Alcohol Availability and Crime: A Robust Approach[1]

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Abstract

We investigate the relationship between alcohol availability and crime in this paper. We first consider common parametric specifications which have been used in the literature. After applying a powerful consistent conditional moment test for correct specification, we find that these common parametric specifications are rejected by the data. We then proceed with a robust nonparametric method which can have a rate of convergence close to that for a correctly specified parametric model when the underlying relationship is somewhat linear. The application of nonparametric methods reveals structure present in the data which would remain undetected when applying common parametric specifications, but more importantly reveals that the impact of alcohol availability is considerably higher than one might believe on the basis of the misspecified parametric model. We also find that the marginal effect of alcohol availability on crime changes with the level of alcohol availability.

KEY WORDS: CRIME, ALCOHOL AVAILABILITY, CENSUS TRACT, DETROIT, PARAMETRIC ESTIMATES, NONPARAMETRIC ESTIMATES

JEL: K4, D23, D62

1 Introduction

This paper uses recently developed nonparametric methods and census tract data from a large U.S. city to investigate the robustness of estimates of the relationship between alcohol availability and crime rates. Much of the empirical work involving economic models of crime has relied on the use of proxy variables and various parametric functional forms which have yielded a variety of results. Such variation of results warrants an investigation of how robust these results are. In the specific case of the relationship between alcohol availability and crime rates, no study that we are aware of investigates the robustness of the estimated relationship. Furthermore, given that the results of alcohol availability/crime studies have implications for alcohol control and crime prevention/fighting policies, sound policy analysis *demands* robust estimates of underlying marginal effects. We therefore focus attention on obtaining robust estimates of the marginal effect of alcohol availability on crime rates as alcohol availability increases. A guiding objective of our investigation into the changing marginal effects of alcohol availability on crime is to facilitate an understanding of whether or not there exist critical levels of alcohol availability at which the marginal probability of crime peaks.

A number of studies in the economics of crime and criminology literatures argue that alcohol availability increases crime rates across jurisdictions (DiIulio (1995), Gyimah-Brempong (2001), Cook and Moore (1993a), Markowitz and Grossman (1998a, 1998b), Parker and Cartmill (1998), Rush *et al* (1986), among others). In these studies, alcohol availability affects crime either in a pharmacological way or through the environment in which alcohol is served and consumed. If alcohol availability positively affects crime rates, then the policy implication is clear: to reduce crime rates, alcohol availability or its concentration in certain neighborhoods should be reduced. These studies indicate that alcohol availability affects crime rates linearly.

Existing studies that find positive relationships between alcohol availability and crime rates leave two questions, one methodological and the other policy related, unanswered. From a methodological standpoint, one needs to know how robust the estimated alcohol availability/crime relationship is, particularly given the absence of a theory to guide functional forms combined with the use of proxy variables rather than theoretically relevant ones. In order to have confidence in estimated alcohol availability/crime relationships based on parametric methods, rigorous testing of the assumed parametric model *must* be undertaken. From a policy standpoint, it is necessary to know what density of alcohol availability induces criminal behavior. The purchase and consumption of alcohol is legal in most societies. Indeed, it is often argued that moderate consumption of alcohol may be welfare enhancing hence the optimal amount of alcohol availability in a community may be positive. The optimal level of alcohol availability (density) is therefore an important policy question that needs to be investigated. However, previous research has not investigated this issue.

We use census tract data and recently developed nonparametric methods to investigate these two issues. We investigate the robustness of parametric results by estimating common parametric specifications of a supply of offense model with alcohol availability as an added regressor and then subjecting this model to a powerful specification test.[1] Cherry and List (2002) argue that aggregation of crime leads to biased coefficient estimates of the supply of offense functions. Therefore in addition to estimating the relationship between alcohol availability and total crime rates, we also estimate the relationship between alcohol availability and violent crime rates, economic crime rates, and homicide rates respectively to see if our results are subject to aggregation bias. Our investigation of the critical levels of alcohol density is based on the behavior of the partial response surfaces obtained from nonparametric estimates of the crime-generating function. Besides confirming the alcohol-crime relationship, the methodology we use here could also be used to test the validity of other empirical estimates of crime supply functions generally.

We find that alcohol availability has a large positive and statistically significant impact on all crime rates. However, common linear parametric models that have been used to estimate alcohol availability/crime relationship impart serious downward bias to the relationship. Linear parametric estimates of the relationship between alcohol availability and crime are 50% lower than those of the nonparametric estimates. These biases are due to the fact that common linear parametric specifications fail to account for possible non-linearities and interactions among the variables in the model. We also find that alcohol availability affects crime rates in a non-linear manner.

The contribution of this paper to the literature is twofold. First, we test for the correct functional specification of common parametric models which are found in the literature. We then use a robust consistent nonparametric estimator that has a number of desirable properties to estimate the model in order to improve the estimates of the underlying relationship between alcohol availability and crime. Given the popularity and importance of the standard Becker 'supply of offense' model in economics of crime research, testing for correct specification and functional form is, in its own right, an important contribution to the literature. Second, we investigate whether there are critical densities at which the alcohol availability/crime relationship changes direction. These are issues that have not previously been investigated in the economics of crime literature yet have important implications for alcohol and crime research and for policy.

The rest of the paper is organized as follows: Section 2 briefly reviews the literature on the relationship between alcohol availability and crime and presents the statistical model we estimate; Section 3 discusses the data and outlines our estimation methodology, while Section 4 presents and discusses the results. Section 5 concludes.

2 Previous Studies and the Econometric Model

2.1 Previous Studies

Criminologists and Sociologists have reported a positive relationship between alcohol availability and crime (Valdez (1995), Blount *et al* (1994), Homel *et al* (1992), Parker (1995a, 1995b), Roizen (1997), Van Oers and Garretsen (1993), Stitt and Giacopassi (1992), Parker and Cartmill (1998), Scribner, MacKinnnon, and Dwyer (1995), Gruenewald *et al* (1992, 1993), and Scribner, *et al* (1999)). Some of these researchers argue that alcohol is a catalyst rather than the cause of crime (Lang and Sibrel (1993)); others argue that alcohol availability affects crime because of the need to obtain resources to purchase alcohol (Rush *et al* (1986)). A third group argue that it is the environment in which alcohol is provided and used that encourages criminal behavior (Homel *et al* (1992)).

