or subtracted from the model with every increase in time (e.g., month, quarter, or year)
Training Data	Data used to calibrate a model so that the model can estimate and forecast quantities
Turning point	The point at which a time series changes direction
Univariate Forecast Methods	Forecast methods for models using only the dependent variable time series with a time index as the basis for independent variables
Variance	A measure of variation equal to the mean of the squared deviations from the mean