

NBER WORKING PAPER SERIES

A CURE FOR CRIME? PSYCHO-PHARMACEUTICALS AND CRIME TRENDS

Dave E. Marcotte  
Sara Markowitz

Working Paper 15354  
<http://www.nber.org/papers/w15354>

NATIONAL BUREAU OF ECONOMIC RESEARCH  
1050 Massachusetts Avenue  
Cambridge, MA 02138  
September 2009

We would like to thank to Erik Nesson and Steve Hemelt for excellent research assistance. Thanks to David Bjerk, Phil Cook, Jens Ludwig, John MacDonald, and participants at IZA's First Annual Meeting on the Economics of Risky Behaviors and the 2009 Annual Workshop on Crime and Population Dynamics for helpful comments. We would also like to acknowledge the Blanche and Irwin Lerner Center for Pharmaceutical Management Studies at the Rutgers University Business School for providing the IMS data. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2009 by Dave E. Marcotte and Sara Markowitz. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

A Cure for Crime? Psycho-Pharmaceuticals and Crime Trends  
Dave E. Marcotte and Sara Markowitz  
NBER Working Paper No. 15354  
September 2009, Revised January 2010  
JEL No. I0,K0

**ABSTRACT**

In this paper we consider possible links between the advent and diffusion of a number of new psychiatric pharmaceutical therapies and crime rates. We describe recent trends in crime and review the evidence showing mental illness as a clear risk factor both for criminal behavior and victimization. We then briefly summarize the development of a number of new pharmaceutical therapies for the treatment of mental illness which diffused during the “great American crime decline.” We examine limited international data, as well as more detailed American data to assess the relationship between crime rates and rates of prescriptions of the main categories of psychotropic drugs, while controlling for other factors which may explain trends in crime rates. We find that increases in prescriptions for psychiatric drugs are associated with decreases in violent crime, with the largest impacts associated with new generation antidepressants and stimulants used to treat ADHD.

Dave E. Marcotte  
Department of Public Policy  
UMBC  
1000 Hilltop Circle  
Baltimore, MD 21250  
marcotte@umbc.edu

Sara Markowitz  
Department of Economics  
Emory University  
Rich Building, 3rd floor  
1602 Fishburne Dr.  
Atlanta, GA 30322  
and NBER  
sara.markowitz@emory.edu

In the early 1990s, the United States began a decline in crime rates that was widespread and large by historical standards (Zimring 2007). This trend was especially pronounced for the violent crime rate, which peaked in 1992. The rate of decline slowed and perhaps stopped in the early part of this decade. Property crime rates have also fallen since the early 1990s. There is a large body of literature attempting to explain the declining crime rates.<sup>1</sup> Previous work by economists has focused on a variety of factors that affect the costs of crime, opportunity costs, and the number of persons in the population at risk of criminal behavior. For example, there is a large amount of evidence that the increase in the number of police on the street lowered urban crime rates, even if evidence about particular policing strategies is less clear (Cook 2008 and Levitt 2004). It appears, too, that crime rates did not recede in response to the economic growth of the 1990s, but the waning of the crack cocaine epidemic was a factor (Levitt 2004); Raphael and Winter-Ebmer 2001).

While much has been learned about recent trends in crime rates, it is clear, too, that many of the social, economic, and policy determinants of crime have had little effect. Zimring (2007) notes that the marked decline in crime rates occurred during a period when the social and economic conditions were not much changed. Consequently, analysts have examined the role of other, less obvious, factors as possible explanatory factors. These include the decline in youth at risk of criminal behavior because of an increase in access to abortions in the 1970s following the *Roe v. Wade* decision (Donohue and Levitt 2001), and a decline in exposure to environmental lead, which has been linked to developmental problems and aggression (Reyes 2007).

One factor that has so far been ignored in the attempt to explain this recent drop in crime is a period of dramatic technological advances in the treatment of mental illness. As we summarize below, mental illness is a clear risk factor both for criminal behavior and for

---

<sup>1</sup> See Cook (2008) for a recent review.

victimization. The decline in crime rates occurred during a period when many new pharmaceutical therapies became available to treat mental illness, resulting in exceptionally large increases in medical treatment of mental illness. For example, during the last two decades the use of antidepressants and antipsychotics has become increasingly common following a series of drug innovations in the late 1980s and early 1990s. The new drugs were marked improvements over the previous therapies in terms of side effects and efficacy, and their use has subsequently become widespread. Anti-depressants and anti-psychotic medications are now the 6<sup>th</sup> and 7<sup>th</sup> largest therapeutic classes of drugs sold globally (IMS Health 2006), and by 2005 there were enough newer anti-depressants sold in the U.S to treat every man, woman, and child with a daily dose for almost two months.

The notion that crime rates should be affected by expanded or improved treatment for mental illness should not be surprising. Economists have long known that persons at risk for criminal behavior respond to incentives (Becker 1968). The economics of crime has focused extensively on how changes in the certainty or severity of punishment deter crime (e.g. Ehrlich 1973), and on related policy questions about the most cost-effective ways to reduce crime. While it is clear the costs of crime matter to criminals, mental illness may shape either the ability to assess those costs, or even how those at risk of crime optimize. One way this may occur is by altering time horizons. Mental illness may cause the afflicted to substantially discount the future, thereby lowering the deterrent effect of established punishments. This possibility is substantially related to Becker and Mulligan's (1997) formulation of impatience. They observe that many people recognize their high rate of time preference as a weakness, and allocate resources to overcome that weakness. One might think of mental health treatment as just such an allocation. The expansion of treatment for mental illness can then affect crime not by changing the certainty

or severity of punishment, but by changing the behavioral response to established costs.

There is some suggestive evidence that the dispersion of such treatment may have affected crime rates. The first are simple time series comparisons: crime rates/victimization for adults peaked just after the introduction of the first of these new psycho-pharmaceutical therapies, and have declined since. Further, crime rates/victimization for juveniles peaked a bit later, then fell until 2004, and rose in 2005; sales of new psycho-pharmaceuticals to juveniles lagged those to adults, and fell sharply after the FDA's 2004 "black box" warning of risks of suicide for young persons treated with newer classes of antidepressants. Beyond these corresponding time-series, recent research has shown the potential for improvements in mental health and reduction in criminal behavior as a result of mental health treatment adherence, including adherence to prescription drug routines. However, much of this literature has been conducted on small samples or specific vulnerable populations.

The purpose of our paper is to examine the link between prescriptions for psychotropic drugs and crime rates in a broad study of the U.S. that moves beyond simple time series comparisons. Specifically, we examine the relationship between crime rates and rates of prescriptions of three main categories of psychotropic drugs—antidepressants, antipsychotics, and stimulants, while controlling for other factors which may explain trends in crime rates. Our goal is to see if increases in prescriptions are associated with changes in crime rates. Any observed reduction in crime as a result of higher prescriptions rates would suggest that expansions in mental health treatment may have substantial benefits for society as a whole beyond improved health.

## **Background**

### *Recent trends in crime*

For those that study crime, the 1990s were remarkable. During the decade, violent crime rates fell from a post-war peak with a speed that was both rapid and unforeseen. The importance of the decade for criminologists is not just the break in trend, but that many questions linger about its causes. One source for gauging trends in crime rates over time is data reported to the U.S. Federal Bureau of Investigation through its Uniform Crime Reports (UCR) program. The UCR is a voluntary program compiling criminal offenses reports to local policing agencies.<sup>2</sup> In Figure 1, we plot rates of violent and property crime (per 100,000 residents) for the period 1960 to 2007.<sup>3</sup>

Violent crime (including murder, rape, robbery and assault) increased fairly steadily from the beginning of the series until 1993. Violent crime rates then fell rapidly, in a period of 7 years reverting back to rates not observed since the early 1970s. Since 2000, the rate of decline in violent crime has slowed and perhaps stopped. Property crime rates increased more rapidly in the early part of the period, but peaked earlier, too. Like violent crime, property crime rates fell rapidly in the 1990s, and somewhat more slowly since 2000.

The fall in crime rates in the 1990s was not only steep, it was broad. Using both the UCR and data from the U.S. Department of Justice's National Crime Victimization Survey, Levitt (2004) reports that crime rates fell in all categories of violent and property crimes. He also

---

<sup>2</sup> An obvious concern is that because this reporting is voluntary, the results might be hard to compare over time or across jurisdictions. However, the view of most analysts is that police departments are diligent and forthright in reporting data (e.g. Cook 2008). In any case, the marked decline witnessed in the 1990s is also apparent in the two other principal sources of data on crime rates, the U.S. Department of Justice's National Crime Victimization Survey and the Center for Disease Control's National Vital Statistics program, which tracks death by cause, including homicide.

<sup>3</sup> No data are available from New York City from 1960 to 1964. Though this is only one jurisdiction, it is clearly an important omission to the first five years of these series.

illustrates that crime fell in all regions of the country, and in cities large and small, and that rates fell fastest in metropolitan areas, although they fell in rural areas too.

Several factors are believed to have contributed to the rapid and broad decrease in crime rates. One factor that appears to have been important is the growth in the size of the collective police force, even if the jury is still out on particular policing strategies (Levitt 2004) and Evans and Owen 2007). Also contributing to the decline was a run up in the proportion of the population incarcerated, and hence unavailable to engage in criminal activity in the community (Levitt 2004 and Zimring 2007). Another factor that was likely affecting violent crime rates during this period was the waning crack cocaine epidemic. There is substantial agreement that the growing market for crack in the 1980s created and sowed substantial violence in urban neighborhoods where it was sold and consumed (Blumstein 2000; Levitt and Venkatesh 2000; and Grogger and Willis 2000). Consequently, several analysts have suggested that a shrinking market for crack has contributed to reduced violence, especially in urban areas (Levitt 2004 and Zimring 2007).

The period of falling crime rates in the 1990s is just as interesting for what did not contribute to the advent of what one prominent analyst has called a renewed “golden age” in urban centers like New York and Chicago, once so affected by high crime rates (Cook 2008, p. 3). Most notably, the economic growth of the period contributed substantively little to the decline in property crime rates, and not at all to declining violent crime (Levitt 2004). There is also no evidence that gun control laws, such as the Brady Act, have reduced homicide (Ludwig and Cook 2000), or that laws permitting registered gun owners to carry concealed weapons have reduced crime (Duggan 2001).

The collection of factors that do not explain the decline of the 1990s includes those generally thought to be especially important, including economic conditions and demographic change. That crime rates could fall so quickly during a period when these important phenomena changed slowly (and to no real effect), has led two prominent analysts to conclude that a central lesson of the decade is that large changes in crime rates can occur without much change in the “social fabric” (Zimring 2007, p. 206) or “underlying socioeconomic conditions” (Cook 2008, p. 24). That marked changes in rates of crime can occur in a period of relative socioeconomic stasis has led analysts to suggest a variety of changes in factors that might provide answers. These include the well-known, though not universally accepted, contention that increased use of abortions in the 1970s reduced the number of young persons in the 1990s at risk of criminal behavior (Donohue and Levitt 2001, 2003; and Joyce 2004). Another is a possible link between decline in exposure to environmental lead and crime (Reyes 2007).

#### *Mental illness and crime*

Our work fits squarely in this line of research looking for alternative explanations. We raise the possibility that the diffusion of vastly improved treatments for various mental illnesses in the community reduced underlying behavioral antecedents to crime. Mental illness (MI) and crime are frequently linked in the scholarly literature as well as in the mass media and the public’s perception. Research in this area is largely comprised of correlational studies showing a link between MI and crime (or violence). These studies most commonly take one of two approaches to demonstrate the relationship. The first examines rates of mental illness among prison populations (e.g., Teplin 1990; Silver et al. 2008). The vastly higher rate of mental illness in prison populations is reflected in a Bureau of Justice Statistics (BJS) survey of inmates in federal, state, and local prisons conducted in 2002 and 2004, reporting that 22 percent of all



inmates had a history of a serious mental health problem in the year before arrest or since admission. This compares to a prevalence rate of approximately 11 percent in the general U.S. population (BJS 2006).

Evidence using registers data from other countries finds results quite similar to the BJS estimates. For example, Wallace et al. (1998) link data from Australian court records to psychiatric-case registers. They estimate that 25 percent of Australian inmates had been previously treated for a psychiatric disorder. Obviously, they do not identify the number untreated. They report that those treated had most commonly been diagnosed with depression, bipolar disease, and schizophrenic disorders, particularly with comorbid substance abuse.

