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Alcohol Consumption, Deterrence and Crime in New York City

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Abstract This paper investigates the relationship between alcohol consumption, deterrence, and crime for New York City. We use monthly time-series data from 1983 to 2001 to analyze the impacts of variations in both alcohol consumption and deterrence on seven "index" crimes. We tackle the endogeneity of arrests and the police force by exploiting the temporal independence of crime and deterrence in these high-frequency data, and we address the endogeneity of alcohol by using instrumental variables where alcohol sales are instrumented with city and state alcohol taxes and minimum drinking age. We find that alcohol consumption is positively related to assault, rape, and larceny crimes but not murder, robbery, burglary, or motor vehicle theft. We find strong deterrence for all crimes except assault and rape. Generally, deterrence effects are stronger than alcohol effects.

Keywords Crime · Alcohol · Alcohol tax · Minimum drinking age · Police · Deterrence

Introduction

Crime imposes enormous costs to society. In a careful accounting over a decade ago, Anderson (1999) estimated the social costs of crime to exceed $1 trillion dollars in the U.S. Recent research has demonstrated that an effective method to reduce crime is to increase deterrence in the form of increased police force and arrests (Draca et al. 2011;

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Machin and Marie 2011; Di Tella and Schargrodsky 2004; Corman and Mocan 2000). It is also potentially important to examine indirect ways through which criminal activity can be impacted. For example, researchers have noted a strong association between alcohol consumption and crime. Over 15 % of victims of violent crime reported the perpetrator being under the influence of alcohol when the crime was committed.[1] The violent crime rate (total homicide, rape, robbery and aggravated assault per 100,000 population) in the United States went down from 597 in 1980 to 404 in 2010, which is a 32 % decline. The property crime went down from 5,353 to 2,942 per 100,000 people: a dramatic 45 % decline. A report by the National Institute on Alcohol Abuse and Alcoholism (NIAAA) (LaVallee and Yi 2012) indicates that consumption of spirits decreased by 29 % between 1980 and 2010. Based on these correlations and trends, it is tempting to infer that the drop in criminal activity is, to a large extent, due to the decline in alcohol consumption. However it is uncertain whether the observed crime-alcohol correlation is the reflection of a cause-and-effect relationship. The issue is important from a public policy perspective. If the correlation between alcohol and crime is due to the impact of confounding factors that influence both the criminal activity and alcohol consumption, then policies that aim to curb alcohol consumption will be ineffective for crime control, as the root cause of criminal behavior is not alcohol consumption but these confounding factors.[2]

There exists a large volume of literature that examines the impact of deterrence variables on crime, while another literature has examined the impact of alcohol policies on crime. Although there is some agreement that alcohol policies that aim to curb alcohol consumption have a negative impact on crime, and that more arrests deter crimes, the literature is still mixed as to which types of crimes are most affected by alcohol policies, which types of crimes are most easily deterred by increased arrests, and the magnitudes of the effects. Furthermore, there exists no credible evidence on the causal impact of *alcohol consumption* on crime.

The purpose of this study is to add to this literature by systematically examining the effects of alcohol consumption, and of arrests and police presence on crimes in New York City over the period 1983 to 2002. High frequency (monthly) time-series data allow us to circumvent reverse causality from crime to deterrence by using lagged values of explanatory variables in empirical specification (Corman and Mocan 2005, 2000). For example, although crime and arrest influence each other contemporaneously, an increase in crime in a given month cannot impact the arrests for that crime in the previous month. Using once-lagged arrests in monthly data enables us to avoid reverse causality from crime to arrests, while allowing us to analyze the impact of last month's arrests on this month's crime. In the case of the relationship between alcohol and crime, we use an instrumental variable approach to estimate the impact of alcohol use on crime, where alcohol use is instrumented with real alcohol tax and legal drinking age.

[1] http://www.bjs.gov/content/pub/pdf/cvus/current/cv0832.pdf and data from the Arrestee Drug Abuse Monitoring Program in 2003 indicate that about 10 % of arrestees tested positive for alcohol, and almost half of arrestees had engaged in binge drinking in the past month (https://www.ncjrs.gov/nij/adam/adam2003.pdf, Table 10).

[2] Also, policies aimed at reducing alcohol consumption may not have as strong an impact on alcohol consumption. Recent work by Ruhm et al. (2011), for example, questions previous estimates of a high price elasticity of demand for beer.

Thus, we are able to address causality-related issues in examining both factors believed to be highly predictive of criminal behavior.

Previous Literature

To frame the existing literature and the contribution of this paper, note that the interrelationship between crime, alcohol use and deterrence can be analyzed within a framework that consists of the following equations.

$$\mathrm{CR}_i = \mathrm{f}(\mathrm{Econ}_i,\ \mathrm{Deter_k},\ \mathrm{X_i},\ \mathrm{A}_i,\ \mathrm{u_i}) \tag{1}$$

$$\mathrm{A_i} = \mathrm{g}(\mathrm{P_k},\ \mathrm{I_i},\ \mathrm{X_i},\ \mathrm{e_i}) \tag{2}$$

Equation (1) is a standard crime supply equation where criminal activity of person i is determined by economic factors pertaining to the person (Econ_i) such as the relevant labor market wage of the person, deterrence variables ($\mathrm{Deter_k}$) that vary at some aggregate level k such as the neighborhood, or city (e.g., the arrest rates, and the size of the police force), and other attributes of the individual, $\mathrm{X_i}$, as well as the alcohol consumption, represented by $\mathrm{A_i}$. Unobservable personal attributes, such as risk aversion or time preference, are captured by u.

Equation (2) represents the demand for alcohol for person i. It is a function of $\mathrm{P_k}$ which stands for the price and availability of alcohol which vary at the aggregate level k, the person's income ($\mathrm{I_i}$), and other personal characteristics $\mathrm{X_i}$. The error term $\mathrm{e_i}$ stands for tastes and unobserved individual characteristics that impact alcohol consumption.

The impact of alcohol consumption on criminal activity is difficult to estimate using the structural Eq. (1). This is because difficult-to-observe attributes, captured by u in Eq. (1), are likely to impact both criminal activity and alcohol consumption. Examples include religiosity, time preference, or peer pressures. Consequently, inference obtained from models that treat alcohol consumption as an exogenous variable in estimating crime equations may be inaccurate.

Recognizing this problem, a number of researchers have estimated reduced form crime equations, which are obtained by substituting Eq. (2) into Eq. (1)

$$\mathrm{CR}_i = \mathrm{h}(\mathrm{P}_k,\ \mathrm{I}_i,\ \mathrm{Econ}_i,\ \mathrm{Deter_k},\ \mathrm{X_i},\ \mathrm{u_i},\ \mathrm{e_i}) \tag{3}$$

In this strategy, the price and availability of alcohol enter the crime equation directly as independent variables as shown by Eq. (3). If the price of alcohol (or alcohol excise tax) or alcohol availability are not influenced by the extent of criminal activity, and if they are not correlated with unobservable factors that influence crime, then the parameters obtained from Eq. (3) are unbiased. However, in this case, the researcher can only make an inference on the relationship between alcohol price and crime, and not on alcohol consumption and crime. Furthermore, the assumption that alcohol prices and alcohol availability are uncorrelated with unobservable factors (depicted by u) may not be valid. For example, if religiosity is a component of u in Eq. (3), it could be plausible that alcohol availability is low and alcohol taxes are high in those locations (counties, cities, states) with strong religious beliefs. If religiosity lowers criminal propensity, then one would observe a positive association between alcohol availability and criminal activity, but this correlation is an artifact of the unobserved religious preferences.

With this background, the key findings of previous research are summarized below.

Criminal Deterrence

There is a voluminous literature on the impact of deterrence on crime, beginning with the seminal empirical work of Becker (1974) and Ehrlich (1973). Much of the literature estimated various forms of Eq. (1), usually by omitting alcohol or drug use.[3] Reverse causality from crime to arrests is addressed by using data on natural experiments in which the extent of deterrence is increased or decreased exogenously (Di Tella and Schargrodsky 2004; Draca et al. 2011; Drago et al. 2009), or by exploiting the timing of crime commission and arrests in high frequency data (Corman and Mocan 2000). We focus on arrests as a key deterrence variable because empirical evidence underlines that arrests have a stronger deterrence impact than conviction (given arrest) or length of incarceration (see Ehrlich 1996 for a review of the literature). Although there is a general consensus that arrests deter crimes, studies find that the elasticity of crime with respect to arrests varies, depending on the crime. For example, Levitt (1998) found stronger arrest elasticities for robbery and burglary than for murder and rape crimes, while Corman and Mocan (2005) found stronger elasticities for robbery and motor vehicle theft than for assaults. Thus, it is important to take into account that different crimes may experience different responses to arrests.

