Developing the U.S. Drug Consequences Indices 2000-2009

August 2013

DEVELOPING THE

U.S. DRUG CONSEQUENCES INDICES,

2000-2009

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Office of National Drug Control Policy
Executive Office of the President

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EXECUTIVE SUMMARY

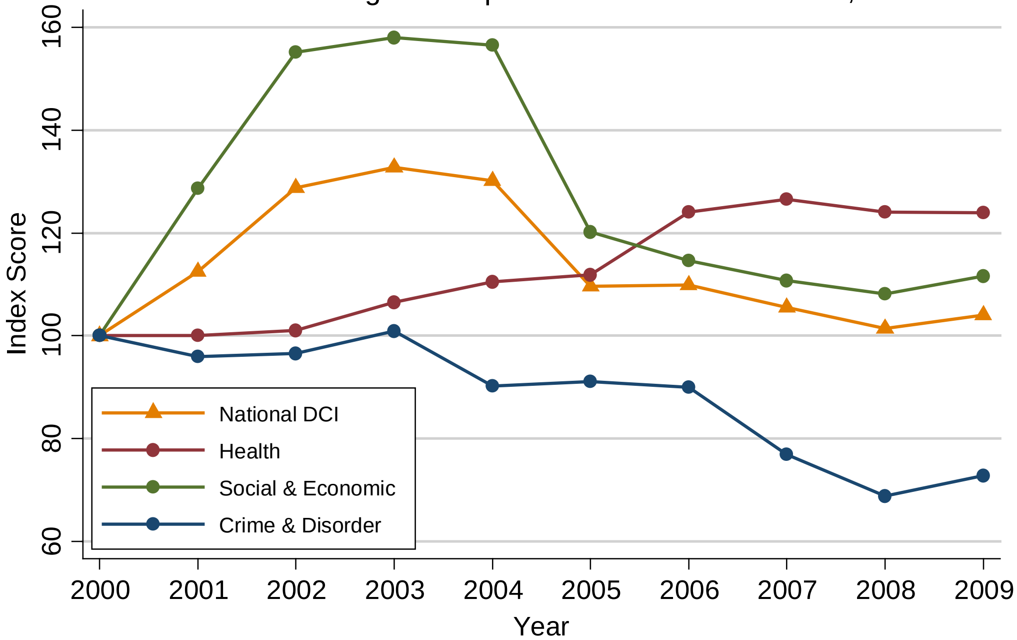
This report presents the results of a project to develop a family of U.S. Drug Consequences Indices (DCIs). The DCIs are a complementary set of indices that measure the harmful consequences of illegal drugs in a standardized way. The National DCIs measure trends in illicit drug-related consequences for the U.S. as a whole, and the State DCIs measure these consequences across both states and years. These various metrics quantify with a single number what is otherwise not directly measurable, that is, the diverse and complex construct of *drug-related consequences*. Each index was constructed from an array of theoretically-relevant social indicators measuring the health, social and economic, and crime and disorder consequences of illegal drug use and distribution during the ten-year period 2000 to 2009. Composite drug harm indices have been developed in recent years for official use in other countries, but the family of DCIs presented in this report are the first indices developed in a U.S. context that summarize over a multi-year period the multidimensional phenomenon of drug-related consequences.

The value of the DCIs is in their ability to summarize different aspects of drug-related harm in a more efficient and parsimonious manner than is possible with a collection of drug-related indicators taken separately. This is no easy task either conceptually or methodologically, but if implemented successfully the DCIs could prove useful to a wide variety of stakeholders in the drug policy community. Indeed, the DCIs have several envisioned applications. They can help monitor trends in drug-related consequences across states and over time, assist with benchmarking and performance assessment, provide data-driven input to policy formulation and resource allocation, and enhance the utility of drug data systems for reporting, outcome evaluation, and policy analysis. The DCIs can also help fulfill statutory reporting requirements, as well as improve the effectiveness of communication with legislators, professionals in drug abuse and law enforcement, the media, and the general public. Future planned updates to the DCIs as more recent data become available will enhance their value to these various stakeholder groups.

The process of constructing the DCIs involved a series of interrelated steps with a view to producing a balanced set of policy tools. First, to guide indicator selection, a conceptual framework was developed to coherently organize the broad spectrum of drug-related consequences. Second, existing drug data systems were inventoried to determine which consequences were actually quantifiable. Third, these data sources were assessed according to a data quality framework to determine their suitability for contributing specific indicators toward construction of the DCIs. Fourth, the chosen data were acquired, and the selected indicators were statistically treated (e.g., to deal with missing data) and operationalized. Finally, the indicators were normalized, weighted, and aggregated into a composite indicator.

The National DCI was constructed for years 2000-2009 from 30 underlying indicators measuring a wide array of illicit drug-related consequences. Figure I presents the overall DCI results, as well as the scores for the three underlying domains that inform the index. DCI scores were set to a benchmark value of 100 for year 2000. Overall, as the graph shows, illicit drug-related consequences in the U.S. increased rapidly during the first two years of the decade, reaching peak levels roughly 30% above baseline during 2002-2004, before returning to near-benchmark levels in 2008-2009. Consequences measured by the *Social and Economic* domain, which increased more than 55% by 2002, drove the initial increase in the National DCI, whereas *Health* domain consequences registered substantially higher only during the latter part of the 2000s, increasing 24-26% over baseline by 2006-2009. Conversely, *Crime and Disorder* consequences decreased steadily throughout the decade, reaching a point 27% below the 2000

Figure I
Trends in National Drug Consequences Index and Domains, 2000-2009



benchmark by 2009 (after a slight one-year uptick). Drug-specific indices were also developed at the national level, revealing divergent ten-year trends in drug-related consequences that ranged from increasing (heroin) to initially increasing then declining (methamphetamine and cocaine) to relatively stable (marijuana).

The State DCIs described interstate variations and trends in drug-related consequences both overall and for the four major drugs of abuse from 2000-2009. They were constructed from a select set of 13-16 underlying drug indicators depending on the specific index. As the interstate variations depicted in Figure II demonstrate, illegal drugs and their associated consequences are highly regionalized in the U.S. According to the State Heroin Index, the heroin problem is primarily concentrated in the New England and mid-Atlantic states, with additional pockets in the midwest and west. The State Methamphetamine Index shows that methamphetamine is a serious problem in the western half of the United States—especially Hawaii and other West

Coast states—but also that states well into the U.S. heartland experience serious consequences due to methamphetamine. According to the State Cocaine Index, states along the Gulf and East Coasts, and Illinois in the midwest, have the most serious cocaine problems, whereas states across a large section of the U.S. extending from the northwest to the upper midwest are relatively less affected by the cocaine problem. Finally, results from the State Marijuana Index show that marijuana-related consequences are the most geographically dispersed, which is at least partly attributable to the drug's overall higher prevalence.

The State DCIs also revealed important state-level trends in drug-related consequences. For example, heroin-related consequences steadily increased from 2000-2009, with 45 states experiencing an uptick in the Heroin Index. Some of this increase may be attributable to prescription opioid abuse, however, as certain indicators informing the Heroin Index unavoidably capture consequences from opiates as well as heroin. The trends for methamphetamine over the period 2000-2009 confirm the general epidemiology of an eastward expansion of the methamphetamine problem from its point of origin in Hawaii and other western states into the American heartland from 2000 to 2006 and its subsequent, albeit partial, retrenchment as of 2009. Although remaining a significant problem in many places, 34 states showed double-digit declining rates in the Methamphetamine Index from 2005-2009. For cocaine, some states experienced steady increases and others steady declines through the early 2000s. However, by 2006, trends in cocaine-related consequences had improved to the point that, between 2005 and 2009, 36 states experienced double-digit declining rates in the State Cocaine Index. Trends in the State Marijuana Index were split roughly 60/40 between states experiencing increases and decreases, respectively, from 2000 to 2009. Lastly, overall drug-related consequences were examined at the state-level, with the north central U.S. ranking consistently better than other states with respect to the range and severity of drug-related problems.

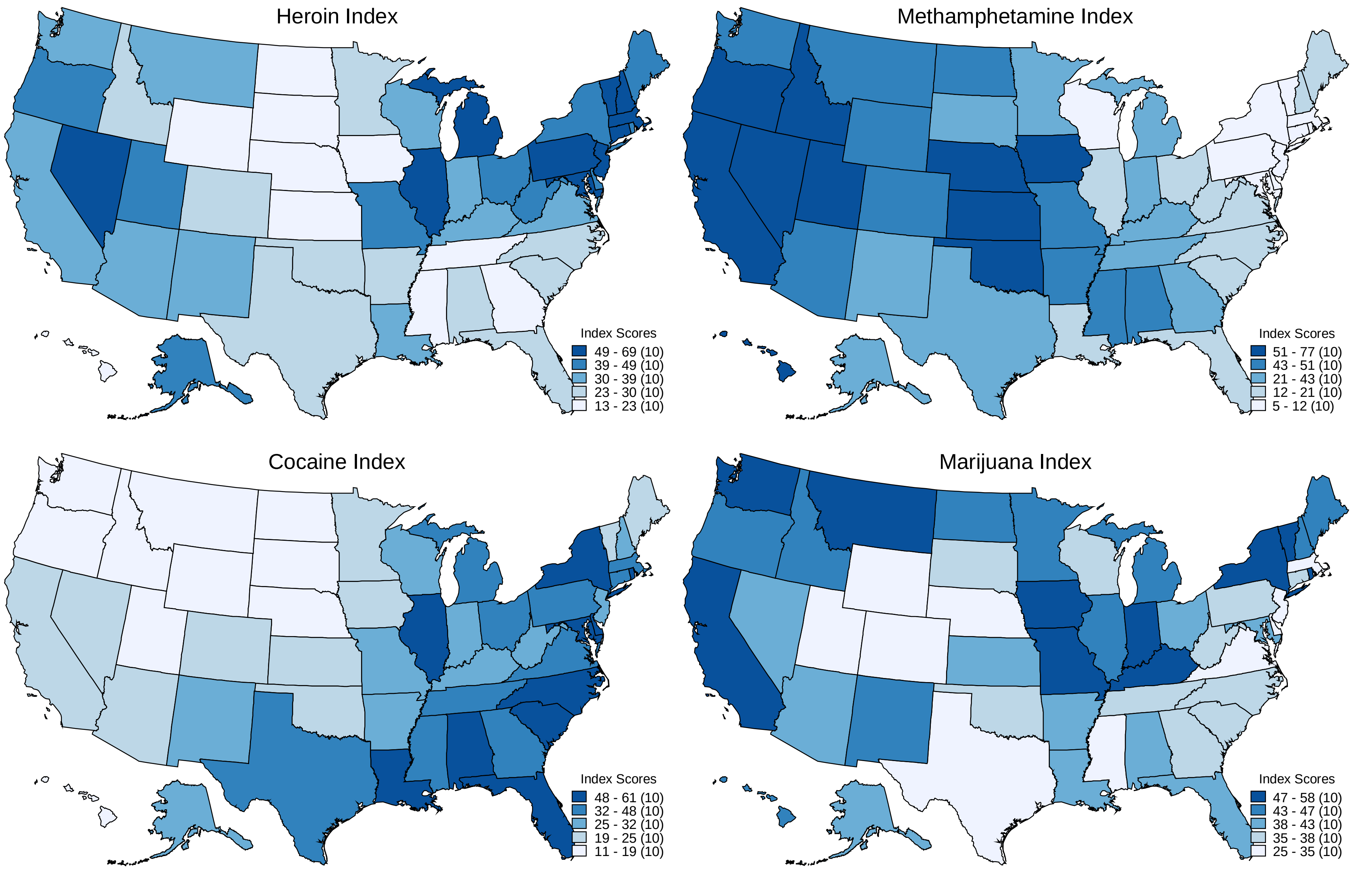
The family of U.S. DCIs has many potential uses and applications. First, they provide a parsimonious yet comprehensive snapshot of trends and variations in drug-related consequences. This can be useful for communicating with policymakers, practitioners, and the general public about drug policy needs, objectives, and progress. Further, the DCIs can support more sophisticated uses such as benchmarking, performance assessment, and related policy analytic work. In this role, the DCIs by themselves are not suited to supporting causal claims about policy effectiveness, but they can inform assessments of whether trends and interstate variations in drug-related problems are in accordance with the intended impact of a particular policy or set of policies. Relatedly, the DCIs provide relevant information on state and regional variations in the nature and extent of illicit drug problems, which can inform strategic thinking about policy objectives, resource allocation, and the prioritization of interventions and initiatives.

Another benefit of the DCIs is that they contribute to federal efforts to increase the utility of existing drug data systems, especially at the state or local level. For example, missing data in drug-related information systems often confounds the ability of interested stakeholders to compare states on relevant outcome and performance indicators. In generating estimates of missing data within a multiple imputation framework, this project was able to utilize key information systems that would not have been possible otherwise. The DCIs employed a conceptually coherent approach to guide measurement of drug-related consequences, keying on a number of relevant dimensions across health, social and economic, and crime and disorder domains. In this respect, the DCIs and their underlying data can facilitate assessments regarding which dimensions are a state’s strongest assets, and which are in need of improvement. They can also inform future data collection efforts by identifying current data gaps in the measurement of drug-related consequences.

Despite their potential utility, the DCIs have a number of limitations. First, the indices are only as valid and reliable as their underlying indicators. We have attempted to address these concerns to the extent possible by employing both a conceptual and a data quality framework for selecting relevant social indicators. Some things could not be overcome, however, such as the error introduced by imprecise measures of drug type in some data systems or long delays in reporting by source agencies and organizations. Also, the issue of weighting is particularly sensitive and subjective when constructing composite indicators. There is no clear consensus among experts on composite index construction for how to best determine a set of weights for combining diverse issues, such as those related to drug consequences. In response to this, we have performed a series of robustness analyses that show the DCIs perform well as constructed.

There are a number of possible future directions for the research begun here. First, and foremost, the DCIs can be updated on a regular basis as new data is released. Indeed, one of the primary objectives for this project was to set up an ongoing monitoring system that could track trends in drug-related consequences over time. There is also opportunity for constructing similar indices involving other substances, such as other illegal drugs, tobacco, alcohol, and prescription drugs. It would also be fruitful to construct comparative indices at the substate level (e.g., counties, cities, zip codes) in order to provide more localized assessments of drug policy and related outcomes. Finally, research on index construction concerning inputs on the policy side would be a logical extension to the current work. Some research of this type has already been done at the international level in the alcohol field. In summary, the DCIs developed in the context of this project sought to measure drug-related consequences in a parsimonious yet comprehensive manner, with the ultimate objective of providing a useful set of communicative and policy analytic tools.

Figure II. State Drug Consequences Indices, 2009



I. INTRODUCTION

When confronted with complex social problems that transect multiple domains and interests—such as the health, crime, economic, and quality of life burdens of illegal drug use—public agencies in the era of government accountability face the difficult task of effectively measuring policy and programmatic success. Composite indices (CIs), also known as composite indicators, have gained increasing acceptance as practical tools for performance assessment, benchmarking, policy analysis, and public communication (Organisation for Economic Co-operation and Development, 2008; Zhou, Ang, and Zhou, 2010). Formally, a CI is a mathematical aggregation of individual social indicators that captures a multidimensional concept in a single model-based number per year or region (OECD, 2008). CIs have therefore shown promise both for parsimoniously monitoring multifaceted phenomena over time and for efficiently comparing complex social problems across jurisdictions, such as countries, states, and cities. Their appeal to policymakers, analysts, and the general public has resulted in the development of literally hundreds of CIs in a broad array of substantive areas, including business and technology, sustainability, quality of life, governance, road safety, violence, and, increasingly, drug policy (see e.g., Bandura, 2008; Brand et al., 2007; Brumbaugh-Smith et al., 2008; Hermans et al., 2009; Ritter, 2009).

This report presents the results of a project to develop a family of U.S. Drug Consequences Indices (DCIs). The DCIs are a complementary set of indices that measure and summarize the harmful consequences of illegal drugs in a standardized way. The National DCIs measure trends in illicit drug-related consequences for the U.S. as a whole, and the State DCIs measure these consequences across both states and years. Both overall and drug-specific outcomes are examined at the national and state levels. These various metrics quantify with a single number what is otherwise not directly measurable, that is, the diverse and complex construct of ‘drug-related consequences.’ Each index was constructed from an array of theoretically relevant social indicators measuring the health, social and economic, and crime and disorder consequences of illegal drug use and distribution during the ten-year period 2000 to 2009.

The value of the DCIs is in their ability to summarize different aspects of drug-related harm in a more efficient and parsimonious manner than is possible with a collection of drug-related indicators taken separately. Indeed, the DCIs have several envisioned applications. They can help monitor trends in drug-related consequences across states and over time, assist with benchmarking and performance assessment, provide data-driven input to policy formulation and resource allocation, and enhance the utility of existing drug data systems for reporting, outcome evaluation, and policy analysis. The DCIs can also help fulfill statutory reporting requirements, as well as improve the effectiveness of communication with legislators, professionals in drug abuse and law enforcement, the media, and the general public. Future planned updates to the DCIs as more recent data become available will enhance their utility among these various stakeholder groups.

Certainly, aggregating various drug indicators poses daunting conceptual and methodological challenges that stem mainly from the type and quality of available data and the combination of these into a common metric. Given these challenges, a good amount of debate surrounds the general utility of CIs and related composite measures both among experts in index construction (Saltelli, 2007) and in the specific arena of drug policy (Caulkins, Reuter, and Coulson, 2011; Nutt, 2009; Reuter and Trautmann, 2009:47; Ritter, 2007, 2009; Stevens, 2008). The DCIs were therefore developed according to a core set of principles: simplicity, soundness, and transparency. Simplicity is driven by the goal that the DCIs be easily understood by a nontechnical audience. Simplicity did not prevail over technical soundness, however, as the DCIs were developed building on recommendations of the OECD (2008) *Handbook on Constructing Composite Indicators* and the lessons derived from statistical analysis of several well-known composite indicators (Saisana, d'Hombres, and Saltelli, 2011; Saisana, Saltelli, and Tarantola, 2005), including those in the substance abuse field (e.g., Brand et al., 2007; MacDonald et al., 2005; McAuliffe and Dunn, 2004). Finally, transparency has been central to the entire exercise, with full documentation of the assumptions and methods behind the DCIs and the accompanying distribution of the underlying indicators used in their construction.

This report proceeds as follows. First, the procedures used to locate and operationalize the indicators employed in the construction of the DCIs are discussed, including development of the conceptual framework, data inventorying process, application of the data quality framework, and measurement operations. Second, the methods used to statistically treat the data and then weight and aggregate the indicators are introduced. Third, the DCI results are presented. The report ends with a summary of the results, a discussion of the utility and limitations of the DCIs, and a look toward future research directions. A series of appendices to this report provide detailed documentation of the measurement operations and statistical methods used in the construction of the DCIs.

II. MEASURING DRUG-RELATED CONSEQUENCES

In constructing the DCIs, the process of identifying and measuring drug-related consequences involved several interrelated steps. First, to guide indicator selection and subsequent aggregation, a conceptual framework was developed to coherently organize the broad spectrum of drug-related consequences. Second, moving from the theoretical to the practical, existing drug data systems were inventoried to determine which consequences were actually measurable. Third, these data sources were assessed according to a data quality framework to determine their suitability for contributing specific indicators toward construction of the DCIs. Fourth, the chosen data were obtained and selected indicators were operationalized.

A. CONCEPTUAL FRAMEWORK

The development of the Drug Consequences Indices (DCIs) was guided by the overarching conceptual framework presented in Figure 1. The framework depicts a policy model that distinguishes between *policy actions* and *policy outcomes* (Dunn, 2008). Policy actions represent inputs (e.g., resources allocated) and processes (e.g., implementation), whereas policy outcomes reflect outputs (e.g., units of services delivered) and impacts (e.g., behavioral or attitudinal change). This distinction has important measurement and analysis implications. Broadly, the framework provides a simple logic model for framing how drug policy actions influence drug policy outcomes. Importantly, for this work, it also makes explicit what *is* and *is not* being measured. A common criticism of CIs is that they often inadvisably commingle input and output measures (OECD, 2008). The conceptual framework therefore encourages precision of measurement by focusing DCI measurement operations squarely on drug policy impacts, which are represented in Figure 1 by a taxonomy of drug-related consequences. These consequences are divided into three broad domains: *Health*, *Social and Economic,* and *Crime and Disorder*. Each of these is further divided into three subdomains that capture specific aspects of the parent domain. Table 1 defines each subdomain and provides specific examples of the types of drug-related consequences included in these definitions. [1]

This taxonomy was developed based on a comprehensive review of the literature, along with feedback from subject area experts. The primary objective at this conceptual development stage was to achieve theoretical exhaustiveness in order to avoid biasing the taxonomy toward more easily quantifiable constructs and, later, to highlight existing data gaps. A preliminary taxonomy was created based on previous scholarship that systematized drug-related harms and consequences into a coherent classification system. This included work on *drug classification and risk assessment* (e.g., European Monitoring Centre for Drugs and Drug Addiction, 2009; Levitt, Nason, and Hallsworth, 2006; Nutt et al., 2007; Nutt, King, and Phillips, 2010; van Amsterdam et al., 2004), the *economic costs of drug abuse* (e.g., Collins and Lapsley, 2008; Mark et al., 2001; Miller et al., 2006; Nicosia et al., 2009; Office of National Drug Control Policy, 2004), *drug policy analysis* (e.g., Babor et al., 2010; Longshore et al., 1998; MacCoun and Reuter, 2001), and other *composite drug indices* (e.g., MacDonald et al., 2005; McFadden, 2006; Slack et al., 2008; United Nations Office on Drugs and Crime, 2005).

To further saturate the taxonomy, a broad-based listing of specific drug harms and consequences was prepared from searches of major reference databases (e.g., CINAHL Plus, Criminal Justice Abstracts, Google Scholar, PsycINFO, PubMed-Medline). The search strategy intersected various combinations of drug type terms (e.g., drug, illegal drug, illicit drug, heroin, methamphetamine, cocaine, marijuana) and drug consequence terms (e.g., harm, consequence, morbidity, mortality, driving, crime, drug-exposed children). The taxonomy evolved as additional drug-related consequences were identified and incorporated into the framework.

[1] See Appendix A for an expanded outline of the taxonomy and a more detailed listing of representative types of drug-related consequences.

Feedback on the taxonomy was elicited throughout its development from subject area experts both informally and at professional conferences. [2] The taxonomy of drug-related consequences presented in Figure 1 is the culmination of this review and feedback process.

[2] Official presentations were made at the annual meetings of the International Society for the Study of Drug Policy (Utrecht, Netherlands, May 2011) and the American Society of Criminology (Washington, DC, November 2011).

Figure 1. Conceptual Framework

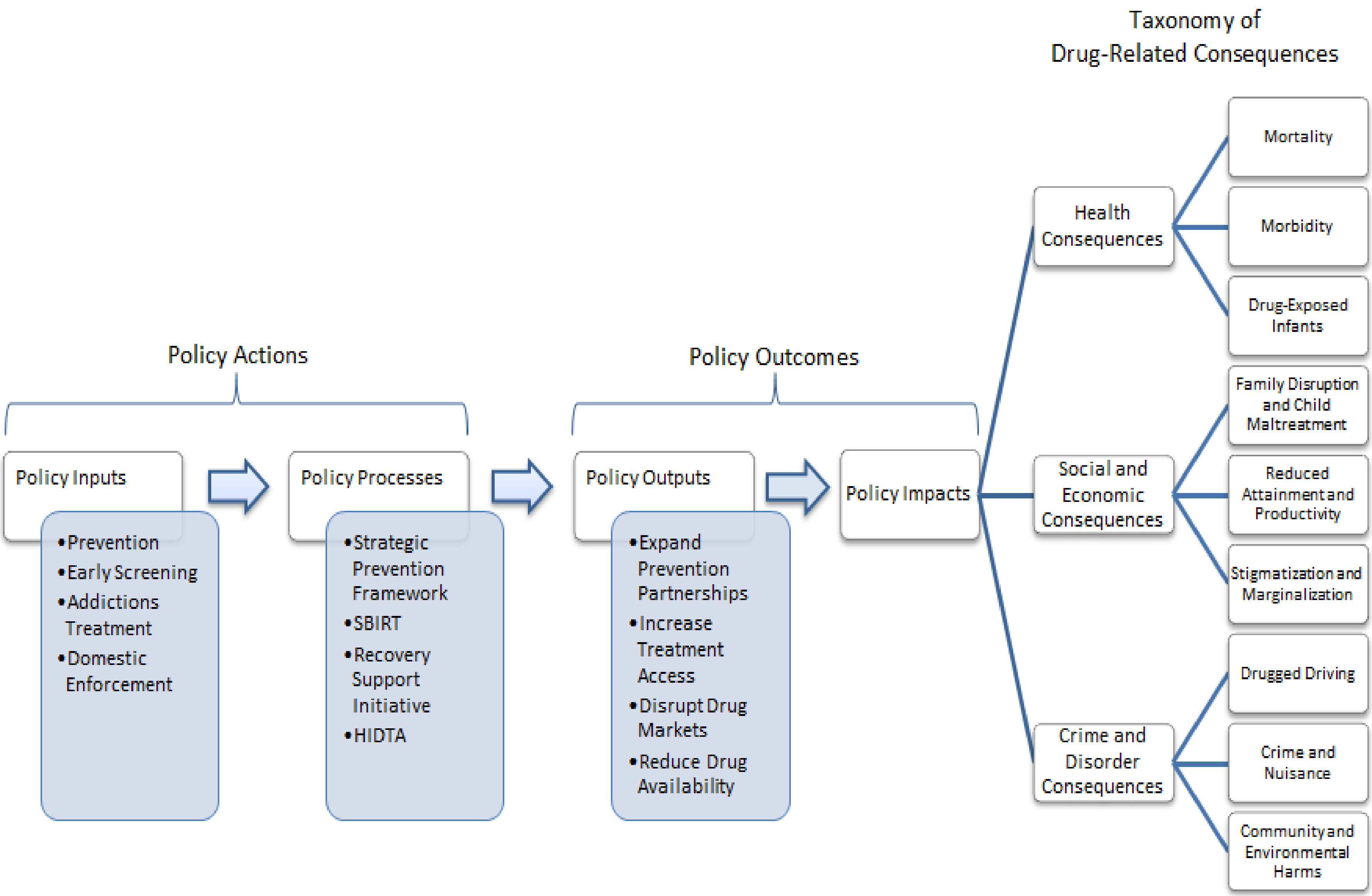


Table 1. Drug Consequence Subdomains and Definitions

Health Consequences

<u>Mortality</u>—Drug-induced or drug-related overdose, disease (e.g., HIV, cancer, organ failure), or trauma (e.g., accidents, suicide) resulting in death.

<u>Morbidity</u>—Drug-induced or drug-related injury, illness, disease, or disorder (including drug use disorders) resulting in physical and/or psychological impairment.

<u>Drug-Exposed Infants</u>—Negative child health outcomes resulting from in utero or postnatal exposure (e.g., through breastfeeding) to drugs, including, e.g., obstetrical complications, HIV exposure, congenital defects, low birth weight, and developmental delays.

Social and Economic Consequences

<u>Family Disruption and Child Maltreatment</u>—Family or child drug involvement contributing to domestic violence, family strain and dissolution (e.g., divorce, separation), child removal (e.g., foster care), loss of parental rights, or child abuse (physical, sexual, emotional) and neglect.

<u>Reduced Attainment and Productivity</u>—Drug involvement that leads to poor educational outcomes (e.g., low academic performance, drop-outs), reduced economic well-being (e.g., unemployment, reduced or diverted income), or lost productivity (e.g., absenteeism, unsafe workplaces).

<u>Stigmatization and Marginalization</u>—Drug use, dependence, or risky drug-taking practices (e.g., injection drug use) that promotes negative outcomes, such as loss of relationships, social alienation, homelessness, impoverishment, drug-using lifestyles, or a generally poor quality of life.

Crime and Disorder Consequences

<u>Drugged Driving</u>—Driving under the influence of drugs and related consequences, including road or transportation accidents, property damage, reduced road safety, and other driving-related risks.

<u>Crime and Nuisance</u>—Drug-related crime (e.g., aggression and violence, stealing to get money for drugs, shoot-outs over drug-selling turf, corruption and money laundering) and public nuisance (e.g., visible dealing, drug litter, fear of crime, graffiti).

<u>Community and Environmental Harms</u>—Drug use, distribution, or production that leads to place-based community deterioration (e.g., diminished social cohesion, devalued housing stock) or environmental degradation (e.g., dumping of hazardous waste, deforestation, watershed diversion).

B. INVENTORY OF DRUG DATA SYSTEMS

Measuring drug-related consequences requires data, preferably data from reputable sources that have been gathered consistently and reliably over time and across jurisdictions. In order to locate relevant data to populate the taxonomy of drug-related consequences with measurable indicators, an exhaustive inventory of current drug data systems was undertaken. This process included reviewing published data directories (Coffey et al., 2009; Collins and Zawitz, 1990; CSR Incorporated, 2008; Ebener, Feldman, and Fitzgerald, 1993; Garnick, Hodgkin, and Horgan, 2002; Hirshon et al., 2009; Manski, Pepper, and Petrie, 2001; NIDA, 2006; ONDCP, 1990; 2003; Rootman and Hughes, 1980), searching data warehouse holdings (e.g., Interuniversity Consortium for Political and Social Research), and surveying the current data systems of key government statistical agencies and other private entities. As documented in Appendix B, this search strategy cataloged more than 120 ongoing or recent drug data systems, ranging from core federally-sponsored systems (e.g., ADAM, DAWN, MTF, NSDUH, TEDS) to less well-known and underutilized ones.

C. DATA QUALITY FRAMEWORK

Much has been written about the limitations of existing drug data systems and the challenges of reliably and validly measuring drug-related outcomes (Caulkins, 2000, 2007; Manski, Pepper, and Petrie, 2001; Haaga and Reuter, 1991; Ebener et al., 1993). Informed by this prior work, the goal here was to assess the identified data systems along six dimensions regarding their quality or "fitness for use": (1) *relevance* to the overarching conceptual framework, (2) *accuracy* of the data and credibility of the data source, (3) *timeliness* and punctuality in availability, (4) *accessibility* in terms of restrictions and cost, (5) *interpretability* in terms of documentation and metadata, and (6) *coherence* in definition and format across jurisdictions and time (OECD, 2008).

Relevance was assessed by reviewing codebooks and metadata to determine whether each data source contained indicators that met specific criteria for constructing the DCIs. The first criterion plainly required that indicators measure a consequence of drug use or drug distribution. The second criterion mandated that relevant indicators be collected serially. The third criterion concerned the geographic unit of analysis, with measurement targeted at either a national or state level of aggregation. The fourth criterion concerned the drug-specificity of the indicators, where measurement focused on either generic indicators of illicit drug consequences or drug-specific indicators for the four major drugs of abuse (i.e., heroin, methamphetamine, cocaine, and marijuana).

Table 2. Matrix of Index Measurement Criteria

	Drug Specificity	
Geographic Unit of Analysis	**All Illicit Drugs (Generic)**	**Major Illicit Drugs (Drug-Specific)**
National	(1) National DCI	(2) Drug-Specific National DCIs
State	(3) Generic State DCI	(4) Drug-Specific State DCIs

As shown in Table 2, these latter two dimensions form a 2 x 2 matrix that highlights possible ways of formulating an index of drug-related consequences. [3] The project focused initial index development efforts on cells (1) and (4). In both cases, the indices were developed from the bottom up using specific indicators that met the indicated measurement criteria (see next section). To fill the matrix, indices corresponding to cells (2) and (3) were developed through a

[3] More complexity could easily be introduced to this rubric by including substate units of analysis (e.g., county, city, zip code) or other substances (e.g., alcohol, tobacco, prescription drugs).

series of supplemental analyses starting with the completed drug-specific State DCIs (4). Although it would have been preferable to build indices representing cells (2) and (3) using a similar protocol, time and resource constraints precluded that work for the current report.

Our assessment revealed that most drug data systems failed to meet one or more of the indicated relevance criteria. Many systems capture only policy inputs, processes, or outputs; that is, they do not directly measure drug-related consequences. This was evident in a number of treatment-oriented data systems (e.g., NCJTPS, N-SSATS), as well as many BJS data systems that collect operational information on law enforcement, courts, and corrections (e.g., LEMAS, NJRP, NCRP). Other data systems collect information primarily on pharmaceuticals and therefore fall outside of the scope of this inquiry (e.g., AERS, ARCOS, TLCS). With respect to serial availability, data coverage was often limited and incomplete. Leaving aside discontinued or superseded data systems, there are recent one-time collections that may or may not have planned future releases (e.g., National Survey of Meth Markets, National Survey of Workplace Health and Safety, NMVCCS, NSYC) as well as serial data collections with long periods of intermittency (e.g., NIS, NRS, SIFSCF, SILJ). A span of eight years, for instance, separates the two most recent installments of the Survey of Inmates in State and Federal Correctional Facilities (i.e., 2012 vs. 2004).

Geographically, most data systems are able to produce statistics at either the national or state level. However, some longitudinal surveys of individuals (e.g., NLSY97, NLSY79) capture person cohort effects more than national trends or state differences, and at least one major data system produces only substate estimates (ADAM). Other data systems represent the coterminous U.S. (e.g., NPHS, NRS) or collect data on a select subset of states (e.g., HCUP, NCANDS, NIBRS, NTSIP, PRAMS). Concerning drug specificity, a number of state-level data systems report only nonspecific drug type information (e.g., AFCARS, CSSS, NCANDS, OTIS, PRAMS). Also, because they use the *International Classification of Diseases* to code drug-related health outcomes, some data systems (e.g., NVSS, HCUP) are not able to capture specific drug types with precision (e.g., opiates vs. heroin, stimulants vs. methamphetamine). In these instances, unless a more accurate indicator was available from another source, we opted for measurement with imprecision rather than no measurement at all.

Data systems that met the initial relevance criteria were then assessed for fitness along the remaining five quality dimensions (i.e., accuracy, timeliness, accessibility, interpretability, coherence). While no single dimension was wholly determinative of a particular data source's utility or fitness, preferred data systems included those that were (i) maintained by national statistical agencies, (ii) released regularly and punctually, (iii) free-of-charge and provided in an easily accessible format, (iv) accompanied by detailed documentation including codebooks and metadata, and (v) consistently reported across time and units.

D. SELECTED INDICATORS

Data judged to be of potential value were obtained for further inspection and assessment. Ultimately, a total of 21 different data systems were selected to contribute one or more indicators toward construction of the DCIs. Statistical analyses (e.g., PCA) helped in refining some of these choices. All chosen indicators have a clear direction with respect to the overall phenomenon, with higher indicator values being undesirable. To represent a fair picture of the various aspects of the phenomenon being measured, indicators were normalized as appropriate (e.g., by general population, specific demographics). As Table 3 shows, 30 indicators were used in the construction of the National DCI. The most populated subdomain is 'morbidity' with nine indicators, and the least populated is ‘community and environmental harms’ with a single indicator. Similarly, Table 4 shows the indicators underlying each of the drug-specific State DCIs, which range from 13 indicators for the State Heroin Index to 16 for the State Marijuana Index. [4] The State DCIs are thus relatively less populated, as three out of four indices contain no indicators for at least one subdomain (only the Methamphetamine Index is fully populated) and all indices have 3-5 subdomains that are populated with only a single indicator. Indirect measures were therefore used if empirically and conceptually defensible. For example, there is reasonable evidence to suggest a link between marijuana potency and psychosis (Di Forti et al., 2009; Hall and Degenhardt, 2011), so [m3] *potency of seized marijuana* was used to measure ‘morbidity’ in the Marijuana Index. In the next section, we address the statistical treatment, weighting, and aggregation of these groups of indicators into their composites.

[4] See Appendix C for detailed indicator definitions, measurement operations, and source information. The data used to construct the DCIs are available upon request from the Office of National Drug Control Policy.

Table 3. Taxonomy of Drug-Related Consequences—Core National Index

Domain and Subdomain		Indicator (Source)
Health	Mortality	[d1] Drug-related deaths per 100,000 (MCD) [d2] IDU-related AIDS deaths per 100,000 (HIV Surveillance Reports)
	Morbidity	[d3] Drug exposure poison center cases per 100,000 (NPDS) [d4] Drug-related emergency department visits per 100,000 (DAWN) [d5] Inpatient hospital drug poisoning discharges per 100,000 (HCUP-NIS) [d6] Inpatient hospital drug use disorder discharges per 100,000 (HCUP-NIS) [d7] Drug treatment admissions per 100,000 (TEDS) [d8] Prevalence of drug dependence or abuse among persons aged 12+ (NSDUH) [d9] IDU-related AIDS diagnoses per 100,000 (HIV Surveillance Reports) [d10] Prevalence of injection drug use among TB patients (OTIS) [d11] Prevalence of noninjection drug use among TB patients (OTIS)
	Drug-Exposed Infants	[d12] Prevalence of illicit drug use among pregnant women aged 15-44 (NSDUH) [d13] Inpatient hospital discharges for drugs affecting baby per 100,000 women aged 15-44 (HCUP-NIS) [d14] Percentage of women aged 15-44 who were pregnant upon entering drug treatment (TEDS)
Social & Economic	Family Disruption & Child Maltreatment	[d15] Percentage of foster care placements precipitated by child drug abuse (AFCARS) [d16] Percentage of foster care placements precipitated by caretaker drug abuse (AFCARS) [d17] Children affected by illicit drug labs per 100,000 (NSS)
	Reduced Attainment & Productivity	[d18] Percentage of people who were unemployed upon entering drug treatment (TEDS) [d19] Drug positivity rate among the U.S. workforce (DTI) [d20] Prevalence of past-year illicit drug use among secondary school students (MTF) [d21] On-campus drug violations per 1,000 enrolled college students (CSSS) [d22] Percentage of high school students offered drugs on school grounds (YRBS)
	Stigmatization & Marginalization	[d23] Percentage of people who were homeless upon entering drug treatment (TEDS) [d24] Lifetime prevalence of drug injection among high school students (YRBS)
Crime & Disorder	Drugged Driving	[d25] Positive drug-tested drivers involved in fatal vehicle accidents per 100,000 (FARS) [d26] Positive drug-tested drivers involved in police-reported crashes per 100,000 (GES) [d27] Prevalence of self-reported drugged driving among persons aged 16+ (NSDUH)
	Crime & Nuisance	[d28] Drug-related violent victimizations per 100,000 (NCVS) [d29] Drug-related murders per 100,000 (UCR)
	Community & Environmental Harms	[d30] Illicit drug production incidents per 100,000 (NSS, DCE/SP)

Table 4. Taxonomy of Drug-Related Consequences—Core State Indices

Domain and Subdomain		Indicator (Source)			
		Heroin Index	Methamphetamine Index	Cocaine Index	Marijuana Index
Health	Mortality	[h1] Heroin/opiate-related deaths per 100,000 (MCD)	[a1] Stimulant-related deaths per 100,000 (MCD)	[c1] Cocaine-related deaths per 100,000 (MCD)	--
	Morbidity	[h2] Primary heroin treatment admissions per 100,000 (TEDS) [h3] Inpatient hospital diagnoses for heroin poisoning per 100,000 (HCUP-SID) [h4] Inpatient hospital diagnoses for heroin/opiate use disorders per 100,000 (HCUP-SID)	[a2] Primary amphetamine treatment admissions per 100,000 (TEDS) [a3] Inpatient hospital diagnoses for stimulant poisoning per 100,000 (HCUP-SID) [a4] Inpatient hospital diagnoses for stimulant use disorders per 100,000 (HCUP-SID)	[c2] Primary cocaine treatment admissions per 100,000 (TEDS) [c3] Inpatient hospital diagnoses for cocaine poisoning per 100,000 (HCUP-SID) [c4] Inpatient hospital diagnoses for cocaine use disorders per 100,000 (HCUP-SID)	[m1] Primary marijuana treatment admissions per 100,000 (TEDS) [m2] Inpatient hospital diagnoses for marijuana use disorders per 100,000 (HCUP-SID) [m3] Potency of seized marijuana (PMP)
	Drug-Exposed Infants	[h5] Prevalence (%) of heroin abuse and pregnancy among females entering drug treatment (TEDS) [h6] Inpatient hospital diagnoses for narcotics affecting fetus or newborn per 100,000 females aged 15-44 (HCUP-SID)	[a5] Prevalence (%) of amphetamine abuse during pregnancy among females entering drug treatment (TEDS)	[c5] Prevalence (%) of cocaine abuse during pregnancy among females entering drug treatment (TEDS) [c6] Inpatient hospital diagnoses for cocaine affecting fetus or newborn per 100,000 females aged 15-44 (HCUP-SID)	[m4] Prevalence (%) of marijuana abuse during pregnancy among females entering drug treatment (TEDS)
Social & Economic	Family Disruption & Child Maltreatment	--	[a6] Children affected by methamphetamine labs per 100,000 (NSS)	--	--
	Reduced Attainment & Productivity	[h7] Prevalence (%) of heroin abuse and unemployment among people entering treatment (TEDS) [h8] Opiate positivity rate among the general U.S. workforce (DTI)	[a7] Prevalence (%) of amphetamine abuse and unemployment among people entering treatment (TEDS) [a8] Methamphetamine positivity rate among the general U.S. workforce (DTI)	[c7] Prevalence (%) of cocaine abuse and unemployment among people entering treatment (TEDS) [c8] Cocaine positivity rate among the general U.S. workforce (DTI)	[m5] Prevalence (%) of marijuana abuse and unemployment among people entering treatment (TEDS) [m6] Marijuana positivity rate among the general U.S. workforce (DTI)

Domain and Subdomain		Indicator (Source)			
		Heroin Index	Methamphetamine Index	Cocaine Index	Marijuana Index
		[h9] Prevalence (%) of lifetime heroin use among high school students (YRBS)	[a9] Prevalence (%) of lifetime methamphetamine use among high school students (YRBS)	[c9] Prevalence (%) of lifetime cocaine use among high school students (YRBS) [c10] Prevalence (%) of past-year cocaine use among 12-17 year olds (NSDUH)	[m7] Prevalence (%) of marijuana use before age 13 among high school students (YRBS) [m8] Prevalence (%) of recent marijuana use on school property among high school students (YRBS) [m9] Average annual marijuana initiation rate among 12-17 year olds (NSDUH)
	Stigmatization & Marginalization	[h10] Prevalence (%) of heroin abuse and homelessness among people entering treatment (TEDS)	[a10] Prevalence (%) of amphetamine abuse and homelessness among people entering treatment (TEDS)	[c11] Prevalence (%) of cocaine abuse and homelessness among people entering treatment (TEDS)	[m10] Prevalence (%) of marijuana abuse and homelessness among people entering treatment (TEDS)
Crime & Disorder	Drugged Driving	[h11] Heroin/opiate positivity rate among drivers involved in fatal accidents (FARS)	[a11] Amphetamine positivity rate among drivers involved in fatal accidents (FARS)	[c12] Cocaine positivity rate among drivers involved in fatal accidents (FARS)	[m11] Marijuana positivity rate among drivers involved in fatal accidents (FARS)
	Crime & Nuisance	[h12] Percentage of police agencies reporting heroin contributes most to violent crime (NDTS) [h13] Percentage of police agencies reporting heroin contributes most to property crime (NDTS)	[a12] Percentage of police agencies reporting methamphetamine contributes most to violent crime (NDTS) [a13] Percentage of police agencies reporting methamphetamine contributes most to property crime (NDTS)	[c13] Percentage of police agencies reporting cocaine contributes most to violent crime (NDTS) [c14] Percentage of police agencies reporting cocaine contributes most to property crime (NDTS)	[m12] Percentage of police agencies reporting marijuana contributes most to violent crime (NDTS) [m13] Percentage of police agencies reporting marijuana contributes most to property crime (NDTS)
	Community & Environmental Harms	--	[a14] Percentage of police agencies reporting local methamphetamine production (NDTS) [a15] Methamphetamine laboratory seizure incidents per 100,000 (NSS)	--	[m14] Percentage of police agencies reporting local marijuana production (NDTS) [m15] Outdoor marijuana plots eradicated per 100,000 (DCE/SP) [m16] Indoor marijuana grows seized per 100,000 (DCE/SP)

III. METHODOLOGICAL APPROACH

Constructing the U.S. Drug Consequences Indices (DCIs) involved a series of methodological steps to statistically treat the indicators and then weight and aggregate them into composites. Although the National and State DCIs were constructed using a unified approach, certain procedures varied given the different purposes and data structures (i.e., time series for the National DCI and time-series cross-section for the State DCIs). This section describes the basic statistical considerations and methodologies employed; additional details on methodology and robustness analyses are presented in Appendix D.