A few studies in the economics of crime literature investigate the effects of alcohol availability on crime. Using census tract data from Milwaukee, Wisconsin, DiIulio (1995) finds that alcohol outlet density is positively related to all indices of crime. The calculated elasticities of crime with respect to alcohol outlet density from the study are generally less than 0.1. Chaloupka and Weschler (1996) find that lower alcohol prices and alcohol availability are positively correlated with binge drinking and crimes among U.S. college students. Further, they find that crime rates are substantially higher among college students when alcohol is available on campus than when it is not. Markowitz and Grossman (1998a, 1998b) find a negative and statistically significant relationship between state alcohol control policies and child abuse. Safer and Chaloupka (1995) find that decriminalization of marijuana increases marijuana consumption by 4%-6%. If a given proportion of those who consume drugs (including alcohol) commit crime or are victims of crime, then increased consumption of the drug due to increased availability may increase crime rates. Cook and Moore (1993b) find that alcohol availability increases alcohol consumption which in turn increases violence in the U.S. Gyimah-Brempong (2001), using census tract data and an Instrumental Variables (IV) estimator, finds a statistically significant positive relationship between alcohol availability and crime rates. The reported crime elasticities with respect to alcohol availability from this study are generally less than 1.

All of the studies mentioned above employ linear parametric models having no interaction terms to generate their results. Parametric modeling requires that one presumes an underlying structure which may or may not be consistent with the true underlying data generating process. It is possible that the assumptions of linearity and no interaction among variables is violated leading to biased, inconsistent estimates and thereby invalid inference. As argued by Lloyd (1990), estimates of the relationship between blood alcohol content and fatal accidents are extremely sensitive to the assumed statistical distribution of the underlying data generating process; so may be the relationship between alcohol availability and crime rates. Second, these studies use different proxy variables as control variables along with different functional forms. With no theory to guide the choice of functional form or the choice of proxy variables, it is not possible to choose between alternative specifications of the alcohol crime relationship on theoretical grounds. It is therefore necessary to use other methods to investigate the robustness of the estimated alcohol availability/crime relationship. None of these studies further investigate the level at which alcohol availability has a statistically significant marginal effect on crime. Yet this has important public policy implications for crime control and the formulation of sound alcohol policies. We attempt to do so in this paper.

2.2 The Underlying Model

The supply of offense model we estimate is the one developed and estimated by Gyimah-Brempong (2001). We briefly describe the model and summarize some key points.[2] The model is the traditional supply of offenses function (Becker (1968), Erhlich (1973), Eide (1998)) that is generalized to include alcohol availability as a regressor. The model postulates that criminal behavior depends positively on the benefits derived from criminal behavior and negatively on the cost of criminal behavior, other things equal. In addition to the traditional variables that determine the net benefit of criminal behavior, we assume that alcohol consumption leads the consumer to either over-estimate the benefits or under-estimate the cost of criminal behavior. We assume that a proportion of those who drink alcohol will be involved in crime either as perpetrators or as victims of crime. Alcohol availability decreases the effective price of alcohol (including time cost), thus leading to more alcohol consumption. Alcohol availability may also lead to increased crime because it may provide a hostile social environment (Homel *et al* (1992), Alaniz *et al* (1998)). Alcohol availability may therefore increase crime both directly and indirectly through the increased consumption of alcohol.

The summary above implies that the crime rate is, in part, dependent on alcohol availability as well as the expected net benefits from criminal behavior and the personal characteristics of the decision maker. We write the general crime generating equation as:

$$CRIME_i = CRIME_i(A, \mathbf{X}, \mathbf{Z}) \quad \text{where} \quad \frac{\partial CRIME_i}{\partial A} > 0 \quad \text{and} \quad \frac{\partial CRIME_i}{\partial \mathbf{X}} > 0, \qquad (1)$$

where $CRIME_i$ is the crime rate for crime i, A is alcohol availability, $\mathbf{X}$ is the expected net return to criminal activity, and $\mathbf{Z}$ is a vector of socioeconomic characteristics. An increase in alcohol availability increases criminal behavior, criminal victimization and, consistent with the economics of crime literature, an increase in the expected benefits from crime will increase criminal activity, other things equal.

To estimate (1) using parametric methods, we need to specify the functional form of the relationship along with defining the elements of **X** and **Z**. We estimate the crime function in (1) using the common linear functional form with no interaction among variables which is often used to estimate crime generating equations in the economics of crime literature. The model summarized above indicates that the crime rate depends positively on the expected net benefits from crime, socioeconomic characteristics, and the availability of alcohol. There are numerous potential benefits from criminal activity—psychic, emotional, and economic. We do not have variables to measure the psychic or emotional benefits and costs of crime for either the perpetrator or the victim. We use per capita income (INC) and the proportion of owner occupied houses in a census tract ($POWN$) to proxy the size of the economic gain from criminal activity (the 'loot'). We proxy the opportunity cost of engaging in criminal activity by the average level of educational attainment ($EDUC$) in the community.[3]

We also lack data on the probability or severity of punishment. Besides, criminal sanctions are imposed at the state, county, or municipality level. Since our unit of analysis is census tract within a single city, the size and probability of punishment is not likely to vary across tracts. We therefore do not include a sanctions variable in our model.[4] The elements included in **Z** in (1) are the proportion of the population that is young ($YOUTH$), population density ($DENS$), and the proportions of the population that are African American ($BLACK$) and Hispanic ($HISPANIC$) respectively.[5] These variables are derived from the empirical economics of crime literature (Erhlich (1973), Myers (1980), Gyimah-Brempong (1997), Eide (1998)).[6] We proxy alcohol availability by the number of alcohol licenses ($LICENSE$) in a census tract.

The reduced form parametric crime equation we estimate is:

$$\begin{aligned} CRIME_i = \alpha_0 + \alpha_1 YOUTH_i + \alpha_2 BLACK_i + \alpha_3 HISPANIC_i + \alpha_4 LICENSE_i \\ + \alpha_5 INC_i + \alpha_6 EDUC_i + \alpha_7 DENS_i + \alpha_8 POWN_i + \epsilon_i, \quad i = 1, 2, \ldots, n, \end{aligned} \tag{2}$$

where ϵ is a stochastic error term and all other variables are as defined in the text above. In accordance with the hypothesis that alcohol availability increases crime rates, we expect a positive relationship between $LICENSE$ and crime rates.