Alcohol Taxes and Crime

There are two categories of studies examining the impact of alcohol on crime in the economics literature. The larger group examines the effect of alcohol using a reduced-form effect of a particular policy using versions of Eq. (3). For example, numerous studies have examined the impact of alcohol taxes on crime. As reviewed by Carpenter and Dobkin (2010), most studies find some evidence that higher alcohol taxes deter at least some crimes. We report on two recent studies which examine the impact of alcohol taxes on specific crimes, while controlling for arrest rates. Markowitz (2005) used data from the National Crime Victimization Surveys from 1992 through 1994 and found that beer taxes significantly decreased assaults in both standard regressions and in fixed effects models, but that there were no significant effects of beer taxes on rape/other sex crimes. The negative effect of beer taxes on crime was marginally significant in her regular regressions, but insignificant in her fixed effects model. Additionally, she found deterrence effects of arrest on assaults and robberies but not on rape crimes in her regular regression models. Desimone (2001), in a study that focused on drug prices, also examined the impact of beer taxes, using aggregated data for 29 cities from 1981 to 1995, and investigating the standard "index" crimes—murder, rape, assault, robbery, burglary, larceny, auto theft. His models included both city- and year- fixed effects, and he found that higher beer taxes significantly reduced rape, assault, larceny and auto theft but not murder, burglary or robbery.

[3] Corman and Mocan (2000) is an exception.

Drinking Age and Crime

Carpenter (2007) has argued that much of the impetus for age restrictions and age-related sanctions on drinking arose from concerns about drunk driving, and not due to concerns with other violent or property crimes. If this is the case, the effects of these laws on property and violent crimes are unlikely to be biased due to issues of policy endogeneity. Carpenter (2007) examined the impact of zero-tolerance laws (which lowered the blood alcohol threshold for drivers under age 21) on aggregated property and violent crime over the period 1988 to 1997 in MSA's. He found, holding constant policy agency and year effects, beer tax rates, and other policy variables, that zero-tolerance laws significantly reduced property (but not violent) crime arrests of 18–20 year olds. Carpenter and Dobkin (2010) used a regression discontinuity design to examine the effect of turning 21 on violent and property crime arrests in California in 2001–2005. They found that turning 21 increases alcohol consumption, and also increases arrests for robbery and assault, but not for murder, rape, larceny, burglary or auto theft. As these authors acknowledge in their literature review, a drawback of the age-related research is that it relies on arrest data in order to ascertain age, and it is possible that the effect of alcohol on arrests is not due to crime commission, but to an increased chance of getting caught.

Alcohol Consumption and Crime

Three recent studies examined the impact of alcohol consumption on crime using a panel of state data. Raphael and Winter-Ebmer (2001) and Lin (2008) both analyzed the impact of unemployment on crime, using state panels from the 1970s to 1997 (Raphael and Winter-Ebmer) and to 2000 (Lin). Because alcohol consumption was not their key variable, possible endogeneity of this variable has not been addressed. Both papers have aggregated crimes into property and violent crime categories. Winter-Ebmer and Lin both found that, controlling for linear trends, alcohol does not seem to impact property crime commission. In their preferred model, the former study does not find a significant positive effect of alcohol consumption on violent crime commission, while the latter does.

Note that studies that employ state-level or county-level aggregated data suffer from the issue of averaging crime and alcohol consumption in urban, suburban, and rural areas. There is at least as much within-state variation in the relationship between alcohol and crime than there is between the states. Second, for aggregated annual panel data, there exists a potential problem in dealing with the sequence of events within the year of the observation. Researchers often assume that price or availability of alcohol are exogenous to crime. However, within a 12-month period, it is possible that increased alcohol-related crime causes legislators to raise taxes or reduce the availability of alcohol. That is, there is enough time for causality to run in the opposite direction from that hypothesized when annual data are employed.

The only recent study to explicitly examine the impact of alcohol consumption on crime is by Zimmerman and Benson (2007), who perform a two-stage least-squares model to examine the impact of beer, wine, and liquor consumption on rape, using a panel of state-level data from 1982 to 2000. They find strong positive effects of alcohol consumption on rape, while finding significant deterrence effects of rape arrest rates lagged by 1 year.

Contribution of this Paper

Despite the volume of two parallel literatures examining the effect of deterrence on crime on one hand, and the effect of alcohol on crime on the other, no study was able to analyze the impact of deterrence and alcohol consumption on a range of crimes within the same framework. Each particular study in the previous literature tends to focus on one aspect while, perhaps, controlling for the other. More specifically, studies that focus on crime-deterrence relationship either omit alcohol use from the analysis, or consider alcohol as an exogenous variable. Papers that investigate the impact of alcohol taxes or alcohol policies on crime do not carefully control for deterrence variables due to data limitations. Furthermore, there exists no study that provides a credible structural estimate of alcohol elasticity of crime with the exception of a couple of papers that addressed the endogeneity of alcohol consumption (Gyimah-Brempong 2001; Zimmerman and Benson 2007).[4] Thus, to arrive at a structural estimate of alcohol elasticity of crime, one needs to calculate the implied instrument-variables estimates using the reduced form crime equations (such as the one depicted by Eq. 3) and the alcohol demand equations (such as Eq. 2). More specifically, denote the impact of P on crime in Eq. (3) by θ, and the impact of price on alcohol in Eq. (2) by β. Then, the implied-IV estimate of the causal impact of alcohol on crime is θ/β. However, this calculation is complicated because both the data sets and the variables employed in the literature widely differ regarding estimating Eqs. (2) and (3); so it is not possible to arrive at a coherent implied-IV estimate.

The current paper takes a different approach to examining the impact of alcohol consumption on crime. We examine high-frequency time-series data for one specific location to examine the impacts of variations in both alcohol consumption and deterrence on seven "index" crimes. Our approach has a number of advantages. By focusing on one location, we can hold constant many of the unobservable factors (such as criminal justice reporting frameworks) unique to different cities or states. By using monthly data, our analyses are not subject to policy endogeneity, since it takes several months to alter policies. By estimating disaggregated crimes, we can allow deterrence and alcohol effects to vary by specific crime. By using high frequency data while controlling for long-run trends, we are not conflating their effects. Finally, the frequent changes in alcohol taxes in our time period (both increases and decreases) allow identification of alcohol consumption in our instrumental variable models.

Empirical Specification and Data

Following previous work which used similar data for New York City (Corman and Mocan 2005 and 2000), time series methods are applied to investigate the impact of

[4] Zimmerman and Benson (2007) used two-stage least squares in identifying the impact of alcohol on rape using state panels from 1982 to 2000, and identifying alcohol using tax rates, minimum drinking age, plus other alcohol-related policies. Gyimah-Brempong (2001) used cross-sectional crime data from over 300 census tracts in Detroit in 1992 to analyze the impact of liquor store density on crime. This study relies on the plausibility of the assumption that the two instruments (gas stations and median rent) significantly explain the location of liquor stores but that they are not related to crime.

alcohol on violent crime, holding constant other potential determinants of criminal activity. Specifically, models of the following form are estimated.

$$\begin{aligned}\mathrm{CR_{it}} = \lambda_i + \sum \alpha_{ij}\mathrm{CR_{i,t-j}} + \sum \beta_{ik}\mathrm{AR_{i,t-k}} + \sum \delta_{iq}\mathrm{POL_{t-q}} + \sum \varphi_{ip}\mathrm{W_{t-p}} \\ + \sum \eta_{id}\mathrm{AFDC/TANF_{t-d}} + \sum \gamma_{ir}\mathrm{ALCOHOL_{t-r}} + \sum \theta_{ig}\mathrm{POP_{t-g}} + \sum \phi_{is}\mathrm{S_s} + \epsilon_{\mathrm{it}},\end{aligned} \tag{4}$$

where $CR_{i,t}$ stands for crime of type *i* in month *t* (i=1 for assault, i=2 for robbery, i=3 for burglary, etc.). AR_i represents arrests for crime type *i*,[5] POL stands for the number of uniformed police officers, W is the real minimum wage, AFDC/TANF is the number of AFDC/TANF cases in New York City, ALCOHOL stands for alcohol consumption and POP is the size of the population ages 15 to 49. In order to account for the seasonality in crime, we include S, which represents a set of monthly (seasonal) dummies. We analyze separately seven "index" felony offenses; that is, we estimate Eq. (4) separately for each type of crime. High frequency data (monthly observations) allow us to circumvent standard problems of simultaneity between crime and its determinants, including alcohol consumption. Following Corman and Mocan (2000, 2005), in this specification it is postulated that the number of crimes committed in 1 month depends on the past levels of the same criminal activity ($j \geq 1$), and the past arrests for that crime ($k \geq 1$). Arrests are lagged 1 month to avoid reverse causality from crime. On the other hand, the contemporaneous values of the police, the minimum wage, AFDC/TANF cases, alcohol consumption and population 15 to 49 are included ($q \geq 0$, $p \geq 0$, $d \geq 0$, $g \geq 0$, $r \geq 0$) in addition to their lagged values.[6]

While an increase in alcohol consumption in a given month is expected to influence criminal activity in that month as depicted by Eq. (4), an increase in crime is unlikely to impact alcohol consumption through a channel of policy modification. This is because a policy alteration or legislative change such as a tax increase would not take place in the same month as the increase in crime. On the other hand, if the change in crime has an impact on criminal income, alcohol consumption can be influenced contemporaneously. It is also possible that alcohol consumption is correlated with unobserved factors that may also influence criminal activity. Because of these concerns we will instrument alcohol consumption with two exogenous variables: alcohol tax and legal minimum drinking age. As our literature review revealed, these two variables are expected to influence alcohol consumption and we demonstrate empirically that they indeed impact alcohol consumption. There is, however, no reason to expect a direct influence of taxes or minimum drinking age on criminal activity.

