What America's Users Spend on Illegal Drugs, 2006–2016

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Preface

Substance use and drug policy are clearly in the national spotlight. Although heroin, prescription opioids, and synthetic opioids (such as fentanyl) receive most of the attention, deaths involving methamphetamine and cocaine are both on the rise. Marijuana continues to receive attention as more states relax their laws.

To better understand changes in drug use outcomes and policies, policymakers need to know what is happening in the markets for these substances: How many people are using them? How much are they using? How much money are they spending? How have these quantities changed over time? This report provides answers to these questions by combining information from multiple data sources. This report, the most recent in the *What America's Users Spend on Illegal Drugs* series, updates and extends estimates of the number of users, expenditures, and consumption from 2006 to 2016 for cocaine (including crack), heroin, marijuana, and methamphetamine, based on a methodology developed by the RAND Corporation for the Office of National Drug Control Policy (ONDCP). Both of these efforts were funded by ONDCP.

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Summary

Substance use and drug policy are clearly in the national spotlight. Provisional data from the Centers for Disease Control and Prevention (CDC) (Ahmad et al., 2019) suggest that drug overdose deaths in 2018 exceeded 68,000, of which more than 47,000 involved opioids—close to the number of AIDS deaths at their peak in 1995 (CDC, 2011). Although heroin, prescription opioids, and synthetic opioids (such as fentanyl) receive most of the attention, deaths involving methamphetamine and cocaine are both on the rise. Marijuana continues to receive attention as more states relax their laws. More than 25 percent of the U.S. population now lives in states that have passed laws that allow for-profit firms to produce and sell marijuana for nonmedical purposes to adults ages 21 and older.[1]

To better understand changes in drug use outcomes and policies, policymakers need to know what is happening in the markets for these substances: How many people are using them? How much are they using? How much money are they spending? How have these quantities changed over time? This report provides answers to these questions by combining information from multiple data sources.[2] This report updates and extends estimates of the number of users, expenditures, and consumption from 2006 to 2016 for cocaine (including crack), heroin, marijuana, and methamphetamine, based on a methodology developed by the RAND Corporation for the Office of National Drug Control Policy (ONDCP) (Kilmer et al., 2014a, and Kilmer et al., 2014b).

The report's main findings include the following:

- People who use drugs in the United States spent on the order of $150 billion (in 2018 dollars) on cocaine, heroin, marijuana, and methamphetamine in 2016. The

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[1] For the purpose of this report, we note classification of marijuana as a Schedule I drug in the federal Controlled Substances Act. Based on this scheduling, production, sale, and possession of the drug are illegal under federal law. At the time of this report, ten states and the District of Columbia have legalized nonmedical marijuana markets that are in conflict with federal law. We do not attempt to differentiate users, expenditures, or consumption in state-legal markets, but the distinction is important to consider.

[2] Note, however, that with changes in the availability of the underlying data—especially discontinuation of the Arrestee Drug Abuse Monitoring (ADAM) program in 2013—and a lack of good information about fentanyl consumption, there is uncertainty surrounding these figures.

marijuana market is roughly the size of the cocaine and methamphetamine markets *combined*, and the size of the retail heroin market is now closer to the size of the marijuana market than it is to the other drugs.

- After falling precipitously from 2006 to 2010, cocaine consumption's decline slowed by 2015. Results suggest there were 2.4 million individuals who used cocaine on four more or days in the past month in 2015 and 2016. Results also suggest that consumption grew in 2016 among a stable number of users as price per pure gram declined.
- Heroin consumption increased 10 percent per year between 2010 and 2016. Whereas most heroin consumed in the United States comes from poppies grown in Mexico (Drug Enforcement Administration, 2018a), the introduction of fentanyl into heroin markets, mostly arriving from China and Mexico (Drug Enforcement Administration, 2018b), has increased the risk of using heroin. Data deficiencies for fentanyl and other drugs limit our ability to determine their impact on estimated heroin expenditure and consumption levels or trends. There was a steady increase in the amount of heroin seized within the United States and at the southwest border from 2007 through 2016. Changes in the composition of heroin users, potentially involving increased use among individuals without criminal histories, have increased the uncertainty underlying these estimates.
- From 2010 to 2016, the number of individuals who used marijuana in the past month increased nearly 30 percent, from 25 million to 32 million. Changes in marijuana markets have made weight-based consumption estimates obsolete and forced a change in how we calculate expenditures. Our new approach for estimating marijuana expenditures suggests a 24 percent increase, from $42 billion to $52 billion, over the same period. Other approaches for estimating national marijuana spending also suggest that annual spending was in the neighborhood of $50 billion circa 2014–2016.
- Methamphetamine estimates are subject to the greatest uncertainty because national data sets do not do a good job of capturing its use. ADAM's first period, ADAM-I, was discontinued when methamphetamine use was believed to be at its first peak (2004 to 2006); ADAM-II (2007–2013) covered very few counties with substantial methamphetamine use and was discontinued when other indicators of use began to climb again.[3] There was a steady increase in the amount of methamphetamine seized within the United States and at the southwest border from 2007 through 2016, and a commensurate increase in use over the 2010–2016 period.

3 ADAM ran in two periods, the first from the late 1990s through 2003, and the second from 2007 through 2013. We refer to the former period as ADAM-I and the latter as ADAM-II.

- For all the drugs, total consumption and expenditures continue to be driven by the minority of daily and near-daily users who consume on 21 or more days each month.

Tables S.1, S.2, and S.3 present estimates of chronic drug users (CDUs) (defined by ONDCP as those using on four or more days in the past month), retail expenditures, and weight consumed, respectively. We present best, lower, and higher estimates for cocaine, heroin, and methamphetamine. The lower and higher ends of the range are meant to give some sense of the uncertainty, but they have a very specific and nuanced meaning that is vulnerable to misinterpretation. They reflect only one source of uncertainty: a 95-percent confidence interval surrounding the share of adult male arrests involving a positive drug test.[4] There are many other sources of uncertainty, but they do not stem from sampling variability and so do not lend themselves to quantification. Thus, readers should not consider these lower or upper bounds as a 95-percent confidence interval for the number of chronic users.

The marijuana results include both *unadjusted* figures, which represent a lower estimate that does not adjust for underreporting, and *adjusted* figures, which are our best estimates given available data.

Table S.1
Chronic Drug Users, 2006–2016 (millions)

Drug	Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Cocaine	Best	3.8	3.4	2.9	2.7	2.5	2.5	2.4	2.3	2.3	2.3	2.3
	Lower–Higher	2.6–5.5	2.3–4.9	2.0–4.3	1.9–4.0	1.7–3.7	1.7–3.6	1.7–3.5	1.6–3.4	1.6–3.3	1.5–3.3	1.6–3.4
Heroin	Best	1.6	1.6	1.7	1.9	1.9	1.9	2.0	2.2	2.2	2.2	2.3
	Lower–Higher	0.8–3.0	0.8–2.8	0.8–3.1	0.9–3.5	1.0–3.3	0.9–3.2	1.0–3.6	1.0–4.0	0.8–4.5	0.9–4.2	0.9–4.6
Marijuana	Adjusted	14.2	13.5	14.6	16.2	17.6	17.7	19.2	19.5	22.2	22.1	22.8
	Unadjusted	10.5	9.9	10.6	12.1	12.9	12.9	14.2	14.3	16.7	16.5	17.2
Methamphetamine	Best	2.2	2.0	1.6	1.7	1.8	1.8	2.1	2.5	2.8	3.4	3.2
	Lower–Higher	1.0–3.8	0.9–3.3	0.7–3.0	0.8–3.1	0.8–3.2	0.8–3.1	0.9–3.6	1.1–4.3	1.1–4.7	1.4–5.5	1.3–5.3

NOTES: CDUs are defined by ONDCP as those using on four or more days in the past month. The lower and higher ends of the ranges for cocaine, heroin, and methamphetamine reflect only one source of uncertainty: a 95-percent confidence interval surrounding the share of adult male arrest events involving a positive drug test. These ranges are meant to give some sense of the uncertainty but do not account for other important sources of uncertainty. Marijuana figures are estimated using a different model that does not yield a comparable uncertainty range.

[4] These numbers are for "arrest events," not arrestees, because an individual can be arrested multiple times.

Table S.2
Retail Expenditures on Illicit Drugs, 2006–2016 (billions, 2018 dollars)

Drug	Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Cocaine	Best	58	48	39	35	31	29	27	24	24	24	24
	Lower–Higher	40–83	32–70	26–57	24–51	21–45	20–42	18–39	16–36	16–34	16–34	16–35
Heroin	Best	31	29	31	36	35	35	37	40	42	41	43
	Lower–Higher	16–57	15–53	16–56	17–66	18–61	17–60	18–66	18–74	16–84	17–79	17–85
Marijuana	Adjusted	34	33	37	39	42	42	42	44	54	51	52
	Unadjusted	25	24	27	29	30	31	31	32	40	38	40
Methamphetamine	Best	22	18	15	16	16	15	17	21	23	29	27
	Lower–Higher	10–37	8–31	6–27	7–28	7–28	7–27	7–31	9–36	9–39	11–46	11–44
Total (all four drugs)	Best	145	128	122	126	124	121	123	129	143	145	146

NOTES: The lower and higher ends of the ranges for cocaine, heroin, and methamphetamine reflect only one source of uncertainty: a 95-percent confidence interval surrounding the share of adult male arrest events involving a positive drug test. These ranges are meant to give some sense of the uncertainty but do not account for other important sources of uncertainty. Marijuana figures are estimated using a different model that does not yield a comparable uncertainty range.

Table S.3
Cocaine, Heroin, and Methamphetamine Consumption, 2006–2016 (pure metric tons)

Drug	Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Cocaine	Best	384	307	203	160	143	143	153	108	111	108	145
	Lower–Higher	261–550	208–450	138–297	109–236	98–209	98–209	105–224	74–160	76–162	74–158	99–213
Heroin	Best	27	27	30	31	27	30	33	42	43	44	47
	Lower–Higher	13–49	14–49	15–53	15–57	14–46	15–52	16–59	19–77	16–87	18–86	18–94
Methamphetamine	Best	50	44	31	38	46	54	63	95	117	151	171
	Lower–Higher	23–84	19–75	13–58	17–68	20–81	23–96	27–112	40–161	46–199	60–241	67–279

NOTES: The lower and higher ends of the ranges for cocaine, heroin, and methamphetamine reflect only one source of uncertainty: a 95-percent confidence interval surrounding the share of adult male arrest events involving a positive drug test. These ranges are meant to give some sense of the uncertainty but do not account for other important sources of uncertainty. Marijuana figures are estimated using a different model that does not yield a comparable uncertainty range.

From 2006 to 2016, the total amount of money spent on cocaine, heroin, marijuana, and methamphetamine fluctuated between $120 billion and $145 billion annually. The combined value of these markets is now in the same ballpark as the value of the U.S. alcohol industry (IWSR, 2018). The major change over this period is the composition of this spending. In 2006, cocaine accounted for most of the spending and marijuana was at the bottom; by 2016, that had reversed.

These estimates were generated by combining data from several sources. Unfortunately, given changes in the markets, the confounding effects of fentanyl, and the weakening data infrastructure, we are not confident about the ability to use the same methodology in future reports.

In this report, we discuss what additional types of data would help quantify the scale of these markets in the future. For marijuana, household and student surveys could be updated to collect more information about the type and quantity of products consumed. Information about marijuana markets is not limited to the traditional surveys. Legalization is producing new types of information through state "seed-to-sale" tracking systems, market surveys, delivery services, loyalty card programs, and other sources (Caulkins, 2016, and Kilmer and Pacula, 2017). Figuring out how data from these new sources can be mined to develop insights about the markets should be a priority.

With respect to the other drugs, bringing back the ADAM program or some version of it would be enormously useful, particularly if it included objective (biological) consumption measures. For example, it is possible to detect fentanyl in urine specimens even if the user did not know he or she had consumed fentanyl because it appeared only as an adulterant in some other drug. Wastewater testing is another approach for estimating consumption that has received much more attention outside of the United States. This method is an active research topic in Europe, and a recent wastewater testing report from Australia finds that fentanyl consumption likely doubled outside of capital city jurisdictions from April 2017 to April 2018 (Australian Criminal Intelligence Commission, 2018). Although the utility of this method will depend on the type of substance examined, the science is advancing, is readily scalable (Keshaviah et al., 2016), and could provide information about drug consumption at the local level.

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Abbreviations

ADAM	Arrestee Drug Abuse Monitoring
CBD	cannabidiol
CBSA	core-based statistical area
CDC	Centers for Disease Control and Prevention
CDU	chronic drug user
CPI-U	Consumer Price Index for All Urban Consumers
DAWN	Drug Abuse Warning Network
FBI	Federal Bureau of Investigation
ICD	International Statistical Classification of Diseases and Related Health Problems
MTF	Monitoring the Future
NESARC	National Epidemiologic Survey on Alcohol and Related Conditions
NFLIS	National Forensic Laboratory Information System
N-SSATS	National Survey of Substance Abuse Treatment Services
NSDUH	National Survey on Drug Use and Health
ONDCP	Office of National Drug Control Policy
PMT	pure metric tons
RASTUD	ratio of amount spent to use days
STRIDE	System To Retrieve Information on Drug Evidence
TEDS	Treatment Episode Data Set

TEDS-A	Treatment Episode Data Set: Admissions
THC-A	tetrahydrocannabinolic acid
THC	tetrahydrocannabinol
UCR	Uniform Crime Reporting
WAUSID	What America's Users Spend on Illegal Drugs

CHAPTER ONE

Introduction

Substance use and drug policy are clearly in the national spotlight.[1] Provisional data from the Centers for Disease Control and Prevention (CDC) (Ahmad et al., 2019) suggest that drug overdose deaths in 2018 exceeded 68,000, of which more than 47,000 involved opioids—close to the number of AIDS deaths at their peak in 1995 (CDC, 2011). Although heroin, prescription opioids, and synthetic opioids (such as fentanyl) receive most of the attention, deaths involving methamphetamine and cocaine are both on the rise. Marijuana continues to receive attention as more states relax their laws. More than 25 percent of the U.S. population now lives in states that have passed laws that allow for-profit firms to produce and sell marijuana for nonmedical purposes to adults ages 21 and older.[2]

To better understand changes in drug use outcomes and policies, policymakers need to know what is happening in the markets for these substances. In August 2017, RAND was contracted by U.S. Office of National Drug Control Policy (ONDCP) to generate national estimates of the total number of chronic users, total expenditures, and total consumption for four drugs: cocaine (including crack), heroin, marijuana, and methamphetamine. This report is the most recent in the *What America's Users Spend on Illegal Drugs* (WAUSID) series (Rhodes et al., 1995; Rhodes et al., 1997; Rhodes et al., 2000; Rhodes et al., 2001; Rhodes et al., 2012; and Kilmer et al., 2014a).

Estimating the size of illicit drug markets—whether in terms of users, expenditures, or quantity consumed—is difficult. The difficulty is not conceptual; essentially, estimation is just a matter of counting. The problem is largely with drug indicator data, which are becoming scarcer. Since the last update to these estimates, two critical data sources have been terminated: the Drug Abuse Warning Network (DAWN)

1 Parts of this introduction are reproduced from previous RAND research for ONDCP (Kilmer et al., 2014a).

2 For the purpose of this report, we note classification of marijuana as a Schedule I drug in the federal Controlled Substances Act. Based on this scheduling, production, sale, and possession of the drug are illegal under federal law. At the time of this report, ten states and the District of Columbia have legalized nonmedical marijuana markets that are in conflict with federal law. We do not attempt to differentiate users, expenditures, or consumption in state-legal markets, but the distinction is important to consider.

in 2011[3] and the Arrestee Drug Abuse Monitoring (ADAM) Program in 2013.[4] That statement is in no way a criticism of those who design and administer the data systems on which we rely. Rather, it is an inevitable consequence of trying to measure sales of something sold in hidden markets or consumption behavior that is both illegal and dominated by a relatively small number of daily/near-daily users in an environment of fewer indicators.

One corollary is that this task requires a great deal of humility. Depending on the substance and the construct being measured, determining the direction of trends may be the best that can be done. Numbers of chronic users can be estimated more accurately than spending, which in turn is subject to less uncertainty than estimates of quantities (weights) consumed. Likewise, there is a stronger foundation of evidence for marijuana than for cocaine and stronger evidence for cocaine than for heroin or methamphetamine. Were someone to trumpet estimates of quantities of the latter as having narrow error bands, those claims should be met with great skepticism.

A second corollary is that the task requires judgment. Most of the uncertainty does not come from sampling variability, for which one can compute statistical confidence intervals. It comes instead from such issues as the extent to which one can trust arrestees' self-reports about their spending on illegal drugs and how to extrapolate from arrestees in just a handful of urban areas to the country as a whole, particularly for methamphetamine, whose user base does not appear to be as concentrated in cities as users of cocaine or heroin.

Technology breakthroughs that link data through the health care, substance use treatment, mental health, and criminal justice systems are among the greatest opportunities to improve drug use surveillance. So-called "syndromic surveillance" may incorporate the panoply of available data to inform our understanding of illicit drug consumption. The Centers for Disease Control and Prevention National Syndromic Surveillance Program Community of Practice is currently constructing implementation guidance.

The rest of the report is organized as follows. In Chapter Two, we describe our estimates of the number of people who use cocaine, heroin, and methamphetamine. In Chapters Three and Four, we address expenditures and the total weight consumed, respectively, for these three substances. For brevity, we display and discuss estimates for 2006–2016 in the body of this report. In Chapter Five, we focus on sizing the national marijuana market, and in Chapter Six, we examine the issue of estimating

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3 Research by Sevigny and Caces (2018) demonstrates that the Nationwide Emergency Department Sample is a viable alternative to DAWN for national-level estimates of drug-related emergency department visits.

4 ADAM ran in two periods: the first from the late 1990s through 2003 and the second from 2007 through 2013. We refer to the former period as ADAM-I and the latter as ADAM-II.

the markets for marijuana and opioids, given significant changes in these markets. In Chapter Seven, we offer some concluding thoughts.[5]

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5 The report also includes five appendixes, which are available on the product page for this report on RAND's website. Appendix A includes plots of chronic drug users, expenditure, and consumption for 2000–2016, along with comparisons to estimates from the prior edition of this report (Kilmer et al., 2014a). Appendixes B and C provide additional information about our approach to estimating the number of cocaine, heroin, and methamphetamine users, and Appendix D presents survey-based data about the size of marijuana purchases. Appendix E extends the consumption estimates based on the limited set of drug use indicators available for 2017.

CHAPTER TWO

Estimating the Number of Chronic Cocaine, Heroin, and Methamphetamine Users

This chapter presents annual estimates of the number of chronic cocaine, heroin, and methamphetamine users in the United States for 2006–2016. A *chronic drug user* (CDU) is one who used a particular drug on four or more days in the previous month; polydrug use and duration of use are not considered under this definition.[1]

To generate estimates of CDUs, we employ a model combining drug use prevalence in ADAM with numerous other drug use indicators and building on prior work, including previous efforts to estimate CDUs for ONDCP. The current approach is a refinement of the model described in the prior edition of this report (Kilmer et al., 2014a, and Kilmer et al., 2014b). ADAM data collection ended in 2013, but there is no alternative data set replicating its strengths in drug use surveillance. It includes an objective measure of substance use (urinalysis) rather than self-reporting only, and it captures daily/near-daily users—who are responsible for the great bulk of consumption—far better than other surveys. ADAM is not nationally representative, however. ADAM-II included only ten counties for 2007–2011 and five for 2012–2013. To fill the information void, we supplement ADAM with other data that provide insights about drug consumption at the state and county levels. We review these indicators later in this chapter.

This chapter gives an overview of our approach and presents estimates of the number of CDUs of cocaine, heroin, and methamphetamine for 2006–2016. A detailed description of our methodology is provided in Appendix B, including a description of the changes to the model and post-ADAM extrapolation process (from 2014–2016).

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[1] This definition considers use of each drug independently. For example, an individual using heroin on four days, methamphetamine on four days, and cocaine on three days is defined as a chronic user of heroin and methamphetamine. The user is not considered a chronic user of cocaine because three days of use is below the four-day chronic user threshold.

