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Arrestee Drug Abuse Monitoring Program II in the United States, 2008

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Technical Documentation Report

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ADAM II

Technical Documentation Report

ARRESTEE DRUG ABUSE MONITORING PROGRAM II

OFFICE OF NATIONAL DRUG CONTROL POLICY
EXECUTIVE OFFICE OF THE PRESIDENT

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Introduction

In 2000, the Arrestee Drug Abuse Monitoring (ADAM) program expanded the scientific value of the National Institute of Justice (NIJ) Drug Use Forecasting (DUF) program by introducing probability-based sampling, developing new instrumentation and adding sixteen new survey sites. After quarterly data collection from 2000 through 2003, the NIJ terminated ADAM. In the fall of 2006, the Office of National Drug Control Policy (ONDCP) revived the ADAM program in ten former ADAM data collection sites. ADAM II retained all of the original ADAM data collection protocol, but added innovative estimation procedures and trend analysis.

This report details the *generic* ADAM II sampling procedure, data collection protocol, quality control procedures and estimation methodology. ADAM II used early data from Portland, Oregon to establish the methodological template that has been modified over time in Portland and specifically adapted to all other nine ADAM II sites. Adaptations are necessary because every site poses its own special problems, and new problems emerge with time, making methodology development dynamic. Typically, these adaptations are minor; for example, some sites provide booking data that are more detailed than the booking data from other sites. Consequently, the estimation methodology takes advantage of greater detail when available, and accommodates lesser detail when necessary. Sometimes the adaptations are more involved. The Atlanta, GA and Washington, DC sites are two examples. Over time, Atlanta built new booking facilities and changed booking practices, complicating the reporting of trends. In Washington, DC the methodology is distinctly different from that used in the other ADAM II sites, in that there are seven roughly equivalent police districts. This report provides a special discussion of the sampling and estimation adaptations in Washington, DC and adaptations used to deal with changes over time such as those found in Atlanta.

This report does not attempt to document or explain all adaptations of the generic sampling procedure, quality control procedures and estimation methodology. The authors felt that since the explanation of the generic approach itself is complex, burdening readers with details about continuously evolving adaptations would detract from this report's objective—explaining the overall ADAM II methodology. However, it is important to document those adaptations for those in the research community who are interested, and the ADAM II project maintains catalogued files of data and annotated computing software that meet professional standards for documentation. That *electronic documentation* is available by request.

Section 1 explains ADAM II sampling procedures. As in ADAM, ADAM II sites were selected purposefully, so they do not represent a random sample of counties across the United States. Within each site, ADAM II represents all but very small booking facilities in the county; and within each booking facility, ADAM II selects a systematic sample of arrestees that mimics a random sample with unequal sampling probabilities.

Section 2 explains ADAM II data collection protocols. It identifies four data collection devices: the ADAM II interview, the associated urine test, the facesheet completed during sample selection, and the booking census data used to identify the sampling frame. This section explains how ADAM II interviewers sample arrestees, approach them for interviews, and replace sampled arrestees who are unavailable or who refuse the interview.

Section 3 explains case weighting, using propensity scores. This section explains the logic of using propensity scores and describes the diagnostic tests applied to each site to assure that the inverse of the estimated propensity scores produces acceptable sampling weights.

Section 4 explains the ADAM II approach to imputation. Urinalysis results are sometimes missing, either because a respondent refuses to provide a urine specimen following his interview or because the respondent is unable to provide a urine specimen. ADAM II uses imputation routines to estimate the proportion of arrestees who would have tested positive for a specific illegal drug had all arrestees been tested.

Section 5 explains point prevalence and trend estimation. Except for data imputation, calculations of point prevalence estimates are straightforward given sampling weights. Trend estimation is more complicated because of the need to control for extraneous factors that may account for changes in the proportion of arrestees testing positive for illegal drugs.

Section 6 provides some concluding comments regarding the technical challenges addressed in ADAM II.

1. The ADAM II Sample

ADAM II comprises a non-probability sample of counties and a probability sample of arrestees booked into jails within those counties. This section explains sampling within each county.

1.1. Sampling in Counties with Multiple Jails

Most ADAM II counties have a single jail or central booking facility where all county arrestees are booked pending further processing. Other ADAM II counties have multiple booking facilities. Where there are multiple jails, small jails are excluded from the study, and the sampling frame comprises arrestees booked into large jails. Within an ADAM II site, each of the large jails is treated as a stratum, and a random sample is drawn from each stratum.

