SYSTEMATIC MEASUREMENT ERROR WITH STATE-LEVEL CRIME DATA: EVIDENCE FROM THE "MORE GUNS, LESS CRIME" DEBATE

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Researchers have recently been cautioned regarding error in the Uniform Crime Reports' (UCR) "Crime by County" cross-sectional time-series data. These data were the basis for analyses of the effects of laws regarding shall-issue concealed carry weapons (CCW) permits on UCR crime rates in the controversial book More Guns, Less Crime *(*MGLC*). The authors conduct a critical analysis of the state-level data used in that study, compare it to readily available state-level UCR data, and discuss issues that may unduly influence the* MGLC *parameter estimates. Using alternative data, they reestimate the* MGLC *models, finding that the majority of the* MGLC *state-level findings are mere artifacts of reporting error and data anomalies resulting from the use of aggregated UCR "Crime by County" data. The authors conclude that any inferences regarding the effects of concealed carry weapons laws on crime rates drawn from analyses of the* MGLC *state-level data are seriously flawed.*

Keywords: *UCR; state-level crime data; crime statistics; aggregation; guns*

In a recent article, Maltz and Targonski (2002) present a thoughtful analysis of errors and their sources in county-level Uniform Crime Reporting (UCR) Program data[1] available from the National Archive of Criminal Justice Data (NACJD) at the Inter-university Consortium for Political and Social Research (ICPSR). These data sets are based on FBI-UCR "Crime by County" files and present counts of arrests and offenses for the Part I index crimes of murder, rape, robbery, assault, burglary, larceny, auto theft, and arson. These data were used by John Lott (2000) for his analyses of the adoption of laws regarding shall-issue concealed carry weapons (CCW) permits in his book *More Guns, Less Crime* (*MGLC*).[2] Maltz and Targonski (2002) conclude that due to errors in reporting, double counting, and imputation, the county-level data "cannot be used with any degree of confidence" (p. 316). Lott and Whitley (2003) have criticized Maltz and Targonski (2002), stating

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that they "provide no systematic test for how bad the data are," nor "provide evidence for the more important issue of whether there is a systematic bias in the data" (2003:197).

Maltz and Targonski (2002) state that the second edition of *MGLC* "includes state-level analyses, which are not subject to this particular problem" (p. 298). However, Lott himself "suggests caution in aggregating these data into such large units as states" (Lott and Mustard 1997:26), noting his "results also confirm some of the potential aggregation problems with state-level data" (Lott 2000:95; see also, Lott and Whitley 2003:197), and commenting that "aggregating observations into such large units as states is a bad idea" (Lott 2000:60; see also, Maltz and Targonski 2002:317).

Ayres and Donohue (2003a, 2003b) have also taken issue with the robustness of the *MGLC* state-level data set. In this attempted replication of the *MGLC* hypotheses they discard the *MGLC* data for state-level UCR data, and produce very different results than are reported by Lott (Ayres and Donohue 2003a:1224-5; 2003b). Although they do use different crime data, they continue to use Lott's arrest rate data,[3] and do not offer any detailed explanation for their choice.

Despite these conflicting assertions, and surprisingly, no one has yet examined the integrity of the state-level *MGLC* data itself, even though numerous research studies aimed at the heart of the gun control debate continue to perform increasingly complex analyses that draw contradictory conclusions and inferences from those data (cf. Plassmann and Whitley 2003).

Many criminologists find these discussions to be lacking in their scope of application, beyond the analysis of firearms control and CCW laws. In spite of this criticism, further analysis of these data provides us with insight into a wider spectrum of problems associated with using state-level data, especially those that are aggregated from county-level reports. The Lott-Mustard data are simply used here as a case study to further examine potential difficulties with these types of crime data.

We have examined the data involved in this issue and find that the *MGLC* state-level crime data are indeed, simply put, wrong. We emphasize that our purpose here is not to assert that any findings we present support or refute any hypotheses, but rather, to only examine the validity and reliability of the data with which they are tested, and to show that data make a difference. Nor do we wish to impugn Lott and Mustard's efforts, or imply any malicious intent on their part, as we are aware "it is only recently that sufficient attention has been paid to the detailed characteristics of the UCR to bring its limitations to the fore" (Maltz and Targonski 2002:298). Rather, we attempt to clarify Maltz and Targonski's (2002) erroneous assumption that the state-level *MGLC* data analyzed by Lott, and others, do not suffer from the problems described in their article, by providing evidence of "systematic bias in the data" that shows "how bad the data are" (Lott and Whitley 2003:197). Clarification of this issue has important and obvious methodological and policy implications for researchers using aggregated UCR county data and the *MGLC* data set, as well as those involved in the gun-control debate. In addition, our study adds to the literature by being one of the very few studies to use data other than the *MGLC* data to examine the effects of concealed carry weapons laws on state-level crime rates (see, e.g., Ludwig 1998; Ayres and Donohue, 2003a).

DATA

We obtained and analyzed (to various degrees) four separate data sets.[4] We initially requested and received the state-level *MGLC* data from John Lott. Our preliminary analyses consisted of comparing these data to state-level UCR annual time-series data available online in spreadsheet format from the Bureau of Justice Statistics (BJS) (U.S. Department of Justice, FBI 1998). However, each state-level UCR data set cautions that the "data were provided by the FBI and have not been independently verified by BJS."[5] These data therefore appear to be presented by the BJS exactly as provided by the FBI, without manipulation. These data will hereafter be referred to as "UCR" data in order to differentiate it from the *MGLC* data.

The state-level UCR data exhibit several characteristics indicative of their reliability. First, they are very consistent with, and predominantly identical to, UCR data available in print editions of *Crime in the United States*. Second, the UCR data are consistent over time, changing smoothly and without volatile shifts in either direction; this is exactly what one would expect with time-series data, as most social variables tend to change smoothly and predictably over time. There are, however, some differences between the two data sources, specifically in how crime counts and population estimates are obtained, that could influence specific parameter estimates, if used in complex analysis.[6]

Data Errors

Our initial comparison of the state-level *MGLC* and UCR data showed several inconsistencies. Some crime rate data differed greatly between the two sets, although the data in both sets for 1993 through 1997 are nearly identical. We noted, in particular, differences for New York in 1980; state-level *MGLC* data show a violence rate per 100,000 population of 455.91 and a robbery rate of 69.57, compared to state-level UCR rates of 1,029.5 and 641.3, respectively. State-level *MGLC* data for New York motor vehicle theft in

TABLE 1: Comparison of County-Level Data for Alaska, 1984

MGLC *Data*				*ICPSR/NACJD 8714*		
Population	*Burglary*	*Burglary Rate/ 100k*	*County*	*Population*	*Burglary*	*Burglary Rate/ 100k*
223,316	3,151	1,411	2020	220,224	3,151	1,431
1,945	1,992	102,416	2070	3,752	1,992	53,092
28,176	19,306	68,519	2090	68,288	19,306	28,271
24,298	16,447	67,689	2110	26,204	16,447	62,765
13,309	9,164	68,856	2122	36,032	9,164	25,433
8,956	6,133	68,479	2130	13,676	6,133	44,845
5,918	4,023	67,979	2150	12,060	4,023	33,358
2,664	1,816	68,168	2170	32,016	1,816	5,672
2,863	1,959	68,425	2180	7,964	1,959	24,598
5,494	4,343	79,050	2185	4,875	4,343	89,087
656	1,256	191,463	2201	5,513	1,256	22,783
9,709	6,579	67,762	2220	8,258	6,579	79,668
956	654	68,410	2231	3,905	654	16,748
2,338	1,604	68,606	2261	10,052	1,604	15,957
6,227	4,238	68,058	2280	7,029	4,238	60,293

NOTE: *MGLC = More Guns, Less Crime*; ICPSR = Inter-university Consortium for Political and Social Research; NACJD = National Archive of Criminal Justice Data.