Arrest, police, and crime data have been compiled from data collected at the Crime Analysis Unit of the New York City Police Department (NYPD). Arrests are compiled through December of 2001, when the NYPD ceased reporting on arrests. We collect crime reports for the same time period. Our analyses focus on the "index" crimes of: murder, rape, robbery, assault, burglary, larceny and motor vehicle theft. Variations in

[5] We use total arrests rather than arrests per crime. This is because we want to avoid imposing a mechanical relationship, by which an increase in crime would necessarily decrease the arrest rate.

[6] Note that the dynamics of this model require multiple lags of the dependent variable on the right-hand side. We further discuss the issue of lag length later in the paper.

the size of the population could affect both alcohol consumption and crime. We hold constant population aged 15 to 49, the group most likely to be committing crimes.[7]

Empirical analyses also include the number of police officers in New York City. The variable is "total uniform strength," and consists of the number of sworn officers on the payroll, and it excludes individuals who have left the police force but are receiving terminal paychecks. Similarly, it does not include civilians, or officers who have been hired but have not completed their 6-month training course at the Police Academy.[8] Data on number of police were compiled from the Office of Management and Planning of the NYPD.[9]

Our two economic variables reflect conditions facing low-wage individuals, who are more likely to engage in criminal behavior than higher-wage individuals. First, we include the number of cases of individuals on cash assistance in New York City (Aid to Families with Dependent Children (AFCD) which became Temporary Assistance to Needy Families (TANF) in 1996. These data are collected from published reports of the New York City Department of Social Services Human Resources Administration. The change in welfare programs had a dramatic impact on the number of cases that were on welfare, both in New York, and in the entire nation (for example, see Schoeni and Blank 2000). To account for this shift in welfare caseloads, we include an indicator for post-welfare reform in New York.[10]

Our second variable pertaining to economic conditions is the real minimum wage. The real minimum wage is calculated by using the nominal minimum wage obtained from the New York State Department of Labor[11] and the monthly New York –Northern New Jersey-Long Island Metropolitan Area Consumer Price Index (CPI), obtained from the US Bureau of Labor Statistics. [12]

Alcohol consumption is proxied by alcohol sales. These data are obtained from the New York State Department of Taxation and Finance (NYDTF). Beginning in 1980, New York City imposed an excise tax on beer and spirits (but not wine). As the tax collector, the NYDTF obtained sales volume for both types of beverages. Sales data were available from April of 1983, onward. Similar to previous studies, cited above, we converted alcohol volume to total ethanol volume, using a weighted average of the two types of beverages.[13]

We focus on two alcohol policies—taxes and the minimum drinking age. Tax rates for New York State and New York City were obtained from the NYDTF. New York State increased the beer tax three times between 1970 and 1995 (from 4.4 cents per gallon in 1970 up to 21 cents per gallon by the end of 1995). Since 1995, New York

[7] Annual data on population by age for New York City was obtained from the New York State Department of Vital Statistics. (http://www.health.ny.gov/nysdoh/vital_statistics/ accessed 11/22/2011). We interpolate monthly figures from the annual ones.

[8] In 1995, the NYPD merged the transit and housing police with the rest of the Department. We have subtracted the estimated number of transit and housing police since those dates to create a consistent series.

[9] Chalfin and McCrary (2012) find administrative data on police strength to be the most accurate source.

[10] Welfare reform was implemented in August of 1997 in New York. Source: http://www.ibo.nyc.ny.us/iboreports/welfarereform98.html accessed 11/09/2012).

[11] http://www.labor.ny.gov/stats/minimum_wage.asp.

[12] 1982–1984 is the base year.

[13] For completeness, it would be preferable to have information on wine consumption, as well. However, these data are not available for New York City. Note that for the State of New York, ethanol consumption from wine comprised the lowest fraction among the three types of alcohol—about 18 % in 1992, for example.

State lowered the beer tax four times, resulting in a tax of 11 cents per gallon by the end of 2005. According to Sack (1995), the 1996 drop in the beer tax was due to intense lobbying of George Pataki and Republican Representatives in New York State by the beer and soda industries. This first reduction, was a 5 cent or over 20 % reduction in taxes. Overall, beer taxes were almost halved during the Pataki administration. New York State raised the nominal spirits tax four times between 1970 and 2005 (from $2.25 per gallon to $6.43 per gallon). New York City imposed a 12 cent tax per gallon of beer and a 26.4 cent tax per liter of spirits in 1980, and has not changed the nominal tax since that date. We also consider the federal beer and spirits taxes.[14] When calculating a combined tax rate, we calculate the tax per gallon of ethanol, weighted by relative ethanol consumption of the two types of alcohol.[15] Taxes are converted to real values, using the NY Metropolitan CPI, described above.

Our second policy variable is the minimum legal drinking age. Information on the minimum legal drinking age was obtained from the Alcohol Policy Information System of the National Institute on Alcohol Use and Alcoholism. The minimum legal drinking age was increased from 18 to 19 in December of 1982, and was raised to 21 in December of 1985.

Patterns in the Data and Descriptive Statistics

Figure 1 presents the behavior of total crime and police officers in New York City between January 1970 and December 2005. Also presented in the graph are the underlying trends for three different time periods. There is a remarkably strong negative relationship between the two variables. When the number of uniformed police officers were declining during the 1970s, crime was rising. The number of police officers first rose and then declined in the 1980s and early 1990s, and crime exhibited the reverse pattern during that period: it declined when the police force was rising and rose when police was declining. Finally, the increase in the number of police officers beginning in 1991 coincided with the steady decline in crime during that same time period.

Figure 2 displays the trends in alcohol consumption and crime in the period of April 1983 to December 2001. Examining the trends, it appears that both criminal activity and alcohol consumption declined during our period of study, but that the steepest declines in alcohol consumption were at the beginning of the time period, whereas the decline in crime appeared to occur later.

Because the alcohol consumption variable is available for the period of April 1983 to December 2001, the main regressions are based on this time period. Later in the paper we also estimate the regressions without the alcohol variable. This exercise allows us to extent the sample back to January 1970 and enables us to investigate the extent to which the estimated impacts of deterrence variables and the poverty indicators are altered by this extension. Descriptive statistics are presented in Table 1 for both the main sample of 1983–2001 as well as for 1970 to 2001.

[14] Data were obtained from the US Bureau of Alcohol, Tobacco and Firearms.

[15] On average, about 57 % of the ethanol consumption in New York City (excluding wine) was from beer and about 43 % was from spirits.

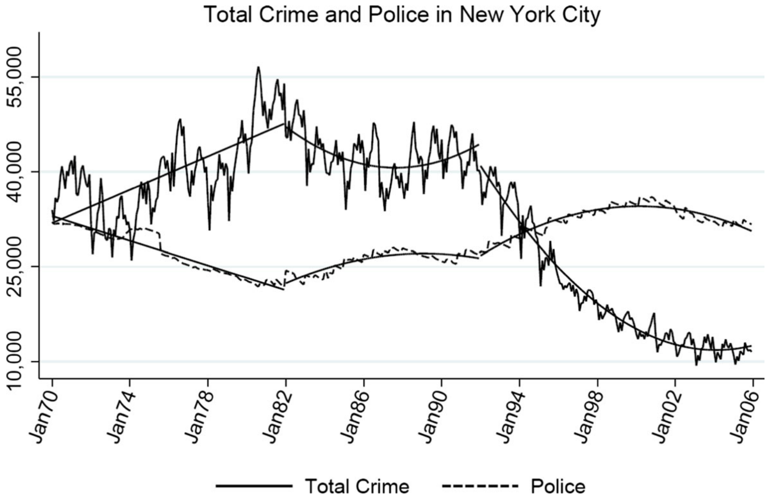

Fig. 1 Total crime and police in New York City

Results

Following Corman and Mocan (2000) and (2005) we applied unit root tests to all variables to investigate whether they are governed by stochastic, rather than deterministic trends. We could not reject the hypothesis of a unit root in all variables with the exception of alcohol consumption and population ages 15 to 49. Therefore we de-trended these two variables by running them on their linear trends and obtaining trend-deviations. All other variables are de-trended by taking first-differences. Following Corman and Mocan (2000, 2005), analyses were conducted to determine the optimal lag length for each variable (Akaike 1973). The variables are in natural logarithms and the standard errors are estimated using robust covariance matrices with serial correlation up to 12 lags.