The second strand of correlational studies on mental illness and crime examines rates of violence, arrest, or incarceration among those who suffer from mental illness (e.g., Hodgins 1992; Swanson et al. 2002). For example, White et al. (2006) find that persons with severe mental illness were many times more likely to be incarcerated in the past 6 months than comparable people in the general population. Fewer studies consider violence, crime and mental illness in the broader population (e.g., Cuellar et al. 2007; Swartz and Lurigio 2007). One source for evidence of this type is studies that follow birth cohorts. The Dunedin Study has followed all children born in Dunedin, New Zealand between April 1, 1972 and March 31, 1973. Estimates from Dunedin suggest that those with mental illness were more than twice as likely to be violent (Arsenault et al. 2000). While persons with one of the disorders examined comprised one-fifth of the birth cohort, this group accounted for half of the violent crimes committed by the Dunedin cohort (Arsenault et al. 2000). Brennan et al. (2000) use data from the Danish national register, and follow persons born between 1944 and 1947. They estimate that persons with a previous psychiatric hospitalization were between 2 and 8 times more likely to engage in

criminal violence, even conditioning on demographic, social, and economic characteristics, and substance abuse.

The existing studies differ in terms of the types of crimes and illnesses studied, as well as in the confounding factors that are considered in the research. This is important as Swartz and Lurigio (2007) show that co-occurring substance use partially confounds the relationship between mental illness and crime. Using a large, nationally representative non-institutionalized sample, these authors show that the positive relationship between serious mental illness and arrests only holds for violent crimes once alcohol and drug use is taken into account. They find no effect for property or drug-related offenses. By contrast, a new population-based study by Elbogen et al. (2009) finds that only co-morbid mental illness and substance use disorders are associated with the perpetration of violence, with the largest effects for substance-related violence. These authors do not examine non-violent crimes.

There are a number of reasons why we might observe the positive correlation between mental illness and crime. The correlation could be causal, although the direction of causality is not clear. The impairment of proper brain functioning may cause a person to engage in violent or other types of criminal behaviors. However, prior or current imprisonment itself may cause mental illness and lead to the observed positive correlation. Conversely, the relationship may be spurious and a result of observed or unobserved factors such as substance abuse, environment, financial strain, family stress, traumatic events, past violence or victimization, unemployment, and the like. In a review of the literature, Link and Stueve (1995) conclude, "... the association appears to be causal. Several alternative explanations—methodological and substantive—have been investigated, but none receives consistent support. It is possible, however, that mental illness only leads to violent behavior under certain conditions."(p. 197)

There are a number of reasons to believe that the symptoms of mental illness contribute to violent and other criminal behavior. Persons with severe mental illness may suffer from delusions, impulse control problems, narcissism, problems controlling affect, and altered risk perceptions that can lead to violent behaviors (Nestor 2002). Link and Stueve (1995) believe that violence may occur when the symptoms of the illness cause the perception of threats, or the illness causes the weakening of self-control.

Because the symptoms and functional impairments of mental illness are thought to be important factors shaping criminal behavior, researchers commonly focus on various illnesses separately.<sup>4</sup> Research regarding schizophrenia and criminal behaviors is probably the most prevalent in the literature. Symptoms of the disease include hallucinations, delusions, apathy, deficits in social functioning and cognitive impairment (Minzenberg et al. 2008). It is these characteristics that are believed to contribute either directly or situationally to violent and non-violent crimes. (Aseneault et al. 2000; Brennan et al. 2000).

There are also possible links to crime for other illnesses such as major depressive disorder (MDD). Symptoms of MDD include a depressed mood, diminished pleasure in daily activities, insomnia or hypersomnia, feelings of worthlessness or guilt that may be delusional, diminished ability to think or concentrate, indecisiveness, and recurring thoughts of death (APA 2000). Depression in children and adolescents may manifest itself differently. Among persons with depression, children and adolescents are more likely than adults to have irritable moods, anxiety, delusions, and engage in disruptive and aggressive behaviors (Brimaher et al. 1998). It is not clear that adults with MDD are more crime-prone than others because of the symptoms of

---

<sup>4</sup> While differences by disease are likely important, Swartz and Lurigio (2007) find that all types of mental illness they examined are associated with an increased risk of violent behavior. In their study, illnesses such as major depression, generalized anxiety disorder, nonaffective psychosis, and panic disorders all are positively related with the probability of arrest for violent crimes.

MDD or because of co-morbid problems (such as substance abuse), and indeed the literature linking MMD specifically to crime shows mixed results (Swartz and Lurigio 2007; Elbogen 2009). However, the manifestation of the symptoms in children and adolescents provides a clearer mechanism for the link between the disease and juvenile criminal behaviors.

Attention-Deficit/Hyperactivity Disorder (ADHD) is another prevalent mental illness that may be linked with crime and violent behaviors, especially among youth. Estimates of the prevalence of ADHD range from 6 to 9 percent in youth and 3 to 6 percent in adults (Kates 2005). ADHD is characterized by inattention, hyperactivity, and impulsivity. The increased impulsivity may lead to fights (Halperin et al. 1995). Youth with ADHD typically have a low frustration tolerance, have temper outbursts, and their relationships with family and school authorities may be combative due to the youth's poor academic achievement (APA 2000). These characteristics make these youth at greater risk for crime and arrest than similar populations without the disorder (Barkley et al. 2004). Adults with attention deficit disorder (ADD) are also thought to be more prone to poor outcomes including work instability, incarceration, and substance abuse (Kates 2005).

An alternative pathway for a relationship between crime and mental illness is the role that mental health status plays in determining risks of victimization. Recent research on individuals suffering from severe mental illnesses shows rates of victimization that are much higher than that of the general population (Silver et al. 2005; Teplin et al. 2005; White et al. 2006; Hodgins et al. 2007). Here, mental illness may result in impaired judgment and perception of reality, poor planning, and impulsive behavior, all of which may make the sufferer an "easy target" or more prone to victimization (Teplin et al. 2005). Another hypothesis suggests that people with mental illnesses may behave in ways which anger others and lead to violence (Silver et al. 2005). In a

review article, Choe et al. (2008) report much higher rates of victimization over perpetration in populations of mentally ill patients. These authors conclude, “Victimization is a greater public health concern than perpetration” (p 153).

#### *Treatment and therapeutic advances*

While there is clear evidence of a strong relationship between mental illness and violent criminal behavior and victimization, this would help us understand recent changes in crime rates only if there were changes in the prevalence or presentation of mental illness in the community. There is no evidence of a change in the prevalence of mental disorders that would coincide with the recent decline in crime. But, there have been large and potentially important changes in the rates of treatment and the treatments available, both of which are likely to affect the symptoms and behavior of the mentally ill in the community.

The best available evidence on changes in prevalence and treatment comes from comparison of the results of the National Comorbidity Survey (NCS) with those of the National Comorbidity Survey Replication (NCS-R). The NCS was a nationally representative sample of non-institutionalized Americans 18 to 54, which collected data on the prevalence of mental disorders in the previous 12 months, and over the lifetime. The NCS was conducted between 1990 and 1992, during the very peak of post-war crime rates in the U.S. Between 2001 and 2003, the NCS-R replicated the NCS design, permitting researchers to examine changes by comparing a similar cohort a decade after the original NCS. Kessler et al. (2005) report no change in the prevalence of a mental disorder between the surveys, with 29.4 percent of the NCS sample suffering from either a non-substance abuse or substance abuse disorder in the early 1990s, and hardly changing to 30.5 percent by 2001-2003.

While there was no change in prevalence, there was a marked increase between the NCS and NCS-R in the proportion of those with mental illness getting treatment. Kessler et al. (2005) estimate that among persons with a mental disorder the percent receiving treatment increased from 20.3 percent to 32.9 percent. This means that nearly 10 million more prime age adults were receiving mental health treatment at the end of the rapid decline in crime than at the beginning. Importantly, it appears that nearly all of this expansion was from treatment with pharmacotherapy. During this period, the share of the population that received outpatient psychotherapy remained unchanged (Olfson et al. 2002). Alternatively, Wang et al. (2006) report a large increase in the use of physicians as the source of mental health care among Americans, with large declines in care from other therapists.

In addition to the substantial expansion at the extensive margin, mental health treatment changed dramatically during the 1990s. In particular, the pharmaceutical therapies available for treatment of the most prevalent disorders changed in important ways. The best known was the change in the treatments available for depressive disorders. There are four broad categories of antidepressants: monoamine oxidase inhibitors (MAOIs); tricyclic antidepressants (TCAs); selective serotonin reuptake inhibitors and serotonin-norepinephrine reuptake inhibitors (SSRIs and SNRIs); and a fourth group that is commonly referred to as the newer generation antidepressants (NGAs). The first SSRIs were approved by the FDA in the late 1980s. The introduction of these drugs represented a new era of antidepressant prescriptions since these drugs were easier to administer, reduced the likelihood of overdose, and offered fewer negative side effects than the previously approved MAOIs and TCAs (USDHHS 1999). Nierenberg et al. (2008) discuss the efficacy of different types of antidepressants including SSRIs and TCAs in the treatment of MDD. After reviewing both controlled clinical trials and studies in broader

populations they conclude, “Antidepressants work for many patients, decreasing their suffering and improving their lives” (p 434). Coyle et al. (2003) reach a similar conclusion for the efficacy of SSRIs in treating MDD in children and adolescents. These authors also place emphasis on cognitive-behavioral therapy as a useful part of mental health treatment. It should be noted that not everyone agrees with the efficacy of antidepressants. Ioannidis (2008) argues that the short term benefits are rather small and the long term benefits are understudied. There is also the possibility that antidepressants increase the risk of suicidal thoughts and behaviors. We refer the reader to Markowitz and Cuellar (2007) for a complete discussion of this issue and the FDA’s black box warning on antidepressants.

Stimulants are used for the treatment of ADHD and it is generally accepted that their use reduces the symptoms of the disorder (Ursano, 2008). The Surgeon General’s Report on Mental Health states that these drugs are highly effective for 75 to 90 percent of children with ADHD (USDHHS 1999). While stimulants have been approved by the FDA for use for many decades, their popularity took off starting in the early 1990s. Mayes et al. (2008) attribute this growth to changes in three different public policies. The first is a 1990 Supreme Court ruling that added ADHD to the list of diseases that enabled low-income children to qualify for the Federal Supplemental Security Income program. The second occurred in 1991 when Congress expanded the Individuals with Disabilities Education Act to include ADHD. This allowed children with the diagnosis to receive special accommodations in school, specifically, more time on tests and homework. The third was the expansion of Medicaid for low-income children, which allowed for increased rates of diagnosis and treatment of ADHD. These factors all contributed to an increased number of ADHD diagnoses and prescriptions for stimulants (Mayes et al. 2008). Another increase in diagnoses and prescriptions occurred in the late 1990s and early 2000s when

pharmaceutical companies gained approval for new versions of stimulants that reduced the number of required doses, making it easier to administer the drug and for patients to adhere.

If there exists a true causal relationship from mental illness to crime/violence (either through perpetrators or victims) and treatment is effective, this suggests that public policy should look towards mental health treatment as a way to reduce crime. This idea is not new to the literature, and numerous studies have recommended exactly that (Teplin et al. 2005; Cuellar et al. 2007; Choe 2008). However, little attention has been focused on pharmaceuticals specifically in the treatment of mental illness as a crime-fighting tool. One example is Cuellar and Markowitz (2007). These authors examine the relationship between state spending by Medicaid on stimulants and antidepressants and adverse outcomes related to ADHD and depression. The outcomes include suicides, violent crimes, property crimes, and fatalities resulting from unintentional injuries. The strategy in this paper is similar to ours here. The authors make the case that the outcomes studied are all closely related to the mental disorders under consideration. If more Medicaid patients receive mental health treatment in the form of pharmaceuticals and these drugs are effective, then one should observe a reduction in the outcomes under consideration. Cuellar and Markowitz find evidence that increases in both spending and prescriptions for stimulants are related to reductions in violent crimes. They also show a negative relationship between spending on older antidepressants (TCAs and MOIs) and violent crime. One caveat is that the generalizability of this study is limited since the study uses drug information for the Medicaid population and links this to outcomes variables including behaviors by individuals who are not necessarily eligible for Medicaid. Our study improves on the previous research by linking psychiatric drug prescription rates to crimes derived from data that is more representative of the U.S. population.



Evidence of any causal link between the use of psychiatric medication and criminal behavior is obviously quite difficult to come by. The randomized clinical trials typically used to establish effectiveness of drugs would provide no information about criminal behavior. Clinical data is limited to data collected by clinicians about physiological and symptomatic response, and data reported by patients about factors related to efficacy and tolerability, such as physical side effects. Patients are hardly likely to be forthcoming about reports of criminal activity. Even if a clinician recorded credible information about criminal behavior, clinical trials are far too small to detect effects that might be important in the community.