3 Data and Estimation Methodology

3.1 Data

The data used to estimate the crime equation in (2) is from Gyimah-Brempong (2001), hence we only provide a brief description of the data. The dependent variable in this model is $CRIME$ and is measured as the Federal Bureau of Investigation (FBI) part 1 index crime rate. We use four alternative measures of crime—total crime index ($TOTCRIME$) encompassing all the 7 FBI part 1 index crimes, violent crime index ($VCRIME$) defined as an aggregate of homicide, rape, aggravated assault, and robbery, economic crime index ($ECRIME$) which aggregates burglary, larceny, and motor vehicle theft, and homicide rates ($HOMICIDE$)—as dependent variables.

The FBI index crimes are based on data supplied by various law enforcement agencies to the FBI. Unlike the National Crime Victimization Survey (NCS) data which is based on a survey of individuals, the FBI index crime data only measure crimes *known* to law enforcement agencies. Changes in the rate at which crimes are reported changes the index crime rates even though actual crimes may not have changed. There is evidence that crimes are under-reported to the police. This measurement error implies that using the FBI index crimes as our measure of crime could potentially lead to biased estimates. However, Myers (1980) finds no evidence of biased estimates when one uses the FBI index crime as the relevant measure of crime.

We measure $LICENSE$ as the total number of alcohol licenses of all types granted per 1,000 people in a census tract. $LICENSE$ aggregates beer, wine, and liquor licenses and makes no distinction between licenses for on-premise consumption or carry-out drinks. Ideally, alcohol licenses should be disaggregated by alcohol type sold—beer, wine, or liquor—and under what conditions alcohol is sold—on-premise consumption versus off-premise consumption—since these conditions could have different effects on crime rates. However, the Michigan Liquor Control Board data neither disaggregate licenses in any way, nor indicate whether the license is currently being utilized to sell alcohol or not. We measure $YOUTH$ as the proportion of the population that is 14 to 34 years old while $BLACK$ and $HISPANIC$ are measured as the proportions of the population that are Black and Hispanic respectively. INC is per capita income from all sources of income in 1991 constant dollars, $POWN$ is the proportion of owner-occupied homes in a census tract, $EDUC$ is the proportion of the adult population with a bachelors degree or more of education, and $DENS$ is population density measured as the number of persons per square mile.

The socioeconomic variables (INC, $BLACK$, $HISPANIC$, $DENS$, $EDUC$, $POWN$) were obtained from *Census of Population and Housing, 1990: Summary Tape Files 1 and 3, Michigan*, (Washington, D.C., Bureau of the Census, 1991). The crime rates ($TOTCRIME$, $VCRIME$, $ECRIME$, $HOMICIDE$) were obtained from the city of Detroit Police Department and were compiled and converted to the census tract level using GIS methodology by the Michigan Metropolitan Information Center (MIMIC). The crime data were for 1992. The alcohol license data was obtained from the Michigan Liquor Control Board (MLCB) (Lansing, Michigan, State of Michigan, 1994) and they are for 1992. There were a total of 323 census tracts in the city of Detroit data. However, there were a few observations that had some missing variables. Excluding those observations left us with a total of 315 usable observations. We limited the sample to the city of Detroit in part because of data availability since crime data by census tract were not available for the entire metropolitan area.

An advantage to using the census tract as the unit of analysis is that the relationship between alcohol availability and crime is less likely to be confounded by other factors, such as policy differences, than is the case where a large geographical area, such as the state, is the unit of analysis. However, the use of census tract as the unit of analysis has disadvantages. Apart from the problem of obtaining data for some of the theoretically relevant variables (e.g. probability and severity of punishment), there is the problem of spillover effects. It is more likely that an individual may buy and consume alcohol in one census tract and commit a crime in another census tract than it is for an individual to consume alcohol in one city (state) and commit crime in another.

Summary statistics for the sample data are presented in Table 1. The average crime rate in Detroit is high but variable across the city's census tracts as shown by the large standard deviations relative to the mean crime rates. Alcohol license density is high, averaging about 1 license per 521 people, and variable as the standard deviation of $LICENSE$ indicates. The number of alcohol licenses across census tracts ranges from zero to 31—an unusually wide range. The correlation between alcohol density and crime rates across the city is relatively high. The Pearson correlation coefficients between $LICENSE$ and $TOTCRIME$, $VCRIME$, $ECRIME$, and $HOMICIDE$ are 0.49, 0.51, 0.39, and 0.36 respectively and all these correlation coefficients are significant at the 99% confidence level. The socioeconomic variables similarly show wide variations across census tracts in the city. One characteristic of the city of Detroit is that racial minorities make up an unusually high proportion of its population—African Americans and Hispanics make up about 78% of the city's population. Per capita income is relatively low and the proportion of the population that is young is relatively large.

3.2 Estimation Method

Parametric regression modeling requires one to specify the functional form of the underlying object *prior to estimation*. Correctly specified parametric models provide consistent estimates of the object being estimated ('$\sqrt{n}$-consistent'), and hypothesis tests based on such estimates are statistically valid, having actual levels equal to their assumed 'nominal' levels. Unfortunately, these properties do not hold for incorrectly specified models in general. We cannot overstate the importance of this issue: incorrectly specified parametric models, generally, produce biased and inconsistent estimates and inference based on such estimates will be invalid. Uncertainty exists about the functional form of the crime equation given that theory does not provide a guide as to an appropriate functional form. In addition, there could be non-linear relationships as well as interaction among the regressors which the popular linear parametric specification may not capture. It is not clear then whether linear parametric estimates will produce consistent and unbiased estimates of the crime generating equation. The concern in the current setting is that any analysis of the relationship between alcohol availability and crime constructed from poorly specified parametric models may yield biased and unreliable estimates of the underlying relationship.

Should specification tests reveal that the parametric model specified by the researcher is not appropriate, one may choose to pursue nonparametric regression methods which are robust to functional specification issues since they allow the data to determine the appropriate model. Nonparametric methods are consistent under a fairly weak set of assumptions and are best suited to situations involving large data sets. Their application is not without cost, however, as nonparametric methods are computationally intensive and are *slower to converge* than correctly-specified parametric models (i.e. slower than the $\sqrt{n}$ rate of correctly specified parametric models). The marginal benefit of nonparametric approaches, however, may well exceed the marginal cost when one does not know the correct specification of the crime generating equation.