Overview of Current Approach

Our general approach involves eight major steps that are implemented separately for cocaine, heroin, and methamphetamine.[2]

1. Model the association between the share of positive drug tests among adult male arrest events in ADAM jurisdictions for 2000–2013 (excluding 2004–2006) and covariates that are available for (or can be interpolated to) all counties in the country for 2000–2016.[3] We extrapolate estimates for 2014–2016 by imposing the associations estimated for 2000–2013 on observed covariate values for 2014–2016.
2. Project the share of positive drug tests among adult male arrest events in all counties using the model generated in Step 1.
3. For counties with the Federal Bureau of Investigation's (FBI's) Uniform Crime Reporting (UCR) Program arrest data, multiply this predicted rate by the number of adult male arrest events. This generates an estimate of the number of drug-positive male arrest events.
4. Sum across these counties and scale up using UCR national estimates to estimate the national total of adult male arrest events involving someone who would test positive.
5. Adjust this total to restrict it to adult male arrest events involving a CDU.
6. Convert the total of adult male arrest *events* involving a CDU to the total of adult male *arrestees* who were CDUs (i.e., convert from events to individuals).
7. Inflate the total of adult male arrestees who were CDUs to the total of adult male CDUs (i.e., include both those who were criminally active but happened to not get arrested in the last year and those who were not criminally active apart from their drug use).
8. Adjust the national total of adult male CDUs to account for women and juveniles.

Each of these steps involves multiple substeps that are described in Appendix B. The remainder of this section presents an overview of our approach, grouping Steps 1–4 and Steps 5–8.

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[2] Cocaine should be understood to mean cocaine in any form, including both powder and crack.

[3] These figures are for arrest events, not arrestees, because an individual can be arrested multiple times.

Steps 1–4: National Total of Drug-Positive Adult Male Arrest Events

Our main task is to relate levels of drug use among arrestees in ADAM counties to state and substate variables that are available for all counties in the country.[4] That relationship can then be used to estimate levels of drug use among arrestees in counties for which ADAM data are not collected. For example, we would expect the proportion of arrestees testing positive for cocaine to be higher in counties with greater overall prevalence of cocaine, greater demand for cocaine treatment, more job applicants testing positive for cocaine, and more cocaine overdose events. Thus, in non-ADAM counties with high rates of those predictors, our model would predict that a high proportion of arrestees would have tested positive had ADAM and its urinalysis monitoring been implemented there. Appendix B includes detailed information about the data sources used in the estimation models, estimated parameters, and the process used for selecting a preferred model.

We determined the best-performing model that best satisfies two criteria. For each drug, we estimated models that optimize the amount of variation in county-level prevalence that is associated with variation in the included covariates. Among candidate models, several may produce similar predicted prevalence estimates. From those alternatives, we chose the most parsimonious model. After determining the best-performing model for each drug, we used that model to predict county-year positive rates for the ADAM and non-ADAM counties based on their observed values for the covariates in each drug's model. This approach generated a predicted value for each county-year as well as 95-percent confidence intervals for these estimates.

We then multiplied these county-specific rates by the number of adult male arrests in each county in the annual UCR "Age, Sex, Race" series. This process generated annual estimates for male arrest events involving an arrestee who is projected to test positive for cocaine, opioids, or methamphetamine.[5]

Steps 5–8: Moving from Predicted Positive Tests to National Number of CDUs

Moving from the predicted number of drug-positive adult male arrest events to the national number of CDUs requires making adjustments. Table 2.1 describes these

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[4] For counties where series are not available, we interpolate from the most-granular available series. For example, we attribute treatment rates for counties outside of core-based statistical areas (CBSAs) in the Treatment Episode Data Set: Admissions (TEDS-A) treatment data from their state non-CBSA annual rate.

[5] As an aggregate of administrative data provided voluntarily from law enforcement agencies, UCR is not the universe of arrests. Maltz (1999) and Lynch and Jarvis (2008) note that the data may be a lower-bound count of actual arrest events. Furthermore, rural areas may be underrepresented in these data. The summed count of arrest events recorded in the UCR age, sex, and race data are nonetheless similar to the adjusted total number of national arrests reported by the FBI each year. An alternative UCR series, county-level aggregate data, explicitly removes arrests from agencies that do not report data consistently. The county-level data show far fewer arrests than the FBI national-level reference figure, with missing values concentrated disproportionately among agencies serving small populations and rural areas. There is no easy fix. We cite this issue as a potential source of uncertainty that we do not attempt to account for in the estimates presented in this report.

Table 2.1
Estimating the Number of CDUs in the United States

Factor	Adjustment	Data	Time Period for Adjustment	User Categories
Start: Number of adult male arrest events with a positive urinalysis test				
F1	For adult male arrest events with a positive test, percentage using on 4 or more days in past month[a]	ADAM-II (based on urinalysis and self-report information)	Average across annual estimates, 2000–2003, 2007–2013	Calculate for three groups: 4–10, 11–20, and 21 or more use days in past month
Multiplying by F1 yields the number of adult male CDU arrest events with a positive urinalysis test				
F2	Number of arrests with a positive test per person arrested and testing positive[a]	ADAM-I and ADAM-II (based on self-report information about arrests in the past year, excluding warrants)	Estimate from pooled ADAM-I and ADAM-II (2000–2003, 2007–2013)	Calculate for two groups: 4–10 and 11 or more use days in past month[b]
Dividing by F2 yields the number of adult male CDUs who are arrested and have a positive urinalysis test				
F3	Proportion of adult male criminally active CDUs who get arrested each year[a]	Take arrests per arrestee from F2, assumes criminally active CDU get arrested according to a Poisson distribution.	Estimate from pooled ADAM I-II (2000-03, 2007-13)	Calculate for two groups: 4–10 and 11 or more use days in past month[b]
Dividing by F3 yields the number of criminally active adult male CDU				
F4	Adult male CDUs who are not criminally active	Number of adult male CDUs who report never having been arrested in NSDUH, multiplied by four[c]	Estimate from pooled NSDUH (2002–2016)	Calculate for three groups: 4–10, 11–20, and 21 or more use days in past month
Adding F4 gives the number of adult male CDUs				
F5	Ratio of adult CDUs (male and female) to just adult male CDUs	Drug-specific ratios from (1) days of use (NSDUH), (2) CDU days of use (NSDUH), (3) number of CDUs (NSDUH), (4) users in treatment (Treatment Episode Data Set [TEDS]), (5) CDUs in treatment (TEDS), and (6) unintentional overdose deaths (CDC)	Generate 2000–2016 average for each of these seven factors, take simple average of these seven values	Calculated for one group: CDUs

Table 2.1—Continued

Factor	Adjustment	Data	Time Period for Adjustment	User Categories
Multiplying by F5 gives the number of adult CDUs				
F6	Ratio of all CDUs (adult and juvenile) to just adult CDUs	Drug-specific ratios from (1) days of use (NSDUH), (2) CDU days of use (NSDUH), (3) number of CDUs (NSDUH), (4) users in treatment (TEDS), (5) CDUs in treatment (TEDS), and (6) unintentional overdose deaths (CDC)	Generate annual average across these five factors, impose linear trend for cocaine and methamphetamine (heroin constant at 0.03)	Calculated for one group: CDUs
Multiplying by F6 gives the number of CDUs				

NOTES: CDUs are defined by ONDCP as those using on four or more days in the past month. NSDUH = National Survey on Drug Use and Health.

[a] ADAM-I and ADAM-II: No weights, do not account for those who refuse urinalysis test, no data for 2004–2006.

[b] To boost the sample, we combine 11- to 20-day users with those using on 21 or more days. Dropping those arrested for outstanding warrants has relatively little effect.

[c] Based on ONDCP's (Rhodes et al., 2012; Kilmer et al., 2014b) assumption that occasional users of cocaine, heroin, and methamphetamine in NSDUH should be multiplied by four because of underreporting.

adjustments and the data sources that the project team consulted. All the adjustments are drug specific. When possible, they are performed separately for three types of CDUs: those who used that particular drug four to ten days, 11 to 20 days, or 21 or more days in the previous month. In defining groups at this level of granularity, we attempt to account for skewness in consumption rates among CDUs, not just between chronic and less-frequent users. ADAM data indicate daily/near-daily users (21 or more days per month) have strikingly different consumption patterns than those who use weekly or even several times a week. It is the daily/near-daily users in particular who account for most of the consumption.

Appendix C includes detailed descriptions of each adjustment. The adjustments that deal with moving from arrest events with a positive test to adult male arrestees who are CDUs (Table 2.1, factors F1 and F2) are based on ADAM and are fairly straightforward.

The third and fourth adjustments move from a measure of adult male CDUs who have been arrested to one of all adult male CDUs (Table 2.1, factors F3 and F4). We first convert total male arrest events involving a CDU to adult male CDUs who were arrested (i.e., from events to people). Then, we supplement with an estimate of adult male CDUs who were criminally active but were not arrested. We divide the number of CDUs arrested by the probability a CDU is arrested in a given year, thus inflating the count to include those who happened not to have been arrested (based on a Poisson assumption only to extrapolate to criminally active CDUs). Moving from the total number of adult male CDUs to a national estimate of all CDUs (Table 2.1, factors F5 and F6) involves making adjustments to include women and juveniles that are based on insights from NSDUH, TEDS, DAWN, and mortality data.

We then make a final adjustment to account for CDUs who had minimal risk of arrest. People who commit no offense other than drug use and who both purchase and consume inside a private residence may be at very little risk of arrest. We estimate the size of this population that is missed by arrestee surveys using NSDUH. Our (imperfect) proxy for a CDU being at negligible risk of arrest is someone who has never been arrested, rather than having avoided arrest in the last 12 months. Because NSDUH misses many cocaine, heroin, and methamphetamine users, we follow previous ONDCP (Rhodes et al., 2012; Kilmer et al., 2014a) adjustments for occasional drug users in NSDUH and multiply this population by four. Adding this result to the CDU total generates an estimate of the number of adult male CDUs in the country.

Figures in Chapters Two, Three, and Four include error bands to visualize the scale of uncertainty underlying our best estimates. These uncertainty ranges reflect only one source of uncertainty: a 95-percent confidence interval surrounding the share of adult male arrest events involving a positive drug test. There are many other sources of uncertainty, but they do not stem from sampling variability and so do not lend themselves to quantification. Thus, readers should not consider these as lower or upper bounds or as a 95-percent confidence interval for the number of CDUs, but rather a basic indicator of uncertainty around each year's estimate.

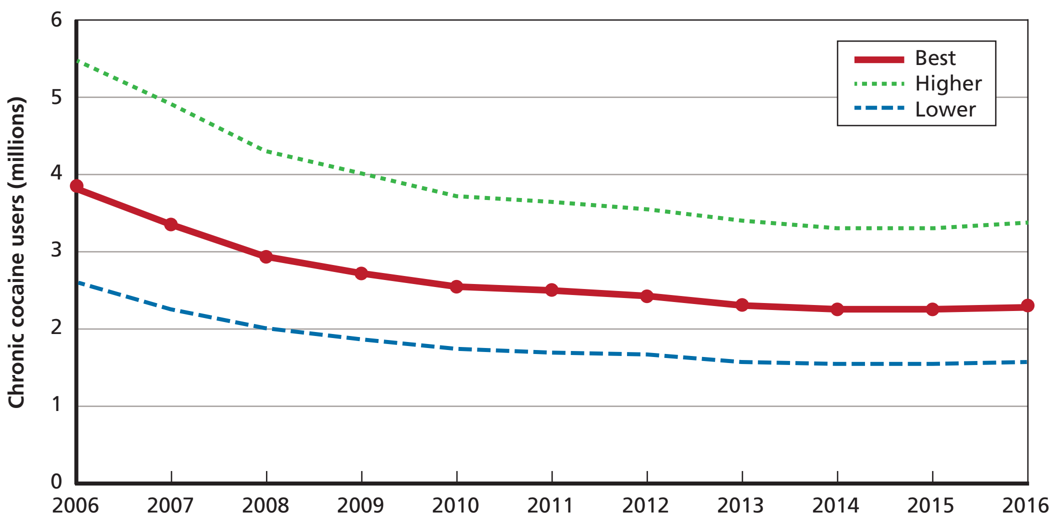
Results

Cocaine

Figure 2.1 presents the best or "point" estimates of the number of chronic cocaine users (i.e., those who used on four or more days in the previous month) surrounded by an error band. The best estimate decreased from 3.8 million in 2006 to 2.5 million by 2010 (Table 2.2).

Given the underlying uncertainty, the best estimate is consistent with the cocaine CDU figures published in the previous version of this report (Kilmer et al., 2014a). Both sets indicate a historic decrease in users between 2006 and 2010; supply- and demand-

Figure 2.1
Estimates of Chronic Cocaine Users



NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in this chapter.

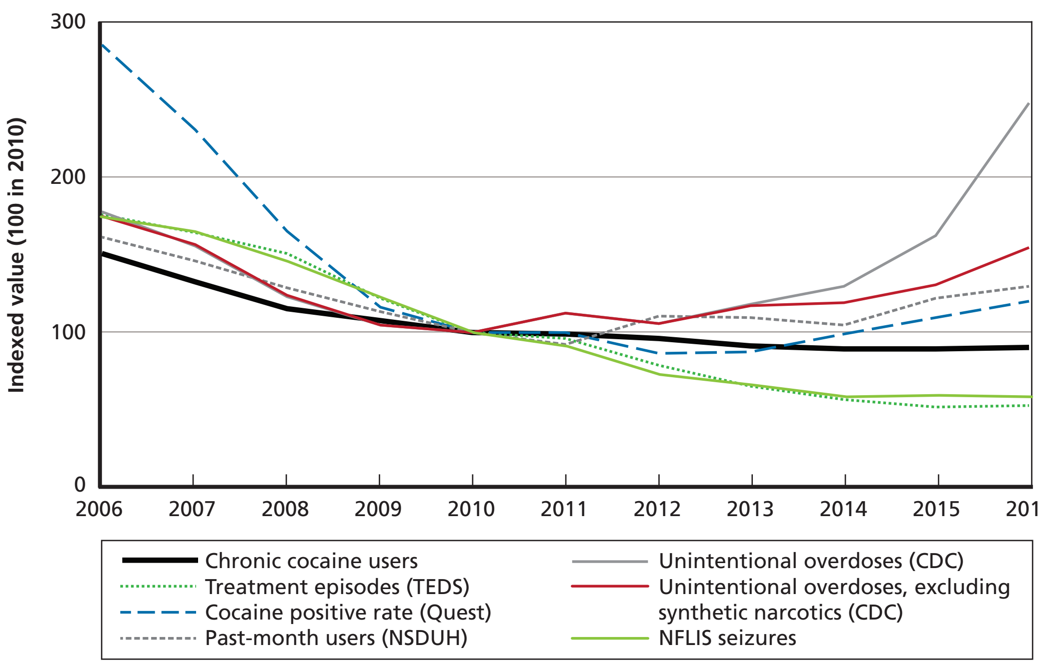
Table 2.2
Estimates of Chronic Cocaine Users (millions)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	3.8	3.4	2.9	2.7	2.5	2.5	2.4	2.3	2.3	2.3	2.3
Higher	5.5	4.9	4.3	4.0	3.7	3.6	3.5	3.4	3.3	3.3	3.4
Lower	2.6	2.3	2.0	1.9	1.7	1.7	1.7	1.6	1.6	1.5	1.6

side indicators corroborate this trend (see Figure 2.2 and Table E.2.) After 2010, our best estimate of chronic cocaine users remains relatively stable at 2.3–2.5 million users.

Because these CDU estimates draw on several data sources (ADAM, self-reported past-month use from NSDUH, treatment admissions in TEDS, workplace drug testing, and overdose mortality), we would expect to see similar trends in some (if not most) of these series as well. Figure 2.2 demonstrates that relationship in the data (scaled to have a value of 100 in 2010) between 2006 and 2010. The story told by the indicators in the time since the last WAUSID report in 2014 is more complex. Cocaine overdose deaths have increased dramatically, though much of the spike includes deaths mentioning both cocaine and synthetic opioids, such as fentanyl.[6] Workplace drug testing and the household survey both indicate an increase in use among those sample frames. TEDS data show that cocaine admissions dropped linearly between 2006 and 2015. TEDS is strongly related to prevalence in ADAM historically and is likely to

Figure 2.2
Comparison of Indexed National Cocaine Use Series



NOTES: Synthetic narcotics refers to International Statistical Classification of Diseases and Related Health Problems (ICD)-10 code T40.4 "poisoning by other synthetic narcotics" in the CDC Multiple Cause of Death records. T40.4 includes fentanyl and its analogs. NFLIS = National Forensic Laboratory Information System.

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[6] The impact of fentanyl is felt almost entirely after the ADAM series ended, so we cannot directly incorporate the drug's effect on overdose deaths through our estimation process. Rather, this is an additional source of uncertainty.

better represent a population with higher reported cocaine use than a data set describing workplace drug testing. This complexity highlights two key points. First, the clear agreement between indicators in the earlier historical period no longer holds. Second, without ADAM, we are limited in our ability to assess whether recent cocaine use among individuals described in NSDUH and Quest Diagnostics data is different from use among individuals who are less likely to be captured in those series.

Table 2.3 breaks down the estimated number of chronic cocaine users by frequency of use: 4-10 use days in the past month, 11–20 days, or 21 or more days. The 21-or-more group is about half the size of the 4–10 group, with the 11–20 group being slightly smaller than the 21-or-more group. Since these proportions are based on the average across all ADAM I and II years (2000–2003, 2007–2013), the ratios do not change over time (i.e., all groups display the same trend).

Heroin

Figure 2.3 and Table 2.4 present estimates of the number of chronic heroin users. Notably, but not surprisingly, chronic heroin use has increased by more than 40 percent from 2006 to 2016. Although heroin use was concentrated in urban areas for decades, particularly in the northeast, its use has expanded across the nation and into rural areas amid the opioid crisis.[7] There are now roughly as many chronic users of heroin as cocaine—on the order of 2.3 million as of 2016.

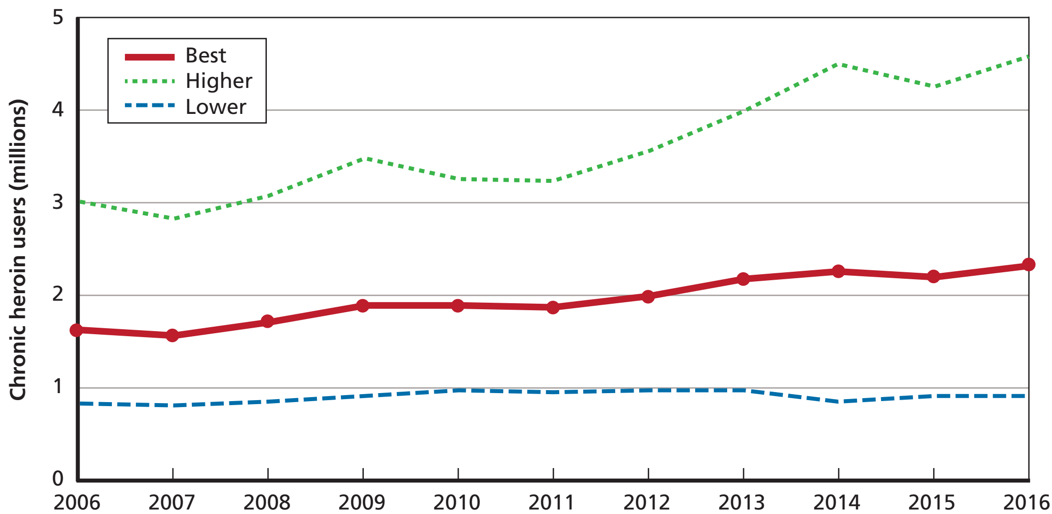
Data on heroin use are noisy, and the changing demographic composition of opioid users presents an enormous challenge to our estimation methods. If the makeup of the population of heroin users in the United States has changed since ADAM was terminated in 2013, we may understate the true number of chronic users. Given that the composition of treatment admissions and overdose decedents is now more female and less concentrated in a few big cities than was the historical norm, the true number of chronic heroin users in the United States could be as much as double our best estimate. In 2000, of all heroin overdoses, 15 percent of decedents were female and 48 per-

Table 2.3
Chronic Cocaine Users by Frequency (millions)

User Category	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
21 or more days in past month	1.0	1.1	0.9	0.8	0.7	0.6	0.6	0.6	0.6	0.5	0.5
11–20 days in past month	0.8	0.8	0.7	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5
4–10 days in past month	1.9	1.9	1.7	1.5	1.4	1.4	1.3	1.3	1.3	1.2	1.2

7 Heroin is a semisynthetic opioid. For a simple typology of opioids, see CDC, 2018b.

Figure 2.3
Estimates of Chronic Heroin Users



NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in this chapter.