Even population-based data that links exposure to treatment of the mentally ill with new psychiatric pharmacotherapies and crime/victimization is hard to come by. One limited source of evidence like this comes from international variation in drug sales and crime. International data on drug sales can be obtained from IMS Health, Inc., which collects data on quarterly drug sales by type in countries across the globe, for the purposes of market research. Though this is a highly aggregated source of variation, there were substantial differences across countries in when new drug therapies were introduced or approved by various regulatory agencies, and also in subsequent rates of sales growth (Ludwig et al. 2007). Data on crime across nations is made difficult by differences in what constitutes criminal behavior, how data are recorded and reported, and the relatively poor quality of these data in many countries (Levitt 2004). Among the most reliable sources of such data is a statistical bulletin from UK Home Office and the Council of Europe (Barclay and Tavares 2003), which provides data on European Union member states and select other countries.

In Figure 2, we display percent change in reported crimes in these countries during the 1990s, along with rates of growth in sales of the most widely used new class of psychiatric

medication, selective serotonin uptake inhibitors (SSRI). Super-imposed on the data is a population-weighted linear fit. This simple comparison makes clear that the countries with largest declines in crime rates in the 1990s were almost exclusively those with the fastest growth in SSRI sales. Italy is the only country in the series that experienced a marked decline in crime, with a slower than average increase in drugs sales.

This series highlights two other interesting cases. The first is Japan, which saw no growth in SSRI sales in the 1990s, and was an outlier among the most developed nations in the world with a marked increase in reported crime during this period.<sup>5</sup> The other notable case here is Canada. In his insightful book, *The Great American Crime Decline* (2007), Franklin Zimring highlights the puzzle of Canada. The puzzle is that crime rates there fell nearly as fast as they had in the U.S., but several of the important explanations for the American experience were absent in Canada. There were no substantial run-ups in the number of law enforcement officers in Canada or in the size of its prison population. Canada didn't go through the ebb and flow of the crack cocaine tide, nor did it see substantial variation in abortion rates. Figure 2 makes clear, though, that like the U.S., Canada was among the world's leaders in the growth in treatment with new psychiatric medication.

Developing more convincing tests of the relationship between drugs sales and crime obviously requires data on crime across populations that can be reliably compared over time, and more information on variation in other factors that might affect crime. To provide this, we conduct a thorough analysis of crime rates in states across the US for the years 1997-2004, focusing specifically on trends in psychiatric drug prescriptions as a possible explanation for the changes crime rates over time.

---

<sup>5</sup> Japan did not approve sales until 1999, 12 years after the U.S.

## Analysis

Developing more convincing analyses of the relationship between increases in psychopharmaceuticals and crime is limited by the paucity of data available. In this paper, we take steps toward this end by developing a U.S. state-level panel data set that brings together data on crime with available information on the diffusion of these drugs at the state level.

The basic empirical model utilized in this paper is given in equation 1:

$$1) \quad \ln C_{jt} = \delta_0 + \delta_1 \ln D_{jt-1} + \delta_2 \ln V_{jt-1} + \delta_3 X_{jt} + \delta_4 \gamma_t + \delta_5 \mu_j + \varepsilon_{jt}.$$

Equation (1) specifies that the log of the crime rate (C) in state (j) for a given time period (t) is a function of the one-period lagged value of the log of psychiatric drug prescriptions ( $D_{jt-1}$ ), one-period lagged value of the log of patient visits ( $V_{jt-1}$ ), other determinants of crime ( $X_{jt}$ ), time effects ( $\gamma_t$ ), and state effects ( $\mu_j$ ). The time effects are modeled alternatively with a linear time trend and a series of fixed effects. The principal hypothesis to be tested is whether or not the different psychiatric drugs are associated with reductions in violent crime rates. We lag prescriptions by one time period for two reasons: first, to minimize any possible reverse causality from crime/victimization to mental illness, and second, to allow for new prescriptions to take effect and possibly change behavior. The log of crime rates are estimated using Weighted Ordinary Least Squares. The weighting matrix is as described in Johnston and Dinardo (1997) for grouped data. The weights will address the potential heteroskedasticity in the error terms that arise from using grouped data.

Data on crime are available monthly, so we could, in principle, construct a state-month panel. However, our data on crime come from the Federal Bureau of Investigation's Uniform Crime Reports (UCR), for which monthly reporting is uneven. The UCR compiles data on all crimes reported from nearly 17,000 state, county, municipal and tribal police agencies. The

program is voluntary, but the vast majority of agencies report. However, the crime data is reported inconsistently at intervals smaller than a year. That is, some precincts only report crimes to the FBI on an annual basis, while others report data every month. In order to avoid biases based on inconsistent reporting, but to explore intra-annual variation, we restrict the crime data used to only those precincts that consistently report data every month, and use these to construct a state-quarter panel. To do this, monthly counts are aggregated to the quarterly level for those jurisdictions consistently reporting. These crime counts are merged with the pharmaceutical prescription data that is available on a quarterly basis.

As a sensitivity check, we construct a state-year panel for all contiguous 48 states and the District of Columbia, using annual crime rates from the Uniform Crime Reports published by the FBI. These are the data the FBI uses in their *Crime in the United States* annual report. This annual level data loses information for jurisdictions that do consistently report, but have the advantage that they are a complete series of state-level crimes reported to the police annually. Figure 3 shows that the annual and quarterly level violent crime rates follow nearly identical trends, with difference only in the level of the rates. The quarterly violent crime counts represent about 21 percent of the annual reports of violent crimes, but about 42 percent of the population is covered by the reporting precincts. This generates the difference in the levels of the rates.

Data on prescriptions come from IMS's National Disease and Therapeutic Index (NDTI). The NDTI is a nationally representative sample of office-based physicians in private practice drawn from a universe of all physicians in the United States. The sample is a randomly drawn, two-stage stratified cluster, where the stages are doctors and workdays. The sample of doctors is selected by primary specialty and the 9 census divisions. All primary specialties involved in direct patient care are included. Data are collected monthly from just under 1,400 physicians.

Each physician reports information quarterly on all patients seen during two consecutive workdays. We sum these to construct a quarterly panel. From this patient data, we create state-level counts of “drug appearances” (defined below) for antidepressants, anti-psychotics, and stimulants. These prescriptions pertain to individuals ages 15 and up. As with the crime data, we use the NDTI data to construct state-quarter and state-year panels.

A drug appearance is a mention of a drug during a patient visit. In the NDTI data, drug appearances include prescriptions, samples, drugs sold or given to the patient from their stock, hospital orders, drug recommendations that were not accompanied by a prescription, and drugs that were not issued during the current visit (i.e. no prescription, no sample and no medication sold, but drugs were issued on a previous visit). We exclude drug recommendations and drugs that were not issued during the current visit from the counts so that our count total represents patients who have obtained or can obtain the drug with a prescription. Actual prescriptions represent the majority of drug appearances, as such we will use the terms appearance and prescription interchangeably.

In addition to the drug appearance counts, we include in all models the log of the total number of patient visits in each state and year for patients 15 and older. By including this variable we account for the total number of visits from which our counts of prescriptions are drawn. We believe this specification is superior to using a drug prescription rate because the rate may move because of changes in both the numerator and denominator. By including the prescription counts separately, we can analyze the effects of prescriptions on crime, holding constant the number of patient visits.

The NDTI identifies four groups of antidepressants: 1) Tricyclics and Tetracyclics (TCAs), 2) MAO Inhibitors (MAOIs), 3) SSRIs/SNRIs, 4) newer generation antidepressants

(NGAs). Examples of TCAs include *Elavil*, *Amitriptyline* and *Imipramine*. Common SSRI/SNRIs include *Zoloft*, *Lexapro*, and *Prozac*. *Wellbutrin* is the most popular newer generation antidepressant. MAOI prescriptions are extremely rare, and therefore we have chosen to exclude MAOIs from the analyses.

The other types of drugs that we consider are stimulants for the treatment of ADHD, and anti-psychotics for the treatment of schizophrenia. In some models we consider an aggregate count of all of the mental illness drugs, including the antidepressants, in order to examine the effect of psychotropic drugs, in general, on crime rates. Alternative models consider only the effects of the three different types of antidepressants by using an aggregated measure that is the sum of TCAs, SSRIs/SNRIs and NGAs. Lastly, we show models that consider certain drugs separately—NGAs, SSRIs/SNRIs, stimulants, and anti-psychotic medications.

The NDTI data has two limitations worth noting. First, the prescription data are from office-based physicians so any prescriptions from in-patient facilities, including mental hospitals, are not included. Second, we have no way of knowing whether or not a prescription was filled or if a prescription was written after a sample was given.

All models include some annual variables that may be important determinants of crime rates. These include a one year lag of state expenditures on criminal justice, the state real income per capita, the state unemployment rate, the percentage of the state population ages 25 years and over that has obtained a bachelor's degree, and the percent of the state living in rural areas. State spending on criminal justice includes spending on police, corrections and judicial activities. This data is provided by the Bureau of Justice Statistics. Per capita income comes from the Department of Commerce, Bureau of Economic Analysis, educational attainment comes from the Department of Commerce, U.S. Census Bureau, the rural population comes from

the U.S. Census Bureau, and unemployment comes from the U.S. Bureau of Labor Statistics. We also include the number of psychiatrists per 100,000 residents in the state to account for the supply of mental health physicians. Additionally, we include the real (1982-1984) excise tax on beer in all models. Beer taxes come from the *Brewers' Almanac*. Beer taxes are included because of the potential relationships between alcohol consumption and crime and alcohol consumption and mental illness. Since alcohol consumption is likely to be endogenous in our model of crime, we include the beer tax instead which is related to consumption, but arguably is not related to the unobserved determinants of crime. Lastly, we rely on state fixed effects to account for some of the other factors that may determine crime rates.

## **Results**

In Table 1, we summarize the characteristics of the quarterly and annual data. The annual data is a balanced panel, with eight years of data on the contiguous 48 states and the District of Columbia. The quarterly crime data is available for select precincts in 40 states.<sup>6</sup> The means are generated using the same samples as used in the empirical models. Since lagged drug counts are used, and the drug variables are available beginning in 1997, the first year of observation in the annual series is 1998. The first observation in the quarterly series is the second quarter of 1997.

The annual average rate of violent crime during the period was 446.5 per 100,000 residents, or 53.66 per 100,000 quarterly.<sup>7</sup> On average there were over 5,700 patient visits per year in our sample. The annual rate at which psychiatric drugs appeared in patient visits to physicians was 5 percent. The mean state per capita income during this period was \$33,290.

---

<sup>6</sup> The nine states with no precincts reporting consistently on a monthly basis are: Alabama, District of Columbia, Florida, Illinois, Kansas, Montana, Rhode Island, Vermont, and Wisconsin.

<sup>7</sup> The annual average will not equal four times the quarterly average because of missing quarterly data for some states.

On average, about 27 percent of the population in a state lived in rural (non-MSA) areas, and just over 25 percent of state residents had bachelor's degrees.

As a first step in assessing the relationship between the expanding access to psychiatric medication and crime, in Figure 4 we plot changes in log of the rate of violent crime within states between 1997 and 2004 against changes in drug appearances for all mental illnesses during the same period. There is a general pattern of larger declines in violent crime rates in states with the largest expansions of psychiatric drug appearances in clinical settings. Further, it appears that states likely to differ on a number of dimensions have seen similar changes in drug take-up rates. For example, Alabama and Maine saw similar increases in the expansion of psychiatric medication during the period, as did Montana and South Carolina. But clearly this bivariate relationship is nothing more than suggestive.

In Table 2 we present regression results on the relationship between the prescriptions for psychiatric medications and violent crimes rates using the quarterly data. In the first panel (Model 1), we present a model with state level controls, state fixed effects, and thirty dummy variables for each unique year/quarter. The specification in the second panel (Model 2) is the same as that of the first panel but adds a state-specific linear time trend. The first column of each panel (columns (a) and (g)) includes the aggregate measure of all psychiatric drugs, which is the sum of prescriptions for antipsychotics, antidepressants, and stimulants. The second columns include the aggregate measure of antidepressant prescriptions. The remaining columns in each panel include, respectively: SSRIs/SNRIs, NGAs, stimulants, and antipsychotic medications. These drugs are included separately in each model because of the potential for multicollinearity between the drugs. However, including the drug counts simultaneously does not alter the results appreciably.