We briefly describe the local linear nonparametric estimator used herein.[7] This estimator was proposed by Fan and Gijbels (1992, 1996), while Li and Racine (2003a) derived its properties when cross-validation is employed for bandwidth selection. Consider a regression model given by

$$y_j = g(x_j) + u_j, \qquad j = 1, ..., n \tag{3}$$

where x_j is a set of regressors of dimension q. As is the case when one employs parametric models, we require information about the conditional expectation $g(x_j)$ and its response gradient, the derivative of $g(x)$ defined as $\beta(x) \stackrel{def}{=} \nabla g(x) \equiv \partial g(x)/\partial x$ ($\nabla g(\cdot)$ is a $q \times 1$ vector).

The unknown conditional expectation $g(\cdot)$ and its derivatives cannot be observed but can be consistently estimated using nonparametric methods. Define $\delta(x) = (g(x), \beta(x)')'$. $\delta(x)$ as a $(q+1) \times 1$ vector-valued function whose first component is $g(x)$ and whose remaining q components are the first derivatives of $g(x)$. Taking a Taylor series expansion of $g(x_j)$ at x_i, we get $g(x_j) = g(x_i) + (x_j - x_i)'\beta(x_i) + R_{ij}$, where $R_{ij} = g(x_j) - g(x_i) - (x_j - x_i)'\beta(x_i)$. We write (3) as

$$\begin{aligned} y_j &= g(x_i) + (x_j - x_i)'\nabla g(x_i) + R_{ij} + u_j \\ &= (1, (x_j - x_i)')\delta(x_i) + R_{ij} + u_j. \end{aligned} \tag{4}$$

We shall use data-driven kernel methods to estimate $\delta(x_i)$, the unknown mean and response. Kernel methods require selecting 'bandwidths', and for what follows this unknown bandwidth vector is selected using a data-driven method known as 'least-squares cross-validation' to be defined below. We use $\hat{h}$ to denote the cross-validation choice of h that minimizes (9) below. Having obtained an appropriate bandwidth vector ($\hat{h}$) we then estimate $\delta(x)$ by ($x \in R^q$ is a fixed point)

$$\hat{\delta}(x) = \begin{pmatrix} \hat{g}(x) \\ \hat{\beta}(x) \end{pmatrix} = \left[\sum_{i=1}^{n} W_{\hat{h},ix} \begin{pmatrix} 1, & (x_i - x)' \\ x_i - x, & (x_i - x)(x_i - x)' \end{pmatrix} \right]^{-1} \sum_{i=1} W_{\hat{h},ix} \begin{pmatrix} 1 \\ x_i - x \end{pmatrix} y_i, \qquad (5)$$

where $W_{\hat{h},ix}$ is a 'kernel' function defined as $W_{\hat{h},ix} = \hat{h}^{-q} W((x_i - x)/\hat{h})$ with $W((x_i - x)/\hat{h})$ being, say, a Gaussian or Epanechnikov function, and we estimate $g(x)$ by

$$\hat{g}(x) = e_1' \hat{\delta}(x). \qquad (6)$$

where e_1 is a $(q+1) \times 1$ vector whose first element is one with all remaining elements being zero.

Note that $\hat{g}(x)$ is the nonparametric estimate of the unknown conditional expectation $g(\cdot)$ while $\hat{\beta}(\cdot)$ is its derivative with respect to the regressors. This local linear method has a potentially valuable property: the more linear the underlying relationship, the faster the rate of convergence (see Li and Racine (2003a) for further details). In fact, if the underlying relationship is truly linear, this cross-validated local linear estimator can have a $\sqrt{n}$ rate of convergence. However, in general, we do not restrict the nature of the underlying relationship nor the rich interaction that might exist between regressors. We also do not restrict the response $\beta(\cdot)$ to be constant as would be the case with a simple linear model. All standard errors reported below are obtained via resampling methods (bootstrapping) to provide robust standard error estimates.

As noted above, we use 'least-squares cross-validation' to select the bandwidth vector h. This is similar to minimizing the sum of squared residuals for a parametric regression model, however, to avoid 'overfitting' we minimize a 'leave-one-out' estimator. A leave-one-out local linear kernel estimator of $\delta(x_i)$ is obtained by a kernel weighted regression of y_j on $(1, (x_j - x_i)')$ given by

$$\hat{\delta}_{-i}(x_i) = \begin{pmatrix} \hat{g}_{-i}(x_i) \\ \hat{\beta}_{-i}(x_i) \end{pmatrix} = \left[\sum_{j \neq i} W_{h,ij} \begin{pmatrix} 1, & (x_j - x_i)' \\ x_j - x_i, & (x_j - x_i)(x_j - x_i)' \end{pmatrix} \right]^{-1} \sum_{j \neq i} W_{h,ij} \begin{pmatrix} 1 \\ x_j - x_i \end{pmatrix} y_j, \qquad (7)$$

where $W_{h,ij} = h^{-q} W((x_j - x_i)/h)$ is the kernel function and $h = h_n$ is a smoothing parameter.

In practice one should use a different h for each different component of x, and for all applications conducted in this paper, we allow h to differ across variables through the use of multidimensional numerical search methods.

The leave-one-out kernel estimator of $g(x_i)$ is given by

$$\hat{g}_{-i}(x_i) = e_1'\hat{\delta}_{-i}(x_i). \tag{8}$$

We choose h to minimize the least-squares cross-validation function (sum of squared leave-one-out estimation errors) given by

$$CV(h) = \sum_{i=1}^{n}[y_i - \hat{g}_{-i}(x_i)]^2, \tag{9}$$

where $\hat{g}_{-i}(x_i)$ is defined in (8). The resulting bandwidth vector is denoted $\hat{h}$.

For the current application, we employ the fully nonparametric cross-validated local-linear estimator described above.[8] As noted above, this method naturally handles interaction among all regressors, and bandwidths are obtained via least-squares cross-validation.[9] The following are a few of the benefits arising from the application of this estimator to our data:

- The traditional local-constant kernel estimator is known to suffer from 'boundary bias', while the local-linear estimator is known to be among the best boundary-correction methods available.

- As noted in Li and Racine (2003a), when the underlying relationship is somewhat linear ('almost linear'), the resulting cross-validated nonparametric estimator can have a convergence rate that is arbitrarily close to the parametric rate.

- The estimator *jointly* models the relationship among all variables thereby allowing us to readily exploit any interaction which may exist for the underlying relationship.

4 Results

This section presents the estimates of the crime equation (2) that we presented in Section 2 above. The presentation of the results are organized as follows. We first present the linear parametric estimates of the crime equation as the base estimates in Section 4.1, followed by the nonparametric estimates of the crime/alcohol relationship in Section 4.2.[10] We then compare the two sets of estimates and discuss whether there are critical levels of alcohol outlet density at which the alcohol availability/crime relationship changes.