A. STATISTICAL TREATMENT OF INDICATORS

The National DCI is based on a selected set of 30 indicators covering the ten-year period 2000-2009. Statistical treatment of these data entailed both imputation and normalization procedures. Overall, data were missing for just 23 (7.7%) of the 300 possible observations (30 indicators × 10 years). Each indicator had a minimum of five years of observed data, with 22 indicators having complete records. Missing data for the remaining 8 indicators were imputed using either linear interpolation [d22, d24] or trend analysis regressing time (i.e., year) on the selected indicator [d4, d8, d12, d21, d27, d28].[5] Second, to render the indicator values comparable, we normalized each indicator by a distance-to-reference value, where year 2000 served as the base year set to a value of 100.

Statistical treatment of indicators for the State DCIs involved multiple imputation of missing data, transformation to address outliers and assure distributional assumptions, and normalization to a common scale. For each state-year matrix of indicators, missing data

[5] Note that the imputations performed here deal with unit nonresponse on the time dimension. Missing data methods dealing with item nonresponse were dealt with at the indicator level and are discussed along with each indicator's operationalization in Appendix C.

characterized 26.0% (1,693 / 6,500) of the Heroin Index, 22.0% (1,652 / 7,500) of the Methamphetamine Index, 24.6% (1,719 / 7,000) of the Cocaine Index, and 21.3% (1,702 / 8,000) of the Marijuana Index. These missing data were imputed independently for each index using a bootstrap time-series cross-sectional expectation-maximization algorithm implemented in the software package Amelia II (Honaker and King, 2010; Honaker, King, and Blackwell, 2012; King et al., 2001). This approach has comparative advantages over other imputation methods (Blankers, Koeter, and Schippers, 2010), and has proven to work efficiently with various datasets and with different degrees of missingness. For our purposes, ten complete datasets were imputed with observed values remaining the same but missing values “filled in with a distribution of imputations that reflect the uncertainty about the missing data” (Honaker, King, and Blackwell, 2012:3). For each missing data point in the state-year matrices, the average of the ten imputed values was taken as the best estimate.

Next, data values outside twice the interquartile range were checked for reporting errors. Potentially problematic indicators that could bias the overall results, identified as those having a skewness greater than |2| and kurtosis greater than 3.5, were treated by Winsorization or logarithmic transformation corrected for zero values. To correct for different ranges and measurement units, the indicators were normalized by min-max scaling. In all cases the minimum value was set at 0, while the maximum value was set at 10% above the reported maximum value for all states over the period 2000-2009. This was done to allow updates to the indices where future indicator values are greater, without having to recalculate index scores for previous years. See Appendix D for additional technical details.

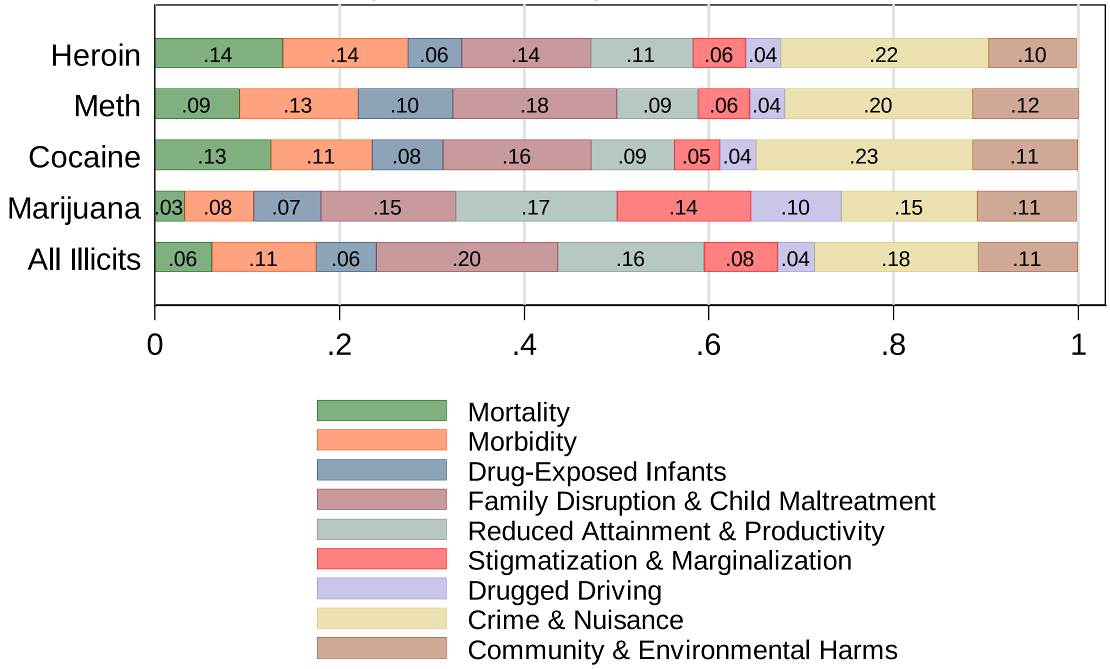
B. WEIGHTING AND AGGREGATION

For the National and State DCIs, individual indicators within subdomains were weighted equally. However, weights across the nine subdomains were not assumed to be equal. The decision on a suitable set of weights was guided by the results of an Analytic Hierarchy Process (AHP) conducted with 19 experts in the drug policy and addiction fields. AHP is a widely used method for multi-criteria decision-making that employs a hierarchical framework to organize and improve problem structuring, measurement, and synthesis (Saaty, 2005; Saaty and Vargas, 2001; Vaidya and Kumar, 2006). For this project, participants engaged in a sequential pairwise comparison of subdomains for each specific drug and all illicit drugs combined, rating which subdomain was the more significant contributor to total drug harm, and by how much. Assessments were framed with respect to nonmedical substance use within the policy environment of the United States from 2000 to the present. Participants expressed preferences on a nine-point scale, ranging from '1' (equally important) to '9' (extremely more important). The resulting averages of the AHP-derived weights for each drug type are shown in Figure 2. Subdomain weights were largest for specific drug types as follows: heroin (mortality, morbidity), methamphetamine (drug-exposed infants, family disruption and child maltreatment, community and environmental harms), cocaine (crime and nuisance), and marijuana (reduced attainment and productivity, stigmatization and marginalization, drugged driving).

The final calculation of the core National and State DCI scores followed three sequential aggregation steps whereby the weighted geometric mean was taken at each level of the framework from its underlying components. Either equal weights or the AHP-derived weights were assigned to the indicators, subdomains, and domains.[6] More specifically, scores for each subdomain were first calculated as simple geometric means of the normalized indicators. Scores

[6] See Appendix D for robustness analyses involving alternative weighting schemes.

Figure 2. AHP Weights for DCI Subdomains



for the three domains were then calculated as the AHP-weighted geometric means of the three subdomains underlying each domain. Finally, the DCI scores represent the AHP-weighted geometric mean of the nine subdomains.

The use of the geometric mean, as opposed to the classical arithmetic average, is done for both conceptual and methodological purposes. Conceptually, perfect substitutability among the index components (as is the case with the arithmetic average) is not desirable. Substitutability (or compensability) is understood here as the undesirable offsetting of poor performance in some indicators with good performance in others. Methodologically, the use of arithmetic average would have been problematic because it would imply that the level of priority given to a dimension of drug consequences is invariant to the level of attainment. Instead, the geometric mean gives more incentives for improvement to low values.

IV. RESULTS: NATIONAL AND STATE DCIs

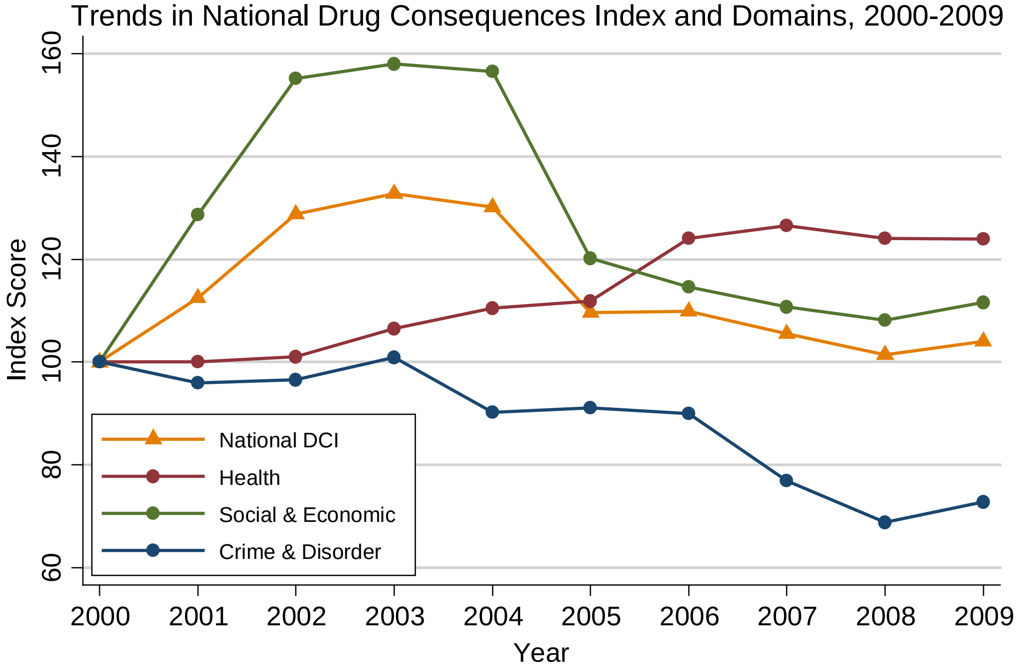
Results are presented in two sections. National-level results are presented first, showing both overall and drug-specific trends in drug-related consequences. State-level results follow, showing both general and drug-specific trends and interstate variations in drug-related consequences.

A. NATIONAL RESULTS

1. National Drug Consequences Index

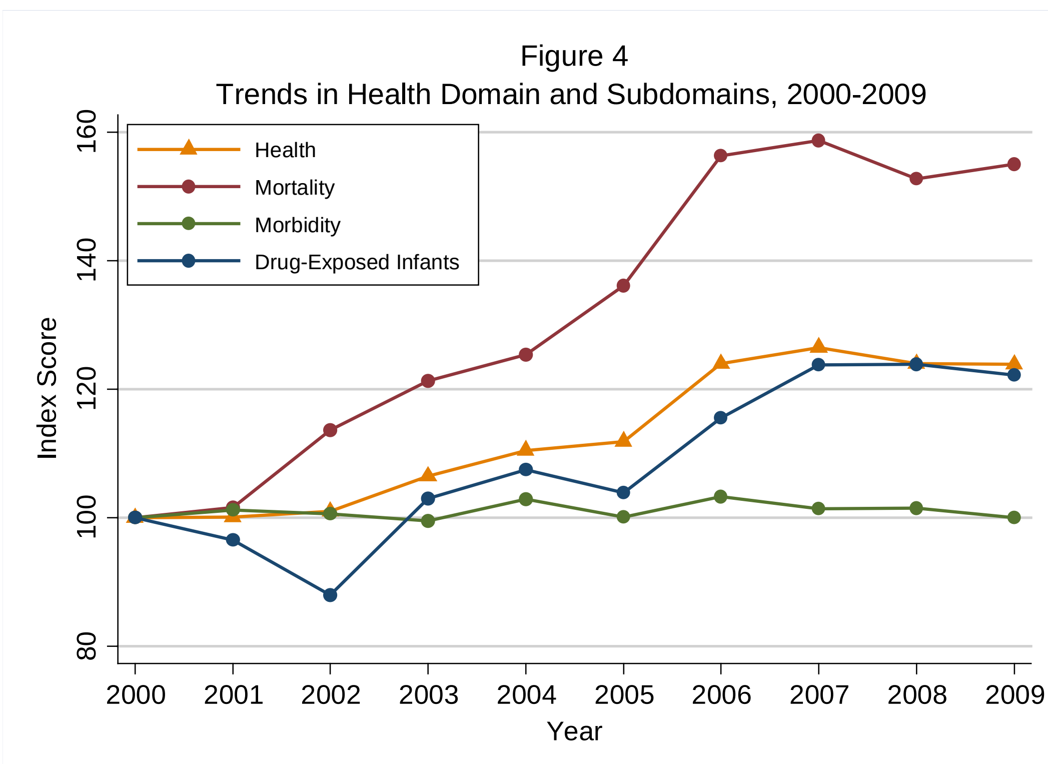
Trends in the overall National Drug Consequences Index (National DCI) and its three major domains (*Health*, *Social and Economic*, and *Crime and Disorder*) are shown in Figure 3 for the years 2000-2009. The National DCI and domain scores are normalized to a year 2000 benchmark score of 100. Index scores reflect the AHP-derived weights. As the figure shows,

Figure 3
Trends in National Drug Consequences Index and Domains, 2000-2009



overall illicit drug-related consequences in the U.S. increased rapidly during the first years of the decade, reaching peak levels roughly 30% above baseline during 2002-2004, before returning to near-benchmark levels in 2008-2009. Consequences measured by the *Social and Economic* domain, which increased more than 55% by 2002, drove the initial increase in the National DCI, whereas *Health* domain consequences registered higher only during the latter part of the 2000s, increasing 24-26% over baseline during 2006-2009. Conversely, *Crime and Disorder* consequences decreased steadily throughout the decade, reaching a point 27% below the 2000 benchmark by 2009 (after a slight one-year uptick).

What is driving the domain-level index scores? Figures 4-6 show trends in the scores for each of the major domains along with their subdomain components. As shown in Figure 4, the increase in *Health* consequences was driven primarily by an upsurge in overall drug-related 'mortality' and, since 2005, the increased burden of 'drug-exposed infants.' In contrast, drug-

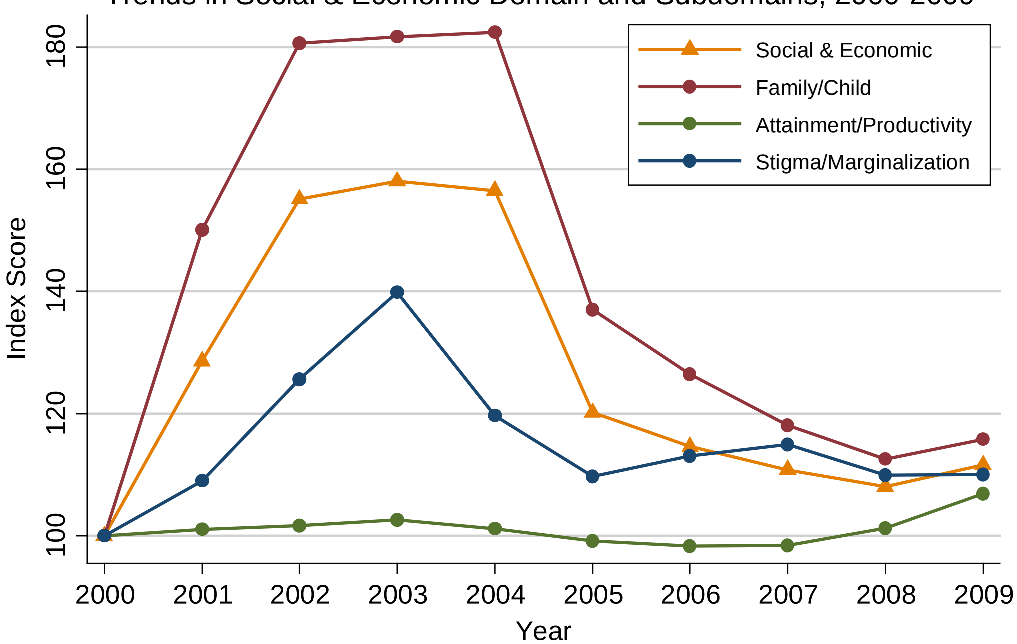


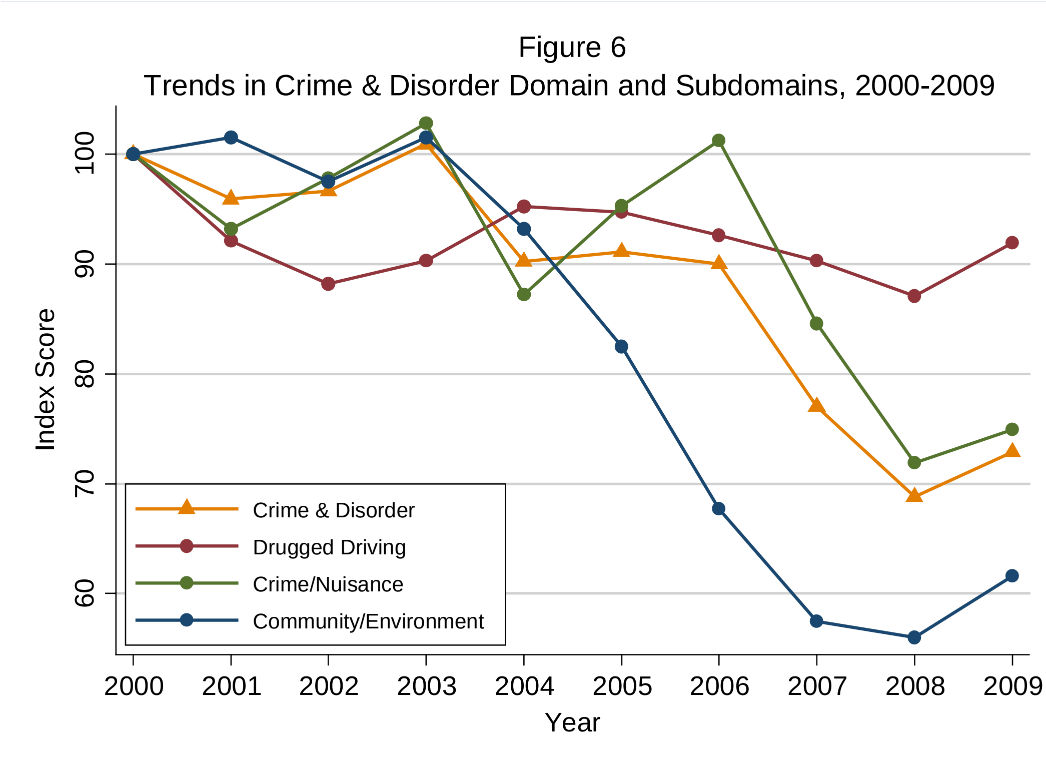
related 'morbidity'—which is measured by an assortment of indicators ranging from poison center calls to IDU-related AIDs diagnoses—remained relatively flat throughout the decade.

Figure 5 depicts trends in *Social and Economic* consequences and its subdomains. The noted spike in the early part of the decade was driven largely by the increase in drug-related consequences stemming from 'family disruption and child maltreatment' (as measured by drug-related foster care placements and children affected by illicit drug labs) and, to a lesser extent, 'stigmatization and marginalization.' In comparison, social and economic consequences in the areas of 'reduced attainment and productivity' generally remained at or slightly above the 2000 benchmark throughout the decade.

Lastly, Figure 6 shows trends in the *Crime and Disorder* domain and its subdomains. Notably, all areas reveal a sizable downward trend. Most dramatic is the roughly 40% decline through 2009 in 'community and environmental harms,' as measured by illicit drug production

Figure 5
Trends in Social & Economic Domain and Subdomains, 2000-2009





incidents (including both methamphetamine lab and marijuana grow seizures). However, all subdomains show a recent one-year uptick in *Crime and Disorder* consequences.

Table 5 reports the actual index scores for the National DCI and its underlying components for the years 2000-2009. The last three columns also report statistics reflecting long-, medium-, and short-term trends. We highlight here both the medium- (2005 to 2009) and short-term (2008 to 2009) changes across the nine DCI subdomains. 'Community and environmental harms' remained a key driver of the downward trend in the DCI, registering a 25% decline from 2005-2009. Other areas contributing to the reduction in drug-related consequences over the medium-term were 'crime and nuisance' and 'family disruption and child maltreatment' (showing 21% and 16% declines, respectively). Conversely, drug-related consequences in the areas of 'drug-exposed infants,' 'mortality,' and 'reduced attainment and productivity' worsened over the medium-term (increasing 18%, 14%, and 8%, respectively).

Table 5. National Drug Consequences Index, 2000-2009

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Percent Change 2000-2009	Percent Change 2005-2009	Percent Change 2008-2009
National DCI	100.0	112.5	128.8	132.7	130.1	109.6	109.9	105.5	101.4	104.0	4.0%	-5.0%	2.6%
Health Consequences	100.0	100.1	101.0	106.5	110.5	111.9	124.0	126.5	124.0	123.9	23.9%	10.7%	0.0%
Mortality	100.0	101.6	113.6	121.3	125.4	136.1	156.3	158.7	152.7	155.0	55.0%	13.9%	1.5%
Morbidity	100.0	101.2	100.6	99.5	102.9	100.1	103.3	101.4	101.5	100.0	0.0%	-0.2%	-1.5%
Drug-Exposed Infants	100.0	96.5	88.0	103.0	107.5	103.9	115.5	123.8	123.9	122.2	22.2%	17.6%	-1.4%
Social & Economic Consequences	100.0	128.6	155.1	158.0	156.5	120.2	114.6	110.8	108.1	111.6	11.6%	-7.1%	3.3%
Family Disruption & Child Maltreatment	100.0	150.1	180.6	181.6	182.4	137.0	126.4	118.1	112.5	115.8	15.8%	-15.5%	3.0%
Reduced Attainment & Productivity	100.0	101.1	101.7	102.6	101.2	99.2	98.3	98.4	101.3	106.9	6.9%	7.7%	5.5%
Stigmatization & Marginalization	100.0	109.0	125.6	139.8	119.7	109.7	113.1	115.0	109.9	110.0	10.0%	0.3%	0.1%
Crime & Disorder Consequences	100.0	95.9	96.6	100.9	90.2	91.1	90.0	77.0	68.8	72.9	-27.1%	-20.0%	5.9%
Drugged Driving	100.0	92.1	88.2	90.3	95.2	94.7	92.6	90.3	87.1	91.9	-8.1%	-3.0%	5.5%
Crime and Nuisance	100.0	93.2	97.8	102.8	87.2	95.3	101.2	84.6	71.9	74.9	-25.1%	-21.4%	4.2%
Community & Environmental Harms	100.0	101.5	97.5	101.5	93.2	82.5	67.7	57.5	56.0	61.6	-38.4%	-25.3%	10.2%

Contrary to long- and medium-terms trends, *Crime and Disorder* consequences increased most sharply over the short-term (reflecting 4% to 10% increases across all three subdomains). Alternatively, there were only modest short-term improvements in the subdomains of 'morbidity' and 'drug-exposed infants,' each decreasing about 1-2%.

2. Drug-Specific National Drug Consequences Indices

As mentioned above, we derived drug-specific national estimates of trends in drug-related consequences using the drug-specific State DCIs as a starting point (refer to next section). We did this by taking the simple annual average of the fifty state index scores for each drug-specific State DCI and its three major consequence domains (*Health*, *Social and Economic*, and *Crime and Disorder*), and then normalizing these mean scores to a value of 100 for year 2000. [7] It is important to recognize that the underlying indicators for the drug-specific national estimates discussed here differ from those used to generate the overall national index reported above. The results are presented in Figures 7-10.

As Figure 7 shows, the National Heroin Index increased 39% between 2000 and 2009. The primary driver of this increase were consequences in the *Health* domain, with index scores increasing 44% over the decade, followed closely by the 36% increase observed for *Social and Economic* consequences. *Crime and Disorder* consequences had a more volatile trend, but still increased by approximately 30% over the course of the decade.

[7] We also produced these estimates weighted by the annual state populations, but there were no substantive differences between the two approaches. We therefore present the simple unweighted results.

Figure 7
Trends in National Heroin Index and Domains, 2000-2009

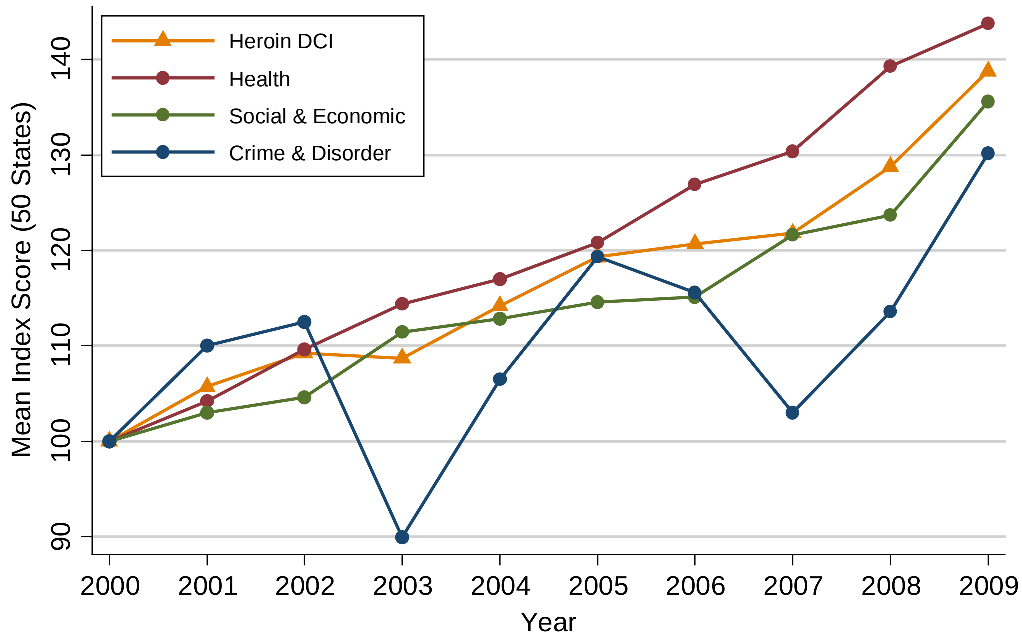
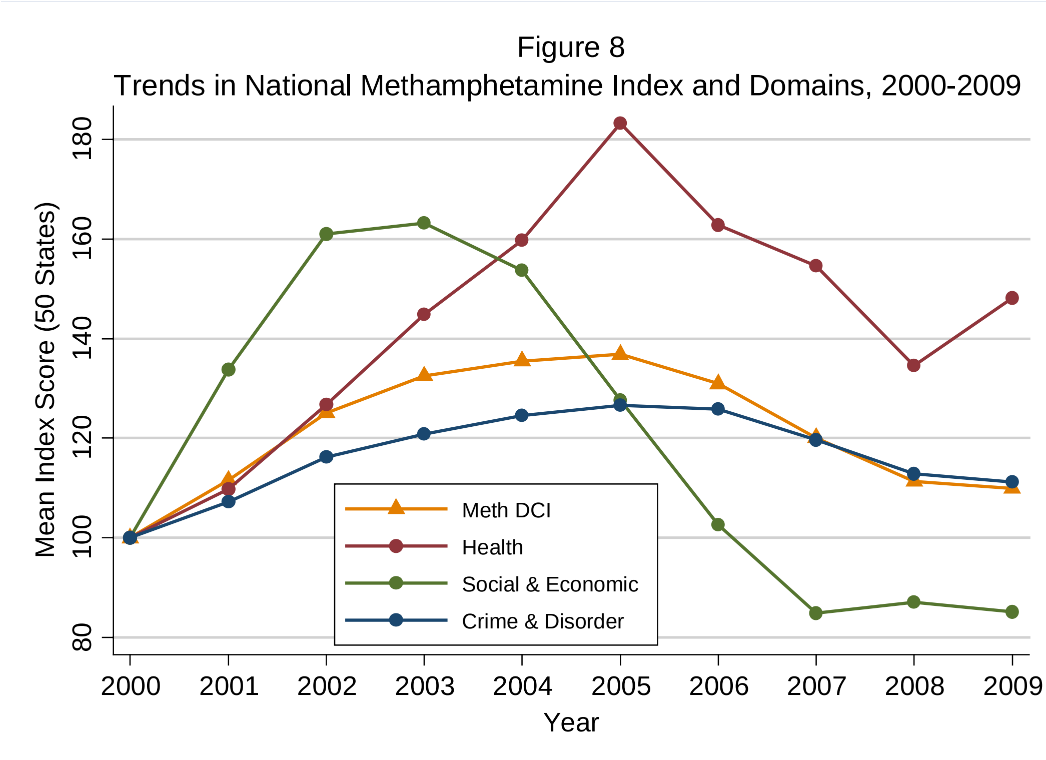


Figure 8 shows the rising and falling trend in methamphetamine-related consequences, with mean National Methamphetamine Index scores increasing 37% from 2000 to 2005, followed by a decline of about 20% through 2009 (to a normalized mean index score of 110). This pattern was driven in different ways by the underlying domains. For example, *Social and Economic* consequences increased by nearly two-thirds between 2000 and 2003, before undergoing a steady decline to below baseline levels reached during 2007-2009 (index scores 85-87). Initial increases in *Health* consequences were less steep but of longer duration, peaking in 2005 before declining to levels that remained well above baseline as of 2009 (with an index score of 148). By comparison, *Crime and Disorder* consequences mirrored the overall rising and falling trend in the National Methamphetamine Index.

In Figure 9 we also see fluctuating trends in cocaine-related consequences, with mean National Cocaine Index scores initially declining 5% between 2000 and 2002, before increasing



16% from 2002 to 2006 and declining again by 19% as of 2009. Notable at the domain level are the cross-cutting trends from 2000 to 2006 in *Health* (33% increase) and *Social and Economic* (11% decrease) consequences. However, since 2006, index scores in both these domains have registered declines of 24% and 36%, respectively.

Lastly, as shown in Figure 10, mean National Marijuana Index scores remained relatively flat throughout the decade, reflecting minimal fluctuations in the *Social and Economic* and *Crime and Disorder* domains. Although less influential because of its relatively lower weighting (AHP weight = 0.18), the *Health* consequences domain registered a sizable 57% increase between 2000 and 2009. Refer to Table 6 for detailed index scores corresponding to each drug specific National DCI and its domains.

Figure 9
Trends in National Cocaine Index and Domains, 2000-2009

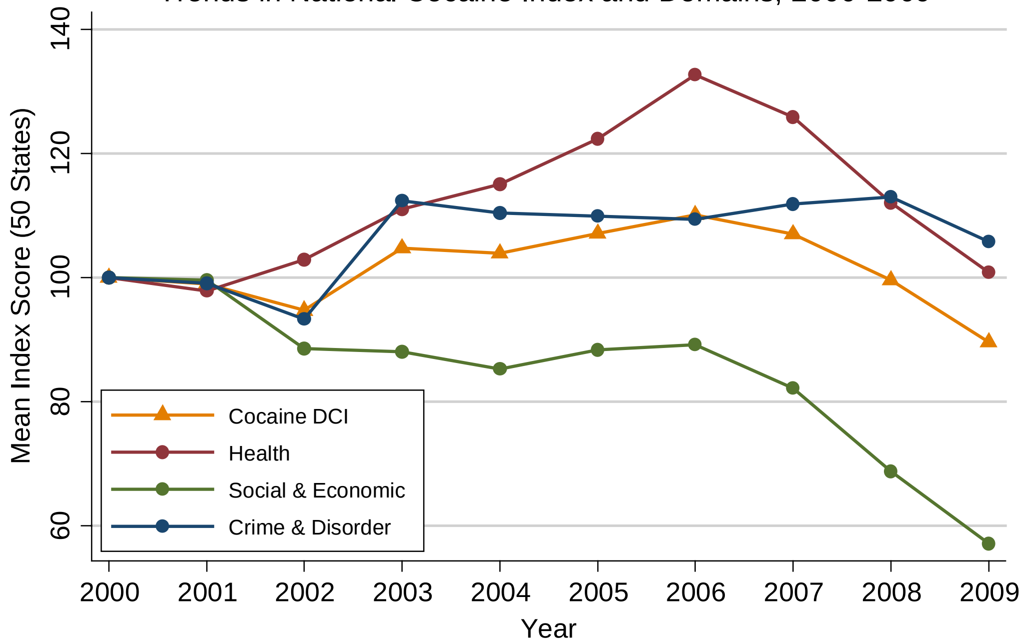


Figure 10
Trends in National Marijuana Index and Domains, 2000-2009

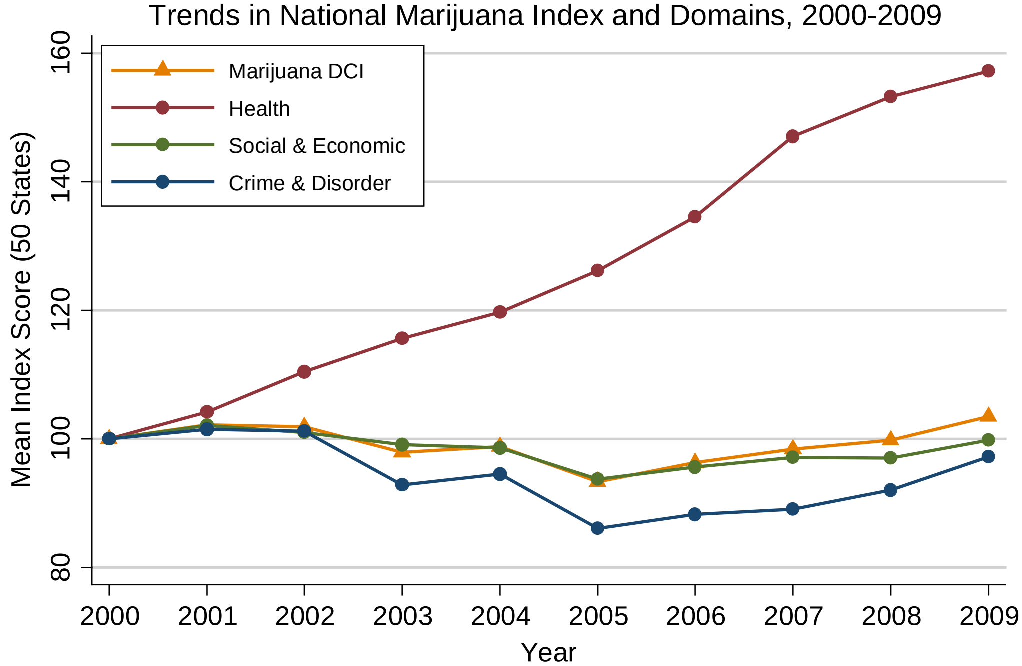


Table 6. Drug-Specific National Drug Consequences Indices, 2000-2009

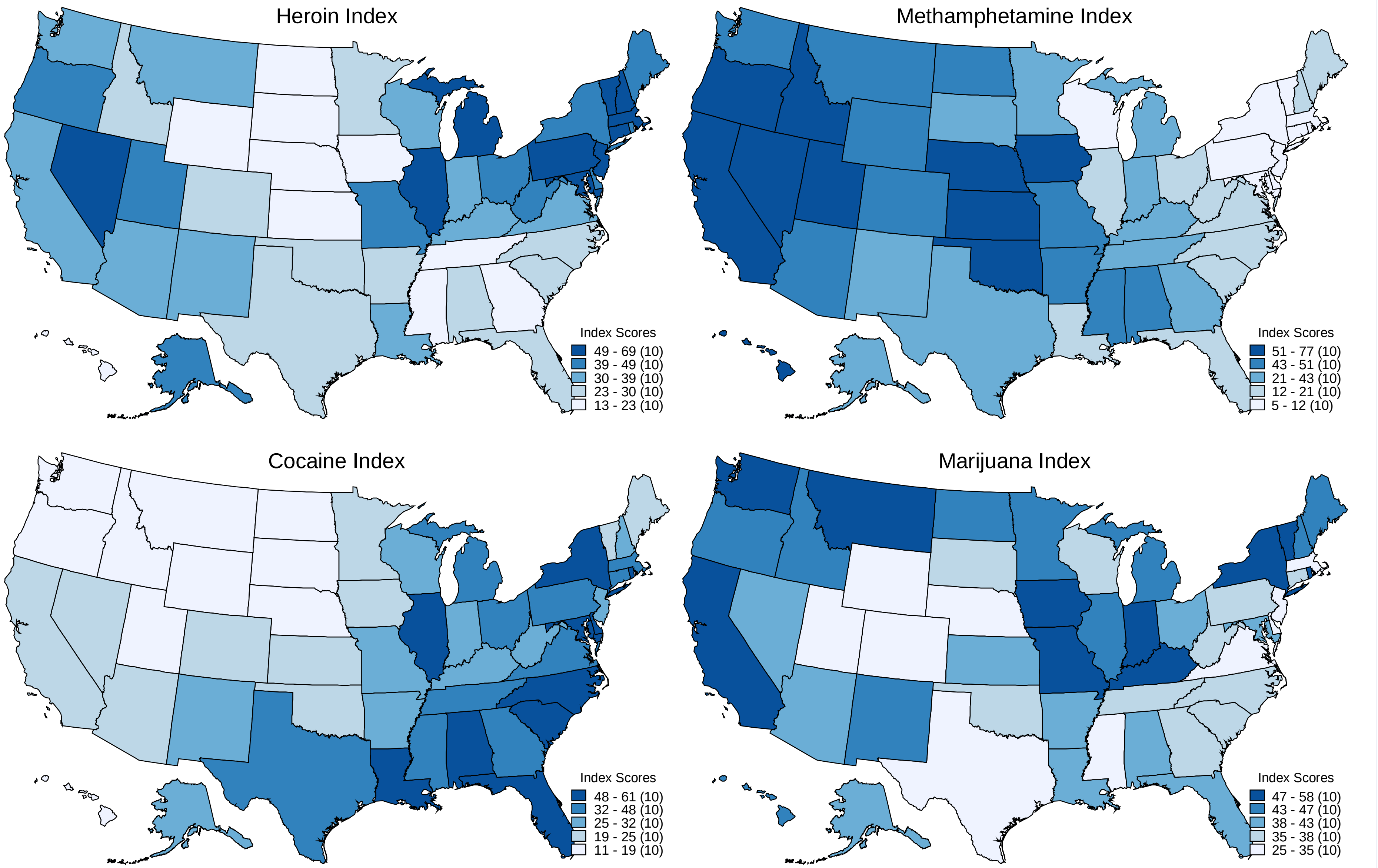
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Percent Change 2000-2009	Percent Change 2005-2009	Percent Change 2008-2009
National Heroin DCI	100.0	105.7	109.2	108.7	114.2	119.3	120.7	121.8	128.8	138.8	38.7%	16.6%	8.0%
Health	100.0	104.2	109.6	114.4	117.0	120.8	126.9	130.4	139.3	143.8	43.9%	19.2%	3.2%
Social & Economic	100.0	103.0	104.6	111.4	112.8	114.6	115.1	121.6	123.7	135.6	35.8%	18.5%	9.8%
Crime & Disorder	100.0	110.0	112.5	89.9	106.5	119.3	115.6	103.0	113.6	130.2	30.4%	9.3%	14.9%
National Methamphetamine DCI	100.0	111.6	125.1	132.5	135.5	136.8	130.9	120.1	111.3	109.9	10.0%	-19.8%	-1.2%
Health	100.0	109.8	126.7	144.8	159.7	183.2	162.8	154.5	134.5	148.2	48.3%	-19.2%	9.7%
Social & Economic	100.0	133.8	161.0	163.2	153.6	127.6	102.6	84.9	87.1	85.2	-14.5%	-32.9%	-1.9%
Crime & Disorder	100.0	107.2	116.2	120.8	124.5	126.6	125.8	119.7	112.9	111.2	11.0%	-12.3%	-1.6%
National Cocaine DCI	100.0	99.0	94.7	104.7	103.9	107.1	110.1	107.0	99.6	89.6	-10.6%	-16.4%	-10.1%
Health	100.0	97.8	102.9	111.0	115.0	122.3	132.7	125.9	112.1	100.8	0.9%	-17.5%	-9.8%
Social & Economic	100.0	99.6	88.6	88.0	85.3	88.3	89.2	82.2	68.8	57.1	-42.9%	-35.3%	-16.9%
Crime & Disorder	100.0	99.1	93.3	112.4	110.4	109.9	109.4	111.8	113.0	105.8	6.0%	-3.7%	-6.4%
National Marijuana DCI	100.0	102.2	101.9	97.9	98.8	93.4	96.3	98.4	99.8	103.5	3.5%	10.8%	3.8%
Health	100.0	104.2	110.5	115.6	119.7	126.2	134.5	147.0	153.2	157.2	57.4%	24.5%	2.6%
Social & Economic	100.0	102.1	101.0	99.1	98.6	93.8	95.6	97.1	97.0	99.8	-0.2%	6.4%	2.8%
Crime & Disorder	100.0	101.5	101.2	92.9	94.5	86.1	88.3	89.1	92.1	97.2	-3.0%	12.6%	5.4%

B. STATE RESULTS

In contrast to the National DCIs, the State DCIs allow us to examine interstate variations in drug consequences over time. Figure 11 presents the first set of results, showing state differences in the four drug-specific State DCIs for a single year, 2009. The four maps clearly highlight the regionalized nature of the drug problem in the United States. The State Heroin Index, for instance, reveals a heavy concentration of New England and Mid-Atlantic states with a relatively serious heroin problem, together with pockets in the midwest and west. Conversely, heroin is a relatively minor problem in the central and north central U.S. and in parts of the southeast. The State Methamphetamine Index shows that methamphetamine is a serious problem in the western half of the United States—especially Hawaii and other West Coast states—but also that states well into the U.S. heartland experience serious consequences due to methamphetamine. Alternatively, states in the northeast hardly register a blip on the Methamphetamine Index.