The results in the first panel (Model 1) estimate the impact of within-state growth in psychiatric medication on crime rates, allowing each quarter to have a unique national effect, thereby imposing no functional form on crime trends. This specification examines whether crime fell faster in states with faster diffusion of psychiatric medication. The results suggest that while the total count of psychiatric drug appearances are negatively related to violent crime rates, have a very small effect that is not statistically different from zero: a 1 percent increase in psychiatric drug appearances is associated with a 0.018 percent decrease in violent crime rates. The small value is not surprising, since the vast majority of treatment is provided to patients at low risk for criminal violence.

The results from the inclusion of the different drugs (columns (b) through (f)) are instructive. We find that the relationship between the psychiatric drug appearances and violent crime rates depends greatly on the drug under consideration. For example, increases in prescriptions for the newer generation antidepressants (NGAs) are associated with a reduction in violent crimes: a 1 percent increase in drug appearances is associated with a 0.065 percent decrease in the violent crime rate. Similarly, prescriptions for stimulants are associated with a slightly larger reduction in violent crimes: 0.086 percent for every 1 percent increase in stimulants. Interestingly, SSRIs/SNRIs and antipsychotics are not statistically associated with violent crimes. The SSRI/SNRI result is surprising given the popularity of these drugs (see Table 1).

One concern with the specification in Model 1 is that states with unusual changes in social or economic conditions might experience atypical changes in factors affecting both crime and access to mental health treatment. Model 2 provides an attempt to mitigate this concern by allowing each state to have its own underlying (linear) trend. The results, presented in the right

panel of Table 2, are similar to those obtained from Model 1, with NGAs and stimulants negatively associated with violent crime. Again, the magnitudes are small, with every 1 percent increase in NGAs prescriptions associated with a 0.057 percent decrease in violent crimes. For stimulants used to treat ADHD, we estimate that every 1 percent increase in prescriptions is associated with a 0.067 percent decrease in violent crimes. Note that the point estimates from models with and without state specific trends are quite similar to one another.

Results from a few of the other state-specific determinants of crime are worth mentioning. The coefficients on the lagged annual expenditures on criminal justice are negative and statistically significant in all models indicating that higher expenditures over time may be an effective way for policy makers to reduce violent crimes. Another useful policy is higher beer taxes. As indicated by the coefficients in the more inclusive model (Model 2), higher beer taxes are associated with reductions in violent crime. However, the beer tax coefficients are generally statistically significant only at the 10 percent level in a two-tailed test.

In Table 3, we repeat the analysis from Table 2 using the annual data instead of the quarterly panel. Our concern is that using the quarterly panel makes the results unrepresentative and/or noisy because we only use a sample of consistently reporting precincts. The annual panel is far more inclusive and representative of crimes in the United States. The drawback to the annual data is the reduced sample size and more limited variation makes it much more difficult to detect relationships between pharmaceuticals and crime. Indeed, the results in Table 3 are almost uniformly statistically insignificant, with a few exceptions, including the negative coefficient on NGAs in Model 1. While this NGA coefficient confirms our story, we must downplay its importance. The statistical insignificance applies not only to the coefficient on the pharmaceuticals but to many of the other determinants of crime as well. This is particularly

surprising for the case of criminal justice expenditures where a strong negative relationship appears with the quarterly crime data. Given the limitations of the annual data, we are hesitant to draw any conclusions from it.

The results from Table 2 suggest that drugs for NGAs and stimulants may be helpful in reducing reported violent crime rates. Naturally, in a quasi-experimental setting one might be concerned that the variation we are observing in the expansion of psycho-pharmaceuticals is associated with pre-existing changes in crime. If so, we might simply be attributing rapid declines in crime to expansion of mental health treatment, while our relatively short panel might have missed related pre-existing trends. The fact that our results are robust to a variety of linear and non-linear and common and state specific controls for underlying trends gives us some comfort that this is not likely. To provide a further check on this possibility, in Figure 5 we plot separate time series of violent crime rates from 1960 to 2004, separately for states that would later have the slowest and fastest rates of growth of NGA prescriptions per capita. To make this distinction, we label states with per capita growth more than a half standard deviation below the mean as slow growth states, and those with per capita growth rates more than a half a standard deviation above the mean as fast growth states. The states identified in each group are listed at the bottom of Figure 5. Both the slow and fast growth states are heterogeneous, and the groups do not seem markedly different from one another. Indeed, most of the states in one group can be matched with a similar/neighboring state in the other group.<sup>8</sup>

Rates of growth in violent crime rates from 1960 were very similar into the 1990s for states that saw different rates of NGA growth beginning in the mid 1990s with our panel.

Clearly, however, starting during the mid 1990s when new psycho pharmaceutical agents began

---

<sup>8</sup> For example, the contiguous (or proximate) slow and fast growth states are; Wyoming and South Dakota; Illinois and Indiana; Kansas and Iowa; West Virginia and Kentucky, and; Vermont and Maine.

to diffuse, crime rates in the states with the fastest growth of newer antidepressant treatments saw the fastest rates of decline in crime.<sup>9</sup> That crime declined most within states with the fastest NGA growth has already been established in our multivariate results. Figure 5 provides some reassurance that the decline was contemporaneous with the expansion of treatment, not pre-existing.

One lingering concern with our estimates is that our measure of use of psychiatric medications may be picking up changes in health care more broadly or other forms of social support, and it is these mechanisms that are associated with improved social conditions, including lower rates of crime. One way to test this is to replace our measure of psychiatric drugs with an alternative drug that would be associated with changes in health care provision or health promotion more broadly, but for which no relationship to criminal behavior can be expected.

To do this, we use data on a common class of non-psychiatric medications, statins, which include drugs marketed under brand names such as Lipitor, Zocor and Crestor. These drugs are used for the treatment of high levels of low-density lipoprotein (or “bad”) cholesterol, a risk factor for heart disease. Because they are intended to treat a condition which is neither debilitating nor neurological, growing use of statins in the community should have no effect on crime rates. At the same time, like many of the most common psychiatric medications, the use of these drugs grew rapidly during the 1990s. Further, they were also widely prescribed by non-specialists and the target of much direct-to-consumer advertising. So, growth of these drugs was likely shaped by some of the same social, economic and policy conditions that led to the rise in

---

<sup>9</sup> Popular NGAs include Wellbutrin (FDA approved in 1989 and again in 1996 in a sustained release form), Trazodone HCL (approved in 1988), Serzone (approved in 1995) and Remeron (approved 1996).

pharmaceutical treatment of mental illnesses. In Figure 6, we show time series of prescriptions for statins, and key classes of psychopharmaceutical from 1997 through 2004. The growth rate of prescriptions for statins was quite similar to rates of growth for psychiatric medications. If our results were simply picking up changes in access to health care or social conditions, then we would expect a similar decline in crime “due” to statins.

In Table 4, we re-estimate all our models, substituting prescriptions of statins in a state for that of psychiatric medications. When we do this, in all models, the point estimates on drug exposure on violent crime are substantially smaller than comparable estimates of the effect of psychiatric medication. The results are universally insignificant, and most are not even negative. There is no evidence in Table 4 that changes in access to one of the most widely used treatments for a highly common condition is related to changes in crime. This provides us with some reassurance that the relationship we see for exposure of a state’s population to psychiatric pharmacotherapy reflects some impact of those treatments, rather than any related changes in general access to health care, or other changes in a state’s social and policy fabric.

## **Discussion**

This paper explores the relationship between trends in treatment for mental illness and violent crime. Crime and mental illness are linked through both the perpetration and victimization sides of criminal activities. There is a sizeable body of evidence that people suffering from mental illness are both more likely to engage in criminal violence, and are themselves more likely to be victims of crimes. We have tried to characterize the behavioral mechanisms for these relationships by summarizing important syndromes and how they might contribute to behaviors leading to criminal acts and also increase risk of victimization.

Coincident with the decline in crime rates has been a remarkable expansion of

pharmaceuticals. Because many of these drugs are relatively effective, and better tolerated by patients, there was a correspondingly rapid increase in treatment.<sup>10</sup> Of course, psychiatric medication can be provided in combination with talk therapy with a mental health professional and with monitoring by physicians. This aspect of treatment is absent from our analysis, but is certainly relevant. Future research should include measures of therapeutic treatment and assess the role of such treatment in reducing perpetration and victimization rates.

We provide evidence that increased prescriptions for mental illness drugs are associated with decreases in violent crime. Our evidence suggests that, in particular, sales of new generation antidepressants and stimulants used to treat ADHD are negatively associated with rates of violent crime. The magnitude of the elasticities estimated here are clearly small. Using the coefficients from Table 2, we estimate that a one percent increase in the NGA prescription rate is associated with a decrease in violent crimes of about 0.06 percent. To put this in perspective, doubling the prescription rate would reduce violent crimes by 6 percent, or by 27 crimes per 100,000, at the average rate of 446.5 crimes per 100,000 population. A similar calculation with stimulants would decrease crimes by a range of 30 to 38 crimes per 100,000. While doubling the prescription rates seems like a large change, it has been estimated that 28 percent of the U.S. adult population in any year has a diagnosable mental or addictive disorder, yet only 8 percent seeks treatment (USDHHS 1999). Doubling the treatment rate would still leave a substantial portion of the ill untreated.

The small elasticities we estimate may of course be due to limited behavioral response to

---

<sup>10</sup> Several analysts have made the case that the shift toward pharmacotherapy was also driven by third-party payers in an attempt to lower treatment costs by shifting away from relatively expensive talk therapy, and by manufacturers via direct-to-consumer marketing as a means to increase demand. For a critical review of changes in treatment for mental illness during the late 20<sup>th</sup> century, see Barber (2008). However, similar increases in the use of pharmacotherapy appears to have occurred in other countries with different health care financing systems, including the UK and Australia (Brugha et al. 2004; Rey et al. 2004).

new therapeutic agents. However, even if the impact of treatment were substantial, effects can be hard to identify in community-based data like ours. A substantial limitation in population level data is that we do not know if treatment is going to those at risk for criminal behavior. There is obvious reason to be concerned that treatment is most available for those who otherwise have few risk factors for engaging in criminal violence. While the UCR provides limited ability to determine rates of crime by different population groups, the NDTI data allow us to know the age and gender of persons receiving prescriptions for various pharmaceuticals.

In Figures 7 and 8 we show rates of sales of new generation antidepressants and stimulants, respectively, for three demographic groups. Of particular interest are men under the age of 20, a group known to be of substantial risk for criminal violence. These figures compare rates of drug diffusion for young men to those of older men and older women. In both cases, prescription rates for these drugs grow relatively fast for young men through 2003, and fall between 2003 and 2004. The fall during this period is consistent with a general decline in pharmacological treatment of psychiatric illnesses for teens following FDA warnings about suicide for teens treated with antidepressants, beginning in 2003 (Gibbons et al., 2006; Markowitz and Cuellar 2007).<sup>11</sup> Nonetheless, the relatively fast growth of these treatments to the group at highest risk of crime is consistent with the relatively large decline in crime observed in states with the most rapid expansion of these treatments.

These age/gender group trends notwithstanding, a study like ours that relies on population level data will not be able to overcome limitations due to the inability to observe expanding treatment margins for those at risk of crime. To the extent that some treatment goes

---

<sup>11</sup> It was in 2003 that the FDA issued its first warning on suicide for teens treated with antidepressants. In 2004 the FDA held a highly publicized hearing, and then issued a requirement to include a “black box” safety warning on selective serotonin reuptake inhibitors. While neither NGAs nor stimulants were covered by the warning, the anxiety about pharmacological treatment of psychiatric illnesses was widespread.

to those at essentially no risk for criminal violence, the resulting attenuation bias would imply that our estimates provide lower bounds of pharmaceutical-crime treatment effects. Even so, the magnitudes of the current estimates, though small, are not unimportant. We make this claim for two reasons. First, our panel is short, and does not cover the early 1990s - a period of the largest expansion of treatment for mental illness and most rapid decline in criminal violence. Second, during the period we observe, prescriptions expanded considerably, so even if the behavioral response was small, the effects can add up. From the beginning to end of our panel, prescriptions per visit increased by 38 percent. For example, our elasticity estimates of newer antidepressants (NGAs) imply that this would reduce the total number of violent crimes committed by about 38,000.<sup>12</sup> In fact, the total number of violent crimes reported to police declined by 300,000 during the period. So, our estimates imply that 12.7 percent was due to expanded mental health treatment.