1980 show a rate of 186.9, compared to 759.9 for the UCR data, and, in 1987, the *MGLC* New York motor vehicle theft rate is 69.84, compared to 703.1 for the UCR data. We assumed that these were data-entry errors.

County-Level Data Anomalies

However, upon examination of basic descriptive statistics, we immediately began to notice anomalistic patterns in the *MGLC* data that could not result from mechanistic entry mistakes. Descriptive frequency statistics immediately drew our attention to immense differences among the 1984 state-level data for Alaska. For instance, the UCR data indicated a burglary rate of 1,236.80, whereas the *MGLC* data showed a burglary rate of 17,976.58.

These results intrigued us enough to obtain the original county-level *MGLC* data.[7] The county-level data we received were in STATA format, which we converted to SPSS format using STAT/TRANSFER. We also obtained ICPSR/NACJD Study No. 8714, *Uniform Crime Reporting Program Data [United States]: County-level Arrest and Offenses Data, 1984*, upon which the 1984 *MGLC* data appear to be based, and calculated county-level crime rates from these data as well.

Table 1 presents the 1984 county-level burglary rates we calculated from both the *MGLC* and ICPSR/NACJD data for Alaska. We present these data

TABLE 2: Comparison of State-Level Data for Alaska, 1984

Source	*Level*	*Population*	*Burglary*	*Burglary Rate*
UCR	State	500,000	6,124	1,236.80
ICPSR/NACJD 8517	County aggregated to State	336,825	82,665	24,542.42
MGLC	County aggregated to State	459,848	82,665	17,976.58

NOTE: UCR = Uniform Crime Reports; ICPSR = Inter-university Consortium for Political and Social Research; NACJD = National Archive of Criminal Justice Data.

for illustrative purposes because Alaska shows the most extreme outliers in the *MGLC* data, and because Lott and Whitely fail to include the state[8] in their discussion of underreporting (Lott and Whitley 2003:189-90). The ICPSR/NACJD data for county 02201 (02 = Alaska: 201 = Prince of Wales-Outer) show the population as 656 and the number of burglaries as 1,256, resulting in an incredible (and highly unlikely) burglary rate of 191,463 per 100,000 population. All the crime rates in Table 1 are clearly univariate outliers, except the first (020 = Anchorage).

Readily apparent from Table 1 is *MGLC*'s direct use of ICPSR/NACJD crime count data, whereas population data for the two sets differ. Maltz and Targonski (2002) note that in the "Crime by County" data, "the listed county total population may not be the actual county population" (p. 300).[9] The *MGLC* appendices note the use of Census Bureau population data for all years except 1990 and 1992, which were estimated by the authors based on the previous years' data (Lott 2000:253-54; Lott and Mustard 1997:67).

State-Level Data Anomalies

We ultimately focused our attention on the state-level data for the years 1977 through 1992, as this period provided the backbone for the *MGLC* analyses.[10] We aggregated the county-level data to the state-level, by year. Examination of descriptive statistics for the two *MGLC* data sets for 1977 to 1992 indicated that our original state-level *MGLC* data obtained from Lott had indeed been aggregated from the county-level *MGLC* data. We reexamined the 1984 Alaska data and found large discrepancies between the three data sets (see Table 2).

Comparison of State-Level Data Sets

To directly compare the data, we then merged the state-level *MGLC* and UCR data sets. Because Lott used natural log transformations in many of his

TABLE 3: Number and Direction of UCR and *MGLC* Differences

	UCR Less Than MGLC		*UCR Equal to MGLC*		*UCR Greater Than MGLC*	
Rate: Raw and Logged	n	%	n	%	n	%
Violence	201	24.63	9	1.10	606	74.26
ln(Y)	196	24.02	10	1.23	610	74.75
Murder	239	29.29	2	0.25	575	70.47
ln(Y)	244	29.90	3	0.37	569	69.73
Rape	217	26.59	9	1.10	590	72.30
ln(Y)	226	27.70	10	1.23	580	71.08
Robbery	240	29.41	2	0.25	574	70.34
ln(Y)	226	27.70	3	0.37	587	71.94
Aggravated assault	194	23.77	2	0.25	620	75.98
ln(Y)	207	25.37	3	0.37	606	74.26
Property	162	19.85	3	0.37	651	79.78
ln(Y)	174	21.32	3	0.37	639	78.31
Burglary	185	22.67	3	0.37	628	76.96
ln(Y)	194	23.77	3	0.37	619	75.86
Larceny	180	22.06	3	0.37	633	77.57
ln(Y)	179	21.94	3	0.37	634	77.70
MV Theft	172	21.08	3	0.37	641	78.55
ln(Y)	193	23.65	3	0.37	620	75.98

NOTE: UCR = Uniform Crime Report; *MGLC* = *More Guns, Less Crime*; MV = motor vehicle.

analyses, we calculated the natural logarithm of the crime rates (or "ln(Y)," referred to hereafter as "logged" rates)[11] for the UCR data in a manner identical to *MGLC*.[12] The *MGLC* crime rates were then subtracted from UCR crime rates to yield differences between the two data sets, both for raw and logged rates. Table 3 shows the number and percentage of state and year crime rate cases that differ between the two sets. On average, the *MGLC* data appear to understate crime rates compared to UCR data over the period 1977 to 1992. Among the nine crime-rate variables, less than 1.25 percent of the data of the two sets are identical; about 19 to 30 percent of the UCR data are lower in value than *MGLC*, although about 69 to 79 percent of the UCR data values are greater.[13] Because population counts for the data sets exhibit a Pearson's r correlation coefficient of 1.0 (i.e., they are, essentially, though not always, identical), crime rate differences occur because of the numerous discrepancies between crime counts for the two data sets, likely due, we believe, to some combination of missing data, entry errors, or imputation in the *MGLC* data. These differences will be readily apparent to any researcher who compares UCR and *MGLC* datum side by side.