According to the State Cocaine Index, states along the Gulf and East Coasts, and Illinois in the midwest, have the most serious cocaine problem, whereas states across a large section of the U.S. extending from the northwest to the upper midwest are relatively less affected by the cocaine problem. Interestingly, if the cocaine and methamphetamine maps were overlaid, one would see that serious stimulant-related consequences affect a wide cross-section of the U.S. Finally, the State Marijuana Index shows that states with the most serious marijuana-related consequences represent a diverse group scattered across different regions of the U.S. This seemingly random pattern is partly attributable to the general pervasiveness of marijuana as an illicit drug, which is reflected in the Marijuana Index's smaller overall range and higher minimum bound relative to the other States DCIs.

Figure 11. State Drug Consequences Indices, 2009



It is noteworthy that in 2009 no jurisdiction appeared among the top ten most affected states for three or more drugs, although eight states fell in this group for two drugs: California and Iowa (methamphetamine, marijuana); Illinois and Maryland (heroin, cocaine); Nevada (heroin, methamphetamine); New York and Rhode Island (cocaine, marijuana), and Vermont (heroin, marijuana). On the other hand, no state appeared among the least affected for all four drugs, although two states fell into this least serious category for three out of four drugs: Nebraska and Wyoming (heroin, cocaine, marijuana).

The following four sections present detailed results on the drug-specific State DCIs. Each section contains a uniform set of graphs and tables. First, a set of choropleth maps shows interstate variations in the indices over four representative years (2000, 2003, 2006, 2009). To accurately show temporal change in the index scores, each year is mapped according to the index's quintile distribution across *all* ten years of data (2000-2009). The parenthetical numbers in each map legend therefore show the number of states that fall within a particular quintile range for a given year. Any change in these numbers reflects the movement of states across the quintiles as a particular drug problem worsens or improves over time.

Second, time-series cross-section graphs present index trends across all 50 states and 10 years of data. These graphs facilitate comparison of index scores across states with respect to both magnitude and trends in the underlying drug problem. A set of accompanying detailed tables reports overall index scores by state and year, with states ordered from highest (undesirable) to lowest (desirable) according to the index scores for 2009. Additionally, color coding highlights the ten states with the least serious drug problem (green) and the ten states with the most serious drug problem (red) for a given year. [8]

[8] Note that in some years eleven states might be highlighted due to ties in the index scores.

A final set of choropleth maps shows interstate variations in the drug-specific State DCIs and their corresponding drug consequence domains (*Health*, *Social and Economic*, and *Crime and Disorder*). These graphs are helpful for understanding how states compare on key underlying features of the larger drug problem. For presentation purposes, states are divided into quintiles based on their respective index and domain scores for 2009. In each instance, barring any ties in index scores, the ten most impacted states are indicated by the darkest shade of blue and the ten least impacted are designated in the lightest shade of blue.

1. State Heroin Consequences Index

Figure 12 shows interstate variations in the State Heroin Index over four select years. The figure highlights the highly regionalized nature of the heroin problem, with New England and mid-Atlantic states figuring most consistently and prominently across all years; however, states in the midwest and west also show elevated index scores across different years. Conversely, index scores for states in the north central region of the U.S consistently indicate that heroin is a relatively minor problem. Importantly, the maps reveal that heroin-related consequences have worsened over the decade. Between 2000-2009, the number of states in the most severe range of the Heroin Index (scores of 43-69) increased from 8 to 13, whereas those falling in the least severe category (scores of 8-16) decreased from 16 to 3. This general pattern of a worsening heroin problem is also captured by the state-specific trends in Figure 13. However, some of this increase likely reflects rising prescription opioid abuse (see, e.g., Gilson and Kreis, 2009; Shah et al., 2008), a phenomenon unavoidably captured by some of the indicators informing the Heroin Index.

Table 7 presents a state-by-year look at the Heroin Index. In 2009, the five states with the most serious heroin problem were Massachusetts, New Jersey, New Hampshire, Connecticut, and Illinois (with index scores ranging from 69 to 55). The first four states, reflecting what might be considered the epicenter of the heroin problem in the U.S., were among the most affected in every single year between 2000-2009. Conversely, the five states in 2009 with the least serious heroin problem included Nebraska, Iowa, North Dakota, Hawaii, and Kansas (with scores ranging from 13 to 17). Two of these states (Nebraska, Iowa) were among the least affected states in every year between 2000-2009. Confirming the general upward trend in the heroin problem noted earlier, 45 states experienced some increase in the Heroin Index between 2000 and 2009, with eight states more than doubling their scores (Arkansas, Wisconsin, Alaska, Montana, Kentucky, West Virginia, Missouri, Oklahoma). Finally, in the context of an overall worsening problem, it is all the more noteworthy that Rhode Island (-23%) and Hawaii (-17%) registered rather sizable double-digit percent declines in the Heroin Index between 2000-2009.

Figure 14 shows interstate variations for 2009 in the Heroin Index and its three domains. As the graph reveals, consequences measured at the domain level are variably distributed across the states. States with the most serious heroin-related *Crime and Disorder* consequences, for instance, are clustered in the northeast and midwest, whereas serious heroin-related *Health* and *Social and Economic* consequences also tend to cluster in the southwest (particularly, Arizona, Nevada, and Utah). However, only Massachusetts and Illinois appear in the top quintile for all three domains. On the other hand, the plains states of Iowa, Kansas, Nebraska, North Dakota, and South Dakota, together with Hawaii, were least affected by heroin-related consequences across all three domains.

Figure 12. Heroin Consequences Index, Interstate Variations, Select Years

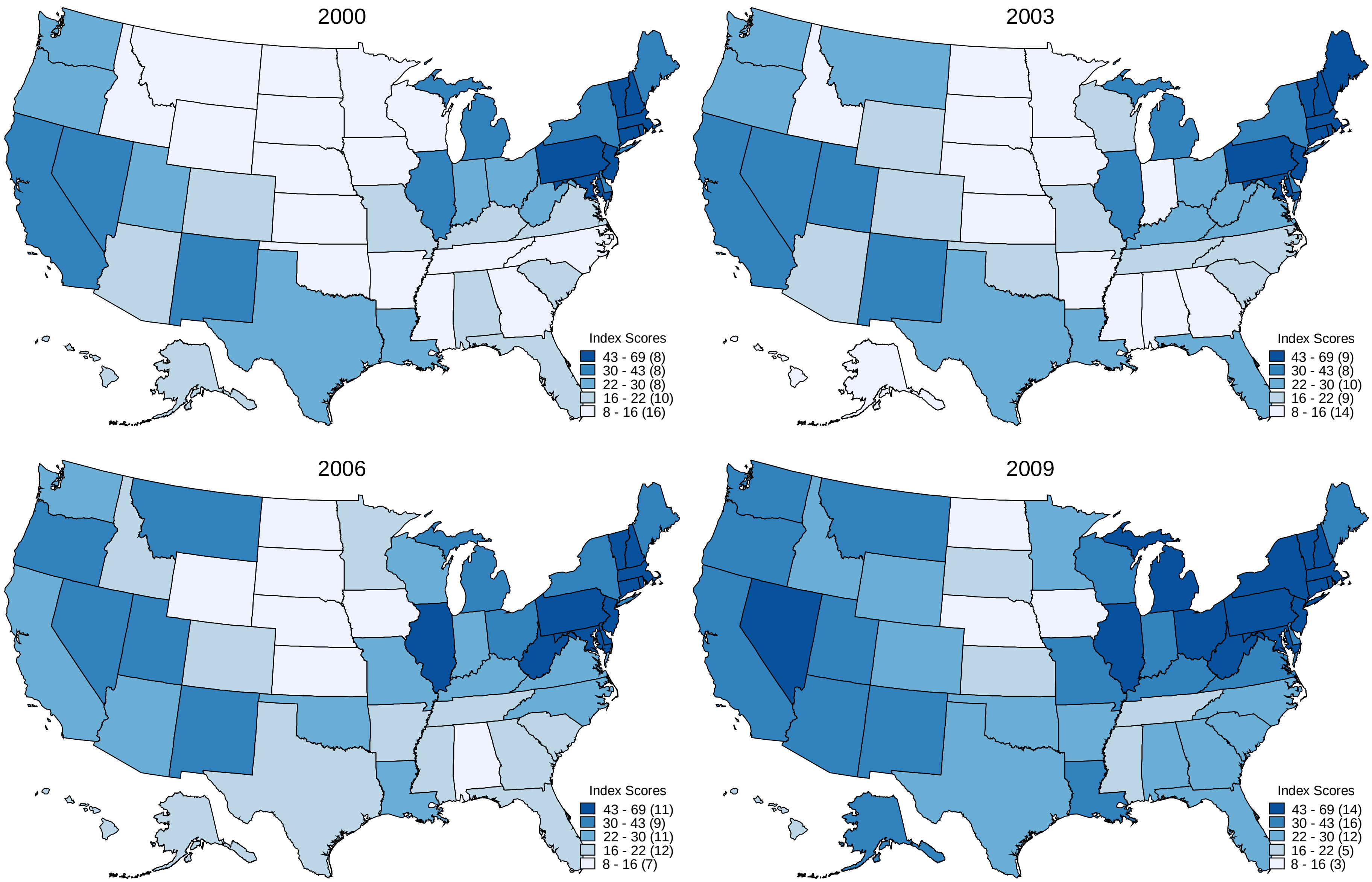


Figure 13. Heroin Consequences Index, Trends by State, 2000-2009

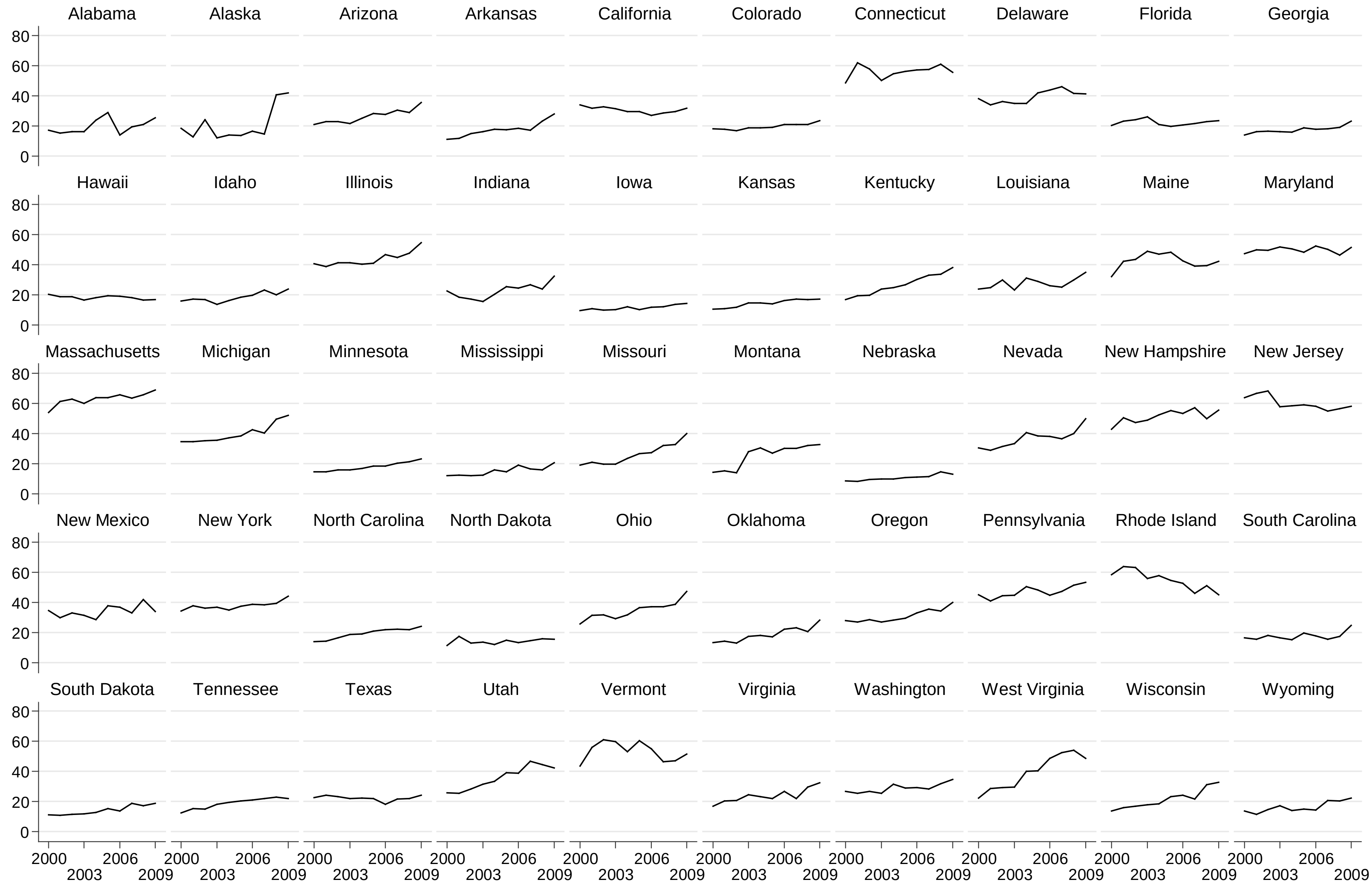
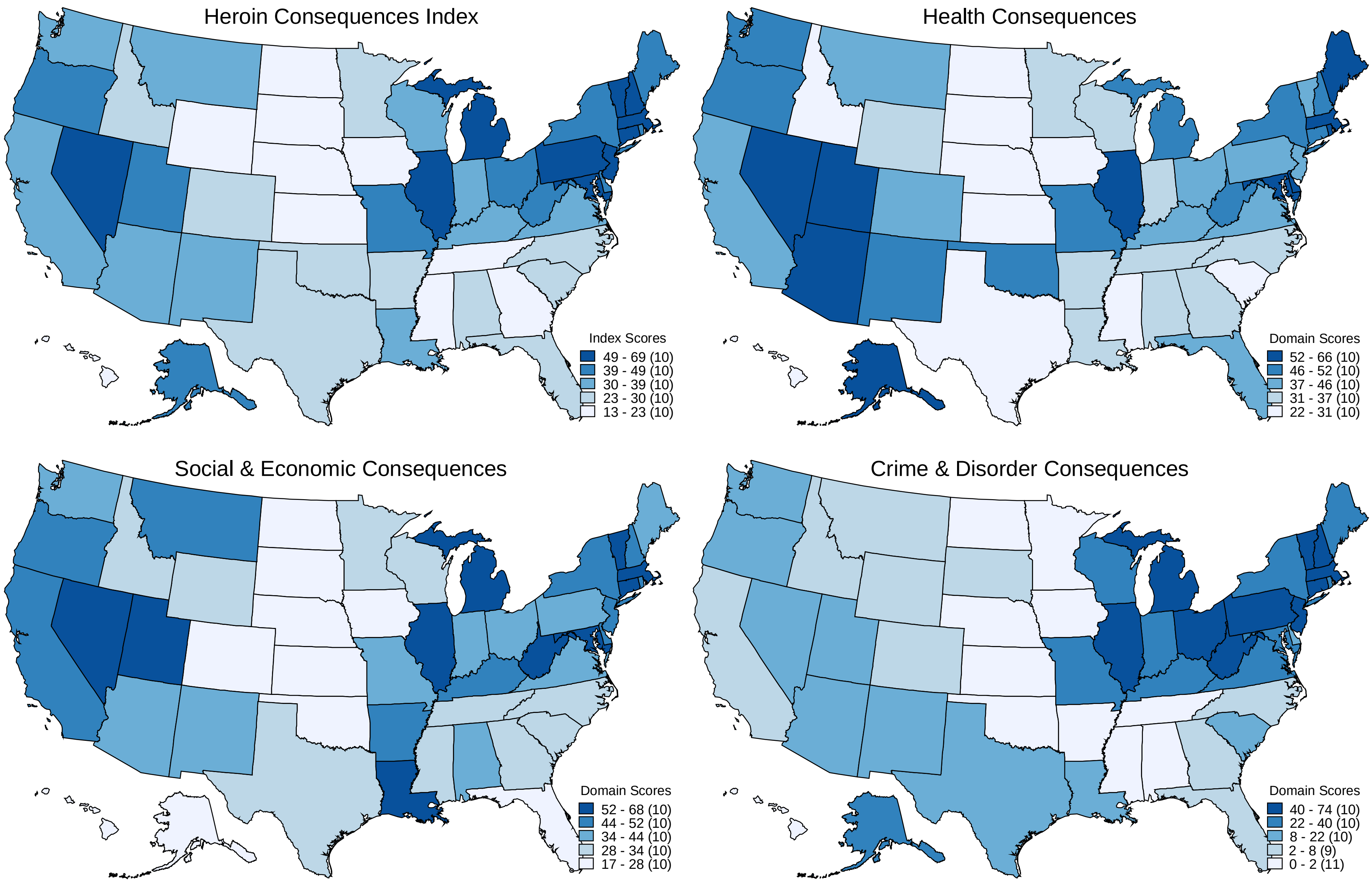


Table 7. State Heroin Consequences Index, 2000-2009

State	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	% Change 2000-2009	% Change 2005-2009
Massachusetts	54.1	61.2	62.9	60.1	63.7	63.9	65.9	63.6	65.8	68.8	27.2%	7.7%
New Jersey	63.9	66.6	68.4	57.9	58.4	59.0	58.2	55.1	56.6	58.2	-8.9%	-1.4%
New Hampshire	43.0	50.5	47.3	48.9	52.5	55.3	53.2	57.2	49.9	55.6	29.3%	0.5%
Connecticut	48.4	61.9	57.8	50.1	54.7	56.1	57.2	57.4	60.9	55.5	14.7%	-1.1%
Illinois	40.5	38.7	41.4	41.2	40.3	41.0	46.8	44.8	47.5	54.5	34.6%	32.9%
Pennsylvania	45.2	41.0	44.5	44.9	50.5	48.2	44.7	47.3	51.5	53.3	17.9%	10.6%
Michigan	34.7	34.5	35.2	35.7	37.0	38.4	42.5	40.2	49.6	52.0	49.9%	35.4%
Vermont	43.5	55.9	61.1	59.9	53.2	60.3	55.0	46.3	47.0	51.6	18.6%	-14.4%
Maryland	47.2	49.7	49.4	51.8	50.4	48.1	52.3	50.1	46.4	51.3	8.7%	6.7%
Nevada	30.4	29.0	31.4	33.4	40.5	38.3	38.2	36.5	40.0	50.0	64.5%	30.5%
West Virginia	22.4	28.7	29.4	29.6	40.1	40.4	48.7	52.6	54.1	48.6	117.0%	20.3%
Ohio	25.8	31.5	31.9	29.3	31.6	36.4	37.3	37.1	38.9	47.2	82.9%	29.7%
Rhode Island	58.6	63.8	63.3	55.9	57.9	54.6	52.8	46.1	51.3	45.2	-22.9%	-17.2%
New York	34.4	37.9	36.2	36.9	34.9	37.4	38.9	38.3	39.4	44.3	28.8%	18.4%
Maine	32.1	42.3	43.4	48.8	47.1	48.1	42.6	39.0	39.4	42.3	31.8%	-12.1%
Utah	25.9	25.3	28.2	31.6	33.5	39.2	38.8	46.6	44.4	42.2	62.9%	7.7%
Alaska	18.2	12.5	24.0	11.9	13.8	13.5	16.4	14.6	40.7	41.9	130.2%	210.4%
Delaware	37.9	33.9	36.1	35.0	35.0	41.8	43.9	45.9	41.5	41.2	8.7%	-1.4%
Missouri	18.9	21.0	19.5	19.7	23.6	26.7	27.4	32.1	32.7	40.1	112.2%	50.2%
Oregon	27.9	26.9	28.5	26.9	28.2	29.6	33.1	35.6	34.2	40.0	43.4%	35.1%
Kentucky	16.9	19.4	19.6	23.9	24.8	26.6	30.1	33.1	33.6	38.0	124.9%	42.9%
Arizona	21.0	22.9	22.7	21.5	25.0	28.3	27.5	30.3	28.8	35.5	69.0%	25.4%
Louisiana	23.6	24.6	29.7	23.2	31.0	28.8	26.0	25.1	29.8	34.8	47.5%	20.8%
Washington	26.8	25.4	26.6	25.6	31.6	29.0	29.4	28.4	31.9	34.7	29.5%	19.7%
New Mexico	34.7	29.8	33.1	31.5	28.5	37.7	36.8	33.1	41.9	34.1	-1.7%	-9.5%
Wisconsin	13.6	15.9	16.8	17.8	18.4	23.1	24.3	21.7	31.3	32.9	141.9%	42.4%
Montana	14.3	15.1	13.9	27.8	30.5	27.0	30.3	30.2	32.2	32.6	128.0%	20.7%
Virginia	16.8	20.3	20.8	24.5	23.3	21.8	26.7	21.9	29.6	32.5	93.5%	49.1%
Indiana	22.6	18.2	17.0	15.5	20.2	25.3	24.5	26.5	23.7	32.3	42.9%	27.7%
California	34.0	31.8	32.7	31.5	29.6	29.5	27.0	28.4	29.6	31.6	-7.1%	7.1%
Oklahoma	13.3	14.1	13.0	17.3	18.2	17.0	22.2	23.1	20.5	28.2	112.0%	65.9%
Arkansas	11.0	11.5	14.7	16.0	17.8	17.3	18.4	17.0	23.0	28.0	154.5%	61.8%
Alabama	17.1	15.2	16.2	16.0	23.6	28.9	14.0	19.4	21.0	25.2	47.4%	-12.8%
South Carolina	16.6	15.5	18.2	16.5	15.2	19.7	17.7	15.7	17.4	24.7	48.8%	25.4%
North Carolina	13.9	14.1	16.4	18.7	18.9	21.1	21.9	22.3	21.8	24.0	72.7%	13.7%
Texas	22.6	24.2	23.3	22.0	22.3	21.8	18.0	21.6	21.9	24.0	6.2%	10.1%
Idaho	15.7	17.2	16.6	13.6	16.1	18.2	19.5	23.2	20.0	23.6	50.3%	29.7%
Colorado	17.9	17.7	16.7	18.5	18.6	19.0	20.8	21.0	20.9	23.5	31.3%	23.7%
Florida	20.1	23.0	23.9	26.0	21.0	19.6	20.6	21.4	22.9	23.4	16.4%	19.4%
Minnesota	14.7	14.4	15.9	15.8	16.8	18.3	18.5	20.3	21.1	23.1	57.1%	26.2%
Georgia	13.9	16.2	16.3	16.1	15.9	18.5	17.6	18.1	19.1	23.0	65.5%	24.3%
Wyoming	13.6	11.3	14.5	17.2	14.0	14.8	14.2	20.8	20.5	22.2	63.2%	50.0%
Tennessee	12.5	15.2	14.8	18.1	19.5	20.2	21.1	22.0	22.9	21.8	74.4%	7.9%
Mississippi	11.9	12.4	12.1	12.4	16.0	14.7	18.9	16.6	15.9	20.7	73.9%	40.8%
South Dakota	11.1	10.7	11.3	11.6	12.6	15.4	13.7	18.6	17.1	18.6	67.6%	20.8%
Kansas	10.3	10.7	11.5	14.4	14.4	14.0	16.1	17.2	16.8	17.0	65.0%	21.4%
Hawaii	20.3	18.8	18.7	16.3	18.1	19.2	18.9	17.9	16.3	16.8	-17.2%	-12.5%
North Dakota	11.3	17.6	13.0	13.5	12.1	14.8	13.3	14.5	15.9	15.5	37.2%	4.7%
Iowa	9.4	10.8	9.6	10.0	11.9	10.2	11.6	12.0	13.7	14.3	52.1%	40.2%
Nebraska	8.6	8.3	9.5	9.9	9.7	10.7	11.2	11.4	14.4	13.0	51.2%	21.5%

Figure 14. Heroin Consequences Index and Domains, Interstate Variations, 2009



2. State Methamphetamine Consequences Index

Figure 15 shows interstate variations in the Methamphetamine Index. Confirming the recent epidemiology of methamphetamine abuse (Maxwell and Rutkowski, 2008), we see the eastward expansion of the methamphetamine problem from its point of origin in Hawaii and other western states into the American heartland from 2000 to 2006 and its subsequent, albeit partial, retrenchment as of 2009. It is also apparent that the methamphetamine problem has been, and continues to be, relatively nonexistent in the northeast U.S. The state-specific trends shown in Figure 16 confirm this stratification across the states, as well as the dramatic rise and fall of the methamphetamine problem in impacted states.

Table 8 provides a state-by-year look at the Methamphetamine Index. In 2009, the five states with the most serious methamphetamine problem were Hawaii, Oregon, Nevada, Oklahoma and Idaho (with index scores ranging from 77 to 59). Four of these states (Hawaii, Oregon, Nevada, and Idaho) were among the most affected in every year between 2000-2009. Conversely, the six states (two states tied for fifth position) with the least serious methamphetamine problem were New Jersey, Maryland, Delaware, Massachusetts, New York and Connecticut (with index scores ranging from 5 to 7). All of these states remained among this least impacted group throughout the decade. With respect to state trends in methamphetamine-related consequences, it is most instructive to look at changes since the middle of the decade when the methamphetamine epidemic peaked. Notably, 34 states showed double-digit declining rates in the Methamphetamine Index between 2005 and 2009. Moreover, the four states (Hawaii, Oregon, Nevada, and Idaho) that had been among the worst affected by methamphetamine in every year of the 2000s experienced declines of 8-23% from 2005 to 2009. It is also noteworthy that eight states—Rhode Island, New York, Vermont, Mississippi, New Jersey, Massachusetts, Michigan, and Alabama—experienced double-digit percent increases in methamphetamine-related consequences over the latter half of the decade, although most of these states started from very low base numbers.

Figure 17 reveals key interstate differences in the consequence domains underlying the Methamphetamine Index. In particular, whereas *Crime and Disorder* consequences mirror the distribution of the overall index in 2009, the most serious methamphetamine-related *Health* consequences cluster in the western U.S. but *Social and Economic* consequences figure more prominently in a swath of central U.S. states running from Mississippi and Alabama to Michigan. Still, only California, Hawaii, and Oklahoma were in the most severe category across all domains in 2009. Conversely, New England and mid-Atlantic states were relatively unaffected by methamphetamine in all three areas. In fact, six regional states (Connecticut, Delaware, Maryland, New Jersey, Pennsylvania, and Vermont) were among the least affected in every consequence domain.

Figure 15. Methamphetamine Consequences Index, Interstate Variations, Select Years

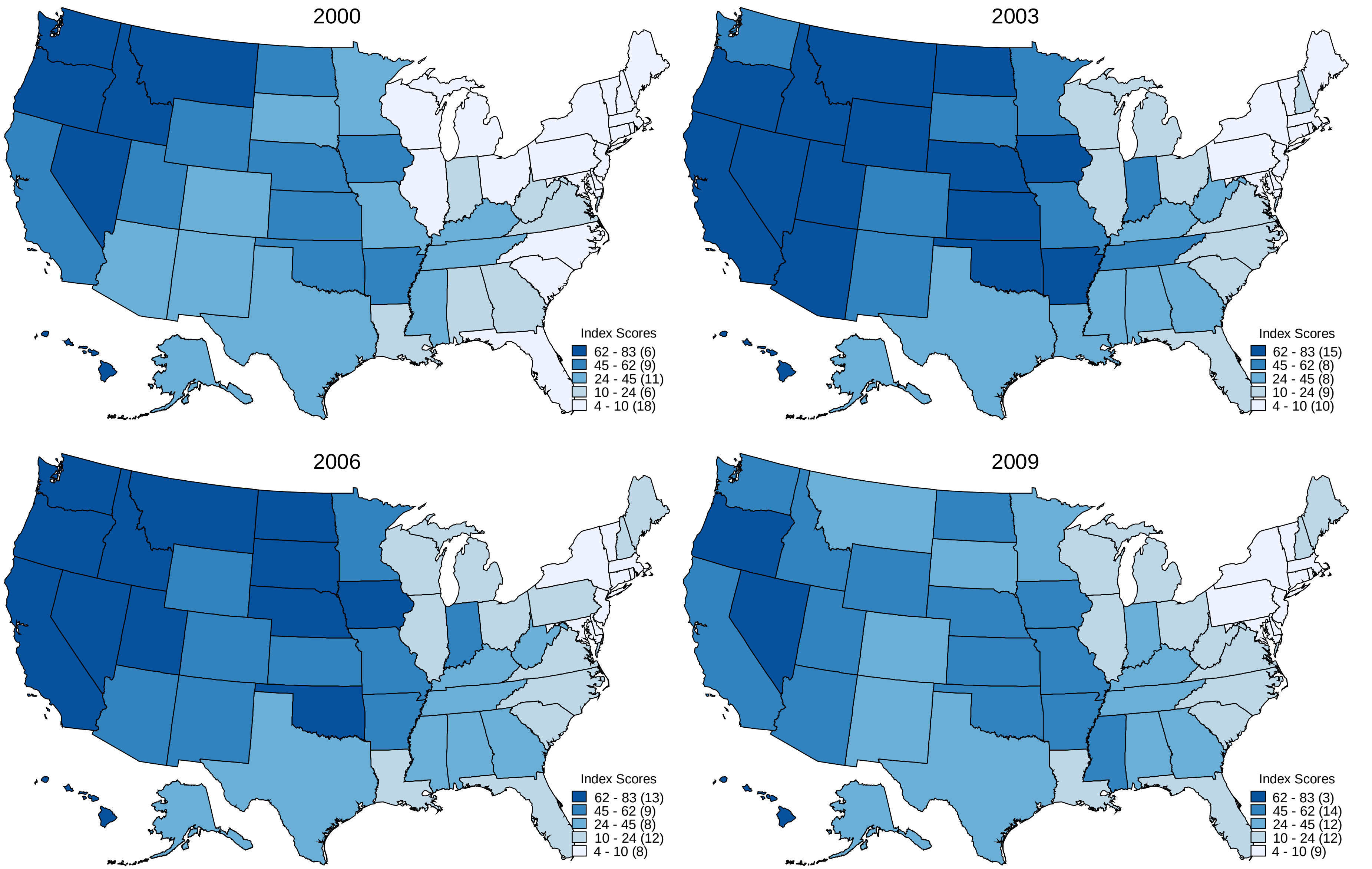


Figure 16. Methamphetamine Consequences Index, Trends by State, 2000-2009

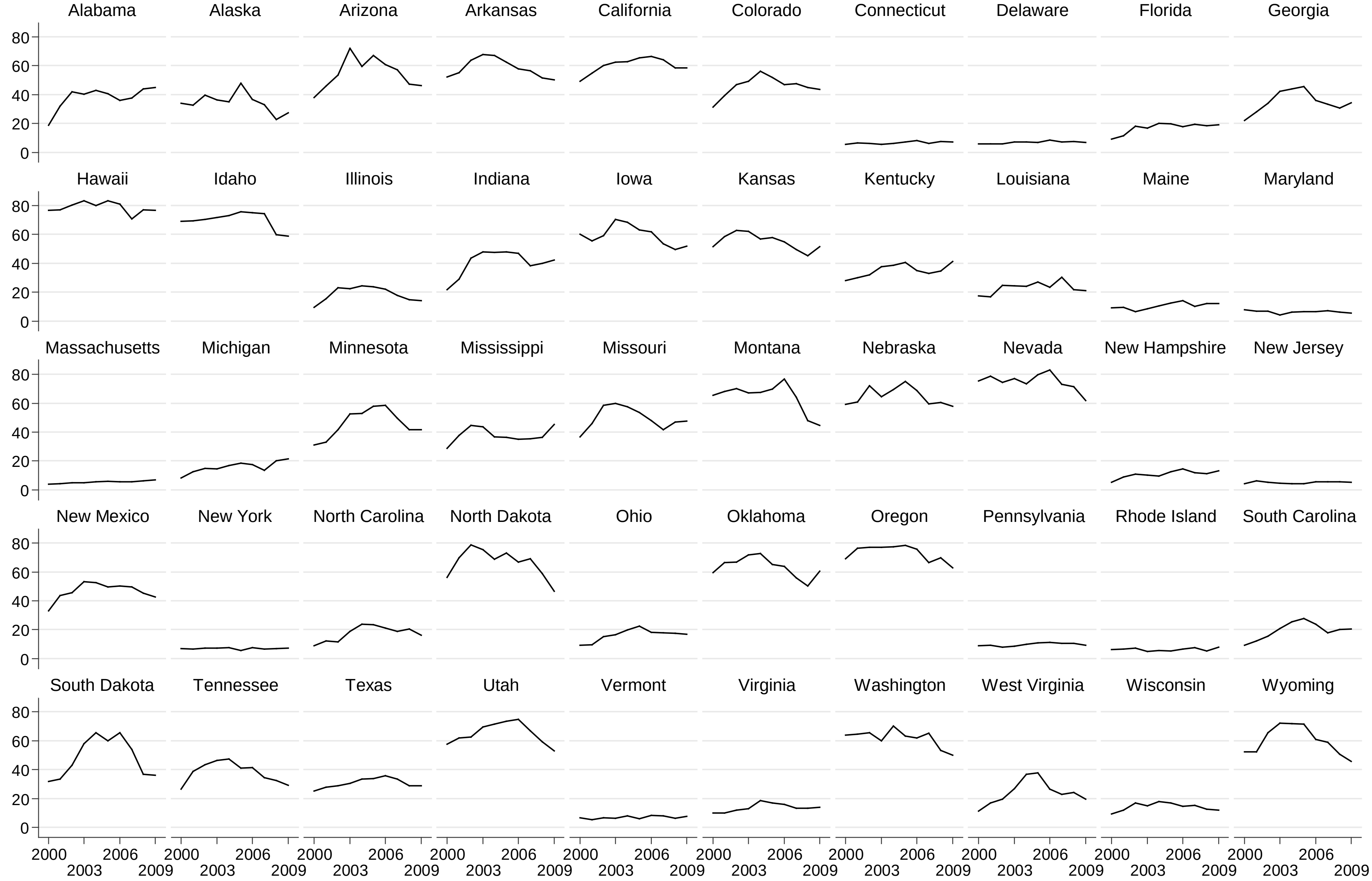
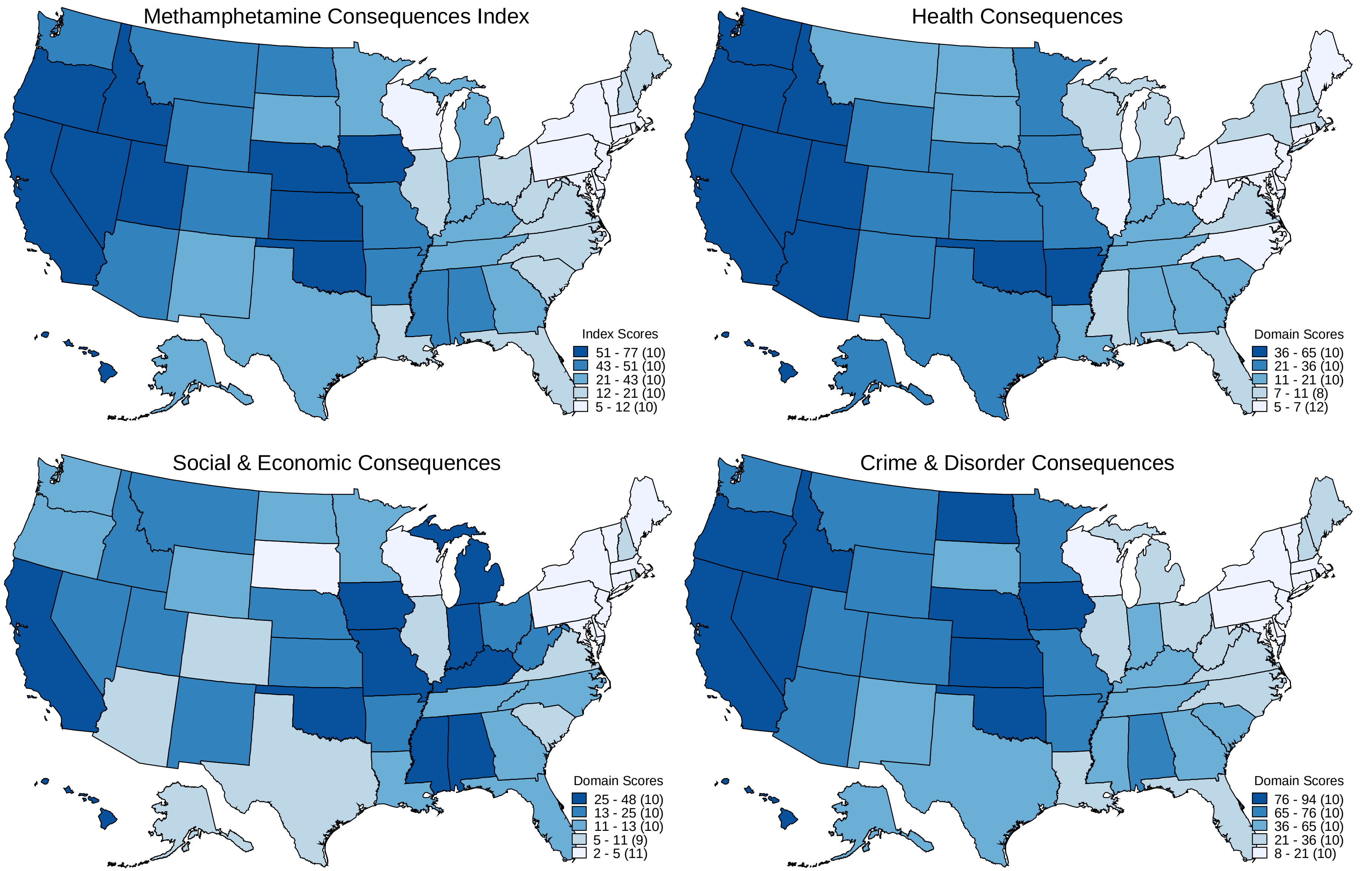


Table 8. State Methamphetamine Consequences Index, 2000-2009

State	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	% Change 2000-2009	% Change 2005-2009
Hawaii	76.7	76.9	80.5	83.2	80.2	83.3	80.9	70.7	76.9	76.6	0.0%	-8.0%
Oregon	69.1	76.6	77.2	77.1	77.4	78.3	75.9	66.4	70.0	62.8	-9.0%	-20.0%
Nevada	75.3	78.7	74.4	77.0	73.6	79.7	83.2	73.0	71.5	61.7	-18.0%	-23.0%
Oklahoma	59.6	66.4	66.7	71.9	72.7	65.1	64.0	56.0	50.4	60.7	2.0%	-7.0%
Idaho	69.1	69.4	70.5	71.9	73.0	75.8	75.1	74.5	59.8	58.8	-15.0%	-22.0%
California	49.3	54.9	60.3	62.5	62.7	65.3	66.3	64.1	58.5	58.4	18.0%	-11.0%
Nebraska	59.1	60.7	72.0	64.6	69.4	75.0	68.8	59.5	60.5	57.8	-2.0%	-23.0%
Utah	57.7	61.9	62.7	69.6	71.5	73.4	74.8	66.8	59.4	53.0	-8.0%	-28.0%
Iowa	60.1	55.5	59.2	70.3	68.4	63.3	61.7	53.7	49.7	51.8	-14.0%	-18.0%
Kansas	51.7	58.4	62.9	62.3	57.0	57.9	54.9	49.7	45.4	51.6	0.0%	-11.0%
Arkansas	52.2	55.3	63.7	67.9	67.0	62.4	57.9	56.6	51.5	50.2	-4.0%	-20.0%
Washington	63.8	64.5	65.7	59.9	70.1	63.3	61.9	65.3	53.4	50.0	-22.0%	-21.0%
Missouri	36.7	46.1	58.4	59.8	57.5	53.6	47.9	41.6	47.1	47.5	29.0%	-11.0%
North Dakota	56.2	69.7	78.7	75.3	68.9	73.1	66.7	69.2	58.8	46.7	-17.0%	-36.0%
Arizona	38.1	45.9	53.6	72.0	59.4	67.0	60.7	57.1	47.2	46.1	21.0%	-31.0%
Wyoming	52.4	52.2	65.7	72.3	71.8	71.6	61.0	58.9	50.7	45.6	-13.0%	-36.0%
Mississippi	28.7	37.7	44.7	43.5	36.7	36.2	34.9	35.2	36.4	45.3	58.0%	25.0%
Montana	65.5	68.1	70.2	67.2	67.5	69.9	76.6	64.2	47.9	44.8	-32.0%	-36.0%
Alabama	18.8	32.1	41.8	40.2	42.8	40.6	36.0	37.7	43.9	44.8	138.0%	10.0%
Colorado	31.2	39.2	46.8	49.1	56.3	51.7	46.9	47.5	44.8	43.6	40.0%	-16.0%
New Mexico	32.9	43.8	45.5	53.3	52.6	49.7	50.4	49.6	45.4	42.6	29.0%	-14.0%
Indiana	21.6	29.0	43.5	48.0	47.7	47.8	46.8	38.2	40.1	42.2	95.0%	-12.0%
Minnesota	31.2	33.2	41.6	52.6	52.9	57.8	58.7	49.6	41.6	41.8	34.0%	-28.0%
Kentucky	28.0	30.1	32.1	37.7	38.8	40.5	35.1	33.1	34.6	41.2	47.0%	2.0%
South Dakota	31.8	33.4	42.9	57.9	65.5	59.9	65.5	53.9	36.8	36.0	13.0%	-40.0%
Georgia	22.2	28.0	33.9	42.3	43.8	45.7	36.0	33.4	30.8	34.2	54.0%	-25.0%
Tennessee	26.6	38.7	43.5	46.5	47.5	41.1	41.3	34.3	32.6	29.1	9.0%	-29.0%
Texas	25.3	27.9	28.7	30.5	33.5	33.7	35.9	33.4	28.9	28.9	14.0%	-14.0%
Alaska	34.0	32.5	39.7	36.3	35.0	48.0	36.5	32.9	22.7	27.2	-20.0%	-43.0%
Michigan	8.1	12.6	14.9	14.5	16.9	18.4	17.6	13.4	20.0	21.3	163.0%	16.0%
Louisiana	17.3	16.9	24.9	24.4	24.0	27.0	23.5	30.4	21.8	21.2	23.0%	-21.0%
South Carolina	9.3	12.3	15.4	20.9	25.5	27.7	23.9	17.7	20.1	20.5	120.0%	-26.0%
West Virginia	11.1	16.8	19.4	26.8	36.6	37.8	26.4	22.8	24.3	19.5	76.0%	-48.0%
Florida	9.2	11.5	18.1	16.6	20.1	19.6	17.8	19.4	18.3	19.0	107.0%	-3.0%
Ohio	9.4	9.5	15.1	16.4	19.7	22.6	18.3	17.7	17.5	16.9	80.0%	-25.0%
North Carolina	9.0	12.3	11.4	18.9	23.7	23.6	21.0	18.8	20.6	16.1	79.0%	-32.0%
Illinois	9.6	15.4	23.0	22.4	24.5	23.9	22.1	17.7	14.9	14.1	47.0%	-41.0%
Virginia	9.9	10.0	11.9	13.0	18.4	16.8	15.9	13.3	13.2	13.8	39.0%	-18.0%
New Hampshire	5.3	8.9	10.9	10.1	9.7	12.5	14.4	11.9	11.2	13.3	151.0%	6.0%
Maine	9.2	9.5	6.5	8.5	10.5	12.4	14.2	10.1	12.2	12.3	34.0%	-1.0%
Wisconsin	9.3	11.8	17.0	15.0	17.8	16.8	14.7	15.1	12.7	12.0	29.0%	-29.0%
Pennsylvania	8.8	9.2	7.8	8.7	10.0	10.8	11.2	10.5	10.5	9.4	7.0%	-13.0%
Rhode Island	6.1	6.5	7.2	5.0	5.5	5.4	6.6	7.5	5.4	7.8	28.0%	44.0%
Vermont	6.5	5.2	6.7	6.4	8.1	6.1	8.2	8.0	6.2	7.7	18.0%	26.0%
Connecticut	5.6	6.4	6.3	5.4	6.0	7.0	8.3	6.3	7.4	7.3	30.0%	4.0%
New York	7.0	6.5	7.3	7.4	7.5	5.7	7.6	6.6	7.0	7.3	4.0%	28.0%
Massachusetts	4.0	4.3	4.8	5.0	5.6	5.9	5.6	5.7	6.3	6.9	73.0%	17.0%
Delaware	5.9	5.8	5.8	7.0	7.0	6.7	8.5	7.2	7.5	6.7	14.0%	0.0%
Maryland	7.9	6.7	6.8	4.3	6.3	6.6	6.6	7.3	6.3	5.6	-29.0%	-15.0%
New Jersey	4.1	6.1	5.3	4.6	4.1	4.3	5.4	5.5	5.5	5.1	24.0%	19.0%

Figure 17. Methamphetamine Consequences Index and Domains, Interstate Variations, 2009



3. State Cocaine Consequences Index

Figure 18 shows interstate variations in the State Cocaine Index for select years. As with heroin and methamphetamine, the maps reveal substantial regional stratification in the cocaine problem. Generally speaking, states along the Gulf and East Coasts as well as in the midwest (namely, Illinois) consistently experience the most serious cocaine-related consequences, whereas Hawaii and states in the north central and northwest regions of the U.S. are consistently among the least affected. The maps also show that after an uptick in the number of states moving into the most serious range of the Cocaine Index (going from 6 in 2000 to 15 in 2006), only 9 states remained in this highest category as of 2009. This general downward trend in cocaine-related consequences, especially since 2006, is reinforced by the state-specific trends shown in Figure 19.

