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Abstract

Previous research suggests that mass incarceration in the United States may have contributed to lower rates of violent crime since the 1990s, but, surprisingly, finds no evidence of an effect of imprisonment on violent crime prior to 1991. This raises what Steven Levitt has called “a real puzzle.” This study offers the solution to the puzzle: the error in all prior studies is that they focus exclusively on rates of imprisonment, rather than using a measure that combines institutionalization in both prisons and mental hospitals. Using state-level panel data regressions over the sixty-eight year period from 1934 to 2001, and controlling for economic conditions, youth population rates, criminal justice and demographic factors, this study finds a large, robust, and statistically significant relationship between aggregated institutionalization (mental hospitals and prisons) and homicide rates, providing strong evidence of what should now be called an institutionalization effect—rather than, more simply but inaccurately, an imprisonment or incapacitation effect.

Date: June 28, 2010
Mass incarceration in the United States is one of the most salient political, social, and economic issues facing the nation. After fifty years of relative stability, state and federal prison populations began rising exponentially in 1973, climbing from under 200,000 to more than 1.3 million persons by 2002. With more than 700,000 additional persons held in local jails, by 2008 the United States incarcerated over two million people, more than one percent of its adult population—the highest number and rate in the world (Pew 2008; BBC 2010).

The issue of mass incarceration has generated significant research across the social sciences, from political science to anthropology, criminology, economics, and sociology (see respectively Gottschalk 2006; Rhodes 2004; Pfaff 2008; Levitt 2004; Wacquant 2001; see generally Loury and Western forthcoming). One dimension that has stimulated considerable controversy is the purported effect of mass incarceration on the level of violent crime in this country. Research along this axis has been fueled, in part, by conflicting historical trends during the twentieth and twenty-first centuries regarding, on the one hand, patterns of imprisonment and, on the other hand, cycles of homicide victimization.

During an earlier period, from the 1920s to the 1970s, incarceration rates remained essentially flat while homicide rates fluctuated wildly, first dropping sharply by more than fifty percent in the 1930s and then rising steeply—in fact more than doubling—in the 1960s and 70s. During the later period, from the 1970s to the present, incarceration rates rose exponentially while homicide rates remained, at first, stable and high, and then began falling sharply in the 1990s. The contrast between these conflicting
trends during these two historical periods has given rise to an important before-and-after mystery.

In the period before the prison expansion of the 1970s, research explored the puzzling homeostasis of imprisonment during periods of sharply fluctuating crime rates and converged on the “stability of punishment hypothesis” (Blumstein and Moitra 1979:389). According to that dominant view, prison populations remained relatively constant despite fluctuations in crime, and there was essentially little net cross-effect: the prison did not have a large incapacitative, nor deterrent effect on crime, and, vice versa, crime rates did not have a significant criminal justice effect on prisons—or at least, any effects cancelled out. In the period after, in other words in the period marked by mass incarceration and the “Great American Crime Decline” of the 1990s (Zimring 2006), the consensus shifted dramatically. The most reliable research from this period finds that changes in prison rates accounted for almost one-fourth to one-third of the drop in crime since 1991 (Levitt 2004:186; Spelman 2000:123). The received wisdom, now, is that rates of imprisonment were not a good predictor of violent crime for any period prior to the 1990s, but are a good predictor after 1991—and the reason for this difference has remained a mystery.

This study offers the answer: the error in all prior research is that it focused exclusively on imprisonment rates and never included in the measure of incapacitation or deterrence the rate of institutionalization in mental hospitals. The metric in all prior studies had always been rates of incarceration in state and federal prisons (and in some cases in jails), but had never included the population in asylums, mental hospitals, or institutions for the “mentally defective.” Yet the startling fact is that the United States institutionalized a massive portion of its population in mental institutions in the 1930s, 40s, and 50s, and those mental hospitalization rates exhibited starkly different patterns than trends for imprisonment.

To be precise, the patterns of mental hospitalization versus incarceration are practically inverted over the twentieth and twenty-first centuries. An early period—from the 1920s through the 1950s—was marked by remarkable stability in both prison and mental hospital populations, but by sharply higher rates of institutionalization in mental hospitals. During this “before” period, the United States institutionalized people in
mental hospitals at extraordinarily high rates, consistently near or above 600 persons per 100,000 adults throughout the 1940s and 50s—with peaks of 627 and 620 persons per 100,000 adults in 1948 and 1955, respectively. The 1970s marked a transition period: prison populations began to rise, while mental health populations plummeted dramatically. Thus, in the “after” period, during the 1980s, 1990s, and into the twenty-first century, mental health populations dwindled to negligible levels, while state and federal prison populations exploded, rising exponentially to their present levels. As evidenced in Figure 1, when the data on mental hospitalization rates are combined with the data on prison rates for 1934 through 2001, the imprisonment revolution of the late twentieth century takes on an entirely different appearance: aggregated institutionalization—in other words, the combination of prison and mental hospital populations—is now returning to the elevated levels of institutionalization that the United States experienced at mid-twentieth century.

Figure 1: Rates of Institutionalization in the United States (per 100,000 adults), 1934-2001

[INSERT FIGURE 1 HERE]

This figure does not include jail populations, because data on jail populations were not reliably or consistently measured until 1970; however, when national-level jail counts are included (linearly interpolate for missing years), the graph is similarly striking, as evidenced by Figure 2.

Figure 2: Rates of Institutionalization, including Jails, in the United States (per 100,000 adults), 1934-2001

[INSERT FIGURE 2]

Despite these sharply different patterns of institutionalization, all of the academic research on the incapacitative or deterrent effect of imprisonment—whether econometric, criminological, sociological, or other—has systematically ignored rates of mental
hospitalization. With one single exception (Harcourt 2006), no existing study includes asylums or mental hospitals in their measure of persons effectively detained and incapacitated.

This is the first study to explore what might be called an “institutionalization effect”—rather than simply an “incapacitation” or “imprisonment” or “incarceration” effect—using state-level panel data. The findings are striking. Over the course of the twentieth century, the effect of institutionalization on homicide rates in the United States is large and statistically significant (at the 0.031 level) only when the data combine the rates of institutionalization in prisons and mental hospitals, but not when the analysis considers only the rate of imprisonment alone or the rate of mental hospitalization alone.

This study relies on an intensive state-by-state data collection effort regarding the number and rate of persons in mental hospitals going back to the early 1930s. It runs a number of quantitative analyses on the state-level panel data—as well as on individual state data—to test the relationship between aggregated institutionalization and homicide, holding constant the seven leading correlates of homicide. The three principle findings from the analyses are as follows:

First, at the national level, the only prior study that broached this topic (Harcourt 2006) actually underestimated the number and rate of persons institutionalized for mental illness by including only residents in public (state, county, and city) mental hospitals. There were significant numbers of persons institutionalized in other types of mental institutions—variously called public and private institutions for “mental defectives and epileptics” or for “the mentally retarded,” “psychopathic” hospitals and wards in general and VA hospitals, and other private mental hospitals. When those additional patients are included in the data, the historical trend over the twentieth century is even more stark: The aggregated institutionalization rates (in all mental hospitals and prisons) between 1936 and 1963 consistently exceeded 700 persons per 100,000 adults—with peaks of 760 in 1955, 757 in 1954, and 756 in 1948.

Second, using a clustered regression model with fixed state and year effects, adjusted for correlated error with robust standard errors, on the state-level panel data over the entire sixty-eight year period from 1934 to 2001, this study finds a large and statistically significant relationship between aggregated institutionalization and homicide
rates. There is, in fact, a remarkable correlation that survives the introduction of control variables for all leading correlates of homicide. The findings are robust and hold under a number of permutations.

Third, analyzing individual states, this study shows a nuanced landscape, with some states, such as Texas, California, Michigan, Georgia, and Massachusetts displaying stronger associations than others. Although the states understandably vary, the more consistent direction of influence is negative: greater aggregated institutionalization tends to correlate with lower homicide rates. An analysis of the largest states especially suggests the pattern.

The bottom line is straightforward: Prison rates alone do not predict homicide, and nor do mental hospitalization rates alone, but when the two are combined, they are significantly and robustly related to homicide rates over a sixty-eight year period across the fifty separate states, holding constant the leading covariates of homicide. This study identifies a previously unnoticed empirical relationship and cautiously speculates on the mechanism. The mechanism, it turns out, may turn on victimization rather than perpetration. Research has consistently shown that persons suffering from mental illness are far more likely to be victims of violent crime than the general population (Teplin et al. 2005; Teasdale 2009). Research has also identified a high correlation between being convicted of a crime and being a crime victim oneself (that is, outside prison): a substantial percentage of murder victims—one study indicates 44 percent overall and 51 percent of non-family murder victims (Dawson and Langan 1994:1)—are individuals with a prior criminal history; and vice-versa, individuals in prison are at higher likelihood of being violent crime victims outside of prison (Karmen 2009: 101-103). What may explain the results, then, is that the large institutionalized populations contain a higher proportion of potential homicide victims than the general population. The size of the institutionalized population may be relevant to homicide rates, not simply through perpetration, but through the higher victimization rates of the persons detained.

This Article proceeds in six parts. Part 1 sets forth the context for this research and reviews related prior areas of research. Parts 2 and 3 discuss the collection of data. Part 4 presents the state-level panel data regressions. Part 5 turns to individual state analyses, and Part 6 explores avenues for future research.
1. PRIOR RESEARCH

This study is located at the intersection of three bodies of prior research: first, studies that explore the flow and relationship between populations in mental hospitals and in prisons; second, research into the stability of correctional populations before mass incarceration starting in the 1970s; and third, studies analyzing the effect of mass incarceration on violent crime since the 1990s. None of the prior studies link these different areas of research.

