More Readers of Gun Magazines But Not More Crimes

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Abstract:

We investigate the relationships between guns ownership and murders, reported rapes, and robberies. Because county-level data on gun ownership are not available, we use data on the number of subscriptions to the gun magazine *Handguns Magazine* as a proxy. To accommodate the count nature of our data, we use a multivariate Poisson-lognormal model that we estimate with the Gibbs sampler. For most of our analyses, we find that the correlation between today's number of guns and future crimes is as strong as the correlation between today's number of crimes and future guns.

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I. INTRODUCTION

Guns can be used to commit crime, but they can also be used to deter crime. It is therefore not obvious *a priori* whether crime will increase or decrease when the number of guns in society changes. Determining the net effect is ultimately an empirical question. In this paper, we use a multivariate Poisson-lognormal model to analyze the relationship between three types of violent crime, murder, rape, and robbery, in the United States and subscriptions to the gun magazine *Handguns Magazine*, which we use as a proxy for gun ownership.

An empirical analysis of the effect of changes in the number of guns needs to address three difficulties. First, while there are fairly reliable data on crime rates, there are few reliable data sets on gun ownership.[1] This makes it necessary to find a suitable proxy for gun ownership. Sociologists and others have long debated using gun magazine sales as proxy (e.g., Lester, 1989 and Kleck, 1997), but economists have used this type of measure only recently (Duggan 2001, Moody and Marvel, 2001 and 2002). In the absence of a more reliable proxy for gun ownership, using gun magazine subscriptions seems to be a promising approach. Second, gun ownership and crime rates are likely to affect each other, which makes it necessary to analyze their relationship with a simultaneous equations model. Because changes in gun ownership and crime rates are likely to affect each other with a lag, such a model needs to account for intertemporal cross-correlation. Third, the number of guns and the number of crimes are 'counts' (non-negative integers), and many counties have only small numbers of certain violent crimes and gun owners in any given year. Because there is evidence that models that ignore the

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[1] Large surveys at the state level are rarely conducted. For research using the voter exit poll surveys that are done nationally and survey as many as 36,000 voters, see Lott (2000, chap. 3 and pp. 113 and 114). For a discussion on using the much smaller General Social Survey data, see Lott and Whitley (2002). Survey information at more disaggregated levels than for states is not available.

count nature of the data lead to unreliable inference (Hausman *et al.* (1984), the econometric model needs to accommodate the characteristics of the data.

Simultaneous equations models and count analyses have been applied numerous times independently of each other, but there are only few analyses of correlated count data (see Munkin and Trivedi, 1999, Ibrahim *et al*., 2000, Chib and Winkelmann, 2001, and Cameron *et al.*, 2003). Models of correlated count data involve multivariate discrete distributions whose closed form solutions are unknown, and their analyses require computer-intensive methods that were not readily accessible until very recently. We follow the approach of Chib and Winkelmann (2001) and analyze our data with the Gibbs sampler, a Markov chain Monte Carlo method.

Finding a non-zero correlation between contemporaneous gun ownership and criminal activity does not shed any light on the question of causality. For example, positive contemporaneous correlation could arise if higher rates of gun ownership lead to more criminal activity but also if people acquire guns in response to high crime rates. To distinguish between these two possibilities, we follow Duggan (2001) and compare the correlations of today's magazine subscriptions and future crime rates with the correlations of today's crimes rates and future subscriptions. If, for example, today's magazine subscriptions turn out to be positively correlated with future crime rates, then this would provide some evidence of a causal relationship between gun ownership and crime.[2] If today's crime rates are positively correlated with future subscription rates, then this would constitute evidence that people acquire guns in response to high crime rates.

For most of our analyses we find that these two types of correlation are of about equal magnitude and that neither type of correlation consistently exceeds the other. This

[2] Alternatively, people might purchase handguns today because they anticipate more crimes in the future.

suggests that either there is no causal relationship between guns and crimes, or that the two causal relationships are equally strong. Only when we analyze the relationship between the numbers of subscriptions and murders in counties with more than 100,000 persons, we find that in 13 out of 15 year-by-year comparisons the correlations between subscriptions and future murders exceed the correlations between murders and future subscriptions.

Our last finding lends some support to the county-level analysis (counties with more than 100,000 persons) of Duggan (2001), whose least squares analyses show statistically significant positive correlations between changes in subscriptions to the gun magazine *Guns&Ammo* and changes in future murder rates, but much smaller and not statistically significant correlations between changes in murder rates and changes in future subscriptions to *Guns&Ammo*. However, when we use Duggan's least squares model to analyze our data, we find that both types of correlation are virtually zero and not statistically significant.

It is possible that the difference between our and Duggan's results is a consequence of qualitative differences in the two data sets. We use county-level data on subscriptions to *Handguns Magazine*, which, as we argue in Section 2, is likely to be a better proxy for gun ownership than *Guns&Ammo* (assuming that gun magazines are suitable proxies for gun ownership in the first place). Duggan declined to share his data with us.[3] Given conversations with the publisher of *Handguns Magazine* and *Guns&Ammo* lead us to believe that *Guns&Ammo* was severely affected by the magazine's own purchases of its copies and given the costs of acquiring and imputing both county level data sets, we decided to gather those data that are more likely to answer

[3] Mark Duggan informed us that he had purchased the data from a commercial source that does not permit him to share these data with other researchers.

the empirical question on the relationship between gun ownership and crime that we are ultimately interested in. We examine state level data for six gun magazines and these tests provide additional evidence that *Guns&Ammo* is a very unique magazine because of these self-purchases.

The paper is organized as follows: we describe our data and motivate the need for a count analysis in Section 2, and we present the multivariate Poisson-lognormal model and the setup of our analysis in Section 3. Section 4 contains our results, and Section 5 our conclusions.

II. The Data

It is reasonable to ask whether subscriptions to gun magazines are sufficiently highly correlated with gun ownership in the United States to permit the use of subscription data in analyses of gun ownership.[4] Duggan (2001) reports various pieces of evidence that suggest that subscription data for the gun magazine *Guns&Ammo* are a suitable proxy for gun ownership.[5] *Guns&Ammo* is the fourth-largest gun magazine in

[4] Academics have used many proxies for gun ownership rates, which include the number of accidental gun deaths or gun suicides, survey data, and the sales of gun magazines. No measure is entirely adequate. For example, accidental gun deaths seem to be more closely related to the level of gun ownership by criminals than by the general population. Gun owners may be reluctant to tell pollsters that they own a gun because of concerns that someone will try to take away their guns or that it is not socially acceptable to own one. The changing social acceptability of gun ownership might help explain the growing gap between the reported rates of gun ownership of married men and women. Those who own guns illegally are likely to underreport ownership. Even a registration system yields a very imprecise measure of gun ownership, and the guns that are registered are unlikely to be the guns that are producing any problems. Magazine sales have been used to proxy gun ownership by Lester (1989), Kleck (1997), Duggan (2001), Moody and Marvel (2001, 2002).

[5] He finds that the characteristics of readers of *Guns&Ammo* are similar to the characteristics of typical gun owners. His analysis also suggests statistically significantly positive correlations between subscription rates to *Guns&Ammo*, and (1) gun shows (a proxy for gun sales), (2) death rates from gun accidents, (3) rates of suicides that are committed with hand guns, (4) membership in the *National Rifle Association* (*NRA*), and (5) state-level gun ownership rates that are provided by the *National Opinion Research Corporation's General Social Survey*. While he acknowledges that these tests do not provide conclusive proof of the adequacy of his proxy, he suggests that they indicate that his "panel data set represents the richest one ever assembled for measuring gun ownership" Duggan (2001, p.1088).

the United States, and it places a stronger emphasis on handguns (based on its product reviews) than the three gun magazines with greater circulation (*American Rifleman*, *American Hunter*, and *North American Hunter*).[6] However, while about 50 percent of the product reviews in *Guns&Ammo* are on handguns, there are two gun magazines (*Handguns Magazine* and *American Handgunner*) whose product reviews focus exclusively on handguns. It is likely that their exclusive foci on handguns make them better proxies for gun ownership in an analysis of gun-related crimes.[7]

Skip Johnson, a vice president for *Guns&Ammo's* and *Handguns Magazine's* parent company *Primedia*, told us that between 5 and 20 percent of *Guns&Ammo's* national sales in a particular year were purchases by his company to meet its guaranteed sales to advertisers. These copies were given away for free to dentists' and doctors' offices. Because the purchases were meant to offset any unexpected declines in sales, own purchases systematically smooth out any national changes. Although we do not have a precise breakdown of how these free samples are counted towards the sales in different counties, Johnson said that they were very selective so that national swings would have produced very large swings in these selected regions. More importantly, these self-purchases were apparently related to factors that helped explain why people might purchase guns, and these factors included changing crime rates. Johnson indicated that the issue of self-purchases is particularly important for *Guns&Ammo* because the magazine had declining sales over part of this period. *Handguns Magazine* was much newer and experienced appreciable growth.

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[6] See Duggan (2001, p.1089). 40 percent of the *American Rifleman's* reviews and 50 percent of the *Guns&Ammo* reviews deal with handguns. Duggan also choose *Guns&Ammo* because sales data for the three gun magazines with greater circulation are not available on the county level from the *Audit Bureau of Circulation*. County level sales data for *American Rifleman* and *American Hunter* are only obtainable directly from the *NRA*.

[7] Column 1 of Table 1 shows 1999 sales rates for the six gun magazines.

The reader profiles for *Guns&Ammo* and *Handguns Magazine* are fairly similar. In 1994, 99.9 percent of *Handguns Magazine* readers owned a gun compared to 98.8 percent for *Guns&Ammo*, the average subscriber for both owned over 15 guns, the median age for both was 35 years, the median incomes ($42,331 for *Guns&Ammo* and $43,179 for *Handguns Magazine*) were within $850 of each other, over 60 percent of both were college educated, and over 80 percent had at least a high school education.[8]

To determine which gun magazine might be a better proxy for gun ownership, we used *General Social Survey* (*GSS*) state level survey data to regress the logarithms of individual and family gun ownership on the logarithm of magazine sales, together with state and year fixed effects.[9] Columns 2 and 3 of Table 1 show that, on the individual level, the circulation data of *Handguns Magazine*, *American Handgunner*, and the two NRA publications, *American Hunter* and *American Rifleman*, are significantly positively correlated with the survey data. Of the six magazines, *Guns&Ammo* ranks fifth in its ability to explain changes in the individual survey data, and its effect is never statistically different from zero. *Guns&Ammo* also has a different relationship to murder rates than the other magazines. Regressing the logarithm of the murder rate on the logarithm of magazine sales lagged one year and two years produces a positive significant relationship only for *Guns&Ammo* (see Lott, 2003, Appendix 1). We decided that *Handguns Magazine* is likely to be a better proxy for gun ownership than *Guns&Ammo*. Because

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[8] Globe Research Corp., "Guns & Ammo Magazine Subscriber Survey Results for 1994," emap-USA: New York, NY, 1995 and Globe Research Corp., "Handguns Magazine Subscriber Survey Results for 1994," emap-USA: New York, NY, 1995. Less detailed information is available from Guns&Ammo.com and Handgunsmag.com.