Finally, even if the effects on crime are small, marginal expansions of mental health treatment likely pass cost-benefit tests, based on impacts on crime alone. If we were to double the current rate of prescriptions, this would mean treatment of an additional 17 million persons.<sup>13</sup> With 1,360,088 violent crimes at the end of our panel, our estimates imply that doubling treatment would reduce the number of violent crimes committed per year by a bit more than 54,000. The social costs of violent crime are on the order of \$925,000 per crime (adapted from Ludwig 2006). Reducing the total by 54,000 implies a savings of \$50.3 billion. This is

---

<sup>12</sup> UCR estimates of the total number of violent crimes nationally decreased from 1,634,770 in 1997 to 1,360,088 in 2004. (FBI Uniform Crime reports as prepared by the National Archive of Criminal Justice Data, downloaded Oct. 15, 2009 from <http://bjsdata.ojp.usdoj.gov/dataonline/Search/Crime/State/RunCrimeTrendsInOneVar.cfm>) The approximate midpoint of our estimates suggest that every one percent increase in the prescription rate is associated with a decrease in crime of 0.06 percent. So a 38 percent increase in prescriptions results in a reduction of crimes of 2.28 percent. Applying this to the total number of violent crimes at the start of the period gives a reduction of about 38,000 crimes.

<sup>13</sup> Based on current estimates of the size of the population of adults in the U.S., and estimates of rates of mental health treatment.



approximately \$3,000 per treated person, below typical costs per treated outpatient.

We started this paper asking if advances in mental health treatment were partly responsible for the dramatic decline seen in crime rates beginning in the 1990s. Using annual data for the U.S., we provide evidence of a negative relationship between crime and psychotropic drugs, but lack the magnitude to explain much of the variation in crime rates for the U.S. Nevertheless the negative relationship is also evident in some preliminary evidence from other countries around the world that also experienced similar trends in drug sales and crime rates. These are the first pieces of evidence, and clearly, more research is needed. From a policy perspective, however, the importance of this research cannot be understated. Improved access to mental illness treatment has the potential to dramatically improve the lives of those afflicted and those around them.

## References

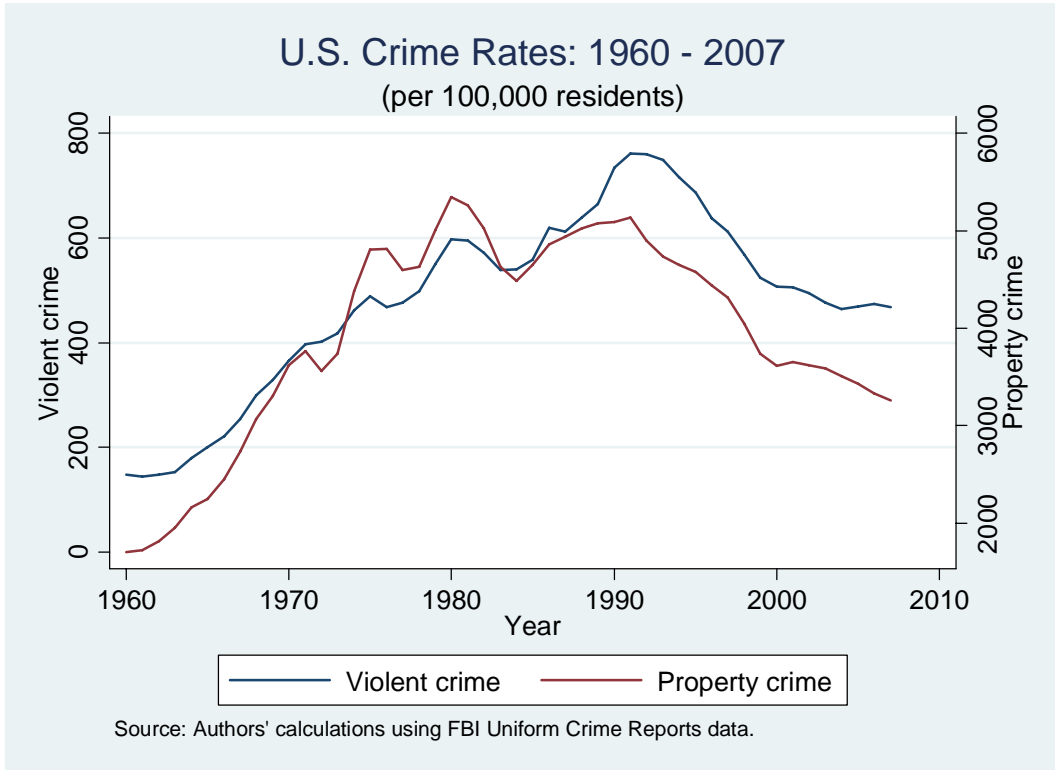
- American Psychiatric Association. 2000. Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (DSM-IV-TR) American Psychiatric Association: Arlington, VA .
- Arseneault, Lousie; Terrie E. Moffit; Avshalom Caspi; Pamela J. Taylor, and Phil A. Silva. 2000. "Mental Disorders and Violence in a Total Birth Cohort: Results from the Dunedin Study," *Archives of General Psychiatry*. V. 57, pp. 979-86.
- Barber, Charles. 2008. *Comfortably Numb: How psychiatry is medicating a nation*. (New York: Pantheon).
- Barkley, Russell A; Fischer, Mariellen; Smallish, Lori; Fletcher, Kenneth. 2004. Young adult follow-up of hyperactive children: antisocial activities and drug use. *Journal of Child Psychology, Psychiatry and Allied Disciplines*. v. 45(2), 195-211
- Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy*, v. 76(2), pp. 169-217.
- Becker, Gary S., and Casey B. Mulligan. 1997. "The Endogenous Determination of Time Preference," *Quarterly Journal of Economics*, v. 112(3), pp. 729-58.
- Blumstein, Alfred. 2000. "Disaggregating the Violence Trends." In Alfred Blumstein, and Joel Wallman (eds.), *The Crime Drop in America*. New York: Cambridge University Press, 13-44.
- Brennan, Patricia A.; Sarnoff A. Mednick; Sheilagh Hodgins. 2000. "Major Mental Disorders and Criminal Violence in a Danish Birth Cohort," *Archives of General Psychiatry*. V. 57, pp. 494-500.
- Brimaher, B.; D.A. Brent; and R.S. Benson. 1998. "Summary of the Practice Parameters for the Assessment and Treatment of Children and Adolescents with Depressive Disorders." *Journal of the American Academy of Child and Adolescent Psychiatry*, p 1234-1238.
- Brugha TS, Bebbington PE, Singleton N, Melzer D, Jenkins R, Lewis G, Farrell M, Bhugra D, Lee A, Meltzer H. 2004. Trends in service use and treatment for mental disorders in adults throughout Great Britain. *The British Journal of Psychiatry*. 185: 378-84.
- Choe, Jeanne Y.; Linda A. Teplin; Karen M. Abram. 2008. "Perpetration of Violence, Violent Victimization, and Severe Mental Illness: Balancing Public Health Concerns." *Psychiatric Services*, v. 59(2), pp. 153-164.
- Cook, Philip J. 2008. "Assessing urban crime and its control: An overview," NBER Working Paper # 13781.

- Coyle, Joseph T. ; Daniel S. Pine, Dennis S. Charney, Lydia Lewis, Charles B. Nemeroff, Gabrielle A. Carlson, et al. 2003. "Depression and Bipolar Support Alliance Consensus Statement on the Unmet Needs in Diagnosis and Treatment of Mood Disorders in Children and Adolescents." *J. Am. Acad. Child Adolesc. Psychiatry*, v. 42(12) pp.1494–1503.
- Cuellar, Alison E. and Sara Markowitz. 2007. "Medicaid Policy Changes in Mental Health Care and their Effect on Mental Health Outcomes." *Health Economics, Policy and Law*, v 2(1) pp. 23-49.
- Cuellar, Alison Evans; Lonnie M. Snowden; Toby Ewing. 2007. "Criminal Records of Persons Served in the Public Mental Health System." *Psychiatric Services*, v. 58(1), pp. 114-120.
- Donohue, John, and Steven Levitt. 2001. "The Impact of Legalized Abortion on Crime," *Quarterly Journal of Economics*, 116(2), pp. 379-420.
- Duggan, Mark. 2001. "More guns, more crime," *Journal of Political Economy*. V. 109(5), pp. 1086-1114.
- Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A theoretical and empirical investigation," *Journal of Political Economy*. v. 81(3), pp. 521-65.
- Elbogen, Eric B., and Sally C. Johnson. 2009. "The Intricate Link Between Violence and Mental Disorder: Results From the National Epidemiologic Survey on Alcohol and Related Conditions." *Arch Gen Psychiatry*, v. 66(2), pp. 152-161.
- Evans, William N. and Emily Owens, 2007. "COPS and Crime." *Journal of Public Economics*, v. 91(1-2), pp. 181-201.
- Grogger, Jeff, and Michael Willis. 2000. "The emergence of crack cocaine and the rise in urban crime rates," *Review of Economics and Statistics*, v. 82, pp. 519-29.
- Halperin JM, Newcorn JH, Matier K, Bedi G, Hall S, Sharma V. 1995. "Impulsivity and the Initiation of Fights in Children with Disruptive Behavior Disorders," *Journal of Child Psychology, Psychiatry, and Allied Disciplines*. v. 36: 1199-1211.
- Hodgins, S. 1992. "Mental Disorder, Intellectual Deficiency, and Crime. Evidence from a Birth Cohort," *Arch. Gen. Psychiatry*, v. 49, pp. 476-483.
- Ioannidis, John PA. 2008. "Effectiveness of antidepressants: an evidence myth constructed from a thousand randomized trials?" *Philosophy, Ethics, and Humanities in Medicine*, v.3(14), pp. 1-9.
- James Doris J. and Lauren E. Glaze, 2006. *Mental Health Problems of Prison and Jail Inmates*. U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics, Special Report, , NCJ 213600.
- Johnston, Jack and John DiNardo. 1997. *Econometric Methods*. (New York: McGraw Hill)

- Kates, Nick. 2005. "Attention Deficit Disorder in Adults: Management in Primary Care." *Canadian Family Physician*, v. 5. January.
- Kessler, Ronald C.; Olga Demler; Richard G. Frank; Mark Olfson; Harold Alan Pincus; Ellen E. Walters; Philip Wang; Kenneth B. Wells; Alan M. Zaslavsky. 2005. Prevalence and Treatment of Mental Disorders: 1990 to 2003." *New England Journal of Medicine*. v. 352, pp 2515-23.
- Levitt, Steven D. 2004. "Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not." *Journal of Economic Perspectives*. v.18(1), pp. 163-90.
- Levitt, Steven D., and Sudhir Venkatesh. 2000. "An economic analysis of a drug-selling gang's finances," *Quarterly Journal of Economics*. v. 115, pp. 755-89.
- Link, Bruce G. and Ann Stueve. "Evidence Bearing on Mental Illness as a Possible Cause of Violent Behavior." *Epidemiologic Reviews* Vol. 17, No. 1, 172-181.
- Ludwig, Jens. 2006. "The Costs of Crime." Testimony. United States Committee on the Judiciary, 19 September.
- Mayes, Rick, Bagwell, Catherine and Erkulwater, Jennifer. 2008. "ADHD and the Rise in Stimulant Use Among Children." *Harvard Review of Psychiatry*, 16:3, 151-166.
- Markowitz, Sara and Alison E Cuellar. 2007. "Antidepressants and Youth: Harmful or Helpful?" *Social Science and Medicine*, v. 64(10), pp. 2138-2151.
- Minzenberg, Michael J.; Jong H. Yoon; Cameron S. Carter. 2008. "Schizophrenia" in *The American Psychiatric Publishing Textbook of Psychiatry*, Fifth Edition. Edited by Robert E. Hales, M.D., M.B.A., Stuart C. Yudofsky, M.D., and Glen O. Gabbard, M.D. American Psychiatric Publishing, Inc.
- Olfson, M., S.C. Marcus, B. Druss, and H.A. Pincus. 2002. National trends in the use of outpatient psychotherapy. *The American Journal of Psychiatry*. 159(11): 1914-20.
- Raphael, Steven and Rudolph Winter-Ebmer. 2001. "Identifying the Effects of Unemployment on Crime," *Journal of Law and Economics*. v. 36, pp. 259-83.
- Rey, J., G. Walter, and M. Giuffrida. 2004. Policy, structural change and quality of psychiatric services in Australia: the views of psychiatrists. *Australian Psychiatry*. 12(2): 118-122.
- Reyes, Jessica Wolpaw. 2007. "Environmental Policy as Social Policy? The Impact of Childhood Lead Exposure on Crime," *The B.E. Journal of Economic Analysis & Policy*: Vol. 7 (1).