The first body of research focuses on the relationship between mental hospital and prison populations. In a prescient paper published in Great Britain in 1939, Professor Lionel Penrose reported the results of a cross-sectional study of eighteen European countries, finding an inverse relationship between the number of persons in prison and the number of mental hospital beds (Penrose 1939). Since then, there have been sporadic efforts—predominantly since deinstitutionalization of mental hospital patients in the 1960s and 70s—to explore the relationship between the prison and mental health systems in the United States (Liska et al. 1999; Grabosky 1980; Steadman et al. 1984; Raphael 2000).

In their 1984 study, Henry Steadman, John Monahan and their colleagues tested the degree of cross-institutionalization between mental health and prison systems on a sample of 3,897 male prisoners and 2,376 male mental hospital patients from six different states over the period 1968 to 1978. They found that in three of the states (New York, Arizona, and Massachusetts), there were relative declines in the percentage of former mental health patients who were incarcerated in 1978, and concluded that “[l]ittle evidence was found to support the idea that mental hospital deinstitutionalization was a significant factor in the rise of prison populations during th[e] period [from 1968 to 1978]” (490). Although the six states were evenly distributed in the direction of the effect, a subsequent reevaluation of their study found that the aggregated numbers told a different story: the number of prison inmates with prior mental hospitalization in 1978 was more than 50% higher than would have been expected, even given prison growth, which supports a hypothesis of some interdependence of the populations (Harcourt 2006:1778-1779). On the other side of the equation, Steadman and Monahan found
evidence that mental hospitals were becoming more “criminal” (487): “In all study states but Iowa, the actual number of hospital admittees with one or more prior arrests is substantially higher (from 11.7% to 99.9%) than would be expected from total admission trends” (486).

Several years later, in an unpublished 2000 paper, Steven Raphael found that mental hospitalization rates had a significant negative effect on prison incarceration rates over the period 1971 to 1996. The magnitude of the effect was large. Translated into real population numbers, Raphael’s findings suggested that deinstitutionalization from 1971 to 1996 resulted in between 48,000 and 148,000 additional state prisoners in 1996, which according to Raphael, “account[ed] for 4.5 to 14 percent of the total prison population for this year and for roughly 28 to 86 percent of prison inmates suffering from mental illness” (12). None of this research, however, addresses the possible effect of such interdependence on crime rates.

A second body of research focuses on the inexplicable “relative stability” or “homeostatic” nature of prison incarceration rates in the face of significant changes in crime rates from the 1930s to the 1970s (Blumstein and Moitra 1979:389). This literature consistently characterized the period from 1926 (when the federal government began compiling prison data) to 1973 as “a fifty-year period of impressive stability” of imprisonment (Blumstein and Wallman 2000:5)—correctly, that is. As Figure 3 demonstrates, prison rates remained relatively flat during the period. Despite this stability, homicide rates fluctuated wildly. First, they tumbled from highs of 10 per 100,000 in the late 1920s to lows of 4.5 per 100,000 in the mid-1950s; and then they doubled back to highs of 10 per 100,000 by the mid-1970s, as evidenced in Figure 4 below. Most of the longitudinal research on incapacitation and deterrence focused on this mismatch and, using pre-1980 data, converged on the “stability-of-punishment hypothesis” (Blumstein and Moitra 1979:389), finding no significant prison–crime nexus (McGuire and Sheehan 1985:73–74; Bowker 1981:206; Chiricos and Waldo 1970:200).

Figure 3: State and Federal Prison Population and Rate (per 100,000 adults) in the United States, 1934-2001.

[INSERT FIGURE 3 HERE]
The shock of the incarceration explosion in the 1980s and 1990s, followed by the crime drop of the 1990s, triggered an outpouring of new research on the effect of incarceration on crime and led many to revise their earlier findings (Spelman 2000:97). Although homicide rates initially undulated between 9 and 11 per 100,000 during the period 1973 to 1991, homicide rates began a steep decline in the 1990s toward their current rate of approximately 6 per 100,000—levels that had not been seen since the early 1960s (as exhibited, again, in Figure 4 above). The sharp rise in incarceration led many researchers, including Blumstein (1995), to revise their earlier findings on the stability of punishment. The studies from this period find that mass incarceration account for between one-fourth to one-third of the crime drop since 1991 (Levitt 2004:186; Spelman 2000:123). This produced the third body of research, which focuses on the effect of mass incarceration on violent crime—this time using primarily post-1980 data.

As a result of the historical discontinuities (and use of different data) between the second and third bodies of research, the explanations for the early and later trends in crime generally diverge sharply: explanations offered to elucidate the sharp rise in crime in the 1960s are consistently different than those offered to illuminate the crime drop of the 1990s. The authoritative treatment of Blumstein and Wallman (2000), for instance, reviews all the usual suspects for the crime rise of the 1960s, namely, the baby-boom generation, lack of political legitimacy, and hard economic times; but it deploys an entirely different set of explanatory variables for the crime drop of the 1990s, including for instance changing patterns of drug use, decreased gun violence, Giuliani-style “broken windows” policing, the federal COPS program, and increased incarceration (Blumstein and Wallman 2000:4).

Practically all the studies that examine the two distinct periods—before and after mass incarceration—find inexplicable discontinuity. This poses, as Steven Levitt has suggested, a “real puzzle,” which Levitt himself observes in his own work (Levitt
In his 2004 article analyzing the explanations for national crime trends, Levitt identifies the prison-population build up as one of the four factors that explain the crime drop since the 1990s. Levitt estimates that the increased prison population over the 1990s accounted for a 12 percent reduction of homicide and violent crime, and an 8 percent reduction in property crime—for a total of about one-third of the overall drop in crime in the 1990s (Levitt 2004:178-79). But when Levitt extends his analysis to discuss the period 1973–1991, Levitt is surprised that the drop in crime did not start sooner (Levitt 2004:186). Regarding the period 1973–1991, Levitt writes:

The one factor that dominates all others in terms of predicted impact on crime in this earlier [1973–1991] period is the growth in the prison population. Between 1973 and 1991, the incarceration rate more than tripled, rising from 96 to 313 inmates per 100,000 residents. By my estimates, that should have reduced violent crime and homicide by over 30 percent and property crime by more than 20 percent. Note that this predicted impact of incarceration is much larger than for the latter [1990s] period. (Levitt 2004:184)

Levitt is left with a significant gap between projected and actual crime rates for the period 1973–1991. “[I]n contrast to the 1990s, the actual crime experience in the 1973–1991 period is not well explained by the set of factors analyzed in this paper. There appears to be a substantial unexplained rise in crime over the period 1973–1991” (Levitt 2004:186). Levitt finds this surprising given the important effect of incarceration in the 1990s. “In the light of the estimates linking increased incarceration to lower crime, it is perhaps surprising that the rising prison population of the 1980s did not induce a commensurate decline in crime in that period” (Levitt 2004:179 n.7). The same puzzle, naturally, applies to the decades prior to 1973—in fact, to the entire period from 1926 to 1991. Levitt concludes his analysis in the following terms: “The real puzzle in my opinion, therefore, is not why crime fell in the 1990s, but why it did not start falling sooner” (Levitt 2004: 186).

Absent from all of the empirical literature, however, are rates of mental hospitalization. All existing research on the prison-crime nexus conceptualizes the level of confinement in society through the lens of imprisonment only, and not institutionalization writ large. In fact, none of the research that uses confinement as an independent variable—in other words, that studies the effect of confinement (and possibly other social indicators) on crime, unemployment, education, or other dependent
variables—includes mental hospitalization in its measure of confinement (see, e.g., DeFina and Arvanites 2002; Levitt 2004). Moreover, none of the studies that explore the specific relationship between confinement and unemployment, or confinement and crime, or confinement and any other non-mental-health-related indicator—uses a measure of coercive social control that includes rates of mental hospitalization (see, e.g., Blumstein and Moitra 1979; Bowker 1981; Chiricos and Waldo 1970; Levitt 1996; McGuire and Sheehan 1985). Even the most rigorous recent analyses of the prison–crime relationship use only imprisonment data (DeFina and Arvanites 2002; Marvell and Moody 1994). Though a tremendous amount of empirical work has been done on long-term crime trends (Cohen and Land 1987), structural covariates of homicide (Land et al 1990), and the prison expansion (see generally Spelman 2000), none of this literature conceptualizes confinement through the larger prism of institutionalization, and none of it aggregates mental hospitalization data with prison rates.¹

In order to properly explore the relationship between aggregated institutionalization (in mental hospitals and prisons) and homicide, and to avoid ecological error, it is necessary to conduct the analysis at the state level. Since the work has never been done before, it is necessary first to collect state-level data on aggregated institutionalization.

2. THE AGGREGATED INSTITUTIONALIZATION DATA

The primary variable of interest is aggregated institutionalization, which is composed of the population in mental hospitals and in prisons.