[9] We analyzed the data with weighted least squares, weighting the survey data by state level demographic characteristics. We used 30 different age, race, and sex demographic groups (five age categories (20-29, 30-39, 40-49, 50-64, and 65 and over), sex, and three racial groupings (black, white, and other)). Moody and Marvell (2001) used the same approach. Duggan (2001) used national demographics to weigh the state level survey data and he used only individual gun ownership. We used *GSS* data for the years 1977, 1980, 1982, 1984, 1985, 1987 to 1991, 1993, 1994, and 1996.

assembling the subscription data proved to be fairly costly (they are only available on paper and are not available free of charge), we choose to only collect data on *Handguns Magazine* and not to recreate the data set on *Guns&Ammo*.

We obtained county-level data on the number of subscriptions to *Handguns Magazine* for the six years 1990, 1993, 1994, 1995, 1996, and 1997 from the *Audit Bureau of Circulation* (*Handguns Magazine* did not collect county level sales data for 1991 and 1992 or for years after 1997). County-level data on the number of murders, reported rapes, and robberies for these years are available from the FBI's *Uniform Crime Report*. After eliminating a few observations for counties and years for which we did not have all the necessary information, our data set contained 18,811 observations for 3,136 counties.[10]

In Appendix 1, we present the results of preliminary least squares analyses of the relationship between the number of subscriptions to *Handguns Magazine* and the number of murders. Because the main purpose of this exercise is to compare our data to Duggan's (2001) data, we replicate his statistical model and regress (a) changes in log-subscriptions on lagged changes in log-murders and lagged changes in log-subscriptions and (b) changes in log-murders on lagged changes in log-murders and lagged changes in log-subscriptions in two separate analyses. To make the results comparable to his, we restrict our analysis to counties with populations of more than 100,00 persons, and use fixed effects dummies together with a very similar set of the covariates that he uses.[11]

[10] The complete data set contains 22,316 observations for the six years for 3,149 counties. We dropped 3,164 observations because of missing information about subscription rates, which left us with 19,152 observations. We dropped the remaining 341 observations because of missing information about the covariates (see Section 3.4. below).

[11] We use three covariates (real per capita income, the state unemployment rate, and the percentage of county population between 10 and 29 years of age). Duggan (2001) also uses year fixed effects, real per capita income, and the state unemployment rate, but he uses the percentage of the population between 18

Duggan finds that changes in murders are significantly positively correlated with lagged changes in subscriptions to *Guns&Ammo*, while changes in subscriptions to *Guns&Ammo* are not significantly correlated with changes in lagged murders. He interprets this as evidence that more guns cause more crime. Our least squares analysis of the *Handguns Magazine* data does not yield significant correlations in either case. So there is some evidence of qualitative differences between the two data sets. However, we do not think that least squares analyses can provide reliable estimates of the relationship between magazine subscriptions and crimes.

County level data on the numbers of murders, reported rapes, robberies, and magazine subscriptions are count data that consist mainly of zeros and small integers.[12] Table 2 shows that more than half of the observations on murders and about one-third of the observations on reported rapes and robberies are zero. About 80 percent of the observations on the number of murders, and about 50 percent of the observations on reported rapes and robberies do not exceed 3, and the distributions have very long right tails.[13] Hausman *et al.* (1984) have shown that the analysis of heavily skewed count data with least squares methods leads to unreliable results. In the next section, we describe a statistical model for correlated count data that we use to test for correlations between subscriptions to *Handguns Magazine* and murders, reported rapes, and robberies.

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and 24. Our data set provides information only on the percentage of the population between 10 and 19 and the percentage of the population between 20 and 29.

[12] Most counties have at least a few property crimes, and the distributions of property crimes are much more bell-shaped with means that are substantially larger than zero. We therefore decided to focus only on violent crimes for which a count analysis is likely to matter most.

[13] The maximum number of murders is 1,944, of reported rapes 4,211, of robberies 65,994, and of subscriptions to *Handguns Magazine* 8,015. All four maxima refer to Los Angeles County, CA.

III. A Model of Correlated Count Data

3.1 Statistical model

Let $s_i = (s_{i1}, \ldots, s_{iT})$ denote the collection of the numbers of gun magazine subscriptions in county i, $i = 1, \ldots, N$, during T years, and let $c_i = (c_{i1}, \ldots, c_{iT})$ denote the collection of the numbers of crimes in a given crime category that are committed in county i, $i = 1, \ldots, N$, during the same T years. The assumption that s_{it} and c_{it}, $t = 1, \ldots, T$, are independently Poisson distributed yields two univariate Poisson models,

$$\begin{aligned} s_{it} &\sim Poisson(\mu(s_{it})), \\ c_{it} &\sim Poisson(\mu(c_{it})), \end{aligned} \tag{1}$$

with parameters $\mu(s_{it}) \in R^+$ and $\mu(c_{it}) \in R^+$ that describe the means and variances of the two distributions.[14] Because $\mu(s_{it})$ and $\mu(c_{it})$ are independent, the model does not incorporate correlation between s_{it} and c_{it}.

One can introduce correlation between s_{it} and c_{it} by assuming that there are three other Poisson distributed random variables, x_{it}, y_i, and z_i, with parameters $\mu(x_{it}) \in R^+$, $\mu(y_i) \in R^+$, and $\mu(z_i) \in R^+$. The assumption that $s_{it} = y_i + x_{it}$ and $c_{it} = z_i + x_{it}$ yields the bivariate Poisson distribution with $\mu(s_{it}) = \mu(y_i) + \mu(x_{it})$ and $\mu(c_{it}) = \mu(z_i) + \mu(x_{it})$. It is straightforward to show that $Cov(s_{it}, c_{it}) = \mu(x_{it})$ and that the correlation coefficient is $corr(s_{it}, c_{it}) = \mu(x_{it}) / \sqrt{\mu(s_{it})\mu(c_{it})}$. However, $Cov(s_{it}, c_{it}) > 0$ because $\mu(x_{it}) \in R^+$ so that this extension does not accommodate the possibility that gun magazine subscriptions and crimes are negatively correlated.[15]

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[14] To avoid double subscripts, we use parentheses to indicate that there are different μ's for c_{it} and for s_{it} (that is, the parentheses do <u>not</u> mean that μ is a function of c_{it} and s_{it}). We maintain this notation throughout the paper.

[15] See Johnson et al. (1997), Cameron and Trivedi (1998), and Winkelmann (2000) for discussions of the multivariate Poisson distribution. Winkelmann (2000) also discusses the multivariate negative binomial and the multivariate Poisson-Gamma distribution, which do not accommodate negatively correlated count data either.

An alternative extension that permits unrestricted positive as well as negative correlation between s_{it} and c_{it} is to assume that $\mu(s_{it})$ and $\mu(c_{it})$ follow a bivariate lognormal distribution, so that s_{it} and c_{it} are bivariate Poisson-lognormally distributed. If $\mu(s_{it}) = \exp(\varepsilon(s_{it}))$ and $\mu(c_{it}) = \exp(\varepsilon(c_{it}))$, where $\varepsilon(s_{it})$ and $\varepsilon(c_{it})$ are bivariate normally distributed with mean vector $\alpha = (\alpha(s_{it}), \alpha(c_{it}))'$ and covariance matrix $\mathbf{\Sigma}$, then it is straightforward to show (see Aitchison and Ho, 1989, p.645) that

$$\begin{aligned}
E[s_{it}] &= \exp(\alpha(s_{it}) + 0.5\sigma_{ss}), \\
E[c_{it}] &= \exp(\alpha(c_{it}) + 0.5\sigma_{cc}), \\
Cov[s_{it}, c_{it}] &= E[s_{it}]E[c_{it}](\exp(\sigma_{sc}) - 1), \\
corr[s_{it}, c_{it}] &= \frac{(\exp(\sigma_{sc}) - 1)}{\sqrt{(\exp(\sigma_{ss}) - 1 + E[s_{it}]^{-1})(\exp(\sigma_{cc}) - 1 + E[c_{it}]^{-1})}},
\end{aligned} \tag{2}$$

where σ_{ss}, σ_{cc}, and σ_{sc} denote the elements of $\mathbf{\Sigma}$. If σ_{sc}, the covariance between $\varepsilon(s_{it})$ and $\varepsilon(c_{it})$, is negative, then s_{it} and c_{it} are negatively correlated.

The model can be extended to include regressors by assuming that $\mu(s_{it}) = \lambda(s_{it})\exp(\varepsilon(s_{it}))$ and $\mu(c_{it}) = \lambda(c_{it})\exp(\varepsilon(c_{it}))$, where $\lambda(s_{it}) = \exp(x(s_{it})'\beta_s)$ and $\lambda(c_{it}) = \exp(x(c_{it})'\beta_c)$, $x(s_{it})$ and $x(c_{it})$ are two covariate vectors, and β_s and β_c are two vectors of coefficients (see Winkelmann, 2000, p.182). Assuming that $\alpha(s_{it}) = -0.5\sigma_{ss}$ and $\alpha(c_{it}) = -0.5\sigma_{cc}$ yields

$$\begin{aligned}
E[s_{it}] &= \lambda(s_{it})\exp(0) = \exp(x(s_{it})'\beta_s), \\
E[c_{it}] &= \lambda(c_{it})\exp(0) = \exp(x(c_{it})'\beta_c), \\
Cov[s_{it}, c_{it}] &= \lambda(s_{it})\lambda(c_{it})(\exp(\sigma_{sc}) - 1).
\end{aligned} \tag{3}$$

The expected values of s_{it} and c_{it} are identical to the expected value of the familiar univariate Poisson regression model. Unlike the univariate Poisson regression model, the variances of s_{it} and c_{it} exceed the means so that the model describes overdispersed data, and the covariance between s_{it} and c_{it} is not restricted to zero.[16]

The bivariate Poisson-lognormal model in equations 2 and 3 accommodates data with contemporaneous correlation between s_{it} and c_{it}. However, while the number of magazine subscriptions in year t might affect the number of crimes in the same year (and/or vice versa), it is possible that this will happen only with a lag of several years. It is also likely that magazine subscriptions (and possibly crime rates) are serially correlated. Such correlations can be incorporated by assuming that $s_i \sim \text{Poisson}(\lambda(s_i)\exp(\varepsilon(s_i))$ and $c_i \sim \text{Poisson}(\lambda(c_i)\exp(\varepsilon(c_i))$, where $\lambda(s_i) = (\lambda(s_{i1}), \ldots, \lambda(s_{iT}))'$, $\lambda(c_i) = (\lambda(c_{i1}), \ldots, \lambda(c_{iT}))'$, $\varepsilon(s_i) = (\varepsilon(s_{i1}), \ldots, \varepsilon(s_{iT}))'$, and $\varepsilon(c_i) = (\varepsilon(c_{i1}), \ldots, \varepsilon(c_{iT}))'$. The assumption that $\varepsilon(s_i)$ and $\varepsilon(c_i)$ follow a $2T$-variate normal distribution with mean vector $\alpha_i = (\alpha(s_i), \alpha(c_i))'$ and $2T \times 2T$ covariance matrix $\mathbf{\Sigma}$ yields the $2T$-variate Poisson-lognormal distribution that permits serial, contemporaneous, and intertemporal correlation between the number of gun magazine subscriptions and the number of crimes.[17] The terms $\varepsilon(s_i)$ and $\varepsilon(c_i)$ can be interpreted as county-and-year-specific latent, or random, effects with mean vector 0 and $2T\times2T$ covariance matrix $\mathbf{\Sigma}$.[18] For the discussion of our results in Section 4, it will be useful to divide $\mathbf{\Sigma}$ into four $T\times T$ submatrices,

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[16] The variance of s_{it} is $\text{Var}(s_{it}) = \lambda(s_{it}) + \lambda(s_{it})^2(\exp(\sigma_{tt})\text{-}1) > \lambda(s_{it})$, and the variance of c_{it} is $\text{Var}(c_{it}) = \lambda(c_{it}) + \lambda(c_{it})^2(\exp(\sigma_{(T+t)\,(T+t)})\text{-}1) > \lambda(c_{it})$. (See Aitchison and Ho, 1989, p.645.)