For example, the Hennepin County sample (Minneapolis) is restricted to the primary county facility, the Hennepin County Jail; the New York City (Borough of Manhattan) sample is restricted to the Manhattan House of Detention, the Borough's main booking facility. In both cases, the included jail captures the overwhelming majority of the jurisdiction's bookings. The Chicago (Cook County) sample is limited to the large Cook County Jail, where all city and county felony arrests and serious misdemeanor arrests from the city are booked; some serious misdemeanants in suburban areas may also be processed though suburban bond courts.[1]

Small facilities in these sites might be represented by using cluster sampling, but this is impractical. Each of these small booking facilities processes so few arrestees that without an excessive expenditure of project resources, interviewers are unable to gather data from anything more than a small, and consequently uninformative, sample of arrestees. Representing small facilities does not alter prevalence estimates materially because small facilities account for a small proportion of the counties' bookings. Furthermore, exclusion of small facilities does not affect trends, provided it is understood that the trends pertain to those jails that are included in the sample.

ADAM II interviews arrestees over fourteen consecutive days in every sampled jail with the exception of Atlanta and Washington, DC. In the case of Atlanta (Fulton County), there are two principal jails. One (Atlanta Detention Center) is a facility where the Atlanta Police Department (APD) books all misdemeanants. The other (Fulton County Jail) is a large county facility where the APD books all felons and county law enforcement books both all felons and misdemeanants.[2] ADAM II samples from one facility in the first week (7 consecutive days) and the second facility in the second week (7 consecutive days).

Seven police districts each have their own booking facilities in Washington, DC; there is no central booking facility to which all persons arrested in the district initially go. Each district facility books

1 A large proportion of misdemeanants is booked and released from over 100 small police precincts in the city itself. Because of costs, it is impractical to sample from those facilities. Felons may also be booked first into those facilities, but they are then transferred to the Cook County Jail before release and, consequently, are captured in the ADAM II sample.

2 The city of Atlanta sits in two counties: Fulton and DeKalb. The city police book in Fulton County because it represents the largest geographic segment of the city.

all offenders arrested in its geographic area regardless of charge. Afterwards, each sends only those arrestees who will be detained for further processing to a central holding facility. ADAM II currently uses a stratified random sampling design for Washington, DC. Days are randomly assigned to each of the facilities, thereby assuring that every jail receives roughly proportional representation over the 14-day period. The largest volume districts collect for three randomly selected days, and the other districts for one or two randomly selected days. The sampling is problematic. Low booking rates and rapid release of offenders sometimes result in samples of 0 or 1 in the smallest jails. Consequently, the project continues to look for ways to improve this sample.

1.2. Sampling Within Each Jail in Counties with Multiple Jails and in Single Jail Counties

Both ADAM and ADAM II lacked sufficient resources to station interviewers in booking facilities twenty-four hours per day for a two week period. Recognizing this constraint, the original ADAM redesign team considered a plan to randomly sample periods during a twenty-four hour day, stationing interviewers in the jails during those sampled periods. This plan proved impractical for three reasons. First, jail personnel both prohibit interviewing of inmates during certain periods and require standard scheduling to minimize disruption of operations. Second, sampling periods of relative quiescence force interviewers to be idle for at least some parts of their work shifts. And third, random sampling of interview periods requires interviewers to work unreasonable duty shifts.

Consequently, the sampling design in each facility divides the data collection day (and the interview cases) into periods of *stock* and *flow*. Interviewers arrive at the jail at a fixed time during the day. Call this H. They work a shift of length S. The *stock* comprises all arrestees booked between H-24+S and H, and the *flow* comprises all arrestees booked between H and H+S. For example, if interviewers start working at 4 PM and work for 8 hours, then the stock period runs from 12PM to 4PM, and the flow period runs from 4PM to 12PM. Cases are sampled from the stock and flow strata.

In the stock period, sampling is done from arrestees who have been arrested between H-24+S and H. This sampling begins at time H, and while arrestees identified as having been brought in during that time remain in the sample frame, interviewers can only interview those arrestees who remain in jail as of time H. In the flow period, sampling is done continuously for arrestees as they are booked between H and H+S.