Table 2.4
Estimates of Chronic Heroin Users (millions)

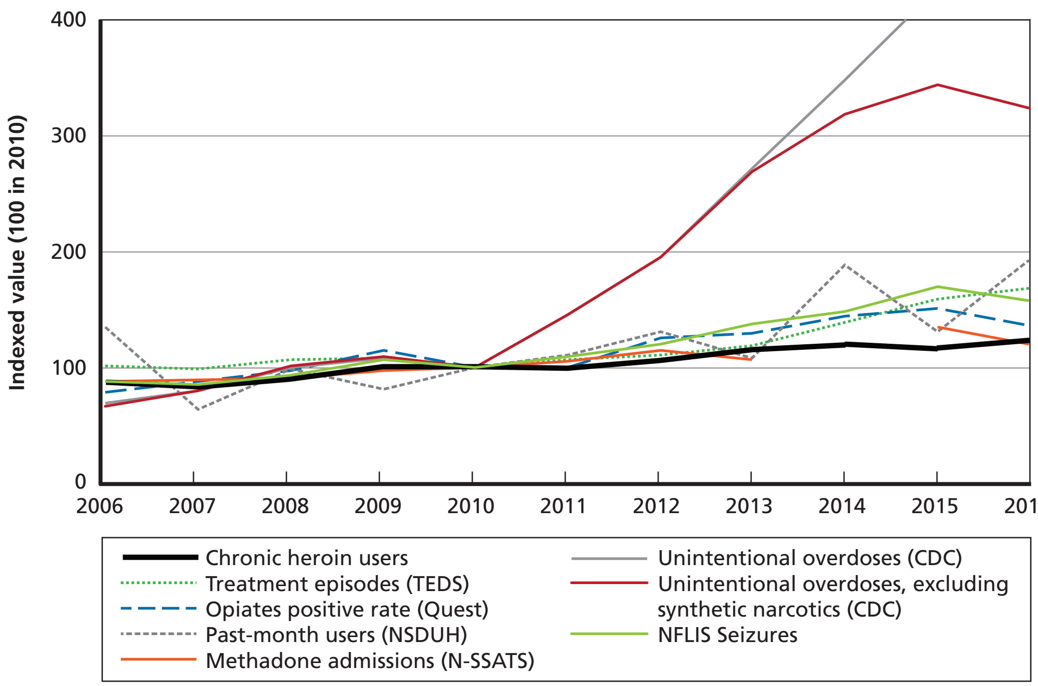
Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	1.6	1.6	1.7	1.9	1.9	1.9	2.0	2.2	2.2	2.2	2.3
Higher	3.0	2.8	3.1	3.5	3.3	3.2	3.6	4.0	4.5	4.2	4.6
Lower	0.8	0.8	0.8	0.9	1.0	0.9	1.0	1.0	0.8	0.9	0.9

cent occurred in a large central metropolitan area; in 2017, those shares were 25 percent and 38 percent, respectively (CDC, 2018a). Similar to Figure 2.1, the error band presented in Figure 2.3 is only driven by one source of uncertainty: the 95-percent confidence interval surrounding the predicted share of adult male arrest events involving a positive drug test for cocaine.

In addition to the upward trend in users, our estimates are about 25 percent larger than our previous estimates (Kilmer et al., 2014a). We previously described a nearly 25 percent increase in heroin CDUs from 2007 to 2010 but could not confidently state that the increase was true, given the uncertainty range. However, we did note "anecdotal reports about prescription opiates becoming a 'gateway drug' to heroin for some individuals" (Kilmer et al., 2014a; p. 24). Unfortunately, the conjecture now appears to have been correct. Alpert, Powell, and Pacula (2018) finds that high rates of OxyContin misuse prior to its reformulation are associated with high rates of heroin overdose deaths thereafter. The authors find that the introduction of the abuse-deterrent version of the drug yielded the unintended consequence of pushing users to substitute drugs, including heroin.

Figure 2.4 presents the main data series that underlie the CDU estimates. Past-month heroin users in NSDUH, heroin treatment admissions, and heroin overdose deaths all show increases starting in 2006 or 2007. The figure is dominated by overdose deaths with evidence of heroin use. The mixing of fentanyl and heroin results in an unprecedented trend in overdose deaths between 2010 and 2016. Overdose deaths from heroin excluding fentanyl still vastly outpace the upward trend displayed in the other use indicators. There is no question, even from the imperfect evidence available, that heroin use rose dramatically during the 2006–2016 period. However, we lack evidence to shed light on the difference between heroin overdoses and the other measures. It may be that heroin consumption has become increasingly concentrated among a small number of very heavy users who are consuming even more than historical trends would suggest. The differences may be because treatment admissions are subject to the

Figure 2.4
Comparison of Indexed National Heroin Use Series



NOTES: CDC total unintentional overdose deaths for 2014–2016 exceed the scale plotted on the y-axis. We retain the limited vertical scale to aid visibility of the other series; total overdoses have an index value of 523 in 2016, which exceeds the y-axis limit. Synthetic narcotics refers to ICD-10 code T40.4 “poisoning by other synthetic narcotics” in the CDC Multiple Cause of Death records. T40.4 includes fentanyl and its analogs. N-SSATS = National Survey of Substance Abuse Treatment Services.

capacity of facilities and cannot respond to spikes in demand, thus potentially compounding overdose risk.

The inadequacy of NSDUH to describe heroin use is more apparent. Our estimate of 2.3 million chronic heroin users in 2016 is nearly five times larger than the NSDUH estimate for past-month use, a more-inclusive definition of heroin users. We estimate there were 1.5 million daily/near-daily heroin users in 2016, more than six times the number estimated from NSDUH's 211,430. To wit, TEDS reports there were almost 450,000 admissions to specialty treatment for heroin in 2016. Although the estimates we derived for this report are uncertain, our exploration of available data made clear that NSDUH is not a useful measure of the level of heroin use in the United States.

It is difficult to estimate the total number of chronic heroin users with great precision and even harder to break those totals down by type of CDU. However, our analyses from ADAM suggest that about two-thirds of chronic heroin users are in the group that uses 21 or more days per month (Table 2.5), a considerably larger proportion than for cocaine.

Methamphetamine

Figure 2.5 and Table 2.6 present estimates of the number of chronic methamphetamine users. Our best estimates of the number of chronic methamphetamine users increased from 2.2 million in 2006 to 3.2 million in 2016, exceeding both heroin and cocaine user counts and driven by increasingly pure and inexpensive product (see Chapter Four). After decreasing in the wake of the Combat Methamphetamine Act of 2005, chronic use has more than doubled since its 2008 low. Similar to Figure 2.1, the error band in Figure 2.5 is driven by only one source of uncertainty: the 95-percent confidence interval surrounding the predicted share of adult male arrest events involving a positive drug test for methamphetamine.

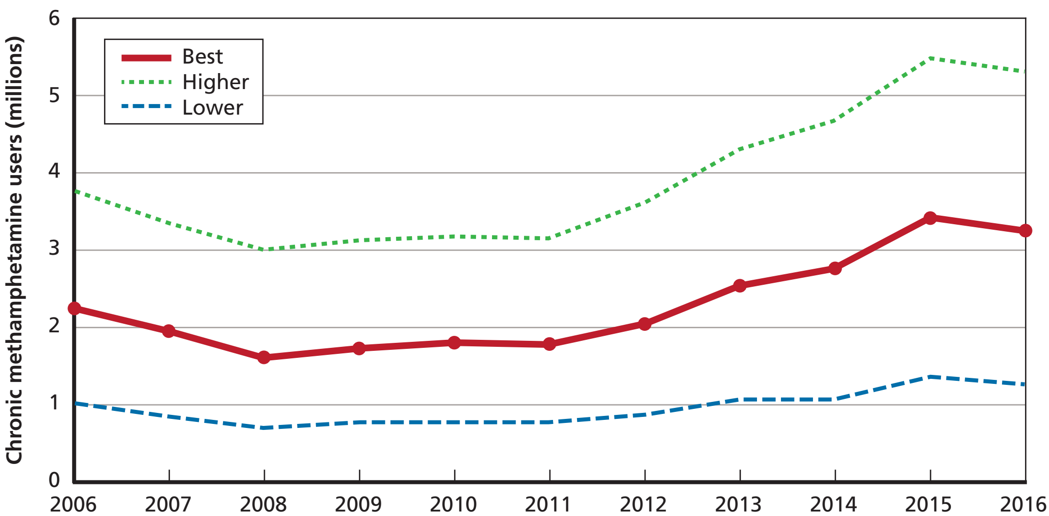
Table 2.5
Chronic Heroin Users by Frequency (millions)

User Category	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
21 or more days in past month	1.1	1.0	1.1	1.2	1.2	1.2	1.3	1.4	1.5	1.4	1.5
11–20 days in past month	0.3	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4
4–10 days in past month	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4

We reiterate the following serious reservations about the data available on methamphetamine expressed in the prior edition of this report:

> Other researchers have noted that national datasets do not do a good job of capturing methamphetamine consumption (Nicosia et al., 2009), and there are several reasons to be concerned for our particular analysis:
>
> - ADAM almost exclusively covers urban counties and meth[amphetamine] has been a serious problem in rural America.
> - We do not have ADAM data for the 2004–2006 period when meth[amphetamine] consumption apparently peaked.
> - NSDUH changed how it asked about methamphetamine in the middle of the decade, making it difficult to compare data about meth[amphetamine] prevalence and use days before and after 2007. . . .

Figure 2.5
Estimates of Chronic Methamphetamine Users



NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in this chapter.

Table 2.6
Estimates of Chronic Methamphetamine Users (millions)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	2.2	2.0	1.6	1.7	1.8	1.8	2.1	2.5	2.8	3.4	3.2
Higher	3.8	3.3	3.0	3.1	3.2	3.1	3.6	4.3	4.7	5.5	5.3
Lower	1.0	0.9	0.7	0.8	0.8	0.8	0.9	1.1	1.1	1.4	1.3

- We cannot separate methamphetamine deaths from other psychostimulants in the mortality data. When counties report drug arrests to the FBI, methamphetamine gets combined with "other dangerous drugs."

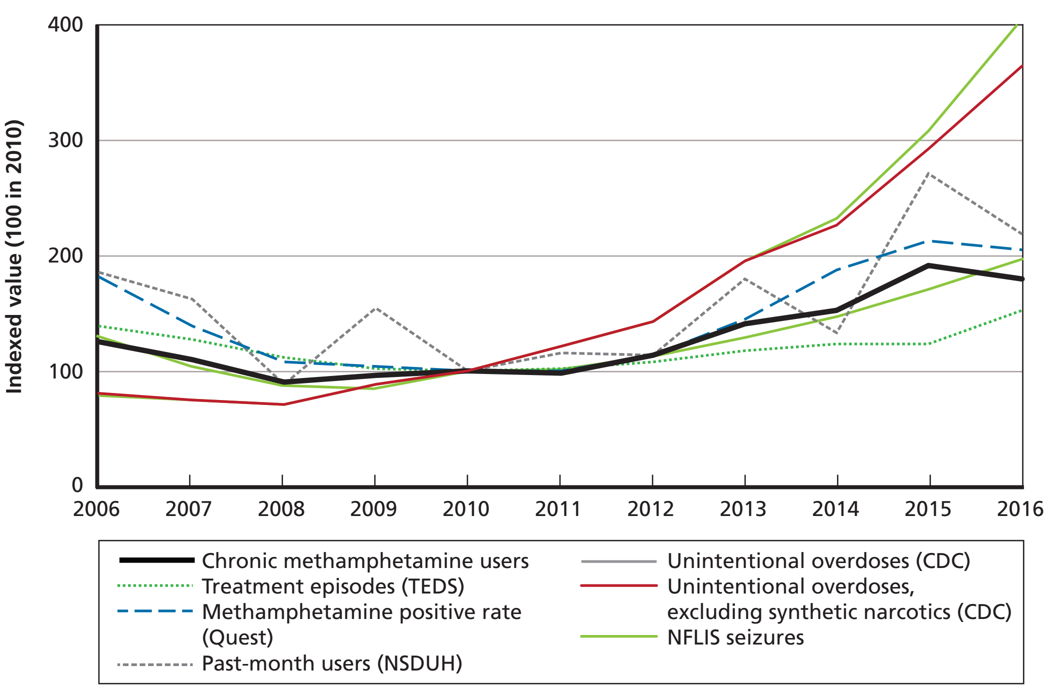
These issues dramatically increase the uncertainty concerning the model results, which is captured in the very large error bands (Kilmer et al., 2014a, p. 26).

Figure 2.6 displays some of the series that underlie our CDU estimates, as well as three other national series. Our CDU estimates split the difference in the trend observed for methamphetamine treatment admissions and death involving psychostimulants, which includes methamphetamine.

All factors considered in our analysis show an increasing trend in methamphetamine consumption until 2015, but there is less agreement for 2016. We suggest that the most-defensible position concerning trends in methamphetamine consumption is to acknowledge that the data are insufficient to assume a reduction in users in 2016.

Table 2.7 presents the composition of chronic methamphetamine users by intensity, with all three user intensity groups containing about one-third of the CDUs. We do not estimate a heavy concentration of daily/near-daily users, as is the case with

Figure 2.6
Comparison of Indexed National Methamphetamine Use Series



NOTE: Synthetic narcotics refers to ICD-10 code T40.4 "Poisoning by other synthetic narcotics" in the CDC Multiple Cause of Death records. T40.4 includes fentanyl and its analogs.

heroin, nor are there large groups of daily/near-daily (21 or more days in the past month) users and relatively infrequent users with few in between, as is the case with cocaine.

Table 2.7
Chronic Methamphetamine Users by Frequency (millions)

User Category	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
21 or more days in past month	0.7	0.6	0.5	0.5	0.6	0.6	0.7	0.8	0.9	1.1	1.1
11–20 days in past month	0.7	0.6	0.5	0.5	0.5	0.5	0.6	0.7	0.8	1.0	0.9
4–10 days in past month	0.9	0.8	0.6	0.7	0.7	0.7	0.8	0.8	1.1	1.3	1.2

CHAPTER THREE

Expenditures on Cocaine, Heroin, and Methamphetamine

This chapter describes annual estimates of total spending on cocaine, heroin, and methamphetamine for 2006 through 2016. We present expenditure estimates for four past-month drug use categories: light (one to three days of use in the past month), weekly (four to ten days), more than weekly (11 to 20), and daily/near-daily (21 or more).

The focus is on the total amount of cash spent by the final purchaser of the drugs. To avoid double counting, we exclude the value of the drugs for those who did not pay cash (e.g., those who got them for free, those who traded them for some other good or service, or those who produced their own).

The estimates presented in this chapter come with an important caveat. Cocaine, heroin, and methamphetamine expenditure data are extremely limited in the United States. We base the estimates derived for this report on the best available data, but the series end in 2013 with the termination of ADAM. We are aware of no reliable, systematically collected, and publicly available data for more-recent years. For our estimates for 2014–2016, we simply assume that expenditure per drug user has remained constant at 2013 levels, increasing only with inflation.

As we will describe further in Chapter Four, prices are not constant over the 2014–2016 period. Therefore, our assumption that users' drug expenditures are flat over 2013–2016 requires that the overall market is unit elastic—that, *on average*, users adjust their consumption proportional to the rise in prices. This is a potentially tenuous assumption and is only weakly informed by existing research. However, it benefits from two characteristics: It is plausible and parsimonious. The highest-frequency drug consumers who dominate consumption estimates may have budget constraints that limit their expenditures. They are also disproportionately likely to be dependent users. In this situation, a decrease in prices would lead to an increase in consumption only as much as users' budgets allow. Conversely, an increase in price could lead to a proportional decrease in use, again because of a binding budget constraint. This argument is simplistic and purely illustrative. Notably, it ignores the potential for substitutes and increased reliance on nonmonetary transfers. We hope further data collection and analysis can help inform these assumptions.

Methodology

To estimate drug user expenditures, we first grouped ADAM adult male arrestees, following the method employed in the previous edition of this report (Kilmer et al., 2014a). We have explicitly modeled drug use frequency categories independently before aggregating to a bottom-line chronic user expenditure estimate to highlight sources of variability and uncertainty. Prices and purchase patterns differ markedly across drug use categories.

We followed six main steps to generate national expenditure estimates for each drug.

1. Generate arrestee-level monthly spending estimates by multiplying the value of the most recent purchase by the number of purchases that day and past-month purchase days reported.
2. Create average ADAM county-level monthly expenditure estimates for each past-month chronic use category (4–10, 11–20, and 21 or more days). For counties in ADAM-I, averages are based on available data from 2000 to 2003. For counties in ADAM-II (which are also in ADAM-I), averages are generated for the 2000–2003 period and the 2007–2013 period.
3. Use the change between the periods 2000–2003 and 2007–2013 for ADAM-II counties to extrapolate the linear growth in expenditures between these periods in the larger set of ADAM-I counties for which only 2000–2003 data are available. Similar to our estimates of CDUs in this report and in previous versions of this report (Rhodes et al., 2012, and Kilmer et al., 2014a), our figures are rooted in ADAM. Unlike the estimates for CDUs, which we extrapolate from 2013–2016 based on annual treatment, overdose death, drug testing, and other complementary series, we lack alternative data to extrapolate expenditures. In the absence of available data, we retain prior estimates used in the most recent report (Kilmer et al., 2014a), follow the same method using 2011–2013 ADAM surveys, then inflate average expenditures using the Consumer Price Index for All Urban Consumers (CPI-U) for all three drugs, or 1 percent annually for 2014–2016.
4. Extrapolate average annual expenditures for each past-month chronic use category from the ADAM-I county estimates to the nation using UCR arrest data, creating an arrest-weighted national average expenditure estimate based on the number of arrestees reported in each UCR county, chronic use category prevalence rates, and average expenditures estimated from ADAM. This extrapolation assumes the distribution of users in each chronic use category in the nation is similar to that seen in ADAM counties.

5. Generate expenditure estimates for CDUs by multiplying the estimated number of users in each chronic use category in each county-year by the average expenditure for that category.
6. Estimate total annual national expenditures by multiplying total CDU annual expenditures by 1.03 to account for spending by non-CDUs.

A detailed account of Steps 1–6 is included in Appendix C.

Steps 1–3: Estimating Average Monthly Spending by User Type

These steps are straightforward and require nothing but data from ADAM-I (2000–2003) and ADAM-II (2007–2013). The first two steps entail cleaning the data and computing county-year averages. To account for the lack of ADAM data for 2004–2006, we use the change between the periods 2000–2003 and 2007–2013 for ADAM-II counties to extrapolate the linear growth by CDU category between these periods in the larger set of ADAM-I counties, for which only 2000–2003 data are available.

Tables 3.1, 3.2, and 3.3 display average monthly spending for cocaine, heroin, and methamphetamine by user type, as well as a weighted average.

Average nominal monthly spending on cocaine declined throughout the 11-year period by 2.0 percent per year, driven by a decrease in average spending for daily/near-daily users. Chronic heroin users spend roughly double what chronic cocaine users spend and 130 percent more than what methamphetamine users spend because of the concentration of expenditures among daily/near-daily users. Average spending on

Table 3.1
Average Monthly Cocaine Expenditures (nominal dollars)

Year	21 or More Days in Past Month	11–20 Days in Past Month	4–10 Days in Past Month	Weighted Average
2006	1,923	903	344	908
2007	1,881	886	337	875
2008	1,840	869	330	841
2009	1,798	851	322	813
2010	1,756	834	315	786
2011	1,714	817	308	766
2012	1,672	800	301	744
2013	1,630	783	294	720
2014	1,657	795	298	729
2015	1,659	796	299	730
2016	1,680	806	303	742

Table 3.2
Average Monthly Heroin Expenditures (nominal dollars)

Year	21 or More Days in Past Month	11–20 Days in Past Month	4–10 Days in Past Month	Weighted Average
2006	1,661	603	332	1,240
2007	1,684	635	341	1,260
2008	1,708	666	351	1,286
2009	1,731	697	360	1,313
2010	1,754	728	370	1,334
2011	1,778	760	380	1,356
2012	1,801	791	389	1,381
2013	1,825	822	399	1,406
2014	1,854	836	405	1,430
2015	1,856	837	405	1,430
2016	1,880	847	411	1,450

Table 3.3
Average Monthly Methamphetamine Expenditures (nominal dollars)

Year	21 or More Days in Past Month	11–20 Days in Past Month	4–10 Days in Past Month	Weighted Average
2006	1,147	559	212	611
2007	1,141	564	211	608
2008	1,135	569	210	604
2009	1,128	573	209	605
2010	1,122	578	208	605
2011	1,116	583	208	604
2012	1,110	588	207	606
2013	1,104	593	206	608
2014	1,122	603	209	619
2015	1,123	603	210	622
2016	1,137	611	212	629

heroin increased by roughly 1.6 percent annually (slightly less than the rate of inflation). Average methamphetamine spending slightly increased over the 11-year period, remaining roughly flat in nominal terms (so spending decreased when considering inflation).