[17] The covariance between gun magazine subscriptions in year t and murders in year k is $\text{Cov}(s_{it}, c_{ik}) = \lambda(s_{it})\,\lambda(c_{it})(\exp(\sigma_{tk})\text{-}1)$.

[18] The intercept of the regression model will absorb the term $0.5\sigma_{ii}$, $0 \le i \le 2T$. Note that observation specific random effects in the Poisson-lognormal model neither require the assumption that the ε_{pi} are realizations from the same distribution nor that they are uncorrelated with the other covariates (the two main objections that are frequently raised against the least squares random effects model).

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_s & \boldsymbol{\Sigma}_{sc} \\ \boldsymbol{\Sigma}_{sc} & \boldsymbol{\Sigma}_c \end{bmatrix}, \tag{4}$$

where $\boldsymbol{\Sigma}_s$ is the covariance matrix of the T latent effects $\varepsilon(s_i)$, $\boldsymbol{\Sigma}_c$ is the covariance matrix of the T latent effects $\varepsilon(c_i)$, and $\boldsymbol{\Sigma}_{sc}$ is the covariance matrix of the $2T$ latent effects $\varepsilon(s_i)$ and $\varepsilon(c_i)$, $i = 1 \ldots N$. If $\sigma_{sc,tk}$ (the element in row t, column k of $\boldsymbol{\Sigma}_{sc}$) is non-zero, then the latent effect of the subscription equation for year k is correlated with the latent effect of the crime equation for year t.

Linear regression models have a simple link between correlations and regression coefficients (one is a scaled version of the other), but no such simple relationship exists in the non-linear Poisson-lognormal regression model. We therefore do not attempt any economic interpretation of our correlation estimates, but take them simply as indicators of whether the intertemporal relationships between magazine subscriptions and crime are positive or negative, and whether one lagged relationship exceeds the other in magnitude by any sizeable distance, given the estimated standard errors.

Because we do not impose any restrictions on $\boldsymbol{\Sigma}$, the model is able to capture any form of contemporaneous and intertemporal correlation. This is especially convenient because we do not have data for either 1991 or 1992. Most of the usual restrictions on $\boldsymbol{\Sigma}$ make it difficult to incorporate the data for 1990 while an unrestricted $\boldsymbol{\Sigma}$ accommodates this gap in the data quite naturally.[19]

The assumption that $\varepsilon(s_i)$ and $\varepsilon(c_i)$ are normally distributed introduces an integral into the likelihood function that does not have a closed form solution. Maximum

[19] This treatment of $\boldsymbol{\Sigma}$ follows Chib and Winkelmann (2001), who estimate a multivariate Poisson-lognormal model of airline incidents of 16 major US passenger air carriers, using an unrestricted covariance matrix that describes contemporaneous dependence between the airline incidents of all 16 carriers. By permitting intertemporal correlation as well, our model is slightly more general. Ibrahim *et al*. (2000) develop a multivariate Poisson-lognormal model for time-series count data, but they have only one group and therefore do not introduce contemporaneous correlation.

likelihood analysis of such a model would be fairly cumbersome, but it is straightforward to estimate the unknown coefficients with simulation-based methods. A Markov chain Monte Carlo (MCMC) method, the Gibbs sampler, is particularly well suited for this type of problem. We closely follow the setup suggested by Chib and Winkelmann (2001) and describe our implementation of the Gibbs sampler in Appendix 2.

3.2. The impact of omitted variables on the estimates of the covariance matrix **Σ**

The two covariate vectors $x(s_{it})$ and $x(c_{it})$ might not contain all relevant covariates that affect the number of crimes and magazine subscriptions. County-specific fixed effects are a standard approach to measure the effects of omitted variables that are mostly constant over time and that are hard to quantify. Such county-specific effects require redefining the parameters of the Poisson processes as

$$\begin{aligned}\mu^*(s_{it}) &= \exp\left(x(s_{it})'\beta_s + \gamma(s_i) + \varepsilon(s_{it})\right)\\ \mu^*(c_{it}) &= \exp\left(x(c_{it})'\beta_c + \gamma(c_i) + \varepsilon(c_{it})\right),\end{aligned} \tag{5}$$

where $\gamma(s_i)$ and $\gamma(c_i)$, $i = 1, \ldots, N$, represent the county-specific effects. Estimation of $\gamma(s_i)$ and $\gamma(c_i)$ is straightforward if sufficiently many observations on magazine subscriptions and crimes are available for every county. If only a few observations per county are available, then separate estimation of $2N$ county-specific effects might not be feasible. Omitting county-specific effects implies that the latent effect in each equation is the sum of the county-specific effect and the old latent effect, or

$$\begin{aligned}\mu^*(s_{it}) &= \exp\left(x(s_{it})'\beta_s + \varepsilon^*(s_{it})\right)\\ \mu^*(c_{it}) &= \exp\left(x(c_{it})'\beta_c + \varepsilon^*(c_{it})\right),\end{aligned} \tag{6}$$

where $\varepsilon^*(s_{it}) = \gamma(s_i) + \varepsilon(s_{it})$ and $\varepsilon^*(c_{it}) = \gamma(c_i) + \varepsilon(c_{it})$.

In the context of the Poisson-lognormal model, county-specific effects can be interpreted as realizations of two bivariate normally distributed random variables with mean vector $\nu = (\nu(s), \nu(c))'$ and covariance matrix $\Omega = ((\omega_s\ \omega_{sc})'(\omega_{sc}\ \omega_c)')$. The latent effects ε^* therefore follow a $2T$-variate normal distribution with mean vector ν^* and covariance matrix $\mathbf{\Sigma}^*$. Because each county-specific effect applies to all observations for a county, the first T elements of ν^* equal $\nu(s)$, and the second T elements of ν^* equal $\nu(c)$. Similar to equation 4, the covariance matrix $\mathbf{\Sigma}^*$ can be divided into the sub-matrices $\mathbf{\Sigma}_s^*$, $\mathbf{\Sigma}_c^*$, and $\mathbf{\Sigma}_{sc}^*$, with $\mathbf{\Sigma}_{s,tk}^* = \sigma_{s,tk} + \omega_s$, $\mathbf{\Sigma}_{c,tk}^* = \sigma_{c,tk} + \omega_c$, and $\mathbf{\Sigma}_{sc,tk}^* = \sigma_{sc,tk} + \omega_{sc}$. Because the elements of the sub-matrices of $\mathbf{\Sigma}$ and $\mathbf{\Sigma}^*$ differ by the same constants (ω_s, ω_c, and ω_{sc}), it is still possible to determine whether the covariances between magazine subscriptions and crimes differ across years, even if the county-specific effects are measured only through the latent effects.[20]

3.3 Monte Carlo simulation

One might ask whether a comparatively complex non-linear model that requires non-standard estimation techniques is worth the effort. We present the results of a Monte Carlo simulation that compares the estimates of a standard linear simultaneous equations model and a multivariate Poisson-lognormal model for the same correlated count data.[21] We used a bivariate Poisson-lognormal distribution to generate pseudo-random count

[20] In addition to omitting two sets of largely constant covariates, one might also omit a set of covariates Z that are correlated with magazine subscriptions and crimes but which are not constant across time and whose impact cannot be captured by county-specific fixed effects (this is the familiar “omitted variable bias” in a somewhat different setting).

[21] The purpose of undertaking the simulation is twofold: first and foremost, we want to motivate the use of our model for the type of data at hand. Second, we want to provide evidence that our estimation routines work as expected. Although self-programmed routines are indispensable tools to overcome the limitations of statistical packages, there is always the possibility that the routines are not debugged completely and that programming errors lead to meaningless results. We know from experience how easy it is to overlook small but nevertheless devastating errors, and we would generally accept empirical results more readily if they were accompanied by some evidence that the underlying computer code works properly. McCullough (1999) and McCullough and Vinod (1999) provide evidence that even commercial econometric software does not always yield correct results.

data with frequency distributions similar to those of the data on magazine subscriptions and murders, assuming a single covariate that alternates between 0 and 1.[22] To keep the experiment simple, we assumed that each group has only two observations and we sampled 18,000 observations per equation (that is, we assumed $T = 1$ and $N = 18{,}000$). Row 1 of Table 3 shows the coefficient values that we used to generate the data.

We first estimated the coefficients using the two regression equations $\ln y_i = \beta_1 + \beta_2 X_i, + \varepsilon_i$ where y_i, β_1, β_2, X_i, and ε_i are 2×1 vectors, β_1 and β_2 represent the reduced form parameters of a simultaneous equations model, and ε_i represents the (correlated) error terms of group i, $i = 1, 2$.[23] The coefficient estimates in Row 2 of Table 3 indicate that none of the 95 percent confidence intervals of the estimates of the four β's include the true parameter value. The Gibbs sampler estimates for the Poisson-lognormal model in Row 3 of Table 3, on the other hand, are very close to the actual values. Because the crime and subscription data are very similar to our artificially generated data, this suggests that the Poisson-lognormal model is more suitable for the data at hand.[24]

3.4 Covariates and data selection

In addition to year-specific effects, we included the following 16 covariates in each of the two equations of the means of gun magazine subscriptions and murders (all

[22] We obtained qualitatively identical results from an experiment with covariates that were sampled from a normal distribution with mean 0 and variance 1.

[23] To be able to use observations with zero value, we replaced all zero values with 0.1 before taking the logarithm. We obtained similar results when we eliminated all zero observations.