2.1 Mental Hospitalization Data

The data on patients in mental hospitals consist of state-by-state panel data with observations running from 1934 to 2001. The regular enumeration of patients in mental

¹ There are only two exceptions: first, an article published in 2006 that uses a single-jurisdiction approach (Harcourt 2006). That study uses national-level data only and discovers a relationship between aggregated institutionalization (in prison and in mental hospitals) and the national homicide rate, holding constant three leading structural covariates of homicide (youth demographics, unemployment, and poverty) (Harcourt 2006:1774-75). Those findings, however, are based on a single-jurisdiction (national-level data) analysis, and therefore present a risk that the national-level findings mask different processes at the sub-unit level (through an ecological fallacy or other potential aggregation error). The second exception is a criminology and economics article that reviews the literature on the prison-crime nexus and, noting the Harcourt 2006 study, mentions the potential relevance of mental hospitalization (Pfaff 2008).
hospitals was first undertaken by the U.S. Census Bureau beginning in the early 1920s. There had been U.S. census counts of patients in mental hospitals and of “the insane and feeble-minded” in 1880, 1890, 1904, and 1910, as well as an extensive census effort in 1922 and 1923, but the U.S. Census Bureau began performing annual enumerations in 1926, producing detailed state-by-state tables that would eventually include population data concerning state, county, city, and private mental hospitals, psychopathic hospitals and psychiatric wards of general and VA hospitals, and public and private institutions “for mental defectives and epileptics” and for “the mentally retarded.” Starting in 1947, the task of enumeration and analysis was turned over to the National Institute of Mental Health, a unit of the U.S. Public Health Service, which continued to issue detailed analyses. Beginning in 1952, the yearly pamphlets were divided into four separate parts focusing on public and private mental hospitals and institutions for persons with mental retardation. Starting in 1970, the survey department of the National Institute on Mental Health took responsibility for tracking these population, but published only census data for state and county mental hospitals.

The American Hospital Association began tracking the population of persons in all mental hospitals in 1946 through surveys of all hospitals in the United States, and have continued to collect data on public and private mental hospitals and institutions for persons with mental retardation to the present. For the year 1969 and the years from 1971 through and including 1995, the American Hospital Association collected and published annual data on average daily census counts for all psychiatric institutions. The data for 1969 and 1971 are average daily census counts at all non-federal psychiatric hospitals; the data for 1972 through 1995 are average daily census counts for all psychiatric institutions.

2 In addition, the government census data also enumerated persons on parole from mental hospitals during the period through 1969. The category of “on parole” covered a number of different statuses, ranging from trial leaves of absence, to extramural or family care, and escaped patients. In 1933, for instance, the official census reports defined “on parole” as the “temporary absence from an institution of a patient who is being carried on the books,” usually “a trial leave of absence preliminary to discharge,” but often also an “absence on a visit or for other purposes.” U.S. Department of Commerce, Bureau of the Census, Patients in Hospitals for Mental Disease 1933: Statistics of Mental Patients in State Hospitals Together with Brief Statistics of Mental Patients in Other Hospitals for Mental Disease, U.S. Government Printing Office, Washington DC 1935, at p. 11. The parole numbers were large. On December 31, 1933, for example, 46,071 mental patients were on parole or otherwise absent, representing a little less than 10 percent of the total institutionalized patient population of 435,571. Id. Because this article focuses on the question of incapacitation, these patients “on parole” have not been included in the data set of persons in mental hospitals. When they are included, however, the statistical relationship with homicide becomes larger, more significant, and more robust.
institutions, including psychiatric hospitals and institutions for “mental retardation.” The AHA surveys achieved very high participation rates and are comparable to the earlier government series, with the exception of a few outlier states, such as Montana or Arkansas, where hospital response rates have been low at times.

In order to maintain the highest level of consistency in mental health populations over the seven decades, two datasets of mental hospital populations were compiled. The first includes only patients in residence in public (state, county, and city) mental hospitals. This first data set is compiled entirely from the federal government census data. The second dataset includes all resident patients in mental hospitals, including not only public mental hospitals but also private mental hospitals, psychopathic hospitals, psychiatric wards at general hospitals and VA hospitals, and public and private institutions for “mental defectives and epileptics” and for “the mentally retarded.” This dataset is compiled from the federal government census data for the period 1934 to 1968 and the American Hospital Association data from 1969 to 2001.

The rates of institutionalization using these two different datasets of mental institutions are reflected in Figure 5:

Figure 5: Rates of Institutionalization in Mental Hospitals in the United States (per 100,000 adults), 1934-2001.

[INSERT FIGURE 5]

3 For the period 1967 to 1996, Professor Steven Raphael at Berkeley compiled a similar state-level dataset of state and county mental hospital populations for a study he conducted in 2000. Those data are practically identical over the thirty year period to the data I compiled for that portion and subtype of the dataset. Because the documents from the National Institute on Mental Health became less formal and are merely photocopied reports starting in 1969 (due in large part to deinstitutionalization and the reduction of the populations), some of the reports are now difficult to obtain. The dataset I compiled therefore relies on the Raphael data for 10 years (1970-71, 1974, 1977, 1980, 1984-87, and 1991). I thank Steven Raphael for generously sharing those data with me. For this first dataset, all other years since 1969, including all the yearly census counts from 1991 to 2001, rely on the NIMH reports.

4 Patients in VA hospitals are reported by their home state in the census reports. As the 1947 government report notes (p. 36, n.1), “Veterans are distributed by home state rather than state of hospitalization.”

5 In those few states where hospital survey response rates were low and where the AHA Hospital census count was lower than the government data on state and county hospitals (there were 173 such cases in the dataset of 1,683 observations over the period 1969 to 1995), the latter government census counts were used rather than the lower AHA survey observations. Data were interpolated for 1970 (which was missing because of the switch from one AHA series, the Guides, to another format, Hospital Statistics). An algorithm was used to interpolate for the period 1996 to 2001, using the total aggregate national data for the period, which continue to be published by the AHA.
2.2 State and Federal Prison Populations

For the period beginning 1977, state and federal prison populations are well enumerated and documented in electronic format by the Bureau of Justice Statistics of the Department of Justice; prior to that, the breakdowns are available in written reports issued since 1926 on a yearly basis with annual counts of state and federal prisoners—first compiled by the Census Bureau along the lines of the mental health population breakdowns. The data on prison populations were thus compiled from the Census Bureau reports titled “Prisoners in State and Federal Prisons and Reformatories [Year]: Statistics of Prisoners Received and Discharged During the Year, for State and Federal Penal Institutions.” For the period beginning 1977, the data are taken directly from the Bureau of Justice Statistics.6

2.3 County Jail Populations

By contrast, the data on jail populations are sparse and not reliable at the state level for the period prior to 1970, the year that the Law Enforcement Assistance Administration (LEAA) conducted the first state-by-state census of jails (Cahalan 1986:73, 76 tbl.4-1). Prior to that, there were decennial Census Bureau counts for 1880, 1890, 1940, 1950, and 1960, but even those Census counts were not entirely reliable.7 Since 1970, the data are more reliable, but they remain extremely spotty. The Bureau of Justice Statistics conducts census counts of jails every five to six years, and those census counts produce state-level data. These censuses are supplemented by the annual survey of jails, which is a sample and does not allow for state-by-state estimates. As a result, since 1970, jail inmate counts by state are available only for 1978, 1983, 1988, and 1993, as well as 1999; in addition, there is a mid-year 2005 state-by-state estimate of jail inmates.

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6 Bureau of Justice Statistics, *Prisoners under State or Federal Jurisdiction*, compiled by George Hill and Paige Harrison, updated by Doris J. James and Paige Harrison [source: National Prisoner Statistics data series (NPS-1); date of version 12/6/05].
7 For instance, in 1970, the Census reported 129,189 inmates in jail, whereas the first Department of Justice LEAA count that same year reported 160,863 inmates in jail—24.5 percent higher than the Census count. *Id.* at 76 tbl.4-1. In addition, between 1904 and at least 1940, the Census counted only jail inmates who were sentenced. *Id.* at 73–74. The 1923 special report, “Prisoners, 1923,” also excluded inmates who were not sentenced and omitted certain jails that were believed not to contain sentenced jail inmates. *Id.* at 73. All that data, including the 1933 “County and City Jails” report, excluded jail inmates who had not been sentenced yet. *Id.*
There are national trends from 1990 to 2005, but those are for the nation, not for the states.

A state-level dataset for jail populations can be compiled using extensive interpolation from these and decennial census counts, but it is not sufficiently reliable to use in state panel data regressions. Aggregated to the national level and interpolated, it can provide some indications of overall trends for national-level analysis. Such a dataset was compiled from the following: (1) Census Bureau data for decennial years 1940, 1950, and 1960, as well as Census Bureau counts of prisoners and jail inmates for 1923 and 1933 (Cahalan 1986:76 tbl.4-1, 78 tbl.4-3); (2) LEAA census data for 1970 (Cahalan 1986:76 tbl.4-1); and (3) the Bureau of Justice Statistics jail inmate counts for 1978, 1983, 1988, 1993, 1999, and 2005. Missing years were linearly interpolated—for 1922, extrapolated—using this data.

2.4 Aggregated Institutionalization and Homicide Trends

When the patients in all mental health facilities are included with prison populations and aggregated at the national level, the rates of institutionalization in the twentieth and twenty-first centuries take on a different air: in the period between 1936 and 1963, the United States consistently institutionalized (in all mental institutions and prisons) at rates above 700 per 100,000 adults—with highs of 760 and 757 in 1955 and 1948 respectively. The trend lines including the two different datasets of mental hospitalization can be visualized in Figure 6:

![Figure 6: Rates of Institutionalization in Mental Hospitals and State and Federal Prisons (per 100,000 adults), 1934-2001: The Two Datasets](INSERT FIGURE 6 HERE)

In this light, the relationship between aggregated institutionalization and homicide rates looks very different. Over the course of the twentieth century, homicide rates appear to have fluctuated in an inverse relationship with rates of aggregated institutionalization.
The relationship is graphically represented in its most basic form, without controlling for other indicators, in Figure 7.