Next, we graphically compared the data by year and state, with the vertical axis representing the differences between the mean logged crime rates. If the

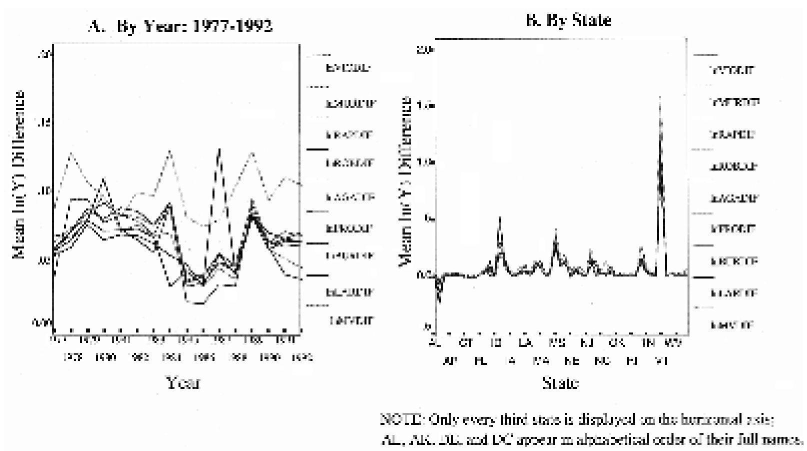

Figure 1: Difference of State-Level Mean Logged Crime Rates: Uniform Crime Report Minus *MGLC* Data, by Year and State
NOTE: *MGLC* = *More Guns, Less Crime*.

data in the two sets were the same across time or place, we would see a flat, horizontal line at the zero value of the vertical axis. Consistent differences across years, whether positive or negative, would appear as horizontal lines at the value of the difference, whereas steep inclines or declines, or spikes in either direction, would indicate explosive differences. Differences by state would appear as peaks, with greater differences being represented by taller peaks. The graphs reveal differing variations by year but highly systematic differences by state (see Figure 1).

We then estimated Pearson's *r* correlation coefficients for the state dummy variables and the overall differences between the data sets, for each type of crime. Large, statistically significant coefficients approaching an absolute value of 1.0 would indicate a strong relationship between that state and the differences in the mean logged crime rates between the *MGLC* and BJS/UCR data sets for the period of 1977 through 1994.[14] Large, significant coefficients would also be indicative of a high degree of imputation (e.g., estimation) over time, and/or the use of different imputation procedures, to replace missing crime and/or population data for the state in question. Conversely, statistically insignificant coefficients would mean there is no meaningful relationship between a given state and the data sets' differences, indicating some level of consistency over time in reporting population and/or data for a particular type of offense within a given state.

Table 4 shows that seven states exhibit significant correlations with the differences among the mean logged crime rates and are the same states that

TABLE 4: Correlation of States and Differences of UCR and *MGLC* Mean Logged Crime Rates, 1977-1992

Crime Rate Difference	*AK*	*IL*	*IN*	*MS*	*NM*	*SD*	*VT*
lnVIOLENT	–.073*	.210**	.042	.175**	.059	.052	.684**
lnMURDER	–.066	.001	.042	.172**	.083*	.072*	.766**
lnRAPE	–.076*	.096**	.041	.179**	.071*	.039	.694**
lnROBBERY	–.082*	.146**	.020	.115**	.020	.037	.556**
lnASSAULT	–.063	.144**	.055	.194**	.067	.056	.691**
lnPROPERTY	–.146**	.040	.079*	.145**	.064	.045	.671**
lnBURGLARY	–.171**	.032	.064	.139**	.057	.056	.697**
lnLARCENY	–.094**	.037	.089*	.143**	.067	.045	.670**
lnMVTHEFT	–.081*	.060	.052	.147**	.061	.046	.679**

*$p < .05$. **$p < .01$.

show large peaks in state-specific differences in Figure 1: Alaska, Illinois, Indiana, Mississippi, New Mexico, South Dakota, and Vermont. These results are consistent with Lott and Whitley's (2003:190, Figure 3) examination of the fraction of state's population with coverage gaps above 30 percent. The results also confirm our *a priori* knowledge of reporting discrepancies among states. For example, Alaska and Vermont are predominantly rural states with numerous small law enforcement agencies that report crime statistics sporadically, if at all, resulting in high levels of estimation by the FBI for all offenses. Similarly, Illinois has consistently failed to report rape data since 1985 for almost every county-level jurisdiction except Cook County (Chicago), and state-level rape data has been imputed by varying methods since 1985.[15]

Descriptive statistics for the raw crime rate differences and differences in the mean logged crime rates are presented in Table 5. Note that positive statistics here indicate that UCR values are greater than *MGLC* values.[16]

Immediately apparent are the rather sizeable differences between mean crime rates in the two data sets, particularly for the violent crime index and all property offenses. This would not be problematic, however, if such differences were randomly distributed, or "consistently inconsistent" (Maltz and Targonski 2002:316) across jurisdictions, years, and offenses. On the other hand, systematic variation could seriously bias the results of any given analysis, and we had already seen such variation by state. As Lott and Whitley (2003) note, "what is more important than the existence of measurement error is whether it is systematically biased" (p. 190).

Figure 2 graphically compares the differences in mean logged crime rates by states grouped according to the nature of their shall-issue CCW law adoption: (1) always shall-issue,[17] (2) enacted shall-issue CCW prior to 1995,[18] (3) enacted shall-issue after 1994,[19] and (4) never shall-issue between 1977 and

TABLE 5: Descriptive Statistics

Crime Rate Difference	n	*Minimum*	*Maximum*	*Mean*	*Mean* SE	SD	*Variance*
Difference of UCR - *MGLC* state-level crime rates, 1977-1992							
VIOLENT	807	–573.61	141.09	–20.22	1.86	52.92	2,800.43
MURDER	814	–6.41	3.55	–.37	0.03	0.90	0.81
RAPE	807	–36.92	18.89	–1.47	0.15	4.12	16.99
ROBBERY	814	–571.74	38.07	–5.28	0.95	27.08	733.10
ASSAULT	814	–246.77	107.67	–12.91	1.05	30.05	902.91
PROPERTY	813	–4,528.06	16,871.18	–207.34	27.80	792.56	628,146.70
BURGLARY	813	–1,436.45	16,739.78	–40.35	21.35	608.76	370,584.75
LARCENY	813	–3,250.60	2,748.34	–129.11	11.48	327.39	107,182.78
MVTHEFT	813	–913.60	241.66	–37.86	3.84	109.36	11,960.57
Valid *n* (listwise)	806						
Difference of UCR - *MGLC* mean logged state-level crime rates, 1977-1992							
lnVIOLENT	806	–2.17	.66	.066	.007	.21	.05
lnMURDER	813	–3.49	.44	.079	.010	.27	.07
lnRAPE	806	–2.68	1.66	.066	.009	.25	.06
lnROBBERY	813	–2.22	.28	.057	.008	.23	.05
lnASSAULT	813	–2.14	.99	.068	.007	.21	.04
lnPROPERTY	813	–2.10	1.41	.065	.007	.20	.04
lnBURGLARY	813	–2.53	2.68	.066	.009	.25	.06
lnLARCENY	813	–1.95	.54	.059	.006	.18	.03
lnMVTHEFT	813	–2.07	.36	.061	.007	.21	.05
Valid *n* (listwise)	806						