Table 9 presents a state-by-year look at the Cocaine Index. In 2009, the five states with the most serious cocaine problem were Maryland, North Carolina, Delaware, South Carolina, and Florida (with index scores ranging from 61 to 55). Four states (Maryland, Delaware, Florida, and Louisiana) were among the most serious in every year between 2000 and 2009. The five least impacted states in 2009 were Oregon, Nebraska, Hawaii, Montana, and South Dakota [9] (with index scores ranging from 11 to 13). All of these states remained among the least impacted group of states throughout the decade. Trends show that the majority of states over both the long- and medium-terms experienced substantial downturns in the Cocaine Index. For example, 36 states experienced double-digit percent declines in the Cocaine Index between 2005 and 2009. Only four states (North Dakota, Iowa, Alabama, and Idaho) experienced double-digit percent increases from 2005 to 2009, although all these states except for Alabama had a relatively minor cocaine problem to begin with.

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[9] Although Wyoming (13.2) was virtually tied with South Dakota (13.1) for fifth position.

Figure 20 shows interstate variations in the underlying components of the Cocaine Index for 2009. With the exception of Alaska, the most serious cocaine-related *Health* and *Crime and Disorder* consequences occur in states within the eastern half of the United States. In contrast, several states outside this region—namely, California, New Mexico, and Texas—experienced relatively severe *Social and Economic* consequences from cocaine. However, just two eastern states (Florida and North Carolina) fell within the most serious category for all three cocaine consequence domains. Generally speaking, the states that are least impacted by cocaine problems are in the north central and northwest United States, although just three states (Montana, Nebraska, Oregon) were in the lowest quintile across all consequence areas.

Figure 18. Cocaine Consequences Index, Interstate Variations, Select Years

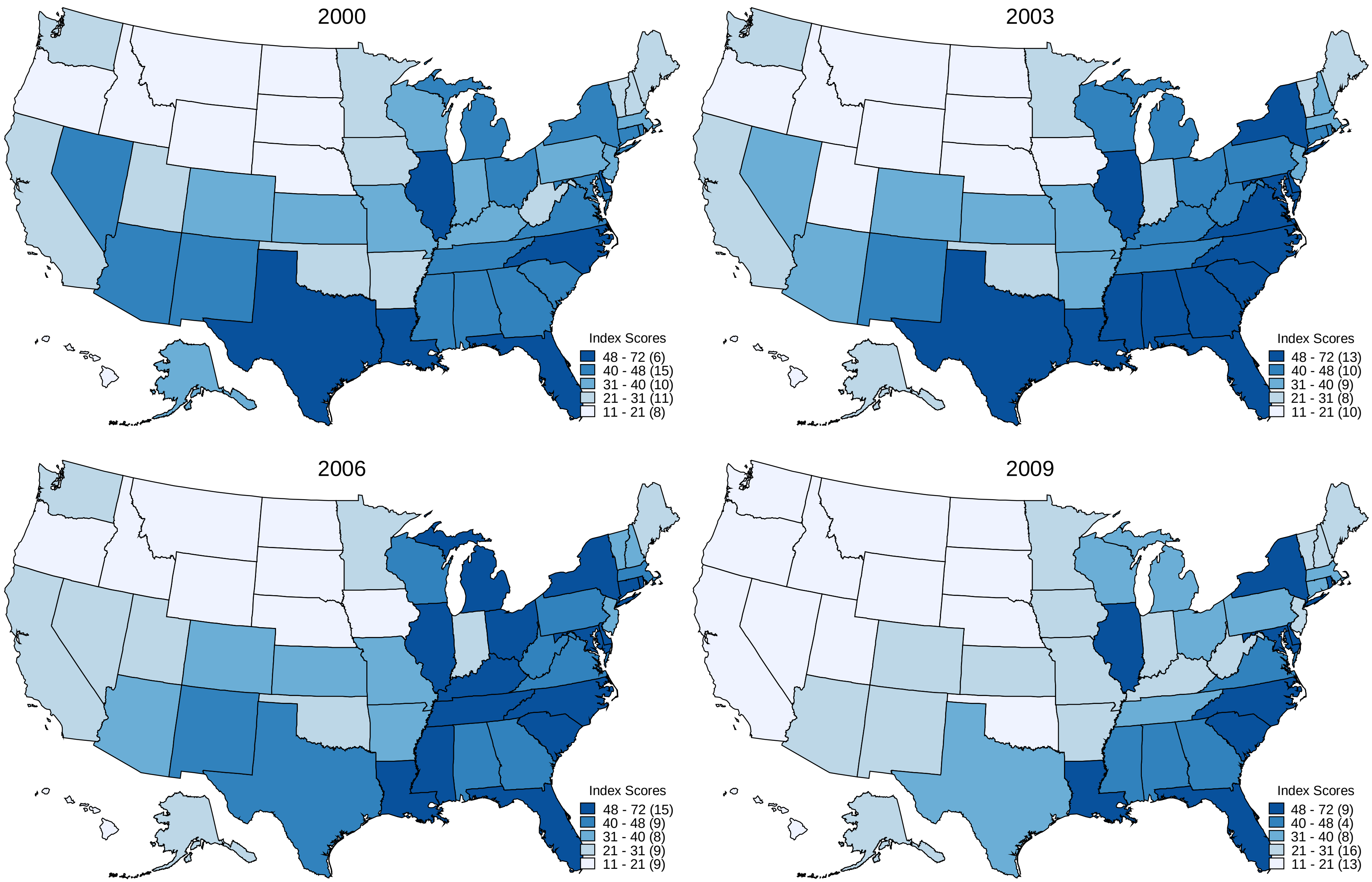


Figure 19. Cocaine Consequences Index, Trends by State, 2000-2009

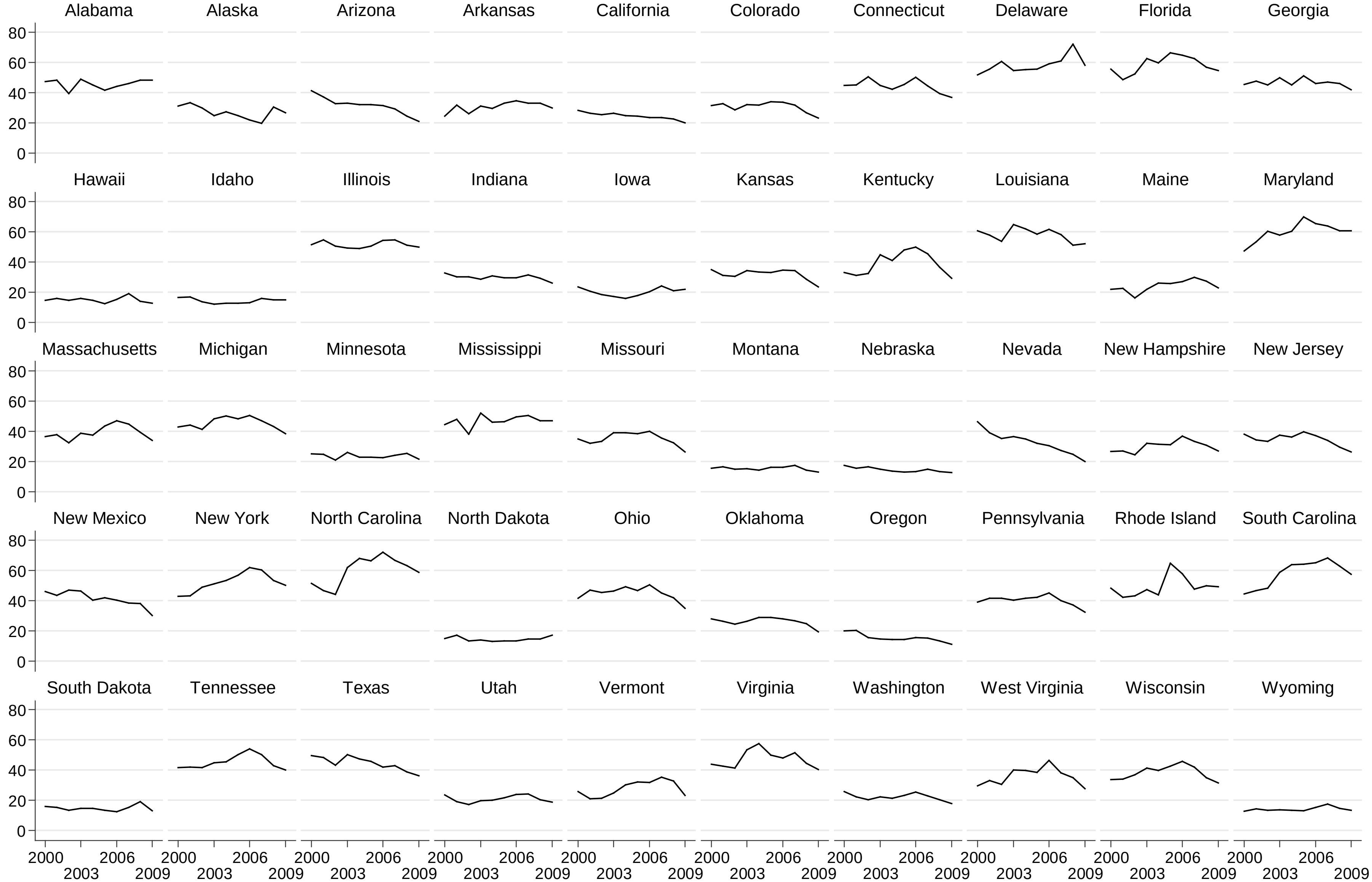
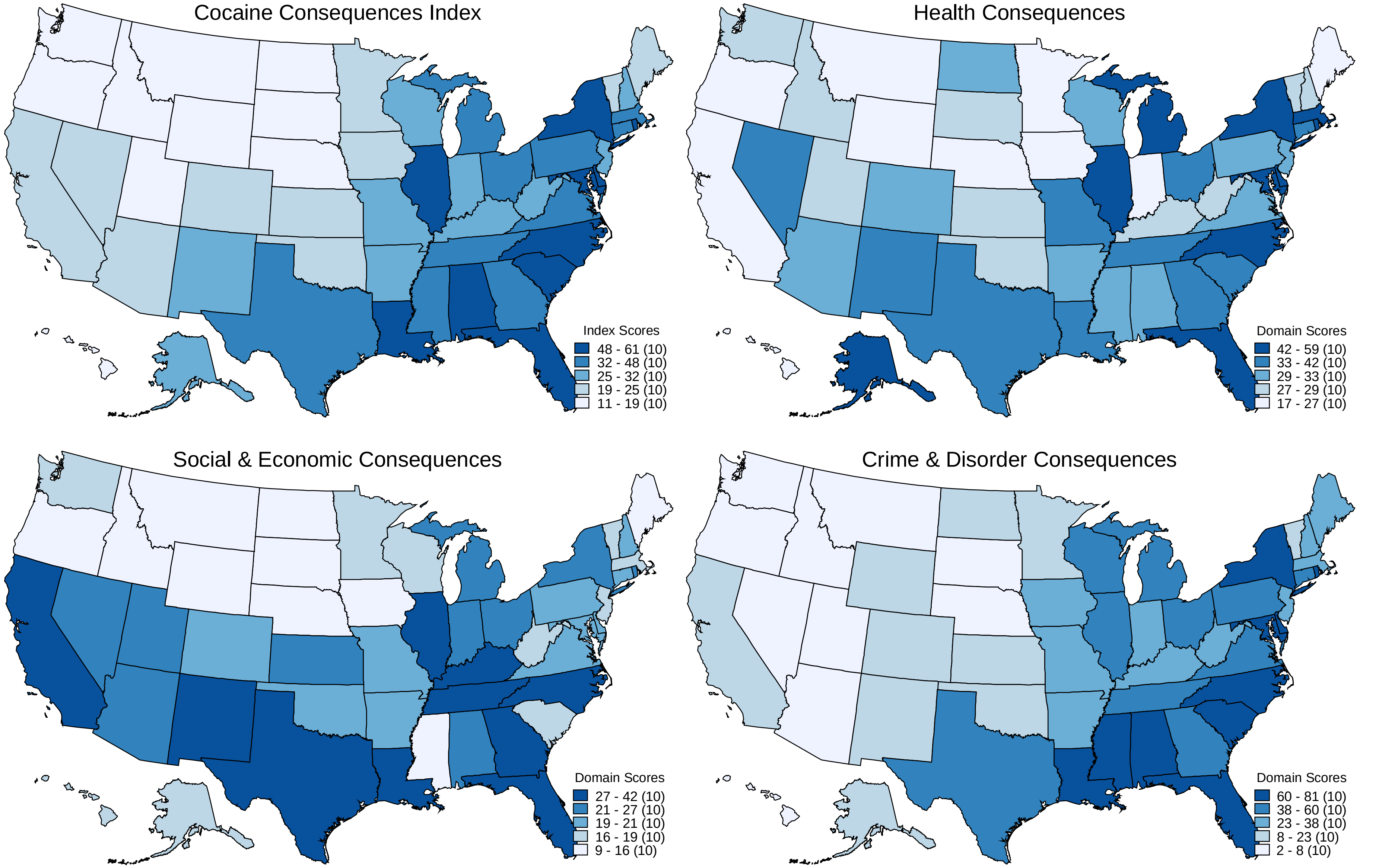


Table 9. State Cocaine Consequences Index, 2000-2009

State	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	% Change 2000-2009	% Change 2005-2009
Maryland	47.2	53.3	60.3	57.8	60.4	70.0	65.3	63.8	60.6	60.5	28.2%	-13.6%
North Carolina	51.6	46.6	44.2	61.9	67.9	66.5	72.1	66.9	63.2	58.7	13.8%	-11.7%
Delaware	51.6	55.4	60.5	54.5	55.2	55.6	58.9	60.9	72.2	58.0	12.4%	4.3%
South Carolina	44.4	46.6	48.2	58.9	63.8	64.3	65.2	68.2	63.0	57.6	29.7%	-10.4%
Florida	55.6	48.4	52.4	62.5	59.6	66.3	64.7	62.5	56.9	54.6	-1.8%	-17.6%
Louisiana	60.7	57.9	53.5	64.8	61.8	58.3	61.7	58.0	51.1	52.1	-14.2%	-10.6%
New York	42.8	43.1	48.8	51.0	53.3	56.9	62.1	60.4	53.5	50.2	17.3%	-11.8%
Illinois	51.5	54.5	50.4	49.2	49.0	50.4	54.4	54.5	51.0	50.0	-2.9%	-0.8%
Rhode Island	48.2	42.3	43.1	47.5	44.0	64.7	57.7	47.8	49.8	49.4	2.5%	-23.6%
Alabama	47.3	48.2	39.2	48.8	45.2	41.4	44.0	46.1	48.1	48.1	1.7%	16.2%
Mississippi	44.6	48.0	38.0	52.1	46.1	46.2	49.7	50.5	47.1	47.1	5.6%	1.9%
Georgia	45.3	47.5	45.2	49.7	45.2	51.1	46.1	47.1	45.9	41.9	-7.5%	-18.0%
Virginia	43.9	42.7	41.4	53.4	57.7	49.8	48.1	51.6	44.4	40.3	-8.2%	-19.1%
Tennessee	41.6	41.9	41.6	44.7	45.5	50.1	54.1	50.1	42.9	40.0	-3.8%	-20.2%
Michigan	42.9	44.1	41.4	48.3	50.2	48.4	50.6	46.9	43.3	38.4	-10.5%	-20.7%
Connecticut	44.8	45.0	50.3	44.6	42.3	45.5	50.1	44.5	39.3	36.8	-17.9%	-19.1%
Texas	49.5	48.4	43.1	50.2	47.5	45.8	42.1	42.8	38.7	36.3	-26.7%	-20.7%
Ohio	41.6	47.0	45.3	46.4	49.2	46.6	50.4	45.1	42.0	35.1	-15.6%	-24.7%
Massachusetts	36.5	37.7	32.4	38.6	37.6	43.5	47.1	44.8	39.4	34.0	-6.8%	-21.8%
Pennsylvania	39.1	41.5	41.7	40.3	41.5	42.2	45.1	39.9	37.2	32.5	-16.9%	-23.0%
Wisconsin	33.7	33.9	36.8	41.4	39.9	42.7	45.7	42.1	35.1	31.5	-6.5%	-26.2%
New Mexico	46.0	43.6	47.1	46.3	40.5	41.9	40.5	38.4	38.2	30.3	-34.1%	-27.7%
Arkansas	24.2	31.8	26.0	31.0	29.5	32.9	34.6	32.8	32.9	29.7	22.7%	-9.7%
Kentucky	33.0	31.2	32.5	44.6	40.9	47.9	49.7	45.3	36.6	29.0	-12.1%	-39.5%
West Virginia	29.7	33.2	30.5	40.2	39.9	38.5	46.3	38.1	35.0	27.6	-7.1%	-28.3%
New Hampshire	26.7	27.1	24.4	32.0	31.3	31.0	36.8	33.2	30.9	26.9	0.7%	-13.2%
Alaska	31.1	33.4	29.8	24.8	27.3	24.7	21.8	19.5	30.3	26.5	-14.8%	7.3%
Missouri	34.8	31.9	33.4	39.0	39.1	38.4	40.0	35.7	32.3	26.2	-24.7%	-31.8%
New Jersey	38.1	34.2	33.2	37.4	36.2	39.8	37.2	33.8	29.5	26.2	-31.2%	-34.2%
Indiana	32.7	30.0	30.0	28.6	30.9	29.6	29.6	31.3	29.1	25.9	-20.8%	-12.5%
Kansas	34.9	31.2	30.5	34.1	33.3	33.0	34.7	34.1	28.4	23.3	-33.2%	-29.4%
Vermont	25.7	20.9	21.2	24.8	30.1	32.0	31.7	35.3	32.6	23.1	-10.1%	-27.8%
Colorado	31.3	32.5	28.5	32.0	31.7	33.8	33.5	31.6	26.7	23.1	-26.2%	-31.7%
Maine	21.7	22.4	16.1	21.9	26.1	25.6	27.0	29.7	27.3	22.8	5.1%	-10.9%
Minnesota	25.0	24.8	21.0	25.9	22.8	22.7	22.5	24.0	25.3	21.7	-13.2%	-4.4%
Iowa	23.4	20.6	18.3	17.2	15.9	17.8	20.4	24.0	20.8	21.7	-7.3%	21.9%
Arizona	41.1	37.2	32.7	32.8	32.1	32.1	31.4	29.0	24.5	21.0	-48.9%	-34.6%
California	28.3	26.4	25.4	26.1	24.7	24.5	23.5	23.3	22.6	20.0	-29.3%	-18.4%
Nevada	46.2	39.0	35.1	36.5	34.8	32.0	30.6	27.3	24.7	19.9	-56.9%	-37.8%
Oklahoma	28.0	26.4	24.3	26.5	28.8	28.8	28.1	26.8	24.9	19.5	-30.4%	-32.3%
Utah	23.5	19.1	17.2	19.7	20.0	21.6	23.7	24.0	20.4	18.6	-20.9%	-13.9%
Washington	25.9	22.3	20.3	22.3	21.4	23.1	25.5	22.9	20.3	17.7	-31.7%	-23.4%
North Dakota	14.8	17.2	13.3	13.8	13.1	13.2	13.4	14.5	14.6	17.0	14.9%	28.8%
Idaho	16.3	16.6	13.7	12.0	12.7	12.7	12.8	15.9	15.0	14.7	-9.8%	15.7%
Wyoming	12.6	14.4	13.5	13.6	13.5	13.1	15.1	17.4	14.5	13.2	4.8%	0.8%
South Dakota	15.8	15.4	13.5	14.6	14.7	13.3	12.3	15.2	19.1	13.1	-17.1%	-1.5%
Montana	15.6	16.5	15.0	15.2	14.1	16.1	16.1	17.4	14.2	13.0	-16.7%	-19.3%
Hawaii	14.4	15.9	14.5	15.7	14.4	12.4	15.1	19.0	14.0	12.7	-11.8%	2.4%
Nebraska	17.3	15.6	16.5	15.0	13.7	13.0	13.4	14.8	13.3	12.5	-27.7%	-3.8%
Oregon	20.0	20.3	15.7	14.7	14.3	14.3	15.4	15.1	13.4	11.1	-44.5%	-22.4%

Figure 20. Cocaine Consequences Index and Domains, Interstate Variations, 2009



4. State Marijuana Consequences Index

Figure 21 shows interstate variations in the State Marijuana Index. This series of maps reveals that marijuana-related consequences are more geographically dispersed than for other drugs. Thus, unlike the other drugs, the maps resemble a checkerboard pattern with comparatively less regionalization and consistency across years. Figure 22 confirms this assessment in revealing that trends in marijuana-related problems are volatile and varied across the states.

The relative inconsistency of the Marijuana Index across states and years is reinforced by the pattern in Table 10. In 2009, Iowa, New York, Vermont, Kentucky and Missouri were the five states with the highest Marijuana Index scores (ranging from 58 to 52). Supporting the notion that marijuana problems are not as concentrated within a particular state or region of the country as with the other drugs, none of these states appeared among the most serious in all ten years of the decade. The six states with a least serious marijuana problem in 2009 were Nebraska, Utah, Mississippi, New Jersey, Wyoming, and Virginia [10] (with index scores ranging from 25 to 33). Only Nebraska fell within this least seriously affected group in all ten years. Regarding long-term trends, 20 states registered double-digit percent increases in the Marijuana Index between 2000 and 2009, whereas 13 experienced double-digit declines.

Lastly, as shown in Figure 23, interstate variations in the Marijuana Index and its domains are also variably distributed with little evidence of regionalization in marijuana-related problems. No states consistently fell within the most serious category, and just three states (Nebraska, Mississippi, Utah) were in the bottom quintile for all three domains. These results are more reflective of the general state-level variability in the Marijuana Index, with seven states (Alabama, Alaska, Maryland, New Mexico, South Carolina, South Dakota, and Wisconsin)

[10] Virginia and Wyoming (32.9) tied for the fifth position on the Marijuana Index.

appearing among the most impacted in one domain but among the least impacted in another. For example, Alaska fell in the bottom (least serious) tier for *Health* consequences, a middle tier for *Social and Economic* consequences, and the top (most serious) tier for *Crime and Disorder* consequences.

Figure 21. Marijuana Consequences Index, Interstate Variations, Select Years

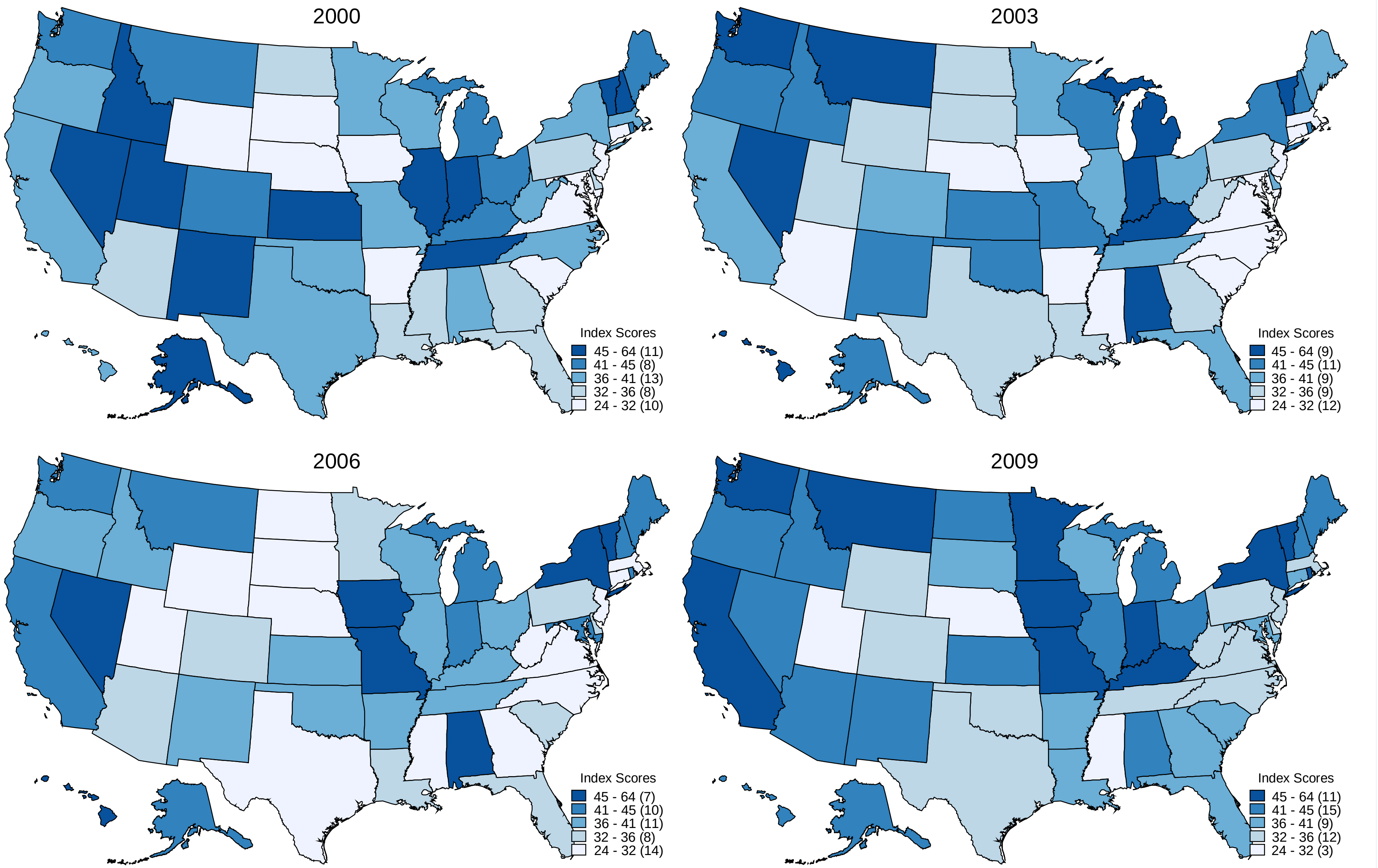


Figure 22. Marijuana Consequences Index, Trends by State, 2000-2009

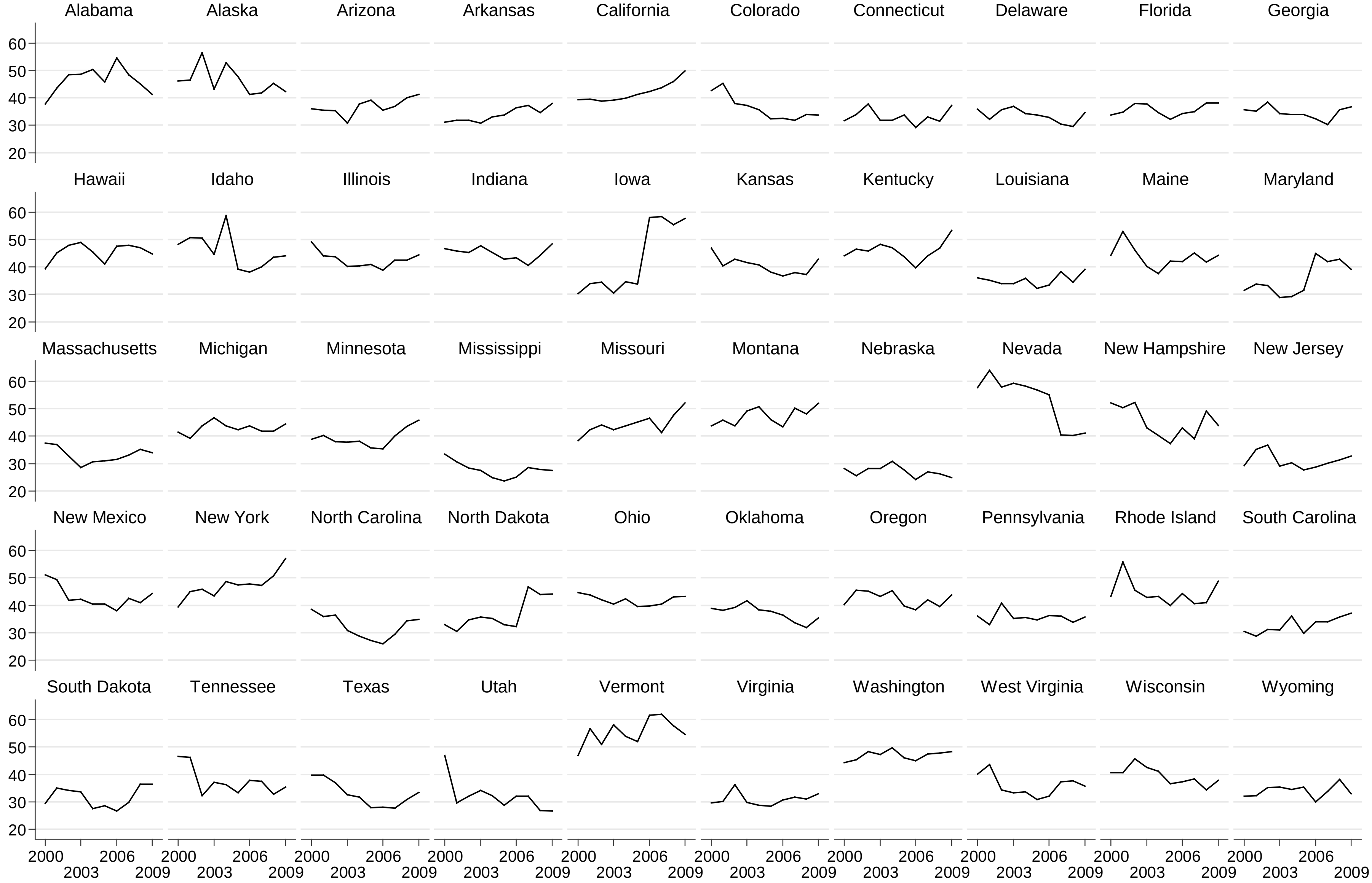
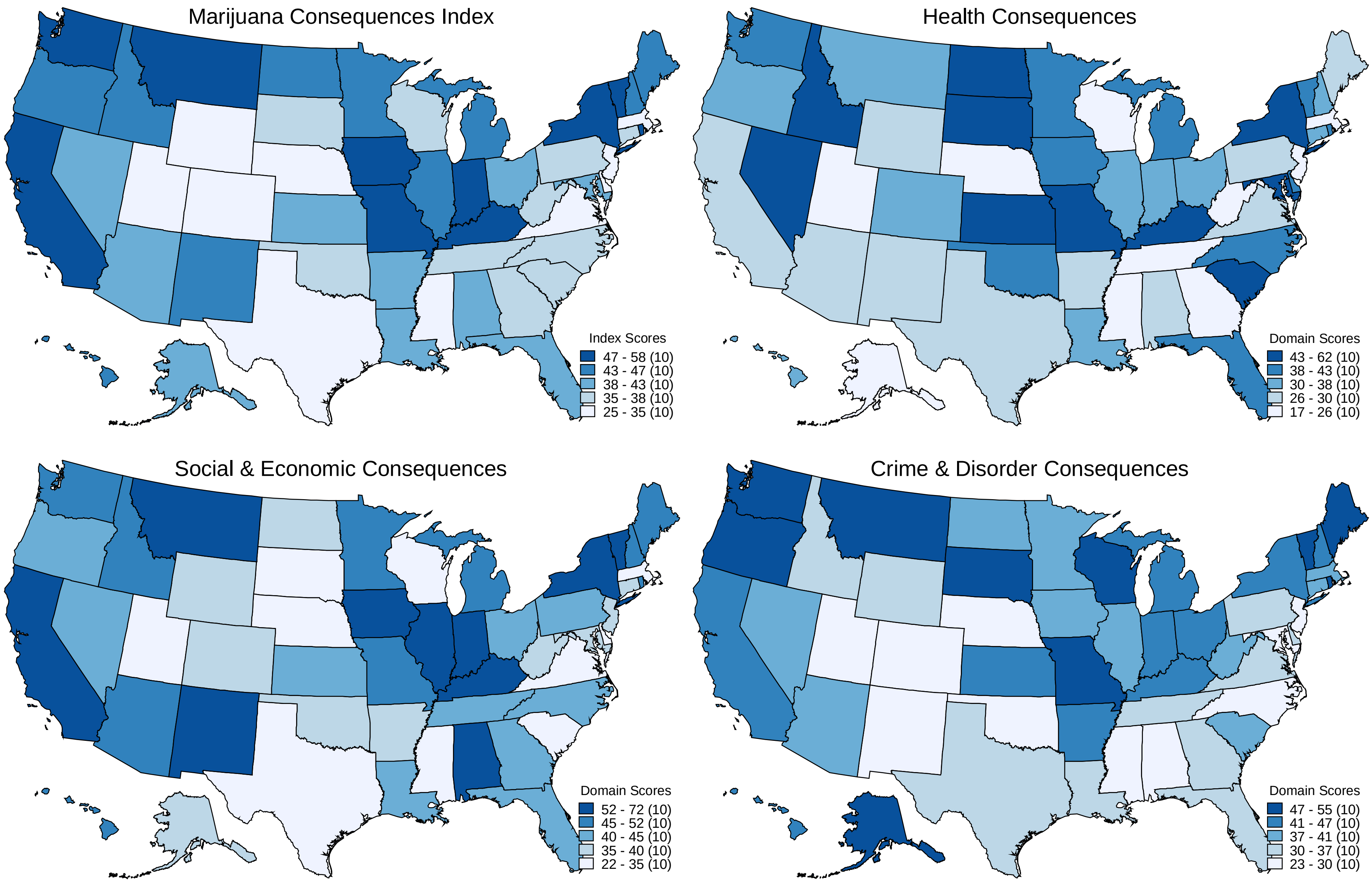


Table 10. State Marijuana Consequences Index, 2000-2009

State	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	% Change 2000-2009	% Change 2005-2009
Iowa	30.2	33.9	34.4	30.5	34.7	33.8	58.0	58.5	55.5	57.7	91.1%	70.7%
New York	39.4	45.0	45.8	43.5	48.7	47.4	47.8	47.3	50.8	57.0	44.7%	20.3%
Vermont	46.9	56.8	51.0	58.1	54.0	52.0	61.6	61.9	57.7	54.7	16.6%	5.2%
Kentucky	44.1	46.5	45.9	48.2	47.1	43.7	39.7	44.0	46.8	53.4	21.1%	22.2%
Missouri	38.3	42.4	44.1	42.3	43.7	45.1	46.5	41.3	47.6	52.1	36.0%	15.5%
Montana	43.7	45.8	43.8	49.1	50.7	46.1	43.4	50.3	48.2	51.9	18.8%	12.6%
California	39.3	39.6	38.9	39.1	39.9	41.3	42.3	43.8	46.0	49.8	26.7%	20.6%
Rhode Island	43.3	55.9	45.5	42.9	43.3	40.0	44.3	40.6	40.9	48.8	12.7%	22.0%
Indiana	46.7	45.8	45.4	47.7	45.4	42.9	43.4	40.6	44.3	48.5	3.9%	13.1%
Washington	44.3	45.3	48.4	47.3	49.8	46.0	45.0	47.4	47.9	48.4	9.3%	5.2%
Minnesota	38.8	40.2	38.0	37.8	38.1	35.7	35.4	40.0	43.6	45.8	18.0%	28.3%
Hawaii	39.4	45.2	47.9	48.9	45.5	41.1	47.6	47.9	47.1	44.7	13.5%	8.8%
Michigan	41.4	39.2	43.7	46.8	43.7	42.3	43.8	41.8	41.9	44.4	7.2%	5.0%
Illinois	49.1	44.1	43.7	40.2	40.5	41.0	38.9	42.6	42.5	44.4	-9.6%	8.3%
New Mexico	51.1	49.4	41.9	42.2	40.5	40.4	38.0	42.5	41.0	44.3	-13.3%	9.7%
North Dakota	32.9	30.5	34.6	35.8	35.2	32.9	32.2	46.7	43.9	44.2	34.3%	34.3%
Maine	44.2	53.0	46.1	40.3	37.6	42.2	41.9	45.2	41.8	44.2	0.0%	4.7%
Idaho	48.3	50.8	50.5	44.6	58.7	39.2	38.1	40.1	43.5	44.1	-8.7%	12.5%
New Hampshire	52.2	50.4	52.4	43.1	40.3	37.2	43.0	39.0	49.1	43.9	-15.9%	18.0%
Oregon	40.3	45.5	45.1	43.3	45.4	39.7	38.4	42.1	39.6	43.7	8.4%	10.1%
Ohio	44.6	43.7	42.0	40.5	42.4	39.5	39.7	40.5	43.0	43.2	-3.1%	9.4%
Kansas	46.8	40.5	42.8	41.7	40.7	38.1	36.8	37.9	37.3	42.8	-8.5%	12.3%
Alaska	46.1	46.5	56.5	43.2	52.9	47.8	41.2	41.8	45.3	42.3	-8.2%	-11.5%
Arizona	36.1	35.5	35.3	30.7	37.8	39.1	35.5	36.9	40.0	41.3	14.4%	5.6%
Alabama	37.7	43.5	48.4	48.6	50.4	45.8	54.6	48.4	45.2	41.2	9.3%	-10.0%
Nevada	57.7	64.0	58.0	59.4	58.3	56.8	55.2	40.4	40.3	41.2	-28.6%	-27.5%
Maryland	31.5	33.7	33.2	28.9	29.2	31.5	44.9	42.0	42.8	39.1	24.1%	24.1%
Louisiana	36.0	35.2	34.0	33.9	35.8	32.2	33.5	38.3	34.5	39.1	8.6%	21.4%
Florida	33.7	34.8	38.0	37.8	34.7	32.1	34.2	34.9	38.2	38.1	13.1%	18.7%
Arkansas	31.1	31.8	31.9	30.7	33.0	33.8	36.4	37.3	34.6	38.0	22.2%	12.4%
Wisconsin	40.6	40.6	45.7	42.5	41.2	36.6	37.3	38.3	34.3	37.9	-6.7%	3.6%
South Carolina	30.4	28.7	31.2	31.0	36.0	29.8	34.0	33.9	35.7	37.2	22.4%	24.8%
Connecticut	31.7	34.0	37.8	31.9	31.9	33.7	29.2	33.1	31.5	37.2	17.4%	10.4%
Georgia	35.6	35.2	38.4	34.3	34.0	33.9	32.3	30.2	35.6	36.7	3.1%	8.3%
South Dakota	29.5	35.1	34.1	33.6	27.5	28.6	26.7	29.8	36.5	36.5	23.7%	27.6%
Pennsylvania	36.1	33.0	40.8	35.2	35.6	34.7	36.3	36.1	33.8	35.8	-0.8%	3.2%
West Virginia	40.1	43.6	34.3	33.3	33.7	30.9	32.1	37.3	37.7	35.8	-10.7%	15.9%
Oklahoma	38.9	38.2	39.3	41.7	38.4	37.8	36.4	33.6	31.9	35.3	-9.3%	-6.6%
Tennessee	46.6	46.2	32.3	37.1	36.2	33.3	37.9	37.4	32.7	35.3	-24.2%	6.0%
North Carolina	38.6	35.9	36.5	30.9	28.8	27.1	25.9	29.5	34.4	34.8	-9.8%	28.4%
Delaware	35.9	32.2	35.6	36.9	34.2	33.7	32.9	30.5	29.6	34.6	-3.6%	2.7%
Massachusetts	37.5	36.9	32.8	28.6	30.6	30.9	31.5	33.0	35.2	33.9	-9.6%	9.7%
Colorado	42.6	45.3	37.9	37.3	35.7	32.3	32.6	31.9	33.9	33.8	-20.7%	4.6%
Texas	39.7	39.8	37.0	32.6	31.7	27.8	28.1	27.7	30.8	33.5	-15.6%	20.5%
Virginia	29.7	30.1	36.2	29.8	28.8	28.3	30.7	31.8	31.0	32.9	10.8%	16.3%
Wyoming	32.1	32.2	35.2	35.3	34.5	35.3	29.9	33.9	38.1	32.9	2.5%	-6.8%
New Jersey	29.3	35.1	36.7	29.1	30.3	27.7	28.8	30.1	31.4	32.7	11.6%	18.1%
Mississippi	33.5	30.7	28.3	27.5	24.9	23.7	25.0	28.6	27.8	27.5	-17.9%	16.0%
Utah	46.9	29.6	32.1	34.2	32.2	28.8	32.0	32.1	26.8	26.6	-43.3%	-7.6%
Nebraska	28.1	25.6	28.2	28.2	30.8	27.7	24.1	26.9	26.3	24.9	-11.4%	-10.1%

Figure 23. Marijuana Consequences Index and Domains, Interstate Variations, 2009



5. Generic State Drug Consequences Index

To provide a more general assessment of drug problems at the state level, we calculated the mean annual state rank of index scores across the four drug-specific State DCIs and the three domains. In particular, we first determined the annual state rankings for the 50 states for each drug-specific index and corresponding domains. We then obtained the drug-specific mean ranks by state for all years combined (2000-2009). Lastly, we took the average of the mean annual ranks across the four drugs. The results, where higher ranks are undesirable, are presented graphically in Figure 24. Table 11 also reports the specific mean rank scores, with color coded cells indicating the bottom (red) and top (green) ten ranked states. Overall, nine states had a mean annual index rank above 30, which was generally consistent with the state appearing among the ten most affected jurisdictions in at least two domains. Only Illinois was ranked in the most serious quintile in all three domains. Conversely, six states had a mean annual rank below 20, which generally corresponded to a state being among the least affected jurisdictions in at least two domains. Three states—Nebraska, South Dakota, and Wyoming—were ranked among the least affected in all three categories. Notably, several states—New Hampshire, Arizona, Tennessee, and Wisconsin—ranked among the top ten in one domain but the bottom ten in another. Regionally, the north central U.S. was least likely to experience severe effects from multiple illegal drugs, and this finding remained consistent across consequence domains.