Figure 7: Rate of Aggregated Institutionalization in Mental Hospitals and Prisons (per 100,000 adults) and Rate of Homicide (per 10,000,000 persons) in the United States, 1934-2001.

[INSERT FIGURE 7 HERE]

To make the point somewhat more dramatically, if the data are sorted in descending order on the homicide rate, the relationship between aggregated institutionalization and homicide rates forms the X-pattern represented in Figure 8:

Figure 8: Rate of Aggregated Institutionalization in Mental Hospitals and Prisons (per 100,000 adults) and Rate of Homicide (per 10,000,000 persons) in the United States, 1934-2001, Sorted on the Homicide Rate (in Descending Order).

[INSERT FIGURE 8 HERE]

The correlation between the aggregated institutionalization rate (all mental hospitals plus state and federal prisons) and the homicide rate is remarkably high: \(-0.8554\). Using a Prais-Winston regression model at the national level, the relationship is statistically significant over the period 1934 to 2001, holding constant three leading correlates of homicide—namely youth demographics, poverty, and unemployment.\(^8\)

3. THE OTHER DATA

3.1 Dependent Variable: Homicide Victimization.

Homicide victimization, as reported by vital statistics, is the only reliable measure of violent crime that goes back as far as the 1930s and is therefore used as the measure of violent victimization in this study. The annual homicide count for each state is derived from the annual report on Mortality Statistics published by the Bureau of the Census.

\(^8\) See Appendix 1 for discussion and results of Prais-Winston regression on the national-level data.
These are vital statistics data compiled from transcripts of certificates of death received from each state. The data were complete for the first time and embraced all the existing states in 1934; prior to 1934, certain states like Texas, Georgia, Nevada, and others were not part of the reporting system.9 For this reason, the state-level panel regressions start in 1934.

3.2 Control Variables.

The state-level panel data regressions include seven control variables related to the four leading covariates of homicide—economic conditions, youth populations, criminal justice enforcement, and demographics:

1) Real per capita income for each state (brought to present dollars using the Consumer Price Index): The data for state-level per capita income are derived from the U.S. Bureau of the Census annual *Statistical Abstract of the United States*, and the values from the *Statistical Abstract* are converted into present dollars using the Consumer Price Index. Lawrence Katz, Steven D. Levitt, and Ellen Shustorovich originally compiled these data for the period 1950 to 1990 (Katz et al. 2003:318-43). John Donohue and Justin Wolfers (2005) extend the datasets to cover the period 1934 to 2000 (Donohue and Wolfers 2005:791-845). John Donohue generously made those data available.

2) Proportion 15 to 19, 19 to 24, non-white, black, and urban: These data are based on decennial census data, linearly interpolated between censuses, and derived from the *Statistical Abstract of the United States*. They were obtained from Donohue and Wolfers (2005), who expanded the Katz, Levitt, Shustorovich (2003) dataset.

3) The annual execution rate for each state: The state-level annual count of executions is collected from official reports of the Bureau of the Census for the period 1926 to 1930, the Federal Bureau of Prisons for the period 1930 to 1970, and the Bureau of Justice Statistics for the period 1977 to 2005. There were no executions between 1971 and 1976 because of the Supreme Court’s decision in *Furman v. Georgia* in 1972.10

4) The rate of police force: The state-level annual count of police officers is drawn from several sources. First, for each year from 1982 to 2005, the Bureau of Justice

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10 See 408 U.S. 238 (1972).
Statistics has police protection employment data by state under the category “Police Protection: full-time equivalent” for state and local governments. The Bureau of Justice Statistics obtains its data from the Census Bureau’s “Annual Survey of Public Employment.” For the years 1953 to 1981, the same publication by the Census Bureau, then titled “Government Employment,” has similar annual census data. Third, for the years prior to 1953, the data were obtained from the decennial Census publications, which divide the labor force by occupation for each state.

In order to compute state rates, the annual state population numbers are collected from the U.S. Bureau of the Census, annual *Statistical Abstract of the United States*.

4. ANALYSIS

In order to test the relationship between aggregated institutionalization and homicide rates at the state level, this study uses clustered regression models on the state panel data with fixed state and year effects and an adjustment for correlated error (robust standard errors). Fixed effects models are especially useful for correcting for the possibility of omitted variable bias and the robust standard error enhances confidence in the tests of statistical significance. The specific estimating equation of this class of models is as follows (Equation (1)):

\[
(1) \quad \text{LOG HOMICIDE RATE}_{sy} = \alpha + \beta \text{ INSTITUTIONALIZATION RATE}_{sy} + \theta \text{ CONTROLS}_{sy} + \gamma_s + \delta_y + \gamma + \epsilon_{sy}
\]

Where \( s \) represents states and \( y \) reflects the year. The dependent variable of interest in this class of models is the natural log of the annual homicide rate for each state, which is obtained by logging the rate of homicide using vital statistics measures of death by homicide. The key explanatory variable of interest is the one-year lagged rate of aggregated institutionalization in state and federal prisons, in public mental hospitals and other institutions for the mentally ill. The model uses a weighted least squares regression, with weights equal to the annual population of the states, clustering standard errors at the state level. The model conditions on state and year fixed effects \((\gamma_s \text{ and } \delta_y)\) to account for unmeasured factors that influence crime and are either constant within states over the study period, or change over time but exert a constant influence over the entire set of
states. The later models also include the seven control variables along four principal dimensions of alternative explanations—namely, indicators of state economic condition, percentage youth populations, criminal law enforcement measures, and demographics. To remove trend in these time-structured data and avoid the possibility of spurious results from non-stationarity, all models incorporate a linear trend variable by adding $\gamma$ (year) as a predictor. The study accounts for arbitrary forms of correlation in the models’ error structure by calculating robust standard errors, again clustered at the level of the state. To maintain commensurability across states, all models use rates of homicide and institutionalization, rather than counts.

The models use the natural logarithm of the homicide rate as the dependent variable and thus imply a nonlinear prediction as to the main independent variable (the institutionalization rate) so as to incorporate some elasticity. The reason to use a nonlinear model is that, as most research has shown, there is likely less of an effect on homicide rates at higher levels of incapacitation: as institutionalization rates rise beyond a certain point, it is likely that the type of people institutionalized are no longer the clearest candidates for institutionalization. For this reason, there is likely some elasticity in the relationship between institutionalization and homicide. In addition, by using a log-linear estimation, the models are multiplicative with regard to the other independent variables. Most of the more reliable studies on the crime-prison nexus use similar non-linear models with elasticity.

Finally, the models use a one-year lagged institutionalization rate. It is common in analyses of the effect of imprisonment on crime rates to use a one-year lag (DeFina and Arvanites 2002; Rosenfeld 2009). A lag is often introduced to address simultaneity concerns, although the possibility of simultaneity in this case would entail only a conservative bias and minimize the correlations. In this particular study, it is more likely that any potential effect would be contemporaneous rather than lagged and so, from a theoretical perspective, one might not necessarily include a lag; however, the data in this case were collected in such a way as to call for a lagged model. All the government census data on mental hospitalization are collected on December 31 of the given year, and thus the entire public mental hospitalization dataset (from 1934 to 2001) and the majority of the second, total mental hospitalization dataset (from 1934 to 1968) are
December 31 data. The prison counts are also December 31 census counts. (The AHA total mental hospitalization data (from 1969 to 2001) are annual averages of daily census counts, but represent a minority of the data). The dependent variable, in contrast, is yearly homicide counts. For this reason, institutionalization rates are lagged one year.\textsuperscript{11}

4.1 Results on All Mental Hospitals and Prisons Dataset

Beginning with the larger dataset of all residents in mental hospitals and aggregating those data with the prison populations, the log-linear model from Equation (1) offers a robust and significant prediction of homicide rates for the period 1934 to 2001, as evidenced in Table 1:

Table 1: State-level Panel-data Regressions (1934–2001)
Dependent Variable = Natural Log of Homicide Rate

[INSERT TABLE 1]

From the first model, the state-level aggregated institutionalization data explain a large amount of the variation in homicide rates, and the models explain more as the control variables are introduced. In the fourth and last model, which has introduced the seven competing control variables, the influence of aggregated institutionalization remains statistically significant (p-value of 0.031): the 95 percent confidence interval is narrow and extends from $-0.068$ to $-0.003$.