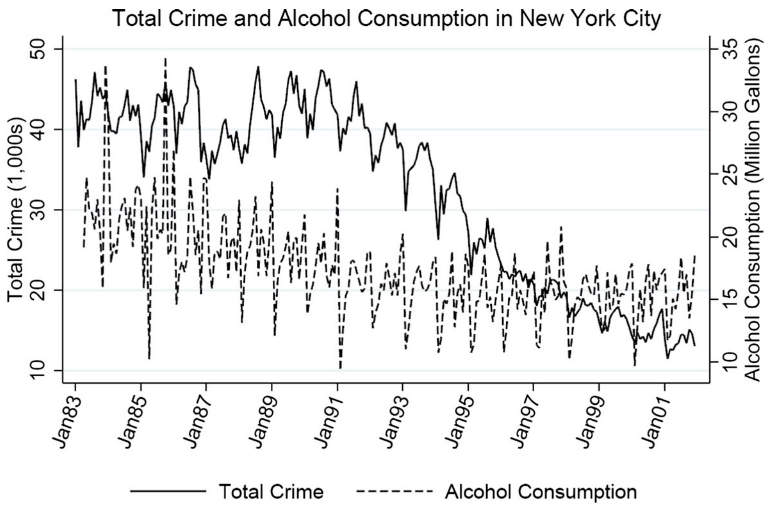

Fig. 2 Total crime and alcohol consumption in New York City

Table 1 Descriptive statistics

Period	April 1983 to December 2001		January 1970 to December 2001	
Variable	Mean	Std. deviation	Mean	Std. deviation
Crimes				
Assault	2,927.63	(736.86)	2,593.61	(734.13)
Murder	119.28	(48.54)	125.14	(41.01)
Rape	232.78	(70.16)	258.45	(74.34)
Robbery	5,770.32	(2,003.23)	6,293.72	(1,802.72)
Burglary	7,769.58	(3,039.50)	10,661.35	(4,350.60)
Mother vehicle theft	7,201.17	(3,073.40)	7,361.09	(2,461.61)
Grand larceny	12,388.18	(2,269.52)	10,777.89	(3,331.84)
Arrests				
Assault	1,656.44	(247.15)	1,448.09	(346.23)
Rape	108.34	(23.47)	117.65	(29.99)
Murder	92.36	(23.64)	93.92	(20.95)
Robbery	1,854.55	(420.57)	1,739.78	(380.03)
Burglary	802.85	(214.67)	1,112.41	(451.41)
Mother vehicle theft	683.94	(343.16)	712.19	(279.63)
Grand larceny	833.40	(241.93)	830.34	(288.23)
Real minimum wage	2.76	(0.18)	3.18	(0.56)
AFCD/TANF cases	243,570.57	(39,945.12)	241,346.84	(31,449.90)
Alcohol (gallons of pure ethanol sold, in millions)	17.31	(3.74)		

Table 2 presents the IV- regression results in a summarized form, where the sum of the estimated coefficients are displayed for each crime category. The top panel of Table 2 contains violent crimes: assault, rape, murder and robbery; the bottom panel pertains to burglary, motor vehicle theft and grand larceny. Entries represent the percent change in the dependent variable due to a one percent increase in the explanatory variable. Robust standard errors of the estimated coefficients (or of the summed coefficients) are reported in parentheses. The arrest data end in December 2001, but the crime data are available beyond that date. Because the crime regressions use lagged arrest as explanatory variables, the estimation sample goes until January 2002. The full set of results is displayed in Table 8 in the appendix. The models are estimated with instrumental variables where alcohol use is instrumented with minimum drinking age and alcohol tax. The first stage results are very strong in that the F-values of the instruments are in range of 21 to 33. The first-stage regressions are reported in Appendix Table 9.

It is evident from results in Table 2 that arrests have a significant negative impact on most crimes. For example, a 10 % increase in murder arrests reduces murder by 2.1 %, and a 10 % increase in grand larceny arrests reduces that crime by about 1 %. Burglaries, motor vehicle thefts and robberies are also significantly deterred by arrests, with magnitudes in the same range. The number of AFDC/TANF cases also have an

Table 2 Instrumental variables regressions. Crime equations for New York City, April 1983–January 2002

	Lags	Assault	Lags	Rape	Lags	Murder	Lags	Robbery	Lags	Burglary	Lags	Motor vehicle theft	Lags	Grand larceny
Arrests	1–2	−0.050	1–4	0.228	1–2	−0.206*	1–2	−0.145***	1–2	−0.230***	1–2	−0.156**	1–2	−0.098**
		(0.093)		(0.246)		(0.110)		(0.053)		(0.068)		(0.065)		(0.041)
Police	0–3	−0.427	0–4	−0.809	0	0.106	0–4	−0.169	0	−0.052	0–2	0.612	0–5	−0.277
		(0.708)		(1.639)		(0.570)		(0.562)		(0.179)		(0.641)		(0.328)
AFCD/TANF	0	0.373**	0–2	−0.101	0–2	1.766	0–1	0.760***	0	0.296**	0–2	−0.105	0	0.095
		(0.176)		(1.052)		(1.312)		(0.210)		(0.147)		(0.359)		(0.101)
Minimum wage	0	−0.059	0	0.054	0–2	0.608	0	0.012	0	0.096	0	0.170	0	0.024
		(0.133)		(0.236)		(0.757)		(0.195)		(0.087)		(0.143)		(0.099)
Alcohol consumption	0	0.104*	0	0.292**	0	−0.079	0	0.016	0	−0.047	0	−0.032	0	0.072***
		(0.054)		(0.123)		(0.122)		(0.065)		(0.047)		(0.050)		(0.027)

Arrests pertain to arrests for each specific crime listed in columns. Robust standard errors are reported in parentheses when the corresponding variable enters with no lag. Otherwise, the values in parentheses are the robust standard errors of the summed coefficients. Sample sizes differ slightly between crimes based on the number of lags in the regressions. The instruments for alcohol consumption are legal minimum drinking age in New York City and real city and state alcohol tax (see the text for the definition). *** $p<0.01$; ** $p<0.05$; * $p<0.10$. Each regression also includes population ages 15–49, monthly dummy variables, and an indicator variable to account for the structural change in AFCD/TANF in November 1986 impact on certain crimes. Specifically, an increase in poverty, approximated by an increase in AFDC/TANF cases, has a positive impact on assaults, robberies and burglaries. Minimum wage does not have a statistically significant effect on any of the seven index crimes. Controlling for crime-specific arrests, the size of the police force, the AFDC/TANF cases, and real minimum wage, we find the strongest impact of alcohol on two violent crimes—assault and rape. This result is consistent with the notion that individuals under the influence may be both more aggressive and less mindful of consequences of their actions. For rape, an additional possible explanation is that increased alcohol consumption increases the likelihood of becoming a victim. It is also the case that these are the two crimes that do not seem to be deterred by arrests or police presence. In case of larceny, we find that it is deterred by its own arrests, and that alcohol consumption increases their occurrence. Again, this result may reflect both greater propensity to steal and greater propensity to become a victim. For our other property-related crimes—robbery, burglary, and motor vehicle theft, we find no significant effects of alcohol on crime commission.

For comparison, we present the OLS results in Table 3. A comparison of Table 3 with Table 2 shows that the effects of own arrests on crimes are not sensitive to whether alcohol is instrumented. In case of rape, the impact of alcohol is much reduced and it is no longer statistically significant when then model is estimated by OLS instead of instrumental variables.[16] We find a similar result for larcenies: the impact of alcohol consumption on larcenies is not different from zero when the model is estimated by OLS. The impact of alcohol consumption on murder is greater in magnitude in the OLS specification compared to the IV results, and it is statistically significant, consistent with the possibility that there is an unobserved factor, unaccounted for in the OLS specification, which might affect both greater drinking and more murders.

Although crime in a given month is expected to be impacted by alcohol consumption in that month, it is possible that consumption of alcohol may not coincide with the month of the sale. That is, alcohol sales in a given month may translate to consumption in the next month. This could be because alcohol is not perishable and consumers may engage in consumption smoothing in the presence of anticipated price changes. For example, if consumers expect a tax increase to be effective in month t, they may increase alcohol demand in month $t-1$ (when the price is still intact) and decrease their demand in t (when the price is higher due to an increase in tax). If this is the case, alcohol sales go down in time t in comparison to $t-1$, but alcohol consumption remains the same over these two periods because of smoothing.

Under this scenario, it would be a better strategy to model crime in month t to depend on alcohol sales in month $t-1$. To entertain this possibility, we estimated the same models with one exception: the contemporaneous value of alcohol is replaced with its once-lagged value and it is instrumented with once-lagged alcohol tax and minimum drinking age. The results, summarized in Table 4, are very similar to those reported in Table 2.

[16] This result is consistent with the findings of Zimmerman and Benson (2007) who attribute the downward bias in the OLS rape results to endogenous victim actions. That is, if women perceive a higher probability of being raped, they may reduce their alcohol consumption. Of course, this interpretation should be made with caution as our results are based on aggregate data.