To determine sampling rate, supervisors estimate the number of bookings that occur during the stock and flow periods based on data for each facility reflecting the two-week period prior to the quarter's collection. Call the daily total N; call the number booked during the stock period N_S; and call the number booked during the flow period N_F. Then $N = N_S + N_F$. Supervisors set quotas from the stock and flow for each site equal to n_S and n_F, respectively, such that:

$$\frac{n_S}{n_F} = \frac{N_S}{N_F}$$

The actual sample size ($n=n_S+n_F$) depends on the number of interviewers and sometimes (for small jails) the number of bookings ($N=N_S+N_F$), since n cannot exceed N.

The supervisor sorts arrestees based on booking time during the stock period and forms n_s equal sized strata based on that ordering. Sampling is systematic within each stratum: 1, n_S+1, n_S+2, etc. If the sampled arrestee is unavailable or unwilling to participate, the supervisor selects the nearest temporal neighbor—meaning the arrestee whose booking time occurs immediately after the arrestee who is unavailable or who declined. Replacement continues until the already established stock quota is filled. Because of administrative practices of jails and courts, arrestees are frequently unavailable to interviewers, i.e., they have been transferred to another facility, have already been released or are in court. The selection of the nearest neighbor is intended to reduce or eliminate any bias that otherwise would occur from apparently low response rates.

During the flow period, the supervisor selects the arrestee booked most recently and assigns an interviewer. If the arrestee is unavailable or unwilling to participate, the supervisor selects the next most recently booked arrestee as a substitute. This process continues until the workday ends at time H+S.

This procedure produces a sample that is reasonably well balanced, meaning that arrestees have about the same probability of being included in the sample. If the sample were perfectly balanced, weighting would be unnecessary for unbiased estimates; and, in fact, estimates based on weighted and unweighted ADAM data are similar. The sample is not perfectly balanced, however, for several reasons.

First, while supervisors attempt to sample proportional to volume during the stock and flow periods based on recent data from the facility, achieving this proportionality requires information that is not available at the time that supervisors set quotas. A supervisor can only estimate N_S and N_F based on recent historical experience; furthermore, the supervisor can not know the length of time required to complete interviews because the length of the ADAM II interview depends on the extent of the arrestee's comprehension and cooperation level, as well as the extent of his reported drug use and market activity. So the achieved value of n_F is variable.

Second, the number of bookings varies from day-to-day, but the number of interviewers arriving each day is constant. Days with a high number of bookings result in lower sampling probabilities than days with a low number of bookings. Furthermore, the number of bookings varies over the flow period, so that arrestees who are booked during periods with the most intensive booking activity have lower sampling rates than do arrestees who are booked during periods with the least intensive booking activity. Sampling rates do not vary as much across the stock period because of the way that the period is partitioned.

Third, as noted above, arrestees can exit the jail during the stock period. The probability that an arrestee has been released prior to being sampled depends on both the time during the stock period when he is booked and his charge. The earlier that booking occurred during the stock period, the greater the opportunity he has had to be released. The more serious the charge, the lower the probability of being released, because serious offenders are more likely to be detained pending trial or require time-consuming checks for outstanding warrants. Neither factor plays an important role during the flow period because of the way that the sample is selected.

2. Data Collection Protocol

Data collection protocols are described in detail in the *ADAM II 2007 Annual Report* and the *ADAM II 2008 Annual Report* available through ONDCP's website. The protocols are briefly summarized here to provide some context for the discussion of weighting and estimation methodologies.

2.1. Selecting Study Subjects

Interviewers work in teams in each jail. As discussed in Section 1, the supervising interviewer samples from the stock and flow. Sampling from the stock requires a list of all individuals who were booked since the interviewer's last work period. Not all arrestees are still in the facility, but the supervising interviewer does not know that. He or she seeks the sampled arrestee, and, if that arrestee is unavailable or unwilling to be interviewed, the supervising interviewer records the reason and seeks a replacement. Sampling from the flow requires a list of individuals as they are booked into the jail. The supervising interviewer continuously compiles a list of incoming arrestees and seeks the most recently booked arrestee. If that arrestee is unavailable or unwilling to be interviewed, the supervising interviewer records the reason and seeks the closest temporal replacement.

When any arrestee is sampled (regardless of their availability), the supervising interviewer completes *a facesheet*. The facesheet contains sufficient identifying information that the arrestee can be matched with census data (that is, a census or records representing all bookings into the jail in each of the fourteen data collection days) that are collected long after sampling. The role of the census data is described in Section 2.2. The supervising interviewers use the facesheet to record that an interview occurred, and if it did not, the reasons why it did not. Analysts use the facesheet to compute response rates. Bar-coded labels are attached to the facesheet, the interview form and the urine specimen bottle, tying all data together. All arrestees sampled have a facesheet, but not all have the other components of the collection (interview, urine specimen). To be eligible for interview an arrestee must be: male, arrested no longer than 48 hours prior, coherent enough to answer questions and not an INS or Federal Marshalls' hold.