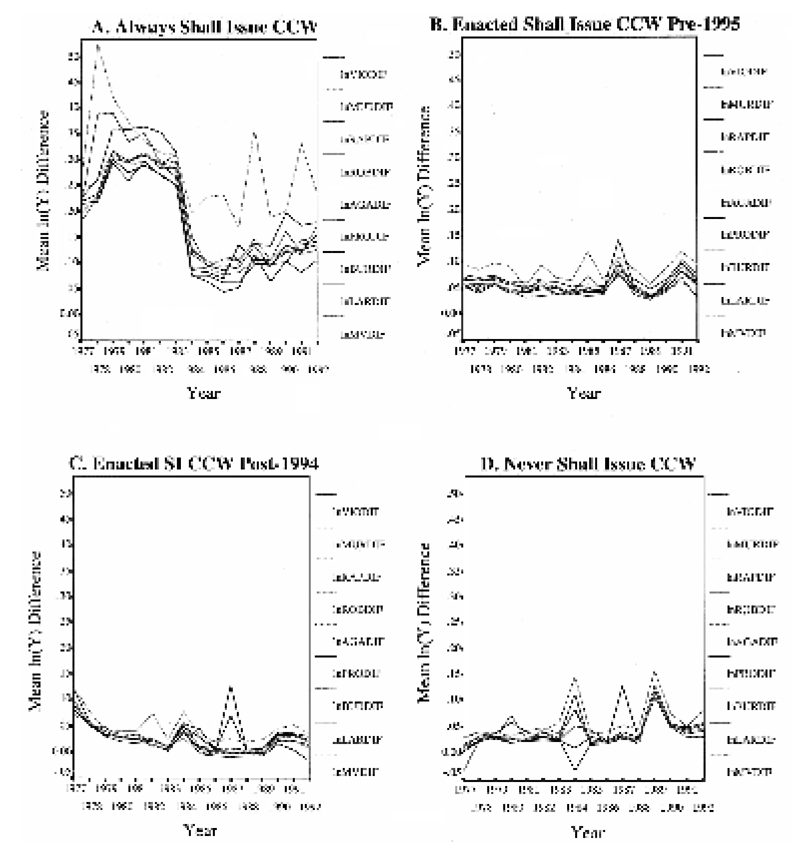

Figure 2: Difference of State-Level Mean Logged Crime Rates, Uniform Crime Report Minus *MGLC* Data, by Year and Nature of Shall-Issue CCW Law Adoption

NOTE: *MGLC* = *More Guns, Less Crime*; CCW = concealed carry weapons.

1992[20] (see, Lott and Mustard 1997:4; Ludwig 1998:243-4). When the difference is positive, the graphs depict how much greater the yearly mean logged UCR crime rates are than the yearly mean logged *MGLC* rates.

If differences between the data sets were randomly distributed, we would expect little variation and an absence of distinguishable patterns across groups. Spikes and steep inclines or declines indicate explosive differences between the two data sets. Least troublesome would be flat, horizontal lines at zero of the vertical axis for each of the groups, indicating no difference between the *MGLC* and UCR data across types of shall-issue law adoption. However, the graphs make clear that the differences between the *MGLC* and UCR data are indeed *systematic* across time, and, perhaps more important, that the disparity operates differentially by nature of shall-issue CCW law adoption. These graphs lend support to Maltz and Targonski's (2002) statement that "those states with the greatest gaps in crime reporting coverage" (and thus the greatest error in crime data) "tend to be states that have (or have changed to) law permitting the carrying of concealed weapons" (pp. 313, 315). The graph depicting the mean differences by year in Figure 1 appears to be a composite of the graphs in Figure 2 for states that were always shall-issue (see Figure 2A) or enacted shall-issue CCW prior to 1995 (Figure 2B), indicating that the *MGLC* and UCR data differences are driven by "shall-issue" states. Of particular interest are the large differences in the data for "always shall-issue CCW" states; the overall differences and those for murder from 1977 to 1983 are of a magnitude of two to four times greater than any other time period and type of CCW law.

We should note here that although these differences may appear to be small, one must recall that these graphs represent *mean*, or average, *differences* between *logged* values of the dependent variables in the two data sets. Our use of the mean differences of logged values has the effect of minimizing extreme raw values and differences. Indeed, brief reviews of Tables 1, 2, and 5 indicate that some differences *are* extreme. Furthermore, note that the graphs in Figure 2 illustrate the *aggregate of state differences by year*, and that within any given year, positive differences can cancel out negative differences. Though one might be tempted to conclude that the differences bias the data against the basic *MGLC* hypothesis, thus strengthening the "more guns equals less crime" theory, our use of aggregate averages precludes such a conclusion.

Particularly troublesome is the steep decline in differences between the data sets from 1983 to 1984 among states that were always shall-issue from 1977 to 1992 (see Figure 2A). It is obvious that such a decline in *always* shall-issue states would have absolutely no causal relationship to the adoption of or change in such laws and is instead indicative of systematic variation in the data itself. Though the *MGLC* analyses use dummy variables for states and years "that control for the average differences in crime rates across places even after demographic, income, and other factors have been accounted for" (Lott 2000:23), Lott acknowledges that with time-series data, "as with cross-sectional data, unexplained differences over time will persist even after all the [control] variables are accounted for" (2000:273).[21] Referring to a post-1993 change in UCR imputation (see, Maltz and Targonski 2002:309) that does not affect the 1977-1992 data, Ayres and Donohue (2003a) state,

> If the break in series caused a uniform jump up or down in crime that applied to all jurisdictions, then our year dummies would control for this problem. Unfortunately, it is generally unlikely that errors in crime data would be uniform across

the country (or even randomly across the country), so the break in the series is a concern. (p. 1265)

The break in the always shall-issue data differences concerns us as well, particularly as the sudden *change* for these states is twice the order of the *total* mean difference in each of the other groups (i.e., about a .2 mean logged difference *change* versus .1 mean logged differences *total*).

METHOD

Having concluded that systematic anomalies exist in both levels of *MGLC* data, we wondered what effect the use of more reliable state-level data might have on the *MGLC* model estimates. We first estimated a series of models using weighted least squares (WLS) regression[22] and the *MGLC* data but with a different statistical software program (SPSS).[23] We then reestimated the models using dependent crime-rate variables derived from the UCR data. Models I through III include arrest rates as an independent variable,[24] although models IV and V exclude arrest rates from estimation. We estimated the last two models without arrests rates because we suspect the county-level arrest data may suffer from some of the same anomalies affecting the crime data. All the independent variables in our analyses, including the shall-issue CCW dummy variable, arrest rates, and all demographic control variables, were used exactly as presented in the *MGLC* data. Finally, because Lott and Whitley (2003) emphasize that "the proper way to deal with the disparity in size (and, thus, importance of estimation) . . . is to weight the analysis by population size" (p. 187), we used the same weighting variable as *MGLC*, each state's population, exactly as the population data appear in the *MGLC* data.