- Silver, Eric; Louise Arseneault; John Langley; Avshalom Caspi; and Terrie E. Moffitt. 2005. "Mental Disorder and Violent Victimization in a Total Birth Cohort." *Am J Public Health*, v. 95, pp. 2015-2021.
- Silver, Eric; Richard B. Felson; Matthew Vaneseltine. 2008. "The relationship between mental health problems and violence among criminal offenders." *Criminal Justice and Behavior*, v. 35(4), pp. 405-426.
- Swanson, JW, Swartz MS, Essock, SM, et al. 2002. "The social-environmental context of violent behavior in persons treated for severe mental illness." *American Journal of Public Health*, v. 9 (2), pp. 1523-1531.
- Swartz, James A, and Arthur J. Lurigio. 2007. "Serious Mental Illness and Arrest: The Generalized Mediating Effect of Substance Use." *Crime & Delinquency*, v. 53(4), pp. 581-604.
- Teplin LA. 1990. "The Prevalence of Severe Mental Disorder Among Male Urban Jail Detainees: Comparison with the Epidemiologic Catchment Area Program." *American Journal of Public Health*, v. 80(6), pp. 663-673.
- Teplin Linda A.; Gary M. McClelland; Karen M. Abram; Dana A. Weiner. 2005. "Crime Victimization in Adults With Severe Mental Illness, Comparison With the National Crime Victimization Survey." *Arch Gen Psychiatry*, v. 62, p.911-921.
- U.S. Department of Health and Human Services. 1999. *Mental Health: A Report of the Surgeon General—Executive Summary*. Rockville: U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services, National Institutes of Health, National Institute of Mental Health.
- Ursano, Amy M.; Paul H. Kartheiser; L. Jarrett Barnhill. 2008. "Disorders Usually First Diagnosed in Infancy, Childhood, or Adolescence" in *The American Psychiatric Publishing Textbook of Psychiatry*, Fifth Edition. Edited by Robert E. Hales, M.D., M.B.A., Stuart C. Yudofsky, M.D., and Glen O. Gabbard, M.D. American Psychiatric Publishing, Inc
- Wang, P.S., Demler, O., Olfson, M., Pincus, H.A., Wells, K.B., Kessler, R.C. 2006. Changing profiles of service sectors used for mental health care in the United States. *American Journal of Psychiatry*, v. 63(7), pp. 1187-1198.
- White, Mary Castle; Linda Chafetz; Gerri Collins-Bride; John Nickens. 2006. "History Of Arrest, Incarceration and Victimization In Community-Based Severely Mentally Ill." *Journal of Community Health*, v. 31(2).
- Zimring, Franklin E. 2007. *The Great American Crime Decline*. (New York: Oxford University Press).

**Figure 1**



**Figure 2**

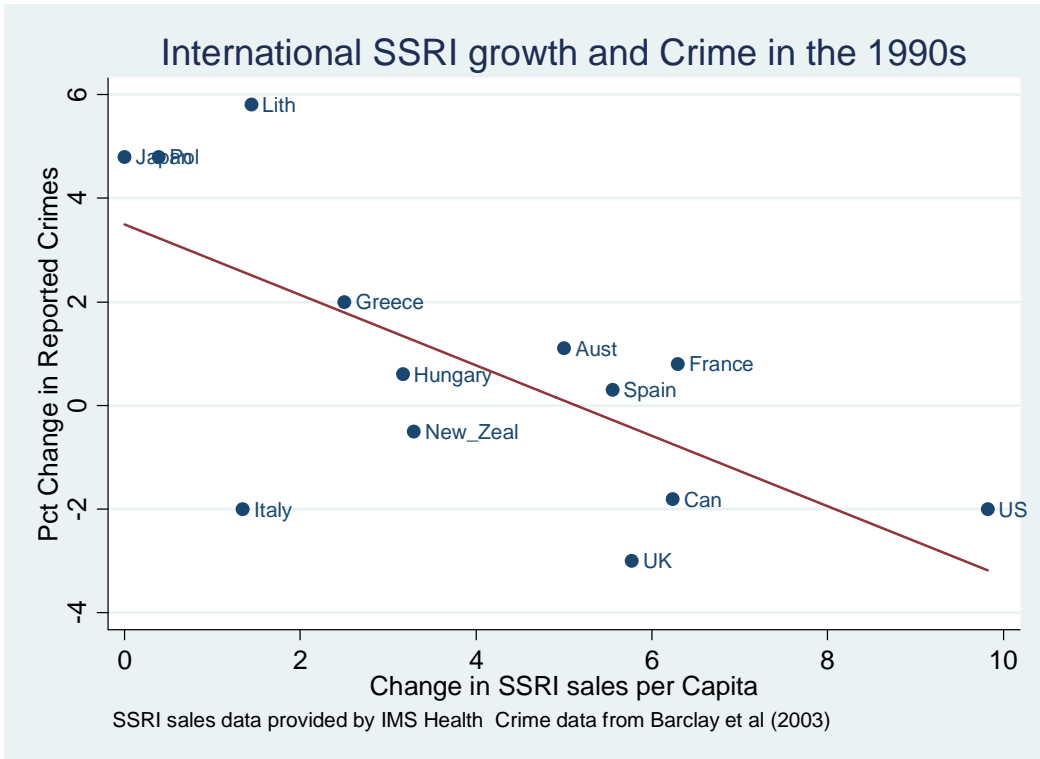


Figure 3

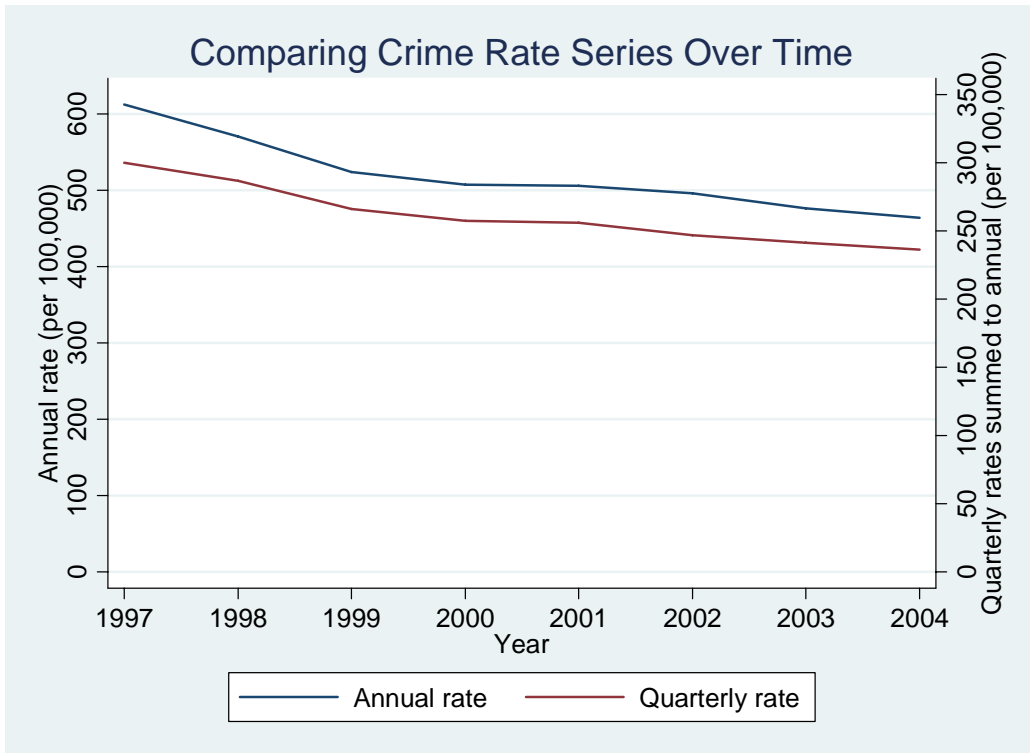
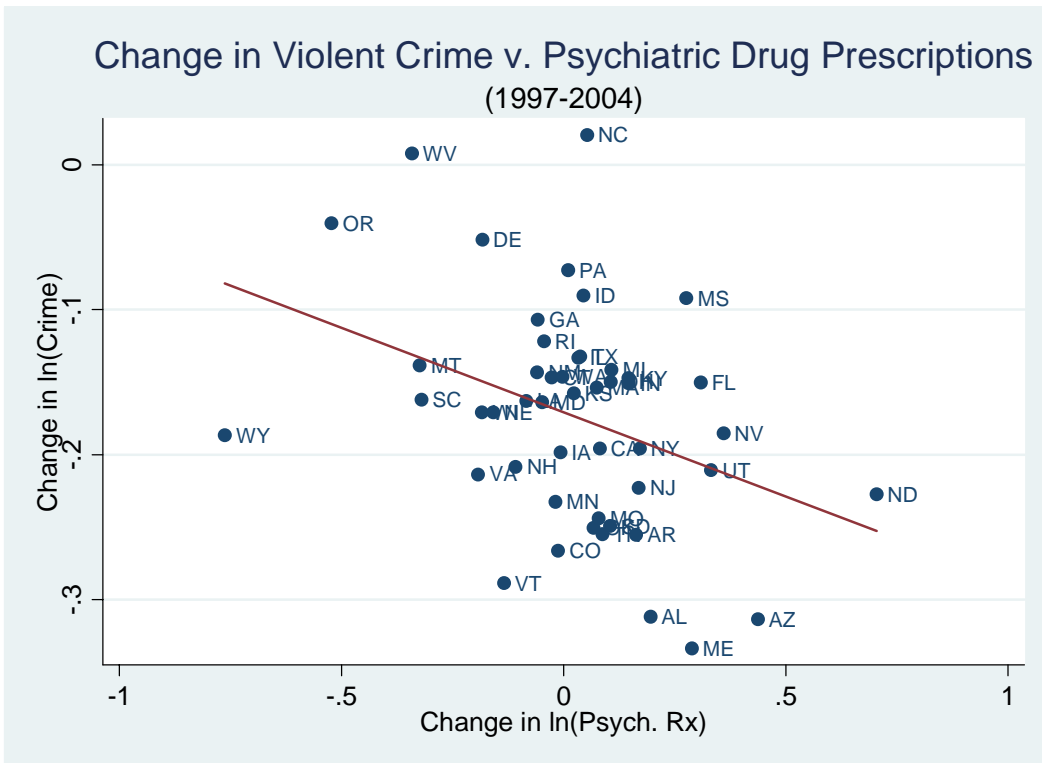
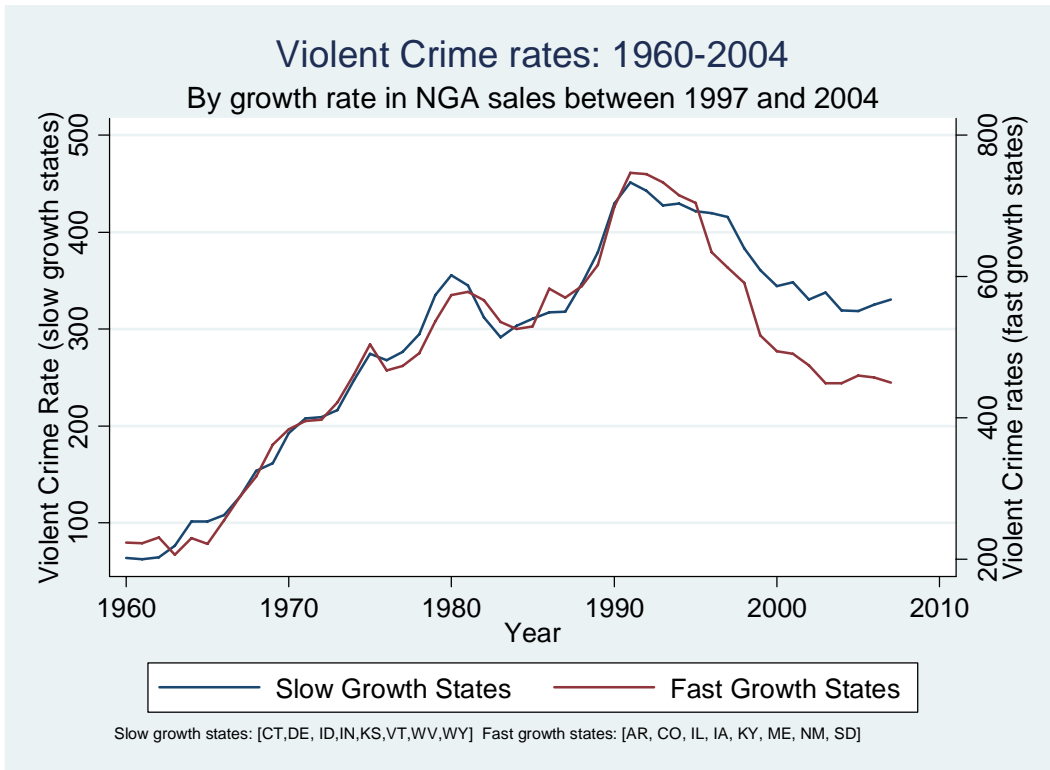