Figure 24. Mean Annual State Ranks Across State DCIs and Domains

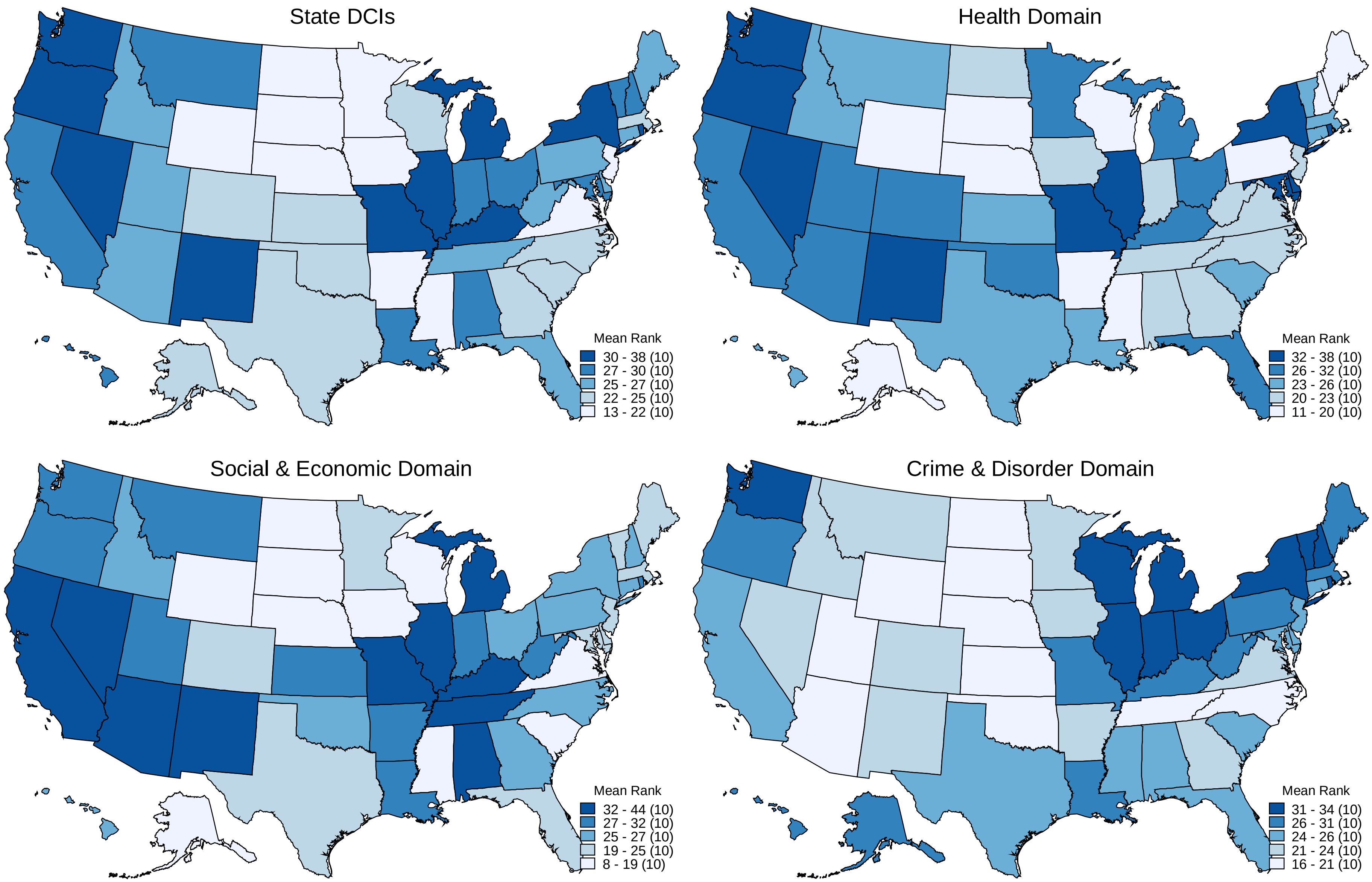


Table 11. Mean Annual Ranks Across State DCIs and Domains, 2000-2009 Combined

State	State DCIs	Health	Social & Economic	Crime & Disorder
Nevada	37.63	38.16	44.03	23.98
Illinois	34.19	34.73	35.30	31.41
New Mexico	33.33	35.23	38.80	21.18
New York	31.80	36.59	26.25	30.76
Rhode Island	31.76	32.40	29.09	30.96
Michigan	31.53	28.49	34.19	31.56
Washington	31.10	35.15	28.03	31.06
Missouri	30.41	35.58	34.35	28.23
Kentucky	30.38	26.98	38.28	27.40
Oregon	29.65	33.43	26.95	28.53
Ohio	29.60	26.43	26.66	33.79
Alabama	29.60	20.55	32.40	26.18
Vermont	29.38	24.88	24.61	30.75
California	29.20	27.03	38.53	24.45
Maryland	28.68	37.09	20.39	26.03
Montana	28.30	24.86	30.99	23.18
New Hampshire	28.26	17.83	26.65	31.19
Louisiana	28.04	25.45	32.03	27.61
Hawaii	27.21	24.76	25.76	26.74
Indiana	26.88	20.84	30.30	30.75
Arizona	26.35	31.31	33.11	20.46
Delaware	25.96	33.69	20.59	26.26
Idaho	25.80	25.69	24.98	22.45
Florida	25.65	30.03	23.86	26.05
West Virginia	25.61	20.04	28.30	29.79
Pennsylvania	25.58	18.80	24.76	29.18
Connecticut	25.30	25.85	24.78	26.10
Tennessee	25.29	21.23	32.61	20.95
Utah	25.09	30.43	28.85	19.85
Maine	24.84	18.74	20.09	28.88
Alaska	24.41	19.59	13.70	30.39
Oklahoma	23.38	30.60	25.99	20.34
Massachusetts	23.29	25.26	22.26	26.34
Kansas	23.26	25.98	30.33	21.15
Texas	23.08	24.69	24.40	25.39
Georgia	22.99	21.66	25.65	23.60
North Carolina	22.64	21.33	25.64	18.65
Wisconsin	22.29	14.95	15.05	30.74
South Carolina	22.24	23.81	17.21	25.74
Colorado	22.03	30.91	20.40	22.83
Arkansas	21.04	17.00	27.60	22.15
Minnesota	20.86	26.18	19.90	23.39
New Jersey	20.74	20.01	18.76	25.61
Virginia	20.38	22.63	15.59	23.79
Iowa	19.73	22.46	18.64	23.23
Mississippi	19.01	15.13	13.59	25.43
North Dakota	18.76	20.56	16.24	17.53
Wyoming	16.93	19.95	18.56	16.46
South Dakota	13.01	19.41	7.56	20.00
Nebraska	12.60	10.70	12.45	16.60

V. SUMMARY AND DISCUSSION

The family of U.S. Drug Consequences Indices (DCIs) offers a parsimonious means to measure drug-related consequences over time and across states. The National DCI was constructed from 30 indicators measuring the health, social and economic, and crime and disorder consequences of illegal drugs. The findings revealed that drug-related consequences, as measured by the index, increased from 2000 through the middle part of the decade, reaching peak levels in 2002-2004, before returning to benchmark levels by 2008. Various underlying factors, often moving in opposite directions, drove these trends. *Social and Economic* consequences, for instance, increased dramatically through the early 2000s before declining to near-benchmark levels by decade's end. *Health* consequences, on the other hand, rose steadily from 2002 to 2006 before leveling off about 25% above baseline. Conversely, *Crime and Disorder* consequences decreased steadily throughout the decade, reaching a point 27% below the benchmark year as of 2009.

A series of drug-specific National DCIs was also constructed using the State DCIs as a starting point. These results showed the divergent national trends in drug-related consequences by drug type. According to the National Heroin Index, for instance, heroin consequences increased steadily over the decade, reaching 39% above baseline by 2009. In contrast, both methamphetamine and cocaine consequences increased through the middle part of the decade before declining back toward baseline levels. In particular, the National Methamphetamine Index increased 37% through 2005, declining to a point that remained 10% above baseline by 2009. The National Cocaine Index, in contrast, began to increase later and less sharply, peaking at 10% above baseline in 2006, before returning to a point 10% below baseline in 2009. Finally, the National Marijuana Index showed an overall flat trend across the decade.

The drug-specific State DCIs, which were based on 13 to 16 indicators each, showed interstate variations and trends in drug-related consequences for the four major drugs of abuse from 2000-2009. One of the main conclusions to be drawn from this series of analyses is that illegal drugs and their associated consequences are highly regionalized in the U.S. According to the State Heroin Index, the most severe heroin problems are largely concentrated in the northeast, with additional pockets in the midwest and west. The State Methamphetamine Index showed that methamphetamine is a primary problem for the western United States, especially Hawaii and other Pacific states, but it also revealed that states well into the U.S. heartland suffer serious consequences from methamphetamine. The State Cocaine Index revealed that states along the Gulf and East Coasts, and Illinois in the midwest, experience the greatest cocaine-related consequences. Finally, results from the State Marijuana Index showed that marijuana-related consequences tend to be the most geographically dispersed.

The State DCIs also uncovered common trends across many states. For example, 45 states experienced an increase in the State Heroin Index between 2000 and 2009. The trends in the State Methamphetamine Index showed that methamphetamine consequences increased substantially in the western half of the U.S. through mid-decade before declining toward baseline levels in 2009. Indeed, 34 states showed double-digit declining rates in the index between 2005 and 2009. For cocaine, some states experienced steady increases and others steady declines through the early part of the decade. However, by 2006, trends in cocaine-related consequences had improved to the point that, between 2005 and 2009, 36 states experienced double-digit percent declines in the State Cocaine Index. Conversely, marijuana-related consequences were highly variable across states and years. Indeed, between 2000-2009, there was roughly a 60/40 split, respectively, in the number of states registering increases versus declines in the State Marijuana Index. Lastly, overall drug-related consequences were examined at the state-level using the mean annual state rank across the four drug-specific State DCIs. These results showed some stratification across the states, with north central U.S. ranking consistently better than other states with respect to the range and severity of drug-related problems.

The family of U.S. DCIs have many potential uses and applications. First, they provide a parsimonious yet comprehensive snapshot of trends and variations in drug-related consequences. From an administrative perspective, this can be useful for communicating with policymakers, practitioners, and the general public about drug policy needs, objectives, and progress. Further, the DCIs can support more sophisticated uses such as benchmarking, performance assessment, and related policy analytic work. In this role, the DCIs by themselves are not suited to supporting causal claims about policy effectiveness, but they can inform assessments of whether trends and interstate variations in drug-related problems are in accordance with the intended impact of a particular policy or set of policies. Relatedly, the DCIs provide relevant information on state and regional variations in the nature and extent of illicit drug problems, which can inform strategic thinking about policy objectives, resource allocation, and the prioritization of interventions and initiatives.

Another benefit of the DCIs is that they contribute to federal efforts to increase the utility of existing drug data systems, especially at the state or local level. For example, missing data in drug-related information systems often confounds the ability of interested stakeholders to compare states on outcome and performance indicators. By generating defensible estimates of missing data within a multiple imputation framework, this project was able to utilize key information systems that would not have been feasible otherwise. The DCIs employed a conceptually coherent approach to guide measurement of drug-related consequences, keying on a number of relevant dimensions across health, social and economic, and crime and disorder domains. In this respect, the DCIs and their underlying data can facilitate assessments regarding which dimensions are a state’s strongest assets, and which are in need of improvement. They can also inform future data collection efforts by identifying current data gaps in the measurement of drug-related consequences. For example, this research showed that there are few drug-specific, state-level indicators of drug consequences in the area of ‘family disruption and child maltreatment.’ Future data collection efforts might therefore focus on the development of indicators at this level of measurement, possibly in connection with existing data systems such as NCANDS and PRAMS.

Despite the utility of the DCIs, they have a number of limitations. First, the indices can only be as valid and reliable as their underlying indicators. We have attempted to address these concerns to the extent possible by employing both a conceptual and a data quality framework for obtaining relevant and quality indicators. Some things could not be overcome, however, like the error introduced by imprecise measures of drug type in some data systems or delays in reporting. Also, the issue of weighting is particularly sensitive and subjective when constructing composite indicators. There is no clear consensus among experts on composite index construction as to how to best determine a set of weights for combining diverse issues, such as those related to drug consequences. We assigned unequal weights based on expert opinion at the level of the subdomain and domain in order to create the DCIs. These weights represent one approach. As explained in the technical appendices, we have attempted to address some of these concerns by conducting various robustness analyses of these assumptions. The results of these analyses lend confidence to the weights ultimately used for the final analyses.

In focusing on select illegal drugs, the DCIs also do not address other substances, such as tobacco, alcohol, or prescription drugs. This is an important delimitation. Whereas certain states may experience relatively less serious consequences for the illegal drugs examined in this report, they may suffer from relatively more serious alcohol-related problems or confront emerging drug threats that are not captured by the DCIs (McAuliffe et al., 2003).

There are a number of possible future directions for the research begun here. First, and foremost, the DCIs can be updated on a regular basis as new data is released. Indeed, one of the primary objectives for this project was to set up an ongoing monitoring system that could track trends in drug-related consequences over time. There is also opportunity for constructing similar indices involving other substances, including other illegal drugs, tobacco, alcohol, and prescription drugs. It would also be fruitful to construct comparative indices at the substate level (e.g., counties, cities, zip codes) in order to provide more localized assessments of drug policy and related outcomes. Finally, research on index construction concerning inputs on the policy side would be a logical extension to the current work. Some research of this type has already been undertaken at the international level in the alcohol field (Brand et al., 2007; Paschall, Grube, and Kypri, 2009), whereby an index was developed to measure the strength of national alcohol control policies in order to assess how these policies related to key outcomes such as heavy drinking and youth initiation. In summary, the DCIs developed out of this project sought to measure drug-related consequences in a parsimonious yet comprehensive manner, with the ultimate objective of providing a useful set of communicative and policy analytic tools.

APPENDIX A: TAXONOMY OF DRUG-RELATED CONSEQUENCES

This appendix provides a detailed outline of the taxonomy of drug-related consequences developed for this project. The taxonomy is meant to be conceptually complete, but does not purport to be exhaustive of all possible drug-related consequences.

Table A-1. Detailed Taxonomy of Drug-Related Consequences

- I. **Health Consequences**
  - A. **Mortality**
    - 1. **Overdose**
    - 2. **Drug-Related Disease**
      - a) **HIV/AIDS**
      - b) **Cancer**
      - c) **Organ Failure**
    - 3. **Drug-Related Trauma**
      - a) **Accidents**
      - b) **Suicide**
  - B. **Morbidity**
    - 1. **Drug-Related Injury**
      - a) **Poisoning/Nonfatal Overdose**
      - b) **Accidents**
      - c) **Intentional Self-Harm/Attempted Suicide**
    - 2. **Drug-Related Physical Illness and Disease**
      - a) **Organ Damage**
      - b) **Poor Oral Health**
      - c) **Infectious Disease**
        - (1) **HIV**
        - (2) **Tuberculosis**
        - (3) **Hepatitis**
        - (4) **Syphilis**
      - d) **Other Physical Illness and Disease**
        - (1) **Soft Tissue Infection**
    - 3. **Drug-Related Mental and Psychological Impairment**
      - a) **Personality/Anxiety/Mood Disorders**
      - b) **Psychosis and Dementia**
      - c) **Other Mental Dysfunction**
    - 4. **Drug Use Disorders**
      - a) **Abuse**
      - b) **Dependence**
  - C. **Drug-Exposed Infants**
    - 1. **Miscarriage and Obstetrical Complications**
    - 2. **Birth Defects**
    - 3. **Infant Health**
      - a) **Low Birth Weight**
      - b) **HIV Exposure**
      - c) **Neonatal Abstinence Syndrome**

d) **Sudden Infant Death Syndrome**
4. **Developmental Delays and Cognitive Deficits**

II. **Social and Economic Consequences**
- A. **Family Disruption and Child Maltreatment**
  - 1. **Family Dysfunction**
    - a) **Domestic Violence**
    - b) **Divorce/Separation**
    - c) **Child Removal from Home**
      - (1) **Child Welfare Services**
      - (2) **Foster Care**
      - (3) **Loss of Parental Rights**
    - d) **Strained Parent-Child Relations**
  - 2. **Child Abuse and Neglect**
    - a) **Drug-Exposed Children**
      - (1) **Accidental Ingestion**
      - (2) **Passive Exposure**
    - b) **Neglect**
      - (1) **Failure to Provide Basic Needs**
      - (2) **Failure to Supervise**
    - c) **Physical Abuse**
    - d) **Sexual Abuse**
    - e) **Emotional Abuse**
- B. **Reduced Attainment and Productivity**
  - 1. **Poor Educational Outcomes**
    - a) **Low Academic Performance**
    - b) **Disrupted Learning Environments**
    - c) **School Drop-Outs**
  - 2. **Reduced Economic Well-Being**
    - a) **Lower Wages and Lifetime Earnings**
    - b) **Diverted Income**
    - c) **Unemployment**
  - 3. **Lost Productivity**
    - a) **Workforce Reduction**
    - b) **Sickness and Absenteeism**
    - c) **Unsafe and Risky Workplace Environments**
- C. **Stigmatization and Marginalization**
  - 1. **Drug-Using Lifestyles**
    - a) **IV Drug Use**
  - 2. **Loss of Relationships**
    - a) **Rejection by Friends and Family**
  - 3. **Social Alienation**
    - a) **Shame and Discrimination**
    - b) **Reduced Access to Healthcare, Prenatal Care, and Treatment**
    - c) **Blocked Avenues for Material Success**
  - 4. **Homelessness**
  - 5. **Impoverishment**

III. **Crime and Disorder Consequences**
- A. **Drugged Driving**
  - 1. **Accidents**
  - 2. **Property Damage**
  - 3. **Reduced Road Safety**
- B. **Crime and Nuisance**
  - 1. **Drug-Related Crime**

- a) **Psychopharmacological Crime**
  - (1) **Aggression and Violence**
  - (2) **Sexual Assault**
- b) **Economic-Compulsive Crime**
  - (1) **Theft for Money to Buy Drugs**
  - (2) **Trading Sex for Drugs**
- c) **Systemic Crime**
  - (1) **Territorial Disputes**
  - (2) **Gun Violence**
- d) **Money Laundering and Corruption**

2. **Public Nuisance**
   - a) **Drug Market Visibility**
     - (1) **Open Air Dealing**
     - (2) **Annexation of Public Space/Lands**
   - b) **Fear of Crime**
     - (1) **Verbal Accosting**
     - (2) **Aggressive Panhandling**
   - c) **Graffiti**
   - d) **Drug Litter**
     - (1) **Used Needles**
     - (2) **Vials**

C. **Community and Environmental Harms**

1. **Community Deterioration**
   - a) **Diminished Social Cohesion and Collective Efficacy**
   - b) **Blight and Decay**
   - c) **Devalued Housing Stock**
     - (1) **House Fires and Explosions from Illicit Manufacturing**
     - (2) **Mold and Chemical Residue from Grow Operations**
     - (3) **Reduced Insurability**
2. **Environmental Degradation**
   - a) **Dumping of Hazardous Byproducts**
   - b) **Trashing and Deforestation of Public Lands**
   - c) **Watershed Diversion**
   - d) **Contamination of Public Water Systems**

APPENDIX B: INVENTORY OF DRUG DATA SYSTEMS

The following table alphabetically lists more than 120 ongoing or recent drug data systems, with information on geographic coverage, years of availability, and whether drug-specific data are collected. In general, data sources that are outdated, superseded, or one-time collections are not included here, although data systems that share a common purpose and lineage are listed together. Geographic coverage indicates whether the data are aggregated at the national, state, and/or local (e.g., county, metropolitan area, zip code) levels. Note that geographic indications are not confirmation of representativeness or completeness of coverage at a particular level of analysis. Years of availability indicates the time period for which data are available, or known to have been collected if not yet released. A plus (+) sign indicates that the data collection is ongoing or has planned future installments. Drug type information indicates whether or not drug-specific data are reported. Finally, an asterisk indicates that the data system was used to develop one or more of the DCIs.

Table B-1. Inventory of Drug Data Systems

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
Adoption and Foster Care Analysis and Reporting System*	ACF NDACAN	Collects data from state agencies on adoptive and foster care children, including caretaker or child drug abuse as reasons for removal.	National, State	1995-2010+ (fiscal years)	No
Adverse Events Reporting System	FDA	Collects surveillance reports of adverse drug events, including death, disability, and hospitalization.	National	1969-2011+	Yes (pharma-ceuticals)

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
Alcohol and Drug Services Study / Services Research Outcome Study / Drug Services Research Survey	SAMHSA	Collects data on substance abuse treatment facilities and clients, including client drug use, treatment history, and length of stay.	National	1996-1999 1995-1996 1990	Yes
Annual Parole Survey / Uniform Parole Reports	BJS	Collects data from local parole agencies on flows and counts of those under supervision, including the number of drug offenders.	National, State	1980-2010+ 1975-1979	No
Annual Probation Survey / National Probation Reports	BJS	Collects data from local probation agencies on flows and counts of those under supervision, including the number of drug offenders.	National, State	1980-2010+ 1977-1979	No
Annual Survey of Jails / Annual Survey of Jails in Indian Country / Census of Jail Facilities / Census of Jail Inmates	BJS	Family of data systems that collect administrative data from local jails, including information on alcohol/drug abuse programming.	National, State (census only)	1970-2010+ (select years)	No
Arrestee Drug Abuse Monitoring Program II / **Arrestee Drug Abuse Monitoring Program /** **Drug Use Forecasting Program**	ONDCP NIJ NIJ	Collects data on recent arrestees, including drug use (urinalysis, self-report) and drug market characteristics.	Local	2007-2010+ 1998-2003 1987-1997	Yes
Automation of Reports and Consolidated Orders System	DEA	Monitors the flow of controlled substances from manufacture through commercial distribution to final point of sale or retail dispensation.	National, State, Local	1970s-2011+	Yes (select controlled substances)
Behavior Risk Factor Surveillance System	CDC	Survey of general population that collects data on health conditions and risk behaviors, including measures of drug abuse counseling and childhood exposure to drug use (select years).	National, State	1984-2010+	No
Buprenorphine Physician and Treatment Program Locator / Opioid Treatment Program Directory	CSAT SAMHSA	Inventory of physicians/programs authorized to treat opioid addiction with pharmacotherapies.	National, State, Local	List updated regularly	Opioids, Buprenorphine
Campus Safety and Security Statistics*	OPE	Collects campus crime statistics from postsecondary institutions, including data on the number of campus drug violations and arrests.	National, State	2001-2010+	No
Cannabis Potency Monitoring Project*	NIDA	Collects and analyzes data from seized marijuana samples, including information on marijuana type (e.g., sinsemilla, hash), form (e.g., kilobricks, buds), and potency.	National, State, Local	1967-2011+	Marijuana

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
Census of Fatal Occupation Injuries	BLS	Compiles information on all U.S work-related fatal injuries, including evidence from toxicology reports.	National, State, Local	1992-2010+	Yes (toxicology reports, U.S.-level only)
Census of Juveniles in Residential Placement / Children in Custody Census	OJJDP	Collects information on youth residing in detention, correctional, and other shelter facilities, including the number housed for drug law violations.	National, State	1997-2010+ (select years) 1971-1996 (select years)	No
Census of Law Enforcement Aviation Units	BJS	Provides operational details of law enforcement agencies that fly aircraft, including participation in drug location/interdiction operations.	National	2007+	No
Census of Publicly Funded Forensic Crime Laboratories	BJS	Collects data on staff and operations of forensic labs, including controlled substances and toxicological analyses.	National	2005+	No
Census of State and Federal Adult Correctional Facilities	BJS	Provides information on the types of inmates housed, facility, staff, and programs, including alcohol/drug abuse programs.	National, State	1974-2005+ (select years)	No
Census of State and Local Law Enforcement Agencies	BJS	Provides data on state and local law enforcement agency personnel and functions, including task force participation in drug trafficking enforcement.	National, State, Local	1992-2008+ (every 4 years)	No
Census of State Court Organization	BJS	Provides detailed information on the structure and framework of state courts, including the number of state drug courts.	National, State	1980-2004+ (select years)	No
Community Epidemiology Work Group	NIDA	Collects, triangulates, and reports local drug-related data from multiple sources.	Local	1976-2011+	Yes
Core Alcohol and Drug Use Survey	Core Institute	Collects data on college student drinking, drug use, and risky behaviors.	National	1989-2009+	Yes
Domestic Cannabis Eradication and Suppression Program*	DEA	Collects data on marijuana eradication operations, including number of plants seized, plots eradicated, and weapons seized	National, State	1979-2010+	Marijuana
Drug Abuse Treatment Outcome Study / Treatment Outcome Prospective Study / Drug Abuse Reporting Program	NIDA	Series of national evaluations that collect treatment process and outcome data, including information on client attributes and program services.	Local	1991-1993 1979-1981 1969-1973	Yes

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
Drug Abuse Warning Network*	SAMHSA	Monitors drug-related hospital emergency department visits and drug-related deaths investigated by medical examiners and coroners.	National, Local	1973-2010+	Yes
Ecstasy Data Testing Project	Dancesafe Erowid MAPS	Collects ecstasy pill testing results from a variety of organizations.	National, State, Local	1996-2012+	MDMA
Fatality Analysis Reporting System*	NHTSA	Collects data on fatal vehicle crashes, including police reported drug involvement and toxicological results.	National, State	1975-2010+	Yes (toxicology reports)
Federal Justice Statistics Program	BJS	Collects data on federal arrests, prosecutions, convictions, and sentences by offense type.	National, State	1979-2009+	Yes (offense codes)
Firearms Trace Data	ATF	Collects data on federal firearm traces, including drug-related firearm traces.	National, State	2006-2010+	No
General Estimates System*	NHTSA	Compiles data from national sample of fatal and nonfatal vehicle crashes, including information on drug-related vehicle crash accidents.	National	1988-2010+	No
Health Behavior in School-Aged Children	NICHD	International survey of youth that collects data on health behavior and risks, including drug use.	National	1983-2010+ (select years, U.S. since 1997)	Yes (limited)
Healthcare Cost and Utilization Project: **Nationwide Inpatient Sample* /** **State Inpatient Databases* /** **Nationwide Emergency Department Sample /** **State Emergency Department Databases**	AHRQ	Family of databases that collect data on hospital admissions, including admissions for drug-related health consequences.	 National State National State	 1988-2009+ 1990-2010+ 2006-2009+ 1999-2010+	Yes (ICD-9-CM codes)
Heroin Signature Program / **Domestic Monitor Program**	DEA	Collects data on heroin seizures and undercover buys, including the geographic source, price, and purity.	Local	1977-2011+ 1979-2011+	Heroin
HIV Surveillance Reports*	CDC	Collects data from state health authorities on HIV/AIDS outcomes, including IDU-related AIDS diagnoses and deaths.	National, State, Local	1983-2009+	No
Inventory of Substance Abuse Treatment Services / **National Master Facility Inventory**	SAMHSA	Provides comprehensive inventory of all U.S. substance abuse treatment facilities.	National, State, Local	Updated regularly	No

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
Juvenile Court Statistics	OJJDP	Collects data on cases handled by juvenile courts, including drug law violations.	National	1985-2008+	No
Law Enforcement and Investigations Management Attainment Reporting System	Forest Service	Internal reporting system for crimes committed on Forest Service lands, including marijuana cultivation and methamphetamine lab operations.	National, GIS coordinates	2000s-2011+	Marijuana, meth-amphetamine
Law Enforcement Management and Administrative Statistics	BJS	Collects data on law enforcement agency staffing, functions, and services, including employee drug testing, drug enforcement activities, and drug education units.	National, State, Local	1987-2007+ (select years)	No
Law Enforcement Survey for Line Officers	Forest Service	Collected information on services, operations, and perceptions of Forest Service officers, including trends in marijuana cultivation and methamphetamine lab activity in national forests.	National	2006	Marijuana, meth-amphetamine
Monitoring of Federal Criminal Sentences	USSC	Collects data on federal criminal sentences, including drug offense incident characteristics.	National, State	1987-2010+	Yes
Monitoring the Future*	NIDA	Collects data from students and young adults on drug use, risks, and attitudes.	National	1975-2011+	Yes
Narcotics-Related Financial Crimes Program	IRS	Collects data on investigations, prosecutions, and sentences involving drug-related financial crimes.	National	1995-2010+	No
National Ambulatory Medical Care Survey	NCHS	Collects data from office-based physicians providing direct patient care, including treatment for drug-related health consequences.	National	1973-1981, 1985, 1989-2009+	Yes (ICD-9-CM codes)
National Child Abuse and Neglect Data System	ACF NDACAN	Collects data from participating states on children coming into contact with state child protective services or individual reporters, including contact due to caretaker or child drug abuse.	State	2000-2010+	No
National College Health Assessment	ACHA	Collects data from college students on health-related behaviors, including drug use.	National	2000-2011+	Yes
National Corrections Reporting Program	BJS	Collects administrative data on prison admissions and releases and parole entries and discharges in participating jurisdictions, including offense type information.	State	1983-2009+	Yes (offense codes)
National Crime Victimization Survey*	BJS	Collects household-based data on criminal victimization, including drug-related incidents.	National	1973-2009+	No

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
National Crime Victimization Survey: School Crime Supplement	BJS	Collects data on student experiences with crime, including the availability of drugs in school.	National	1989, 1995, 1999-2009+ (odd years)	Yes
National Criminal Justice Treatment Practices Survey	NIDA	Collected data from public safety agencies, treatment and corrections administrators and line staff on substance abuse treatment practices for offenders.	National	2002/08	No
National Drug Threat Survey*	NDIC	Collects data from local law enforcement agencies on drug availability, drug threats, gang involvement in drug distribution, and illicit manufacturing and production in community.	National, State	2003-2011	Yes
National Epidemiologic Survey on Alcohol and Related Conditions	NIAAA	Collects general population data on alcohol use disorders and associated disabilities, including information on drug use and dependence.	National	2001/02, 2004/05	Yes
National Forensic Laboratory Information System	DEA	Collects data from forensic labs on the analysis of drugs seized by law enforcement agencies.	National, State, Local	1997-2011+	Yes
National Health and Nutrition Exam Survey III	NCHS	Collects national data on the health status of individuals, including information on drug use, age of onset, frequency of use, and IV drug use.	National, State	1999-2010+	Yes
National Hospital Care Survey / National Hospital Ambulatory Medical Care Survey / National Hospital Discharge Survey	NCHS	Collects data on health care delivery in hospital-based settings and freestanding ambulatory surgery centers, including information drug-related health consequences. Combines the two surveys from earlier years.	National	2011+ 1992-2010 1965-2010	Yes (ICD-9-CM codes)
National Incident-Based Reporting System	FBI	Collects data from participating jurisdictions on crimes known to police, including drug crime characteristics.	State, Local	1991-2009+	Yes
National Incidence Study of Child Abuse and Neglect	ACF	Collects data from community professionals on incidents of child maltreatment, including caretaker/child drug use and drug-affected newborns.	National	1979/80, 1986/87, 1993, 2005/6	No
National Judicial Reporting Program	BJS	Collects felony sentencing data from national sample of state courts, including information on conviction offense and the type and length of sentence.	National	1986-2006+ (biennially)	Yes (limited)

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
National Longitudinal Survey of Youth 1997 / National Longitudinal Survey of Youth 1979 / NLSY79 Children and Young Adult Surveys	BLS	Collect data on labor market activities and other significant life events from panel of respondents, including information on drug use, age of onset, use at work/school, use during pregnancy, and drug selling involvement.	National, State, Local (with geocode supplement)	1997-2008+ 1979-2008+ 1988-2006+	Yes (limited for NLSY97)
National Motor Vehicle Crash Causation Survey	NHTSA	Collects data on events and factors leading up to vehicle crashes, including measures on police reported drug involvement, recent medication use, and drugs taken.	National	2005/07+	Yes
National Poison Data System* / Toxic Exposure Surveillance System	AAPCC	Data system contains information and human poison exposure case phone calls into all U.S. poison centers. Data also contain fatality abstracts from human exposure events.	National, State, Local	1983-2010+	Yes
National Pregnancy and Health Survey	NIDA	Collected national data on nature and extent of substance abuse among pregnant women in U.S., including self-report and urinalysis of drug use.	Coterminous U.S.	1992	Yes
National Roadside Survey	NHSTA	Collects data from drivers on alcohol- and drug-involved driving, including self-reports of the type and recency of drug use and drug testing results (2007 survey).	Coterminous U.S.	1973, 1986, 1996, 2007	Yes
National Seizure System* / Federal-Wide Drug Seizure System / Clandestine Laboratory Seizure System	DEA EPIC	Compiles data from various law enforcement agencies on drug seizures, trafficking routes, and children affected by labs.	National, State	1970s-2011+	Yes
National Survey of American Attitudes on Substance Abuse	CASA	Collects data from teenagers and parents on the use, availability, and risks of drugs.	National	1995-2011+	Yes (limited)
National Survey of Homeless Assistance Providers and Clients	HUD	Collected data from homeless clients and service providers, including information on drug use, onset, addiction severity, consequences, and treatment history.	National	1996	Yes
National Survey of Meth Markets	NIDA	Collected data from law enforcement agencies on the characteristics of the methamphetamine market, including public health and safety risks.	National	2008	Meth-amphetamine

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
National Survey of Parents and Youth	NIDA	Collected data from national sample of youth (9-18) and their parents concerning youth drug use, perceptions of use, availability, parent-child communication, antidrug media awareness, and drug prevention activities.	National	1998-2004	Yes (limited)
National Survey of Substance Abuse Treatment Services / **Uniform Facility Data Set /** **National Drug and Alcoholism Treatment Unit Survey /** **National Alcoholism and Drug Abuse Program Inventory /** **National Drug and Alcoholism Treatment Utilization Survey /** **National Drug Abuse Treatment Utilization Survey**	SAMHSA NIAAA	Census of substance abuse treatment facilities, providing data on location, organization, structure, services, and utilization, including measures on the type of pharmacotherapy and detox services provided.	National, State	2000-2010+ 1995-1998 1987-1993 (excl. ’88) 1984 1979-1982 (excl. ’81) 1976-1978	Yes (for detox and pharmaco-therapies)
National Survey of Workplace Health and Safety	NIAAA	Collected data from nation sample of employed individuals (18-65), including information on workplace substance use norms and employee substance use.	Coterminous U.S.	2002/03	Yes
National Survey of Youth in Custody	BJS	Collected data from youth in juvenile facilities as part of the BJS National Prison Rape Statistics Program. About 10% of the sample received an alternative survey on substance use and treatment.	National	2008/09+	Yes
National Survey on Drug Use and Health* (formerly National Household Survey on Drug Abuse)	SAMHSA	Collects data from U.S. population 12 and older on drug use, onset, consequences, and treatment.	National, State (since 1999)	1971-2010+ (select years, annual since 1990)	Yes
National Toxic Substance Incidents Program / **Hazardous Substances Emergency Events Surveillance**	ATSDR	Collects data on spills and leaks of toxic substances from participating states, including information on incidents related to illicit drug production.	National (under development), State	2010+ 1990-2009	Meth-amphetamine
National Vital Statistics System—Mortality Data*	NCHS	Compiles data from death certificates filed by the states with the National Vital Statistics System, including information on drug-related causes of death.	National, State	1968-2008+	Yes (ICD-10 codes for 1999 and later)

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
National Youth Survey Family Study / National Youth Survey	HHS NIJ	Collects information from sample of youth on life events, including information on drug use and consequences.	National	2000-2006 1976-1993	Yes
Online Tuberculosis Information System*	CDC	Collects information on TB cases reported to CDC from state and local health departments, including information on drug use (injection and noninjection).	National, State	1987-2009+	No
Partnership Attitude Tracking Study	PDFA	Collects information from students (grades 7-12) and parents on drug use and associated risks and attitudes, parent-child communication, antidrug media awareness, and drug prevention activities.	National	1993-2010+	Yes
Pregnancy Risk Assessment Monitoring System	CDC	Collects data from women in participating states who recently gave birth, including information on stressors (someone close has a drinking/drug problem) and healthcare provider interventions (discussing drug use fetal health).	State	1988-2009+	No
Pride Surveys	ISA	Collects data from students (grades 4-12), parents, and teachers on drug use, onset, risks, perceptions, availability, and prevention messages.	National, State, Local	1982-2010+	Yes
Quest Diagnostics Drug Testing Index*	Quest Diagnostics	Collects and reports data on positivity rates from workplace drug testing.	National, State, Local	1988-2011+	Yes
School Survey on Crime and Safety	OSDFS	Collects crime and safety data from public elementary and secondary schools, including information in the use of drug-sniffing dogs, student drug testing, drug-free school initiatives, drug education, and drug-related incidents and disciplinary actions.	National	2000, 2004-2010+ (even years)	No
State Court Processing Statistics / National Pretrial Reporting Program	BJS	Collects data from sample of state court felony cases, including information on pretrial drug monitoring, drug court participation, and offense type.	National	1996-2006+ 1988-1994	No
Survey of Adults on Probation	BJS	Collected data from probationers, including information on drug use, treatment history, supervision conditions (drug testing, drug treatment), current offense, and criminal history.	National	1995	Yes

Data System	Sponsor	Description	Geographic Coverage	Years of Availability	Drug Type Information
Survey of Inmates in Federal and State Correctional Facilities	BJS	Collets data from state and federal (since 1991) inmates, including information on drug use, treatment history, drug offense incident characteristics, and criminal history.	National	1974, 1979, 1986, 1991, 1997, 2004+	Yes
Survey of Inmates in Local Jails	BJS	Collects data from jail inmates, including information on drug use, treatment history, current offense, and criminal history.	National	1978, 1983, 1989, 1996, 2002+	Yes
System to Retrieve Information from Drug Evidence	DEA	Compiles administrative and investigative data on drug purchases and seizures made by federal, state, and local agencies, including information on drug price, purity, and quantity.	National, State, Local	1971-2011+	Yes
Theft or Loss of Controlled Substances	DEA	Collects data from surveillance program of incident characteristics and drug information following the theft or loss of controlled substances.	National, State, Local	1970s-2011+	Yes (prescription drugs)
Treatment Episodes Data Set* / Client-Oriented Data Acquisition Process	SAMHSA	Collects data on substance abuse treatment admissions and client characteristics from publically funded treatment programs.	National, State	1992-2011+ 1973-1981	Yes
Uniform Crime Reports	FBI	Compiles data from local law enforcement agencies on the volume and rate of criminal offenses, including information on the type of drug involved in arrest.	National, State, Local	1960-2011+	Yes (limited)
Uniform Crime Reports—Supplementary Homicide Report*	FBI	Collects data from local law enforcement agencies on homicide cases, including whether the homicide was drug-related.	National, State	1980-2011+	No
Worldwide Survey of Substance Abuse and Health Behaviors Among Military Personnel	DOD	Collects data from military personnel on substance use and health, including information on the nature, extent, and consequences of drug use and abuse.	National	1980, 1982, 1988, 1992, 1995, 1998, 2002, 2005, 2008+	Yes
Youth Risk Behavior Survey*	CDC	Collects data from students on health-risk behaviors, including information on drug use and offerings of drugs on school property.	National, State, Local	1991-2011+ (odd years)	Yes

APPENDIX C: INDICATOR DEFINITIONS, SOURCES, AND MEASUREMENT

This appendix defines and operationalizes the indicators used in the National and State DCIs, and provides source information. Unless otherwise indicated, rates are events per 100,000 people in the general population.[11] Where applicable, missing data methods used to address item nonresponse are discussed. Indicator missingness for entire states and/or years is also noted, although missing data methods used to address this type of unit nonresponse are discussed in Appendix D of this report.