Comparative Regressions

Table 6 reports the comparative regression results. Model I presents the state-level results reported by Lott and Mustard (1997:27),[25] and model II presents the estimates we calculated using SPSS and the state-level *MGLC* data. As can be seen from the analyses, our findings in model II are in general agreement with those of Lott and Mustard; most shall-issue CCW law adoption dummy variable coefficients are in the same (negative) direction and are of similar magnitude and significance,[26] with one notable difference: burglary.

However, the picture changes when we analyzed alternate crime rate data. Using state-level UCR data in model III, only two shall-issue coefficients are

TABLE 6: Shall-Issue CCW Law Adoption and Arrest Rates Coinciding with Dependent Variables: Coefficients Estimated from Different State-Level Cross-Sectional Time-Series Data

Model	*Dependent Variable Data: Software*	*Unit of Analysis*	*Variable*	*ln Violent Rate*	*ln Murder Rate*	*ln Rape Rate*	*ln Aggravated Assault Rate*	*ln Robbery Rate*	*ln Property Rate*	*ln Auto Theft Rate*	*ln Burglary Rate*	*ln Larceny Rate*
I.	Lott snd Mustard:	County	Shall–	–.1011*	–.0862*	–.0607*[a]	–.1090*	–.1421*	–.0419	–.0088	–.0825*	–.0314
	STATA	aggregated	issue	(3.181)	(2.297)	(1.955)	(3.365)	(3.071)	(1.907)	(.206)	(3.146)	(1.452)
		to State	Arrest	–.000802*	–.00073*	–.0105*	–.00153*	–.0105*	–.00599*	–.00145*	–.00715*	–.00657*
			rate	(2.920)	(3.979)	(21.030)	(4.230)	(21.030)	(4.591)	(3.727)	(3.772)	(6.257)
II.	Lott and Mustard:	County	Shall–	–.0764*	–.0869*	–.0465	–.1024*	–.0979*	–.0170	.0265	–.0502	–.0052
	SPSS	aggregated	issue	(–2.385)	(–2.299)	(–1.496)	(–3.198)	(–2.104)	(–.766)	(.711)	(–1.898)	(–.237)
		to State	Arrest	–.0008*	–.0007*	–.0002	–.0016*	–.0104*	–.0061*	–.0252*	–.0069*	–.0067*
			rate	(–2.867)	(–3.870)	(–.631)	(–4.499)	(–20.927)	(–4.714)	(–15.125)	(–3.654)	(–6.412)
III.	UCR: SPSS	State	Shall–	–.0627*	–.0554	–.0210	–.0721*	–.0565	.0110	.0038	–.0247	.0212
			issue	(–3.321)	(–1.907)	(–.953)	(–2.954)	(–1.917)	(.867)	(.133)	(–1.335)	(1.761)
			Arrest	–.0001	–.0006*	–.0003	–.0009*	–.0008*	–.0006	–.0046*	–.0014	–.0006
			rate	(–.546)	(–4.073)	(–1.525)	(–3.315)	(–2.486)	(–.828)	(–3.611)	(–1.036)	(–1.005)
IV.	Lott and Mustard:	County	Shall–	–.0778*	–.0994*	–.0466	–.1027*	–.0720	–.0248	–.0136	–.0533*	–.0151
	SPSS	aggregated to State	issue	(–2.420)	(–2.558)	(–1.502)	(–3.163)	(–1.216)	(–1.106)	(–.319)	(–1.998)	(–.676)
V.	UCR: SPSS	State	Shall–	–.0566*	–.0492	–.0161	–.0705*	–.0385	.0165	.0016	–.0159	.0257*
			issue	(–3.067)	(–1.696)	(–.739)	(–2.927)	(–1.322)	(1.323)	(.057)	(–.875)	(2.171)

NOTE: All *t*-statistics are in parentheses. CCW = concealed carry weapons. UCR = Uniform Crime Reports.

a. Barely significant at alpha level of .05. Compare Lott and Mustard (1997), who provide *t*-statistics as absolute values. All models are identical to those presented in Lott and Mustard (1997:20-3, 27). Coefficients for state and year dummy variables are not reported here for the sake of clarity (cf. Lott and Mustard 1997:27). All regressions are estimated through weighted least squares (WLS), where the weighting is each state's population.

*$p < .05$, two-tailed.

negative and significant: aggravated assault and violent crime rates. That these two variables would exhibit similar coefficients is not surprising, as those familiar with UCR methodology understand that minor Part I offenses heavily influence composite index rates.[27] Under model III, then, the effects of the adoption of shall-issue CCW laws are effectively limited to the reduction of aggravated assault.

In model IV, using *MGLC* data but excluding arrest rates, the results show four statistically significant negative coefficients: violent crime, murder, aggravated assault, and burglary. However, using UCR data and excluding arrest rates, we again find only two significant negative effects for the shall-issue variable, violent crime and aggravated assault.[28] We find there is a significant positive effect for larceny, though, interestingly, the shall-issue effect on overall property crime rates is statistically insignificant.[29]

Readers should note that in each of our models using the UCR data, the direction of the state-level coefficients for violent crime and aggravated assault are consistent with those reported in *MGLC* for both the county and state-level data. However, our finding of a significant positive effect of shall-issue CCW adoption on larceny rates is consistent with the *MGLC* county-level results but *opposite* to those for the *MGLC* state-level data (Lott 2000:52, 59; Lott and Mustard 1997:20, 27).[30]

Finally, we note that, based on prior experience, various statistical programs use different estimation procedures that can result in varying parameter estimates and that other methods may be more appropriate to test the *MGLC* hypothesis. Time-series analyses using least squares with dummy variables (LSDV) would appear to us to be a more suitable method for estimation of state-level time-series data, although multilevel/hierarchical models could illuminate effects that may very well differ by state, region, or other aggregate units.

Regardless of how one might interpret the *MGLC* findings, one further concern regarding the *MGLC* models and estimates bears consideration: multicollinearity. Multicollinearity exists when two or more independent variables in a regression equation are highly correlated, e.g., Pearson's $r \geq .80$ (Berry and Feldman 1985:43; Lewis-Beck 1980:60), and is a threat to validity. In effect, highly correlated variables do not contribute any unique information to the estimation. "Multicollinearity constitutes a threat — and often a very serious threat — both to the proper specification and the effective estimation of the type of structural relationship commonly sought through the use of regression techniques" (Farrar and Glauber 1967:93). In other words, regression coefficients become unreliable and extremely unstable, and can change dramatically depending upon sample coverage and which variables are included in the equation (i.e., model specification; Farrar and Glauber 1967:94; Lewis-Beck 1980:58-60).