Table 3 OLS regressions. Crime equations for New York City, April 1983–January 2002

	Lags	Assault	Lags	Rape	Lags	Murder	Lags	Robbery	Lags	Burglary	Lags	Motor vehicle theft	Lags	Grand larceny
Arrests	1–2	−0.047	1–4	0.205	1–2	−0.207*	1–2	−0.145***	1–2	−0.236***	1–2	−0.156**	1–2	−0.106***
		(0.092)		(0.247)		(0.108)		(0.053)		(0.070)		(0.065)		(0.038)
Police	0–3	−0.433	0–4	−0.713	0	0.081	0–4	−0.170	0	−0.062	0–2	0.486	0–5	−0.269
		(0.713)		(1.797)		(0.561)		(0.557)		(0.165)		(0.627)		(0.305)
AFCD/TANF	0	0.352*	0–2	−0.448	0–2	1.933	0–1	0.759***	0	0.327**	0–2	−0.028	0	0.064
		(0.181)		(0.976)		(1.261)		(0.210)		(0.155)		(0.327)		(0.091)
Minimum wage	0	−0.077	0	−0.171	0–2	0.689	0	0.009	0	0.118	0	0.209	0	−0.014
		(0.131)		(0.175)		(0.771)		(0.186)		(0.155)		(0.145)		(0.089)
Alcohol consumption	0	0.071**	0	0.015	0	0.117*	0	0.011	0	0.012	0	0.034	0	0.021
		(0.034)		(0.052)		(0.070)		(0.022)		(0.027)		(0.021)		(0.018)

Arrests pertain to arrests for each specific crime listed in columns. Robust standard errors are reported in parentheses when the corresponding variable enters with no lag. Otherwise, the values in parentheses are the robust standard errors of the summed coefficients. Sample sizes differ slightly between crimes based on the number of lags in the regressions. *** $p<0.01$; ** $p<0.05$; * $p<0.10$. Each regression also includes population ages 15–49, monthly dummy variables, and an indicator variable to account for the structural change in AFCD/TANF in November 1986

Table 4 Instrumental variables regressions with lagged alcohol consumption. Crime equations for New York City, April 1983–January 2002

	Lags	Assault	Lags	Rape	Lags	Murder	Lags	Robbery	Lags	Burglary	Lags	Motor vehicle theft	Lags	Grand larceny
Arrests	1–2	−0.043	1–4	0.181	1–2	−0.219**	1–2	−0.166***	1–2	−0.242***	1–2	−0.156**	1–2	−0.109***
		(0.094)		(0.249)		(0.109)		(0.048)		(0.071)		(0.065)		(0.034)
Police	0–3	−0.755	0–4	−0.972	0	0.145	0–4	−0.051	0	−0.050	0–2	0.569	0–5	−0.317
		(0.729)		(1.573)		(0.566)		(0.549)		(0.175)		(0.635)		(0.348)
AFCD/TANF	0	0.294	0–2	−0.472	0–2	1.925	0–1	0.761***	0	0.338**	0–2	−0.058	0	0.036
		(0.208)		(1.035)		(1.284)		(0.192)		(0.159)		(0.351)		(0.087)
Minimum wage	0	−0.088	0	−0.059	0–2	0.678	0	−0.025	0	0.091	0	0.182	0	−0.010
		(0.138)		(0.217)		(0.756)		(0.194)		(0.089)		(0.146)		(0.098)
Alcohol consumption	1	0.110*	1	0.289**	1	−0.052	1	0.057	1	−0.048	1	−0.019	1	0.089***
		(0.062)		(0.118)		(0.139)		(0.070)		(0.044)		(0.052)		(0.032)

Arrests pertain to arrests for each specific crime listed in columns. Robust standard errors are reported in parentheses when the corresponding variable enters with no lag. Otherwise, the values in parentheses are the robust standard errors of the summed coefficients. Sample sizes differ slightly between crimes based on the number of lags in the regressions. The instruments for lagged alcohol consumption are lagged legal minimum drinking age in New York City and lagged real city and state alcohol tax (see the text for the definition). *** $p<0.01$; ** $p<0.05$; * $p<0.10$. Each regression also includes population ages 15–49, monthly dummy variables, and an indicator variable to account for the structural change in AFCD/TANF in November 1986

Robustness of the Results and Extensions

Exploring Lag Length

To investigate the sensitivity of the results to variations in lag lengths, we estimate the models with arbitrary lag lengths. For each crime, we keep the lag lengths of the lagged dependent variable and that of alcohol intact and change the lag lengths of other variables arbitrarily. For example, in case of robbery, the benchmark model includes 2 lags of robbery as explanatory variables in addition to lags 0 to 4 for police, and the contemporaneous value of AFDC, as well as its first lag, along with the contemporaneous values of the real minimum wage and alcohol consumption. We keep the length of the lagged dependent variable the same as in the benchmark model for robbery (2 lags in this case) and employ the contemporaneous value of alcohol consumption, but we enter other explanatory variables with haphazard lags, ranging from 1 lag to 6 lags. These are arbitrary specifications, nevertheless the results, presented in Appendix Table 6, show that the impact of each variable is similar to those reported in Table 2, although as expected, the statistical significance of the estimated impacts is spotty. Nevertheless, consistent with the benchmark results reported in Table 2, the impact of alcohol is positive and significant in case of assault, rape and grand larceny.

Inclusion/Exclusion of Alcohol Consumption

To examine the extent to which the impacts of the explanatory variables are sensitive to the alcohol consumption, we dropped alcohol consumption from the crime regressions and re-estimated the models. The results, reported in Appendix Table 7 show that excluding alcohol does not influence the effect of other variables on crime. For example, the impact of own-arrests have a significant deterrent effect in the case of murder, robbery, burglary and grand larceny as was the case in the IV-regressions of Table 2 that included alcohol consumption.

Although the alcohol data go back only until April 1983, the crime, arrest and police data as well as data on AFDC are available since 1970. Therefore, we estimated the models without the alcohol variable for the sample 1970–2001. Table 5, which is similar to Table 2, presents the summary of the results. In these regressions, which are based on a larger sample period, police has a significant impact on assault, robbery and burglary. Note that robbery arrests have an additional impact on robberies; burglary arrests reduce burglaries and motor vehicle arrests have a negative impact on motor-vehicle thefts. The impact of police is significant, with elasticities of −0.3 in the case of burglary, −0.7 in the case of robbery and about −1.0 in the case of assault.

Summary and Conclusion

This paper has two purposes. First, it aims to shed new light into the impact of alcohol consumption on criminal activity. Second, it aims to investigate the relative impacts of alcohol and deterrence on crime. While there is substantial evidence on the causal effect of police and arrests on crime, the causal effect of alcohol consumption on crime is less certain. Previous work has encountered major empirical challenges to identify the effect

Table 5 OLS regressions. Crime equations for New York City, January 1970–January 2002

	Lags	Assault	Lags	Rape	Lags	Murder	Lags	Robbery	Lags	Burglary	Lags	Motor vehicle theft	Lags	Grand larceny
Arrests	1–2	−0.039	1–4	0.143	1–2	−0.159*	1–2	−0.210***	1–2	−0.162***	1–2	−0.110**	1–2	−0.009
		(0.083)		(0.181)		(0.091)		(0.056)		(0.058)		(0.049)		(0.045)
Police	0–3	−0.876**	0–4	1.018	0	0.197	0–4	−0.668**	0	−0.270*	0–2	−0.278	0–5	−0.985*
		(0.406)		(1.957)		(0.491)		(0.343)		(0.146)		(0.424)		(0.576)
AFCD/TANF	0	0.339	0–2	0.537	0–2	2.498**	0–1	0.615***	0	0.322**	0–2	−0.420	0	0.128
		(0.240)		(1.043)		(1.113)		(0.179)		(0.149)		(0.383)		(0.131)
Minimum wage	0	−0.008	0	0.174	0–2	−0.631	0	−0.109	0	0.079	0	−0.110	0	−0.039
		(0.140)		(0.248)		(0.589)		(0.154)		(0.131)		(0.165)		(0.125)

Arrests pertain to arrests for each specific crime listed in columns. Robust standard errors are reported in parentheses when the corresponding variable enters with no lag. Otherwise, the values in parentheses are the robust standard errors of the summed coefficients. Sample sizes differ slightly between crimes based on the number of lags in the regressions. *** $p<0.01$; ** $p<0.05$; * $p<0.10$. Each regression also includes population ages 15–49, monthly dummy variables, and an indicator variable to account for the structural change in AFCD/TANF in November 1986 of alcohol consumption on crime. This is because of the difficulty in finding convincing and viable instruments for alcohol consumption in crime regressions. In micro data, it is exceedingly difficult to find instruments that are correlated with an individual's alcohol consumption but are unrelated to his criminal propensity. Instruments that are not individual-specific but that vary at the aggregate level (such as state-level alcohol taxes) tend not to be powerful enough to explain individual-level variation in alcohol consumption, and they are likely to be correlated with local attributes that also impact crime. Alternative strategies, such as estimating reduced form crime equations using aggregate data by employing price and availability of alcohol as exogenous variables are viable, but they do not provide estimates of the impact of alcohol *consumption* on crime.

In this paper we estimated the impact of deterrence and alcohol consumption on crime within the same empirical framework. We tackled the endogeneity of arrests and the police force by exploiting the temporal independence of crime and deterrence in these high-frequency data. We tackled the endogeneity of alcohol by instrumenting alcohol sales with city, state, and federal alcohol taxes and minimum drinking age.