To give a sense of the actual relationship between aggregated institutionalization and the homicide rate—recall that these models use the natural logarithm of homicide—we can exponentiate the coefficient for the variable institutionalization in the models. In model 1, the coefficient of $-0.133$ translates to $0.8755$, meaning that, if the rate of aggregated institutionalization increased by 1 person per 1,000 (or, in other words, 100 persons per 100,000), the expected homicide rate would be 87.55 percent of what it was before. In other words, the homicide rate would decline by about 12.45 percent. In model

\textsuperscript{11} To clarify, as a result of the one-year lag, for all the public mental hospitalization data and for the total hospitalization data from 1934 to 1968, the models use institutionalization rates on December 31 of the previous year (for example, 1950) and the homicide rate for the full following year (for example, 1951); for the total hospitalization data from 1969 to 2001, the models use average daily census rates from the previous year (for example, 1990) and the homicide rate of the following year (for example, 1991).
4, the coefficient of $-0.036$ translates to $0.9646$, meaning that an increase in institutionalization of 100 per 100,000 would likely result in homicides at 96.46 percent of what they were before, or a decline of 3.54 percent. These are significant numbers.\footnote{The results are slightly sensitive to weighting by population; although the regression coefficients are substantially similar using non-population-weighted clustered regressions, the reliability of the predictions in model 4 decreases (see Appendix 2).}

To help visualize this, it may be useful to plot the predicted (non-logged) values of the homicide rate in the final model (Model 4) against the aggregated institutionalization rate. Figure 9 graphically represents the predicted values of the homicide rate using Model 4, which includes all the control variables. Figure 10 focuses on the values of the homicide rate lower than 12 in order to give a better sense of the elasticity of the predicted values by magnifying the area of greatest interest:

Figure 9: Predicted Values of Homicide Rate Based on State-Level Panel Data Regression Using Log of Homicide Rate as Dependent Variable, With Fixed Year and State Effects, Including All Independent Variables, 1934-2001.

[INSERT FIGURE 9]

Figure 10: Predicted Values of Homicide Rate Below 12 per 100,000 Based on State-Level Panel Data Regression Using Log of Homicide Rate as Dependent Variable, With Fixed Year and State Effects, Including All Independent Variables, 1934-2001.

[INSERT FIGURE 10 HERE]

What is entirely remarkable about these findings is that they span such a lengthy period of time—sixty-eight years from 1934 to 2001—and cover all fifty states, resulting in more than 3,200 observations, they control for all of the leading correlates of homicide, and they achieve statistical significance at the 0.031 level.

Several results on control variables are also interesting. The important influence of youth population is entirely consistent with what many social scientists have argued, namely that one of the most important driving factors in rates of violent crime is the size of the youth cohort.\footnote{See generally Fox 2000:288 (“Crime statistics that overlook differences by demography can easily lead to misinterpretation.”); see also South and Messner 2000:84; but see Marvell and Moody 1991: 250–54.} Research has consistently attributed a large portion of the rise in
crime during the 1960s to the post–World War II baby boom which spanned the period 1946–1964 and produced a large number of high-risk persons aged fourteen to twenty-four during the 1960s and 1970s (Blumstein & Nagin 1983:183, 192-94). There is debate, though, over the extent of the influence, as well as over how to interpret the results. On the one hand, Lawrence Cohen and Kenneth Land studied the relationship between the proportion of the population between fifteen and twenty-four and variations in homicide and auto theft rates, and found a highly significant statistical relationship accounting for a substantial fraction of the change (Cohen and Land 1987:170, 172-75). On the other hand, Steven Levitt conducted a study titled The Limited Role of Changing Age Structure in Explaining Aggregate Crime Rates, and found that “the changing age distribution can explain only 10–20% of the dramatic rise in crime observed between 1960 and 1980” (Levitt 1999:581, 582). Levitt characterizes this as “a limited impact” (Levitt 1999:581). By contrast, James Alan Fox and Alex Piquero contend that about 10 percent of the drop in crime in the 1990s was due to changing demographics and refer to this as “deadly demographics” (Fox and Piquero 2003:339, 354). So the estimates, and especially the interpretations, vary significantly.

What is particularly interesting about the regression results here, though, is that the effect shows up with the twenty to twenty-four cohort when all the variables are introduced, but not the fifteen to nineteen cohort. This suggests that the actual ages chosen may have a significant effect on the results. In other words, it may not be enough to focus on “fourteen to twenty-four” or other age-groups; it may be important to slice the age groups in more refined ways, perhaps even year-by-year.

The race effects are also remarkable and, in all likelihood, have to do with high victimization rates in the African-American community. As Lawrence Bobo notes, “Blacks are more likely to be the victims of crime than Whites and to live in communities with higher levels of crime and disorder” (Bobo and Johnson 2004:156; see also Blumstein 2001; Kennedy 2001). This is consistent with research that shows that, at the individual level, “young people, males, and members of disadvantaged minorities are at comparatively high risk of becoming offenders and victims, at least with respect to the common ‘street’ crimes” (South and Messner 2000:83, 84).
The findings regarding both criminal justice variables are interesting as well. The first, the execution rate, does not seem to play any discernible role. In both models, the execution rate is positively related to homicide but the estimates are entirely unreliable, with a 95 percent confidence interval in the fourth model that spans –0.254 to +0.336. Much has been written recently about the deterrent effects of capital punishment. John Donohue and Justin Wolfers (2005) have carefully reviewed the recent studies, including state-level panel data analyses, and concluded that “none of these approaches suggested that the death penalty has large effects on the murder rate” (Donohue and Wolfers 2005:841). A recent study by Kenneth Land, Raymond Teske, and Hui Zheng (2009) on Texas-only data suggests that any modest short-term reductions in homicide may be attenuated by displacement of homicides from one month to another. The findings from this analysis are consistent with these conclusions.

The findings regarding the police force indicate some mild and slightly significant negative effect on homicide rates, which is also consistent with the most reliable evidence. Steven Levitt attributes a portion of the 1990s crime drop to increased police forces and suggests that an increased number of police officers on the beat—regardless of their exact policing technique—seems to correlate with reductions in violent crime (Levitt 2004). The findings of this study are consistent again.

The single economic indicator—real per capital income—does not seem to be statistically important in the analysis. In their seminal study, Structural Covariates of Homicide Rates: Are There Any Invariances Across Time and Social Space?, Kenneth Land, Patricia McCall, and Lawrence Cohen review twenty-one of the leading homicide studies and find that “[b]y far, the strongest and most invariant effect is due to the resource-deprivation/affluence index; consistently across the four decennial census periods, cities, metropolitan areas, or states that are more deprived have higher homicide rates, and those that are more affluent have lower rates” (Land et al. 1990:922, 951). It may be that the state per capital income is not the best proxy for an affluence index. It could also be that using a model that controls for fixed state effects might mute the expected relationship between affluence and homicide. The lack of a relationship is nonetheless surprising.
Overall, this study identifies a robust relationship between the larger measure of aggregated institutionalization, which includes all mental hospitals and prisons, and homicide rates.

4.2 Results on the Public Mental Hospital and Prison Dataset

Similar results obtain using the aggregated dataset that includes only public (state, county, and city) mental hospitals. The log-linear model from Equation (1) again offers a robust and significant prediction of homicide rates for the period 1934 to 2001, as evidenced in Table 2:

Table 2: State-level Panel-data Regressions (1934–2001)
Dependent Variable = Natural Log of Homicide Rate

[INSERT TABLE 2 HERE]

Again, from the first model, aggregated institutionalization explains a large amount of the variation in homicide rates and even by the fourth model, which has introduced all seven competing control variables, this measure of aggregated institutionalization remains statistically significant (at the level of 0.038). The 95 percent confidence interval runs from –0.078 to –0.002. Again, a sense of the actual relationship is useful: in Model 1, the coefficient of –0.142 translates to 0.8676, meaning that, if the rate of aggregated institutionalization (in public mental hospitals and prisons) increased by 100 person per 100,000, the expected homicide rate would be 86.76 percent of what it was before or, in other words, the homicide rate would decline by 13.24 percent. In Model 4, the coefficient of –0.04038 translates to 0.9604, meaning that an increase in institutionalization of 100 per 100,000 would likely result in a decline in homicides of 3.96 percent. Again, these are significant numbers of homicides. The visualization of the relation can be plotted using non-logged values of the homicide rate in the final model (Model 4) against the measure of aggregated institutionalization. Figure 11 represents the predicted values of the homicide rate in Model 4. Figure 12 focuses on the values of homicide rate lower than 12 to give a better sense of the elasticity:

Figure 11: Predicted Values of Homicide Rate Based on State-Level Panel Data Regression Using Log of Homicide Rate as Dependent Variable, With Fixed Year and State Effects, Including All Independent Variables, 1934-2001.
Once again, these findings are remarkable since they cover such a lengthy period of time and all fifty states, and control for the leading correlates of homicide. The results on the control variables are substantially similar to the previous discussion.

4.3 Comparison with Imprisonment or Mental Hospitalization Only

Aggregating mental hospital and prison populations offers a far stronger prediction of homicide rates than using either the mental hospitalization rate alone or the imprisonment rate alone. In fact, using the prison rate alone does not come close to predicting homicide rates with the high degree of reliability that aggregated institutionalization rates do. This is demonstrated in the next table, Table 3, which distinguishes and compares all the possible institutionalization variables and displays the statistical results using the model that includes all control variables (essentially Model 4 above). The primary independent variable of interest in Table 3 remains total aggregated institutionalization (Model 5), but for the sake of completeness, Table 3 includes models for every possible permutation, including public mental hospitals alone (Model 1), total mental institutions alone (Model 2), prisons alone (Model 3), public mental hospitals and prisons (Model 4), total mental institutions and prisons (Model 5), and a horse-race comparison of total mental institutions versus prisons (Model 6).