[24] It has been suggested to us that we should estimate a linear simultaneous equations model with state level data (which has no zeros) to avoid the problem that is posed by the many zeros in our county-level data. However, aggregation of county level data to the state level is likely to lead to aggregation bias because counties within a state are not homogeneous. Use of state level data avoids the difficulty posed by the zeros (which our model addresses) at the cost of an unknown aggregation bias. Of course, our county level data might suffer from aggregation bias as well, so that estimation on, say, the census tract level would be even more appropriate. Unfortunately, magazine subscription data are not available at a level more disaggregate than the county level. We do not accept the argument that, if one cannot avoid aggregation bias completely, then one might as well ignore the issue and use state-level data.

non-dummy variables are measured in logs): the percentage of county population between 10 and 19 years of age, between 20 and 29 years, between 30 and 39 years, between 40 and 49 years, between 50 and 64 years, over 64 years, the percentage of county population that is black, the percentage of county population that is female, the county average of real per capita personal income, the county average of real per capita unemployment insurance, the county average of real per capita income maintenance, the county average of real per capita retirement payments per person over 65, the county population density, the state unemployment rate, and two trend variables that measure the effects of adopting a shall-issue law.[25] We assume that the expected numbers of magazine subscriptions and murders are proportional to the county population, and include county population as a multiplicative constant with a coefficient of one.[26] This effectively weighs the estimates by county population.

Counties are fairly heterogeneous and our 16 covariates are unlikely to be the only determinants of gun magazine subscriptions and crimes; we therefore attempted to estimate a model that included county-specific effects (equation 5). Although the Gibbs sampler of this model seemed to converge for the covariance matrix $\mathbf{\Sigma}$, it failed to

[25] There is evidence that the adoption of a shall-issue law has a statistically significant impact on violent crimes (see, among others, Lott, 2000, and Plassmann and Tideman, 2001). The most likely explanation for this result is that arming potential victims raises the cost of committing a crime: criminals who face a greater risk of being shot while committing crimes are less likely to commit crimes. The two trend variables measure the trends in the number of crimes before and after the adoption of such a law.

[26] This restriction is plausible, because if two counties were to be combined into a single county, then the expected number of murders in the new larger county should equal the sum of the expected numbers of murders in the two smaller counties; this can only be achieved when population enters the regression equation multiplicatively with a coefficient of 1. See Chib and Winkelmann (2001) and Plassmann and Tideman (2001) for previous uses of such multiplicative constants. Because population density is defined as POP_{it} / $Area_{it}$, and $Area_{it}$ is constant for a county, substituting the log of population for the log of density as a covariate would affect only the coefficient of this variable but not the coefficients of the other covariates.

converge for the covariates and the year-specific effects.[27] We therefore decided to estimate the model without county-specific effects, so that our regression equations are

$$\begin{aligned}\mu^*(s_{it}) &= pop_{ct}\exp\left(x(s_{it})'\beta_s + \varepsilon^*(s_{it})\right)\\ \mu^*(c_{it}) &= pop_{ct}\exp\left(x(c_{it})'\beta_c + \varepsilon^*(c_{it})\right),\end{aligned} \tag{7}$$

where pop_{ct} is the population in county c in year t.[28] The derivation of $\mathbf{\Sigma}^*$ in Section 3.2 indicates that omitting constant county-specific effects shifts all elements of $\mathbf{\Sigma}^*_{sc}$ by a constant. Because we are mainly interested in the question of whether the elements of the covariance matrix vary in a systematic pattern, estimating county-specific effects through the latent effects does not affect our conclusions.

IV. Results

4.1 Analysis of murder

Table 4 shows estimates of the coefficients of the 16 covariates of our joint analysis of the number of murders and subscriptions to *Handguns Magazine*. The upper half of the table suggests that subscribers to *Handguns Magazine* are mainly males between 20 and 29 and over 40 years of age, and the number of subscriptions increases with income and decreases with population density. The percentage of the population that is black has a slight positive impact, while the state unemployment rate does not affect the number of subscriptions. Because we measure the covariates in logs, the

[27] We tried various versions of hierarchical centering as well as a wide variety of starting values.

[28] It has been suggested to us that we ought to regress crime on lagged subscriptions and subscriptions on lagged crime in two separate analyses as we did in our preliminary least squares analysis in Appendix 1. Given that magazine subscriptions and crimes are likely to be determined jointly, we consider a simultaneous equations model more appropriate. Also note that our estimate of the full 12×12 covariance matrix incorporates the complete correlation between subscriptions and crime as well as the correlation with all lead and lagged years of subscriptions and crime. Our model is therefore substantially more general than a model that includes only one or two lags.

coefficients represent elasticities. For example, our estimates imply that an increase in the unemployment rate by 1 percentage point raises the number of subscribers to *Handguns Magazine* by 2.95 percent.[29] These results are similar to previous research using survey evidence on gun ownership (Glaeser and Glendon, 1998, p. 460, and Lott, 2000).[30] The lower half of the table suggests that the number of murders is high in counties with an older population, a high population density, and a high percentage of blacks, and that the murder rate increases with per capita income.[31] The impact of the unemployment rate is positive but not statistically significant.[32]

Because differences in variances make it difficult to compare covariances across years, we followed Chib and Winkelmann (2001) and computed the correlation matrix $\boldsymbol{\Lambda}^* = (\mathrm{diag}(\boldsymbol{\Sigma}^*))^{-0.5}\boldsymbol{\Sigma}^*(\mathrm{diag}(\boldsymbol{\Sigma}^*))^{-0.5}$ from each run of the Gibbs sampler. Table 5 shows our estimates of the lower diagonal elements of the 12×12 correlation matrix $\boldsymbol{\Lambda}^*$ for gun magazine subscriptions and murders. The numbers behind the letters ‘S’ (subscriptions) and ‘M’ (murders) indicate the years; the horizontal and vertical lines divide the matrix

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[29] Note that the interpretation of the age coefficients is more complex. Because the percentages over all age groups need to sum to 100, our estimates do not imply that, for example, a one percent increase in the population between 10 and 19 years lowers subscriptions to Handguns Magazine by about 42 percent. If the percentage of the population between 10 and 19 increases, then the percentages of other age groups must simultaneously decrease, and the decrease of 42 percent must be added to the changes in subscriptions that result from the reductions of the other age groups. Because we do not know the simultaneous percentage changes of the other age groups, it is not possible to infer the total effect from the (marginal) age group coefficients.

[30] One difference with the Glaeser and Glendon results is that they find gun ownership to be highest for those between 20 and 29 and those over sixty.

[31] The estimates of the coefficients of the four trend variables that measure the before and after-adoption trends of shall issue laws suggest that adoption of such a law reverses an upward sloping trend in the number of subscriptions to gun magazines, while it flattens a downward sloping trend in the number of murders. Because alternative specifications did not affect our estimates of Σ and because the effect of shall issue laws is tangential to the current analysis, we leave further discussion for future research.

[32] Gould, Mustard, and Weinberg (2002) have argued that wages provide a better explanation of crime than the unemployment rate.

into the sub-matrices $\mathbf{\Lambda}_s^*$, $\mathbf{\Lambda}_c^*$, and $\mathbf{\Lambda}_{sc}^*$.[33] Note two interesting general results: first, the estimates of the correlations between murders in different years are fairly constant, which suggests that murders are not serially correlated.[34] Second, the estimates of the correlations between magazine subscriptions are relatively constant for the years 1993 to 1997, but much lower if they involve the year 1990, and the correlation between any two years of subscriptions decreases as the time period between them increases. This suggests that magazine subscriptions are serially correlated. Most estimates of the covariate coefficients of the covariates and especially of the correlations within $\mathbf{\Lambda}_s^*$and $\mathbf{\Lambda}_c^*$ are fairly intuitive, and we conclude that our model is unlikely to be badly misspecified.

The lower left quadrant of Table 5 shows the estimates of the correlations between the 6 years of magazine subscriptions and murders, $\mathbf{\Lambda}_{sc}^*$. The underlined numbers show the contemporaneous correlation between gun magazine subscriptions and murders; the italicized numbers show the one-year lagged correlation, and the bold numbers show the two-year lagged correlation. A disadvantage of not restricting the covariance matrix is that we obtain 15 different estimates of correlations instead of a single coefficient whose interpretation would be straightforward. It is interesting to note, however, that all correlations decrease between 1993 and 1997, and that several of the correlations in 1997 are statistically significantly higher than those in 1993. This shows the real benefit of estimating the full correlation matrix between any two years in the

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[33] The definitions of $\mathbf{\Lambda}s^*$, $\mathbf{\Lambda}c^*$, and $\mathbf{\Lambda}sc^*$ correspond to those of $\mathbf{\Sigma}s^*$, $\mathbf{\Sigma}c^*$, and $\mathbf{\Sigma}sc^*$.

[34] The estimates of the elements of $\mathbf{\Lambda}_c^*$ are positive and fairly sizeable (their mean value is 0.316) because $\mathbf{\Lambda}_c^*$ measures the effects of omitted variables in addition to the serial correlation between murders. The variance of the elements of $\mathbf{\Lambda}_c^*$ is very small (0.0013) which suggests that the serial correlation between murders in different years is fairly small as well (if the serial correlation were different from zero, then we would find it very surprising that the correlation does not decrease over time as it is the case with subscriptions).

sample. A more traditional model that assumes an identical lag structure across years would not have accounted adequately for such non-monotonic variations in serial and cross-correlation. While it is true that a model that assumes an identical lag structure would be easier to interpret because one would have to compare only 2 numbers instead of 30, we do not think that inference from such a misspecified model would be reliable. Unfortunately we do not know any way of summarizing our results other than to count and analyze the number of incidences in which one correlation exceeds the other.

Comparison of the correlations between murders and one-year lagged subscriptions and between subscriptions and one-year lagged murders does not indicate a clear pattern. The first correlation is higher in three instances (M94|S93 exceeds S94|M93, M95|S94 exceeds S95|M94, and M97|S96 exceeds S97|M96) and the second correlation exceeds the first in one case (S96|M95 exceeds M96|S95). Only the differences between the 95/96 and the 96/97 estimates exceed two standard errors. The results are similar for higher lags. In 6 instances (90/97, 90/95, 93/95, 93/97, 94/97, 95/97), the correlation between murders and two-year, three-year, four-year, five-year, and six-year lagged subscriptions exceeds the reverse correlation, while in the remaining 5 cases (90/93, 90/94, 90/96, 93/96, 94/96), the correlation between subscriptions and lagged murders exceeds the reverse correlation. The differences never exceed two standard errors.[35]

The latent effects ε^* capture the correlation between magazine subscriptions and murders as well as their correlations with omitted variables. Omitted covariates that are

[35] It would be interesting to determine what these estimates imply about the correlations between gun ownership (rather than subscriptions to *Handguns Magazine*) and murder rates. Moody and Marvell (2002) describe a method of translating one set of estimates into the other, using an estimate of the elasticity of gun ownership and magazine subscriptions. Unfortunately, their method applies only to linear models but not to our estimate of $\mathbf{\Lambda}^*$.

more or less constant during the six years do not affect the differences between the estimates of $\mathbf{\Lambda}_{sc}^{*}$ (see Section 3.2), but the omission of relevant non-constant covariates might affect the estimates of the elements of $\mathbf{\Lambda}_{sc}^{*}$. We illustrate the effect of omitting such non-constant covariates in Table 6, which shows the correlations between the elements of $\mathbf{\Lambda}^{*}$ in a model with only three covariates (percentage of county population between 10 and 29 years, state unemployment, and real per capita income).[36] The correlation between murders and lagged subscriptions exceeds the corresponding correlation between subscriptions and lagged murders in 12 out of 15 cases, even though this difference exceeds two standard errors only in two cases (90/95 and 93/95). On this basis, one might erroneously conclude that the correlation between murders and lagged subscriptions exceeds the corresponding reverse correlation. Because of the possibility that we may have omitted relevant non-constant covariates, it seems prudent to conclude only that our analysis fails to show differences between the estimates, rather than to conclude that there are no differences.