The results show that between the years of 1983 and 2002, controlling for the impact of arrests, police, the minimum wage, the number of the AFDC cases, and the size of the population ages 15 to 49, an increase in alcohol consumption has a positive impact on assaults, rapes and grand larcenies, but alcohol has no impact on murders, robberies, burglaries and motor-vehicle thefts. On the other hand, murder arrests deter murders, robbery arrests deter robberies. Similarly, an increase in own-arrests generate reduction in burglaries, motor-vehicle thefts and grand larcenies. The magnitude of the impact of arrests, in terms of elasticities, are greater than the impact of alcohol, except for rape and assault.

These results are robust to various model modifications. Estimating the models for a longer time span allows us to incorporate more variation in the deterrence variables, but it comes at the expense of omitting alcohol because alcohol data are not available prior to 1983. These specifications confirm the deterrent effect of arrests and reveal additional deterrence of police.

Taken together, these results indicate that although variations in alcohol consumption have an impact on certain crimes, the effectiveness of deterrence variables in reducing crime is stronger in magnitude and it is pertinent for a larger set of crimes. It should also be noted that because rape is a violent crime that is not easily deterred through police, alcohol policies may be a viable alternative for reducing this crime. It should be kept in mind, however, that the relative cost effectiveness of policies designed to reduce alcohol consumption and to enhance deterrence is unclear. Curbing alcohol consumption may be a simpler policy lever in comparison to enhancing deterrence because a tax increase or an increase in drinking age is less costly to implement for the policy maker from a financial point of view, although they may be complicated to implement politically. An increase in the size of the police force, on the other hand, may be less complicated politically but it is more costly financially.

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Appendix

Table 6 Instrumental variables regressions with arbitrary lag lengths. Crime equations for New York City, April 1983–January 2002

Lags	Arrest	Police	AFCD/TANF	Min wage	Alcohol
Assault					
1	−0.025 (0.051)	0.104 (0.367)	0.245 (0.283)	0.166 (0.209)	0.098* (0.055)
2	−0.044 (0.097)	0.280 (0.679)	0.371 (0.637)	0.401* (0.223)	0.105* (0.056)
3	−0.060 (0.117)	−0.445 (0.691)	0.524 (0.879)	0.518 (0.333)	0.118** (0.057)
4	0.150 (0.172)	−0.448 (0.703)	0.500 (0.899)	0.676 (0.668)	0.124** (0.050)
5	0.260 (0.229)	−0.818 (0.763)	0.565 (0.896)	0.725 (0.641)	0.137*** (0.050)
6	0.227 (0.271)	−0.427 (0.984)	0.180 (0.873)	0.769 (0.599)	0.134*** (0.052)
Rape					
1	0.038 (0.040)	−0.461 (0.922)	−0.752* (0.404)	−0.208 (0.354)	0.270** (0.125)
2	0.099 (0.084)	−0.963 (1.103)	−0.227 (1.062)	0.237 (0.419)	0.289** (0.129)
3	0.222 (0.185)	−1.519 (1.259)	1.151 (1.311)	−0.110 (0.350)	0.307** (0.128)
4	0.218 (0.251)	−1.213 (1.642)	1.714 (1.327)	−0.880 (0.617)	0.289** (0.125)
5	0.384* (0.231)	−1.914 (1.571)	2.270* (1.312)	0.283 (0.954)	0.323** (0.129)
6	0.417 (0.324)	−0.042 (1.866)	2.433** (1.148)	0.388 (1.096)	0.269** (0.112)
Murder					
1	−0.031 (0.048)	0.394 (1.048)	1.610** (0.651)	0.089 (0.697)	−0.107 (0.120)
2	−0.204** (0.111)	−0.104 (1.321)	1.795 (1.334)	0.626 (0.757)	−0.074 (0.119)
3	−0.299 (0.189)	0.578 (1.757)	0.904 (1.579)	0.088 (0.884)	−0.111 (0.114)
4	−0.202 (0.233)	0.196 (2.125)	0.107 (1.741)	0.432 (0.916)	−0.106 (0.104)
5	−0.391 (0.321)	−0.332 (2.548)	−0.556 (1.786)	0.271 (1.082)	−0.101 (0.100)
6	−0.412 (0.373)	−1.245 (3.108)	−0.489 (1.743)	−0.615 (1.197)	−0.102 (0.096)

Table 6 (continued)

Lags	Arrest	Police	AFCD/TANF	Min wage	Alcohol
Robbery					
1	−0.060* (0.034)	0.452 (0.350)	0.780*** (0.211)	−0.052 (0.153)	0.014 (0.068)
2	−0.141*** (0.054)	0.246 (0.539)	0.072 (0.318)	−0.126 (0.190)	0.006 (0.064)
3	−0.048 (0.106)	0.322 (0.528)	0.102 (0.501)	−0.141 (0.193)	0.001 (0.064)
4	−0.115 (0.143)	−0.138 (0.529)	0.063 (0.466)	−0.085 (0.240)	0.007 (0.063)
5	−0.026 (0.191)	−0.571 (0.853)	−0.057 (0.600)	−0.171 (0.320)	0.011 (0.063)
6	−0.005 (0.245)	−0.378 (0.950)	−0.326 (0.600)	−0.072 (0.338)	0.011 (0.059)
Burglary					
1	−0.094*** (0.033)	0.515 (0.374)	0.154 (0.217)	0.194 (0.125)	−0.047 (0.047)
2	−0.244*** (0.070)	0.614 (0.452)	0.161 (0.438)	0.432*** (0.157)	−0.040 (0.044)
3	−0.345*** (0.083)	1.130** (0.492)	0.085 (0.565)	0.570** (0.254)	−0.044 (0.045)
4	−0.286*** (0.085)	0.792 (0.647)	0.344 (0.504)	0.722*** (0.244)	−0.037 (0.046)
5	−0.310*** (0.107)	0.425 (0.741)	0.029 (0.534)	0.641** (0.287)	−0.029 (0.047)
6	−0.401*** (0.142)	0.417 (0.780)	−0.012 (0.584)	0.653* (0.379)	−0.033 (0.044)
Motor vehicle theft					
1	−0.002 (0.037)	0.770 (0.513)	0.434*** (0.168)	0.200 (0.194)	−0.021 (0.052)
2	−0.159** (0.066)	0.598 (0.646)	−0.106 (0.355)	0.312 (0.221)	−0.027 (0.050)
3	−0.241* (0.137)	0.712 (0.552)	−0.929 (0.580)	0.499 (0.331)	−0.036 (0.052)
4	−0.108 (0.165)	0.804 (0.583)	−0.805 (0.650)	0.600 (0.411)	−0.025 (0.052)
5	−0.012 (0.164)	0.391 (0.705)	−0.933 (0.636)	0.403 (0.384)	−0.010 (0.052)
6	0.001 (0.206)	0.259 (0.927)	−1.084* (0.610)	0.273 (0.375)	−0.006 (0.049)

Table 6 (continued)

Lags	Arrest	Police	AFCD/TANF	Min wage	Alcohol
Grand larceny					
1	−0.019 (0.018)	−0.091 (0.252)	−0.091 (0.252)	0.040 (0.078)	0.071*** (0.028)
2	−0.097** (0.042)	−0.413 (0.320)	0.074 (0.196)	−0.039 (0.096)	0.071*** (0.027)
3	−0.045 (0.073)	−0.315 (0.352)	0.075 (0.281)	0.092 (0.152)	0.071*** (0.026)
4	−0.107 (0.089)	−0.129 (0.332)	0.161 (0.318)	0.062 (0.257)	0.071*** (0.027)
5	−0.116 (0.103)	−0.265 (0.352)	0.159 (0.299)	0.124 (0.291)	0.075*** (0.027)
6	−0.155 (0.124)	−0.061 (0.358)	0.136 (0.286)	0.033 (0.287)	0.072*** (0.024)

Crime lags for each crime regression are the same as in the benchmark models reported in Table 2. Alcohol consumption enters with no lag and it is instrumented with legal minimum drinking age in New York City and lagged real city and state alcohol tax (see the text for the definition) as in the benchmark model. Arrests enter with lags 1 to N. Police, AFCD/TANF and Minimum wage enter with lags 0 to N. The values in parentheses are the robust standard errors of the summed coefficients. Arrests pertain to arrests for each specific crime listed in columns The instruments for alcohol consumption legal minimum drinking age in New York City and real city and state alcohol tax (see the text for the definition). *** $p<0.01$; **$p<0.05$; *$p<0.10$. Each regression also includes population ages 15–49, monthly dummy variables, and an indicator variable to account for the structural change in AFCD/TANF in November 1986

Table 7 OLS regressions. Crime equations for New York City, April 1983-January 2002. Without alcohol consumption

	Lags	Assault	Lags	Rape	Lags	Murder	Lags	Robbery	Lags	Burglary	Lags	Motor vehicle theft	Lags	Grand larceny
Arrests	1–2	−0.042	1–4	0.203	1–2	−0.207*	1–2	−0.146***	1–2	−0.235***	1–2	−0.156**	1–2	−0.110***
		(0.090)		(0.248)		(0.109)		(0.053)		(0.069)		(0.065)		(0.037)
Police	0–3	−0.446	0–4	−0.707	0	0.096	0–4	−0.173	0	−0.060	0–2	0.551	0–5	−0.265
		(0.732)		(1.806)		(0.565)		(0.551)		(0.168)		(0.631)		(0.306)
AFCD/TANF	0	0.306	0–2	−0.467	0–2	1.833	0–1	0.756***	0	0.321**	0–2	−0.068	0	0.051
		(0.187)		(0.974)		(1.280)		(0.211)		(0.152)		(0.340)		(0.087)
Minimum wage	0	−0.116	0	−0.184	0–2	0.641	0	0.001	0	0.113	0	0.189	0	−0.030
		(0.127)		(0.173)		(0.749)		(0.188)		(0.083)		(0.141)		(0.086)