Steps 4–6: Estimating Average Monthly Spending by User Type

The next steps move from average CDU spending in ADAM counties to the rest of the country, including non-CDUs (i.e., those using one to three days in the previous month).

We use UCR adult male arrests to extrapolate our ADAM county estimates to represent county-level drug expenditures among arrestees nationally. We assume that the share of arrests reporting light, weekly, more than weekly, and daily/near-daily use in ADAM is representative of the true mix of use among arrestees, and we generate a single estimate of expenditures among arrestees for the ADAM counties. We generate a weighted average expenditure based on the number of arrests reported in each county; relatively more weight is given to expenditures in counties with more arrests and higher past-month prevalence rates. National expenditures for each drug are estimated by multiplying the weighted average annual expenditure by the number of CDUs for each drug. To account for spending by non-CDUs, we multiply CDU expenditures by 1.03.

We adjust the annual expenditure estimate for inflation using the Bureau of Labor Statistics' CPI-U, which increased by 24 percent from 2006 to 2018 (Bureau of Labor Statistics, 2019). Note that trends in expenditure estimates for all three drugs will directly mirror CDU trends for 2014–2016 because, as described earlier in the chapter, expenditures are assumed to be fixed over the most recent period.

Results

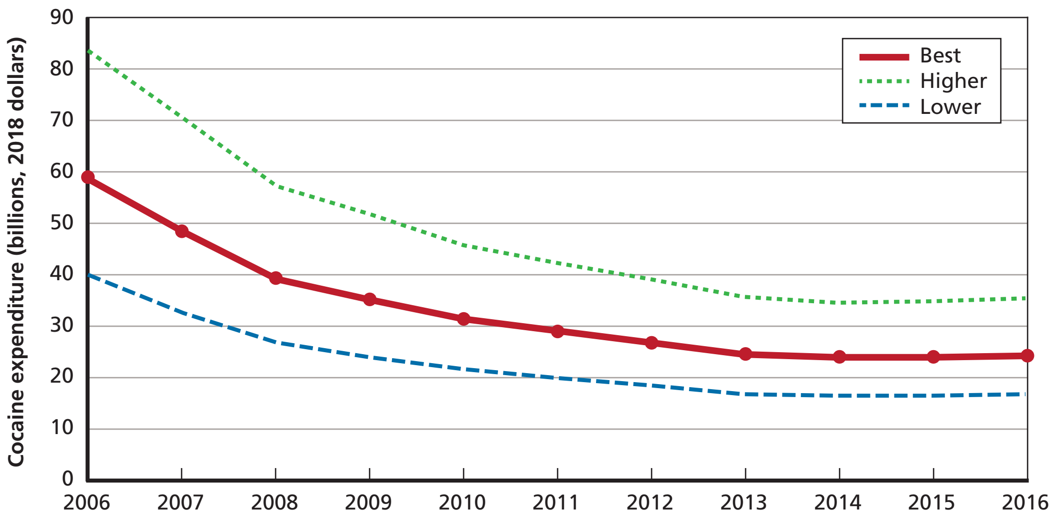
Cocaine

Commensurate with CDU estimates, cocaine expenditures remained near $25 billion from 2013 to 2016, falling roughly 60 percent from $58 billion in 2006 (Figure 3.1 and Table 3.4). Figure 3.2 and Table 3.5 report cocaine expenditures by user type from 2006 to 2016. Daily/near-daily users account for a disproportionate share of the reduction in expenditures, decreasing 63 percent over the period versus a 55 percent decrease for the less-frequent user categories.

Heroin

We estimate that annual expenditures for heroin rose to approximately $43 billion in 2016. Over the 11-year period, heroin expenditures grew by 39 percent overall (Figure 3.3 and Table 3.6).

Figure 3.1
Cocaine Expenditure Estimates



NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in Chapter Two.

Table 3.4
Cocaine Expenditure Estimates (billions, 2018 dollars)

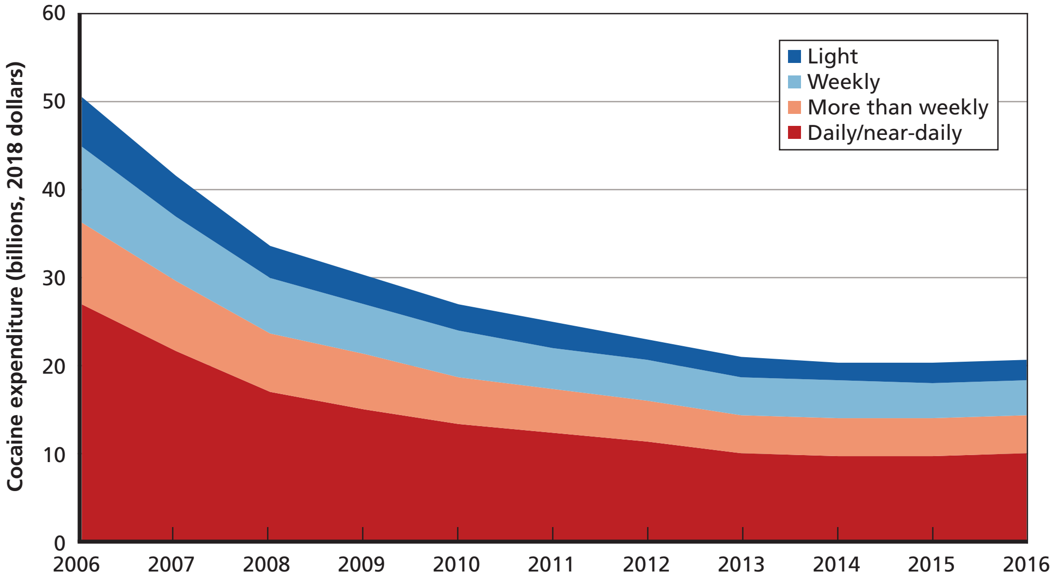
Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	58	48	39	35	31	29	27	24	24	24	24
Higher	83	70	57	51	45	42	39	36	34	34	35
Lower	40	32	26	24	21	20	18	16	16	16	16

The vast majority of heroin expenditures come from daily and near-daily users. However, expenditures among light, weekly, and more than weekly users grew by 81 percent over the period, faster than among the daily/near-daily group (Figure 3.4 and Table 3.7). We estimate that consumption increased steadily over the period, though we note the wide range of feasible higher expenditure estimates.

Methamphetamine

Figure 3.5 and Table 3.8 detail methamphetamine expenditure estimates for 2006 through 2016. Enforcement and treatment efforts, such as the Combat Methamphetamine Epidemic Act of 2005, and substitution of legal prescription psychostimulant drugs potentially reduced expenditures temporarily, but the market recovered by 2016. After reaching a temporary floor between 2008 and 2011, methamphetamine expenditures increased roughly 80 percent by 2016. Over the period, the expenditure growth

Figure 3.2
Cocaine Expenditures by User Type



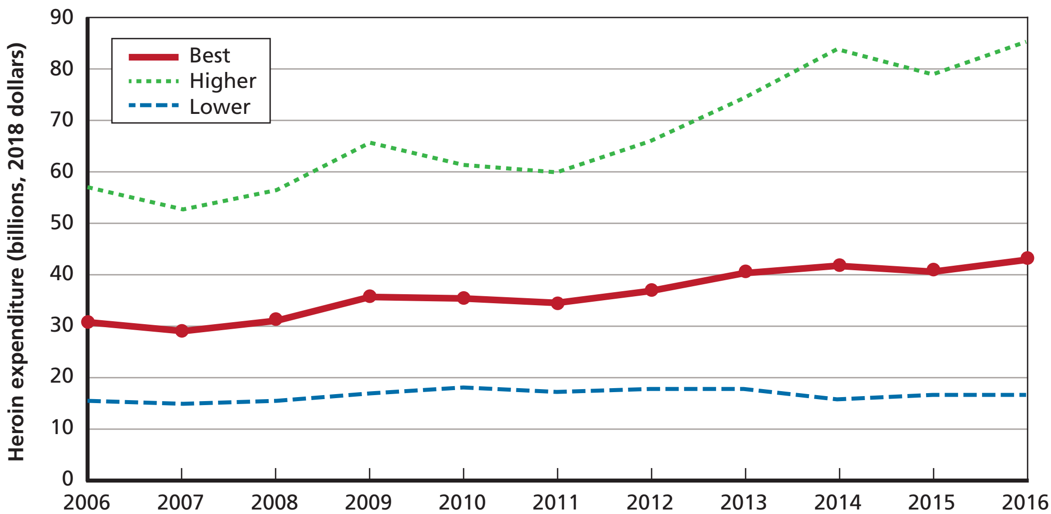
NOTE: Figure does not include expenditures by non-CDUs.

Table 3.5
Cocaine Expenditures by User Type (billions, 2018 dollars)

User Type	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Light	5.6	4.6	3.7	3.4	3.0	2.8	2.6	2.3	2.3	2.3	2.3
Weekly	8.6	7.3	6.1	5.7	5.1	4.8	4.5	4.1	4.1	4.1	4.1
More than weekly	9.5	8.0	6.6	6.1	5.5	5.1	4.8	4.4	4.3	4.3	4.4
Daily/near-daily	26.9	21.7	17.2	15.2	13.3	12.3	11.3	10.1	9.9	9.8	10.1

rate among daily/near-daily users (81 percent) exceeded that among the less-frequent user categories (76 percent) (Figure 3.6 and Table 3.9).

Figure 3.3
Heroin Expenditure Estimates

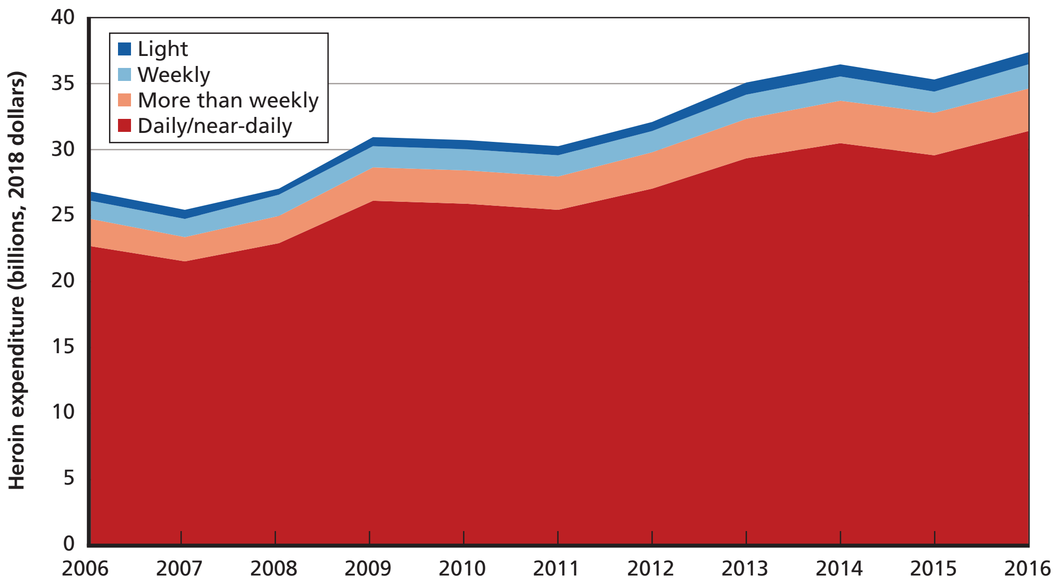


NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in Chapter Two.

Table 3.6
Heroin Expenditure Estimates (billions, 2018 dollars)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	31	29	31	36	35	35	37	40	42	41	43
Higher	57	53	56	66	61	60	66	74	84	79	85
Lower	16	15	16	17	18	17	18	18	16	17	17

Figure 3.4
Heroin Expenditures by User Type

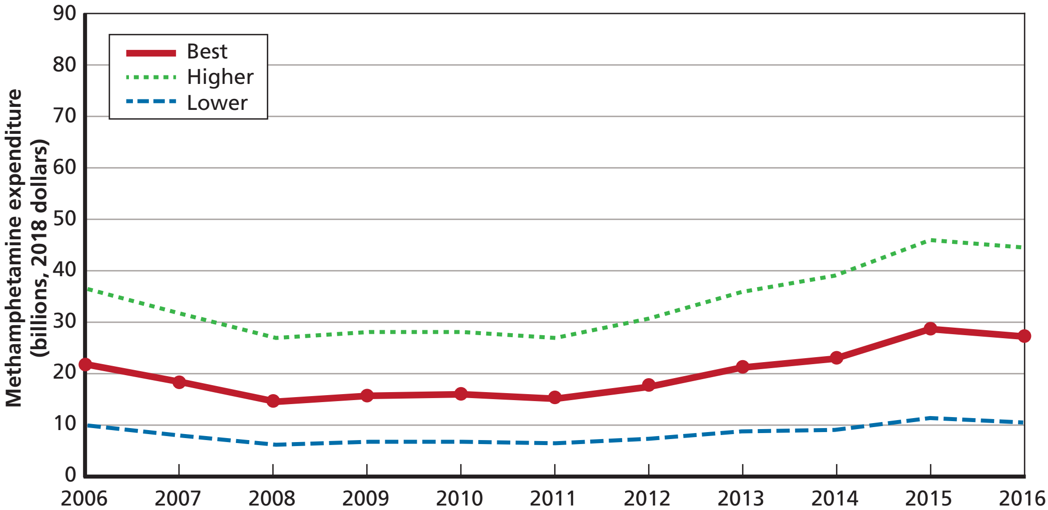


NOTE: Figure does not include expenditures by non-CDUs.

Table 3.7
Heroin Expenditures by User Type (billions, 2018 dollars)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Light	0.6	0.6	0.7	0.8	0.7	0.7	0.8	0.8	0.9	0.9	0.9
Weekly	1.3	1.3	1.4	1.6	1.6	1.6	1.7	1.8	1.9	1.8	1.9
More than weekly	2.0	1.9	2.1	2.5	2.5	2.5	2.8	3.1	3.2	3.1	3.2
Daily/ near-daily	22.8	21.5	23.0	26.2	25.9	25.3	27.0	29.3	30.4	29.6	31.3

Figure 3.5
Methamphetamine Expenditure Estimates

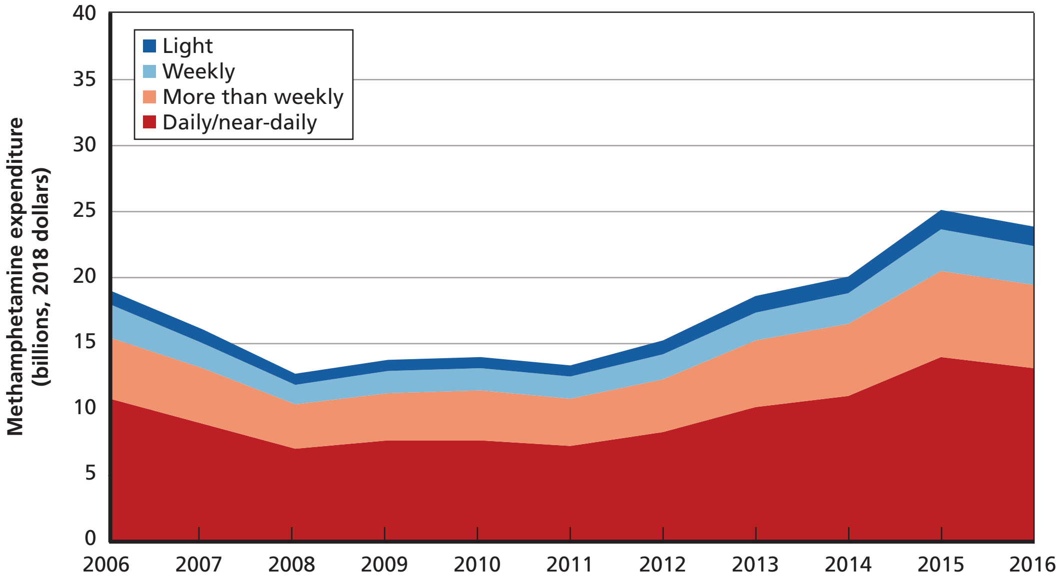


NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in Chapter Two.

Table 3.8
Methamphetamine Expenditure Estimates (billions, 2018 dollars)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	22	18	15	16	16	15	17	21	23	29	27
Higher	37	31	27	28	28	27	31	36	39	46	44
Lower	10	8	6	7	7	7	7	9	9	11	11

Figure 3.6
Methamphetamine Expenditures by User Type



NOTE: Figure does not include expenditures by non-CDUs.

Table 3.9
Methamphetamine Expenditures by User Type (billions, 2018 dollars)

User Type	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Light	1.1	1.0	0.8	0.8	0.8	0.8	0.9	1.1	1.2	1.5	1.4
Weekly	2.4	2.0	1.6	1.7	1.8	1.7	1.9	2.3	2.5	3.0	2.9
More than weekly	4.8	4.1	3.3	3.6	3.7	3.5	4.0	4.9	5.4	6.7	6.3
Daily/ near-daily	10.6	8.9	6.9	7.5	7.6	7.2	8.2	10.1	11.0	13.8	13.1

CHAPTER FOUR

Estimating Cocaine, Heroin, and Methamphetamine Consumption

In this chapter, we derive estimates for the pure quantities of cocaine, heroin, and methamphetamine consumed. Our approach is a continuation of the method described in the previous edition of this report (Kilmer et al., 2014a) and generally similar to previous studies. We generate the total annual value of each substance consumed in the United States based on the amount acquired through cash purchases (described in Chapter Three), adjusted to account for in-kind transfers, and divide by the national average price paid per pure gram purchased. We estimate the price figures using purchase value information from ADAM and by applying the RAND/Institute for Defense Analyses method for generating purity-adjusted price information from the Drug Enforcement Administration's System To Retrieve Information on Drug Evidence (STRIDE) database and its replacement, STARLIMS (Arkes et al., 2004, and Fries et al., 2008).[1]

Methodology

Details of our methodological approach are reported in Appendixes B and C. This chapter provides a brief overview of how we calculated the numerators and denominators for our consumption estimates.

Generating the Numerator

We estimate cash expenditures on each substance explicitly in Chapter Three, but the true amount of each substance consumed includes a share acquired through noncash transfers, including barter, trade, and gifts. Similar to past efforts, (e.g., Rhodes et al., 2001, and Kilmer et al., 2014a), we increase monetary expenditures by one-eighth (multiply by 1.125) to account for acquisition and use in excess of the amount purchased with money. This adjustment equates to approximately 11 percent of acquisi-

1 This report does not estimate consumption by region within the United States nor the route that internationally sourced drugs take to reach the final markets within the United States.

tions and ignores domestic production. Although domestic production of marijuana may be increasing, especially in states that allow production for the adult market, domestic production of heroin and cocaine by U.S. consumers has long been assumed negligible, and the increasing potency of seized methamphetamine, along with tight domestic regulation of precursor chemicals, suggests most methamphetamine is produced abroad.

The factor of 1.125 is more subjective than data-driven. If a reader believes that barter-based acquisitions were more or less common than the 1.125 figure would suggest, it is a simple exercise to modify this assumption. For example, if one-fifth of product consumed was acquired via in-kind transfers, then the factor would be 1.25, and quantity consumed would be 11 percent larger than the estimates in this chapter.

Generating the Denominator

We estimate prices from STRIDE and STARLIMS.[2] In doing so, we confront an inevitable question regarding the representativeness of drug enforcement data on the market as a whole. Basing price series for referent purchases on STRIDE makes the strong implicit assumption that prices in the market, which we do not observe, generally are comparable with those made by enforcement agents and/or their confidential informants, which we do observe. There has been serious debate regarding that assumption (Horowitz, 2001, and Kilmer et al., 2014a).