To circumvent the problem posed by data with many zeros and small integers, researchers often focus exclusively on counties with large populations. Such counties are likely to have large numbers of crimes, so that the problem of having 'too many zeros' does not arise. Researchers often examine only counties with more than 100,000 persons, which excludes about 25 percent of the United States population and more than two thirds of all counties from the analysis. It is often argued that the results from such an analysis apply to all counties. Table 7 shows the correlation matrix $\mathbf{\Lambda}^{*}$ that we estimated

[36] We chose these covariates to replicate Duggan's (2001) regression equation as closely as possible. See our brief discussion of Duggan's covariates in Section 2, footnote 11.

from large counties with populations of more than 100,000 persons.[37] The correlation between murders and lagged subscriptions exceeds the corresponding correlation between subscriptions and lagged murders in 13 out of 15 cases, and the difference exceeds two standard errors in eight cases. This suggests that there may be a causal relationship between higher subscription (that is, gun ownership) rates and higher murder rates in future years for large counties. No such relationship exists for all counties as a whole and the reverse appears to be true for rural counties.[38] The results of an analysis of large counties therefore do not apply to all counties (note that we weigh our two regression equations by county population).

4.2 Analyses of reported rapes and robberies

Tables 8 to 10 show the coefficient estimates and the estimates of $\mathbf{\Lambda}^*$ of analyses of the correlations between subscriptions to *Handguns Magazine* and reported rapes and robberies.[39] The estimates of $\mathbf{\Lambda}_{sc}^*$ for reported rapes and robberies do not indicate any recognizable pattern. The correlations between subscriptions and lagged rapes in Table 9 exceed the reverse correlations in 6 out of 15 cases, but this difference exceeds two standard errors in only two cases. The correlations between reported rapes and lagged subscriptions exceed the reverse correlations by more than two standard errors in 6 cases, but 5 of these are correlations between reported rapes in 1990 and future subscriptions. It is possible that this year somehow differed from the other years. We consider evidence

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[37] The reduced data set included 2,930 observations from 508 counties.

[38] We repeated the analysis using only data from the remaining counties that have populations of fewer than 100,000 persons, but the correlation matrix was similar to the matrix in Table 5. We did not determine which particular selection of smaller counties suggests the reverse causation.

[39] The estimates of the coefficients for the magazine subscription equation differed by less than one standard error from those reported in the upper part of Table 4, and are therefore not shown.

that stems mainly from a single year insufficient to suggest a general causal relationship between reported rapes and gun magazine sales.

The correlations between subscriptions and lagged robberies in Table 10 exceed the reverse correlations in 7 out of 15 cases. The differences exceed two standard errors in 8 cases, but four of these are correlations between subscriptions in 1993 and robberies in future years, while the other four are correlations between robberies in 1990 and subscriptions in future years. Again, the results are driven almost entirely by two years. Although there are several large differences for both crimes, the overall pattern does not suggest a clear pattern in either case. We repeated both analyses using only data from counties with populations of more than 100,000 persons. The estimated correlation matrices were very similar to those shown in Tables 9 and 10, and did not indicate that there is a significant difference between counties with small and counties with large populations in the cases of reported rapes and robberies.

V. CONCLUSION

It is possible that more guns will lead to more crimes and it is also possible that more crimes will lead to more guns. A simple analysis of the correlation between guns and crimes cannot differentiate between these two possibilities, which makes it necessary to examine the individual correlations between crime and gun ownership rates across time. We report the results of such an empirical simultaneous equations analysis that uses the number of subscriptions to *Handguns Magazine* as a proxy for gun ownership. If this proxy is adequate, then our analysis provides an insight into the relationship between handgun ownership and murders, reported rapes, and robberies.

We find little evidence that the correlation between today's number of subscriptions and future crimes exceeds the correlation between the today's crimes and future subscriptions. Our analysis suggests that if there are causal relationships between guns and crimes, then the relationships between guns and crimes and between crimes and guns are equally strong. Only our analysis of counties with populations of more than 100,000 persons provides some evidence that increases in the number of subscriptions cause the number of murders to increase, which indicates that urban and rural areas may face different relationships between guns and crime. However, we do not find similar evidence for causal relationships between the numbers of subscription and reported rapes and robberies, respectively, in counties with large populations.

Table 1. Sales rates of different gun magazines and estimated <u>state-level</u> relationship between changes in gun ownership and changes in gun magazine sales

	Number of national sales in 1999	Coefficient of percentage change in subscriptions to indicated magazine in explaining the percentage change in statewide gun ownership	
		Individual level	Household level
	(1)	(2)	(3)
	General gun magazines		
American Rifleman	1,328,805	0.0272** (0.0087)	0.0076* (0.0045)
American Hunter	1,027,854	0.0630** (0.0253)	0.0243 (0.0168)
North American Hunter	766,326	0.0200 (0.3704)	0.1000 (0.2439)
Guns&Ammo	569,109	0.0230 (0.0169)	0.0081 (0.0205)
	Handgun magazines		
Handguns Magazine	148,308	0.0710** (0.0267)	0.0310 (0.0208)
American Handgunner	147,110	0.0360** (0.0172)	0.0220** (0.0098)

Notes:

(1) The analyses in Column 2 use percentage changes in the reported rate at which individuals own guns as the dependent variable, and the analyses in Column 3 use percentage changes in a calculated rate at which households own guns.

(2) Estimated standard errors are shown in parentheses. A '**' indicates statistical significance at the 5 percent level, and a '*' indicates statistical significance at the 10 percent level.

Table 2. Frequency distributions of the data on murders, reported rapes, robberies, and on subscriptions to *Handguns Magazine*

	0	1	2	3	4	5	6	7	8	≥ 9
Number of murders	9609	2928	1653	961	681	415	337	239	168	1820
Number of rapes	5753	1755	1271	939	806	616	534	495	387	6255
Number of robberies	6400	1830	1159	795	635	487	407	368	314	6416
Number of subscriptions to *Handguns Magazine*	951	1158	1149	1103	1007	975	775	671	596	10426

Table 3. Results of the Monte Carlo Experiment

	Equation 1		Equation 2		Covariance matrix **Σ**		
	Intercept	Slope	Intercept	Slope			
	β_1	β_2	β_1	β_2	σ_{ss}	σ_{cc}	σ_{sc}
True values	2.0	1.0	0.5	-2.0	2	2	0.21
Linear simultaneous equation model	1.851 (0.0175)	1.090 (0.0247)	0.1536 (0.0166)	-1.645 (0.0234)	0.2967	0.6766	-0.4481
Poisson-lognormal model	2.0211 (0.0156)	0.9958 (0.0221)	0.4890 (0.0188)	-1.9827 (0.0301)	1.9937 (0.0243)	1.9734 (0.0398)	0.1931 (0.0211)

Notes:
(1) Estimated standard errors are shown in parentheses.
(2) In the linear simultaneous equations model, we used the covariance matrix of the residuals of both equations as estimates of Σ.
(3) We obtained the Poisson-lognormal results from 500 runs of the Gibbs sampler after a burn-in of 20 samples.

Table 4. Coefficient estimates of the analysis of subscriptions to *Handguns Magazine* and murders

	Mean	Standard deviation	Lower 2.5%	Upper 97.5%
	Dependent variable: Number of subscriptions to *Handguns Magazine*			
% between 10 and 19	-0.4157	0.1045	-0.6199	-0.2098
% between 20 and 29	0.1862	0.0646	0.0576	0.3077
% between 30 and 39	-0.5872	0.1077	-0.7945	-0.3701
% between 40 and 49	0.6603	0.1054	0.4542	0.8706
% between 50 and 64	0.1930	0.1030	-0.0057	0.3939
% 65 and over	-0.1570	0.0602	-0.2762	-0.0404
% black	0.0084	0.0038	0.0009	0.0156
% female	-0.9820	0.2545	-1.4861	-0.4975
Real per capita income	0.4505	0.0497	0.3529	0.5468
Real per capita unemp. ins.	0.0973	0.0103	0.0763	0.1178
Real per capita inc. maint.	-0.1640	0.0193	-0.2009	-0.1261
Real per capita ret. paym.	0.4210	0.0447	0.3329	0.5072
Population density	-0.0590	0.0075	-0.0734	-0.0442
Unemployment rate	0.0295	0.0205	-0.0099	0.0710
Shall issue trend (before)	0.0364	0.0038	-0.0440	-0.0290
Shall issue trend (after)	-0.0044	0.0029	-0.0013	0.0101
	Dependent variable: Number of murders			
% between 10 and 19	-1.0535	0.1782	-1.4164	-0.7057
% between 20 and 29	-0.4935	0.1118	-0.7124	-0.2741
% between 30 and 39	-0.7485	0.1959	-1.1346	-0.3646
% between 40 and 49	-0.7536	0.1900	-1.1237	-0.3862
% between 50 and 64	0.9739	0.1821	0.6111	1.3208
% 65 and over	-1.1428	0.1071	-1.3516	-0.9346
% black	0.1630	0.0070	0.1489	0.1767
% female	0.6637	0.4430	-0.2120	1.5465
Real per capita income	0.4445	0.0907	0.2709	0.6259
Real per capita unemp. ins.	-0.1470	0.0201	-0.1877	-0.1088
Real per capita inc. maint.	0.8061	0.0347	0.7370	0.8761
Real per capita ret. paym.	-0.1880	0.0824	-0.3440	-0.0247
Population density	0.0410	0.0120	0.0178	0.0650
Unemployment rate	0.0574	0.0498	-0.0444	0.1507
Shall-issue trend (before)	-0.0764	0.0066	-0.0636	-0.0892
Shall-issue trend (after)	-0.0062	0.0051	-0.0038	0.0159

Note: All variables except the shall-issue law trend dummies are measured in logs. Both regression equations are weighted by county population. Estimates of year specific effects are not shown. The entries in the columns 'Lower 2.5%' and 'Upper 97.5%' denote the lower 2.5th and upper 97.5th percentiles of the runs of the Gibbs sampler.
All results are based on 5,500 runs of which the first 500 were discarded. We used the program *Bayesian Output Analysis* (BOA) by Brian Smith, Department of Biostatistics, University of Iowa, for convergence diagnostics.