Arrests pertain to arrests for each specific crime listed in columns. Robust standard errors are reported in parentheses when the corresponding variable enters with no lag. Otherwise, the values in parentheses are the robust standard errors of the summed coefficients. Sample sizes differ slightly between crimes based on the number of lags in the regressions. The instruments for lagged alcohol consumption are lagged legal minimum drinking age in New York City and lagged real city and state alcohol tax (see the text for the definition). *** $p<0.01$; ** $p<0.05$; * $p<0.10$. Each regression also includes population ages 15–49, monthly dummy variables, and an indicator variable to account for the structural change in AFCD/TANF in November 1986

Table 8 Full Set of coefficients of the instrumental variables regressions. Crime equations for New York City, April 1983–January 2002

Assault	Rape	Murder	Robbery	Burglary	Motor vehicle theft	Grand larceny
(τ) Lagged arrests: 1–2	(τ) Lagged arrests: 1–4	(τ) Lagged arrests: 1–2	(τ) Lagged arrests: 1–2	(τ) Lagged arrests: 1–2	(τ) Lagged arrests: 1–2	(τ) Lagged arrests: 1–2
(β) Lagged police: 0–3	(β) Lagged police: 0–4	(β) Lagged police: 0	(β) Lagged police: 0–4	(β) Lagged police: 0	(β) Lagged police: 0–2	(β) Lagged police: 0–5
(γ) Lagged AFDC: 0	(γ) Lagged AFDC: 0–2	(γ) Lagged AFDC: 0–2	(γ) Lagged AFDC: 0–1	(γ) Lagged AFDC: 0	(γ) Lagged AFDC: 0–2	(γ) Lagged AFDC: 0
(δ) Lagged min wage: 0	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0–2	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0
(ρ) Alcohol use: 0	(ρ) Alcohol use: 0	(ρ) Alcohol use: 0	(ρ) Alcohol use: 0	(ρ) Lagged alcohol: 0	(ρ) Lagged alcohol: 0	(ρ) Lagged alcohol: 0
(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0
τ_1= −0.022 (0.059)	τ_1= 0.079 (0.054)	τ_1= −0.085 (0.059)	τ_1= −0.088*** (0.034)	τ_1= −0.131*** (0.039)	τ_1= −0.053 (0.042)	τ_1= −0.044* (0.024)
τ_2= −0.027 (0.052)	τ_2= 0.086 (0.089)	τ_2= −0.121* (0.064)	τ_2= −0.057* (0.034)	τ_2= −0.100** (0.039)	τ_2= −0.104*** (0.037)	τ_2= −0.054*** (0.021)
β_0= −0.036 (0.250)	τ_3= 0.068 (0.083)	β_0= 0.106 (0.570)	β_0= −0.085 (0.171)	β_0= −0.052 (0.179)	β_0= 0.045 (0.277)	β_0= −0.178 (0.123)
β_1= 0.045 (0.220)	τ_4= −0.004 (0.061)	γ_0= −0.432 (0.390)	β_1= 0.361 (0.271)	γ_0= 0.296** (0.147)	β_1= 0.631** (0.296)	β_1= −0.074 (0.163)
β_2= 0.074 (0.473)	β_0= −0.735 (0.509)	γ_1= 1.859*** (0.337)	β_2= −0.197 (0.215)	δ_0= 0.096 (0.087)	β_2= −0.063 (0.298)	β_2= −0.145 (0.120)
β_3= −0.510* (0.260)	β_1= 0.219 (0.580)	γ_2= 0.337 (1.095)	β_3= −0.007 (0.303)	ρ_0= −0.047 (0.047)	γ_0= 0.726*** (0.187)	β_3= 0.060 (0.109)
γ_0= 0.373** (0.176)	β_2= −0.337 (0.508)	δ_0= −0.097 (0.504)	β_4= −0.242 (0.211)	η_0= 0.011*** (0.003)	γ_1= −0.505*** (0.155)	β_4= 0.126 (0.113)
δ_0= −0.059 (0.133)	β_3= −0.327 (0.670)	δ_1= 0.290 (0.458)	γ_0= 0.741*** (0.193)		γ_2= −0.326 (0.283)	β_5= −0.065 (0.124)
ρ_0= 0.104* (0.054)	β_4= 0.372 (0.401)	δ_2= 0.415 (0.352)	γ_1= 0.019 (0.118)		δ_0= 0.170 (0.143)	γ_0= 0.095 (0.101)
η_0= 0.002 (0.005)	γ_0= 0.966* (0.500)	ρ_0= −0.079 (0.122)	δ_0= 0.012 (0.195)		ρ_0= −0.032 (0.050)	δ_0= 0.024 (0.099)
	γ_1= −1.499*** (0.490)	η_0= 0.027*** (0.010)	ρ_0= 0.016 (0.065)		η_0= 0.013*** (0.004)	ρ_0= 0.072*** (0.027)
	γ_2= 0.433 (0.776)		η_0= 0.008** (0.003)			η_0= −0.001 (0.001)
	δ_0= 0.054 (0.236)			$\sum\tau_i$= −0.230*** (0.068)	$\sum\tau_i$= −0.156** (0.065)	$\sum\tau_i$= −0.098** (0.041)
	ρ_0= 0.292** (0.123)				$\sum\beta_i$= 0.612 (0.641)	$\Sigma\beta_i$= −0.277 (0.328)
	η_0= −0.002 (0.009)				$\sum\gamma_i$= −0.105 (0.359)	
$\sum\tau_i$= −0.050 (0.093)	$\sum\tau_i$= 0.228 (0.246)	$\sum\tau_i$= −0.206* (0.110)	$\sum\tau_i$= −0.145*** (0.053)			
$\sum\beta_i$= −0.427 (0.708)	$\sum\beta_i$= −0.809 (1.639)	$\sum\gamma_i$= 1.766 (1.312)	$\sum\beta_i$= −0.169 (0.562)			
	$\sum\gamma_i$= −0.101 (1.052)	$\sum\delta_i$= 0.608 (0.757)	$\sum\gamma_i$= 0.760*** (0.210)			
Obs. 226	Obs. 226	Obs. 226	Obs. 226	Obs. 226	Obs. 226	Obs. 226

Table 9 Full set of coefficients of the first stage regressions dependent variable: alcohol consumption. Crime equations for New York City, April 1983–January 2002