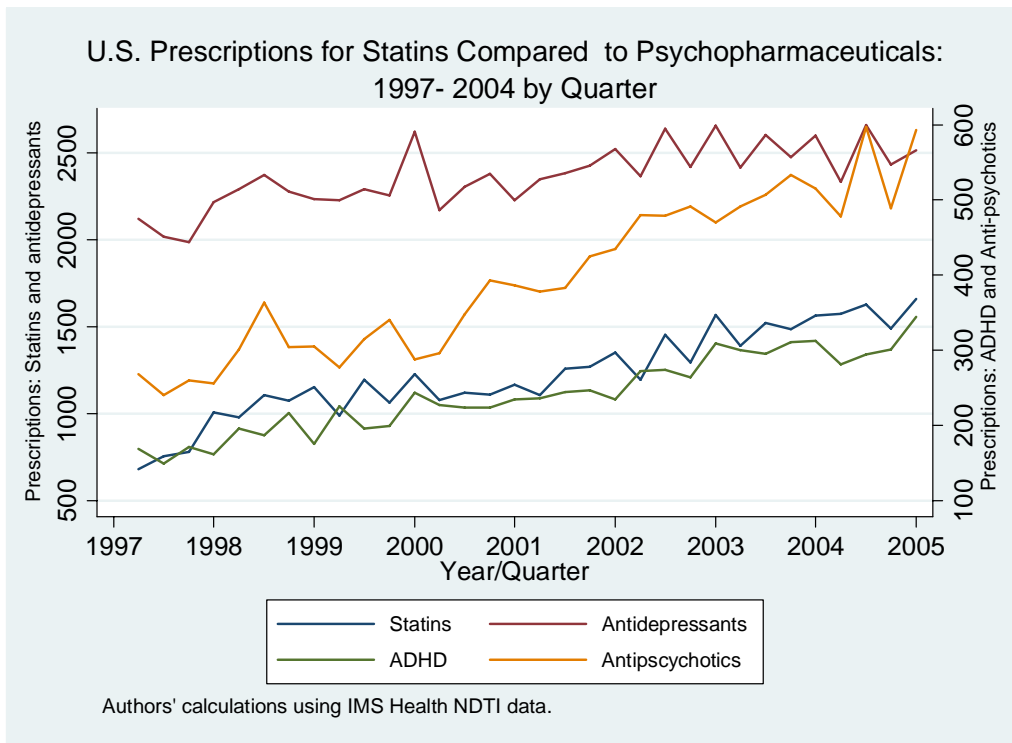
Figure 4



**Figure 5**

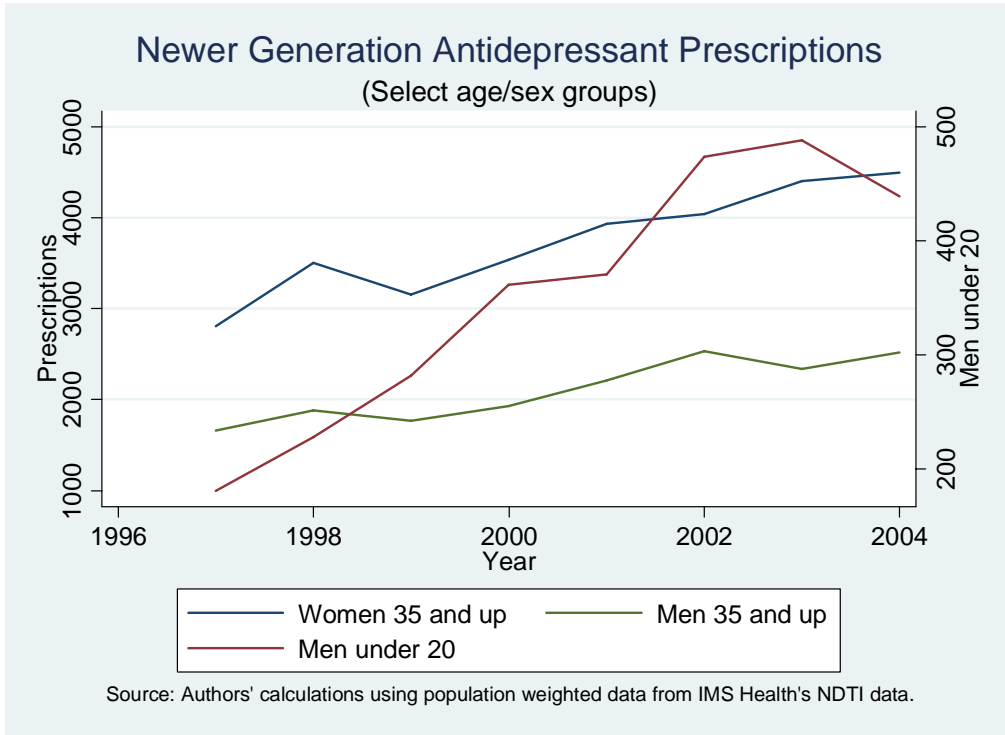


**Figure 6**

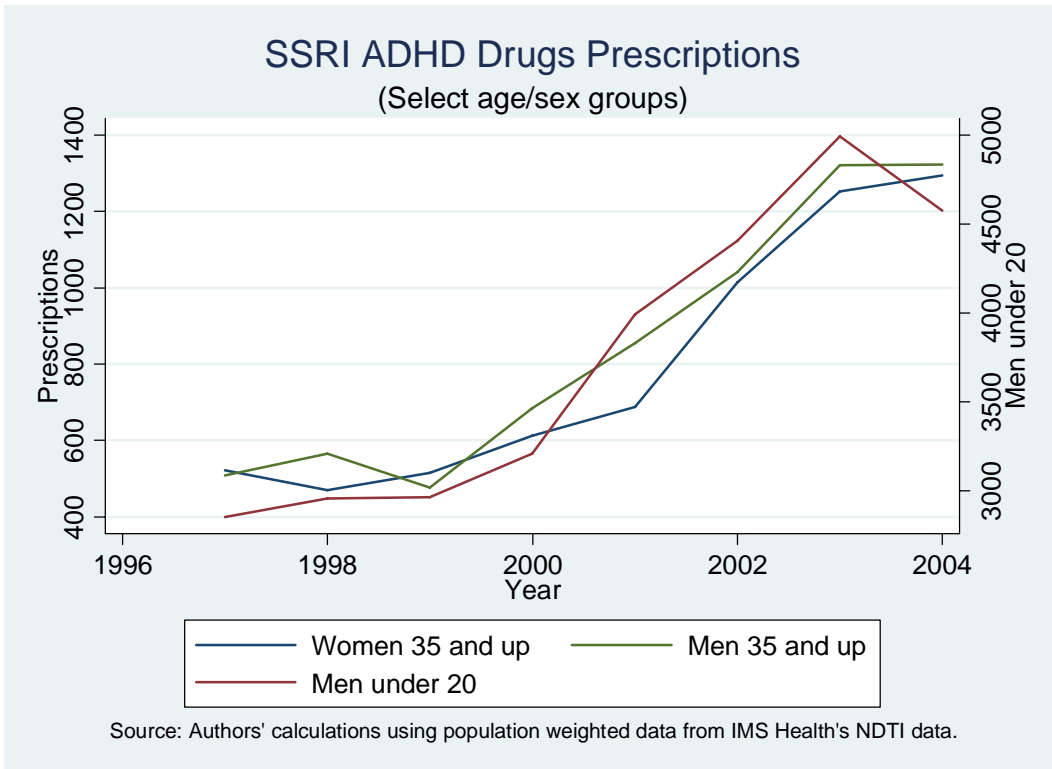




**Figure 7**



**Figure 8**



**Table 1**  
Means and Standard Deviations

|   | Quarterly Data<br>(n=1,240) |           | Annual Data<br>(n=343) |           |
|---|-----------------------------|-----------|------------------------|-----------|
|   | Mean                        | Std. Dev. | Mean                   | Std. Dev. |
| Violent crime rate, per 100,000   | 53.66                       | 27.38     | 446.50                 | 254.48    |
| All psychiatric drugs count   | 264.53                      | 272.57    | 1048.84                | 1066.11   |
| All psychiatric drugs rate  | 0.05                        | 0.03      | 0.05                   | 0.02      |
| All antidepressants count   | 205.33                      | 206.54    | 811.88                 | 811.90    |
| All antidepressants rate  | 0.04                        | 0.02      | 0.04                   | 0.02      |
| SSRI/SNRI count   | 140.46                      | 146.42    | 559.11                 | 576.99    |
| SSRI/SNRI rate  | 0.03                        | 0.01      | 0.03                   | 0.01      |
| NGA count   | 41.16                       | 44.83     | 165.06                 | 171.39    |
| NGA rate  | 0.01                        | 0.01      | 0.01                   | 0.00      |
| Stimulants count  | 20.10                       | 26.64     | 82.54                  | 97.17     |
| Stimulants rate   | 0.003                       | 0.004     | 0.004                  | 0.005     |
| Anti-psychotics count   | 34.12                       | 44.85     | 135.11                 | 167.08    |
| Anti-psychotics rate  | 0.01                        | 0.01      | 0.01                   | 0.01      |
| Patient visits  | 5352.52                     | 5390.95   | 21117.08               | 21370.66  |
| Psychiatrists per 100,000 population                                      | 25.75                       | 13.53     | 28.37                  | 19.43     |
| Lagged per capita state expenditures on criminal justice, in real dollars | 235.08                      | 62.78     | 249.57                 | 88.51     |
| Percent of state population rural   | 27.84                       | 14.04     | 27.67                  | 15.22     |
| Percent of state population with bachelor's degree                        | 25.27                       | 4.95      | 25.73                  | 5.24      |
| Real state income per capita, in 1000s                                    | 33.04                       | 5.22      | 33.29                  | 5.45      |
| Unemployment rate   | 4.56                        | 1.19      | 4.73                   | 1.18      |
| Real beer tax   | 0.46                        | 0.09      | 0.47                   | 0.13      |