4.1 Parametric Results

All parametric estimates which follow were obtained via maximum likelihood estimation (code and data is available from the authors upon request). Coefficient estimates of the parametric linear crime equation are presented in Table 2. Column 2 presents the estimates for $TOTCRIME$, column 3 the estimates for $VCRIME$, column 4 the estimates for $ECRIME$, and column 5 the estimates for $HOMICIDE$. The regression statistics lead us to reject the null hypothesis that all slope coefficients are jointly equal to zero at $\alpha = 0.01$ or better for all crime indices. Moreover, most the coefficient estimates are of the expected signs and are significantly different from zero at conventional levels. However, only a small proportion of the variation in crime rate is explained by the model for all crime types as indicated by the low adjusted R^2s.

The coefficient of $YOUTH$ is positive and significantly different from zero at $\alpha = 0.10$ or better in all crimes rates, confirming the conjecture that criminal behavior is higher among young adults than among the population as a whole. The coefficients of INC and $POWN$ are positive but only significant in the $TOTCRIME$ and $ECRIME$ equations. The coefficient estimate of $EDUC$ is negative but only significant in the equations for violent crime and homicide. These coefficient estimates suggest that income and home ownership are reasonably good proxies for the benefit derived from criminal activity in a community while education acts as a reasonable proxy variable for the opportunity cost of engaging in crime. The coefficient of $HISPANIC$ is negative and significantly different from zero at any reasonable level in all crime equations. The coefficient of

$BLACK$ is positive but only significant in the $HOMICIDE$ equation. The coefficient estimates of $BLACK$ and $HISPANIC$ suggest that crime rates are significantly correlated with ethnicity in the city of Detroit. The coefficient of $DENS$ is significantly positive in only the $VCRIME$ equation suggesting that population density is a relevant factor in only violent crimes. Our estimates are consistent with the economic model of crime (Becker (1968), Eide (1998)) and are similar to results obtained by earlier researchers who have used parametric methods to estimate crime generating equations (Erhlich (1973), Gyimah-Brempong (1997), (2001), and Myers (1980), among others).

The coefficient of $LICENSE$ is positive, relatively large, and significantly different from zero at $\alpha = 0.05$ or better in all crime equations. A unit increase in $LICENSE$ is associated with 14.45, 2.93, 11.53, and 0.04 unit increases in total crime, violent crime, economic crime, and homicide rates respectively. The estimates indicate that alcohol availability has positive and significant effect on both violent and economic crimes. The calculated elasticities of crime with respect to alcohol availability from these coefficient estimates are 0.23, 0.18, 0.27, and 0.10 for total crime, violent crime, economic crime, and homicide respectively.[11] Our estimates are consistent with the results obtained by researchers who find a positive relationship between alcohol availability and crime (Cook and Moore (1993), DiIulio (1995), Greenfeld (1998), Rush *et al* (1986), Scribner *et al* (1995), among others. The results are also similar to those obtained by Gyimah-Brempong (2001) who used the same data set to investigate the effects of alcohol availability on crime rates.[12]

The estimates in Table 2 indicate that there is a positive relationship between alcohol availability and crime, results that are consistent with previous research results. How robust are the estimated results? Is the crime equation correctly specified? We investigate these issues by using a consistent nonparametric conditional moment test to test for the correct specification of the estimated equation.[13] The null hypothesis is that the equation is correctly specified while the alternative is that it is not. The test we use exploits the properties of the 'benchmark' residuals from a correctly specified model by using nonparametric methods to detect departures from this benchmark. The results of the specification test are presented in Table 3. The test results lead us to reject the null hypothesis at $\alpha = 0.01$ or better for all crime equations. We therefore conclude that the linear parametric model misspecifies the relationship between alcohol availability and crime rates. Inference based on such an incorrectly specified model is therefore likely to be incorrect. We therefore estimate the crime equation with the robust cross-validated local linear nonparametric estimator of Li and Racine (2003a).

4.2 Nonparametric Results

Given that the conditional moment specification test results presented in Table 3 reject the null hypothesis of correct specification for the parametric crime equation, we proceed to use the nonparametric local linear estimator to estimate the model. The nonparametric estimates for the relationship between crime and alcohol availability are presented in Figures 1 and 2. Figure 1 presents the partial regression surfaces plots of crime rates and alcohol licenses while Figure 2 presents the partial response surface plots of crime rates and alcohol licenses.

Interpretation of nonparametric methods is more involved than that for linear parametric models for one simple reason—the simple linear model has the property that the response of the dependent variable to changes in an explanatory variable is assumed to be constant regardless of the level of the explanatory variable(s). On other words, simple linear parametric models have the property that $\partial y/\partial x_j = \beta_j$, which does not change as x_j changes by assumption. As the nonparametric method places no such restrictions on the data, one must then consider how best to interpret the results. One popular method is to consider the 'partial regression' ($\hat{g}(x_i)$) and 'partial response' ($\hat{\beta}(x_i)$) surfaces which simply measure how the dependent variable and its response change with respect to the level of the explanatory variable in question when all other explanatory variables are held constant at their means. One nice aspect of this method is that it is directly comparable to the parametric method due to the well known property that linear models pass through the data means. As noted above, we use robust resampling methods to calculate the standard errors of the estimates.

The plots in Figures 1 and 2 present the expected crime rates and marginal effects of alcohol on crime rates respectively as the level of alcohol availability changes. We also plot the parametric results along with the nonparametric results as we hope that this gives the reader a 'validity check' on the nonparametric results. We focus on the crime/alcohol availability relationship as it is the focus of this paper. All remaining estimates are available from the authors upon request. We can see from the partial regression plots that there is a significantly positive relationship between all crime indices and alcohol availability (see Figure 1) at all levels of alcohol availability. Although the nonparametric estimator allows the response of crime rate to changes in alcohol availability to vary with the level of alcohol availability, the response rate is positive at all levels of alcohol availability. This is best appreciated by noting that the pointwise error bars in Figure 2 ($\hat{\beta}(x_i) \pm 2\hat{\sigma}(\hat{\beta}(x_i))$) lie strictly above, and do not include, zero over their support. For comparison purposes we maintain common scaling of the vertical axis in Figure 1 which highlights how various crime indices compare with one another. The only downside to this scaling is that the expected number of homicides is so small relative to the total number of crimes that the partial regression surface for the homicide equation appears to be collapsed on the horizontal axis, though the partial response surfaces, being unscaled, are well behaved and show a positive relationship between alcohol availability and crime rates.