Table 3: State-level Panel-data Regressions (1934–2001) Dependent Variable = Natural Log of Homicide Rate

[INSERT TABLE 3 HERE]
Notice that both the mental hospitalization rates alone and the prison rates alone have relatively similar magnitudes of effect, but are not reliable or precise in their prediction of homicide rates. The public mental hospitals coefficient in Model 1 (−0.048) is only significant at the 0.129 level, which means that the 95 percent confidence interval spans widely, from −0.112 to +0.015. The total mental institutions coefficient in Model 2 (−0.036) is also unreliable, with a significance at the 0.135 level and a 95 percent confidence interval that spans, again, a wide range from −0.083 to +0.0115. The prisons coefficient in Model 3 (−0.041) is even less reliable, with significance standing at the 0.14 level and a 95 percent confidence interval that spans −0.096 to +0.014. In the horse-race comparison in Model 6, neither mental institutions, nor prisons fare well in terms of their reliability.14 The bottom line is that combining mental hospitals and prisons in an aggregated measure of institutionalization produces by far the best and most reliable predictor of homicide rates over the twentieth century.

5. STATE VARIATIONS

State variation can be expected and is interesting to explore. The individual state data are each single-jurisdiction time series data and, as a result, are highly autocorrelated—the value in the time series at any one time depends heavily on the value in the preceding period or periods. In order to adjust for error autocorrelation, a Prais-Winsten regression model is used with an autocorrelation adjustment at one time lag.15 The Prais-Winsten model, which corrects for first-order autocorrelated error, fits the data well because the correlograms (autocorrelation function plots) and partial correlograms (partial autocorrelation function plots) of the residuals from the OLS regression analyses reveal that an AR1 effect is the principal time series error component at the individual state level.

14 In the race horse comparison in Model 6 of Table 3, a joint F-test of the two separate institutionalization variables (mental hospitalization versus imprisonment) yields a result of 0.0889. That result is significant at the 10% level, but does not match the level of significance (0.031) of aggregated institutionalization in Model 5. In essence, this means that using a single coefficient on the more constrained aggregated variable performs better than allowing each separate element to have its own coefficient. This confirms that aggregated institutionalization remains a more significant predictor of homicide than the two separate elements, and the most significant and strongest predictor of homicide in Table 3.

The Prais-Winsten model is a straightforward model for the study of time-series data. The method produces an unbiased regression estimate and, as a result, the coefficient is typically very close in value to the OLS coefficient. Apart from the adjustment for error autocorrelation, the regression model is simple: the log of the national homicide rate serves as the dependent variable, and the rate of aggregated institutionalization (all mental institutions plus prisons) for each state (lagged one year), as well as the seven control variables, are the regressors. The control variables employed in these individual state regressions are the same ones that are employed in the state panel-data analyses. Again, to remove trend in these time-structured data and avoid the possibility of spurious results, the model incorporates a linear trend variable \( \gamma \) as a predictor. The analysis runs a single model for each state that takes account of the effect of these other seven indicators.

The individual state findings reveal a complex and nuanced picture. Looking first at the five largest states, which combined constitute more than one third of the total United States population, there are very strong and robust relationships in Texas and California, where the results remain statistically significant with all control variables included. In both states, the negative coefficients of \(-0.1\) and \(-0.122\), respectively, are large and significant. Wherever there is a significant relationship, it is in the direction predicted by the state-level panel-data: more aggregated institutionalization results in lower homicide rates. Among these five states, there is not a single model that produces a positive and statistically significant relationship.16

A useful way to visualize the key results is to plot the coefficient of the independent variable of interest (aggregated institutionalization), as well as the band represented by adding and subtracting two robust standard errors—which is very close to the 95 percent confidence intervals. The following graph, Figure 13, represents just this, mapped against the overall population of the five largest states:

Figure 13: Coefficient of Aggregated Institutionalization Plus/Minus Two Robust Standard Errors for the Five Most Populous States, Including All Controls, 1934–2001

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16 See Appendix 3 for the results of the Prais-Winston regressions for the five largest states.
Figure 13 reveals that there are, indeed, slightly different relations within the five largest states, though the general direction of the relationship (with the possible exception of Florida) is clearly negative. The next graph, Figure 14, plots the same values of interest for the fifty states. Notice that the majority of predicted values are in the negative zone, especially for the larger states on the left hand side of the graph.

Figure 14: Coefficient of Aggregated Institutionalization Plus/Minus Two Robust Standard Errors: Individual States, with All Controls, 1934-2001.

6. CONCLUSION AND AVENUES FOR FURTHER RESEARCH

This study provides strong evidence of what should now be called an “institutionalization effect.” Naturally, these findings raise a number of questions that warrant further research. The first has to do with the mechanism that might explain the correlations. In all likelihood, mental hospitalization and imprisonment rates have an effect on homicide rates through the potential victimization of these populations. Research has consistently shown that persons with mental disorders are at far higher risk of violent victimization than the general population—one recent study finding that a quarter of persons with serious mental illness are victims of violent crime annually, at a rate that is eleven times higher than the general population (Teplin et al. 2005; see generally Teasdale 2009). This also holds true of prison and jail inmates: a large portion of murder victims, in fact a majority of non-family murder victims (Dawson and Langan 1994:1), have a prior criminal history, and correlativey, inmates in prison have a higher likelihood of being the victims of violent crime outside of prison (Karmen 2009: 101-103). Institutionalized populations therefore contain a higher proportion of potential homicide victims than the general population. This hypothesis—that the mechanism may
well relate to victimization—is corroborated by recent demographic trends regarding both institutionalized and victimized populations. Residents at mental institutions at mid-century were characterized by sharply different demographic features than prison inmates today—they were whiter, older, and more female—and, inversely, today’s prison population is, on the whole, far more young, male, and African-American (Harcourt 2006:1777-84). These demographic shifts track the pattern of changes in victimized populations closely (Smith and Zahn 1999:13-14; see generally Karmen 2009).

The second area for further research builds on these demographic shifts among the institutionalized populations. Demographic changes at the national level need to be placed in a richer historical context. On the issue of racial composition, the aggregate national picture may mask important differences at the state and regional level. The early surveys by the Census Bureau are revealing in this respect. Aggregated to the national level, African-Americans represented a small fraction of residents in mental hospitals enumerated on January 1, 1923—7.6 percent to be exact—and had a relatively low institutionalization rate (192 persons per 100,000 African-Americans). Whites, in contrast, represented 92.9 percent of mental hospital residents and had a significantly higher ratio of 259.8 per 100,000 whites. But things look very different within and between states and regions. The New England and Pacific regions had high rates of black institutionalization, in fact far higher than white institutionalization in those regions, and also far higher than black institutionalization in the South. Table 4 illustrates some of these disparities in state breakdowns:

| Table 4: Rate of Mental Hospitalization (“per 100,000 of same race”) |
| January 1, 1923 |
| [INSERT TABLE 4 HERE] |

17 The Census Bureau in 1932 hinted at one possible explanation: “This is undoubtedly due to the lack of adequate hospitals for negroes in the South. In the parts of the country in which negro patients are admitted to State hospitals without discrimination, the rate for negroes generally exceeds that for whites. In Massachusetts, for example, the rate for resident negro patients is 644.4 and for resident white patients, 408.8.” Census Bureau, *Patients in Hospitals for Mental Disease 1923*, p. 19.
Notice how the comparative rates differ as between states and regions. The racial
demographics of mental hospitalization varied at the state level and will require further
investigation and more nuanced analysis.

A third question is comparative. The United States today has an extraordinarily
high rate of imprisonment, especially compared to other Western or industrialized
countries. It has the highest rate and raw number of inmates in the world, but the contrast
is even more shocking with peer countries, naturally. One immediate question that comes
to mind is whether Western or industrialized countries with currently low prison
populations use their mental health systems as an alternative form of social control.

Preliminary research suggests that the answer is a nuanced yes and no. Rates of
mental hospitalization are higher in most countries, for instance, in the European Union,
and they tend to be higher than their respective imprisonment rates, though the numbers
do not reach the magnitudes achieved in the United States. The highest rate regarding the
number of beds in psychiatric hospitals per 100,000 inhabitants in 2000 was in the
Netherlands, which had a rate of 188.5. Other highs were posted in Belgium (161.6),
Switzerland (119.9), France (113), and Finland (102.9). The average for the 25 European
Union countries in 2000 was 90.1, down from 115.5 in 1993.18 These figures are, indeed,
higher than the corresponding prison rates for the same countries, which stood in 2006 at
128 per 100,000 persons in the Netherlands, 91 in Belgium, 83 in Switzerland, 85 in
France, and 75 in Finland (Walmsley 2006:5). But they certainly do not reach the rates of
aggregated institutionalization in the United States.19

On a related issue, though, there is evidence that in the past some European
countries used institutions other than the prison more than they do now to control those
deemed deviant—in other words, that the trends identified in the United States may bear
some resemblance to trends in Europe. The Republic of Ireland, for example, had much
higher rates of institutionalization in a wide range of facilities, including psychiatric

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19 These are preliminary findings, and more research needs to be conducted on these comparative figures.
The Russian Federation, for example, has a prison rate of 611 per 100,000 adults, which, when combined
with mental health institutionalization, may offer some competition to the United States. There are, in fact,
troubling reports concerning mental health institutionalization in Russia. See International Helsinki
Federation for Human Rights, 2006 Annual Report, Russian Federation report at p. 335; Kim Murphy,
“Speak Out? Are You Crazy? In a throwback to Soviet times, Russians who cross the powerful are
institutions and homes for unmarried mothers, at mid-century—in fact, eight times higher—than at the turn of the twentieth century (O’Sullivan and O’Donnell 2006:27-48). In Belgium, the number of psychiatric hospital beds per 100,000 inhabitants fell from 275 in 1970 to 162 in 2000; in France, it fell from 242 in 1980 to 111 in 2000; in the UK, from 250 in 1985 to 100 in 1998; and in Switzerland, from 300 in 1970 to 120 in 2000.\textsuperscript{20} Again, this requires more research, but there may be a parallel. The implications for the comparative international study of institutionalization are important.