NATIONAL DRUG CONSEQUENCES INDEX

The 30 indicators used to construct the National Index are described below; they are numbered [d1] to [d30] for easy reference.

[d1] Drug-related deaths per 100,000

Definition: Measures the number of U.S. resident deaths in which drug poisoning or a drug-related mental or behavioral disorder was listed as a contributing cause of death.

Source: Multiple Cause of Death data for 1999-2009, CDC WONDER Online Database, National Center for Health Statistics, Centers for Disease Control and Prevention.

Notes: Drug-related deaths include any mention of the following *International Classification of Diseases, Version 10* (ICD-10) diagnostic codes: F11.0-F11.9 (Mental and behavioral disorders due to use of opioids), F12.0-F12.9 (Mental and behavioral disorders due to

[11] Population data are drawn from U.S. Census Bureau, Population Division (September 2011), Intercensal Estimates of Resident Population by Five-Year Age Groups, Sex, Race and Hispanic Origin for States and the United States: April 1, 2000 to July 1, 2010 (ST-EST00INT-ALLDATA).

use of cannabinoids), F13.0-F13.9 (Mental and behavioral disorders due to use of sedatives or hypnotics), F14.0-F14.9 (Mental and behavioral disorders due to use of cocaine), F15.0-F15.9 (Mental and behavioral disorders due to use of other stimulants), F16.0-F16.9 (Mental and behavioral disorders due to use of hallucinogens), F18.0-F18.9 (Mental and behavioral disorders due to use of volatile solvents), F19.0-F19.9 (Mental and behavioral disorders due to multiple drug use and use of other psychoactive substances), R78.1 (Finding of opiate drug in blood), R78.2 (Finding of cocaine in blood), R78.3 (Finding of hallucinogen in blood), R78.4 (Finding of other drugs of addictive potential in blood), T40.0 (Opium poisoning), T40.1 (Heroin poisoning), T40.2 (Other opioids poisoning), T40.3 (Methadone poisoning), T40.4 (Other synthetic narcotics poisoning), T40.5 (Cocaine poisoning), T40.6 (Other and unspecified narcotics poisoning), T40.7 (Cannabis poisoning), T40.8 (Lysergide [LSD] poisoning), T40.9 (Other and unspecified psychodysleptics [hallucinogens] poisoning), T42.3 (Barbiturates poisoning), T42.4 (Benzodiazepines poisoning), and T43.6 (Psychostimulants with abuse potential poisoning).

[d2] IDU-related AIDS deaths per 100,000

Definition: Measures the estimated number of all-cause deaths of persons with AIDS in which injection drug use was a risk factor for HIV transmission.

Source: *HIV Surveillance Reports, 2004-2010* (Annual), Division of HIV/AIDS Prevention, National Center for HIV/AIDS, Viral Hepatitis, STD, and TB Prevention, Centers for Disease Control and Prevention.

Notes: Because data for previous years is updated with each newly released report, the most current estimates were extracted from the following reports and tables: Vol. 16 (2005)

Table 7 for 2000; Vol. 17 (2007 Revised) Table 7 for 2001, Vol. 18 (2008) Table 7 for 2002; Vol. 19 (2009) Table 8 for 2003-2004; Vol. 20 (2010) Table 12a for 2005; Vol. 21 (2011) Table 12a for 2006. Vol. 22 (2012) Table 12a for 2007-2009. CDC's estimates statistically adjust for missing risk-factor information and jurisdiction reporting delays.

[d3] Drug exposure poison center cases per 100,000

Definition: Measures the number of human exposure cases called into poison control centers involving 'stimulant and street drugs.'

Source: *2000-2009 Annual Report of the American Association of Poison Control Centers' National Poison Data System (NPDS)*, Table 22B, (Annual), American Association of Poison Control Centers.

Notes: 'Stimulant and street drugs' is an AAPCC general reporting category that includes marijuana, cocaine, heroin, methamphetamine, GHB, MDMA, LSD, mescaline/peyote, PCP, and other illicit drugs. NPDS was formerly called the Toxic Exposure Surveillance System (TESS).

[d4] Drug-related emergency department visits per 100,000

Definition: Measures the number of hospital emergency department visits involving any mention of illicit drugs.

Source: *Drug Abuse Warning Network, 2009: Selected Tables of National Estimates of Drug-Related Emergency Department Visits*. (2010). Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration.

Notes: Data coverage includes only years 2004-2009, as prior years are not directly comparable due to DAWN's 2003 redesign.

[d5] Inpatient hospital drug poisoning discharges per 100,000

Definition: Measures the number of inpatient hospital discharges with a principal diagnosis of drug poisoning.

Source: HCUPnet, Healthcare Cost and Utilization Project, Nationwide Inpatient Sample, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 965.00-965.09 (Poisoning by opiates and related narcotics), 967.0-967.9 (Poisoning by sedatives and hypnotics), 968.0-968.9 (Poisoning by other central nervous system depressants and anesthetics), 969.0-969.9 (Poisoning by psychotropic agents), 970.0-970.9 (Poisoning by central nervous system stimulants), E850 (Accidental poisoning by analgesics, antipyretics, and antirheumatics), E851 (Accidental poisoning by barbiturates), E852 (Accidental poisoning by other sedatives and hypnotics), E853 (Accidental poisoning by tranquilizers), E854 (Accidental poisoning by other psychotropic agents), and E855 (Accidental poisoning by other drugs acting on central and autonomic nervous system). [12]

[d6] Inpatient hospital drug use disorder discharges per 100,000

Definition: Measures the number of inpatient hospital discharges with a principal drug-related psychosis, dependence, or abuse diagnosis.

Source: HCUPnet, Healthcare Cost and Utilization Project, Nationwide Inpatient Sample, Agency for Healthcare Research and Quality.

[12] For indicators [d5] and [d6], data were obtained from http://hcupnet.ahrq.gov/ using the following operational sequence: National Statistics on All Stays → Researcher, medical professional → Trends → Specific diagnoses by ICD-9-CM → Principal diagnosis → [Enter codes] → All codes combined → Next.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 292.0-292.9 (Drug-induced mental disorders), 304.0 (Opioid type dependence), 304.1 (Sedative, hypnotic or anxiolytic dependence), 304.2 (Cocaine dependence), 304.3 (Cannabis dependence), 304.4 (Amphetamine and other psychostimulant dependence), 304.5 (Hallucinogen dependence), 304.6 (Other specified drug dependence), 304.7 (Combinations of opioid type drug with any other), 304.8 (Combinations of drug dependence excluding opioid type drug), 304.9 (Unspecified drug dependence), 305.2 (Cannabis abuse), 305.3 (Hallucinogen abuse), 305.4 (Sedative, hypnotic or anxiolytic abuse), 305.5 (Opioid abuse), 305.6 (Cocaine abuse), 305.70 (Amphetamine or related acting sympathomimetic abuse), 305.8 (Antidepressant type abuse), 305.9 (Other, mixed, or unspecified drug abuse).

[d7] Drug treatment admissions per 100,000

Definition: Measures the number of admissions to publicly funded treatment programs for a primary illicit drug use disorder.

Source: *Treatment Episode Data Set (TEDS), 1999-2009: National Admissions to Substance Abuse Treatment Services*, Table 1.2. (2011). DASIS Series: S-56, HHS Publication No. (SMA) 11-4646, Rockville, MD: Substance Abuse and Mental Health Services Administration.

[d8] Prevalence (%) of drug dependence or abuse among persons aged 12+

Definition: Measures the percentage of individuals aged 12 and older who met DSM-IV criteria for past-year illicit drug dependence or abuse.

Source: *Results from the 2010 National Survey on Drug Use and Health: Detailed Tables*, Table 7.40B. (2011). Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration.

Notes: Data coverage includes 2002-2009, as methodological changes in the NSDUH design affect comparability with earlier years.

[d9] IDU-related AIDS diagnoses per 100,000

Definition: Measures the estimated number of annual AIDS diagnoses in which injection drug use was a risk factor for HIV transmission.

Source: *HIV Surveillance Reports, 2004-2010* (Annual), Division of HIV/AIDS Prevention, National Center for HIV/AIDS, Viral Hepatitis, STD, and TB Prevention, Centers for Disease Control and Prevention.

Notes: Because data for previous years is updated with each release, the most current estimates were extracted from the annual reports and tables as follows: Vol. 16 (2005) Table 3 for 2000; Vol. 17 (2007 Revised) Table 3 for 2001, Vol. 18 (2008) Table 3 for 2002; Vol. 19 (2009) Table 4 for 2003-2004; Vol. 20 (2010) Table 2a for 2005; Vol. 21 (2011) Table 2a for 2006; Vol. 22 (2012) Table 2a for 2007-2009.

[d10] Prevalence (%) of injection drug use among TB patients

Definition: Measures the percentage of verified tuberculosis (TB) patients aged 15 and older who reported illegal injection drug use within 12 months of their diagnosis.

Source: Online Tuberculosis Information System, National Tuberculosis Surveillance System, United States, 1993-2009. (April 2011). CDC WONDER Online Database, Centers for Disease Control and Prevention.

Notes: Prevalence calculations were based on valid (i.e., nonmissing) data.

[d11] Prevalence (%) of noninjection drug use among TB patients

Definition: Measures the percentage of verified tuberculosis (TB) patients aged 15 and older who reported illegal noninjection drug use within 12 months of their diagnosis.

Source: Online Tuberculosis Information System, National Tuberculosis Surveillance System, United States, 1993-2009. (April 2011). CDC WONDER Online Database, Centers for Disease Control and Prevention.

Notes: Prevalence calculations were based on valid (i.e., nonmissing) data.

[d12] Prevalence (%) of illicit drug use among pregnant women aged 15-44

Definition: Measures the percentage of pregnant women aged 15-44 who reported past-month illicit drug use.

Source: *Results from the 2002-2009 National Survey on Drug Use and Health: Summary of National Findings*. (Annual 2003-2010). Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration.

Notes: Data coverage includes 2002-2009, as methodological changes in the NSDUH design affect comparability with earlier years.

[d13] Inpatient hospital discharges for drugs affecting baby per 100,000 women aged 15-44

Definition: Measures the number of inpatient hospital discharges among women aged 15-44 with a principal diagnosis of drug-related harm to a fetus or newborn.

Source: HCUPnet, Healthcare Cost and Utilization Project, Nationwide Inpatient Sample, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 648.3 (Drug dependence complicating pregnancy), 655.5 (Suspected damage to fetus from drugs), 760.72 (Narcotic affecting fetus or newborn via placenta or breast milk), 760.73 (Hallucinogen affecting fetus or newborn via placenta or breast milk), 760.75 (Cocaine affecting fetus or newborn via placenta or breast milk), 779.5 (Drug withdrawal syndrome in newborn).

[d14] Percentage of women aged 15-44 who were pregnant upon entering drug treatment

Definition: Measures the percentage of women aged 15-44 who were pregnant upon admission to publicly funded treatment for a primary illicit drug use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Calculations are based on pregnancy data that was overall 90-96% complete for females in reporting states during 2000-2009.

[d15] Percentage of foster care placements precipitated by child drug abuse

Definition: Measures the percentage of children in foster care in which child drug abuse (including addiction at birth) was reported as a contributing factor for the child's out-of-home placement.

Source: Adoption and Foster Care Analysis and Reporting System, Foster Care Files, 2000-2009 [computer files]. Children's Bureau, Administration on Children, Youth and Families. Ithaca, NY: National Data Archive on Child Abuse and Neglect [distributor]. [13]

Notes: The datasets are reported by federal fiscal year ending September 30th. Estimates are based on states with at least 75% reporting on this item, which excluded the following state-years from the calculations: Alaska (2000-2004), Maryland (2007), New York (2000-2009).

[d16] Percentage of foster care placements precipitated by caretaker drug abuse

Definition: Measures the percentage of children in foster care in which caretaker drug abuse was reported as a contributing factor for the child's out-of-home placement.

Source: Adoption and Foster Care Analysis and Reporting System, Foster Care Files, 2000-2009 [computer files]. Children's Bureau, Administration on Children, Youth and Families. Ithaca, NY: National Data Archive on Child Abuse and Neglect [distributor].

Notes: The datasets are reported by federal fiscal year ending September 30th. Estimates are based on states with at least 75% reporting on this item, which excluded the following state-years from the calculations: Alaska (2000-2004), Maryland (2007), New York (2000-2009).

[13] AFCARS data used to create indicators [d15] and [d16] used in this report were made available by the National Data Archive on Child Abuse and Neglect, Cornell University, Ithaca, NY; and have been used by permission. Data from the 2000-2009 AFCARS Foster Care data sets (Nos. 97, 101, 105, 118, 124, 131, 137, 143, 149, and 153) were originally collected by the Children's Bureau, U.S> Department of Health and Human Services. Neither the collector of the original data, the funder, the Archive, Cornell University, or its agents or employees bear any responsibility for the analyses or interpretations presented here.

[d17] Children affected by illicit drug labs per 100,000

Definition: Measures the number of children affected, injured, or killed by a clandestine drug laboratory.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the National Seizure System, El Paso Intelligence Center, Drug Enforcement Administration.

[d18] Percentage of people who were unemployed upon entering drug treatment

Definition: Measures the percentage of people who were unemployed upon admission to publicly funded treatment for a primary illicit drug use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Estimates are based on employment data that was overall 95-99% complete across all reporting states during 2000-2009.

[d19] Drug positivity rate among the U.S. workforce

Definition: Measures the proportion of positive drug test results relative to all drug tests performed among the combined U.S. workforce, which includes the general workforce and federally mandated, safety-sensitive workers.

Source: Quest Diagnostics Drug Testing Index, Table 1. (September 2, 2011). Online: http://www.questdiagnostics.com/dms/Documents/DTI-Reports/2011-09-02_DTI.pdf.

[d20] Prevalence (%) of past-year illicit drug use among secondary school students

Definition: Measures the annual prevalence of illicit drug use among students in grades 8, 10, and 12 combined.

Source: Johnston, L. D., O'Malley, P. M., Bachman, J. G., and Schulenberg, J. E. (2011). *Monitoring the Future National Survey Results on Drug Use, 1975–2010: Volume I, Secondary School Students*, Table F-2. Ann Arbor: Institute for Social Research, The University of Michigan.

[d21] On-campus drug violations per 1,000 enrolled college students

Definition: Measures the combined number of arrests and disciplinary infractions for drug-related violations committed on school property or in areas under school jurisdiction.

Source: Campus Safety and Security Statistics, Data Analysis Cutting Tool, Office of Postsecondary Education. Online: http://ope.ed.gov/security/.

Notes: Campus Safety and Security Statistics (CSSS) began collecting crime data in 2001. Denominator data on fall enrollment at degree-granting institutions was obtained from the Integrated Postsecondary Education Data System (IPEDS), National Center for Education Statistics, U.S. Department of Education.

[d22] Percentage of high school students offered drugs on school grounds

Definition: Measures the percentage of high school students who reported being offered, sold, or given an illegal drug by someone on school property within the past year.

Source: *2001-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline.

Notes: Data are collected biennially in odd numbered years.

[d23] Percentage of people who were homeless upon entering drug treatment

Definition: Measures the percentage of people who were homeless upon admission to publicly funded treatment for a primary illicit drug use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Estimates are based on living arrangement data that was 68-95% complete across all reporting states during 2000-2009.

[d24] Lifetime prevalence of drug injection among high school students

Definition: Measures the percentage of high school students who reported ever using a needle to inject an illegal drug into their bodies.

Source: *1991-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline.

Notes: Data are collected biennially in odd numbered years.

[d25] Positive drug-tested drivers involved in fatal vehicle accidents per 100,000

Definition: Measures the estimated number of drivers involved in fatal vehicle crashes who tested positive for illicit drugs (i.e., cannabinoids, heroin/opiates, cocaine, or amphetamines) or for whom there was police-reported drug involvement.

Source: 2000-2009 Analytic Files, Fatality Analysis Reporting System, National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

Notes: Because of high rates of missing data on drug-related variables, multiple imputation was used to estimate missing driver-level crash data. The imputation model used is analogous to NHTSA's multiple imputation procedures for alcohol-related variables (Heitjan and Little, 1991; Rubin, Schafer, and Subramanian, 1998; Subramanian, 2002). First, the FARS accident, vehicle, and person level datafiles were merged; the merged file was then restricted to drivers to make a driver-level dataset (FARS also collects person-level information on passengers and pedestrians). Key variables were operationalized in the merged dataset, [14] and multiple imputation was then performed using Stata 11 to create ten imputed datasets. [15] Finally, the number of drugged drivers involved in fatal vehicle accidents—defined as drivers who tested positive for cannabinoids, heroin/opiates, cocaine, or amphetamines, or for whom there was police-reported drug involvement—was estimated from the ten imputed datasets using Rubin's rules for combining estimates (Royston, Carlin, and White, 2009).

[14] Variables included age, gender, restraint use (yes, no), driver fatality (yes, no), valid license (yes, no), nighttime (yes, no), weekend (yes, no), setting (rural, urban), roadway (on, off), prior moving violations (none, one, multiple), vehicle role (non-collision, struck, striking), vehicle class (passenger car, light truck/van, motorcycle, other), cannabis positive (yes, no), heroin/opiate positive (yes, no), cocaine positive (yes, no), amphetamine positive (yes, no), police-reported drug involvement (yes, no), police-reported alcohol involvement (yes, no), alcohol BAC, NHTSA region, and mandatory testing state (yes, no). The latter variable was constructed based on states that "permit the forced taking of a specimen for a chemical test over the objection of a driver" (Walsh, 2009:5).

The FARS drug codes used to construct the drug testing variables were as follows: marijuana (600/695), heroin/opiates (101/104 106/110 115 117/123 126 127 129/135 137/141 143 145 146 148/150 153 154 156 158 160/162 168/171 174/178 180/186 190 195 196 199/202 204/207 210 213 215/217 220 221 223 225 230 231 236/238), cocaine (402 407 410 430), and amphetamines (401 417).

[15] The Stata imputation command was as follows: `mi ice aged male restrnt fatal lstat tod weekend area roadway o.nviol m.vehrole m.class marpos herpos cocpos mthpos druginv alcinv alcbac i.region forcspec, add(10) seed(2011) match(aged alcbac) cycles(10)`.

[d26] Positive drug-tested drivers involved in police-reported crashes per 100,000

Definition: Measures the number of drivers with police-reported drug involvement who were involved in a vehicle accident resulting in fatality, injury, or property damage.

Source: 2000-2009 Analytic Files, General Estimates System, National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

Notes: GES collects accident data from a nationally representative sample of police-reported motor vehicle crashes resulting in fatality, injury, or property damage. Because of high rates of missing data on drug-related variables, multiple imputation was used to estimate missing driver-level crash data. A similar multiple imputation procedure that used for FARS was also employed for GES [16] (see [d25]). However, there were some key differences. First, since GES is based on a probability sample, the sampling design was accounted for in the imputation and estimation procedure. Second, policy variables were not included because there are no state identifiers in the GES. Third, drug testing results were not used since GES only began collecting this information in 2009.

[d27] Prevalence of self-reported drugged driving among persons aged 16+

Definition: Measures the percentage of individuals aged 16 and older who reported driving under the influence of illicit drugs in the past year.

[16] The GES imputation model included variables for age, gender, restraint use (yes, no), serious driver injury (yes, no), valid license (yes, no), nighttime (yes, no), weekend (yes, no), roadway (on, off), vehicle role (non-collision, struck, striking), speed factor (yes, no), hazardous road conditions (yes, no), vehicle class (passenger car, light truck/van, motorcycle, other), police-reported drug involvement (yes, no), police-reported alcohol involvement (yes, no), and Census region. The Stata imputation command was `mi ice aged male restrnt incap tod weekend roadway m.vehrole speeder hazard m.class druginv alcinv i.region [pw=weight], add(5) seed(2011) match(aged) cycles(10)`.

Source: NSDUH special tables as published in *National Drug Control Strategy: Data Supplement 2011*, Table 52. (2011). Washington, DC: Executive Office of the President. Based on special tabulation of National Survey on Drug Use and Health data.

Notes: Data coverage includes 2002-2009, as methodological changes in the NSDUH design affect comparability with earlier years.

[d28] Drug-related violent victimizations per 100,000

Definition: Measures the number of successful and attempted violent victimizations involving rape, robbery, or assault in which the victim perceived the offender to be under the influence of drugs.

Source: *Criminal Victimization in the United States, 2000-2008 Statistical Tables*, Tables 26 and 32. (Annual 2002-2010). Washington, DC: Bureau of Justice Statistics, Office of Justice Programs.

Notes: The number of drug-related victimizations was estimated by multiplying the number of crimes of violence (from Table 28) with the percentage of violent crimes in which the victim perceived the offender to be under the influence of drugs (whether alone or in combination with alcohol) (from Table 32). Year 2006 estimates are not used due to concerns over comparability with other years (see Rand, 2008), and year 2009 estimates were not available at the time of publication.

[d29] Drug-related murders per 100,000

Definition: Measures the number of murders in which either drug distribution or drug intoxication was a contributing factor in the homicide.

Source: *Crime in the United States, 2004-2009*. (Annual 2005-2010). Washington, DC: Federal Bureau of Investigation.

Notes: The number of drug-related murders is derived from *CUIS* expanded homicide tables indicating whether investigators determined that drug distribution (i.e., 'narcotic drug laws') or drug intoxication (i.e., 'brawl due to influence of narcotics.') was a primary contributing factor in the murder.

[d30] Illicit drug production incidents per 100,000

Definition: Measures the total number of methamphetamine labs and marijuana grow operations seized by law enforcement.

Sources: *National Drug Control Strategy: Data Supplement 2011*, Table 88. (2011). Washington, DC: Executive Office of the President. Based on data extract from the National Seizure System, El Paso Intelligence Center, Drug Enforcement Administration; *Sourcebook of Criminal Justice Statistics* [Online], Table 4.39 for year 2000, Table 4.38 for years 2001-2009, Bureau of Justice Statistics, based on data collected from the Domestic Cannabis Eradication/Suppression Program, Drug Enforcement Administration.

Notes: Illicit drug production incidents include (i) methamphetamine laboratory, chemical/glassware/equipment, and dumpsite seizures and (ii) eradicated outdoor marijuana plots and seizures of indoor marijuana grows. In 2007, the DEA began including outdoor marijuana seizures made on public lands, which may affect comparability with earlier years.

STATE DRUG CONSEQUENCES INDICES

Heroin Index

[h1] Heroin/opiate-related deaths per 100,000

Definition: Measures the number of U.S. resident deaths in which heroin/opiate poisoning or a heroin/opiate-related mental or behavioral disorder was listed as a contributing cause of death.

Source: Multiple Cause of Death data for 1999-2009, CDC WONDER Online Database, National Center for Health Statistics, Centers for Disease Control and Prevention.

Notes: Heroin/opiate-related deaths include any mention of the following *International Classification of Diseases*, *Version 10* (ICD-10) diagnostic codes: F11.0-F11.9 (Mental and behavioral disorders due to use of opioids), R78.1 (Finding of opiate drug in blood), T40.0 (Opium poisoning), T40.1 (Heroin poisoning), T40.2 (Other opioids poisoning), T40.3 (Methadone poisoning), T40.4 (Other synthetic narcotics poisoning), and T40.6 (Other and unspecified narcotics poisoning). Note that as of May 23, 2011, subnational data representing 0-9 deaths are suppressed in CDC WONDER; state-year data points in that range that we used in developing the indices were retrieved prior to that date.

[h2] Primary heroin treatment admissions per 100,000

Definition: Measures the number of admissions to publicly funded substance abuse treatment programs for a primary heroin use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health

Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: For each reporting state in a given year, the counts for cases with unreported primary substance of abuse were proportionately reallocated according to the distribution of cases with validly reported data on substance type (including alcohol and other drugs). [17]

[h3] Inpatient hospital diagnoses for heroin poisoning per 100,000

Definition: Measures the number of all-listed inpatient hospital diagnoses for heroin poisoning.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 965.01 (Poisoning by heroin) and E850.0 (Accidental poisoning by heroin). [18]

[h4] Inpatient hospital diagnoses for heroin/opiate use disorders per 100,000

Definition: Measures the number of all-listed inpatient hospital diagnoses for heroin abuse or dependence.

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[17] This assumes that the primary substance of abuse for missing and nonmissing cases are similar. Multiple imputation was initially explored to handle this pattern of item nonresponse; however, with nearly 2 million cases annually, TEDS datafiles were simply too large to support this type of estimation procedure.

[18] For indicators [h3], [h4], [h6], [a3], [a4], [c3], [c4], [c6], and [m2], data were obtained from http://hcupnet.ahrq.gov/ using the following operational sequence: State Statistics on All Stays → Researcher, medical professional → Trends → [Select state] → Specific diagnoses by ICD-9-CM → All-listed Diagnoses → [Enter codes] → All codes combined → Next. As of 2009, 44 states participated in SID; however, only 35 states made their data freely available through HCUPnet (up from 15 in 2000). HCUPNet data were suppressed for confidentiality when state-year values were based on 10 or fewer discharges or fewer than 2 hospitals.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases*, *Version 9*, *Clinical Modification* (ICD-9-CM) diagnostic codes: 304.00-304.03 (Opioid type dependence), 304.70-304.73 (Combinations of opioid type drug with any other), and 305.50-305.53 (Opioid abuse).

[h5] Prevalence (%) of heroin abuse and pregnancy among females entering treatment

Definition: Measures the percentage of women who were both primary heroin abusers and pregnant upon admission to publicly funded substance abuse treatment programs.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or pregnancy status.

[h6] Inpatient hospital diagnoses for narcotic affecting fetus or newborn per 100,000 females aged 15-44

Definition: Measures the number of all-listed inpatient hospital diagnoses among women aged 15-44 for narcotics affecting a fetus or newborn.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 760.72 (Narcotics affecting fetus or newborn via placenta or breast milk).

[h7] Prevalence (%) of heroin abuse and unemployment among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary heroin abusers and unemployed.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or employment status.

[h8] Opiate positivity rate among the general U.S. workforce

Definition: Measures the proportion of positive opiate test results relative to all such tests performed among the combined U.S. workforce, which includes the general workforce and federally mandated, safety-sensitive workers.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the Quest Diagnostics Drug Testing Index.

[h9] Prevalence (%) of lifetime heroin use among high school students

Definition: Measures the percentage of high school students who reported ever using heroin one or more times in their life.

Source: *2001-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline. Unweighted estimated for certain states in 2001 and 2003 were obtained from the *Morbidity and Mortality Weekly Report* (June 28, 2002, Vol. 51, No. SS-4; May 21, 2004, Vol. 53, No. SS-2).

Notes: Data are collected biennially in odd numbered years. State participation increased from 37 (22 weighted) in 2001 to 47 (42 weighted) in 2009. Weighted results mean that the overall response rate was at least 60%.

[h10] Prevalence (%) of heroin abuse and homelessness among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary heroin abusers and homeless.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or living arrangements.

[h11] Heroin/opiate positivity rate among drivers involved in fatal accidents

Definition: Measures the estimated number of drivers involved in fatal vehicle crashes who tested positive for heroin/opiates.

Source: 2000-2009 Analytic Files, Fatality Analysis Reporting System, National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

Notes: Because of high rates of missing data on drug-related variables, multiple imputation was used to estimate missing driver-level crash data. See [d25] for further details.

[h12] Percentage of police agencies reporting heroin contributes most to violent crime

Definition: Measures the percentage of police agencies in a state reporting that heroin is the drug that most contributes to violent crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[h13] Percentage of police agencies reporting heroin contributes most to property crime

Definition: Measures the percentage of police agencies in a state reporting that heroin is the drug that most contributes to property crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

Methamphetamine Index

[a1] Stimulant-related deaths per 100,000

Definition: Measures the number of U.S. resident deaths in which stimulant poisoning or a stimulant-related mental or behavioral disorder was listed as a contributing cause of death.

Source: Multiple Cause of Death data for 1999-2009, CDC WONDER Online Database, National Center for Health Statistics, Centers for Disease Control and Prevention.

Notes: Stimulant-related deaths include any mention of the following *International Classification of Diseases, Version 10* (ICD-10) diagnostic codes: F15.0-F15.9 (Mental and behavioral disorders due to use of other stimulants) and T43.6 (Psychostimulants with abuse potential poisoning). Note that as of May 23, 2011, subnational data representing 0-9 deaths are suppressed in CDC WONDER; state-year data points in that range that we used in developing the indices were retrieved prior to that date.

[a2] Primary amphetamine treatment admissions per 100,000

Definition: Measures the number of admissions to publicly funded substance abuse treatment programs for a primary amphetamine use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: For each reporting state in a given year, the counts for cases with unreported primary substance of abuse were proportionately reallocated according to the distribution of cases with validly reported data on substance type (including alcohol and other drugs).

[a3] Inpatient hospital diagnoses for stimulant poisoning per 100,000

Definition: Measures the number of all-listed inpatient hospital diagnoses for stimulant poisoning.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 969.7 (Poisoning by psychostimulants) [19] and E854.2 (Accidental poisoning by psychostimulants).

[a4] Inpatient hospital diagnoses for stimulant use disorders per 100,000

Definition: Measures the number of inpatient hospital all-listed diagnoses for stimulant abuse or dependence.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 304.40-304.43 (Amphetamine and other psychostimulant dependence), and 305.70-305.73 (Amphetamine or related acting sympathomimetic abuse).

[a5] Prevalence (%) of amphetamine abuse and pregnancy among females entering treatment

[19] Beginning in 2009, the ICD-9-CM coding for 969.7 changed to include subcodes 969.70-969.79 for specific drugs (e.g., caffeine, amphetamine, methylphenidate). All possible codes were used for 2009 as the use of the new subcodes was not fully implemented.

Definition: Measures the percentage of women who were both primary amphetamine abusers and pregnant upon admission to publicly funded substance abuse treatment programs.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or pregnancy status.

[a6] Children affected by methamphetamine labs per 100,000

Definition: Measures the number of children affected, injured, or killed by a clandestine methamphetamine laboratory.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the National Seizure System, El Paso Intelligence Center, Drug Enforcement Administration.

Notes: The data extract covers all drug labs types (e.g., LSD), the vast majority of which are for illicit methamphetamine production.

[a7] Prevalence (%) of amphetamine abuse and unemployment among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary amphetamine abusers and unemployed.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health

Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or employment status.

[a8] Methamphetamine positivity rate among the general U.S. workforce

Definition: Measures the proportion of positive methamphetamine test results relative to all such tests performed among the combined U.S. workforce, which includes the general workforce and federally mandated, safety-sensitive workers.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the Quest Diagnostics Drug Testing Index.

Notes: Data coverage begins in 2002 because generic tests for amphetamine were performed in previous years.

[a9] Prevalence (%) of lifetime methamphetamine use among high school students

Definition: Measures the percentage of high school students who reported ever using methamphetamine one or more times in their life.

Source: *2001-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline. Unweighted estimated for certain states in 2001 and 2003 were obtained from the *Morbidity and Mortality Weekly Report* (June 28, 2002, Vol. 51, No. SS-4; May 21, 2004, Vol. 53, No. SS-2).

Notes: Data are collected biennially in odd numbered years. State participation increased from 37 (22 weighted) in 2001 to 47 (42 weighted) in 2009. Weighted results mean that the overall response rate was at least 60%.

[a10] Prevalence (%) of amphetamine abuse and homelessness among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary amphetamine abusers and homeless.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or living arrangements.

[a11] Amphetamine positivity rate among drivers involved in fatal accidents

Definition: Measures the estimated number of drivers involved in fatal vehicle crashes who tested positive for amphetamines.

Source: 2000-2009 Analytic Files, Fatality Analysis Reporting System, National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

Notes: Because of high rates of missing data on drug-related variables, multiple imputation was used to estimate missing driver-level crash data. See [d25] for further details.

[a12] Percentage of police agencies reporting methamphetamine contributes most to violent crime

Definition: Measures the percentage of police agencies in a state reporting that methamphetamine is the drug that most contributes to violent crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[a13] Percentage of police agencies reporting methamphetamine contributes most to property crime

Definition: Measures the percentage of police agencies in a state reporting that methamphetamine is the drug that most contributes to property crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[a14] Percentage of police agencies reporting local methamphetamine production

Definition: Measures the percentage of police agencies in a state reporting any level of illicit methamphetamine production in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[a15] Methamphetamine laboratory seizure incidents per 100,000

Definition: Measures the total number of methamphetamine laboratory seizure incidents, including operational labs, dumpsites, and chemicals and equipment.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the Quest Diagnostics Drug Testing Index.

Cocaine Index

[c1] Cocaine-related deaths per 100,000

Definition: Measures the number of U.S. resident deaths in which cocaine poisoning or a cocaine-related mental or behavioral disorder was listed as a contributing cause of death.

Source: Multiple Cause of Death data for 1999-2009, CDC WONDER Online Database, National Center for Health Statistics, Centers for Disease Control and Prevention.

Notes: Cocaine-related deaths include any mention of the following *International Classification of Diseases, Version 10* (ICD-10) diagnostic codes: F14.0-F14.9 (Mental and behavioral disorders due to use of cocaine), R78.2 (Finding of cocaine in blood), and T40.5 (Cocaine poisoning). Note that as of May 23, 2011, subnational data representing 0-9 deaths are suppressed in CDC WONDER; state-year data points in that range that we used in developing the indices were retrieved prior to that date.

[c2] Primary cocaine treatment admissions per 100,000

Definition: Measures the number of admissions to publicly funded treatment programs for a primary cocaine use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: For each reporting state in a given year, the counts for cases with unreported primary substance of abuse were proportionately reallocated according to the distribution of cases with validly reported data on substance type (including alcohol and other drugs).

[c3] Inpatient hospital diagnoses for cocaine poisoning per 100,000

Definition: Measures the number of all-listed inpatient hospital diagnoses for cocaine poisoning.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 968.5 (Poisoning by surface and infiltration anesthetics), 970.8 (Poisoning by other specified central nervous system stimulants) [20] and E854.3 (Accidental poisoning by central nervous system stimulants).

[c4] Inpatient hospital diagnoses for cocaine use disorders per 100,000

Definition: Measures the number of all-listed inpatient hospital diagnoses for cocaine abuse or dependence.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

[20] Beginning in 2010, code 970.8 was broken into subcodes allowing specific reporting for cocaine.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 304.20-304.23 (Cocaine dependence), and 305.60-305.63 (Cocaine abuse).

[c5] Prevalence (%) of cocaine abuse and pregnancy among females entering drug treatment

Definition: Measures the percentage of women who were both primary cocaine abusers and pregnant upon admission to publicly funded treatment programs.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or pregnancy status.

[c6] Inpatient hospital diagnoses for cocaine affecting fetus or newborn per 100,000 females aged 15-44

Definition: Measures the number of all-listed inpatient hospital diagnoses among women aged 15-44 for cocaine affecting a fetus or newborn.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 760.75 (Cocaine affecting fetus or newborn via placenta or breast milk).

[c7] Prevalence (%) of cocaine abuse and unemployment among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary cocaine abusers and unemployed.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or employment status.

[c8] Cocaine positivity rate among the general U.S. workforce

Definition: Measures the proportion of positive cocaine test results relative to all such tests performed among the combined U.S. workforce, which includes the general workforce and federally mandated, safety-sensitive workers.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the Quest Diagnostics Drug Testing Index.

[c9] Prevalence (%) of lifetime cocaine use among high school students

Definition: Measures the percentage of high school students who reported ever using cocaine one or more times in their life.

Source: *2001-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline. Unweighted estimated for certain states in 2001 and 2003 were obtained from the *Morbidity and Mortality Weekly Report* (June 28, 2002, Vol. 51, No. SS-4; May 21, 2004, Vol. 53, No. SS-2).

Notes: Data are collected biennially in odd numbered years. State participation increased from 37 (22 weighted) in 2001 to 47 (42 weighted) in 2009. Weighted results mean that the overall response rate was at least 60%.

[c10] Prevalence (%) of past-year cocaine use among 12-17 year olds

Definition: Measures the percentage of 12-17 year olds in the household population who reported using cocaine within the past 12 months.

Source: *State Estimates of Substance Use and Mental Disorders from the 2002-2009 National Survey on Drug Use and Health* (Annual 2004-2011). Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration.

Notes: Data coverage includes 2002-2009, as methodological changes in the NSDUH design affect comparability with earlier years. Except for 2002, the estimates for a given year represent the combined estimates for the indicated and prior year.

[c11] Prevalence (%) of cocaine abuse and homelessness among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary cociane abusers and homeless.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health

Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or living arrangements.

[c12] Cocaine positivity rate among drivers involved in fatal accidents

Definition: Measures the estimated number of drivers involved in fatal vehicle crashes who tested positive for cocaine.

Source: 2000-2009 Analytic Files, Fatality Analysis Reporting System, National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

Notes: Because of high rates of missing data on drug-related variables, multiple imputation was used to estimate missing driver-level crash data. See [d25] for further details.

[c13] Percentage of police agencies reporting cocaine contributes most to violent crime

Definition: Measures the percentage of police agencies in a state reporting that cocaine is the drug that most contributes to violent crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[c14] Percentage of police agencies reporting cocaine contributes most to property crime

Definition: Measures the percentage of police agencies in a state reporting that cocaine is the drug that most contributes to property crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

Marijuana Index

[m1] Primary marijuana treatment admissions per 100,000

Definition: Measures the number of admissions to publicly funded treatment programs for a primary marijuana use disorder.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: For each reporting state in a given year, the counts for cases with unreported primary substance of abuse were proportionately reallocated according to the distribution of cases with validly reported data on substance type (including alcohol and other drugs).

[m2] Inpatient hospital diagnoses for marijuana use disorders per 100,000

Definition: Measures the number of all-listed inpatient hospital diagnoses for marijuana abuse or dependence.

Source: HCUPnet, Healthcare Cost and Utilization Project, State Inpatient Databases, Agency for Healthcare Research and Quality.

Notes: Definition includes the following *International Classification of Diseases, Version 9, Clinical Modification* (ICD-9-CM) diagnostic codes: 304.30-304.33 (Cannabis dependence), and 305.20-305.23 (Cannabis abuse).

[m3] Potency of seized marijuana

Definition: Measures the THC concentration of marijuana seized by law enforcement.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the Marijuana Potency Monitoring Program, University of Mississippi/National Institute on Drug Abuse.

Notes: State-year values represent three-year moving averages of the indicated year and the two previous years. Thus, year 2000 values are moving averages of 1998-2000 data. The estimates were weighted by seizure quantity to reflect a market share interpretation of THC potency.

[m4] Prevalence (%) of marijuana abuse and pregnancy among females entering drug treatment

Definition: Measures the percentage of women who were both primary marijuana abusers and pregnant upon admission to publicly funded treatment programs.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or pregnancy status.

[m5] Prevalence (%) of marijuana abuse and unemployment among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary marijuana abusers and unemployed.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or employment status.

[m6] Marijuana positivity rate among the general U.S. workforce

Definition: Measures the proportion of positive marijuana test results relative to all such tests performed among the combined U.S. workforce, which includes the general workforce and federally mandated, safety-sensitive workers.

Source: Unpublished data extract provided by the Office of National Drug Control Policy from the Quest Diagnostics Drug Testing Index.

[m7] Prevalence (%) of marijuana use before age 13 among high school students

Definition: Measures the percentage of high school students who reported first using marijuana before the age of 13.

Source: *2001-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline. Unweighted estimated for certain states in 2001 and 2003 were obtained from the *Morbidity and Mortality Weekly Report* (June 28, 2002, Vol. 51, No. SS-4; May 21, 2004, Vol. 53, No. SS-2).

Notes: Data are collected biennially in odd numbered years. State participation increased from 37 (22 weighted) in 2001 to 47 (42 weighted) in 2009. Weighted results mean that the overall response rate was at least 60%.

[m8] Prevalence (%) of recent marijuana use on school property among high school students

Definition: Measures the percentage of high school students who reported first using marijuana on school property within the past 30 days.

Source: *2001-2009 High School Youth Risk Behavior Survey Data*, Centers for Disease Control and Prevention. Online: http://apps.nccd.cdc.gov/youthonline. Unweighted estimated for certain states in 2001 and 2003 were obtained from the *Morbidity and Mortality Weekly Report* (June 28, 2002, Vol. 51, No. SS-4; May 21, 2004, Vol. 53, No. SS-2).

Notes: Data are collected biennially in odd numbered years. State participation increased from 37 (22 weighted) in 2001 to 47 (42 weighted) in 2009. Weighted results mean that the overall response rate was at least 60%.

[m9] Average annual marijuana initiation rate among 12-17 year olds

Definition: Measures the percentage of 12-17 year olds in the household population who first used marijuana in the past 12 months.

Source: *State Estimates of Substance Use and Mental Disorders from the 2002-2009 National Survey on Drug Use and Health* (Annual 2004-2011). Rockville, MD: Center for

Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration.

Notes: Data coverage includes 2002-2009, as methodological changes in the NSDUH design affect comparability with earlier years. Except for 2002, the estimates for a given year represent the combined estimates for the indicated and prior year.

[m10] Prevalence (%) of marijuana abuse and homelessness among people entering treatment

Definition: Measures the percentage of people admitted to publicly funded substance abuse treatment programs who were both primary marijuana abusers and homeless.

Source: Treatment Episode Data Set—Admissions (TEDS-A), 2000-2009 [computer files]. Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor].

Notes: Data were excluded for state-years in which there was more than 20% missing data on either primary substance of abuse or living arrangements.

[m11] Marijuana positivity rate among drivers involved in fatal accidents

Definition: Measures the estimated number of drivers involved in fatal vehicle crashes who tested positive for marijuana.

Source: 2000-2009 Analytic Files, Fatality Analysis Reporting System, National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

Notes: Because of high rates of missing data on drug-related variables, multiple imputation was used to estimate missing driver-level crash data. See [d25] for further details.

[m12] Percentage of police agencies reporting marijuana contributes most to violent crime

Definition: Measures the percentage of police agencies in a state reporting that marijuana is the drug that most contributes to violent crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[m13] Percentage of police agencies reporting marijuana contributes most to property crime

Definition: Measures the percentage of police agencies in a state reporting that marijuana is the drug that most contributes to property crime in the area.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[m14] Percentage of police agencies reporting local marijuana production

Definition: Measures the percentage of police agencies in a state reporting any level of illicit marijuana production in the area, including indoor and outdoor grows.

Source: Unpublished data tables from the National Drug Threat Survey (2003-2009) provided by the National Drug Intelligence Center.

Notes: Surveys administered prior to 2003 were not representative at the state level.