Assault	Rape	Murder	Robbery	Burglary	Motor vehicle theft	Grand larceny
(α) Lagged crime: 1–9	(α) Lagged crime: 1–13	(α) Lagged crime: 1–7	(α) Lagged crime: 1–5	(α) Lagged crime: 1–12	(α) Lagged crime: 1–2	(α) Lagged crime: 1–3
(β) Lagged Police: 0–3	(β) Lagged Police: 0–4	(β) Lagged Police: 0	(β) Lagged Police: 0–4	(β) Lagged Police: 0	(β) Lagged Police: 0–2	(β) Lagged Police: 0–5
(γ) Lagged AFDC: 0	(γ) Lagged AFDC: 0–2	(γ) Lagged AFDC: 0–2	(γ) Lagged AFDC: 0–1	(γ) Lagged AFDC: 0	(γ) Lagged AFDC: 0–2	(γ) Lagged AFDC: 0
(δ) Lagged min wage: 0	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0–2	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0	(δ) Lagged min wage: 0
(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0	(η) Pop1549: 0
(τ) Lagged arrest: 1–2	(τ) Lagged arrest: 1–4	(τ) Lagged arrest: 1–2	(τ) Lagged arrest: 1–2	(τ) Lagged arrest : 1–2	(τ) Lagged arrest : 1–2	(τ) Lagged arrest : 1–2
(ψ) Overall tax: 0	(ψ) Overall tax: 0	(ψ) Overall tax: 0	(ψ) Overall tax: 0	(ψ) Overall tax: 0	(ψ) Overall tax: 0	(ψ) Overall tax: 0
(φ) Min age: 0	(φ) Min age: 0	(φ) Min age: 0	(φ) Min age: 0	(φ) Min age: 0	(φ) Min age: 0	(φ) Min age: 0
α_1= 0.113 (0.082)	α_1= 0.001 (0.078)	α_1= 0.026 (0.047)	α_1= 0.236 (0.157)	α_1= 0.309* (0.183)	α_1= 0.048 (0.109)	α_1= −0.237 (0.306)
α_2= 0.028 (0.082)	α_2= −0.073 (0.072)	α_2= 0.028 (0.058)	α_2= 0.323* (0.168)	α_2= 0.262** (0.133)	α_2= 0.154 (0.133)	α_2= 0.495* (0.289)
α_3= 0.130 (0.088)	α_3= 0.048 (0.083)	α_3= 0.076 (0.064)	α_3= 0.301* (0.155)	α_3= 0.191 (0.146)	β_0= 0.180 (0.401)	α_3= 0.075 (0.409)
α_4= 0.104 (0.089)	α_4= 0.109 (0.093)	α_4= 0.062 (0.074)	α_4= 0.219 (0.154)	α_4= 0.337** (0.135)	β_1= 0.479 (0.434)	β_0= −0.252 (0.385)
α_5= 0.242** (0.117)	α_5= −0.011 (0.084)	α_5= 0.093 (0.066)	α_5= 0.106 (0.149)	α_5= 0.079 (0.141)	β_2= 1.001* (0.515)	β_1= −0.017 (0.447)
α_6= -0.043 (0.122)	α_6= −0.008 (0.098)	α_6= 0.085 (0.060)	β_0= −0.053 (0.542)	α_6= 0.047 (0.141)	γ_0= −0.538 (0.338)	β_2= 0.805* (0.483)
α_7= 0.166 (0.115)	α_7= −0.025 (0.093)	α_7= −0.041 (0.044)	β_1= 0.098 (0.533)	α_7= 0.429*** (0.142)	γ_1= 0.475 (0.425)	β_3= −1.759** (0.740)
α_8= 0.096 (0.088)	α_8= −0.063 (0.091)	β_0= −0.030 (0.389)	β_2= 0.651 (0.545)	α_8= 0.218 (0.172)	γ_2= −0.510 (0.667)	β_4= −0.184 (0.410)
α_9= 0.010 (0.080)	α_9= 0.033 (0.096)	γ_0= −0.733** (0.361)	β_3= −1.829*** (0.529)	α_9= 0.093 (0.179)	δ_0= −0.357 (0.299)	β_5= −0.268 (0.459)
β_0= -0.094 (0.428)	α_{10}= −0.009 (0.095)	γ_1= 0.715* (0.409)	β_4= −0.191 (0.525)	α_{10}= 0.281* (0.162)	η_0= 0.030*** (0.009)	γ_0= −0.543 (0.386)
β_1= 0.164 (0.422)	α_{11}= −0.026 (0.063)	γ_2= −0.208 (0.710)	γ_0= −0.455 (0.479)	α_{11}= −0.059 (0.152)	τ_1= −0.030 (0.069)	δ_0= −0.488** (0.196)
β_2= 0.825* (0.420)	α_{12}= −0.026 (0.080)	δ_0= −0.423 (0.321)	γ_1= 0.367 (0.505)	α_{12}= −0.066 (0.184)	τ_2= 0.054 (0.073)	η_0= 0.027*** (0.009)
β_3= -1.709** (0.746)	α_{13}= 0.035 (0.068)	δ_1= 0.102 (0.227)	δ_0= −0.514 (0.438)	β_0= 0.098 (0.400)	ψ_0= −0.014* (0.007)	τ_1= −0.037 (0.064)
γ_0= -0.547 (0.350)	β_0= −0.027 (0.351)	δ_2= 0.602 (0.391)	η_0= 0.024*** (0.008)	γ_0= −0.594 (0.493)	φ_0= −0.077*** (0.011)	τ_2= −0.105 (0.069)
δ_0= -0.351 (0.264)	β_1= −0.063 (0.335)	τ_1= −0.022 (0.037)	τ_1= −0.022 (0.087)	δ_0= −0.152 (0.301)		ψ_0= −0.010 (0.007)

Table 9 (continued)

Assault	Rape	Murder	Robbery	Burglary	Motor vehicle theft	Grand larceny
η_0= 0.027*** (0.008)	β_2= 0.800* (0.443)	τ_2= 0.002 (0.042)	τ_2= −0.018 (0.088)	η_0= 0.023*** (0.008)		φ_0= −0.079*** (0.010)
τ_1= -0.016 (0.101)	β_3= −1.676** (0.817)	η_0= 0.027*** (0.009)	ψ_0= −0.011 (0.009)	τ_1= −0.021 (0.110)		
τ_2= 0.091 (0.075)	β_4= −0.178 (0.382)	ψ_0= −0.015** (0.007)	φ_0= −0.078*** (0.011)	τ_2= 0.133 (0.095)		
ψ_0= -0.011* (0.006)	γ_0= −0.457 (0.437)	φ_0= −0.080*** (0.011)		ψ_0= −0.013*** (0.005)		
φ_0= -0.076*** (0.011)	γ_1= 0.309 (0.332)			φ_0= −0.080*** (0.013)		
	γ_2= −0.504 (0.704)					
	δ_0= −0.499* (0.290)					
	η_0= 0.029*** (0.010)					
	τ_1= 0.016 (0.084)					
	τ_2= 0.033 (0.066)					
	τ_3= −0.053 (0.046)					
	τ_4= −0.023(0.058)					
	ψ_0= −0.010 (0.007)					
	φ_0= −0.078*** (0.012)					
1st stage F 25.71	1st stage F 21.30	1st stage F 25.71	1st stage F 26.23	1st stage F 21.75	1st stage F 24.43	1st stage F 33.01
Obs. 226	Obs. 226	Obs. 226	Obs. 226	Obs. 226	Obs. 226	Obs. 226

References

Akaike H (1973) Information theory and the extension of the maximum likelihood principle. In: Petrov BN, Csaki F (eds) The second international symposium on in-formation theory. Akademiai Kiado, Budapest, pp 267–281

Anderson DA (1999) The aggregate burden of crime. J Law Econ 42(2):611–642

Becker GS (1974) Crime and punishment: an economic approach. In Essays in the economics of crime and punishment (pp. 1–54). UMI

Carpenter C (2007) Heavy alcohol use and crime: evidence from underage drunk-driving laws. J Law Econ 50:539–557

Carpenter C, Dobkin C (2010) The drinking age, alcohol consumption, and crime. Working Paper available at website: http://web.merage.uci.edu/~kittc/Carpenter_Dobkin_Crime_website_01192011.pdf (accessed 11/14/12)

Chalfin A, McCrary J (2012) The effect of police on crime: new evidence from U.S. cities, 1960–2010. Working Paper. Retrieved from: http://emlab.berkeley.edu/~jmccrary/chalfin_mccrary2012.pdf

Corman H, Mocan N (2000) A time-series analysis of crime, deterrence, and drug abuse in New York city. Am Econ Rev 90(3):584–604

Corman H, Mocan N (2005) Carrots, sticks, and broken windows. J Law Econ 48(1):235–266

Desimone J (2001) The effect of cocaine prices on crime. Econ Inq 39(4):627–643

Di Tella R, Schargrodsky E (2004) Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. Am Econ Rev 94(1):115–133

Draca M, Machin S, Witt R (2011) Panic on the streets of London: police, crime, and the july 2005 terror attacks. Am Econ Rev 101(5):2157–2181

Drago F, Galbiati R, Vertova P (2009) The deterrent effects of prison: evidence from a natural experiment. J Polit Econ 117(2):257–280

Ehrlich I (1973) Participation in illegitimate activities: a theoretical and empirical investigation. J Polit Econ 81(3):521–565

Ehrlich I (1996) Crime, punishment, and the market for offenses. J Econ Perspect 10(1):43–67

Gyimah-Brempong K (2001) Alcohol availability and crime: evidence from census tract data. South Econ J 68(1):2–21

LaVallee RA, Yi H-Y (2012) Surveillance Report No. 95: apparent per capita alcohol consumption: national, state, and regional trends, 1977–2010. The national institute on alcohol abuse and alcoholism, U.S. department of health and human services, public health service, national institutes of health

Levitt SD (1998) Why do increased arrest rates appear to reduce crime: deterrence, incapacitation, or measurement error? Econ Inq 36(3):353–372

Lin M-J (2008) Does unemployment increase crime? Evidence from U.S. data 1974–2000. J Hum Resour 43(2):413–436

Machin S, Marie O (2011) Crime and police resources: the street crime initiative. J Eur Econ Assoc 9(4):678–701

Markowitz S (2005) Alcohol, drugs and violent crime. Int Rev Law Econ 25(1):20–44

Raphael S, Winter-Ebmer R (2001) Identifying the effect of unemployment on crime. J Law Econ 44(1):259–283

Ruhm CJ, Jones AS, Kerr WC, Greenfield TK, Terza JV, Pandian RS, McGeary KA (2011) What U.S. data should be used to measure the price elasticity of demand for alcohol? NBER Working Paper No.17578

Sack K (1995) How Albany works, lesson 1: lobbying; the beverage industry pushes hard for a tax break, and succeeds. The New York Times. http://www.nytimes.com/1995/06/12/nyregion/albany-works-lesson-1-lobbying-beverage-industry-pushes-hard-for-tax-break.html?pagewanted=all&src=pm (accessed 11/14/12)

Schoeni RF, Blank RM (2000) What has welfare reform accomplished? Impacts on welfare participation, employment, income, poverty, and family structure. National Bureau of Economic Research Working Paper #7627

Zimmerman PR, Benson BL (2007) Alcohol and rape: an “economics-of-crime” perspective. Int Rev Law Econ 27:442–444