The *MGLC* estimates suffer from severe multicollinearity, the source of which is readily apparent from an examination of the *MGLC* models (Ayres and Donohue 2003a:1230, 1239). Although this potential problem with Lott's analysis is pointed out in past research (Ayres and Donohue 2003a: 1239), there have been no quantitative measures of multicollinearity reported in attempting to assess its potential effects. The state-level model (Table 4, Lott and Mustard 1997:27) estimates coefficients for 113 variables: the shall-issue dummy, 45 control variables, 1 state dummies (including the District of Columbia), and 16 year dummies.[31] Among the control variables, every possible race-gender-age combination is included, as are, apparently, every state and year dummy variable. This specification invites perfect multicollinearity (Ayres and Donohue 2003a:1230, 1239).

In the interest of diagnosing, measuring, and quantifying the level of multicollinearity in Lott's (1998, 2000) analysis, one least squares regression diagnostic statistic to detect covariance is the variance inflation factor (VIF) (Fox 1991; Mansfield and Helms 1982). This statistic can be automatically estimated for each independent variable by both STATA and SPSS. VIFs are calculated by estimating auxiliary regressions using a particular independent variable as a dependent variable.[32] The resulting VIF statistic is interpreted as the percentage of variation in a particular independent variable that is explained by all other independent variables due to collinearity. Multicollinearity is indicated when VIF values exceed one (1.0), and severe multicollinearity that "may be unduly influencing the least squares estimates" exists when VIF values exceed 10 (Neter et al. 1996:387).

Table 7 presents variance inflation factors for the variables in the equation estimated using the *MGLC* data for violent crime rates; VIFs for all other equations are similar. In each equation we estimated, SPSS automatically excluded three variables: the dummy variables for 1994 and California, and the percentage of Black males aged 10 to 19. Exclusion of these variables is necessary in order to avoid perfect collinearity of the year, state, and race/gender/age variables. It is noteworthy that *MGLC* nowhere reports that any variables were excluded by the statistical software with which their coefficients were estimated. Though our SPSS output did not report the VIF values for 1994 or California, the VIF for the percentage of Black males aged 10 to 19 was 15,159.13 in equations estimating violent crime rates, and greater than 14,000 for all of the equations we estimated. In every set of estimates, VIFs for more than 100 of the 109 variables are greater than 10.[33] The *average* VIF across all of the variables for the equation explaining violent crime rates is more than 1,200. The expected sum of the squared errors in the coefficients is thus more than 1,200 times as large as it would be if the independent variables were uncorrelated (Neter et al. 1996, p. 388). However, two of the few variables exhibiting single-digit VIFs are arrest rates (VIF < 2.0 in all

TABLE 7: Multicollinearity Statistics: Variance Inflation Factors (VIF) for Variables Predicting Violent Crime Rates, *MGLC* State-Level Data

Included Variable						*Excluded Variable*	
Variable	*VIF*	*Variable*	*VIF*	*Variable*	*VIF*	*Variable*	*VIF*
SHALLISS	6.55	PNF10-19	4,277.82	IA	83.73	PBM10-19	15,159.13
VIOARRRT	1.52	PNF20-29	5,551.64	KS	54.23	1994	*
POPSQM	2,670.10	PNF30-39	5,262.41	KY	87.94	CA	*
RPCPI	77.19	PNF40-49	3,079.10	LA	303.10		
RPCUI	5.42	PNF50-64	4,445.84	ME	48.17		
RPCIM	38.98	PNF>65	2,668.68	MD	156.68		
RPCRPO	45.30	1977	186.58	MA	217.57		
POPSTATE	847.22	1978	178.08	MI	156.20		
PBM20-29	4,586.90	1979	170.12	MN	141.57		
PBM30-39	4,510.70	1980	166.43	MS	302.87		
PBM40-49	3,683.95	1981	157.27	MO	85.18		
PBM50-64	3,673.83	1982	145.98	MT	52.35		
PBM>65	2,296.28	1983	130.20	NE	53.65		
PBF10-19	1,028.87	1984	116.47	NV	77.16		
PBF20-29	5,833.39	1985	103.04	NH	44.45		
PBF30-39	3,946.52	1986	84.59	NJ	314.98		
PBF40-49	4,855.97	1987	64.83	NM	81.33		
PBF50-64	5,271.86	1988	46.67	NY	251.44		
PBF65	2,931.27	1989	36.72	NC	210.51		
PWM10-19	6,654.69	1990	25.19	ND	46.12		
PWM20-29	804.76	1991	15.49	OH	150.89		
PWM30-39	2,371.41	1992	7.96	OK	91.55		
PWM40-49	1,629.47	1993	3.17	OR	103.64		
PWM50-64	1,457.01	AL	216.75	PA	140.75		
PWM65	1,907.35	AK	100.85	RI	56.36		
PWF10-19	7,267.34	AZ	121.98	SC	228.25		
PWF20-29	1,065.46	AR	73.22	SD	45.14		
PWF30-39	2,031.83	CO	122.47	TN	111.66		
PWF40-49	1,507.94	CT	96.76	TX	235.54		
PWF50-64	1,565.85	DC	2,803.88	UT	106.95		
PWF65	1,615.83	DE	18.99	VT	26.50		
PNM10-19	4,781.64	FL	284.20	VA	162.09		
PNM20-29	5,022.38	GA	301.70	WA	158.09		
PNM30-39	7,441.85	HI	1,609.39	WV	57.58		
PNM40-49	3,138.77	ID	58.96	WI	138.29		
PNM50-64	3,460.49	IL	88.23	WY	38.71		
PNM<65	3,878.57	IN	111.52				

NOTE: Variables are ordered as presented in Table 3, Lott and Mustard (1997:20-3). *MGLC* = *More Guns, Less Crime*; PBM = Percent Black Male; PWM = Percent White Male; PNM = Percent Other Male; PBF = Percent Black Female; PWF = Percent White Female; PNF = Percent Other Female.

equations) and the shall-issue CCW dummy variable (VIF = 6.5 to 6.7). It has been said that VIFs are "only relevant when individual coefficients are of direct interest" (Fox and Monette 1992:178), and these two values are indeed below the rule-of-thumb upper VIF limit of 10.

DISCUSSION

Even a cursory examination and analysis of the data shows that state-level *MGLC* data suffer from many of the same errors in reporting, double counting, and imputation as discussed by Maltz and Targonski regarding the "Crime by County" data. The NACJD abstracts provided with each county-level data set hint at the source of these problems.

First, only beginning with ICPSR/NACJD Study no. 6669 (1994) does the NACJD note "*these UCR county-level files are not official FBI UCR releases* and are being provided for research purposes only" (emphasis added).[34]

This contrasts with the UCR data, which are virtually identical to the official FBI UCR data published in *Crime in the United States*. It should also be remembered that both the FBI and the BJS are agencies of the federal government, whereas the ICPSR and the NACJD are research programs administered by a state-level academic institution.