Table 5. Estimated correlation matrix Λ^* for the analysis of the number of gun magazine subscriptions and the number of murders

	S90	S93	S94	S95	S96	S97	M90	M93	M94	M95	M96	M97
S90	1											
	0											
S93	0.5275	1										
	(0.0187)	0										
S94	0.4726	0.7325	1									
	(0.0199)	(0.0115)	0									
S95	0.4871	0.7234	0.7125	1								
	(0.0204)	(0.0122)	(0.0125)	0								
S96	0.4567	0.6981	0.6873	0.7797	1							
	(0.0207)	(0.0129)	(0.0130)	(0.0101)	0							
S97	0.3598	0.5784	0.6234	0.6579	0.6564	1						
	(0.0219)	(0.0159)	(0.0147)	(0.0137)	(0.0135)	0						
M90	0.1184	0.1610*	0.1299*	0.1283	0.1211*	0.0888	1					
	(0.0267)	(0.0298)	(0.0305)	(0.0301)	(0.0306)	(0.0299)	0					
M93	0.1383	0.1775	*0.1376*	**0.1326**	0.1258*	0.0807	0.2920	1				
	(0.0274)	(0.0293)	(0.0295)	(0.0291)	(0.0289)	(0.0293)	(0.0254)	0				
M94	0.1234	*0.1514**	0.1069	*0.1093*	**0.1035***	0.0581	0.2871	0.3554	1			
	(0.0272)	(0.0283)	(0.0290)	(0.0292)	(0.0292)	(0.0292)	(0.0253)	(0.0244)	0			
M95	0.1392*	**0.1713***	*0.1295**	0.1326	*0.1303**	**0.0893**	0.2789	0.3517	0.3563	1		
	(0.0271)	(0.0295)	(0.0297)	(0.0296)	(0.0293)	(0.0287)	(0.0258)	(0.0239)	(0.0242)	0		
M96	0.0877	0.1062	**0.0658**	*0.0688*	0.0671	*0.0423*	0.2448	0.3192	0.3338	0.3350	1	
	(0.0271)	(0.0285)	(0.0288)	(0.0282)	(0.0287)	(0.0280)	(0.0257)	(0.0246)	(0.0248)	(0.0245)	0	
M97	0.1042*	0.1350*	0.0940*	**0.1040***	*0.1040**	0.0609	0.2540	0.3222	0.3423	0.3398	0.3260	1
	(0.0272)	(0.0301)	(0.0301)	(0.0296)	(0.0297)	(0.0297)	(0.0262)	(0.0251)	(0.0241)	(0.0244)	(0.0248)	0

Note: The numbers are the mean estimates of 5,500 runs of the Gibbs sampler of which the first 500 were discarded. The numbers in parentheses are the estimated standard errors. The label 'S' indicates 'subscriptions' and 'M' indicates 'murders;' the number indicates the year. An asterisk indicates that the correlation exceeds the reverse correlation.

Table 6. Estimated correlation matrix Λ^* for the analysis of the number of gun magazine subscriptions and the number of murders when only 3 covariates are included in each equation

	S90	S93	S94	S95	S96	S97	M90	M93	M94	M95	M96	M97
S90	1											
	0											
S93	0.5441	1										
	(0.0184)	0										
S94	0.4960	0.7605	1									
	(0.0195)	(0.0107)	0									
S95	0.5049	0.7520	0.7473	1								
	(0.0197)	(0.0111)	(0.0111)	0								
S96	0.4714	0.7272	0.7226	0.8081	1							
	(0.0198)	(0.0118)	(0.0118)	(0.0089)	0							
S97	0.3499	0.5930	0.6401	0.6824	0.6865	1						
	(0.0218)	(0.0156)	(0.0141)	(0.0131)	(0.0128)	0						
M90	0.0276	0.0329	-0.0165	-0.0422	-0.0266	-0.0354	1					
	(0.0257)	(0.0269)	(0.0267)	(0.0269)	(0.0266)	(0.0266)	0					
M93	0.0475*	0.0455	_-0.0066_	__-0.0352__	-0.0199	-0.0370	0.5640	1				
	(0.0252)	(0.0257)	(0.0254)	(0.0252)	(0.0249)	(0.0254)	(0.0190)	0				
M94	0.0287*	_0.0157_*	-0.0381	_-0.0619_	__-0.0458__*	-0.0613	0.5633	0.6042	1			
	(0.0248)	(0.0268)	(0.0264)	(0.0265)	(0.0260)	(0.0255)	(0.0189)	(0.0178)	0			
M95	0.0456*	__0.0355__*	_-0.0171_*	-0.0400	_-0.0221_*	__-0.0363__*	0.5567	0.5996	0.6022	1		
	(0.0249)	(0.0264)	(0.0262)	(0.0263)	(0.0260)	(0.0254)	(0.0189)	(0.0177)	(0.0172)	0		
M96	0.0064*	-0.0101*	__-0.0608__	_-0.0831_	-0.0646	_-0.0687_	0.5310	0.5726	0.5807	0.5770	1	
	(0.0242)	(0.0262)	(0.0263)	(0.0258)	(0.0255)	(0.0258)	(0.0197)	(0.0185)	(0.0185)	(0.0183)	0	
M97	0.0249*	0.0194*	-0.0320*	__-0.0482__	_-0.0289_*	-0.0466	0.5363	0.5774	0.5874	0.5824	0.5671	1
	(0.0248)	(0.0262)	(0.0266)	(0.0263)	(0.0260)	(0.0256)	(0.0201)	(0.0185)	(0.0181)	(0.0183)	(0.0187)	0

Note: The numbers are the mean estimates of 5,500 runs of the Gibbs sampler of which the first 500 were discarded. The numbers in parentheses are the estimated standard errors. The label 'S' indicates 'subscriptions' and 'M' indicates 'murders;' the number indicates the year. An asterisk indicates that the correlation exceeds the reverse correlation.

Table 7. Estimated correlation matrix Λ^* for the analysis of the number of gun magazine subscriptions and the number of murders, using only observations from counties with populations of more than 100,000 persons

	S90	S93	S94	S95	S96	S97	M90	M93	M94	M95	M96	M97
S90	1											
	0											
S93	0.6990	1										
	(0.0281)	0										
S94	0.5276	0.7706	1									
	(0.0373)	(0.0215)	0									
S95	0.7140	0.7303	0.6378	1								
	(0.0267)	(0.0247)	(0.0307)	0								
S96	0.6497	0.6719	0.5922	0.9100	1							
	(0.0305)	(0.0288)	(0.0329)	(0.0099)	0							
S97	0.4808	0.4230	0.5721	0.6128	0.6048	1						
	(0.0390)	(0.0414)	(0.0341)	(0.0326)	(0.0327)	0						
M90	0.2003	0.2416*	0.1026	0.0951	0.0632	-0.0570	1					
	(0.0514)	(0.0504)	(0.0530)	(0.0524)	(0.0532)	(0.0513)	0					
M93	0.1869	0.2464	*0.1035*	**0.0949**	0.0657	-0.0660	0.6475	1				
	(0.0499)	(0.0493)	(0.0512)	(0.0506)	(0.0510)	(0.0495)	(0.0372)	0				
M94	0.1710*	*0.2509**	0.1055	*0.1075*	**0.0788**	-0.0736	0.6347	0.8565	1			
	(0.0501)	(0.0489)	(0.0511)	(0.0501)	(0.0508)	(0.0497)	(0.0376)	(0.0182)	0			
M95	0.1965*	**0.2694***	*0.1309**	0.1385	*0.1121**	**-0.0147**	0.5938	0.8374	0.8543	1		
	(0.0499)	(0.0491)	(0.0505)	(0.0503)	(0.0509)	(0.0505)	(0.0398)	(0.0204)	(0.0183)	0		
M96	0.1598*	0.2292*	**0.0958***	*0.0970*	0.0734	*-0.0264*	0.5325	0.8031	0.8256	0.8362	1	
	(0.0507)	(0.0504)	(0.0511)	(0.0516)	(0.0520)	(0.0507)	(0.0440)	(0.0244)	(0.0219)	(0.0204)	0	
M97	0.1263*	0.2302*	0.1051*	**0.1324***	*0.1146**	-0.0530	0.5474	0.8029	0.8335	0.8322	0.8157	1
	(0.0516)	(0.0498)	(0.0507)	(0.0510)	(0.0516)	(0.0499)	(0.0424)	(0.0244)	(0.0203)	(0.0209)	(0.0228)	0

Note: The numbers are the mean estimates of 5,500 runs of the Gibbs sampler of which the first 500 were discarded. The numbers in parentheses are the estimated standard errors. The label 'S' indicates 'subscriptions' and 'M' indicates 'murders;' the number indicates the year. An asterisk indicates that the correlation exceeds the reverse correlation.

Table 8: Coefficient estimates of the analysis of subscriptions to *Handgun Magazine* and reported rapes/robberies

	Mean	Standard deviation	Lower 2.5%	Upper 97.5%
	Dependent variable: Number of reported rapes			
% between 10 and 19	-0.3450	0.2424	-0.8211	0.1264
% between 20 and 29	-0.1307	0.1552	-0.4391	0.1698
% between 30 and 39	0.1843	0.2452	-0.3017	0.6478
% between 40 and 49	-0.8139	0.2439	-1.2711	-0.3405
% between 50 and 64	-0.0394	0.2377	-0.5072	0.4323
% 65 and over	-0.4664	0.1401	-0.7476	-0.1935
% black	0.0811	0.0094	0.0628	0.0995
% female	0.6742	0.6198	-0.5012	1.8924
Real per capita income	0.9029	0.1161	0.6743	1.1345
Real per capita unemp. ins.	0.1222	0.0237	0.0770	0.1672
Real per capita inc. maint.	0.2966	0.0433	0.2115	0.3832
Real per capita ret. paym.	0.1361	0.0912	-0.0444	0.3165
Population density	0.0834	0.0179	0.0492	0.1176
Unemployment rate	-0.0427	0.0427	-0.1274	0.0392
Shall issue trend (before)	-0.0287	0.0062	-0.0407	-0.0168
Shall issue trend (after)	0.0006	0.0065	-0.0135	0.0118
	Dependent variable: Number of robberies			
% between 10 and 19	-0.9207	0.2366	-1.3709	-0.4530
% between 20 and 29	-0.4814	0.1535	-0.7850	-0.1804
% between 30 and 39	-0.4753	0.2546	-0.9612	0.0288
% between 40 and 49	-0.9941	0.2479	-1.4829	-0.5048
% between 50 and 64	-0.2709	0.2393	-0.7409	0.1943
% 65 and over	-0.8325	0.1362	-1.0942	-0.5683
% black	0.2730	0.0095	0.2542	0.2915
% female	0.8474	0.5836	-0.2836	1.9680
Real per capita income	1.5404	0.1137	1.3251	1.7658
Real per capita unemp. ins.	0.0590	0.0244	0.0108	0.1063
Real per capita inc. maint.	0.5688	0.0435	0.4823	0.6537
Real per capita ret. paym.	0.1791	0.0907	-0.0025	0.3543
Population density	0.3315	0.0176	0.2980	0.3671
Unemployment rate	0.1572	0.0442	0.0699	0.2457
Shall issue trend (before)	-0.0219	0.0064	-0.0346	-0.0097
Shall issue trend (after)	-0.0239	0.0068	-0.0373	-0.0109

Note: All variables except the shall issue trend dummies are measured in logs. Estimates of year specific effects are not shown. The entries in the columns 'Lower 2.5%' and 'Upper 97.5%' denote the lower 2.5th and upper 97.5th percentiles of the runs of the Gibbs sampler. All results are based on 5,500 runs of which the first 500 were discarded.