Finally, this study raises serious questions about the alternative explanations for homicide that are traditionally offered. The conclusions here pose a challenge to criminological theory in general and to specific theories in particular—whether cultural, conflict, rational choice, differential association, biological or other. The findings suggest a “social physics” explanation of crime: homicide is largely related to the number and rate of individuals involuntarily detained in closed institutions. This should not be entirely surprising and confirms a basic intuition, namely that safely incapacitating portions of the population will have negative effects on crime rates (at least, outside of those closed facilities). But this raises the stakes and presents us with a sharp trade-off. If this is indeed true, society chooses its level of incapacitation and victimization at the very same time and in the very same movement that it chooses its level of freedom. How we choose, given the trade-off, is ultimately a reflection on us and a mirror of our values—nothing more, nothing less.

\textsuperscript{20} European Commission, \textit{Health statistics: Key data on health 2002}, Table 6.2.6 at p. 358 [Eurostat]
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APPENDIX 1
PRAIS-WINSTON REGRESSION ON NATIONAL LEVEL DATA

The national-level data represent single-jurisdiction time series data, and as a result are highly autocorrelated. In order to adjust for error autocorrelation, a Prais-Winsten regression model is used with an autocorrelation adjustment at one time lag. The Prais-Winsten model fits the data well and produces an unbiased regression estimate. Prais-Winsten is used here so that the significance tests on the regression coefficients are correct; this would not be the case using an OLS regression since there is first order autocorrelation in the error terms. Apart from the adjustment for error autocorrelation, the regression model is straightforward: the log of the national homicide rate serves as the dependent variable, and the rate of aggregated institutionalization (all mental hospitals plus prison rate) and three control variables are the regressors. Aggregated institutionalization is lagged one year. To remove trend in the time-structured data, the model also incorporates a linear trend variable ($\gamma$ or year) as a predictor.

The national-level control variables consist of the three leading structural covariates for homicide: the unemployment rate, the changing youth population age structure, and the poverty rate. The three control variables are summarized here:

1. **Unemployment**: The measure of unemployment is the official unemployment rate reported by the U.S. Census and Department of Labor, which consists of the percentage of the civilian labor force that is unemployed, in thousands of persons sixteen years old and over (prior to 1947, fourteen years old and over), in annual averages. These data draw on the U.S. Census Bureau’s *Historical Statistics of the United States: Colonial Times to 1970* for the period 1925–1970 and on reports from the U.S. Department of Labor, Bureau of Labor Statistics, for the period 1940–2004.

2. **Youth Population**: The measure of youth demographics is drawn from the U.S. Census Bureau, *Current Population Reports*. Based on those reports, the annual percentage of the total population represented by fifteen to twenty-four year olds was calculated.

3. **Poverty**: This study uses the official poverty rate from the U.S. Census Bureau. The rates are only available from 1959 onwards, when the poverty line was first
measured—so the regressions including this variable use a smaller number of observations ($N = 42$, rather than 68 as in all the other regressions).

Several models are used that take account of each control variable individually, as well as the combined effect of these other indicators. The results are reproduced in Table Appendix 1 below.

<table>
<thead>
<tr>
<th>Table Appendix 1: Prais-Winsten Regression of Aggregated Institutionalization Rates (All MH and Prisons) on Homicide</th>
</tr>
</thead>
<tbody>
<tr>
<td>National-level Data (1934–2001)</td>
</tr>
<tr>
<td>Dependent Variable = Log of Homicide Rates</td>
</tr>
</tbody>
</table>

As Table A1 shows, regardless of the model specification, the aggregated institutionalization rate has a statistically significant relationship on the logged homicide rate. The institutionalization variable is lagged in this specification, which addresses simultaneity concerns. It is important to add, though, that the leading alternative explanation—that increases in homicide produce higher incarceration rates as more individuals are apprehended, convicted, and sentenced—would work in the opposite direction: the higher the homicide rate, the higher the institutionalization rate. In other words, the leading alternative mechanism would dampen any effect that we observe in the data and would entail a conservative bias.
APPENDIX 2

Table A2: Table 1 Results But Not Population-Weighted.
Log-linear Model with Fixed State and Year Effects

[INSERT TABLE APPENDIX 2 HERE]
APPENDIX 3

Table A3: Prais-Winston Regressions for Five Most Populous States
Dependent Variable = Log of Homicide Rates
(1934–2001)

[INSERT TABLE APPENDIX 3]
TABLES
**TABLE 1**

<table>
<thead>
<tr>
<th>Aggregated Institutionalization Rate per 1,000 (all MH and prisons)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td></td>
<td>-0.133***</td>
<td>-0.040**</td>
<td>-0.037**</td>
<td>-0.036**</td>
</tr>
<tr>
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<td>[0.017]</td>
<td>[0.017]</td>
<td>[0.016]</td>
<td>[0.016]</td>
</tr>
<tr>
<td>Percent 15 to 19</td>
<td>0.036</td>
<td>0.026</td>
<td>0.031</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.046]</td>
<td>[0.044]</td>
<td>[0.045]</td>
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<tr>
<td>Percent 20 to 24</td>
<td>0.091**</td>
<td>0.089***</td>
<td>0.088**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.035]</td>
<td>[0.033]</td>
<td>[0.035]</td>
<td></td>
</tr>
<tr>
<td>Percent Urban</td>
<td>-0.013***</td>
<td>-0.011**</td>
<td>-0.011**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.004]</td>
<td>[0.004]</td>
<td></td>
</tr>
<tr>
<td>Percent Black</td>
<td>0.037***</td>
<td>0.037***</td>
<td>0.036***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.006]</td>
<td>[0.006]</td>
<td>[0.006]</td>
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</tr>
<tr>
<td>Rate of Execution per 100,000</td>
<td>0.039</td>
<td>0.041</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.144]</td>
<td>[0.147]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Police Officer Rate per 100,000</td>
<td>-0.002**</td>
<td>-0.002**</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>[0.001]</td>
<td>[0.001]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Per Cap Income</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.002]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3285</td>
<td>3235</td>
<td>3235</td>
<td>3235</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.89</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

**NOTE:** Dependent variable = Log of homicide rate; institutionalization rate lagged one year, population-weighted least squares regression, standard errors clustered at the state level, controlling for year and state fixed effects, detrended.
TABLE 2

<table>
<thead>
<tr>
<th></th>
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<tr>
<td>Public MH and Prison Rate per 1,000</td>
<td>-0.142***</td>
<td>-0.044***</td>
<td>-0.042**</td>
<td>-0.040**</td>
</tr>
<tr>
<td></td>
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<td>[0.020]</td>
<td>[0.019]</td>
<td>[0.019]</td>
</tr>
<tr>
<td>Percent 15 to 19</td>
<td>0.039</td>
<td>0.028</td>
<td>0.034</td>
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<tr>
<td></td>
<td>[0.044]</td>
<td>[0.044]</td>
<td>[0.045]</td>
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</tr>
<tr>
<td>Percent 20 to 24</td>
<td>0.091***</td>
<td>0.090***</td>
<td>0.088**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.034]</td>
<td>[0.032]</td>
<td>[0.034]</td>
<td></td>
</tr>
<tr>
<td>Percent Urban</td>
<td>-0.013***</td>
<td>-0.011**</td>
<td>-0.011***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.004]</td>
<td>[0.004]</td>
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</tr>
<tr>
<td>Percent Black</td>
<td>0.038***</td>
<td>0.038***</td>
<td>0.037***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.006]</td>
<td>[0.006]</td>
<td>[0.006]</td>
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</tr>
<tr>
<td>Rate of Execution per 100,000</td>
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<td></td>
<td>0.042</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.142]</td>
<td>[0.145]</td>
</tr>
<tr>
<td>Police Officer Rate per 100,000</td>
<td>-0.002**</td>
<td>-0.002**</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>[0.001]</td>
<td>[0.001]</td>
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</tr>
<tr>
<td>Real Per Cap Income</td>
<td></td>
<td></td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.002]</td>
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<tr>
<td>Observations</td>
<td>3285</td>
<td>3235</td>
<td>3235</td>
<td>3235</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.89</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
NOTE: Dependent variable = Log of homicide rate; institutionalization rate lagged one year, population-weighted least squares regression, standard errors clustered at the state level, controlling for year and state fixed effects, detrended.
<table>
<thead>
<tr>
<th>Institution</th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tbody>
<tr>
<td>S/C MH</td>
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<td>-0.036</td>
<td>-0.041</td>
<td>-0.040**</td>
<td>-0.036**</td>
<td>-0.033</td>
</tr>
<tr>
<td>All MH</td>
<td>0.031</td>
<td>0.024</td>
<td>0.027</td>
<td>0.019</td>
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<tr>
<td>Prison</td>
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<td>0.030</td>
<td>0.043</td>
<td>0.034</td>
<td>0.031</td>
<td>0.032</td>
</tr>
<tr>
<td>Percent 15 to 19</td>
<td>0.045</td>
<td>0.044</td>
<td>0.043</td>
<td>0.045</td>
<td>0.045</td>
<td>0.044</td>
</tr>
<tr>
<td>Percent 20 to 24</td>
<td>0.083**</td>
<td>0.084**</td>
<td>0.095***</td>
<td>0.088**</td>
<td>0.088**</td>
<td>0.088**</td>
</tr>
<tr>
<td>Percent Urban</td>
<td>0.034</td>
<td>0.036</td>
<td>0.035</td>
<td>0.034</td>
<td>0.035</td>
<td>0.037</td>
</tr>
<tr>
<td>Percent Black</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Rate of Execution per 100,000</td>
<td>0.029</td>
<td>0.025</td>
<td>0.036</td>
<td>0.045</td>
<td>0.041</td>
<td>0.042</td>
</tr>
<tr>
<td>Police Officer Rate per 100,000</td>
<td>0.015</td>
<td>0.015</td>
<td>0.147</td>
<td>0.145</td>
<td>0.147</td>
<td>0.146</td>
</tr>
<tr>
<td>Real Per Cap Income</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Observations</td>
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<td>3236</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
NOTE: Dependent variable = Log of homicide rate; institutionalization lagged one year; population-weighted least squares regression; standard errors clustered at the state level; controlling for year and state fixed effects; detrended.
### TABLE 4