Is the crime response to alcohol availability constant over all feasible ranges of alcohol availability as the parametric estimates suggest? An examination of the partial nonparametric regression plots in the first panel of Figure 1 reveals that the effects of alcohol availability on total crime accelerates after alcohol availability reaches 10 licenses per census tract. This trend continues until alcohol outlet density reaches a threshold of 25 licenses per census tract. Beyond that density, the response of crime rate to alcohol availability stabilizes. This pattern of the response of total crime to alcohol availability is confirmed by the first panel of Figure 2 which presents the marginal response of total crime to changes in alcohol availability at various levels of alcohol availability. The partial response plots reveal that the marginal effect of alcohol availability on total crime rates starts at 25 crimes when alcohol outlet density is one license, falls to about 20 when outlet density is 10 licenses, and accelerates to about 27 crimes at about 25 licenses per census tract. It then stays at that level for all further levels of alcohol availability.

The pattern of the response of total crime to changes in alcohol availability we find in the nonparametric estimates contrasts sharply with the linear parametric regression estimates which suggest that the response of total crime rate to alcohol availability stays constant at 15 for all levels of alcohol availability. The linear parametric estimates could lead to wrong policy choices since it suggests that the response of crime RATES to alcohol availability is unrelated to the *level* of alcohol availability, hence changing the distribution of alcohol outlets will have no impact on aggregate crime rates. The nonparametric estimates on the other hand, suggests that redistributing alcohol outlet densities could reduce aggregate crime rates in a city. With the exception of homicide, the behavior of the relationship between crime and alcohol availability for other crime indices shown in Figures 1 and 2 parallel the total crime/alcohol availability relationship. This pattern of changing response of crime to alcohol availability at different levels of alcohol availability is consistent with the results obtained by Alaniz *et al* (1998) who argue that the concentration of alcohol outlets in a neighborhood often leads to the breakdown of all social controls and hence leads to increased crime rates in that neighborhood.

How do the nonparametric estimates compare to the linear parametric estimates presented in Table 2 above? In order to facilitate a direct comparison of results, we present a summary of the goodness-of-fit[14] of the parametric and nonparametric estimates (R^2 and root mean square error (RMSE)), along with the calculated elasticities of crime with respect to alcohol availability computed at the mean number of licenses and crime rates, $\mathcal{E}_{c,a}$ in Table 4.

An examination of Table 4 reveals that the nonparametric model provides a better fit to the underlying relationship between crime rates and alcohol availability than the linear parametric model. Specifically, the R^2s shown in Table 4 indicate that the nonparametric model explains at least twice as much of the variation in crime rates as the linear parametric model does. We also note that the regression standard errors are much lower for nonparametric estimates than their parametric counterparts. One might be tempted to conclude that the nonparametric model is simply 'over-fitting' the relationship. However, this is clearly not the case as can be seen from examining the partial regression results plotted in Figure 1. In part, the difference in explanatory power of the two estimates may be mainly due to the fact that the parametric estimates we present here ignore non-linearities and interaction terms among the regressors. The nonparametric estimator on the other hand, automatically accounts for non-linearities and interactions terms.

More important, Figure 2 along with the elasticities of crime with respect to alcohol availability computed at the mean number of licenses, $\mathcal{E}_{c,a}$, indicates that the parametric model appears to substantially underestimate the impact of alcohol availability on crime rates. The calculated nonparametric elasticities are, at least, 50% larger than the parametric elasticities for all crime indices. It appears that the misspecification of the linear parametric model results in a downward bias of the effects of alcohol availability on crime rates. We note that the nonparametric elasticity estimates are not only larger than the parametric estimates presented in this paper, they are also larger than the estimates obtained by Scribner *et al* (1995, 1999), Cook and Moore (1993a), Parker and Cartmill (1998) and DiIulio (1995). Our results suggest that previous researchers may have underestimated the effects of alcohol availability on crime rates.

There are interesting research and policy implications which arise from our results. From a research perspective, our finding that the traditional linear parametric model imparts substantial downward bias on the effects of alcohol availability on crime due, possibly, to neglected non-linearities and interactions, implies that researchers should explore these non-linearities as well as interactions among the regressors when choosing parametric specifications. Alternatively, researchers should consider using more powerful nonparametric methods to estimate the alcohol availability/crime relationship as a means to overcome the downward bias inherent in the linear parametric estimates. The policy implication arising from our finding that the marginal effect of alcohol availability on crime varies with the level of alcohol availability is that the efficiency of alcohol control policy as a crime fighting policy will vary with the level of alcohol availability.

DiIulio (1995), Cook and Moore (1993a), Jewell and Brown (1995), and Parker (1995), among others advocate increasing alcohol taxes or increasing the legal drinking age as a means of decreasing alcohol related crimes. The usual approach to such policies is to set a single tax rate regardless of the level of crime attributable to alcohol availability. This will be an efficient crime fighting policy if the marginal effect of alcohol availability on crime rates remains constant for all levels of alcohol availability. Our results suggest that the marginal effect of alcohol availability on crime rates accelerates beyond 10 licenses in a census tract. An efficient alcohol control policy should charge higher taxes on alcohol for areas having higher alcohol induced crime as a result of higher densities of alcohol availability. Optimality requires that, at the margin, alcohol tax rates be set equal to the marginal social harm (crime rates) caused by alcohol availability at every level of alcohol availability. This implies setting alcohol taxes higher at densities above 10 licenses than at densities below 10 licenses. Another policy implication of our results is that, perhaps, alcohol outlets should be dispersed throughout the city so that no particular neighborhood has an alcohol density which exceeds this critical density.

5 Concluding Remarks

This paper used census tract data and robust nonparametric estimation methods to investigate the relationship between alcohol availability and crime rates. We find that there is a positive and statistically significant relationship between crime rates and alcohol availability with calculated elasticities of .34, .37, .35, and .27 for total crime, violent crime, economic crime, and homicide respectively. We find that the linear parametric model that has been used to estimate the effects of alcohol availability on crime rate seriously misspecifies the alcohol availability/crime relationship. Specifically, we find that the linear parametric model imparts substantial downward bias to the estimated effects of alcohol availability on crime rates for all indices of crime. Second, our results suggest that the effects of alcohol availability on crime rates vary with the density of alcohol availability. This implies that alcohol control policies should be evaluated at different levels of alcohol availability in contrast to current policies that are based on the assumption that the effect of alcohol control policies is the same regardless of the level of alcohol availability.