[m15] Outdoor marijuana plots eradicated per 100,000

Definition: Measures the number of outdoor marijuana plots eradicated by law enforcement.

Source: *Sourcebook of Criminal Justice Statistics* [Online], Table 4.39 for year 2000, Table 4.38 for years 2001-2009, Bureau of Justice Statistics, based on data collected from the Domestic Cannabis Eradication/Suppression Program, Drug Enforcement Administration.

Notes: In 2007, the DEA began including outdoor marijuana seizures made on public lands, which may affect comparability with earlier years.

[m16] Indoor marijuana grows seized per 100,000

Definition: Measures the number of indoor marijuana grows seized by law enforcement.

Source: *Sourcebook of Criminal Justice Statistics* [Online], Table 4.39 for year 2000, Table 4.38 for years 2001-2009, Bureau of Justice Statistics, based on data collected from the Domestic Cannabis Eradication/Suppression Program, Drug Enforcement Administration.

APPENDIX D: DETAILED METHODOLOGY AND ROBUSTNESS ANALYSES

This technical appendix provides detailed documentation of the statistical methods used in the construction of the core U.S. Drug Consequences Indices (DCIs), including statistical treatment of the indicators, internal consistency analysis, weighting and aggregation methods, and robustness analyses. The National DCI is discussed first followed by the drug-specific State DCIs.

A. NATIONAL DCI

1. Missing Data

All of the 30 indicators that inform the National DCI had data availability of at least five years over the ten-year period 2000 to 2009. Overall, 22 indicators had complete records, with missing data representing just 7.7% of the matrix of 300 observations (30 indicators × 10 years). As indicated in Table D-1, missing data for the remaining 8 indicators were imputed using either linear interpolation or linear trend analysis. Linear interpolation was used for indicators collected biennially (i.e., YRBS indicators collected in odd-numbered years), whereas trend analysis was employed for indicators with other missing data patterns. For the interpolation procedure, values for 1999 were used to interpolate year 2000 values. For the linear trend analysis, bivariate regression was employed to predict missing values with time (i.e., year) as the independent variable.

Table D-1. National DCI Imputation Methods

Indicator	Missing Years	Method
[d4] Drug-related emergency department visits per 100,000 (DAWN)	2000-2004	Linear trend analysis
[d8] Prevalence (%) of drug dependence or abuse among persons aged 12+ (NSDUH)	2000-2001	Linear trend analysis
[d12] Prevalence (%) of illicit drug use among pregnant women aged 15-44 (NSDUH)	2000-2001	Linear trend analysis
[d21] On-campus drug violations per 1,000 enrolled college students (CSSS)	2000	Linear trend analysis
[d22] Percentage of high school students offered drugs on school grounds (YRBS)	2000, 2002, 2004, 2006, 2008	Linear interpolation
[d24] Lifetime prevalence (%) of drug injection among high school students (YRBS)	2000, 2002, 2004, 2006, 2008	Linear interpolation
[d27] Prevalence (%) of drugged driving among persons aged 16+ (NSDUH)	2000-2001	Linear trend analysis
[d28] Drug-related violent victimizations per 100,000 (NCVS)	2006, 2009	Linear trend analysis

2. Normalization

To render the indicator values comparable, we normalized by a distance-to-reference value, where year 2000 was used as the base year (set to value 100) using equation (1) whereby low values are undesirable. It is important to note that this direction was kept only during the calculations (for reasons that are explained next in the section on Weighting and Aggregation). All final results are presented with high values being undesirable.

(1)
$$x_{new,t} = 200 - \frac{x_{raw,t}}{x_{raw,t\ 0=2000}} \times 100$$

3. Weighting and Aggregation

In order to derive a plausible set of weights for use in constructing the DCIs, we consulted with 19 experts in the drug policy and addictions fields.[21] The consultation was constructed around an Analytic Hierarchy Process (AHP), a widely used technique for multi-criteria decision-making (Saaty, 1987; Saaty, 1980, 2005). AHP employs ordinal pairwise comparisons of indicators, in which the strength of preference is expressed on a semantic scale typically ranging from '1' (equally important) to '9' (extremely more important). The relative weights of the indicators are then calculated using an eigenvector technique that serves to resolve inconsistencies (e.g., loops such as A better than B better than C better than A; see discussion below). For this project, the panel of experts independently assessed the relative importance of the nine subdomains for each drug type separately (i.e., heroin, methamphetamine, cocaine, and marijuana) and then again for 'all illicit drugs.'[22] The latter set of responses was used for the National DCI.

An intrinsic feature of AHP is that it exploits the level of inconsistency in a respondent's assessment of the relative importance of drug consequence subdomains. For example, if one expert claims that A is much more important than B, B slightly more important than C, and C slightly more important than A, his/her judgment is inconsistent and the results are less trustworthy. Inconsistency, however, is part of human nature. For the DCI framework with nine

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[21] We contacted 36 individuals representing a cross-section of academic backgrounds and expertise for this consultation. Of these 36 individuals, 19 agreed to participate, 11 could not be reached or did not respond to the invitation, 3 agreed to participate but were not able to fulfill their commitment, and 3 declined to participate.

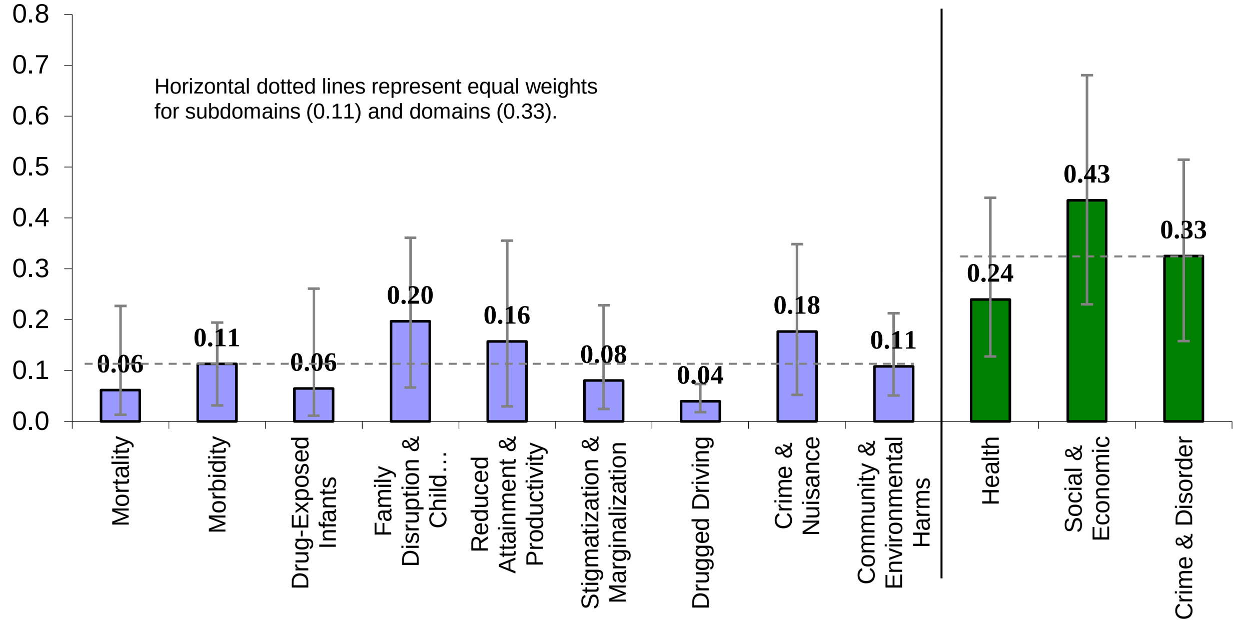
[22] It was not feasible to require indicator-level comparisons due to the different indicators used across the DCIs and the burden that would have been placed upon the AHP participants. Ratings were based on the following scale: (1) Equally important—Evidence and judgment suggest the subdomains contribute equally to total harm, (3) Somewhat more important—Evidence and judgment slightly favors the influence of one domain over another, (5) Much more important—Evidence and judgment strongly favors the influence of one domain over another, (7) Very much more important—Evidence and judgment very strongly favors the influence of one domain over another, (9) Extremely more important—Evidence and judgment favors the influence of one domain over another to the highest possible degree.

subdomains, only eight comparisons are actually required to establish weights.[23] However, the number of comparisons performed in the AHP exercise was $(9 \cdot 8)/2 = 36$. The greater number of comparisons results in a set of weights that is less sensitive to errors of judgment. In addition, this redundancy allows for an estimation of judgment error, the so called *inconsistency ratio*. It might therefore be adequate to measure the degree of inconsistency in order to make judgments about whether to include a particular respondent's assessment in the final weighting. Small inconsistency ratios—the suggested rule-of-thumb is less than 0.1, although 0.2 is often cited—do not drastically affect the weights (Saaty, 1980). Higher inconsistency ratios are an indication that the experts have probably responded to the AHP exercise in a nonsystematic fashion. Of the 19 expert responses, 13 were considered to meet minimum reliability requirements (i.e., inconsistency ratios 0.2 or less). These 13 responses were used to calculate the average weights for the National DCI.

Figure D-1 presents information on the expert-based weights for the subdomains and domains of the National DCI; mean, minimum, and maximum weights are shown by the bars and error bars. There are considerable differences in the weights proposed by the experts for the same subdomain. Interestingly, unanimity is achieved in judging that the 'drugged driving' subdomain should receive the lowest weight (4%) across the nine areas. On the other hand, experts on average agree that the highest weights should be assigned to three of the nine subdomains, namely 'family disruption & child maltreatment,' 'crime & nuisance,' and 'reduced attainment & productivity' (between 16-20%).

[23] The ninth equation is that of the unity sum of weights.

Figure D-1. Expert-based Weights for the Subdomains and Domains of the National DCI



We derived weights for the three domains,[24] showing that the *Social & Economic* domain was given relatively more weight (43%), followed by *Crime & Disorder* (33%), and *Health* (24%). Furthermore, although equal weights (0.11) fall within the upper and lower bounds over the sample of experts, no panel member proposed to weigh all consequences equally. For these reasons, we opted not to assume equal weights for the consequences during the development of the National DCI. If a single set of weights was to be used to represent the expert panel in its entirety, then the mean (or median) weight value would be a proper choice. We used the mean weight value across the experts. Below, in the section on robustness analysis, we assess the impact that variations in weighting have on the National DCI results.

[24] Experts were requested via AHP to assess the relative importance of the nine subdomains only. Conclusions on the domains can be derived indirectly, but note that experts were not explicitly asked to do so.

The calculation of the National DCI followed three aggregation steps. First, the scores for the subdomains were calculated as simple geometric averages of the normalized indicators using equation (2), exemplified for *Mortality*.

(2) $$\text{Mortality}_t = \left((\text{drug-related deaths}_t) \times (\text{IDU-related AIDS deaths}_t)\right)^{1/2}$$

Next, scores for the three domains were calculated as expert-weighted geometric averages of the three subdomains underlying each domain using equation (3), exemplified for *Health* consequences.

(3) $$\text{Health}_t = (\text{Mortality})_t^{w_1} \times (\text{Morbidity})_t^{w_2} \times (\text{Drug-Exposed Infants})_t^{w_3}$$

Finally, the expert-weighted geometric mean of the three domains was calculated as follows:

(4) $$Y_t = (\text{Health})_t^{w_{10}} \times (\text{Social \& Economic})_t^{w_{11}} \times (\text{Crime \& Disorder})_t^{w_{12}}$$

Note that equation (4) is equivalent to the expert-weighted geometric average of the nine subdomains. The final results for the DCI and the three domains on *Health*, *Social & Economic*, and *Crime & Disorder* were then scaled using equation (5), whereby high values are undesirable. This is done for communication purposes with a view to have the results in the same direction as that of the raw indicators.

(5) $$\text{DCI}_t = 200 - Y_t$$

The use of the geometric mean, as opposed to the classical arithmetic mean, to aggregate the components of the DCI is guided by both a conceptual and a methodological need. Conceptually, in the present context, perfect substitutability among the index components (as is the case with an arithmetic mean) is not desirable. Substitutability (or compensability) is understood here as the undesirable offsetting of poor performance in some area with good performance in others. Methodologically, the use of the arithmetic average would be problematic because it would imply that the level of priority to be given to a drug consequences subdomain is invariant to the level of attainments. Instead, the geometric mean gives more incentives for improvement to low values. Furthermore, the geometric mean is only partially compensatory and the rankings produced by the geometric mean are not affected by choice of the reference year at the normalization stage. In the case of the arithmetic mean or functions with a constant nonunitary elasticity of substitution, multiplying any of the DCI components by a scalar factor would lead to a change in the relative weight of that variable. The only functional form that allows us to avoid this undesirable result is the geometric mean. In fact, Fleming and Wallace (1986) demonstrate that the geometric mean is the only correct mean when averaging normalized results that are presented as ratios to reference values.

4. Robustness Analysis

Various methodological choices were made when constructing the National DCI: structure of the framework, indicator selection, imputation, weighting scheme, aggregation formula. The aim of the robustness analysis is to assess the extent to which these choices have affected the final results. Hence, robustness analysis is an essential ingredient for validating an index by anticipating criticism (Saisana, Saltelli, and Tarantola, 2005; OECD, 2008; Saltelli et al., 2008). The robustness assessment carried out here aimed to estimate the impact of a particularly consequential issue: the weights assigned to the nine subdomains.

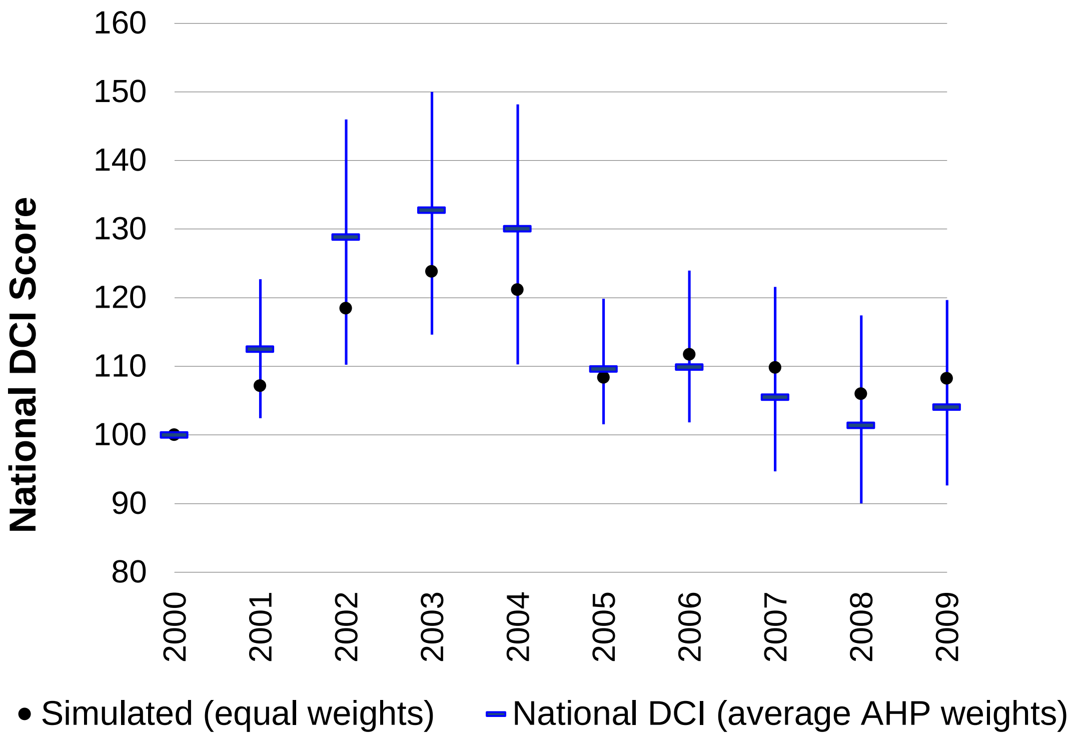
In the field of composite indicators, the issue of weighting is a particularly sensitive and subjective. There is no clear consensus among the expert community on composite indicator construction as to how to best determine a set of weights for combining diverse issues, such as those related to drug consequences. Cox et al. (1992) summarize these difficulties and conclude that many published weighting schemes are either based upon too complex multivariate methods or have little meaning to society. Cherchye et al. (2007) observe that the “lack of consensus” on the relative weights is a defining property of composite indicators, and that while one may hypothesize consensus on the indicators to be included in an index, the weights to be assigned to them will most likely remain controversial. The point of these considerations is that subjectivity and fitness need not be antithetical. They are in fact both at play when constructing a composite indicator (OECD, 2008). These, only apparently conflicting, properties underpin composite indicators’ suitability for advocacy (Saltelli, 2007).

As explained above, we assigned equal weights to the indicators and expert-based weights derived from the AHP exercise to the subdomains and domains in order to create the National DCI. In order to better understand the impact on the DCI scores of different sets of weights, we performed two robustness analyses. First, we used the range of information supplied by the experts in the AHP exercise, not just the average weight across the experts. Second, we compared the National DCI results to those obtained had an equal weighting scheme been used throughout all aggregation steps. These two procedures are described in turn.

The impact on the National DCI scores of the thirteen sets of AHP-derived weights (those corresponding to inconsistency 0.2 or below) is shown in Figure D-2. The horizontal lines are the

National DCI scores (i.e., the reference scores obtained using the average AHP weights), the bullets show the scores had equal weights been used, and the vertical lines depict the minimum and maximum scores calculated on the basis of the range in thirteen experts' sets of weights. The equal weight scores follow the general trend of the reference DCI scores, and in most years are comparable to the AHP-derived weights. The largest differences are found for 2002-2004, when an equal weights assumption would have underestimated index scores relative to the reference situation by 7-8%. The highest uncertainties in the DCI scores, as reflected by the vertical error bars, occur in these same years. Nevertheless, the general conclusion still holds under these varying assumptions that drug-related consequences increased during the early 2000s before declining and stabilizing in the latter part of the decade.

Figure D-2. National DCI Scores Under Different Weighting Assumptions



B. STATE INDICES

1. Missing Data

For each state-year matrix of indicators, missing data characterized 26.0% (1,693 / 6,500) of the Heroin Index, 22.0% (1,652 / 7,500) of the Methamphetamine Index, 24.6% (1,719 / 7,000) of the Cocaine Index, and 21.3% (1,702 / 8,000) of the Marijuana Index. These missing data were imputed independently for each index using the time-series cross-sectional bootstrap expectation-maximization algorithm implemented in the software package Amelia II (Honaker and King, 2010; Honaker, King, and Blackwell, 2012; King et al., 2001). This approach has comparative advantages over other imputation methods (Blankers, Koeter, and Schippers, 2010), and has proven to work efficiently with various datasets and with different degrees of missingness.

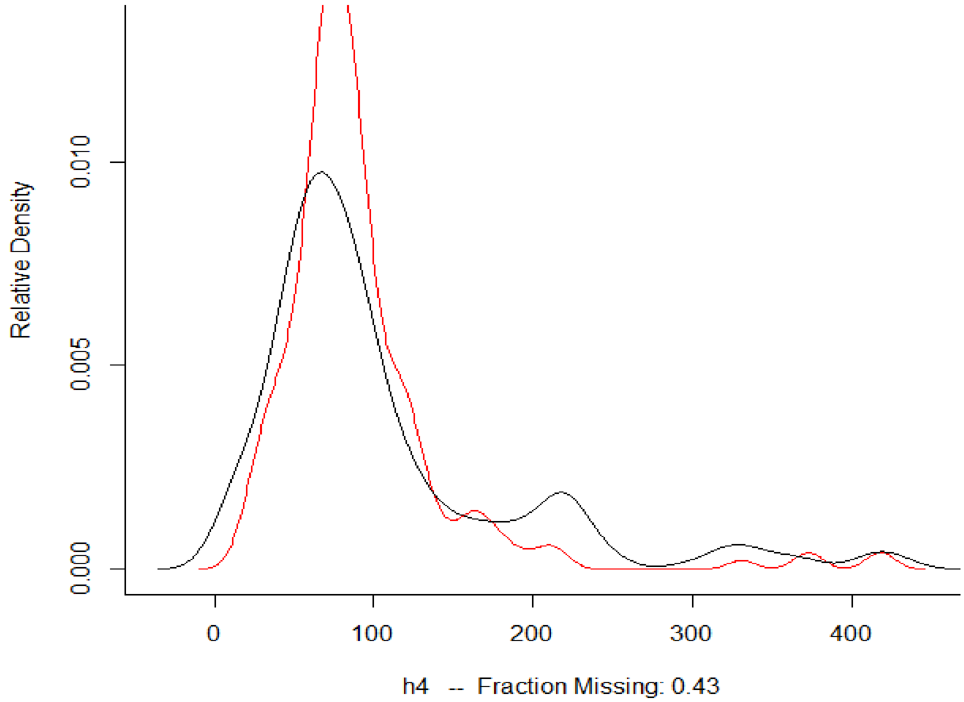
Imputation of missing state-year cells in each DCI matrix proceeded as follows. First, the nature and distribution of each indicator was assessed, and transformations were applied as appropriate in order to improve imputation estimates. These transformations were executed within Amelia II, which has the advantage that the imputation results are reported back in the original metric. A ladder of powers framework including tests for normality and visual inspection of histograms supported selection of appropriate transformations. The ultimate transformations that were used in the imputation models are reported in Table D-2. "Identity" refers to untransformed indicators. For indicators transformed logarithmically, a small constant value (e.g., 0.01, 0.1) was added prior to imputation if zeros were present. Similarly, for indicators transformed logistically, percentages were first expressed as proportions and then values of 0 and 1 were replaced with 0.01 and .99 respectively since the logit of 0 or 1 is undefined. The transformed indicator values were then passed to Amelia II for imputation. Ten complete datasets were created where missing values were "filled in with a distribution of imputations that reflect the uncertainty about the missing data" (Honaker, King, and Blackwell, 2012:3). For each missing data point in the state-year matrices, the average of the ten imputed values was taken as the best estimate. Finally, any previous manual transformations (e.g., adding a constant, changing from percentage to proportion) were reversed to return the indicators to their original format.

Table D-2. State DCI Indicator Transformations Used for Imputation Models

Heroin Index	Methamphetamine Index	Cocaine Index	Marijuana Index
[h1] Square root	[a1] Square root	[c1] Logarithm	[m1] Square root
[h2] Logarithm	[a2] Logarithm	[c2] Square root	[m2] Logarithm
[h3] Square root	[a3] Square root	[c3] Logarithm	[m3] Square root
[h4] Logarithm	[a4] Square root	[c4] Logarithm	[m4] Square root
[h5] Logistic	[a5] Logistic	[c5] Logistic	[m5] Square root
[h6] Logarithm	[a6] Square root	[c6] Square root	[m6] Square root
[h7] Logistic	[a7] Logistic	[c7] Logistic	[m7] Identity
[h8] Logarithm	[a8] Square root	[c8] Square root	[m8] Identity
[h9] Identity	[a9] Identity	[c9] Identity	[m9] Identity
[h10] Logistic	[a10] Logistic	[c10] Logarithm	[m10] Square root
[h11] Square root	[a11] Logarithm	[c11] Square root	[m11] Identity
[h12] Logistic	[a12] Logistic	[c12] Square root	[m12] Logistic
[h13] Logistic	[a13] Logistic	[c13] Logistic	[m13] Logistic
	[a14] Logistic	[c14] Logistic	[m14] Logistic
	[a15] Logarithm		[m15] Logarithm
			[m16] Logarithm

Several diagnostics were performed to assess and improve the quality of the imputation results (Honaker, King, and Blackwell, 2012). First, we compared the densities of the imputed and observed values to assess whether the imputed values were plausibly distributed, that is, that they did not fall radically outside the range of the observed data. Figure D-3 shows the graph for [h4] *Inpatient hospital diagnoses for heroin/opiate use disorders per 100,000*, indicating that

Figure D-3. Observed and Imputed Values of [h4]



imputations for cases with missing data (43%) were reasonably distributed relative to the indicator's observed values. Second, we examined time series graphs by indicator and state to check whether the mean imputed values and imputation distributions (95% CIs) were consistent with the state-specific trends. Figure D-4 shows the graph for indicator [h4] for Arkansas, confirming the plausibility of the mean imputations for missing years 2000 to 2003. Third, we performed the "overimputation" technique developed by Honaker and colleagues (2012) to compare observed values to imputations of these values *as if they had been missing*. Figure D-5 presents these results for indicator [h4], revealing that for the majority of the observations the 90% confidence intervals contain the $y = x$ line of perfect agreement. The color coding indicates the overall amount of missing information when imputing the observation. These checks were performed iteratively for all indicators to arrive at a final imputation model.

Figure D-4. Time Series of [h4] for Arkansas

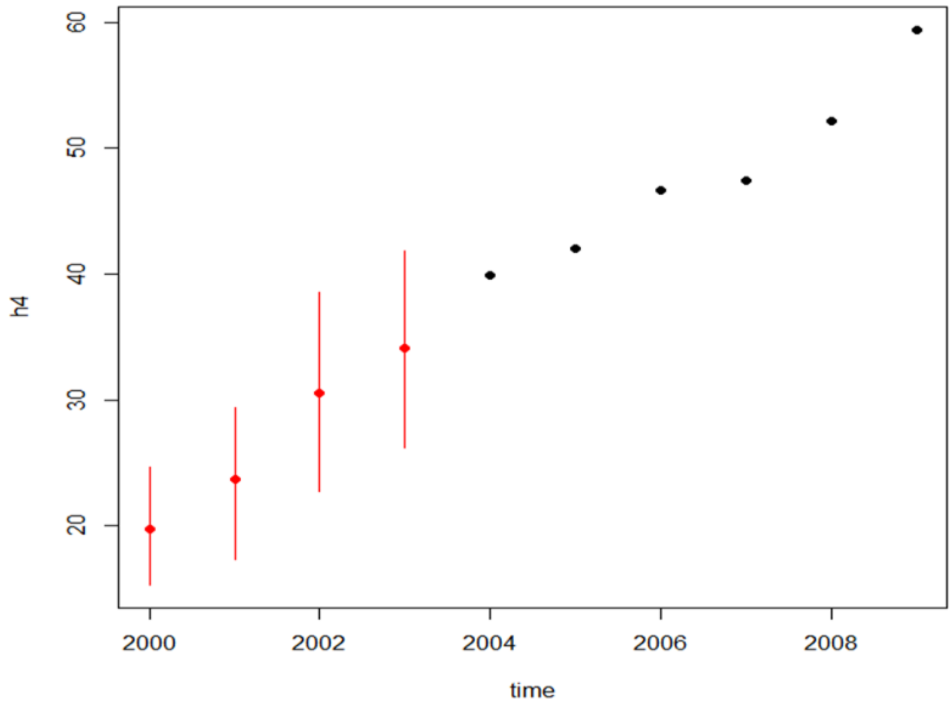
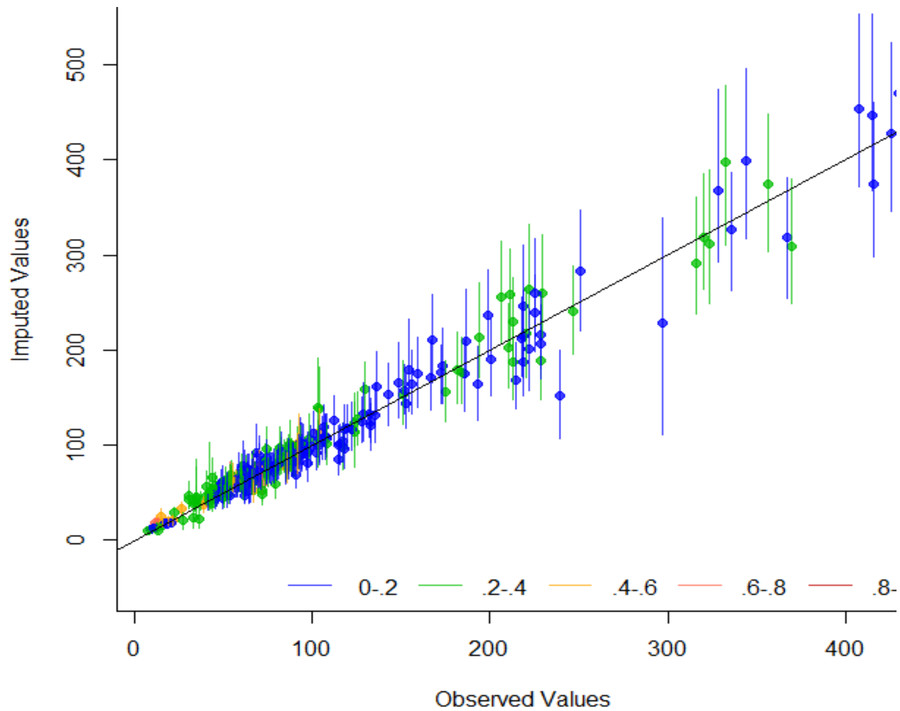


Figure D-5. Observed versus Imputed Values of [h4]



2. Data Treatment

For each indicator in the final imputed datasets, values falling outside twice the interquartile range were checked for reporting errors.[25] As shown in Table D-3, potentially problematic indicators (n = 21) that could bias the overall results were identified as having a skewness (absolute) greater than 2.0 and kurtosis greater than 3.5,[26] and were treated by logarithmic transformation (corrected for zero values by adding a constant of 1). After transformation, indicator distributions were checked again to verify that the skewness and kurtosis entered within the specified ranges. This was confirmed for all indicators but three ([h8], [h11], and [m10]). We treated indicator [h11] with Winsorization since there was only one offending value (Alaska 2002 = 9.7), which we recoded to the next highest value + 1 SD (new value = 4.4 + 0.8 = 5.2). Alternatively, indicators [h8] and [m10] were truncated to the 95th percentile.

Table D-3. State DCI Normality Statistics for Potentially Problematic Indicators Before and After Logarithmic Transformation

Indicator	Before Transformation		After Transformation	
	Skewness	Kurtosis	Skewness	Kurtosis
[h2] Primary heroin treatment admissions per 100,000 TEDS)	2.3	4.6	0.2	-0.8
[h4] Inpatient hospital diagnoses for heroin/opiate use disorders per 100,000 (SID)	2.3	6.1	-0.2	1.4
[h5] Prevalence (%) of heroin abuse and pregnancy among females entering treatment (TEDS)	3.6	18.1	1.8	3.9
[h7] Prevalence (%) of heroin abuse and unemployment among people entering treatment (TEDS)	2.2	5.2	0.7	-0.4
[h8] Opiate positivity rate among the general U.S. workforce (DTI)	3.5	15.8	2.4	8.1
[h10] Prevalence (%) of heroin abuse and homelessness among people entering treatment (TEDS)	2.7	8.0	1.2	0.7

[25] The interquartile range (IQR) is the difference between the upper (75% of values) and the lower (25% of values) quartiles, denoted Q3 and Q1 respectively. Thus, values greater than Q3+2(IQR) or values lower than Q1-2(IQR) were checked for reporting errors.

[26] Groeneveld and Meeden (1984) set the criteria for absolute skewness above 1 and kurtosis above 3.5. The skewness criterion was relaxed here to the value 2.

Indicator	Before Transformation		After Transformation	
	Skewness	Kurtosis	Skewness	Kurtosis
[h11] Heroin/opiate positivity rate among drivers involved in fatal accidents (FARS)	3.5	29.0	1.7	4.9
[h12] Percentage of police agencies reporting heroin contributes most to violent crime (NDTS)	2.2	4.3	0.9	-0.6
[a1] Stimulant-related deaths per 100,000 (MCD)	2.5	7.7	1.3	1.2
[a5] Prevalence (%) of amphetamine abuse and pregnancy among females entering drug treatment (TEDS)	2.2	5.7	1.1	0.3
[a6] Children affected by methamphetamine labs per 100,000 (NSS)	2.7	8.7	1.2	0.7
[a7] Prevalence (%) of amphetamine abuse and unemployment among people entering treatment (TEDS)	2.0	4.4	0.6	-0.7
[a8] Methamphetamine positivity rate among the general U.S. workforce (DTI)	2.2	7.2	1.5	2.6
[a10] Prevalence (%) of amphetamine abuse and homelessness among people entering treatment (TEDS)	3.8	18.1	1.8	3.1
[a15] Methamphetamine laboratory seizure incidents per 100,000 (NSS)	2.7	8.3	0.6	-0.8
[c3] Inpatient hospital diagnoses for cocaine poisoning per 100,000 (SID)	2.9	11.2	0.1	0.9
[c4] Inpatient hospital diagnoses for cocaine use disorders per 100,000 (SID)	2.2	6.3	-0.5	1.2
[m10] Prevalence (%) of marijuana abuse and homelessness among people entering treatment (TEDS)	4.9	32.2	2.2	9.0
[m12] Percentage of police agencies reporting marijuana contributes most to violent crime (NDTS)	2.2	6.5	0.2	-1.1
[m15] Outdoor marijuana plots eradicated per 100,000 (DCE/SP)	8.7	84.9	1.5	2.6
[m16] Indoor marijuana grows seized per 100,000 (DCE/SP)	5.2	32.1	1.6	3.6

3. Normalization

To correct for different ranges and measurement units across the indicators, the (imputed and transformed) indicator scores were normalized by a min-max scaling using equation (6). In all cases the minimum threshold was set to 0, while the maximum threshold was set at 10% above the maximum reported (or estimated) value over 2000-2009 for the 50 U.S. states. This was done in order to be able to calculate index scores in cases where future values are greater than those reported for 2000-2009, without having to recalculate index scores for the previous years. Normalization by formula (6) is a linear transformation that converts indicators to a common scale in the range 1 to 100. This scaling allows indicators to be next summarized by a geometric average, where zero values would have been problematic since they would have produced a zero average.

(6) $$x_{new,t} = \frac{\max - x_{raw,t}}{\max} \times 99 + 1$$

4. Internal Consistency

Internal data consistency within each subdomain was verified by principal component analysis (PCA), a multivariate exploratory technique that is particularly suitable for statistically summarizing data in a parsimonious manner. In other words, PCA is a dimensionality reduction technique that is designed to reduce relevant information into a smaller number of transformed dimensions. The usefulness of PCA in DCI development is easy to understand: each subdomain in the DCI is designed to describe a particular aspect of the latent phenomenon to be measured (i.e., drug consequences). Since these aspects are not directly observable, they are measured by a set of observable indicators which, by definition, are related to the aspect they are supposed to describe and, consequently, to each other. In an ideal situation, each subdomain would show a unique, most relevant PCA component accounting for a large degree of the variability associated with the full set of indicators underlying the subdomain. Moreover, all indicators within a subdomain should contribute roughly to the same extent and point in the same direction as the most relevant principal component.

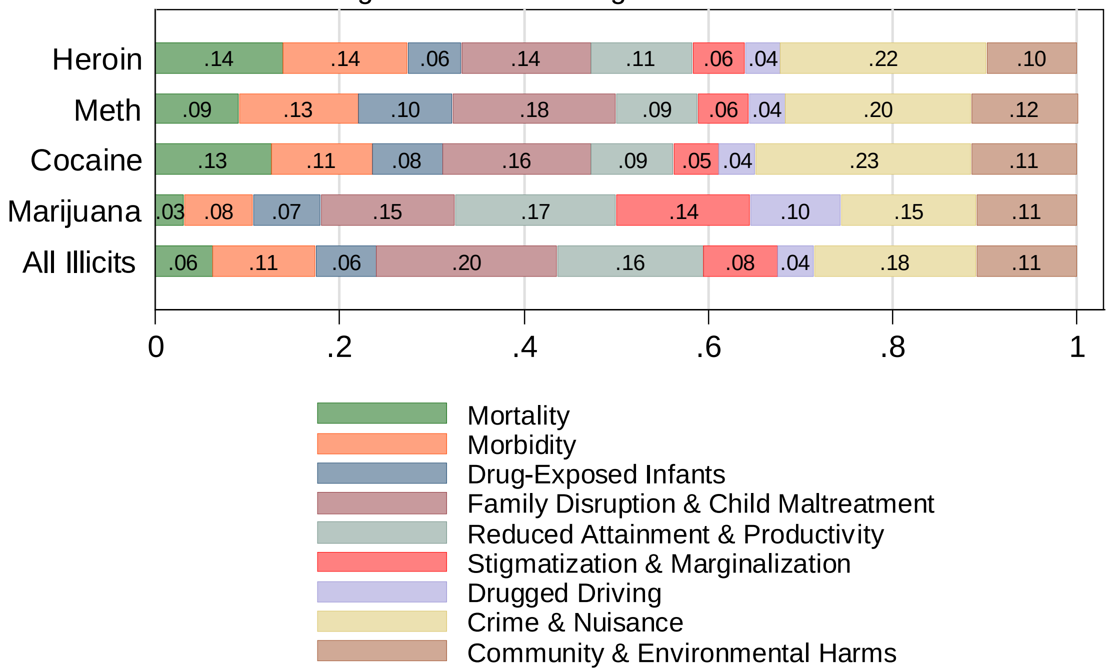
PCA was helpful in refining the DCI framework. It allowed us to detect noninfluential indicators, or indicators describing something else than they were supposed to. We analyzed subdomains with three or more indicators, so as to allow for the use of PCA, across all states and years. As shown in Table D-4, the results in the final framework suggest that there is a clear and unique "statistical" dimension with a well-balanced contribution of indicators within each subdomain. For example, the morbidity subdomain for heroin can be summarized by a single principal component that captures 75.8% of the variance in the three underlying indicators, which have the same degree of correlation to the first principal component (roughly 0.85-0.88). The only exception is the 'reduced attainment and productivity' subdomain for cocaine, where two principal components were needed to capture most of the variance in the four underlying indicators.

Table D-4. Principal Component Analysis Results within DCI Subdomains

#	Eigen-value	Total Variance Explained (%)	Indicators	Loadings 1st Latent Dimension	Loadings 2nd Latent Dimension
Heroin—Morbidity					
1	2.27	75.80	[h2] Primary heroin treatment admissions per 100,000 (TEDS)	0.85	
2	0.41	89.49	[h3] Inpatient hospital diagnoses for heroin poisoning per 100,000 (SID)	0.88	
3	0.32	100.0	[h4] Inpatient hospital diagnoses for heroin/opiate use disorders per 100,000 (SID)	0.88	
Heroin—Reduced Attainment & Productivity					
1	1.22	40.79	[h7] Prevalence (%) of heroin abuse and unemployment among people entering treatment (TEDS)	0.59	
2	0.95	72.50	[h8] Opiate positivity rate among the general U.S. workforce (DTI)	0.58	
3	0.83	100.0	[h9] Prevalence (%) of lifetime heroin use among high school students (YRBS)	0.73	
Methamphetamine—Morbidity					
1	2.37	79.08	[a2] Primary amphetamine treatment admissions per 100,000 (TEDS)	0.89	
2	0.43	93.30	[a3] Inpatient hospital diagnoses for stimulant poisoning per 100,000 (SID)	0.84	
3	0.20	100.0	[a4] Inpatient hospital diagnoses for stimulant use disorders per 100,000 (SID)	0.93	
Methamphetamine—Reduced Attainment & Productivity					
1	1.91	63.71	[a7] Prevalence (%) of amphetamine abuse and unemployment among people entering treatment (TEDS)	0.88	
2	0.89	93.47	[a8] Methamphetamine positivity rate among the	0.94	

#	Eigen-value	Total Variance Explained (%)	Indicators	Loadings 1st Latent Dimension	Loadings 2nd Latent Dimension
			general U.S. workforce (DTI)		
3	0.20	100.0	[a9] Prevalence (%) of lifetime methamphetamine use among high school students (YRBS)	0.50	
Cocaine—Morbidity					
1	2.29	76.45	[c2] Primary cocaine treatment admissions per 100,000 (TEDS)	0.75	
2	0.57	95.55	[c3] Inpatient hospital diagnoses for cocaine poisoning per 100,000 (SID)	0.92	
3	0.13	100.0	[c4] Inpatient hospital diagnoses for cocaine use disorders per 100,000 (SID)	0.93	
Cocaine—Reduced Attainment & Productivity					
1	1.59	39.81	[c7] Prevalence (%) of cocaine abuse and unemployment among people entering treatment (TEDS)	0.11	0.88
2	1.47	76.45	[c8] Cocaine positivity rate among the general U.S. workforce (DTI)	0.49	0.72
3	0.54	89.94	[c9] Prevalence (%) of lifetime cocaine use among high school students (YRBS)	0.83	-0.20
4	0.40	100.0	[c10] Prevalence (%) of past-year cocaine use among 12-17 year olds (NSDUH)	0.81	-0.35
Marijuana—Morbidity					
1	1.38	45.87	[m1] Primary marijuana treatment admissions per 100,000 (TEDS)	0.68	
2	0.85	74.06	[m2] Inpatient hospital diagnoses for marijuana use disorders per 100,000 (SID)	0.71	
3	0.78	100.0	[m3] Potency of seized marijuana (PMP)	0.64	
Marijuana—Reduced Attainment & Productivity					
1	2.72	54.47	[m5] Prevalence (%) of marijuana abuse and unemployment among people entering treatment (TEDS)	-0.46	
2	0.87	71.92	[m6] Marijuana positivity rate among the general U.S. workforce (DTI)	0.59	
3	0.77	87.25	[m7] Prevalence (%) of marijuana use before age 13 among high school students (YRBS)	0.82	
4	0.44	95.99	[m8] Prevalence (%) of recent marijuana use on school property among high school students (YRBS)	0.88	
5	0.20	100.0	[m9] Average annual marijuana initiation rate among 12-17 year olds (NSDUH)	0.85	
Marijuana—Community & Environmental Harms					
1	1.52	50.68	[m14] Percentage of police agencies reporting local marijuana production (NDTS)	0.77	
2	0.82	77.92	[m15] Outdoor marijuana plots eradicated per 100,000 (DCE/SP)	0.71	
3	0.66	100.0	[m16] Indoor marijuana grows seized per 100,000 (DCE/SP)	0.65	

Figure D-6. AHP Weights for DCI Subdomains



5. Weighting and Aggregation

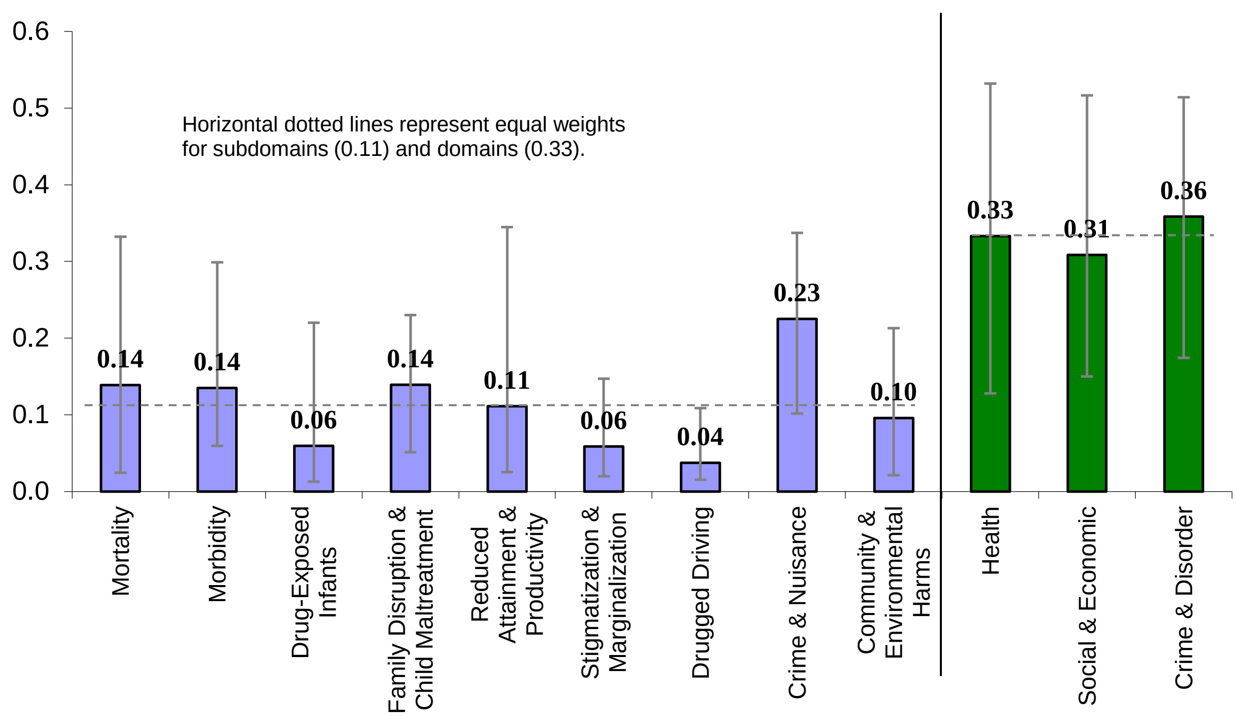
The panel of experts that were consulted via AHP also provided assessments of the relative importance of drug-related consequences by drug type. Figure D-6 summarizes the mean expert-derived weights used for the development of the drug-specific State DCIs. Weights for the consequence subdomains clearly differ across the drugs. For example, the weight for 'mortality' varies between 3% for marijuana to 14% for heroin. However, the expert weighting, on average, suggests that the most important drug consequences are 'family disruption & child maltreatment' (14-20%) and 'crime & nuisance' (15-23%) in almost all cases. On the opposite side, the expert weighting, on average, suggests that the least important drug consequences in terms of overall harm are 'drugged driving,' and 'drug-exposed infants' (4-10%).