We retain the referent quantities (meaning the amount typically purchased in a street-level sale) described in the previous WAUSID (Kilmer et al., 2014a), still assuming the median retail purchase size that arrestees report for cocaine powder, crack, heroin, and methamphetamine is only $20 (based on ADAM data). Mean figures are well below the expenditure required to purchase a pure gram of any of the four substances. These quantities are listed in Table 4.1.

Figure 4.1 and Table 4.2 display prices per pure gram for cocaine, heroin, and methamphetamine, and Figure 4.2 and Table 4.3 show the average purity estimates for those drugs from 2006 to 2016. Of particular note is the rise in methamphetamine purity, with an average remaining above 90 percent over the 2013–2016 period. The estimated fall in its price from 2008 to 2016 is dramatic. We estimate a purchase in 2016 yields nearly three times the product as it did in 2008. Heroin prices also appear

Table 4.1
Pure Gram Price Evaluation Levels

	Crack Cocaine	Powder Cocaine	Heroin	Methamphetamine
Evaluation level	0.25 pure grams	0.25 pure grams	0.1 pure grams	0.25 pure grams

2 For this analysis, we received data-comparable extracts from STRIDE and STARLIMS. The data systems may be considered interchangeable for the purpose of this work.

Figure 4.1
Price Per Pure Gram for Each Drug

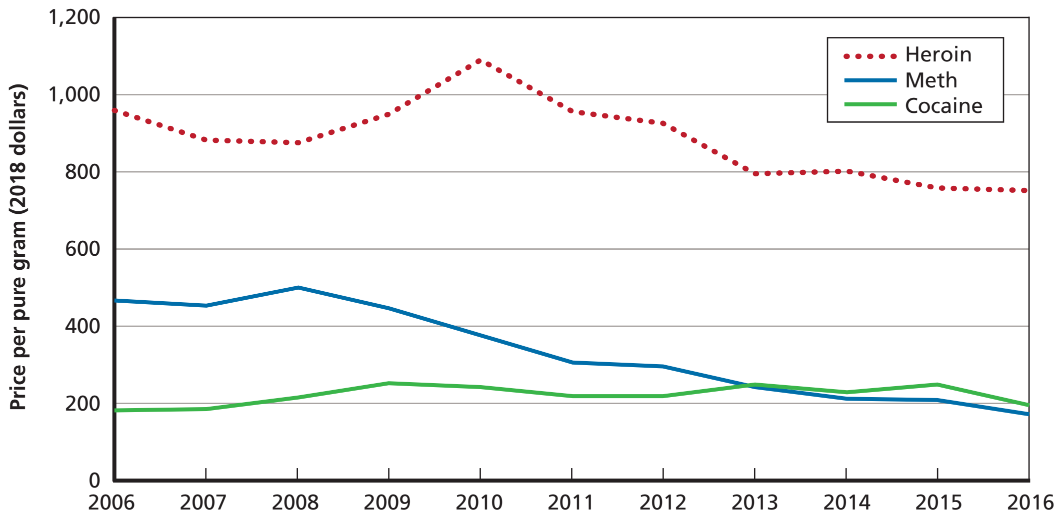


Table 4.2
Price Per Pure Gram for Each Drug (2018 dollars)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Heroin	958	880	873	949	1,090	955	924	795	800	758	750
Methamphetamine	466	451	498	444	374	303	295	241	211	205	171
Cocaine	181	183	214	251	242	218	218	247	227	249	194

Figure 4.2
Average Purity for Each Drug

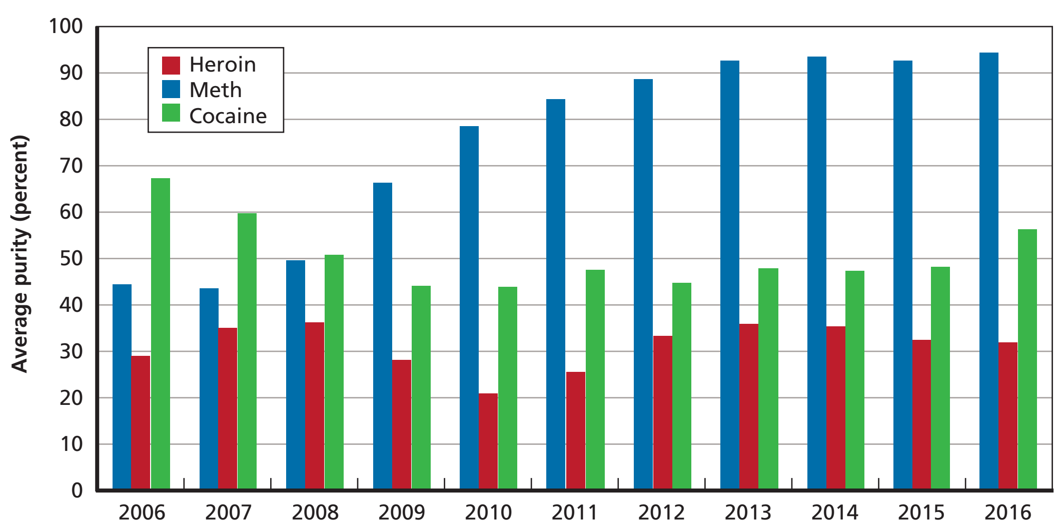


Table 4.3
Average Purity for Each Drug (percent)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Methamphetamine	44	44	50	66	79	84	89	93	94	93	94
Heroin	29	35	36	28	21	26	33	36	35	32	32
Cocaine	67	60	51	44	44	48	45	48	47	48	56

to have fallen 30 percent since 2010. Although fentanyl-laced heroin, methamphetamine, and cocaine have been reported, we cannot assess the impact of fentanyl on heroin or other drug prices due to data limitations. We discuss this challenge in Chapter Six.

Results

This section summarizes consumption in pure metric tons of cocaine, heroin, and methamphetamine. Each graph plots the best estimate for annual consumption as a solid line. The uncertainty ranges for each point are plotted as dotted lines. As discussed earlier, this range of uncertainty represents only the uncertainty in drug-positive arrest events from ADAM. Generally, the magnitude of this uncertainty changes from year to year and across drugs based on the magnitude of the best estimate itself, where larger estimates will have proportionately larger uncertainty due to magnification from arrest events in ADAM when compared with consumption nationwide. The uncertainty range also increases if there is greater disagreement among drug use indicators used to predict drug-positive events. When these indicators are more correlated, the uncertainty range will be relatively smaller, all else constant.

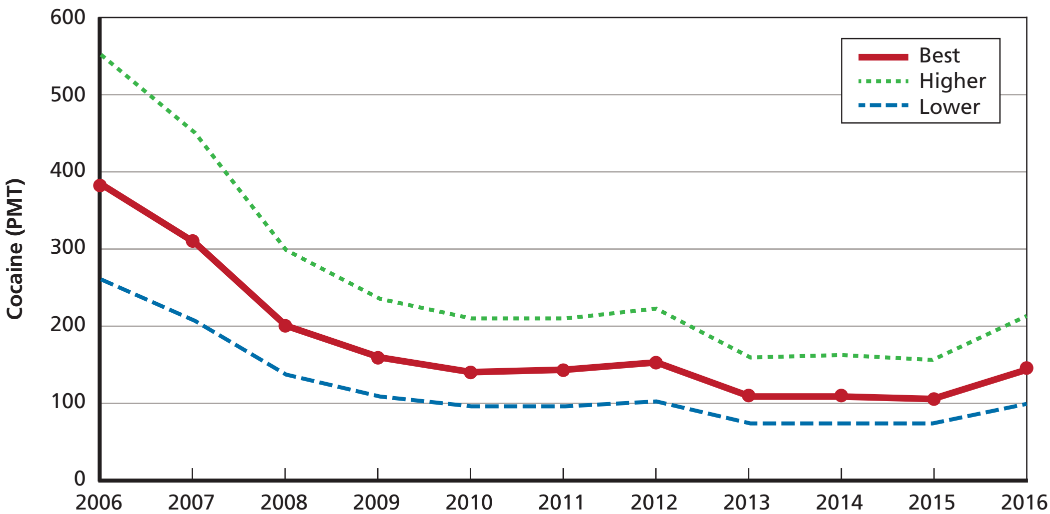
Cocaine

Figure 4.3 and Table 4.4 show that estimated cocaine consumption fell dramatically, from 366 pure metric tons (PMT) in 2006 to approximately 100 PMT from 2013 through 2015. The 34 percent increase in 2016 is also considerable, though single-year fluctuations should be viewed with skepticism given the uncertainty underlying these estimates.

Heroin

Figure 4.4 and Table 4.5 show estimated heroin consumption remained essentially flat from 2006 through 2011 at around 25–30 PMT per year but jumped to 47 PMT by 2016. With this general upward trend comes considerable uncertainty, given the sparse available data on heroin and the effect of fentanyl and its analogs on recent consumption trends.

Figure 4.3
Cocaine Consumption Estimates



NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in Chapter Two.

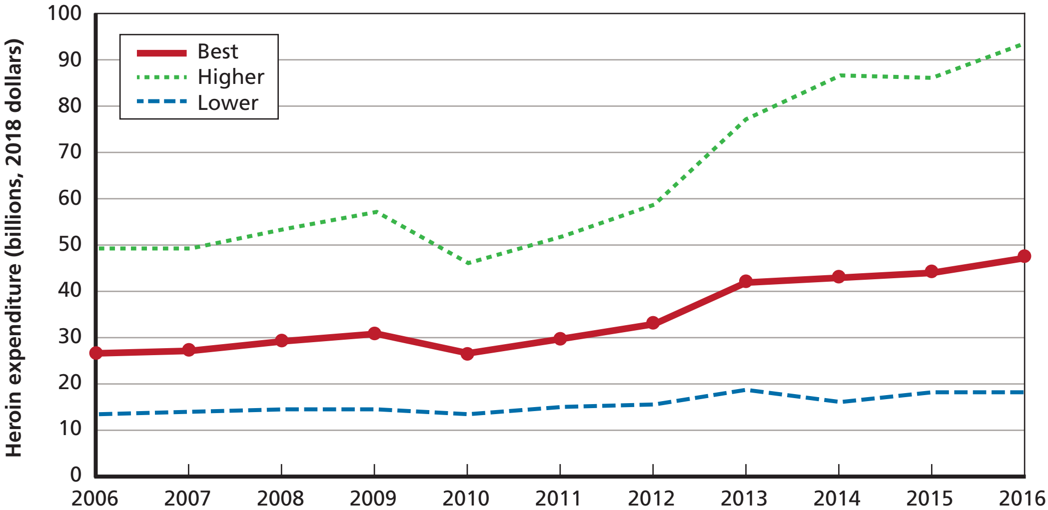
Table 4.4
Cocaine Consumption Estimates (PMT)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	384	307	203	160	143	143	153	108	111	108	145
Higher	550	450	297	236	209	209	224	160	162	158	213
Lower	261	208	138	109	98	98	105	74	76	74	99

Methamphetamine

Figure 4.5 and Table 4.6 show that estimated methamphetamine consumption has potentially exploded, based on an increase in estimated users, a dramatic increase in potency in observed samples, and falling price per pure gram. If it is correct that methamphetamine consumption eclipsed 170 PMT in 2016, consumption will have increased by more than 450 percent from the bottom of the market in 2008. However, methamphetamine surveillance data give us serious pause. We can be confident that methamphetamine consumption is increasing, perhaps dramatically, but we cannot make any claim beyond that. As was discussed in Chapter Two, the range depicted by the "higher" and "lower" estimates reflects only a portion of the uncertainty in these estimates.

Figure 4.4
Heroin Consumption Estimates

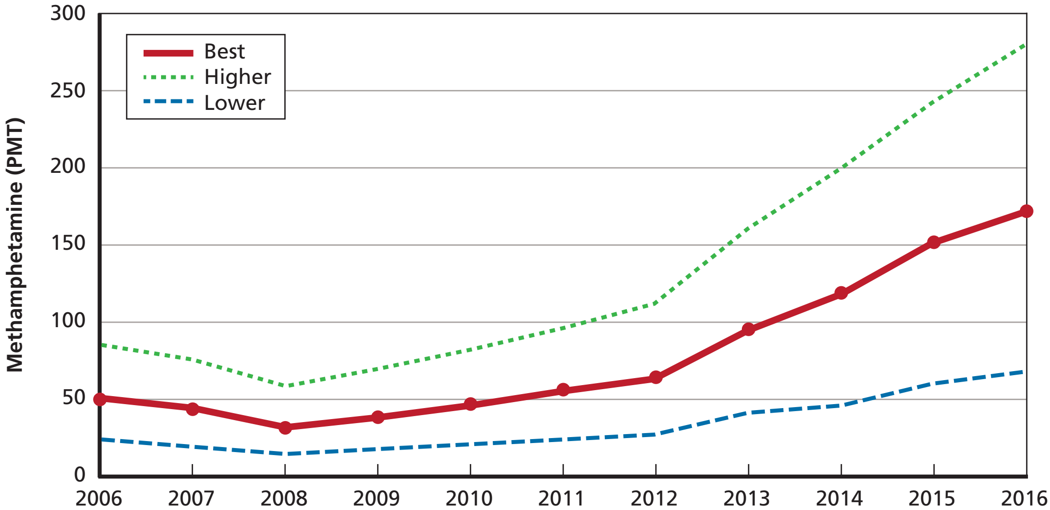


NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in Chapter Two.

Table 4.5
Heroin Consumption Estimates (PMT)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	27	27	30	31	27	30	33	42	43	44	47
Higher	49	49	53	57	46	52	59	77	87	86	94
Lower	13	14	15	15	14	15	16	19	16	18	18

Figure 4.5
Methamphetamine Consumption Estimates



NOTE: Lower and higher estimates have a very specific and nuanced meaning that is vulnerable to misinterpretation; please see accompanying text in Chapter Two.

Table 4.6
Methamphetamine Consumption Estimates (PMT)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Best	50	44	31	38	46	54	63	95	117	151	171
Higher	84	75	58	68	81	96	112	161	199	241	279
Lower	23	19	13	17	20	23	27	40	46	60	67

CHAPTER FIVE

Marijuana

As with past reports, the marijuana market estimates rely primarily on data from NSDUH questions relating to marijuana use, acquisition, and purchasing activity, making adjustments for underreporting and other factors. However, this report introduces some innovations, necessitated by NSDUH canceling its marijuana market module after 2014 and changes in marijuana markets since 2010. More than 25 percent of the U.S. population now lives in states where state-licensed cultivation, production, and retail sale of marijuana was passed into law, and the number of states allowing marijuana for medicinal purposes has also increased. Accompanying these changes, multiple indicators suggest potency has risen (e.g., ElSohly et al., 2016, and Smart et al., 2017) and the market has witnessed substantial product innovation, with alternative types of marijuana products being sold in significant quantities (Caulkins et al., 2018; Orens et al., 2018; and Oregon Liquor Control Commission, 2019).

As will be discussed in greater detail in the next chapter, these changes might well have influenced the average quantity consumed per day of use and even threatened how meaningful it is to measure consumption in terms of product weight. Hence, the approach used in previous versions of this report is no longer the best for estimating consumption and expenditure. We offer a new approach for the latter and do not produce estimates of consumption; however, we offer some ideas for addressing such estimates in Chapter Six.

This chapter focuses on the total number of cannabis users in the United States and how much they spent on cannabis from 2006 to 2016. We do not attempt to differentiate users, expenditures, or consumption by state laws or whether the use was for medical and/or nonmedical purposes.

Estimating Marijuana Users and Use Days

This section describes the methodology for estimating marijuana users and use days using data from NSDUH and other sources.

Marijuana Users

NSDUH asks all respondents whether they have ever used marijuana and, if so, whether they have used in the past year or the past month.[1] Tabulating these data can generate estimates for the number of past-year and past-month users.

The counts of marijuana users and use days include not only those who indicate directly that they have used marijuana, but also a modest number of individuals who deny using it in the standard battery of questions on marijuana use but indicate later in the survey that they have used blunts containing marijuana. Blunts are hollowed-out cigars or cigarillos filled with marijuana or joints rolled with empty cigar wraps (as opposed to typical rolling papers). That some people deny marijuana use while admitting the use of blunts may reflect the extent to which particular terms have different meanings in different communities around the country. The number of respondents reporting blunt use but no marijuana use has been stable over time (accounting for roughly 300,000 to 500,000 estimated past-month users). Including these blunt users increases the estimated number of marijuana users by between 1.5 percent and 3 percent, depending on the year; the impact on the number of use days is somewhat greater.

General population surveys tend to undercount users (see, for example, Hunt et al., 2015; Kilmer et al., 2013). As in our previous report (Kilmer et al., 2014a), we use three approaches to adjust for underreporting. We adjust (1) the prevalence rates of youth users to match the (age-specific) prevalence rates reported in the Monitoring the Future (MTF) survey of students, (2) the prevalence rates of NSDUH-reported criminally involved users to match those reported in the ADAM survey for the years we have those data available (through 2013), and (3) the remaining adult non–criminal justice–involved population, using an adjustment factor discussed later in this chapter. We also present estimates for infrequent marijuana users who report consuming in the past year but not in the past month.

Among youth, reported past-month prevalence is substantially and consistently lower according to NSDUH data in comparison with MTF data. As in the previous report (Kilmer et al., 2014a), we assume that the MTF survey can more reliably elicit honest responses from young participants because it is administered in schools, when students are away from their parents or guardians and other family members (NSDUH is completed in the household). We therefore tabulate counts of youth in the NSDUH-based population by age group (i.e., 12–13, 14–15, and 16–17 years old) and then multiply these counts by the MTF-based age-specific prevalence rates. Specifically, we apply rates reported by eighth graders to the 12–13-year-olds, tenth graders to the 14–15-year-olds, and 12th graders to the 16–17-year-olds. This process effectively raises the past-month use rates by a different amount for each group, as follows:

[1] Respondents are first asked, "Marijuana is usually smoked, either in cigarettes, called joints, or in a pipe. It is sometimes cooked in food. Hashish is a form of marijuana that is also called "hash." It is usually smoked in a pipe. Another form of hashish is hash oil. Have you ever, even once, used marijuana or hashish?" Respondents reporting marijuana use are then asked, "How long has it been since you last used marijuana or hashish?"

- Among 12–13-year-olds, prevalence increases roughly twofold to threefold.
- Among 14–15-year-olds, prevalence increases 1.5 to two times.
- Among 16–17-year-olds, prevalence increases 1.25 to 1.5 times.

For adults in NSDUH reporting arrest, probation, or parole in the past year, we multiply reported prevalence by 1.9, a factor that is consistent with historical ratios between ADAM and NSDUH of marijuana prevalence rates among justice-involved individuals. Finally, as in previous reports, we multiply user estimates among NSDUH adults not recently involved in the criminal justice system by a factor of 1.25.[2] This might be an overadjustment in recent years if changes in public support for marijuana have reduced stigma associated with reporting past-month use, but there have been no recent studies of underreporting that would support revising this factor, and keeping it consistent enhances comparability across reports.

We distinguish five categories of users: (1) those who report use in the past year but not in the past month, (2) occasional users (those who report one to three days of use in the past month), (3) weekly users (those who report four to ten days of use per month), (4) more than weekly users (those who report 11–20 days of use per month), and (5) daily/near-daily users (those who report 21 or more days of use in the past month).

Table 5.1 provides estimates of the number of marijuana users by user group (both unadjusted and adjusted). The unadjusted series considers only those days of use reported to NSDUH; the adjusted series considers all use, after adjusting for underreporting. The total number of past-year but not past-month users was fairly stable from 2006 to 2008 but grew steadily through 2016. Trends within other user groups are similar to the infrequent-user trend but more variable; the notable exception is the daily/near-daily user group, which saw the biggest growth both by percentage and total number of users.

Figure 5.1 compares the new results with those in the previous report. It shows that the new numbers closely match those in the prior report.

Marijuana Use Days

Merely tracking the number of users (also known as *prevalence*) can overlook important changes in aggregate demand and the composition of the user base. A better indicator of these phenomena is the total number of days of use, which is essentially a weighted sum of the number of users, weighting by their frequency of use.