Notes

[1]In this paper, we use the terms "supply of offense function", "crime equations", "crime generating function" and "supply of crime equations", interchangeably.

[2]We do not develop the model here for space considerations. Readers are referred to Gyimah-Brempong (2001) for further details.

[3]We note that using the unemployment rate or poverty rate does not affect our results.

[4]We tried to obtain data on police patrol patterns at the census tract level from the Detroit Police Department without success.

[5]The inclusion of racial minorities does not imply that race *per se* causes crime. Race is only a proxy for some unobserved variables that may be highly correlated with race. For more on the correlation between race and crime, see Gyimah-Brempong (1997).

[6]Other socioeconomic variables that have been included in crime generation equations are the unemployment rate, poverty rate, and percent on public assistance. These variables are, however, all highly correlated with income and education. In the interest of parsimony, we do not include these variables in our model.

[7]Those interested mainly in the resulting estimates may skip this section and proceed directly to Section 4.

[8]For other estimators that have similar properties, see Racine and Li (2003) and Li and Racine (2003b).

[9]In the interest of brevity we do not present the details; we refer the interested reader to Li and Racine (2003a).

[10]For the sake of brevity, we do not attempt to summarize all marginal effects in this paper, however, all results are available upon request from the authors.

[11]The elasticities are calculated at the means of the variables.

[12]We note that our estimates are not directly comparable to those of Gyimah-Brempong (2001) since he used an IV estimator and his equations were estimated in log-linear form.

[13]Details of this test are presented in Appendix A.

[14]There is no adjustment for the number of explanatory variables in the nonparametric R^2 figures, hence strictly speaking, they are comparable only to the unadjusted parametric figures. However, the differences between the adjusted and unadjusted parametric figures are negligible.

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A A Consistent Test for Correct Parametric Specification

Out of concern that this model may not be correctly specified, we apply the test for correct parametric specification (Hsiao, Li, & Racine (2003)) to the fully parametric model and *reject* the null of correct specification. Briefly, this is a consistent conditional moment test. We are interested in testing the null hypothesis that a parametric model is correctly specified which we state as

$$H_0: \; P[E(y_i|x_i) = m(x_i, \gamma)] = 1, \tag{10}$$

where $m(\cdot)$ is a known function (the assumed parametric regression model) with γ being a $p \times 1$ vector of unknown parameters. The alternative hypothesis is the negation of H_0, i.e.,

$$H_1: \; P[E(y_i|x_i) = m(x_i, \gamma)] < 1. \tag{11}$$

We therefore employ a test statistic that is based on $I \simeq E[u_i E(u_i|x_i) f(x_i)]$, where $u_i = y_i - m(x_i, \gamma)$ and where $f(\cdot)$ is a joint PDF. Note that $I = E\{[E(u_i|x_i)]^2 f(x_i)\} \geq 0$, and $I = 0$ if and only if H_0 is true. Therefore, I serves as a valid candidate for testing H_0.

The sample analogue of I is

$$\begin{aligned} I_n &= n^{-1} \sum_{i=1}^{n} \hat{u}_i \hat{E}_{-i}(u_i|x_i) \hat{f}_{-i}(x_i) = n^{-1} \sum_{i=1}^{n} \hat{u}_i \left\{ n^{-1} \sum_{j=1, j \neq i}^{n} \hat{u}_j W_{h,ij} L_{\lambda,ij} \right\} && (12) \\ &= n^{-2} \sum_{i} \sum_{j \neq i} \hat{u}_i \hat{u}_j K_{h,ij}, && (13) \end{aligned}$$

where $\hat{u}_i = y_i - m(x_i, \hat{\gamma})$ is the residual obtained using the parametric null model, $\hat{\gamma}$ is a $\sqrt{n}$-consistent estimator of γ (under H_0), and $\hat{E}_{-i}(u_i|x_i)\hat{f}_{-i}(x_i)$ is a leave-one-out kernel estimator of $E(y_i|x_i)f(x_i)$. We use a wild-bootstrap to obtain the test statistic's null distribution, and results appear in Table 3.

Table 1: Summary Statistics of Sample Data

Variable	**Mean***	**Standard Deviation**	**Minimum**	**Maximum**
TOTCRIME	374.20	161.3536	66.00	1088.00
ECRIME	302.409	133.5295	56.041	929.71
VCRIME	73.281	37.3202	10.8127	312.0871
HOME	22.754	1.1019	22.845	7.2065
LICENSE	6.1620	4.5752	0.00	31.00
DENS	8,364.00	3182.0074	219.00	16,774.00
BLACK (%)	75.55	29.3667	1.00	100.00
HISPANIC (%)	2.956	7.6623	0.00	58.00
POWN (%)	51.18	21.1607	0.00	96.00
EDUC	9.257	8.0877	0.68	55.28
YOUTH (%)	33.92	4.5441	14.00	64.00
INC ($)	9444.00	4463.77	3565.00	40469.00
N	315			

* these are unweighted averages.

Table 2: Parametric Crime Equation Estimates

Variable	Coefficient	Estimates		
	TOTCRIME	VCRIME	ECRIME	HOMICIDE
constant	-98.160	12.170	-86.060	-0.3811
	(1.088)+	(0.563)	(1.178)	(0.0571)
LICENSE	14.450***	2.926***	11.530***	0.0369**
	(7.297)	(6.166)	(7.186)	(2.521)
YOUTH	7.517***	1.365***	6.150***	0.0242*
	(4.021)	(3.048)	(4.062)	(1.757)
INC	0.0097***	0.00007	0.0097***	0.00001
	(2.268)	(0.065)	(2.799)	(0.275)
EDUC	-0.031	-82.93*	-225.20	-2.609*
	(1.478)	(1.675)	(1.347)	(1.709)
POWN	1.200**	13.570	1.0606***	0.0026
	(2.543)	(1.201)	(2.775)	(0.673)
HISPANIC	-0.461***	-1.033***	-3.577***	-0.0197**
	(3.425)	(3.202)	(3.280)	(1.975)
BLACK	0.020	0.0131	0.0067	0.0079***
	(0.530)	(1.445)	(0.220)	(2.839)
DENS	.0002	0.0016***	-0.0014	0.00002
	(0.078)	(2.618)	(0.220)	(1.086)
N	315	315	315	315
F	12.90	9.438	15.160	5.439
p-value	0.00000	0.00000	0.00000	0.000002
Std. error of est.	141.30	33.86	114.50	1.044
$\bar{R}^2$	0.2327	0.1769	0.2652	0.1016