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>Negro</th>
<th>Indian</th>
<th>Chinese</th>
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<tr>
<td>New York</td>
<td>391.9</td>
<td>529.0</td>
<td>327.1</td>
<td>466.1</td>
</tr>
<tr>
<td>New Jersey</td>
<td>276.6</td>
<td>391.9</td>
<td>--</td>
<td>336.1</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>232.4</td>
<td>362</td>
<td>--</td>
<td>273.4</td>
</tr>
<tr>
<td>Illinois</td>
<td>291.2</td>
<td>370.9</td>
<td>--</td>
<td>324.2</td>
</tr>
<tr>
<td>California</td>
<td>350.4</td>
<td>528.9</td>
<td>864.0</td>
<td>281.1</td>
</tr>
<tr>
<td>Arkansas</td>
<td>137.0</td>
<td>77.7</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Georgia</td>
<td>172.0</td>
<td>102.9</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Mississippi</td>
<td>188.2</td>
<td>107.8</td>
<td>90.5</td>
<td>274.7</td>
</tr>
</tbody>
</table>
TABLE APPENDIX 1

<table>
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<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All MH and Prison</td>
<td>-0.159***</td>
<td>-0.155***</td>
<td>-0.147***</td>
<td>-0.145***</td>
<td>-0.160***</td>
<td>-0.158***</td>
</tr>
<tr>
<td>Rate per 1,000</td>
<td>[0.026]</td>
<td>[0.026]</td>
<td>[0.035]</td>
<td>[0.035]</td>
<td>[0.025]</td>
<td>[0.038]</td>
</tr>
<tr>
<td>Percent of</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>civilian labor</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>force unemployed</td>
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<td>[0.005]</td>
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<td>Percent of</td>
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<td>0.008</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>population 15 to</td>
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<tr>
<td>24</td>
<td>[0.021]</td>
<td>[0.019]</td>
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<td></td>
<td>[0.025]</td>
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<td>67</td>
<td>67</td>
<td>67</td>
<td>43</td>
<td>43</td>
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<tr>
<td>OLS R-squared21</td>
<td>0.78</td>
<td>0.85</td>
<td>0.79</td>
<td>0.85</td>
<td>0.85</td>
<td>0.86</td>
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</tbody>
</table>

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

NOTE: Dependent variable = Log of Homicide rate

21 The R-squared from the OLS regression, rather than the Prais-Winsten R-squared, better describes how well the regression model will perform. Accordingly, I report the OLS R-squared values here.
### TABLE APPENDIX 2

<table>
<thead>
<tr>
<th>All MH and Prison Rate per 1,000</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>-0.111***</td>
<td>-0.040**</td>
<td>-0.038*</td>
<td>-0.034</td>
</tr>
<tr>
<td>(0.016)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.021)</td>
<td></td>
</tr>
<tr>
<td>Percent 15 to 19</td>
<td>0.032</td>
<td>0.033</td>
<td>0.049</td>
<td></td>
</tr>
<tr>
<td>(0.038)</td>
<td>(0.039)</td>
<td>(0.041)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent 20 to 24</td>
<td>0.071**</td>
<td>0.072**</td>
<td>0.066**</td>
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</tr>
<tr>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.031)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Urban</td>
<td>-0.011***</td>
<td>-0.010***</td>
<td>-0.010***</td>
<td></td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Black</td>
<td>0.035***</td>
<td>0.033***</td>
<td>0.031***</td>
<td></td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rate of Execution per 100,000</td>
<td></td>
<td>0.140*</td>
<td>0.148*</td>
<td></td>
</tr>
<tr>
<td>(0.074)</td>
<td>(0.078)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Police Officer Rate per 100,000</td>
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<td>-0.000</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Per Cap Income</td>
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<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3285</td>
<td>3235</td>
<td>3235</td>
<td>3235</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.89</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

NOTE: Dependent variable = Log of homicide rate; institutionalization lagged one year; not population-weighted, least squares regression; standard errors clustered at the state level; controlling for year and state fixed effects; detrended.
TABLE APPENDIX 3

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All MH and Prison Rate per 1,000</td>
<td>California</td>
<td>Texas</td>
<td>New York</td>
<td>Florida</td>
<td>Illinois</td>
</tr>
<tr>
<td></td>
<td>-0.122*</td>
<td>-0.100***</td>
<td>-0.054</td>
<td>0.003</td>
<td>-0.153</td>
</tr>
<tr>
<td></td>
<td>[0.072]</td>
<td>[0.028]</td>
<td>[0.048]</td>
<td>[0.078]</td>
<td>[0.095]</td>
</tr>
<tr>
<td>Percent 15 to 19</td>
<td>-0.079</td>
<td>-0.023</td>
<td>-0.007</td>
<td>0.111</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>[0.090]</td>
<td>[0.059]</td>
<td>[0.096]</td>
<td>[0.088]</td>
<td>[0.100]</td>
</tr>
<tr>
<td>Percent 20 to 24</td>
<td>0.220</td>
<td>0.233***</td>
<td>0.216*</td>
<td>0.100</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>[0.135]</td>
<td>[0.059]</td>
<td>[0.110]</td>
<td>[0.082]</td>
<td>[0.080]</td>
</tr>
<tr>
<td>Percent Urban</td>
<td>-0.034</td>
<td>-0.009</td>
<td>-0.123</td>
<td>-0.073*</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>[0.044]</td>
<td>[0.010]</td>
<td>[0.090]</td>
<td>[0.042]</td>
<td>[0.078]</td>
</tr>
<tr>
<td>Percent Black</td>
<td>0.004</td>
<td>-0.020</td>
<td>0.040</td>
<td>-0.111**</td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td>[0.079]</td>
<td>[0.084]</td>
<td>[0.036]</td>
<td>[0.045]</td>
<td>[0.083]</td>
</tr>
<tr>
<td>Rate of Execution per 100,000</td>
<td>0.482</td>
<td>-0.144</td>
<td>-0.429</td>
<td>-0.182*</td>
<td>0.765</td>
</tr>
<tr>
<td></td>
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<td>[0.209]</td>
<td>[0.608]</td>
<td>[0.095]</td>
<td>[0.648]</td>
</tr>
<tr>
<td>Police Officer Rate per 100,000</td>
<td>0.004*</td>
<td>0.001</td>
<td>-0.002</td>
<td>0.005*</td>
<td>0.005**</td>
</tr>
<tr>
<td></td>
<td>[0.002]</td>
<td>[0.002]</td>
<td>[0.001]</td>
<td>[0.003]</td>
<td>[0.002]</td>
</tr>
<tr>
<td>Real Per Cap Income</td>
<td>-0.007*</td>
<td>-0.009**</td>
<td>0.000</td>
<td>0.002</td>
<td>-0.001</td>
</tr>
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<td>[0.004]</td>
<td>[0.004]</td>
<td>[0.004]</td>
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</tr>
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<td>66</td>
<td>66</td>
<td>66</td>
<td>66</td>
</tr>
<tr>
<td>OLS R-squared</td>
<td>0.93</td>
<td>0.88</td>
<td>0.96</td>
<td>0.90</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

NOTE: Dependent variable = Log of homicide rate

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22 Again, the R-squared from the OLS regression, rather than the Prais-Winsten R-squared, better describes how well the regression model will perform. Accordingly, I report the OLS R-squared values here.
FIGURES
FIGURE 1

[Graph showing trends over time for Prison Rate, All Mental Hospital Rate, and Aggregated Institutionalization Rate.]
FIGURE 3
FIGURE 4

![Chart showing the Homicide Rate per 100,000 persons over several years.]
FIGURE 5
FIGURE 6

[Line graph showing data over time for Public MH and Prisons and All MH and Prisons.]
FIGURE 9

![Graph showing the relationship between Homicide Rate (per 100,000) and Institutionalization Rate (per 100,000).]
FIGURE 10
FIGURE 11

![ Scatter plot showing the relationship between Homicide Rate (per 100,000) and Institutionalization1 Rate (per 100,000). ]
FIGURE 12
FIGURE 13

* significant at 10%; ** significant at 5%; *** significant at 1%

NOTE: Dependent variable = Log of homicide rate
FIGURE 14
* significant at 10%; ** significant at 5%; *** significant at 1%
NOTE: Dependent variable = Log of homicide rate
*** END ***