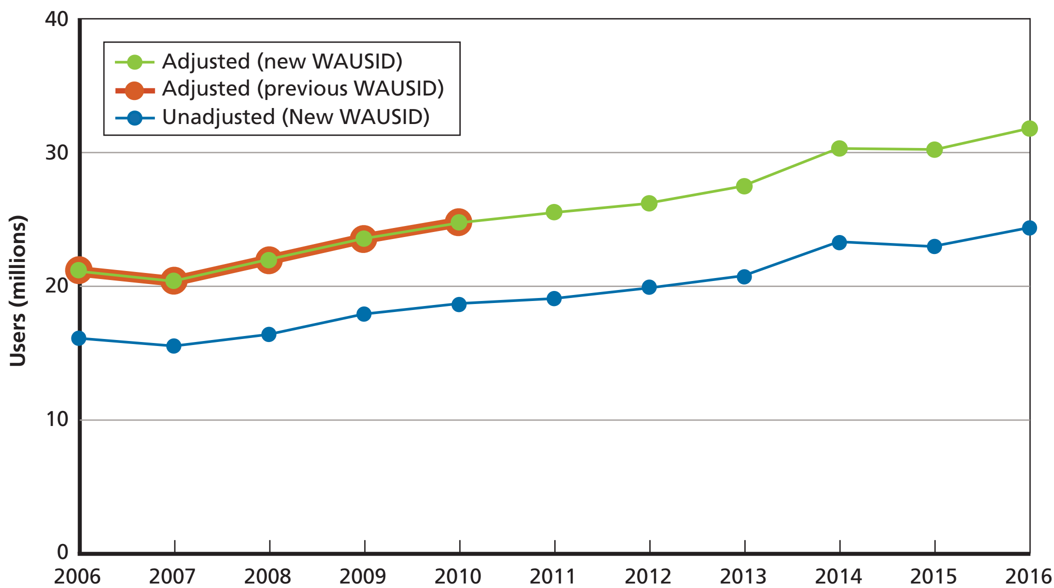
Past-month use days are calculated for the following four groups of past-month users: occasional (reporting fewer than four days of use in the past month), weekly

[2] Kilmer et al. (2013) concludes that a plausible aggregate adjustment could range from 1.02 to 1.43 for Washington state in 2013, but that arguments could be made for values outside of that range. The appropriate parameter for nationwide adjustment may be higher if underreporting is less common in Washington state. The middle values for several national NSDUH adjustments are close to 1.25 (Kilmer et al., 2011, and Rhodes et al., 2012).

Table 5.1
Past-Year Marijuana Users, by Frequency of Use (millions)

Year	Past Year, Not Past Month	Fewer than 4 Past-Month Days	4–10 Past-Month Days	11–20 Past-Month Days	21 or More Past-Month Days	Total Past-Year Users (Adjusted)	Total Past-Year Users (Unadjusted)
2006	10.2	6.5	4.5	4.0	5.8	30.9	25.6
2007	10.6	6.4	4.5	3.0	6.0	30.5	25.3
2008	10.3	6.9	4.1	3.8	6.7	31.8	26.0
2009	11.8	7.1	5.2	3.8	7.1	35.0	29.1
2010	11.6	6.8	5.6	3.9	8.1	36.1	29.7
2011	11.4	7.6	5.3	4.1	8.4	36.8	29.9
2012	12.6	6.9	5.9	4.4	8.9	38.7	32.0
2013	13.0	8.0	5.5	4.3	9.7	40.4	33.2
2014	12.7	8.2	6.0	5.1	11.1	43.1	35.7
2015	13.8	8.1	6.5	4.7	10.8	44.1	36.5
2016	13.7	9.1	6.5	5.3	11.0	45.6	37.8

Figure 5.1
Comparison of New and Legacy Estimates of Past-Month Marijuana Users



(four to ten days of use), more than weekly (11–20 days of use), and daily/near daily (21 or more days of use). For users who report using blunts but not marijuana, unless they later clarified that their blunt use did not include marijuana, the maximum number of their blunt-use days was taken as their number of marijuana-use days.

Because these data relate to use days reported for the past month, we multiply by 12 to extrapolate to an annual estimate. Just as we create both an unadjusted and an adjusted series for the numbers of users, we create two estimates for the number of use days (Table 5.2).

Figure 5.2 shows these totals by year, broken down by user group. There has been a large increase in the number of use days among daily/near-daily users, while the number of use days among occasional and weekly users has risen by a much smaller amount.

Marijuana Expenditures Through 2014

Because of changes in the marijuana market, we no longer advise using the methodology that has been used to estimate expenditures in previous versions of this report. This section highlights these changes and discusses an alternative approach.

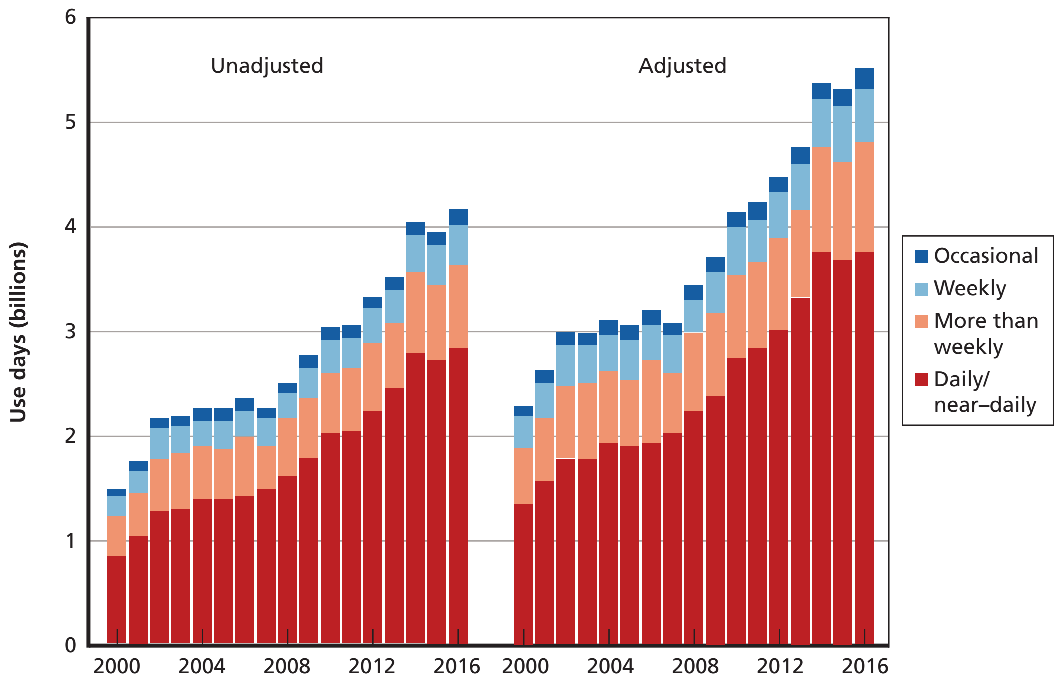
Market Changes Require a New Approach for Estimating Expenditures

The previous method of estimating marijuana expenditures involved four steps. First, estimates of the number of occasional, weekly, more than weekly and daily/near-daily

Table 5.2
Estimated Marijuana-Use Days (billions)

Year	Unadjusted Total Use Days	Adjusted Total Use Days
2006	2.4	3.2
2007	2.3	3.1
2008	2.5	3.5
2009	2.8	3.7
2010	3.0	4.2
2011	3.1	4.3
2012	3.3	4.5
2013	3.5	4.8
2014	4.1	5.4
2015	4.0	5.3
2016	4.2	5.5

Figure 5.2
Total Annual Marijuana-Use Days by User Type, 2000–2016



marijuana users (i.e., use categories) were constructed in the same way as earlier in this chapter. Second, for each of these use categories, estimates of the average number of grams consumed per day of use were assembled from various data sources, as this information was not available in NSDUH.[3] Third, these average quantities consumed per day of use were multiplied by the numbers of users and the average frequency of days of use by user group (self-reported in NSDUH, adjusting for underreporting and other factors) to obtain the total number of metric tons of marijuana consumed. Finally, total expenditure was calculated by multiplying the average price per gram of marijuana (evaluated at the typical purchase size of about one-half of an ounce from NSDUH respondents) in a given year by the number of grams consumed. Although this quantity is referred to as an expenditure estimate, it is perhaps more precisely described as the market value of what is consumed because it includes an imputed value for marijuana that was grown by the user or acquired for free or by trade.

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3 Analysis of ADAM response data from 2000 to 2003 identified an average of 0.43 grams per joint (Kilmer et al., 2010). Analysis of 2011 and 2012 National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) data provided parameters for average numbers of joints consumed per day, estimated separately for each past-month user group: occasional (1.68), weekly (1.92), more than weekly (1.92), and daily/near-daily users (3.87) (Kilmer et al., 2014b).

Two longstanding issues with this method have become increasingly worrisome. First, the potency of marijuana has risen sharply (Burgdorf, Kilmer, and Pacula, 2011; Kilmer et al., 2014a; and ElSohly et al., 2016). Today, flower with tetrahydrocannabinol (THC) levels below 10 percent has all but disappeared from the legal market in Washington state, with the exception of a small proportion targeting medical marijuana users that has little to no THC but does contain cannabidiol (CBD) (Smart et al., 2017).

Changes in potency could influence the number of grams consumed per day of use, which the previous methodology assumed remained constant. Discussing some hypothetical scenarios helps explain the point. In one extreme scenario, if users held fixed the amount of THC consumed per day of use, then the number of grams consumed per day would have fallen by the same (substantial) amount that potency rose. A second scenario is that users consume the same amount of marijuana by weight, irrespective of its THC content; this case would imply quite large increases in consumption of THC, given how much potency has risen. That scenario would be analogous to someone who switched from beer to whiskey continuing to consume the same number of fluid ounces even though whiskey has a far higher alcohol content.

Changes in price could also influence daily consumption. If users respond to decreases in the price of THC by increasing their consumption, people may be using fewer grams of marijuana per day but consuming more milligrams of THC, even while spending less money.

There is some evidence consistent with declines in the number of grams consumed per day. For example, as shown in Table D.1 and Figure D.1 in Appendix D, the median NSDUH respondent's reported purchase size has fallen from "at least five but less than ten grams" to "at least one but less than five grams."

We do not think these data demonstrate clearly that the number of grams consumed per day of use has fallen, or by how much. There is a serious lack of hard data over time on grams consumed per day of use. In the absence of strong evidence of stability, we are not willing to presume there have been no changes during a period when potency has changed so much.

A second limitation of the legacy model is that the variety of types of intoxicating marijuana products has broadened substantially beyond the traditional smoked products, such as joints and blunts. In Washington state's legal market, extract-based products, such as edibles, vaping oils, and waxes, accounted for more than 20 percent of sales by the latter part of 2016 (Smart et al., 2017); and this has increased (Kilmer et al., 2019). It is not sensible to add grams of wax (which can be more than 75 percent THC by weight) to grams of conventional marijuana that are, on average, 20 percent THC by weight, let alone to grams of THC-infused brownies or beverages (which can have a very low THC concentration even if they contain a significant quantity of THC because the food itself is so bulky).

Calculating the Ratio of Amount Spent to Use Days

In light of the aforementioned limitations, we consider a new approach that makes direct use of self-reported information in NSDUH regarding the amount spent on marijuana at the time of the last purchase. This method estimates retail spending on marijuana rather than the dollar value of all marijuana consumed, as the legacy method did.

In this new approach, we first define a set of *qualified buyers* who gave plausible answers to questions about spending. The two key spending questions ask how often the respondent bought in the last month and how much they spent on their most-recent purchase.[4] We multiply the number of use days reported by people who bought marijuana by the *ratio of amount spent to use days* (RASTUD) derived from qualified buyers. We do this multiplication separately for each of the four past-month use categories. Multiplying each user's reported number of use days by his or her appropriate RASTUD yields an estimate of how much that person spent on marijuana in the past month. We provide more detail below.

To reduce the risk of double-counting purchases meant for resale, we disqualify buyers who report resale of any portion of a purchase or report implausibly large spending. Because respondents might be reluctant to self-report drug selling, we also exclude those who report a most-recent purchase that was so large that it probably was not all for their own use (i.e., five ounces or larger), even if they did not admit to reselling any of it. People who were disqualified because their spending numbers seemed implausibly large, but who gave no indication of selling the drugs they bought, are included in the estimate of total retail spending in an indirect fashion that does not take their reported spending at face value. Finally, people who report consuming without buying—e.g., because they received marijuana for free—are excluded because they did not spend any money on marijuana and because the marijuana they got for free was likely purchased by someone else.

To implement this approach, a RASTUD is computed for each of the four past-month user groups (i.e., one to three, four to ten, 11–20, and 21 or more past-month use days). Each group-specific RASTUD is multiplied by the number of use days reported by that group's *past-month buyers who did not report reselling*. Multiplying by 12 converts from past-month to past-year spending.

This approach estimates the spending of users with implausible reports based on their reported days of marijuana use. Effectively, it uses data from qualified buyers on spending per day of use to impute the spending of respondents whose past-month spending reports were disqualified for being suspect.

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[4] We judged spending reports to be implausibly large if they led to (1) annual spending on marijuana greater than $20,000, (2) annual spending greater than half of the respondents' reported household income, (3) spending per day of use that is greater than $50 for those who used all they bought, or (4) spending per day greater than $100 for respondents who reported giving away some of their most-recent purchase.

This approach makes one strong assumption: that the most-recent purchase is the average or typical size (in dollar value) for that individual. In 2014, there was a concern with that assumption because of a potential problem called *random incidence*—i.e., that larger-than-average purchases would be followed by longer-than-average time gaps before the next purchase and so be more likely to be sampled by a randomly timed interview. Since that time, two data sets emerged that asked respondents to describe not just their most-recent purchase but also their second- and third-most-recent purchases. Perhaps surprisingly, purchase sizes seemed to be very consistent over time for any given person (Bond et al., 2014). If a respondent said his or her most-recent purchase was for $50, for example, then he or she often reported that the second- and third-most-recent purchases were also for $50.

That stability in purchase size suggests that the random incidence problem does not compromise this method. Still, we must attend to outliers. If someone routinely spent $10 per day and reported 30 past-month purchases but, for whatever reason, happened to spend $250 on the day before taking the survey, his or her imputed spending of $7,500 (30 days of purchases times $250) would be much greater than his or her actual spending of $540 (29 purchases of $10 plus one purchase of $250). For this reason, we imputed spending for respondents whose answers would have suggested very high rates of annual spending (more than $20,000 or more than half their income) or spending per day of use ($100 if the most recent purchase was shared with others as a gift, $50 if not) from the answers of other respondents who were like them in terms of frequency of use.

Using RASTUD to Generate Spending Estimates Through 2014

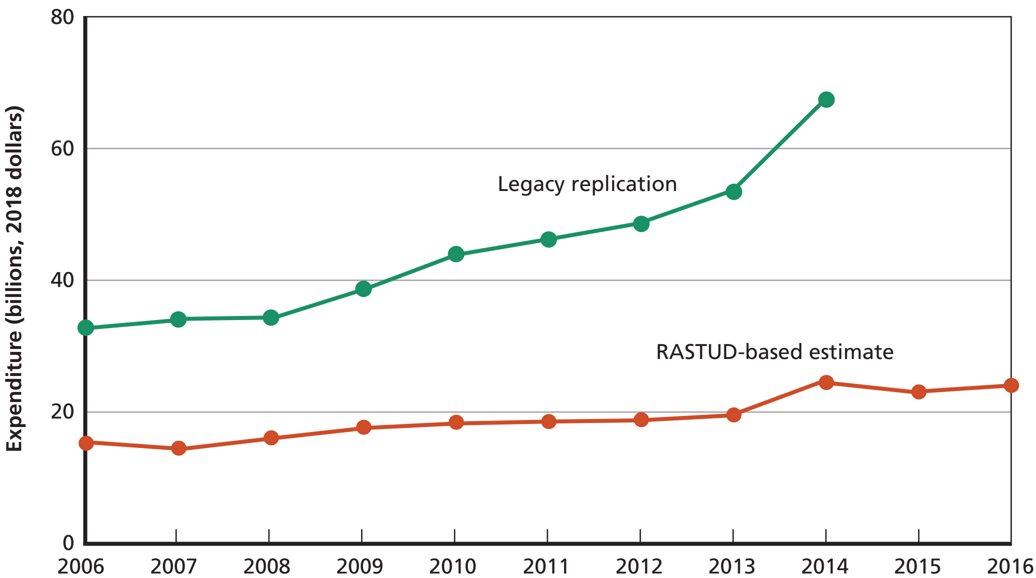
There are multiple reasons why expenditures may be underreported to a larger extent than use. For example, respondents may feel comfortable admitting to use but not to purchasing, or they may misremember or underreport the number of days they purchased in the past month or how much they spent on their last purchase.

Unfortunately, although the literature on underreporting of use is weak, there is even less evidence on the extent of underreporting of spending, so we cannot simply adjust for the underreporting of spending by multiplying by some factor derived from the literature. Instead, we take the trends found with the RASTUD-based model and adjust them upward to fit estimates from the legacy model.

Figure 5.3 plots these two "ingredients" that factor into our final marijuana expenditure estimates (in 2018 dollars). It is important to stress that these should *not* be considered good estimates of marijuana expenditures by themselves. The green line simply replicates and extends the legacy model through 2014.[5] It shows that if the

[5] The replication did not provide a perfect copy of those expenditure estimates because the data set used to fit price regressions was slightly different from that in the original WAUSID study due to minor changes in data cleaning and/or subsequent revisions to the NSDUH data for those years.

Figure 5.3
Two NSDUH-Based Series Related to Marijuana Expenditures



NOTE: Our preferred series draws on both of these approaches but not the midpoint.

legacy method were still valid, which we think is not the case, then it would have suggested that national expenditures increased by approximately 50 percent from 2010 to 2014.

The red line in Figure 5.3 shows self-reported spending after using the answers from qualified buyers to impute spending estimates for those who gave implausible answers. It has increased, but quite slowly. We think the red line is probably a better depiction of the trend in retail spending, although the level is presumably too low—perhaps quite a bit too low—because of underreporting.

However, we can combine these two ingredients to produce a better estimate of spending on marijuana over time. In particular, we adjust the RASTUD-based series upward so that it matches the legacy series on average from 2008 to 2010.[6] That period represents the final years before the recent market changes made the legacy method unreliable and before the ADAM data collection was discontinued. (ADAM is used in adjusting NSDUH responses for underreporting.) This combination produces the two expenditure estimates: one calibrated to the unadjusted legacy estimates, and one calibrated to the legacy estimates after adjusting for underreporting (see Figure 5.4).

This approach assumes that the rate of underreporting of spending is stable over time. That seems more tenable than the legacy method's assumption that the weight of

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[6] The adjustment parameter was 1.635—i.e., the legacy series' spending estimates from 2008 to 2010 were, on average, 63.5 percent higher than the RASTUD-based series.

marijuana consumed per day of use has been stable despite the many changes in marijuana potency, product variety, and legal status at the state level.

Extending Marijuana Expenditures Through 2016

Because NSDUH did not include the marijuana market module in 2015 or 2016, estimating spending for those years inevitably involves some extrapolation from earlier years. The question is what gets extrapolated. To obtain our estimates for 2015–2016, we extrapolate the trends in RASTUD by user group. The RASTUD values show smooth trends over time, which makes extrapolating them to 2015 and 2016 less risky than extrapolating other quantities that might be more volatile. The extrapolation is done in a straightforward way by fitting a linear trend to each user group's RASTUD during the years 2010–2014, and then extending this line to generate RASTUD estimates in 2015 and 2016. Table D.2 in Appendix D provides details.

In theory, spending in 2015 and 2016 could be computed by multiplying the extrapolated RASTUDs by the number of use days for those who bought marijuana. But without the market modules, we also do not know which users bought marijuana and which received it for free. Thus, we also extrapolate the proportion of all use days that are reported by people who bought (and did not resell) marijuana. Then the spending estimates for 2015 and 2016 are the product of the extrapolated RASTUD values, total use days, and the extrapolated proportion of those use days that are by people who bought marijuana but did not resell.

Figure 5.4 and Table 5.3 present two estimates of annual expenditures on retail purchases in constant 2018 dollars.[7] The unadjusted series considers only those days of use reported to NSDUH; the adjusted series accounts for underreporting. Figure 5.5 presents spending by user group. Both series show substantial growth since 2006, growing between 53 percent (adjusted series) and 56 percent (unadjusted) from 2006 through 2016. Recent trends in expenditure represent the balance of two opposing trends. The rising number of reported use days drives quantity used upward; during the same period, falling ratios of amount spent to amount used push expenditure estimates downward, producing a net effect near zero for the years since 2014.