Table 9. Estimated correlation matrix Λ^* for the analysis of the number of gun magazine subscriptions and the number of reported rapes

	S90	S93	S94	S95	S96	S97	R90	R93	R94	R95	R96	R97
S90	1											
	0											
S93	0.5255	1										
	(0.0191)	0										
S94	0.4714	0.7299	1									
	(0.0198)	(0.0116)	0									
S95	0.4850	0.7215	0.7120	1								
	(0.0203)	(0.0124)	(0.0126)	0								
S96	0.4544	0.6973	0.6863	0.7793	1							
	(0.0207)	(0.0132)	(0.0134)	(0.0101)	0							
S97	0.3578	0.5782	0.6211	0.6572	0.6564	1						
	(0.0215)	(0.0162)	(0.0148)	(0.0139)	(0.0138)	0						
R90	<u>0.1645</u>	0.2212*	0.1533*	0.1756*	0.1801*	0.1657*	1					
	(0.0236)	(0.0223)	(0.0230)	(0.0226)	(0.0227)	(0.0224)	0					
R93	0.1285	<u>0.1857</u>	*0.1077*	**0.1366**	0.1476	0.1333	0.5922	1				
	(0.0238)	(0.0224)	(0.0229)	(0.0229)	(0.0226)	(0.0225)	(0.0169)	0				
R94	0.1082	*0.1798**	<u>0.1024</u>	*0.1359**	**0.1506***	0.1405*	0.7160	0.6514	1			
	(0.0237)	(0.0222)	(0.0221)	(0.0222)	(0.0222)	(0.0218)	(0.0134)	(0.0151)	0			
R95	0.1036	**0.1776***	*0.1042*	<u>0.1379</u>	*0.1537**	**0.1445**	0.7096	0.6500	0.8380	1		
	(0.0236)	(0.0224)	(0.0225)	(0.0225)	(0.0222)	(0.0222)	(0.0137)	(0.0152)	(0.0079)	0		
R96	0.0924	0.1740*	**0.0977**	*0.1297*	<u>0.1448</u>	*0.1270*	0.6831	0.6178	0.8034	0.8132	1	
	(0.0237)	(0.0220)	(0.0224)	(0.0223)	(0.0223)	(0.0222)	(0.0143)	(0.0159)	(0.0094)	(0.0090)	0	
R97	0.0941	0.1774*	0.1054	**0.1447***	*0.1573**	<u>0.1395</u>	0.6790	0.6196	0.7953	0.8062	0.8051	1
	(0.0234)	(0.0221)	(0.0225)	(0.0222)	(0.0222)	(0.0223)	(0.0145)	(0.0160)	(0.0097)	(0.0096)	(0.0093)	0

Note: The numbers are the mean estimates of 5,500 runs of the Gibbs sampler of which the first 500 were discarded. The numbers in parentheses are the estimated standard errors. The label 'S' indicates 'subscriptions' and 'R' indicates 'reported rapes;' the number indicates the year. An asterisk indicates that the correlation exceeds the reverse correlation.

Table 10. Estimated correlation matrix Λ^* for the analysis of the number of gun magazine subscriptions and the number of robberies

	S90	S93	S94	S95	S96	S97	R90	R93	R94	R95	R96	R97
S90	1											
	0											
S93	0.5300	1										
	(0.0192)	0										
S94	0.4730	0.7325	1									
	(0.0202)	(0.0117)	0									
S95	0.4869	0.7231	0.7119	1								
	(0.0206)	(0.0123)	(0.0123)	0								
S96	0.4559	0.6975	0.6863	0.7786	1							
	(0.0206)	(0.0132)	(0.0132)	(0.0100)	0							
S97	0.3565	0.5756	0.6215	0.6552	0.6539	1						
	(0.0219)	(0.0164)	(0.0148)	(0.0141)	(0.0141)	0						
R90	0.2667	0.3210*	0.2524*	0.2655*	0.2517*	0.1716*	1					
	(0.0231)	(0.0218)	(0.0225)	(0.0225)	(0.0226)	(0.0235)	0					
R93	0.2120	0.2706	_0.1894_	__0.2041__	0.1967	0.1414	0.6135	1				
	(0.0236)	(0.0216)	(0.0226)	(0.0224)	(0.0220)	(0.0228)	(0.0160)	0				
R94	0.2093	_0.2838_*	0.2006	_0.2234_*	__0.2216__*	0.1598	0.5973	0.7927	1			
	(0.0238)	(0.0212)	(0.0222)	(0.0221)	(0.0216)	(0.0224)	(0.0165)	(0.0100)	0			
R95	0.2064	__0.2792__*	_0.2006_	0.2195	_0.2197_*	__0.1572__	0.5747	0.7818	0.8216	1		
	(0.0236)	(0.0215)	(0.0226)	(0.0219)	(0.0219)	(0.0221)	(0.0166)	(0.0102)	(0.0086)	0		
R96	0.1716	0.2425*	__0.1616__	_0.1877_	0.1888	_0.1310_	0.5139	0.7245	0.7717	0.7850	1	
	(0.0236)	(0.0215)	(0.0223)	(0.0219)	(0.0217)	(0.0221)	(0.0180)	(0.0120)	(0.0105)	(0.0101)	0	
R97	0.1707	0.2412*	0.1623*	__0.1946*__	_0.1953_*	0.1323	0.5354	0.7443	0.7840	0.7965	0.7821	1
	(0.0234)	(0.0219)	(0.0222)	(0.0221)	(0.0214)	(0.0223)	(0.0176)	(0.0114)	(0.0101)	(0.0099)	(0.0100)	0

Note: The numbers are the mean estimates of 5,500 runs of the Gibbs sampler of which the first 500 were discarded. The numbers in parentheses are the estimated standard errors. The label 'S' indicates 'subscriptions' and 'R' indicates 'robberies;' the number indicates the year. An asterisk indicates that the correlation exceeds the reverse correlation.

APPENDIX 1: REPETITION OF DUGGAN'S (2001) LEAST SQUARES ANALYSES WITH OUR *HANDGUNS MAGAZINE* DATA.

We report the results of two preliminary least squares analyses of our *Handguns Magazine* data set that we compare with county-level results reported by Duggan (2001). Duggan (2001) undertakes two county-level analyses: first he regresses the change in the log-homicide rate on the one-period lagged change in the log-homicide rate, $\Delta\ln(M_{t\text{-}1})$, and on the one-period lagged change in the log-subscription rate to *Guns&Ammo*, $\Delta\ln(S_{t\text{-}1})$.[40] He then repeats the analysis with the change in the log-subscription rate to *Guns&Ammo* as the dependent variable.[41] Because almost half of the observations on changes in homicides are zero, he restricts his analyses to counties with populations of more than 100,000 persons to circumvent the difficulties that arise with data that have a mass point at zero. Table A.1, Columns 1 and 2, show the results that he reports.[42] We repeat his analysis using data from counties with populations that exceed 100,000 persons (Table A.1, Columns 3 and 4), and we also undertake an analysis that uses data from all counties (Table 1, Columns 5 and 6).[43]

The conclusions that one might draw from his and our least squares analyses differ considerably. While our estimates of the coefficient of $\Delta\ln(M_{t\text{-}1})$ are very similar to Duggan's estimates, our estimates of the coefficient of $\Delta\ln(S_{t\text{-}1})$ are very different.

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[40] Duggan also includes the percentage of population between 18 and 24, the real per capita income, the state unemployment rate, and year fixed effects, and weights both equations by county population. He does not indicate whether he took account of the correlation in the residuals that is likely to result from the simultaneity of subscriptions and murders. We treated the regressions reported in Table A1 as unrelated, and did not account for correlation between the residuals.

[41] Duggan undertakes two additional analyses that include two-period lags of homicide rates and subscription rates, as well as county trend dummies. Because our data set includes only five consecutive years, we decided not to repeat those analyses.

[42] The numbers are taken from his Table 8, Columns 1 and 5 (Duggan, 2001, p.1102).

[43] To avoid taking the logarithm of zero, we follow the usual (mal)practice of replacing all observations of zero with 0.1.

Duggan reports estimates that are statistically significantly positive coefficient for the murder equation, but our estimates are virtually zero and not statistically significant (Columns 1, 3, and 5). Conversely, while Duggan's estimate for the subscription equation is not statistically different from zero, our estimate is negative and statistically significant. Taken together, Duggan's estimates suggest a causal relationship between increases in subscriptions to *Guns&Ammo* and increases in murder rates. Neither of our two analyses suggests such a causal relationship; our results simply indicate that there is considerable regression to the mean in murder as well as subscription rates. We tested additional specifications with the whole set of covariates that we describe in Section 4 of our paper, and the results remained the same.

Moody and Marvell (2002) point out that the above interpretation of causality from Duggan's results requires that subscriptions to *Guns&Ammo* are a one-to-one proxy for gun ownership. Using national data on gun sales, they argue that simply regressing homicides on *Guns&Ammo* magazine sales overestimates the relationship from guns to homicide by a factor of 3, thus underestimating the relationship from homicide to guns by an equal amount. Duggan (2001, p.1093) estimates that the elasticity of *GSS* gun ownership with respect to subscriptions to *Guns&Ammo* is 0.354. Moody and Marvel (2002, pp. 2-4) use this estimate to argue that the long-run elasticity of *guns* (<u>not</u> subscriptions to *Guns&Ammo*) with respect to homicide is 0.147 and the long-run elasticity of homicides with respect to *guns* is 0.090, and that there is no statistically significant difference between the two elasticities.[44] We estimate that the elasticity of *GSS* gun ownership with respect to subscriptions to *Handguns Magazine* is 0.7665 with a

[44] Repeating their analysis for the county-level estimates in Columns 1 and 2 of Table 1 yields an elasticity of guns with respect to homicide of 0.0354 and an elasticity of homicides with respect to guns of -0.0846.

standard error of 0.4770.[45] Together with our estimates in Columns 3 and 4 of Table A.1, this suggests that the long-run elasticity of guns with respect to homicide is 0.004 and the long-run elasticity of homicides with respect to guns is –0.0037; the two estimates are not statistically significantly different from each other.

It is interesting to compare our least-squares results with the results from our Poisson-lognormal analyses in Section 4 of our paper. For the data set that includes all counties and the whole set of covariates, we find that murder and subscription rates are intertemporally correlated, although we do not find a pattern that would suggest a causal relationship from guns to murders. However, when we use the reduced set of covariates, our Poisson-lognormal analysis (Table 7 in the paper) suggests that the correlation between past subscription rates and current murder rates exceeds the correlation between past murder rates and current subscription rates. That is, the results from our Poisson-lognormal analysis of large counties yields are similar to Duggan's results, but they differ considerably from our least squares estimates. It would therefore be informative to analyze Duggan's data set (to which we have no access) with the Poisson-lognormal model to determine whether the two data sets are qualitatively different, or whether his results would remain unchanged if his data were analyzed with a more appropriate statistical model.