**Table 2**  
The Relationship between Psychiatric Drugs and Violent Crime Rates  
(Estimates from state-quarter panel)

| Dependent Variable:<br>log violent crime rate | Model 1<br>(includes state and year/quarter fixed effects) |                   |                   |                   |                   |                   | Model 2<br>(includes state and year/quarter fixed effects and state-specific time trend) |                   |                   |                   |                   |                   |
|---|--|-------------------|-------------------|-------------------|-------------------|-------------------|--|-------------------|-------------------|-------------------|-------------------|-------------------|
|   | (a)  | (b)               | (c)               | (d)               | (e)               | (f)               | (g)  | (h)               | (i)               | (j)               | (k)               | (l)               |
| Lagged log all psychiatric drug count         | -0.018<br>(-0.83)  |                   |                   |                   |                   |                   | -0.005<br>(-0.32)  |                   |                   |                   |                   |                   |
| Lagged log antidepressant count               |  | 0.003<br>(0.13)   |                   |                   |                   |                   |  | 0.012<br>(0.79)   |                   |                   |                   |                   |
| Lagged log SSRIs/SNRIs count                  |  |                   | 0.041<br>(1.30)   |                   |                   |                   |  |                   | 0.050<br>(1.50)   |                   |                   |                   |
| Lagged log NGAs count                         |  |                   |                   | -0.065<br>(-3.01) |                   |                   |  |                   |                   | -0.057<br>(-3.08) |                   |                   |
| Lagged log stimulants count                   |  |                   |                   |                   | -0.086<br>(-2.23) |                   |  |                   |                   |                   |                   | -0.067<br>(-1.71) |
| Lagged log antipsychotic count                |  |                   |                   |                   |                   | -0.027<br>(-0.80) |  |                   |                   |                   |                   | -0.032<br>(-0.76) |
| Lagged log patient visits                     | 0.065<br>(1.21)  | 0.044<br>(0.98)   | -0.014<br>(-0.36) | 0.076<br>(1.63)   | 0.081<br>(1.05)   | 0.056<br>(1.16)   | 0.037<br>(0.62)  | 0.017<br>(0.28)   | -0.037<br>(-0.59) | 0.054<br>(0.94)   | 0.100<br>(1.19)   | 0.046<br>(0.83)   |
| Psychiatrists per 100,000 pop.                | -0.006<br>(-0.41)  | -0.007<br>(-0.46) | -0.009<br>(-0.57) | -0.006<br>(-0.38) | -0.006<br>(-0.33) | -0.005<br>(-0.36) | -0.008<br>(-0.59)  | -0.008<br>(-0.62) | -0.011<br>(-0.90) | -0.013<br>(-1.07) | -0.011<br>(-0.90) | -0.006<br>(-0.41) |
| Lagged expenditures on criminal justice       | -0.006<br>(-2.43)  | -0.005<br>(-2.43) | -0.005<br>(-2.42) | -0.006<br>(-2.65) | -0.006<br>(-2.28) | -0.005<br>(-2.65) | -0.007<br>(-3.34)  | -0.007<br>(-3.34) | -0.006<br>(-3.28) | -0.008<br>(-3.22) | -0.007<br>(-3.16) | -0.006<br>(-3.78) |
| Percent rural                                 | -0.026<br>(-0.55)  | -0.029<br>(-0.62) | -0.031<br>(-0.69) | 0.002<br>(0.04)   | -0.012<br>(-0.28) | -0.026<br>(-0.56) | -0.881<br>(-0.86)  | -0.836<br>(-0.85) | -0.723<br>(-0.81) | -0.489<br>(-0.41) | -0.940<br>(-0.87) | -0.980<br>(-0.89) |
| Percent with bachelor's degree                | -0.002<br>(-0.10)  | -0.003<br>(-0.15) | -0.004<br>(-0.23) | 0.005<br>(0.26)   | -0.006<br>(-0.31) | 0.001<br>(0.03)   | -0.020<br>(-1.28)  | -0.022<br>(-1.34) | -0.024<br>(-1.37) | -0.011<br>(-0.80) | -0.022<br>(-1.29) | -0.020<br>(-1.21) |
| Real state income per capita, in \$1000s      | 0.151<br>(2.43)  | 0.151<br>(2.43)   | 0.148<br>(2.43)   | 0.135<br>(2.32)   | 0.135<br>(2.52)   | 0.146<br>(2.50)   | 0.004<br>(0.06)  | 0.002<br>(0.03)   | -0.005<br>(-0.08) | 0.004<br>(0.06)   | 0.009<br>(0.12)   | 0.006<br>(0.08)   |
| Unemployment                                  | -0.011<br>(-0.24)  | -0.009<br>(-0.19) | -0.004<br>(-0.08) | -0.022<br>(-0.48) | -0.024<br>(-0.45) | -0.014<br>(-0.30) | 0.057<br>(1.04)  | 0.057<br>(1.02)   | 0.058<br>(0.99)   | 0.052<br>(1.11)   | 0.044<br>(0.81)   | 0.054<br>(1.02)   |
| Real beer tax                                 | -13.72<br>(-1.49)  | -13.62<br>(-1.49) | -13.46<br>(-1.49) | -13.44<br>(-1.48) | -14.09<br>(-1.61) | -14.01<br>(-1.49) | -6.595<br>(-1.73)  | -6.495<br>(-1.80) | -6.138<br>(-1.89) | -6.115<br>(-1.51) | -8.815<br>(-1.77) | -7.056<br>(-1.66) |
| N   | N=1,240  |                   |                   |                   |                   |                   | N=1,240  |                   |                   |                   |                   |                   |
| R2  | 0.844  | 0.844             | 0.845             | 0.849             | 0.85              | 0.845             | 0.879  | 0.879             | 0.88              | 0.883             | 0.882             | 0.879             |

Note: T-statistics calculated using state-clustered standard errors are in parentheses and intercept not shown. All models include state fixed effects.

Model 1 includes thirty dummy variables for each unique quarter/year. Model 2 adds to model 1 a state-specific linear time trend.

**Table 3**  
The Relationship between Psychiatric Drugs and Violent Crime Rates  
(Estimates from annual panel)

| Dependent Variable:<br>log violent crime rate | Model 1<br>(includes state and year fixed effects) |                    |                   |                    |                    |                   | Model 2<br>(includes state and year fixed effects and state-specific time trend) |                    |                    |                    |                   |                   |
|---|--|--------------------|-------------------|--------------------|--------------------|-------------------|--|--------------------|--------------------|--------------------|-------------------|-------------------|
|   | (a)  | (b)                | (c)               | (d)                | (e)                | (f)               | (g)  | (h)                | (i)                | (j)                | (k)               | (l)               |
| Lagged log all psychiatric drug count         | -0.004<br>(-0.13)                                  |                    |                   |                    |                    |                   | 0.008<br>(0.26)  |                    |                    |                    |                   |                   |
| Lagged log antidepressant count               |  | 0.001<br>(0.05)    |                   |                    |                    |                   |  | 0.009<br>(0.26)    |                    |                    |                   |                   |
| Lagged log SSRIs/SNRIs count                  |  |                    | 0.029<br>(0.87)   |                    |                    |                   |  |                    | 0.037<br>(1.15)    |                    |                   |                   |
| Lagged log NGAs count                         |  |                    |                   | -0.041<br>(-2.12)  |                    |                   |  |                    |                    | -0.016<br>(-0.96)  |                   |                   |
| Lagged log stimulants count                   |  |                    |                   |                    | -0.011<br>(-0.57)  |                   |  |                    |                    |                    |                   | -0.024<br>(-1.36) |
| Lagged log antipsychotic count                |  |                    |                   |                    |                    | 0.007<br>(0.51)   |  |                    |                    |                    |                   | 0.015<br>(1.83)   |
| Lagged log patient visits                     | 0.059<br>(0.77)                                    | 0.054<br>(0.64)    | 0.012<br>(0.12)   | 0.116<br>(2.44)    | 0.050<br>(0.74)    | 0.015<br>(0.14)   | -0.013<br>(-0.09)  | -0.015<br>(-0.10)  | -0.040<br>(-0.28)  | 0.005<br>(0.04)    | -0.025<br>(-0.19) | -0.009<br>(-0.07) |
| Psychiatrists per 100,000 pop.                | -0.004<br>(-0.94)                                  | -0.004<br>(-0.89)  | -0.004<br>(-0.80) | -0.007<br>(-1.35)  | -0.006<br>(-1.28)  | -0.004<br>(-0.71) | 0.008<br>(0.88)  | 0.008<br>(0.88)    | 0.007<br>(0.87)    | 0.005<br>(0.52)    | 0.006<br>(0.64)   | 0.006<br>(0.72)   |
| Lagged expenditures on criminal justice       | -4.8E-5<br>(-0.06)                                 | -2.7E-5<br>(-0.03) | 0.0001<br>(0.11)  | -0.0004<br>(-0.40) | -0.0002<br>(-0.19) | 0.0002<br>(0.33)  | -0.0004<br>(-0.45)   | -0.0004<br>(-0.45) | -0.0002<br>(-0.22) | -0.001<br>(-0.59)  | -0.001<br>(-0.71) | 0.00001<br>(0.01) |
| Percent rural                                 | -0.032<br>(-1.17)                                  | -0.034<br>(-1.31)  | -0.039<br>(-1.53) | -0.013<br>(-0.60)  | -0.026<br>(-0.92)  | -0.037<br>(-1.40) | 0.043<br>(0.05)  | 0.045<br>(0.05)    | 0.154<br>(0.20)    | 0.198<br>(0.27)    | 0.082<br>(0.11)   | -0.015<br>(-0.02) |
| Percent with bachelor's degree                | 0.010<br>(0.70)                                    | 0.010<br>(0.72)    | 0.010<br>(0.74)   | 0.010<br>(0.73)    | 0.009<br>(0.57)    | 0.009<br>(0.59)   | -0.001<br>(-0.05)  | -0.001<br>(-0.05)  | 0.001<br>(0.05)    | -0.0003<br>(-0.03) | -0.002<br>(-0.20) | -0.003<br>(-0.29) |
| Real state income per capita, in \$1000s      | 0.032<br>(1.26)                                    | 0.032<br>(1.28)    | 0.031<br>(1.26)   | 0.027<br>(1.14)    | 0.032<br>(1.24)    | 0.037<br>(1.73)   | 0.046<br>(1.40)  | 0.046<br>(1.36)    | 0.041<br>(1.13)    | 0.048<br>(1.41)    | 0.053<br>(1.61)   | 0.048<br>(1.55)   |
| Unemployment                                  | -0.037<br>(-0.88)                                  | -0.038<br>(-0.88)  | -0.039<br>(-0.90) | -0.024<br>(-0.60)  | -0.035<br>(-0.84)  | -0.030<br>(-0.84) | -0.039<br>(-1.12)  | -0.039<br>(-1.08)  | -0.038<br>(-1.14)  | -0.022<br>(-0.58)  | -0.030<br>(-0.96) | -0.033<br>(-0.94) |
| Real beer tax                                 | -2.661<br>(-1.28)                                  | -2.650<br>(-1.30)  | -2.569<br>(-1.26) | -2.480<br>(-1.21)  | -2.669<br>(-1.22)  | -3.019<br>(-1.49) | 3.901<br>(1.75)  | 3.913<br>(1.74)    | 3.943<br>(1.77)    | 4.104<br>(2.13)    | 3.667<br>(1.49)   | 3.608<br>(1.65)   |
| N   | N=343  |                    |                   |                    |                    |                   | N=343  |                    |                    |                    |                   |                   |
| R2  | 0.982  | 0.982              | 0.982             | 0.983              | 0.982              | 0.982             | 0.991  | 0.991              | 0.991              | 0.991              | 0.991             | 0.991             |

Note: T-statistics calculated using state-clustered standard errors are in parentheses and intercept not shown. All models include state fixed effects. Model 1 includes dummy variables for year. Model 2 adds to model 1 a state-specific linear time trend.

Table 4  
Falsification Check: The Relationship between Statins and Violent Crime Rates

|  | Model 1            | Model 2           | Model 3            | Model 4            |
|--|--------------------|-------------------|--------------------|--------------------|
| Lagged log statin count                  | 0.009<br>(0.30)    | 0.033<br>(1.03)   | -0.004<br>(-0.21)  | 0.010<br>(0.49)    |
| Lagged log patient visits                | 0.030<br>(0.66)    | -0.010<br>(-0.18) | 0.062<br>(0.84)    | -0.017<br>(-0.12)  |
| Psychiatrists per 100,000 pop.           | -0.007<br>(-0.44)  | -0.009<br>(-0.69) | -0.004<br>(-0.86)  | 0.006<br>(0.72)    |
| Lagged expenditures on criminal justice  | -0.006<br>(-2.42)  | -0.007<br>(-3.29) | -0.0001<br>(-0.08) | -0.0003<br>(-0.31) |
| Percent rural                            | -0.028<br>(-0.61)  | -0.926<br>(-0.88) | -0.034<br>(-1.53)  | 0.046<br>(0.06)    |
| Percent with bachelor's degree           | -0.003<br>(-0.16)  | -0.024<br>(-1.52) | 0.010<br>(0.72)    | -0.002<br>(-0.14)  |
| Real state income per capita, in \$1000s | 0.151<br>(2.43)    | 0.001<br>(0.01)   | 0.032<br>(1.28)    | 0.044<br>(1.18)    |
| Unemployment                             | -0.008<br>(-0.18)  | 0.057<br>(1.03)   | -0.039<br>(-0.93)  | -0.033<br>(-1.13)  |
| Real beer tax                            | -13.852<br>(-1.47) | -6.825<br>(-1.81) | -2.597<br>(-1.27)  | 3.905<br>(1.80)    |
| N  | 1,240              | 1,240             | 343                | 343                |
| R squared                                | 0.844              | 0.879             | 0.982              | 0.991              |
| Data set, quarterly or annual?           | Quarter            | Quarter           | Annual             | Annual             |
| State specific time trend?               | No                 | Yes               | No                 | Yes                |

Note: T-statistics calculated using state-clustered standard errors are in parentheses and intercept not shown. All models include state fixed effects. Model 1 includes thirty dummy variables for each unique quarter/year. Model 2 includes thirty dummy variables for each unique quarter/year and a state-specific linear time trend. Model 3 includes dummy variables for each year. Model 4 includes dummy variables for each year and a state-specific linear time trend.