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[7] This approach generates a substantial increase from 2013 to 2014 (nearly 25 percent), which is driven by increases in reported marijuana use and purchase activity, especially among heavier users. Self-reported daily/near-daily users (21 or more past-month use days) increased from 9.7 million to 11.1 million (a 14-percent increase). That group's RASTUD increased from \$8.39 to \$8.92 (or 6 percent), and the proportion who recently purchased marijuana for personal consumption increased from 68.7 percent to 71.2 percent (4 percent). When multiplied against each other, these changes amount to a 25-percent increase in estimated expenditures for the daily/near-daily user group.

Figure 5.4
Estimated Marijuana Expenditures

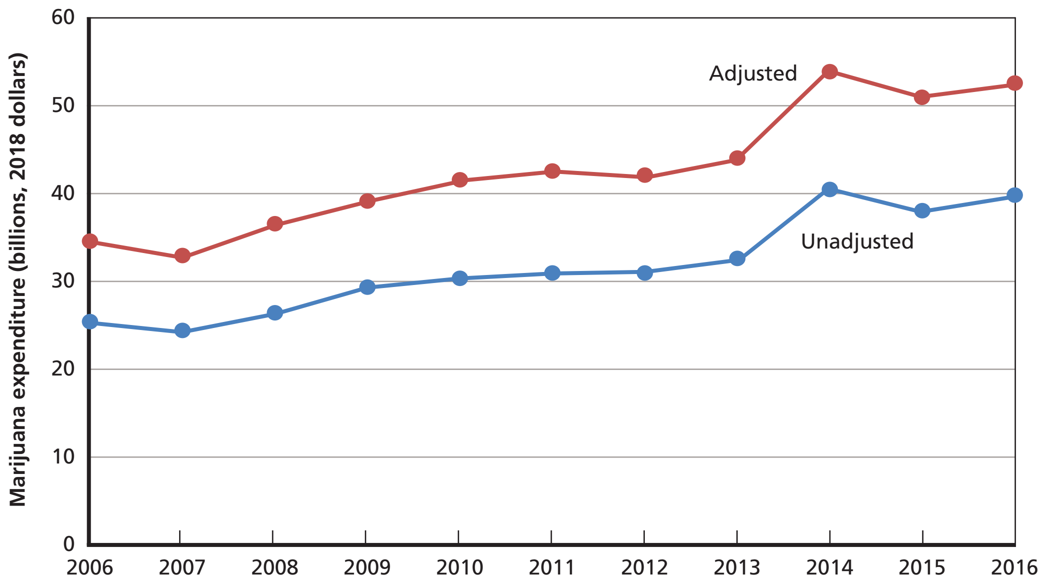


Table 5.3
Estimated Marijuana Expenditures (billions, 2018 dollars)

Estimate	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Unadjusted	25	24	27	29	30	31	31	32	40	38	40
Adjusted	34	33	37	39	42	42	42	44	54	51	52

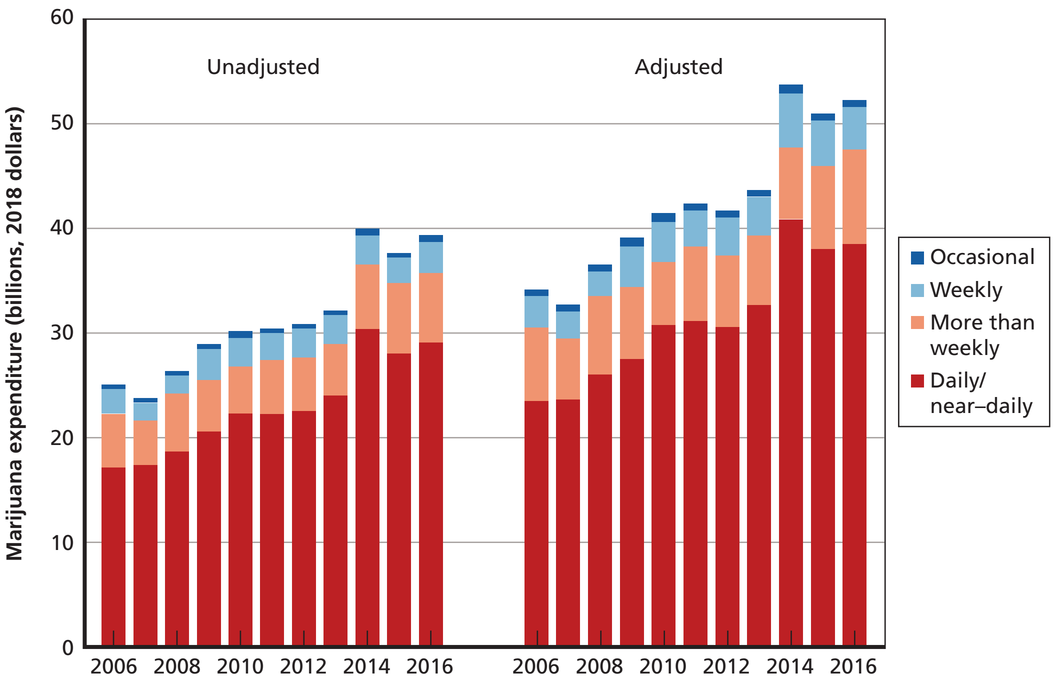
Corroborating Evidence on National Marijuana Expenditures

There may be some concern that even if the new method gets the trend in spending right, the levels might be wrong if the legacy method's estimates for 2008 to 2010 were off the mark. This section presents two calculations that may help ease this concern, because the level of spending reported in the previous section is roughly consistent with the results of these two calculations.

Applying the Alcohol Adjustment Factor to Unadjusted Reports of Spending

Alcohol researchers have noted that survey-based estimates of consumption often fall well below what is known to be consumed based on tax receipts or other supply-side evidence. That is, underreporting of quantities consumed could be more severe than underreporting of prevalence. Although it is extremely difficult to generate convincing estimates of marijuana supply given the illicit nature of large segments of the market (even in states with recreational cannabis laws) (Kilmer et al., 2019), it is relatively easy to measure alcohol sales because alcohol is a legal substance that generates tax revenue

Figure 5.5
Estimated Marijuana Expenditures, by User Group



and other sales-related data (Cook, 2007, and Nelson et al., 2010). Cook (2007, p. 54) uses NESARC—another national survey akin to NSDUH—and alcohol sales data from the National Institute on Alcohol Abuse and Alcoholism to argue that NESARC "provides an estimate of per capita consumption that is about half of recorded per capita sales." This claim is consistent with an international review that found general population surveys underestimate alcohol consumption, sometimes by more than 50 percent (Gmel and Rehm, 2004). These studies suggest that it may be appropriate to inflate the NSDUH-only consumption estimates, perhaps by a substantial margin.

If one assumed that marijuana expenditures were underreported in NSDUH by the same proportion as found in the alcohol literature (50 percent) and doubled the RASTUD-based expenditure series in Figure 5.3, this adjustment generates an estimate of $49.2 billion of spending for 2014, which is close to what is reported in Table 5.3 ($53.7 billion).

Extrapolating from Washington State

Caulkins et al. (2019) estimates that Washington state's 755,000 NSDUH-identified past-month users spent $1.66 billion annually on marijuana over 2015–2016.[8] Nation-

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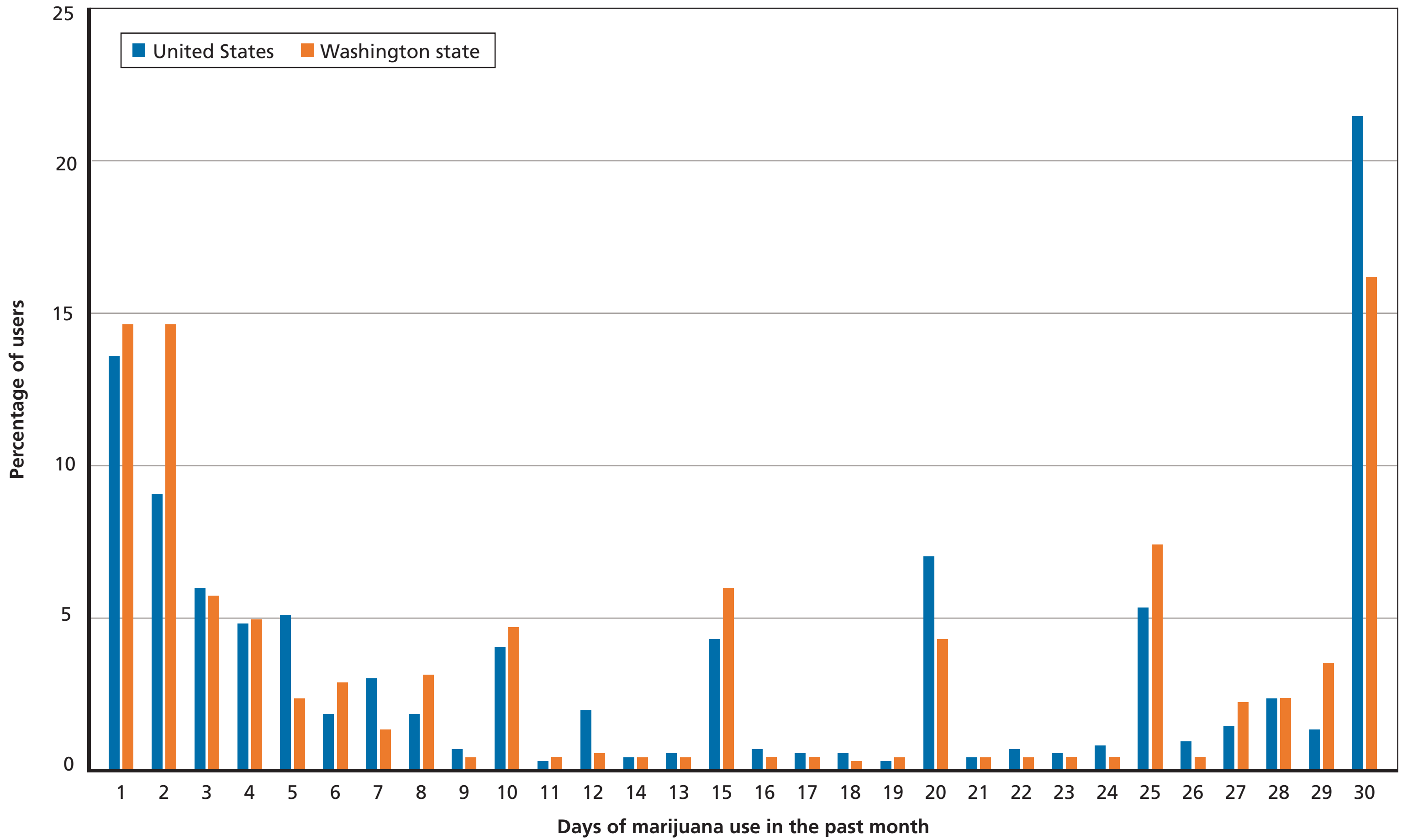
[8] Using consumption estimates from a Washington state web survey and a 22 percent adjustment for underreporting.

ally, Table B.3 suggests that NSDUH identified an average of 23.4 million past-month users in the same period (22.7 million for 2015 and 24.1 million for 2016). Applying Washington's spending per reported past-month user estimate to the rest of the country (i.e., $1.66 divided by 0.755, then multiplied by 23.4), generates an annual spending estimate of $51 billion for the 2015–2016 period.

Of course, if Washington's spending per past-month user did not match the rest of the country, that could bias the expenditure estimates. However, Figure 5.6 contrasts the distributions of the numbers of days of past-month use in Washington with the country as a whole for 2015–2016. The distributions are similar; e.g., the share of past-month users using 25 or more days is about 32 percent for both Washington and the entire country. Of course, there could be other differences, such as in prices paid and quantities consumed, but the available NSDUH data for 2015–2016 do not allow for those comparisons.

We do not want to make too much of the similarities between the results of these two approaches and our preferred model; they could just be coincidences. However, these similarities support the idea that an annual spending figure of about $50 billion for the 2014–2016 period is not unreasonable.

Figure 5.6
Distribution of Past-Month Use Days Among Past-Month Users for 2015–2016



CHAPTER SIX

Measurement of the Modern Marijuana and Opioid Markets

Drug use and drug markets evolve over time. Changes have been particularly dramatic in recent years in the marijuana and opioid markets. What were once relatively simple markets dominated by one principal product each now are a series of interrelated markets for multiple distinct forms within a broad family of related products. Those changes challenge traditional ways of measuring those markets, particularly in terms of quantity consumed. This chapter discusses alternative approaches to estimating market size that may transcend these challenges—though, in some cases, only if the right additional data collection is undertaken.

Changes in Marijuana Markets

Marijuana markets have been changing rapidly due to innovations in production techniques, a new variety of products, and increased availability through state and substate policies relaxing restrictions on marijuana access and penalties on possession. Discussions often focus on changes in the motive for consumption (so-called "medical" marijuana versus "recreational" purposes) or its legal status under state and local law. Changes in the nature of the marijuana products are equally dramatic and undermine the utility and feasibility of measuring the market size in terms of metric tons.

There are two distinct challenges: (1) increasing potency and (2) proliferation of product forms. Multiple sources agree that marijuana potency has increased throughout the country. For example, the average THC content of marijuana seized in the United States did not reach 5 percent until 2000 (ONDCP, 2016, p. 80) but reached 12 percent by 2012 (ElSohly et al., 2016). Furthermore, the average reported potency of flower products sold in Washington state's licensed marijuana market exceeds 20 percent (Smart et al., 2017).

Changes in potency complicate efforts to describe changes in consumption. Consider this hypothetical question: If consumption changed from 1,000 metric tons of material that was 5 percent THC to 500 metric tons of material that was 20 percent THC, has marijuana consumption gone up or down? The unadjusted weight fell by 50 percent, but consumption of the principal intoxicant doubled, from 50 to 100 metric tons.

One could ask something similar with alcohol. Suppose someone turned down a 12-ounce glass of beer that was 9 percent alcohol and instead drank four 1.5-ounce shots (6 ounces total) of whiskey that was 36 percent alcohol. Many might see that as drinking more, even though the volume of liquid consumed was less. The alcohol literature often solves this problem by counting so-called "standard drinks" (12 ounces of beer, 5 ounces of wine, or 1.5 ounces of a spirit that is 40-percent alcohol) (National Institute on Alcohol Abuse and Alcoholism, 2005).

Analogs to the standard drink have been suggested for marijuana, but they are not yet widely used. In particular, Kögel et al. (2017) suggests defining a "standard joint unit" as 7 milligrams of THC, and the THC limit for an edibles dose ranges from 5 to 10 milligrams depending on the state. We discuss the potential for measuring market size in terms of THC obtained or consumed later in this chapter.

The proliferation of marijuana product forms poses an equal if not greater challenge.[1] Traditionally, most marijuana was consumed in the United States by combusting dried plant material in joints, pipes, or bongs. Often, only the parts of the plant that contained higher concentrations of THC (notably the flowers or buds) were used, and other material (leaves, trim) might be discarded. The discarded material contained lower concentrations of THC, but there was more of it. Thus, from a grower's perspective, much of the THC was not being converted into saleable product.

In jurisdictions where marijuana businesses are state-legal, it is common to use devices of various sorts to extract cannabinoids from this other material (and sometimes from buds, too). The extracted oils can be used directly via vaping, which involves heating to volatilize the cannabinoids without combusting them. Extracts can also be used to make edibles (such as candy, brownies, and cookies), and some extracts are concentrated into a waxy or solid form that can be flash-vaporized ("dabbed").[2]

This proliferation complicates market measurement because it is not sensible to add the weight in grams of a marijuana-infused brownie to the weight in grams of a joint; most of the weight of the brownie is sugar, flour, and egg. Nor is it sensible to add grams of dabs (which can be greater than 75 percent THC by weight) to grams of flower.

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1 We leave aside discussion of "hemp" products that contain little THC, are not intoxicating, and exploit other aspects of the plant, such as fiber or seed oil. We also leave aside discussion of high-CBD products that are low in THC. They are conceptually distinct because, without THC, they are not intoxicating (as we understand it) in the same sense that traditional marijuana is. High-CBD, low-THC products are probably a small part of the market nationally, as Smart et al. (2017) shows they are a small part of Washington state's legal market among flower and extracts for inhalation.

2 Edibles are sometimes made directly with flower, and there are other products that mix product forms, so it is not literally the case that all of the edibles and all other products mentioned are made with extracts, but most are.

Edibles and extract-based products have always existed, but they were less common and often homemade; the final retail sale was of some ingredient, not the finished product. Now, however, edibles and extract-based products comprise an important segment of the market. Data on marijuana use patterns in 2014 from a national consumer panel survey reveal that although the traditional form (flower) dominated consumption among regular users, 16.1 percent of past-month marijuana users reported consuming marijuana-infused edibles or drinks, and 7.6 percent reported vaporizing marijuana oils (Schauer et al., 2016).

The corresponding proportions are even higher in Washington state's legal market, where extract-based products, such as edibles, vaping oils, and dabs, accounted for roughly one-third of sales in mid-2017 (see Chapter Five). It is no longer reasonable to treat nonflower consumption as unimportant.

The next few sections discuss some measures of market size that respond, at least partially, to these changing market conditions.

Users, Dollars, and Use Days

Before proceeding to novel metrics, we note that two traditional measures of market size remain viable: dollar value and number of users. One can add $20 spent on brownies to $40 spent on dabs to get $60 in total spending in a way that one cannot add grams of brownies to grams of dabs. Likewise, one can sum the number of people who used marijuana-infused edibles, joints, or both.[3]

Another valuable measure that already exists has received less attention to date, and that is the number of days of use. NSDUH asks respondents how many days they used marijuana in the past month. Summing the total number of self-reported past-month use days is just taking a weighted sum of the number of past-month users, weighting by the number of days of use reported. It is, in many respects, a more valuable measure of market activity than the prevalence (i.e., number) of users, because it weights high-frequency users more heavily than low-frequency users.

In light of the proliferation of types of marijuana products, it would be helpful if NSDUH revised its wording to encompass a broader spectrum of products. As noted earlier, there are already respondents who report they have not used marijuana when asked in the standard battery of questions, but who indicate later in the survey that they have used blunts that contain marijuana.

That some people deny marijuana use while admitting to using blunts may reflect the extent to which particular terms have different meanings in different communities around the country. That sort of challenge may grow over time as forms of marijuana products proliferate.

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[3] There can, however, be subtleties even with these measures. If someone pays a $20 cover charge to enter a marijuana lounge, would that $20 cover charge get captured by surveys asking about marijuana spending? And should it be?

If estimates of spending and weight purchased become more salient, it would also be useful if the NSDUH marijuana market module used more-refined response categories. Typically, more than 75 percent of the most-recent purchases fall in the 1–5-gram or 5–10-gram bins. Those bins are so wide that replacing them with midpoints creates a coarseness that could be avoided if the question simply asked the number of grams directly, rather than via categories.[4]

Metric Ton Equivalents

Marijuana market size has often been measured in terms of metric tons. Weight consumed was computed in past WAUSID reports (e.g., Rhodes et al., 2001, and Kilmer et al., 2014a) by estimating the number of days of use broken down by type of user, and then multiplying those figures by an estimate of the average number of grams consumed per day of use. Those reports distinguished between higher- and lower-frequency users because those using daily or near-daily (21 or more days per month) are thought to consume two to three times as much per day of use as those using only rarely. Hence, two markets with identical numbers of days of use could differ in estimated quantity consumed if a greater proportion of the use days in one market were attributable to high-frequency users.

More-recent efforts have taken this measure a step further, breaking down the calculation not only by days of use but also by gender and age, while controlling for other factors, such as levels of educational attainment (Caulkins et al., 2019).

A principal challenge with this approach is the weak data on amounts consumed per day of use. Based on NESARC and ADAM data from the early 2000s, the last report in this series (Kilmer et al., 2014a) assumed that daily/near-daily users consume an average of 1.66 grams per self-reported day of use. For weekly and more than weekly users, the corresponding value is 0.83 grams per self-reported day of use; for light users, 0.72 grams. However, these numbers may have changed over time because of changes in potency, for example, and there are no consistently recorded, nationally representative data on weight consumed per day of use.