Figures D-7 to D-10 summarize the expert-based weights for the subdomains and domains of each drug-specific State DCI, showing mean, minimum, and maximum weights.

There are considerable differences in the weights proposed by the experts both within and across drug types—although there is also a general degree of consistency in their relative rankings of consequence areas, especially for the harder drugs (heroin, methamphetamine, cocaine). As demonstrated in the following discussion, we did not assume equal weights in development of the State DCIs due to the variability in expert-based weights at the domain and subdomain levels. Instead, the mean weight value across the experts was used. As for the National DCI, only experts with inconsistency ratios 0.2 or below were taken into account in the calculation of the mean expert-weights. Thus, we used 12 questionnaires for the Heroin and Methamphetamine Indices, 13 questionnaires for the Cocaine Index, and 16 questionnaires for the Marijuana Index.

For the Heroin Index (Figure D-7), experts suggested that ‘drugged driving,’ ‘stigmatization & marginalization,’ and ‘drug-exposed infants’ should, on average, receive the lowest weights (4-

Figure D-7. Expert-based Weights for the Subdomains and Domains of the Heroin Index



6%) across the nine subdomains. On the other hand, experts on average agreed that the highest weight should be assigned to ‘crime & nuisance’ (23%). Despite variability at the subdomain level, weights at the domain level are relatively similar: *Crime & Disorder* (36%), *Health* (33%), *Social & Economic* (31%).

For the Methamphetamine Index (Figure D-8), the experts suggested that ‘drugged driving’ and ‘stigmatization & marginalization’ should, on average, receive the lowest weights (4% and 6%, respectively). On the other hand, experts on average agreed that the highest weight should be assigned to ‘crime & nuisance’ (20%), followed by ‘family disruption & child maltreatment’ (18%). Once again, despite weight differences at the subdomain level, weights for the three domains are roughly equal: *Crime & Disorder* (36%), *Health*, *Social & Economic* (32% each).

Figure D-8. Expert-based Weights for the Subdomains and Domains of the Methamphetamine Index

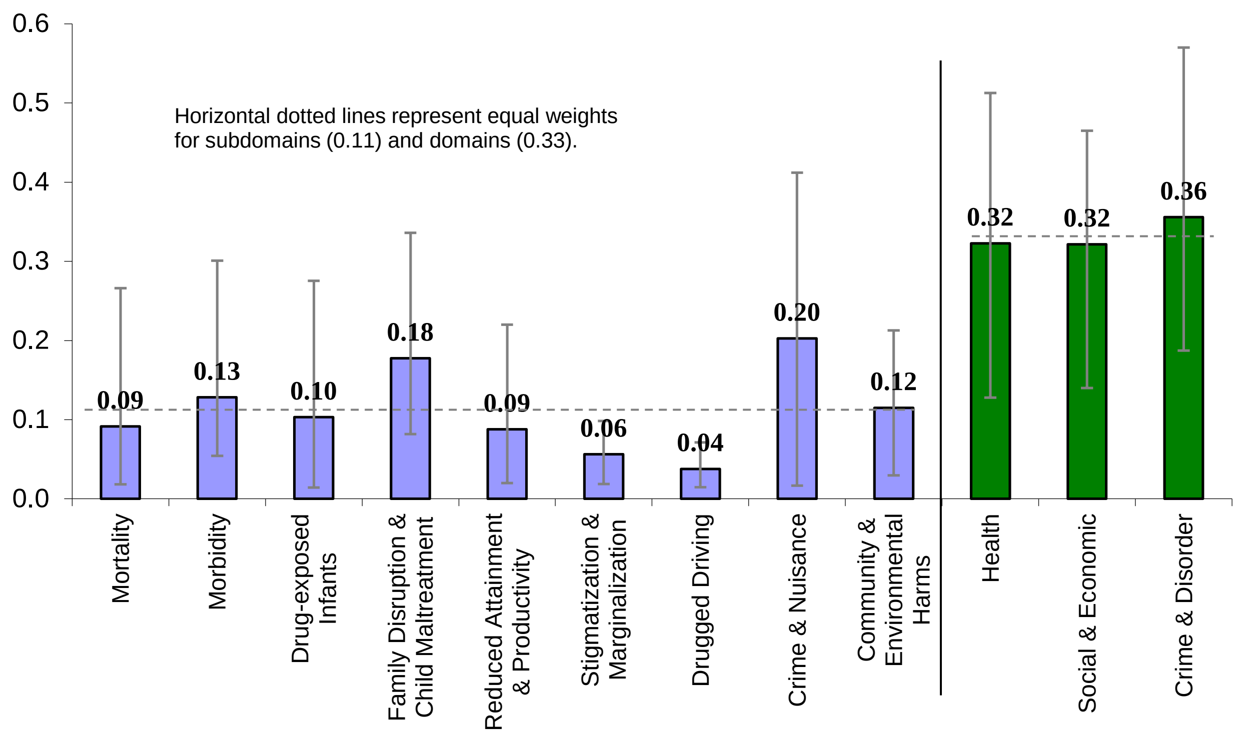
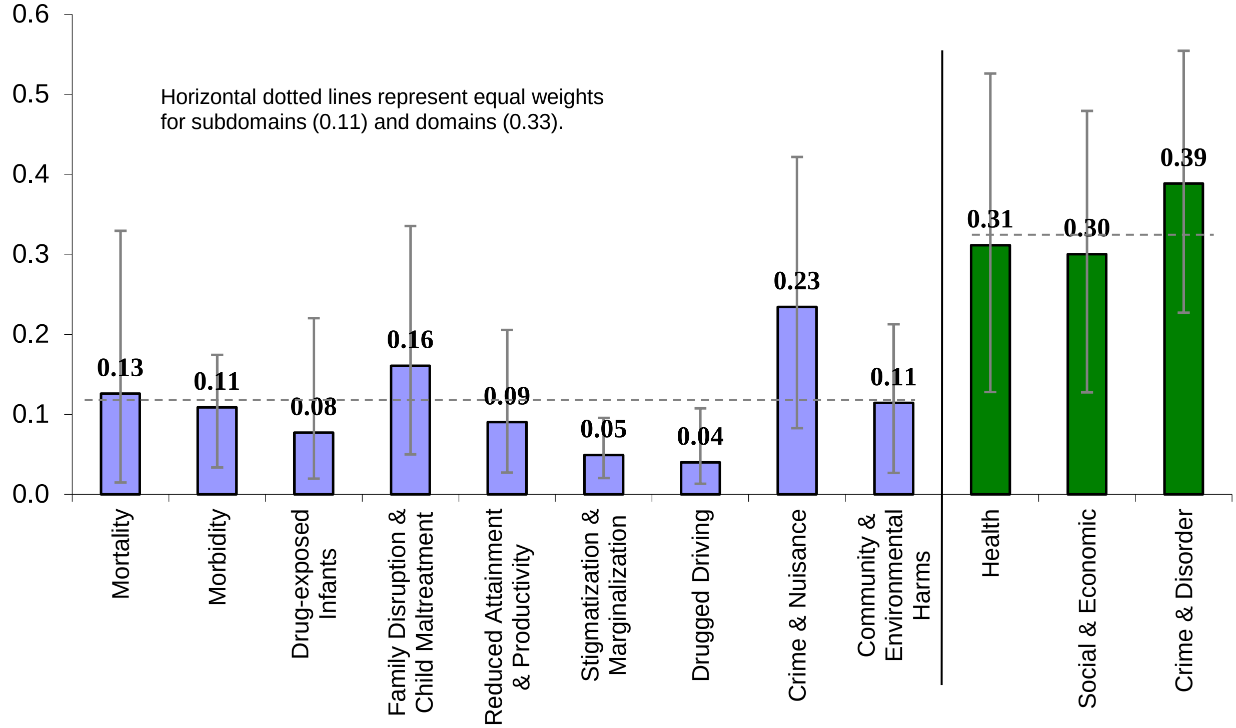


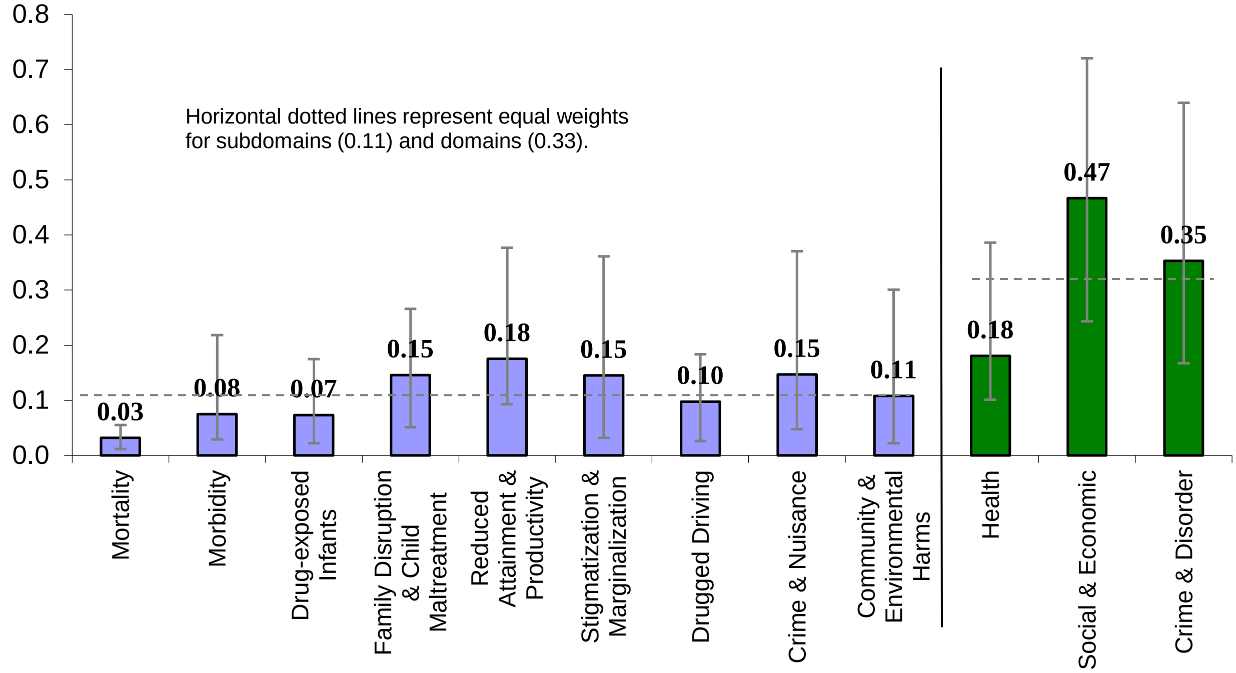
Figure D-9. Expert-based Weights for the Subdomains and Domains of the Cocaine Index



For the Cocaine Index (Figure D-9), experts suggested that ‘drugged driving’ and ‘stigmatization & marginalization’ should, on average, receive the lowest weights (4% and 5%, respectively). Conversely, experts on average agreed that the highest weight should be assigned to ‘crime & nuisance’ (23%). Overall, *Health* (30%) and *Social & Economic* (31%) domains received almost equal weights, whereas *Crime & Disorder* was weighted higher (39%).

Finally, for the Marijuana Index (Figure D-10), experts offered a very different picture than for the other three drugs. Intuitively, experts unanimously suggested that ‘mortality’ should receive the lowest weight (3%). On the other hand, experts on average agreed that the highest weight should be assigned to ‘reduced attainment & productivity’ (18%), followed by ‘family disruption & child maltreatment,’ ‘stigmatization & marginalization,’ and ‘crime & nuisance’

Figure D-10. Expert-based Weights for the Subdomains and Domains of the Marijuana Index



(15% each). Overall, it can be derived that the three domains should not receive equal weights: *Social & Economic* consequences outweigh *Crime & Disorder* and in turn *Health* (weights 47%, 35%, and 18%, respectively).

Next, the calculation of each drug-specific DCI followed three aggregation steps. First, the scores for the subdomains were calculated as simple geometric averages of the normalized indicators. Scores for the three domains were then calculated as expert-weighted geometric averages of the three subdomains underlying each domain. Finally, each State DCI is the expert-weighted geometric average of the three domains. Note that this is equivalent to calculating a drug-specific DCI as the expert-weighted geometric average of the nine subdomains. The use of the geometric average, as opposed to the classical arithmetic average, in order to aggregate the components of the State DCIs is underlined by a conceptual need to avoid the perfect substitutability among the index components in an arithmetic average. This was explained in detail in the National DCI section above.

Currently, due to data limitations, some subdomains do not have underlying indicators. In these cases, the expert-driven weights for the other subdomains within a given domain were rescaled to the sum of the three subdomains. For example, marijuana has no indicators for ‘family disruption and child maltreatment.’ Essentially during the calculations, that subdomain becomes zero-weighted despite receiving an average 15% weight from the experts. The average weights for the other two subdomains—‘reduced attainment and productivity’ and ‘stigmatization and marginalization’— which were 18% and 15% respectively, were rescaled by dividing them by the sum of all three weights (15%+18%+15%). Hence, the adjusted weights for ‘reduced attainment and productivity’ and ‘stigmatization and marginalization’ are 26% and 21%, respectively. This re-scaling was done in order for the *Social and Economic* domain to have the same weight despite one subdomain having no measurable indicators and, at the same time, to not change the ratio of the weights assigned to the two remaining subdomains.

The calculation of the drug-specific State DCIs followed three aggregation steps. First, the scores for the subdomains were calculated as simple geometric averages of the normalized indicators using equation (7), exemplified for *Morbidity* for heroin.

$$\text{Morbidity}_t = \Big((\text{treatment admissions}_t) \times (\text{poisoning diagnoses}_t) \times (\text{drug use disorder diagnoses}_t)\Big)^{1/3} \tag{7}$$

Next, scores for the three domains were calculated as expert-weighted geometric averages of the three subdomains underlying each domain using equation (8), exemplified for *Health* consequences.

$$\text{Health}_t = (\text{Mortality})_t^{w_1} \times (\text{Morbidity})_t^{w_2} \times (\text{Drug-Exposed Infants})_t^{w_3} \tag{8}$$

Finally, the expert-weighted geometric mean of the three domains was calculated as follows:

$$Y_t = (\text{Health})_t^{w_{10}} \times (\text{Social \& Economic})_t^{w_{11}} \times (\text{Crime \& Disorder})_t^{w_{12}} \tag{9}$$

Note that equation (9) is equivalent to the expert-weighted geometric average of the nine subdomains. The final results for the DCI and the three domains on *Health*, *Social & Economic*, and *Crime & Disorder* were then scaled using equation (10), whereby high values are undesirable. This is done for communication purposes with a view to have the results in the same direction as that of the raw indicators. [27]

$$\text{DCI}_t = 100 - Y_t \tag{10}$$

[27] Note that during calculations, high values are preferred over low values. This is necessitated by the use of the geometric average, which actually "incentives" a state to make an improvement in those indicators where it performs worse (i.e., low values), so as to improve its overall score. However, for communication purposes, scores for the subdomains, domains, and overall indices are reported as 100-value, where high values correspond to higher drug consequences.

6. Post-Aggregation Analysis

The DCIs aggregate three domains using weights derived from AHP which are understood to reflect an indicator's importance in the index. We have measured the importance of a domain within a DCI via Pearson's 'correlation ratio' (briefly denoted as main effect) with a view toward assessing whether the declared importance of the three domains and their main effect are similar. The main effect (henceforth S_i) describes the expected reduction in the variance of DCI scores that would be obtained if a given DCI domain could be fixed. As discussed in Paruolo, Saisana and Saltelli (2012), we can take this as a measure of importance. Thus, if all three DCI domains are expected to contribute significantly to determining the DCI classification of the states in a given year, their S_i values should not differ too much. On the contrary, if some domains are expected to have a higher weight, then their S_i values should be greater.

Table D-5. Measures of Importance (S_i) of the Domains in the Overall DCI

	Heroin	Meth-amphetamine	Cocaine	Marijuana
Health	0.79	0.75	0.67	0.22
Social & Economic	0.78	0.70	0.59	0.75
Crime & Disorder	0.84	0.97	0.87	0.40
Average of the AHP-Derived Expert Weights				
Health	0.33	0.32	0.31	0.18
Social & Economic	0.31	0.32	0.30	0.47
Crime & Disorder	0.36	0.36	0.39	0.35

Table D-5 presents the S_i values together with the average AHP-derived weights. Results are reassuring as the declared importance of the three domains and their main effect are similar. For example, for marijuana, the *Social and Economic* consequences are assessed (based on average AHP weights) to be more important than *Crime and Disorder* and in turn more important than *Health* consequences. This order of importance is confirmed by the values for the main effects of these domains. Note, however, that assigning a higher weight to some domains does not necessarily guarantee a higher impact of those domains on the variance of the DCI scores. An example where this occurs is for cocaine, where despite the roughly equal AHP weights assigned to *Health* and *Social and Economic* consequences, their contribution to the variance of the Cocaine Index scores is not the same (*Health* consequences are more influential than *Social and Economic* consequences). This type of analysis is included here in order to provide a better understanding of the "importance" of the domains, which cannot be assessed by looking at the weights alone.

7. Robustness Analysis

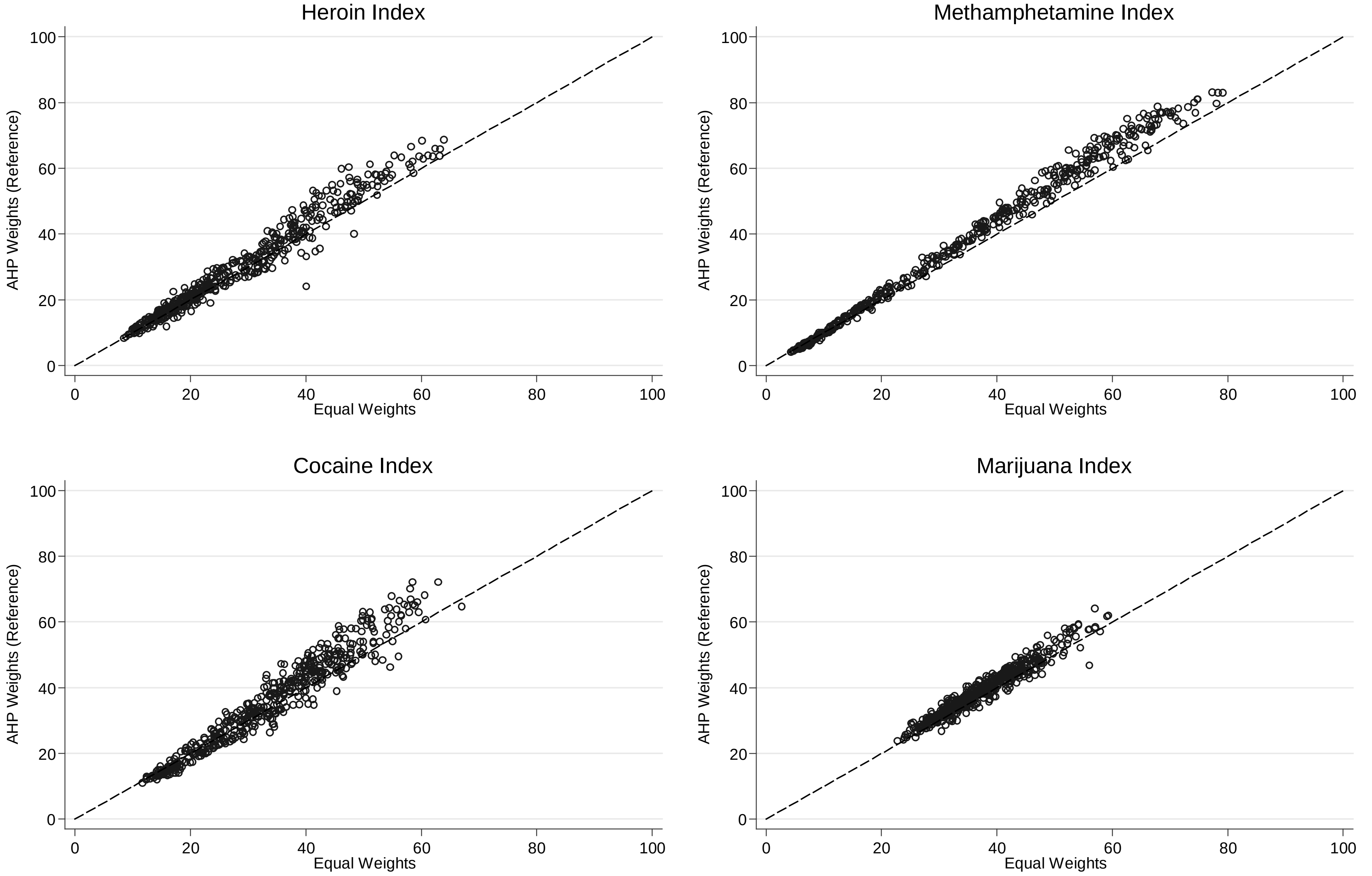
Various choices must be made when setting up a composite indicator: structure of the framework, indicator selection, weighting scheme, aggregation, and many others. The aim of the robustness analysis is to assess to what extent these choices might affect the scores or rankings of composite indicators (Saisana et al., 2005). The robustness analysis of an index is therefore an essential ingredient for validating its message by anticipating criticism (Saisana et al., 2005, OECD, 2008; Saltelli et al., 2008). The robustness assessment of the DCI aimed to assess the impact of the uncertainty in the weights assigned to the DCI subdomains to the overall index scores and ranks.

Uncertainty Analysis

For the main results, we assigned equal weights to the indicators and expert-based weights to the subdomains and domains to derive the drug-specific State DCIs. In order to better understand the impact on the DCI scores of different sets of weights, we performed three robustness analyses. First, we compared the DCI results to those obtained had equal weighting been used. Second, we used all the information from the AHP assessment, not just the average weight across the experts. Third, we performed *data envelopment analysis*. These three procedures are described in turn.

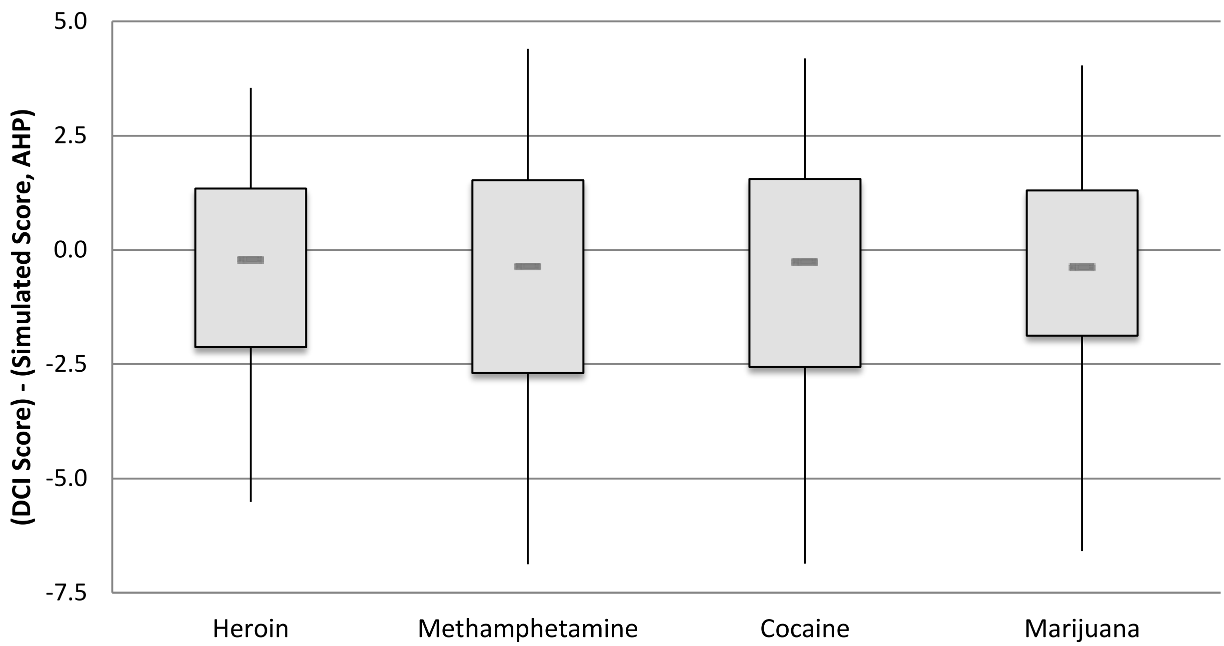
Equal weights. The impact of using equal weights for the nine subdomains, as opposed to the average expert-derived weights, on the drug-specific DCI scores is shown in Figure D-11. The simulated results assuming equal weights are plotted on the horizontal axes. Overall, the impact of assuming equal weights for the nine subdomains on the DCI scores is minimal. The Pearson product correlation coefficients between the reference and the simulated scores are .982 for Heroin, .997 for Methamphetamine, .972 for Cocaine, and .969 for Marijuana. It is interesting to note that for all drugs, but for Methamphetamine especially, the equal weight scores are in general lower (most points lay above the diagonal) compared to the reference scores, which suggests that drug consequences are higher under the AHP assumption for weights.

Figure D-11. Impact of Weights on the DCI Scores: Equal Weights vs. AHP Weights



AHP exercise. Next, to exploit all the information on the weights from the AHP exercise, we incorporate the "disagreement" in the weights among the experts in the calculation of the DCIs, and assess the impact on the results. Figure D-12 summarizes the difference between the reference DCI score (based on the average AHP weight) and a simulated score using any of the AHP-derived set of weights. [28] The horizontal black line is the median across all cases (50 States

Figure D-12. Impact of Weights on DCI Scores: Simulated AHP Weights vs. Average AHP Weights (Reference)



× 10 years × 12 to 16 sets of weights) and the boxes include 75 percent of the cases. The whole distribution of the score differences is displayed by the vertical thin black lines. A median close to zero with a small box and a short vertical line indicates that the average expert weight in the calculation of the DCIs is suitable in summarizing the panel members opinion, as the use of the

[28] Each set of weights derived from a single expert. We remind the reader that only those experts with AHP inconsistency ratios 0.2 or below were considered.

AHP weights does not affect the final scores in a significant manner. For all four drugs, the median is close to zero, and the difference is less than 2 points for 75 percent of the cases.

Data envelopment analysis. If one opts to compare the multidimensional performance of different states by subjecting them to a fixed set of weights, this may prevent acceptance of the index on grounds that a given weighting scheme might not be fair to a particular state. This issue is addressed here using data envelopment analysis.

In the absence of reliable information about the true weights to be attached to the nine subdomains underlying the DCI conceptual framework, we endogenously selected those state-specific weights that maximize a state's score with respect to all states using data envelopment analysis (Cherchye, Moesen, and Van Puyenbroeck, 2004; Melyn and Moesen, 1991). This gives the following linear programming problem for each state *i*:

$$Y_i = \max_{wij} \frac{\sum_{j=1}^{9} y_{ij} w_{ij}}{\max_{y_c \in \{dataset\}} \sum_{j=1}^{9} y_{cj} w_{ij}} \qquad \text{(bounding constraint)}$$

Subject to

$$w_{ij} \geq 0 \text{, where } j = 1,\ldots,9 \text{, } i = 1,\ldots,8 \qquad \text{(non-negativity constraint)}$$

In this basic programming problem, the weights are non-negative and a state's score is between 0 (worst) and 1 (best). [29]

However, in the traditional data envelopment analysis approach a state could achieve a perfect index score simply by assigning zero weight to those subdomains for which its performance is very low. To deal with this limitation, Cherchye et al. (2008) propose an

[29] In this calculation, the scores for the nine subdomains are expressed as the higher the better.

application of the approach, which imposes restrictions on the pie shares. In our case, the pie shares are expressed as the ratio of the weighted subdomain values over the overall DCI score. This application of data envelopment analysis is particularly interesting as it directly reveals how the respective pie shares contribute to a DCI score as the pie shares have a unity sum. The pie shares were elicited from the results of the AHP above, given the minimum and maximum values suggested by the experts, and are shown in Table D-6.

Table D-6. Ranges for the Weights' Bounds in the Data Envelopment Analysis

	Heroin	Meth-amphetamine	Cocaine	Marijuana
Mortality	[0.025,0.332]	[0.018,0.266]	[0.015,0.329]	[0.012,0.055]
Morbidity	[0.060,0.299]	[0.054,0.301]	[0.033,0.174]	[0.029,0.218]
Drug-Exposed Infants	[0.013,0.220]	[0.014,0.275]	[0.020,0.220]	[0.022,0.175]
Family Disruption & Child Maltreatment	[0.051,0.230]	[0.082,0.336]	[0.050,0.335]	[0.051,0.266]
Reduced Attainment & Productivity	[0.025,0.345]	[0.020,0.220]	[0.027,0.205]	[0.093,0.377]
Stigmatization & Marginalization	[0.020,0.147]	[0.019,0.099]	[0.021,0.096]	[0.032,0.361]
Drugged Driving	[0.015,0.109]	[0.015,0.071]	[0.013,0.108]	[0.026,0.184]
Crime & Nuisance	[0.102,0.337]	[0.017,0.412]	[0.083,0.422]	[0.048,0.371]
Community & Environmental Harms	[0.021,0.213]	[0.030,0.213]	[0.027,0.213]	[0.022,0.301]

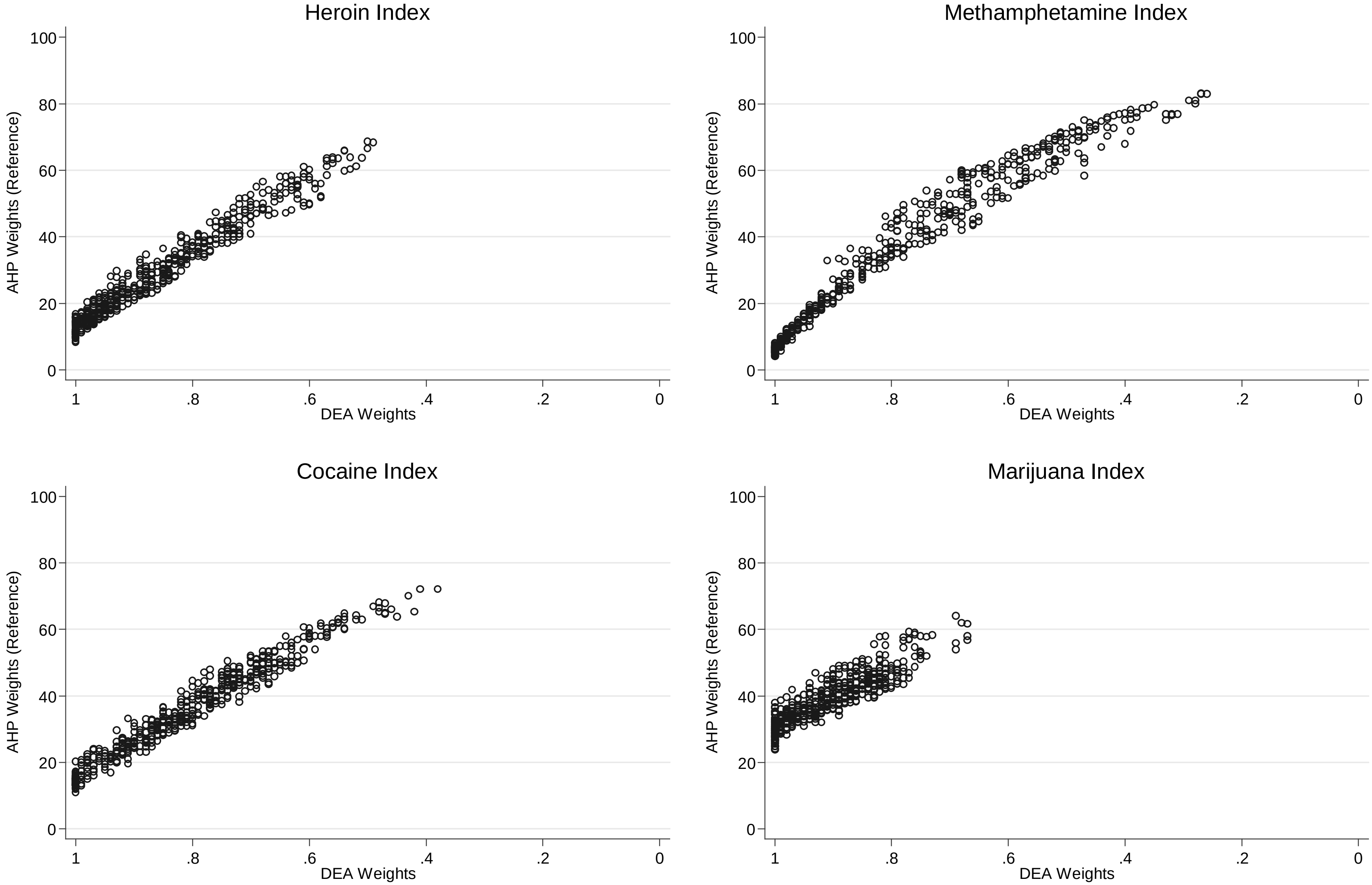
As the data show, 'mortality' can account for 2.5% to 33.2% of the DCI score for Heroin, or merely 1.2% to 5.5% of the DCI score for Marijuana. Each state is therefore free to decide—statistically speaking—on the relative contribution of the subdomains to the overall drug-specific DCI score, so as to place the state in the best possible position. In other words, the method assigns a higher contribution to those subdomains for which a state is strong and a lower weight to those subdomains for which the state is comparatively weak. However, by assigning these bounds for the shares of the subdomains, we ensure that each state includes all the subdomains and no single subdomain dominates the DCI score. In practical terms, given that some subdomains are not currently populated with indicators, the bounds for the data envelopment analysis were adjusted as described previously.

Though suitable for classifying states into efficient and inefficient ones, the traditional data envelopment analysis approach is not very appropriate for ranking states, since the weights are state-specific. The cross-efficiency evaluation method, proposed by Sexton et al. (1986), is an extension tool that could be utilized to identify good overall performers and to rank states. The main idea is to use data envelopment analysis in a peer evaluation instead of a self-evaluation. There are at least three advantages for the cross-efficiency evaluation method. First, it provides a unique ordering of the states. Second, it eliminates unrealistic weight schemes without necessarily requiring the elicitation of weight restrictions from subject area experts (Anderson, Hollingsworth, and Inman, 2002). However, given that an AHP exercise was conducted for the purposes of the DCI, such restrictions on the weights (more accurately on the pie shares) were introduced in the analysis below. Finally, the cross-efficiency evaluation method can effectively differentiate between good and poor performers (Boussofiane, Dyson, and Thanassoulis, 1991). Therefore, this method is widely used for ranking the performance of decision-making units (Sexton et al., 1986).

In the cross-efficiency data envelopment analysis, the linear programming problem is solved for each state and the fifty sets of weights are used to calculate fifty scores for each state. The average of these fifty scores for each state is used for the overall assessment of states' relative performance. Figure D-13 presents the comparison between the drug-specific DCI scores for the 50 states obtained using the average AHP-derived expert weights versus the simulated scores obtained using the cross-efficiency data envelopment analysis. Overall, the impact on the results is moderate as suggested by the high values for the Pearson product correlation coefficients between the reference and the data envelopment analysis scores (.981 for heroin, .978 for methamphetamine, .981 for cocaine, and .900 for marijuana).

An important final remark is that the uncertainty results presented herein do not inform on the quality of the framework of the drug-specific DCIs; this was already done in the previous sections. Instead, the results here can only provide information on the validity of inferences associated with the state scores for the four drug-specific DCIs over 2000-2009. In fact, the four drug-specific DCIs proved to be very robust to changes in the weights for the majority of the states.

Figure D-13. Impact of Weights on the DCI Scores: DEA Weights vs. AHP Weights



ACRONYM GLOSSARY

AAPCC	American Association of Poison Control Centers
ACF	Administration for Children and Families
ACHA	American College Health Association
ADAM	Arrestee Drug Abuse Monitoring
AERS	Adverse Event Reporting System
AFCARS	Adoption and Foster Care Analysis and Reporting System
AHP	Analytic Hierarchy Process
AHRQ	Agency for Healthcare Research and Quality
ARCOS	Automation of Reports and Consolidated Orders System
ATF	Bureau of Alcohol, Tobacco, Firearms and Explosives
ATDSR	Agency for Toxic Substances and Disease Registry
BJS	Bureau of Justice Statistics
BLS	Bureau of Labor Statistics
CASA	Center on Addiction and Substance Abuse
CDC	Centers for Disease Control and Prevention
CI	Composite Index
CSAT	Center for Substance Abuse Treatment
CSSS	Campus Safety and Security Survey
DAWN	Drug Abuse Warning Network
DCE/SP	Domestic Cannabis Eradication/Suppression Program
DCI	Drug Consequences Index
DEA	Drug Enforcement Administration
DOD	Department of Defense
DTI	Drug Testing Index
EPIC	El Paso Intelligence Center
FARS	Fatality Analysis Reporting System
FBI	Federal Bureau of Investigation
FDA	Food and Drug Administration
GES	General Estimates System
HCUP	Healthcare Cost and Utilization Project
HCUP-NIS	Healthcare Cost and Utilization Project-National Inpatient Sample
HCUP-SID	Healthcare Cost and Utilization Project-State Inpatient Databases
HHS	Department of Health and Human Services
HIDTA	High Intensity Drug Trafficking Areas
HUD	Department of Housing and Urban Development
IDU	Injection Drug Use
ISA	International Survey Associates
IRS	Internal Revenue Service
LEMAS	Law Enforcement Management and Administrative Statistics
MAPS	Multidisciplinary Association for Psychedelic Studies
MCD	Multiple Cause of Death
MTF	Monitoring the Future
NCANDS	National Child Abuse and Neglect Data System

NCHS	National Center for Health Statistics
NCJTPS	National Criminal Justice Treatment Practices Survey
NCRP	National Corrections Reporting Program
NCVS	National Crime Victimization Survey
NDACAN	National Data Archive on Child Abuse and Neglect
NDIC	National Drug Intelligence Center
NDTS	National Drug Threat Survey
NHTSA	National Highway Traffic Safety Administration
NIAAA	National Institute on Alcohol Abuse and Alcoholism
NIBRS	National Incident Based Reporting System
NICHD	National Institute of Child Health and Human Development
NIDA	National Institute on Drug Abuse
NIJ	National Institute of Justice
NIS	National Inpatient Sample
NJRP	National Judicial Reporting Program
NLSY97	National Longitudinal Survey of Youth 1997
NLSY79	National Longitudinal Survey of Youth 1979
NMVCCS	National Motor Vehicle Crash Causation Survey
NPDS	National Poison Data System
NPHS	National Pregnancy and Health Survey
NRS	National Roadside Survey
NSDUH	National Survey on Drug Use and Health
NSS	National Seizure System
N-SSATS	National Survey of Substance Abuse. Treatment Services
NSYC	National Survey of Youth in Custody
NTSIP	National Toxic Substance Incidents Program
NVSS	National Vital Statistics System
OECD	Organisation for Economic Co-operation and Development
OJJDP	Office of Juvenile Justice and Delinquency Prevention
ONDCP	Office of National Drug Control Policy
OPE	Office of Postsecondary Education
OSDFS	Office of Safe and Drug-Free Schools
OTIS	Online Tuberculosis Information System
PDFA	Partnership for a Drug Free America
PMP	Potency Monitoring Program
PRAMS	Pregnancy Risk Assessment Monitoring System
SAMHSA	Substance Abuse and Mental Health Services Administration
SBIRT	Screening, Brief Intervention, and Referral to Treatment
SIFSCF	Survey of Inmates in Federal and State Correctional Facilities
SILJ	Survey of Inmates in Local Jails
TEDS	Treatment Episodes Data Sets
TLCS	Theft or Loss of Controlled Substances
UCR	Uniform Crime Reports
USSC	United States Sentencing Commission
YRBS	Youth Risk Behavior Survey

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