+ absolute value of "t" statistics in parentheses.
* 2-tail significance at $\alpha = 0.10$
** 2-tail significance at $\alpha = 0.05$
*** 2 tail significance at $\alpha = 0.01$

Table 3: Specification Test Results for the Parametric Crime Equations

Equation	p-value	Outcome
TOTCRIME	0.0011***	Reject H_0
VCRIME	0.0000***	Reject H_0
ECRIME	0.0031***	Reject H_0
HOMICIDE	0.00097***	Reject H_0

H_0: Parametric model is correctly specified

*** significant at $\alpha = 0.01$.

Table 4: Summary Comparison of Parametric versus Nonparametric Models

Model	Par R^2	NP R^2	Par RMSE	NP RMSE	Par $\mathcal{E}_{c,a}$	NP $\mathcal{E}_{c,a}$
TOTCRIME	0.23	0.60	141.30	103.70	0.23	0.34
VCRIME	0.18	0.51	33.86	26.51	0.24	0.37
ECRIME	0.27	0.53	114.50	92.40	0.23	0.35
HOMICIDE	0.10	0.26	1.04	0.95	0.17	0.27

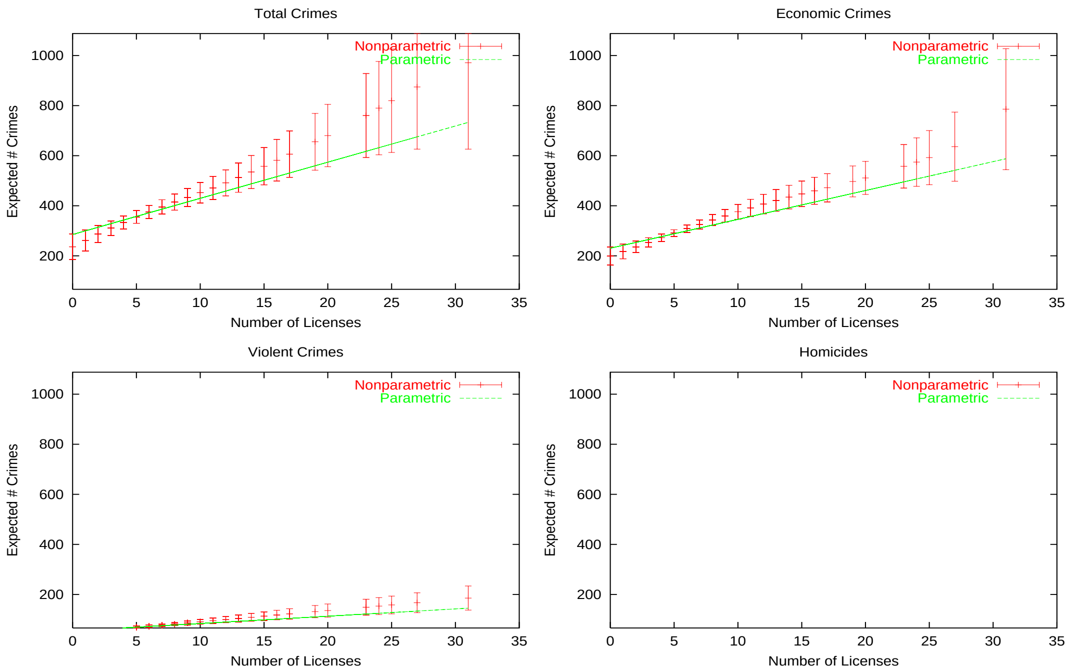

Figure 1: Partial parametric and nonparametric regression plots: expected crimes and alcohol availability. The top left plot is for total crimes, top right economic crimes, bottom left personal crimes, bottom right homicides.

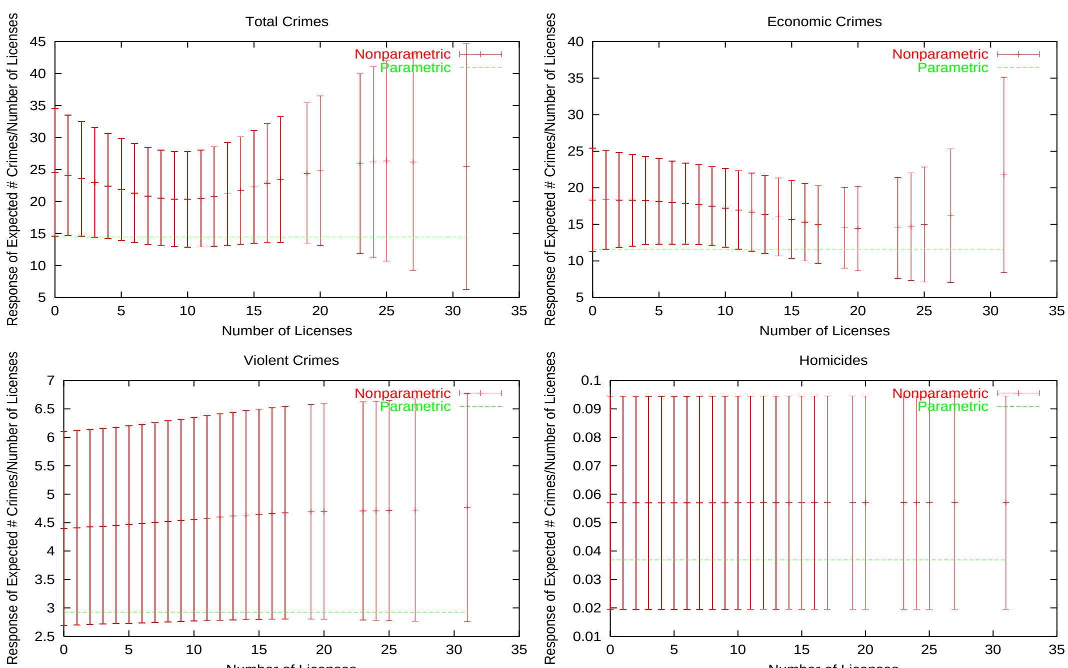

Figure 2: Partial parametric and nonparametric response plots: response of expected crimes to alcohol availability. The top left plot is for total crimes, top right economic crimes, bottom left personal crimes, bottom right homicides.