Second, the abstracts explicitly report aggregation and imputation procedures. The abstract for NACJD Study No. 8703, covering the years 1977 through 1983 states:

> Data have been aggregated to the county level. Within each county, data for agencies reporting 6 to 11 months of information were weighted to produce 12-month equivalents. Agencies reporting less than 6 months of data were excluded from the aggregation. Data from agencies reporting only statewide figures were allocated to counties proportionate to their share of the state population. (U.S. Department of Justice, FBI 1984)

This imputation strategy continued until 1994. The abstract for NACJD Study No. 6669 (U.S. Department of Justice, FBI 1994) notes that after consultation with the FBI, the NACJD thereafter incorporated the same imputation strategy utilized by the FBI.

Similarly, the abstract for NACJD Study No. 9785 (U.S. Department of Justice, FBI 1990) states,

> Data from agencies reporting only statewide figures were allocated to counties in proportion to each county's share of the state population (which totaled the populations of those county agencies reporting six months or more of data).

These advisories make it clear that the county-level crime data relied upon by *MGLC* is *both* aggregated from agency-level data as well as disaggregated from state-level data.[35] Any errors in crime reporting are thus likely to be aggravated in different ways, for different years, and for different jurisdictions,[36] seriously compromising the reliability of the *MGLC* data. The presence of extreme outliers (see Table 1) is indicative of this problem. Some of these outliers are likely to be influential, meaning they could have a disproportionate impact on the regression estimates.

Third, accurate population data matter immensely. A close review of the population data in the "Crime by County" data should raise concern about the resulting rate estimates. Inaccuracies in the population data used in the imputation process could obviously affect the disaggregating of crime data and induce error. Compounding this error, *MGLC*'s use of Census Bureau population data to calculate crime rates may inflate some crime rates while concurrently deflating others. Perhaps the most egregious oversight is that these errors are systematic by year, state, and nature of shall-issue CCW law adoption.

CONCLUSION

We find that when using data that are not subject to the numerous problems addressed by Maltz and Targonski (2002), or which are, at least, subject to fewer such issues, the state-level effects of shall-issue CCW law adoption are moderated or, for most offenses, eliminated. It thus appears that the majority of *MGLC*'s state-level findings are artifacts of reporting errors and data anomalies resulting from the use aggregated "Crime by County" data. Unfortunately, there is no alternative source of county-level crime data for us to conduct a similar comparison with *MGLC*'s county-level results.

We therefore believe it is prudent to apply the same cautions expressed by Maltz and Targonski (2002) regarding the *MGLC* county-level data to the use of any state-level data created by aggregating the ICPSR/NACJD UCR "Crime by County" data, including the *MGLC* state-level data. Though numerous researchers and commentators have praised Lott for making his data widely available, it appears clear that the state-level *MGLC* data are not without serious problems. Lott (2000) notes, "In general, larger studies that rely on more data have better chances of reliably incorporating more relationships" (p. 273), and claims that the *MGLC* data set is "by far the largest data set that has ever been put together for any study of crime, let alone for the study of gun control" (p. 147). We would submit that the size of a data set does not make up for a lack of integrity and reliability in the underlying data. Lott laments that he finds it "ironic that [his] study is attacked for not having enough data" (p. 147). We find it ironic that those using the data set have not examined the data closely enough to recognize obvious errors and anomalies yet continue to perform increasingly complex analyses to draw their conclusions (see, e.g., Plassmann and Whitley 2003). Regarding criminology, Sampson (2002) has noted, "as a field we are characterized by sophisticated statistical analysis of weak or fundamentally flawed data" (p. 219). It is our hope that our relatively simple analyses demonstrate the truth of Sampson's statement.

The sophisticated methods of analysis that are common to criminology, combined with a number of elegant theories, demand much better large, national data sources than are currently available through the state- and county-level UCR. Perhaps one, or many, of the public and private agencies who have a vested interest in the use of these data should assemble, or at least fund a group familiar with the UCR to produce a clean version for public consumption. Agencies such as the FBI, the ICPSR, and the BJS understand how the data are used, the need for increased accuracy and participation in reporting, and the extremely high stakes of poor data and the subsequent effects that it can have on policy analysis and, eventually, policy itself.

Finally, we note that a consistent source of frustration in attempting to establish the validity and reliability of data used in many studies is the failure of researchers to be explicit regarding the actual sources of their data, and the software and methods used in their analyses. We commend Lott for making his data widely available but have noted several times that the precise sources of his data and software are obscured. We have attempted in this work to provide researchers with as complete a record of our sources, methods, and software as possible, so that others may replicate our data and analyses, and we encourage others to do the same in the future.

NOTES

1. See also, "Bridging Gaps in Police Crime Data: A Discussion Paper from the BJS Fellows Program," NCJ 176365 (Maltz 1999).

2. Although we note that this data was used by Lott, nowhere in either the original article (Lott and Mustard 1997) or the second edition of *MGLC* (Lott 2000) is any specific source cited other than "the Uniform Crime Report (UCR)" or "the FBI's *Uniform Crime Reports*" (1997:13, 66-8; 2000:47, 251-5).

3. These arrest data are "for each type of crime in every county from 1977 to 1992 . . . provided by the FBI's *Uniform Crime Reports*" (Lott, 2000:47). Considering that these data were compiled in the same fashion as the crime data discussed here, they may be subject to the same severe shortcomings.

4. The data sets are (1) *MGLC*, state-level; (2) UCR, state-level; (3) *MGLC*, county-level; and (4) ICPSR/NACJD Study No. 8714, county-level.

5. Available: http://www.ojp.usdoj.gov/bjs/datast.htm [July 2, 2001]. The note to each data set also states, "The numbers presented in the spreadsheet are State level estimates and, therefore, may vary from those previously published or available from other sources." Michael Maltz is listed as the coordinator for each data set.

6. For a detailed discussion of the different methods for estimating and reporting data, and the potential effects on data analysis, see Maltz and Targonski (2002:301-6).

7. We attempted to obtain the data directly from John Lott, but, ultimately, Carlisle Moody graciously provided us with the county-level *MGLC* data.

8. Hawaii is also excluded. Lott and Whitely (2003) provide no explanation why their most recent analysis is limited to the "48 contiguous states" (p. 188), even though the *MGLC* results were estimated using data for all 50 states.

9. See Maltz and Targonski (2002:301-6) for a more complete discussion of population data anomalies.

10. Note that the data underlying the main analyses in the second edition of *MGLC* are for 1977 to 1992 (Lott 2000:52-3, 59). The county-level *MGLC* data provided to us by Moody spans 1977 to 1992. However, the state-level *MGLC* data provided to us by Lott includes complete data for all variables for 1977 to 1996, and complete crime rate data for 1977 through 1997, inclusive. We noted that in the state-level *MGLC* data provided to us by Lott himself, the *MGLC* data are, with very few exceptions, almost identical to the UCR data available online for 1993 to 1997. We do not know whether the state-level data provided to us by Lott was used to update the *MGLC* statistics (see Lott 2000:167-243), though we suspect they may have been. Lott (1998:242) states in his response to Black and Nagin (1998) that his "forthcoming book extends the sample period to 1994 for the county-level data and to 1995 for the state-level data." We believe this implies that the county and state data used in the updates derive from two *different* sources.