REFERENCES FOR APPENDIX 1:

Duggan, Mark. 2001. "More Guns, More Crime." *Journal of Political Economy*, **109**: pp.1086-1114.

Moody, Carlisle and Thomas Marvel, "Pitfalls of Proxy Variables: Inferring the Relationship between Guns and Crime with no Data on Guns." College of William and Mary working paper, 2002.

[45] We used weighted (by state population) least squares to estimate ln(*GSS* gun ownership) = $a + b$ ln(sales of *Handguns Magazine*) + state fixed effects + year fixed effects.

Table A.1 Least squares county-level estimates of the relationship between changes in the rates of murders and gun ownership

	Results reported by Duggan (2001, Table 8) with data on subscriptions to *Guns&Ammo* between 1980 and 1998		Results obtained with data on subscriptions to *Handguns Magazine* between 1993 and 1997			
	Use only counties with more than 100,000 persons		Use only counties with more than 100,000 persons		Use data from all counties	
	$\Delta\ln(M_t)$	$\Delta\ln(S_t)$	$\Delta\ln(M_t)$	$\Delta\ln(S_t)$	$\Delta\ln(M_t)$	$\Delta\ln(S_t)$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln(M_{t-1})$	-0.425*	0.001	-0.488*	-0.004	-0.487*	0.007
	(0.024)	(0.003)	(0.055)	(0.013)	(0.034)	(0.008)
$\Delta\ln(S_{t-1})$	0.142*	-0.030	0.008	-0.424*	-0.007	-0.391*
	(0.054)	(0.032)	(0.045)	(0.168)	(0.028)	(0.106)
Observations	7,766	7,963	1,498	1,498	9,407	9,407
R^2	0.201	0.260	0.200	0.157	0.211	0.156

Note: '*M*' stands for 'murder,' and '*S*' stands for 'subscription to a gun magazine.' White standard errors are shown in parentheses. An asterisk indicates statistical significance on the 5 percent level. Coefficient estimates of the other three covariates and the year fixed effects are not shown. Each regression is weighted by county population. To avoid taking the logarithm of zero, we follow the usual (mal)practice of replacing all observations of zero with 0.1.

APPENDIX 2: ESTIMATION OF THE MULTIVARIATE POISSON-LOGNORMAL MODEL WITH THE GIBBS SAMPLER

Implementation of the Gibbs sampler requires knowledge of the full-conditional distributions of all parameters of interest. Such full conditional distributions are derived from the joint distribution of the data and the model parameters of interest. In our model, the parameters of interest are the two parameter vectors that describe the impact of the 16 covariates and the year dummies, β_s and β_c, as well as the covariance matrix Σ.

Denote the collections of numbers of magazine subscriptions and crimes for all counties i, $i = 1, ..., N$ and all years t, $t = 1, \dots, T$, by the vectors $s = (s_{11}, \dots, s_{TN})$ and $c = (c_{11}, \dots, c_{TN})$, respectively, and the two sets of covariates by the $NT\times16$ matrices $X(s)$ and $X(c)$, where $X(s_{it})$ and $X(c_{it})$ are the $(it)^{\text{th}}$ rows of $X(s)$ and $X(c)$. We assume that s_{it} and c_{it} follow univariate Poisson distributions with density functions $f_P(s_{it} \mid \mu(s_{it}))$ and $f_P(c_{it} \mid \mu(c_{it}))$, with $\mu(s_{it}) = \exp(X(s_{it})\beta_s + \varepsilon^*(s_{it}))$ and $\mu(c_{it}) = \exp(X(c_{it})\beta_c + \varepsilon^*(s_{it}))$. We introduce correlation between s_{it} and c_{it}, by assuming that the latent effects $\varepsilon^* = (\varepsilon^*(s_{i1}),...,\varepsilon^*(s_{iT}),\varepsilon^*(c_{i1}),...\varepsilon^*(c_{iT}))'$ follow a $2T$-variate normal distribution with density function $f_{\varepsilon^*}(0, \mathbf{\Sigma}^*)$. The distributional assumptions on ε^* imply that all latent effects of county i are dependent on each other across years and across subscriptions/crimes.

With respect to the specification of the priors of the parameters of interest, we follow the standard assumptions that β_s and β_c follow multivariate normal distributions with density functions $f_\beta(\beta_s \mid b_s, B_s^{-1}))$ and $f_\beta(\beta_c \mid b_c, B_c^{-1}))$, respectively, and that the inverse of the covariance matrix Σ^* follows a Wishart distribution with density function

$f_{\mathbf{\Sigma}^*}(\mathbf{\Sigma}^{*-1} \mid \delta, R)$. These assumptions yield the posterior density function $f(s, c, \beta_s, \beta_c, \Sigma^* | X(s), X(c))$ as

$$\begin{aligned}
f(s,c,\beta_s,\beta_c,\mathbf{\Sigma}^* \mid X(s), X(c)) = {} & \prod_{i=1}^{N}\prod_{t=1}^{T} f_P\left(s_{it} \mid \mu(s_{it})\right) \cdot \prod_{i=1}^{N}\prod_{t=1}^{T} f_P\left(c_{it} \mid \mu(c_{it})\right) \cdot \\
& \prod_{i=1}^{N} f_{\varepsilon^*}(0, \mathbf{\Sigma}^*) \cdot \\
& f_{\mathbf{\Sigma}^*}(\mathbf{\Sigma}^{*-1} \mid \delta, R)) \cdot \\
& f_\beta(\beta_s \mid b_s, B_s^{-1})) \cdot f_\beta(\beta_c \mid b_c, B_c^{-1})), \\
\mu(s_{it}) = {} & X(s_{it})\beta_s + \varepsilon^*(s_{it}), \\
\mu(c_{it}) = {} & X(c_{it})\beta_c + \varepsilon^*(c_{it}).
\end{aligned} \tag{A1}$$

Convergence of the Gibbs sampler will be slow if the posterior correlations of the parameters are high, and reparameterization can help to reduce the posterior correlations.[46] We follow Ibrahim *et al*. (2000) and center the latent effects on their means, so that $\varepsilon^*(s_{it}) = \mu(s_{it}) - X(s_{it})\beta_s$ and $\varepsilon^*(c_{it}) = \mu(c_{it}) - X(c_{it})\beta_c$. This permits us to write the posterior density as

$$\begin{aligned}
f(s,c,\beta_s,\beta_c,\mathbf{\Sigma}^* \mid X(s), X(c)) = {} & \prod_{i=1}^{N}\prod_{t=1}^{T} f_P\left(s_{it} \mid \mu(s_{it})\right) \cdot \prod_{i=1}^{N}\prod_{t=1}^{T} f_P\left(c_{it} \mid \mu(c_{it})\right) \cdot \\
& \prod_{i=1}^{N} f_{\varepsilon^*}(\mu_i - X_i\beta, \mathbf{\Sigma}^*) \cdot \\
& f_{\mathbf{\Sigma}^*}(\mathbf{\Sigma}^{*-1} \mid \delta, R)) \cdot \\
& f_\beta(\beta_s \mid b_s, B_s^{-1})) \cdot f_\beta(\beta_c \mid b_c, B_c^{-1})),
\end{aligned} \tag{A2}$$

where $\mu_i = \left(\mu(s_{i1}),\ldots,\mu(s_{iT}),\mu(c_{i1}),\ldots,\mu(c_{iT})\right)'$, $X_i = \left(X(s_{i1}),\ldots,X(s_{iT}),X(c_{i1}),\ldots,X(c_{iT})\right)'$ and $\beta = \left(\beta_s, \beta_c\right)'$. Besides reducing the posterior correlation and thereby improving convergence, centering the latent effects removes the coefficients of the covariates from

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[46] See, for example, Gelfand *et al*. (1995).

$f_P(s_{it} \mid \mu(s_{it}))$ and $f_P(c_{it} \mid \mu(c_{it}))$. The centered model in (A2) leads to full conditional distributions of β that are multivariate normal, while the full conditional distributions of β that emerge from the non-centered model in (A1) can be determined only up to the normalizing constant. Sampling from non-standard distributions is time consuming, while sampling from multivariate normal distributions is very fast. This makes it possible to update all components of β for each equation simultaneously, even if the number of covariates is large. Simultaneous updating of the model components greatly improves mixing of the Gibbs sampler.

It is straightforward to show that the full conditional distributions of β_s and β_c that follow from the model assumptions in (A2) are multivariate normal, or[47]

$$\begin{aligned}\beta_s \mid \cdot \sim N\left[V_s^{-1}\left(B_s^{-1}b_s + \sum_{i=1}^{N} X(s_i)\mathbf{\Sigma}^{*-1}\eta\right);V_s\right],\\ \beta_c \mid \cdot \sim N\left[V_c^{-1}\left(B_c^{-1}b_c + \sum_{i=1}^{N} X(c_i)\mathbf{\Sigma}^{*-1}\eta\right);V_c\right],\end{aligned} \qquad \text{(A3)}$$

with

$$\begin{aligned}V_s &= \left(B_s^{-1} + \sum_{i=1}^{N} X(s_i)\mathbf{\Sigma}^{*-1}X(s_i)'\right),\\ V_c &= \left(B_c^{-1} + \sum_{i=1}^{N} X(c_i)\mathbf{\Sigma}^{*-1}X(c_i)'\right).\end{aligned}$$

Similarly, the full conditional distribution of Σ^{-1} is Wishart, or[48]

$$\mathbf{\Sigma}^{-1} \mid \cdot \sim W\left[\left(R + \sum_{i=1}^{N}(\mu_i - X_i\beta)(\mu_i - X_i\beta)'\right)^{-1}, \delta + N\right]. \qquad \text{(A4)}$$

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[47] The dot indicates the full set of conditioning variables.

[48] See, for example, Gelfand *et al*. (1990, p.979).

For both distributions, very efficient algorithms are available to generate pseudo random numbers.[49] The densities of the full conditional distributions of $\mu(s_{it})$ and $\mu(c_{it})$ can be derived only up to the normalizing constant, so that

$$\begin{aligned} f(\mu(s_{it})) &\propto f_P\left(s_{it} \mid \mu(s_{it})\right) \cdot f_{\varepsilon^*}(\mu_i - X_i\beta, \mathbf{\Sigma}), \\ f(\mu(c_{it})) &\propto f_P\left(c_{it} \mid \mu(c_{it})\right) \cdot f_{\varepsilon^*}(\mu_i - X_i\beta, \mathbf{\Sigma}). \end{aligned} \tag{A5}$$

Chib *et al*. (1998) show how to use the Metropolis-Hastings algorithm to sample from (A5). Because these distributions are log-concave, one can also use the adaptive rejection method of Gilks and Wild (1992) to draw samples from these distributions.[50]

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[49] To generate samples from the multivariate normal distribution, we used the algorithm based on the Cholesky decomposition that is described in Ripley (1987, pp. 98-99). To generate samples from the Wishart distribution, we used the algorithm described in Odell and Feiveson (1966).

[50] See, for example, Chen *et al*. (2000, p.42).

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