Table 6.1 displays the weight of marijuana that would have been consumed if daily patterns of consumption had continued along the lines of what was observed in the early 2000s.[5] We describe the resulting figures as being measured in "metric ton equivalents," not metric tons.

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[4] Whether the accuracy of these responses can be improved with visual prompts remains to be seen.

[5] These figures were produced by (1) estimating the number of marijuana use days per year-user group and (2) multiplying by estimates for the average number of grams consumed per use day. Marijuana-use days are estimated by counting respondents' reported number of past-month use days, aggregating by user group, and multiplying by 12; this process is repeated once without adjusting for underreporting and again with underreporting adjustments. Next, estimates of the average number of grams consumed per day of use for each of these categories were assembled from various data sources, as this information was not available in NSDUH. Analysis of ADAM response data from 2000 to 2003 identified an average of 0.43 grams per joint (Kilmer et al., 2010). Analysis of

Table 6.1
Marijuana Consumption Using "Constant Grams" Assumption (metric ton equivalents)

Year	Unadjusted	Adjusted
2006	3,132	4,259
2007	3,126	4,257
2008	3,424	4,725
2009	3,788	5,079
2010	4,207	5,731
2011	4,260	5,888
2012	4,627	6,236
2013	4,963	6,722
2014	5,696	7,606
2015	5,551	7,472
2016	5,814	7,694

Two studies suggest that weights consumed per day of use may have been steady. Data from a convenience sample of marijuana users in Washington state in 2013 suggest that daily/near-daily users consumed between 1.3 and 1.9 grams per use day, with a best estimate close to 1.6 grams (Kilmer et al., 2013). A similar survey conducted for the Colorado Department of Revenue in 2014 led researchers to conclude that "results confirm that a preliminary estimate of 1.6 grams per day for heavy users is close to the Colorado average as well" (Light et al., 2014, p. 17).

A third study suggests a slight increase. Mariani et al. (2011) presents a study of 251 individuals enrolled in two marijuana dependence pharmacotherapy trials at a university-based treatment clinic between December 1, 2004, and March 31, 2009. Given that this is a treatment-seeking sample, these estimates might be higher than what we would get for daily/near-daily users in the general population. The mean weight for joints was 0.66 grams. If we multiply this weight by the NESARC-II estimates covering 2004 and 2005, we get 1.8 grams per day (1.6–2.0).

However, that evidence is thin, and there are reasons why weight consumed per day may have gone up or down. Weight consumed may have gone up simply because the price has gone down. Consumption tends to go up when price goes down (Gallett, 2014, and Pacula and Lundberg, 2013). A price-induced change in consumption

2011 and 2012 NESARC data provided parameters for the average numbers of joints consumed per day, estimated separately for each past-month user group: occasional (1.68), weekly (1.92), more than weekly (1.92), and daily/near-daily users (3.87) (Kilmer et al., 2014b).

is generally understood to be driven only partly by increases in numbers of users, with a portion coming from increases in the intensity of use.

Furthermore, potency has gone up considerably, and it is possible that users titrate their dose as potency goes up. The hypothesis concerning titration is usually expressed within a particular session of use; in a particular session, do users consume fewer grams if the marijuana is more potent? There is a small literature on that question (Kilmer, 2018). No consensus has emerged, but one study finds that there is some titration, though it is partial (van der Pol et al., 2014). That is, when potency goes up, the quantity consumed per session goes down but the amount of THC consumed goes up. Here, the question is similar but distinct. When potency goes up, does the quantity consumed per *day*, not per session, go down?

Overall, market conditions make it entirely possible that weight consumed per day of use has changed, and data are insufficient to settle the matter empirically. Hence, we do not think it is safe to make any particular assumption about stability or change in consumption per day of use and do not view the metric-ton-equivalent figures as reliable estimates of the actual weight consumed in recent years. They do, however, provide a way of thinking about changes in consumption over time in a set of units that is both standardized across years and sensitive to the fact that frequent users tend to use more per day of use.

THC

The cannabis plant contains scores of cannabinoids, but two (THC and CBD) receive the most attention, and CBD alone is not intoxicating in the same way that THC is. Furthermore, the potency of marijuana products is often described in terms of their THC content.[6]

Hence, there is sometimes interest in characterizing consumption in terms of the mass (weight) of THC consumed, rather than the mass of all of the plant and processed material containing some detectable amount of THC. This is reminiscent of past calls to base sentences for LSD on the weight of LSD, not on the weight of the material carrying the LSD, to avoid giving longer prison sentences for selling LSD on blotter paper than for the same number of doses in a different form (Gonyer, 1998).

There are some subtleties, however. To begin with, THC generally appears in the plant as tetrahydrocannabinolic acid (THC-A) and only becomes intoxicating after it is decarboxylated into THC. That step alters the molecular weight, so it is not uncommon to convert the weight of THC and THC-A into a total equivalent weight of THC by adding the weight of THC plus 0.877 times the weight of THC-A.

[6] Potency as used in this sentence differs from the way neuroscientists use the term. We use it as we would the word "purity" for such drugs as cocaine or heroin to denote the proportion of total weight that is the principal intoxicant. Purity is not an appropriate word to use for conventional marijuana, however, because the other material is not an adulterant or diluent. Rather, it is just plant material that is not THC.

However, not all the THC in a marijuana product necessarily enters the user's body. When smoked, an important share is lost to side-stream smoke. Furthermore, some THC that is eaten never makes it into the blood stream, let alone the brain, if it passes through the alimentary canal without being absorbed. THC in edibles also encounters first-pass metabolism in the liver before reaching the brain, unlike THC that enters the body through the lungs. Because the modes of consumption vary and are not well documented, it is probably unrealistic at this time to estimate THC consumption in the sense of the amount of THC that reaches users' brains.

The quantity of THC purchased is better defined, but focusing on it would fail to record material that is grown by the user, given to or shared with others by the growers, or obtained by barter (such as when workers in the illegal marijuana industry are paid in kind).

A better concept might be the quantity of THC *obtained*, including via gifts, sharing, and self-grows (Kilmer et al., 2019). At present, the data simply do not exist to support THC estimates for the nation or over time. Key data sets, such as STRIDE, never reported marijuana potency the way they reported the purity of cocaine and heroin. Seizure data analyzed by the University of Mississippi did record potency, but there can be differences between the characteristics of materials seized as opposed to materials used because the risk of seizure is greater for some kinds of transactions than others. User reports on informal websites, such as Price-of-Weed, often only include coarse measures of potency, such as "low-," "medium-," or "high-quality," with no quantification or mechanism for ensuring that different people use consistent definitions over time or across cities.

The seed-to-sale tracking systems in state-legal markets record not just the dollar value of all retail sales but also the total weight of the item purchased and its THC potency as reported by a testing lab for the two largest product categories (marijuana flower and extracts). There are questions as to whether some testing labs inflate reported potency to please the producers (Jikomes and Zoorob, 2018). Nonetheless, these seed-to-sale data demonstrate what these THC estimates might look like (Caulkins et al., 2019).

Changes in Opioid Markets and Associated Challenges

Fentanyl and other synthetic opioids have emerged as the leading causes of drug overdose deaths, so it is natural to wish to add fentanyl to the list of drugs for which estimates of market size are produced. There are, however, conceptual and practical challenges.

One problem is that many data collection systems do not ask about purchases of fentanyl; at present, key data are lacking. Even if such questions were added to NSDUH, respondents to NSDUH have accounted for a very small share of high-frequency heroin use (Caulkins et al., 2015). They might likewise account for only a modest share of fentanyl use.

The estimates for heroin (and cocaine and methamphetamine) in WAUSID reports has depended heavily on ADAM data. It has been difficult to extrapolate forward from the last ADAM data in 2013 for those two drugs, and there is no way to use ADAM data to estimate fentanyl use.

Another problem is that fentanyl distribution and consumption appear to be changing very rapidly and manifesting very significant regional variations (e.g., fentanyl is much less prominent to date in the West). This variation can be seen in Figure 6.1 by plotting data series for two other fentanyl-related measures for the entire country and by geographic region: (1) total mortality attributed to synthetic opioids, derived from the CDC's Multiple Cause of Death report, and (2) per capita incidence of fentanyl in forensic seizures via the NFLIS (see Figure 6.1).

When a market is stable or has a simple, consistent trend, it is easier to weave together data taken at different times to produce a coherent estimate. That would not be the case for fentanyl post-2013.

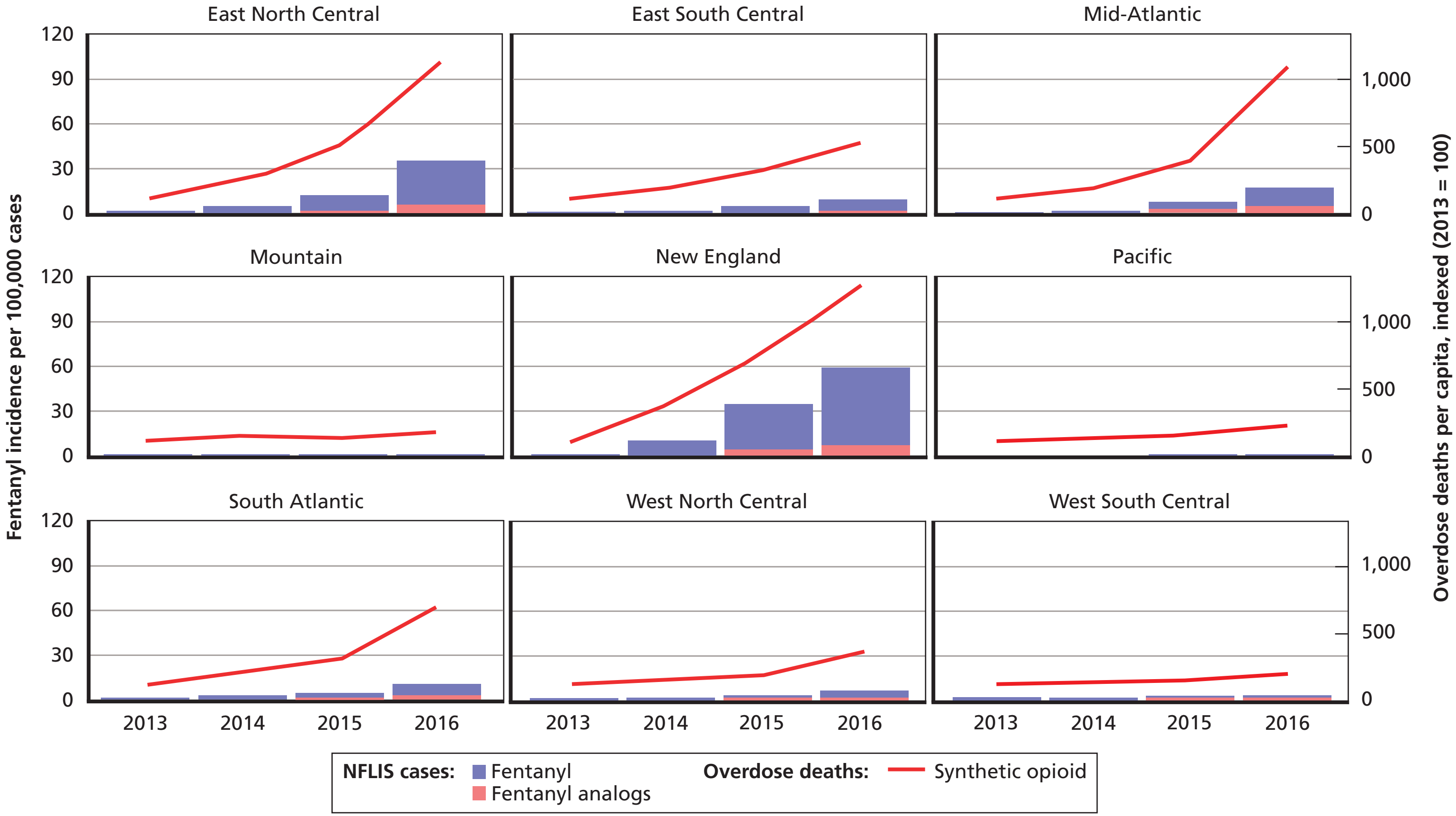
Another fundamental problem with estimating fentanyl consumption from user surveys is that much of the illicit-market fentanyl appears as an adulterant in a bag that the user believes is primarily something else. For example, a bag sold as heroin might also contain fentanyl. This is not an entirely new phenomenon; in the past, MDMA tablets were frequently adulterated with other drugs, such as methamphetamine. But the impact may be different with fentanyl.

Suppose a user spends \$20 buying a bag that is described as containing heroin but which also contains fentanyl. Should that \$20 be considered to have been spent on heroin (only) or should the national drug user spending estimates prorate that \$20 in some fashion between heroin and fentanyl? Does the answer change if the user knows that the bag contains fentanyl and heroin? If the spending should be prorated across the two drugs, should that proration be based on weight, morphine-equivalent doses, or some other measure? For example, the proration could be based on how much the dealer spent on each drug; thus, if the dealer spent \$5 buying the heroin and \$5 on the fentanyl that appeared in the bag for which the dealer charged the user \$20, would the \$20 the user spent be split evenly between heroin and fentanyl? If so, how does one establish what the dealer spent on each "ingredient"?

Whatever the ideal, data limitations will dramatically constrain choices for the foreseeable future. For instance, it is not clear how one would determine what the dealer spent on each component drug or whether the user did or did not know the bag contained fentanyl.

Another approach would be to estimate some proportionality relationship with a better-measured proxy indicator. For example, if one somehow determined that there were 50 fentanyl overdose deaths for every kilogram of fentanyl consumed, then one could just track deaths and apply that conversion factor. However, the ratio of fentanyl

Figure 6.1
Fentanyl-Related Indicators by Region, 2013–2016



deaths to fentanyl consumption might vary sharply over time with the deployment of naloxone. It could also vary based on what drug the fentanyl is adulterating. Because heroin users tend to have tolerance to opioids, they may be less likely to die if their heroin is adulterated with fentanyl than if a cocaine user's cocaine is adulterated with fentanyl.

Yet another challenge is that fentanyl is not so much a single drug as it is a family of related synthetic opioids.

Other countries might develop fentanyl consumption estimates from wastewater testing, but that approach is much less widely developed and deployed in the United States.

A Method for Estimating Fentanyl Consumption

This section describes another approach that might be used, at least for the fentanyl sold as an adulterant. The basic idea would be to estimate how much fentanyl appears in heroin that is seized over the relevant period, expressed as a ratio: X kilograms of fentanyl appearing as an adulterant per kilogram of heroin seized. Multiplying that ratio by estimates of heroin consumption would provide one estimate of the amount of fentanyl that was consumed as a heroin adulterant. The same could be done for cocaine and, in theory, any drug that is routinely adulterated with fentanyl. We might call those the "other" or "carrier" drug.

The calculations could be done by region (and possibly by state) because the penetration of fentanyl into the carrier drug market can vary by region of the country. For example, fentanyl-adulterated heroin is more common on the East Coast than it is on the West Coast, perhaps because it is hard to mix fentanyl into Mexican black tar heroin.

More formally, let i index the region (i.e., north, south, Midwest, and west regions of the United States) and d index the carrier drug (e.g., heroin, cocaine or crack, or methamphetamine).

One could estimate fentanyl consumption using law enforcement seizure data sets, such as STRIDE and/or NFLIS (if quantities are made available in NFLIS extract),

$$R_{di} = \frac{\text{Pure weight of fentanyl in all seizures of drug } d \text{ in region } i}{\text{Pure weight of drug } d \text{ in all seizures of drug } d \text{ in region } i}.$$

In principle, this estimation would be done using only retail-level transactions, but retail seizures are scarce in federal data. In practice, it would be done for all transactions in amounts for which one commonly sees the fentanyl adulteration, which would be determined from the data. For example, if it is rare for 100-kilogram packages of cocaine to be adulterated with fentanyl, suggesting that fentanyl is added to cocaine further down the distribution chain, then the R_{di} calculation for cocaine should exclude 100-kilogram seizures of cocaine.

Let W_d equal the weight of drug d consumed in the United States and W_{di} equal the weight of drug d consumed in region i. Because heavy users dominate consumption, we might estimate W_{di} as

$$W_{di} = \left(\frac{\text{TEDS admissions for drug } d \text{ in region i}}{\text{TEDS admissions for drug } d \text{ in total}} \right) \times W_d .$$

Then the national estimate of fentanyl consumption is

$$\text{Total fentanyl consumption} = \sum \text{drugs } d \times \sum \text{regions } i \times R_{di} \times W_{di} .$$

This estimate could be improved or extended in the following ways:

- summing across types of fentanyls (e.g., folding in carfentanil weights recorded in STRIDE by applying the morphine milligram equivalents to the more-common fentanyl)
- expanding the list of carrier drugs to include counterfeit prescription drugs
- including state-level data on how frequently seizures of the carrier drug are adulterated with fentanyl
- adding an estimate of how much fentanyl is sold and consumed as fentanyl, not as an adulterant.

One important limitation of this approach is that law enforcement may be differentially targeting distributors of the carrier drug whose products are believed to be adulterated with fentanyl. To the extent that targeting occurs, this method would tend to overestimate the amount of fentanyl being consumed.

CHAPTER SEVEN

Concluding Thoughts

This report provides rich insights about the U.S. markets for cocaine, heroin, marijuana, and methamphetamine. Covering the years 2006–2016, it calculates the number of users, amount consumed, and the amount that users spent on each of these substances. The total amount of money spent on these four substances fluctuated between $120 billion and $145 billion annually. The major change over this period is the composition of this spending. In 2006, cocaine accounted for most of the spending and marijuana was at the bottom; by 2016, that had reversed.

These estimates were generated by combining data from several sources. Unfortunately, given changes in the markets, the confounding effects of fentanyl, and our weakening data infrastructure, we are not confident about using our current methodology in our future research.

A contribution of this report is foreshadowing what additional types of data would help to quantify the scale of these markets in the future. It is clear that household and student surveys must be updated, not only to collect more information about the type of cannabis products consumed but also to ask about the quantity of these products consumed. But our information about these markets is not limited to large, nationally representative surveys. Regardless of how one feels about marijuana policy, there is no denying that legalization is producing a tremendous amount of information through seed-to-sale tracking systems, market surveys, delivery services, loyalty card programs, and other sources (Caulkins, 2016, and Kilmer and Pacula, 2017). Figuring out how data from these new sources can be aggregated and manipulated to develop scientifically based insights should be a priority for those who want better information about changes in marijuana markets and the related consequences.

With respect to the other drugs, it would be immensely helpful to bring back the ADAM program—or some version of it—so we can collect real-time drug market data, including objective (biological) consumption measures for cocaine, heroin, methamphetamine, and other drugs. For example, it is possible to detect fentanyl in urine specimens. Wastewater testing is another approach for collecting information about consumption that has received much more attention outside of the United States. This method is an active research topic in Europe,[1] and a recent wastewater testing report from Australia finds that fentanyl consumption likely doubled outside of capital city jurisdictions from April 2017 to April 2018 (Australian Criminal Intelligence Commission, 2018). Although the utility of this method will depend on the type of substance examined, the science is advancing, and it is a readily scalable approach (Keshaviah et al., 2016) that could provide a wealth of information about drug consumption at the local level.

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1 See, for example, European Monitoring Centre for Drugs and Drug Addiction, undated.

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Substance use and drug policy are clearly in the national spotlight. Provisional data from the Centers for Disease Control and Prevention suggest that drug overdose deaths in 2018 exceeded 68,000, of which more than 47,000 involved opioids. Although heroin, prescription opioids, and synthetic opioids (such as fentanyl) receive most of the attention, deaths involving methamphetamine and cocaine are both on the rise. In addition, more than 25 percent of the U.S. population lives in states that have passed laws that allow for-profit firms to produce and sell marijuana for nonmedical purposes to adults ages 21 and older. To better understand changes in drug use outcomes and policies, policymakers need to know what is happening in the markets for these substances. This report updates and extends estimates of the number of users, retail expenditures, and amount consumed from 2006 to 2016 for cocaine (including crack), heroin, marijuana, and methamphetamine in the United States, based on a methodology developed by the RAND Corporation for the Office of National Drug Control Policy. The report also includes a discussion of what additional types of data would help quantify the scale of these markets in the future, including the new types of information produced by the legalization of marijuana at the state level.

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