11. A logarithm is an "exponent of a base number indicating the power to which that number must be raised to produce another number" (Vogt 1993:130). The use of logged transformations is common to linearize a nonlinear variable, remedy heteroscedasticity of model error terms, or eliminate or reduce interaction effects, in order to meet regression assumptions (Neter et al. 1996:126-32, 240). We use mean, or average, logged crime rates in our analyses because any linear regression line will pass through the mean of the dependent variable, and because they provide an easily understandable reference point.

12. "If the true rate equals zero, we added .1 before we took the natural log" (Lott and Mustard 1997:66). We also reestimated each equation by adding 1.0 to zero values instead of .1; all of the results were identical.

13. Graphic depictions of the crime count differences are available from the authors upon request.

14. We thank an anonymous reviewer who has suggested that we add graphs for the crime rates of each of the states who adopted shall-issue laws during this period. We highly recommend that anyone who specifically tests these hypotheses in the future use this type of test with specific regressions for each state.

15. The first statement regarding Illinois' reporting irregularities appeared in footnotes to Tables 5 and 6 in the 1985 edition of *Crime in the United States*. The 2002 UCR lists the history of states' reporting anomalies and estimation procedures since 1985 (*Crime in the United States: Uniform Crime Reports* 2002:437-40).

16. The one case difference between violent and property crimes is due to missing *MGLC* data for all crime rates for Iowa for 1991. Data for all Florida and Kentucky crime rates for 1988 are also missing from the *MGLC* data set. Thus, though there are 816 cases in the state-level set for 1977 to 1992, the valid number of cases listwise (i.e., valid data for all of the variables) is 806.

17. States that were shall-issue throughout 1977 to 1992: AL, CT, IN, NH, ND, SD, VT, and WA.

18. States enacting shall-issue CCW prior to 1995: FL, GA, ID, ME, MS, MT, OR, PA, VA, and WV.

19. States enacting shall-issue CCW after 1994: OK, TN, TX, and UT.

20. States that were never shall-issue: AK, AZ, AR, CA, CO, DE, DC, HI, IL, IA, KS, KY, LA, MD, MA, MI, MN, MO, NE, NV, NJ, NM, NY, NC, OH, RI, SC, and WI.

21. See Maltz and Targonski (2003:202-3) for a brief discussion of "stochastic variation" in crime rates.

22. This is the same technique used in the initial *MGLC* analyses, as presented in Tables 3 and 4 in Lott and Mustard (1997:20-3, 26), and Tables 4.1 and 4.3 in Lott (2000:52-3, 59).

23. Nowhere in any of the *MGLC* analyses is it stated which statistical software was used, but because the county-level *MGLC* data were provided to us in STATA format, we assume this was the software used for the *MGLC* analyses.

24. We identify variables as *independent* (predictor) or *dependent* (effect), whereas *MGLC* uses the terms *exogenous* (predictor) or *endogenous* (effect). Though technically different, particularly when describing variables in a path analysis, the respective terms are interchangeable within the context of our discussion.

25. These results are not presented in the later edition of *MGLC* (Lott 2000). Rather than unstandardized coefficients and *t*-values, the state-level findings in the second edition of *MGLC* are instead presented as "(1) the percent change in the crime rate attributed to a particular change in the explanatory variable," and "(2) the percentage of the variation in the crime rate that can be explained by the variation in the explanatory variable" (Lott 2000:51).

26. Most *t*-ratios are also of a similar magnitude, though we report the true value as opposed to the absolute values reported in MGLC.

27. *MGLC* reports that in 1992, aggravated assaults accounted for 59.4 percent of violent crimes, whereas larceny accounted for 63.1 percent of property crimes (see Table 2.1, Lott 2000:27). The *MGLC* authors note that the violent and property crime index categories are "somewhat problematic in that all crimes are given the same weight" (Lott 2000:27; Lott and Mustard 1997:7; see also, Black and Nagin 1998:210).

28. The weakening of the coefficients in the *MGLC* hypothesis when using alternate data is discussed in detail by Ayres and Donohue (2003a; 2003b). It may be of note that when these data were extended through 1999 the effects of CCW laws on violent crime was further weakened (see Ayres and Donohue 2003a).

29. *MGLC* suggests that violent crime "involving direct contact between the victim and the criminal" would be deterred because, "when crime becomes more difficult, less crime is committed" (Lott 2000:28, 19; Lott and Mustard 1997:7). A "substitution" effect is concurrently posited for other offenses; "some criminals turn away from crimes like robbery that require direct attacks and turn instead to crimes such as auto theft, where the probability of direct contacts with victims is small" (Lott 2000:28, 19). We offer no comments or conclusions regarding these or any other *MGLC* hypotheses.

30. This may be an example of "Simpson's Paradox, also sometimes referred to as aggregation bias" (Ayres and Donohue 2003a:1270; see also, Bickel, Hammel, and O'Connell 1975). The paradox occurs when one disaggregates data by some theoretically important covariate and observes a reversal of the sign of the coefficient (i.e., reversal of the effect: positive to negative, or negative to positive). For an excellent, intuitive example, see Appleton, French, and Vanderpump (1996).

31. Lott and Mustard (1997) note, "Except for the use of state dummies in place of county dummies, the control variables are the same as those used in Table 3 including year dummies, though they are not all reported" (p. 26). See, also, Table 4.3 (Lott 2000:59).

32. The auxiliary regressions ultimately estimate an auxiliary R^2, or the amount of variation in a particular independent variable that is explained by all other independent variables ($VIF_j = 1 / 1 - R_j^2$).

33. An alternative indication of multicollinearity is the number of eigenvalues greater than or equal to 1.0. In the equation for violent crime rates, there are 64 eigenvalues ≥ 1.0.

34. More recently, ICPSR/NACJD notes, "County-level UCR files are *created by NACJD* based on agency records in a file obtained from the FBI that also provides aggregated county totals. NACJD imputes missing data and then aggregates the data to the county-level." See http://www.icpsr.umich.edu/NACJD/ucr.html [February 12, 2003].

35. For 1994 and later data, the abstract for NACJD Study No. 6669 (U.S. Department of Justice, FBI 1994) notes, As in past years, data were aggregated to the county level. However, two major changes to the UCR county-level files are being implemented with the 1994 release. A new imputation algorithm to adjust for incomplete reporting by individual law enforcement jurisdictions has been adopted. Within each county, data from agencies reporting 3 to 11 months of information were weighted to yield 12-month equivalents. Data for agencies reporting less than 3 months of data were replaced with data estimated by rates calculated from agencies reporting 12 months of data located in the agency's geographic stratum within their state. Secondly, a new Coverage Indicator has been created to provide users with a diagnostic measure of aggregated data quality in a particular county. Data from agencies reporting only statewide figures were allocated to the counties in the state in proportion to each county's share of the state population.

36. See note 12 above. See also, *Crime in the United States: Uniform Crime Reports* (2002:437-40).

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