Arrestees who consent to an interview answer an interview lasting on average about twenty minutes—longer when the arrestee's drug use or drug market behavior is extensive. The interview is the source of self-report data. The request for a urine sample is made at the beginning of the interview and repeated at its completion. If the arrestee consents, he is given a specimen bottle which he takes to a nearby lavatory to produce a sample. The bottle is returned to the interviewer, bagged and sent at the end of the shift to a national laboratory for testing. In most sites over 80% of arrestees consent to provide a urine specimen. The urine specimen is linked to the facesheet and the interview through common bar-coded labels.

2.2. The Role of Census Data

Developing propensity scores for case weighting requires complete data on all bookings (a census) that occurred in each ADAM II facility during the two-week period of data collection. These data are provided by each law enforcement agency participating in ADAM II and sent to the Abt Data Center for processing. Site law enforcement partners submit census data in a variety of forms: electronic files listing each case, PDF or other text files of cases and paper format listing all cases. The Abt

Data Center staff transforms each into site and facility specific data sets containing the following data elements for each arrestee:

- Date of Birth and or Age
- ID (computer generated number)
- Most serious charge
- Time of arrest
- Time of booking
- Day of arrest
- Race

Whether the census data are transmitted electronically, as a PDF file, or a paper file, the data are transformed into a SAS dataset. The census data become the sampling frame. As noted, ADAM interviewers complete a facesheet that includes the above variables for every arrestee sampled for the study, records whether the arrestee answered the interview and whether he provided a urine specimen.

Figure 1 represents the steps included in the manipulation of the raw census data done in preparation for matching with the ADAM facesheet data. The raw census data received from booking facilities are cleaned to correct invalid data and reformatted for compatibility with the other data components. The census data typically have one row of data per charge and must be converted to single records identifying arrestees with multiple charges. First, arrestees are excluded in the census data who are ineligible for the ADAM survey: juveniles, women and people booked on days other than those when ADAM surveys were conducted. Second, charges recorded in the census data are converted into a set of standardized ADAM charges. Additionally, the top severity, top charge and top charge category (violent, property, drug, other) are determined for each individual.

Figure 1: First Step in Matching Process

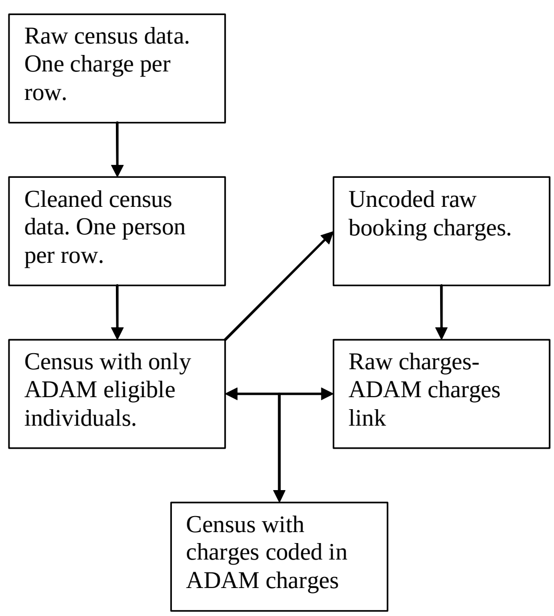


Figure 2 shows the process of matching the census records to the ADAM facesheet records. The variables common to both the facesheet and the census data that are used to match the records are: booking date/booking time, date of birth, arrest date/arrest time, charges and race. Potential matches are outputted if records match on any single key variables; they are then ranked into tiers based on the goodness of the fit. For example, a facesheet record that matches a census record on just booking date/booking time and charges will be superseded in rank by a facesheet-census match that links on booking date/booking time, charges and date of birth. Out of all the potential matches the best census match is selected for each facesheet. If, in fact, multiple census records match the same facesheet, and these duplicate matches have equivalent rankings, booking date/time is used as a tiebreaker. The output dataset from this process is a one-to-one match between each facesheet record and census records.

Rarely, a facesheet fails to match any booking record. When this happens, a pseudo-booking sheet is created and inserted into the booking data. This process is represented by the right-hand flow in **Figure 2**.

Figure 2: Matching Census with Facesheet Data

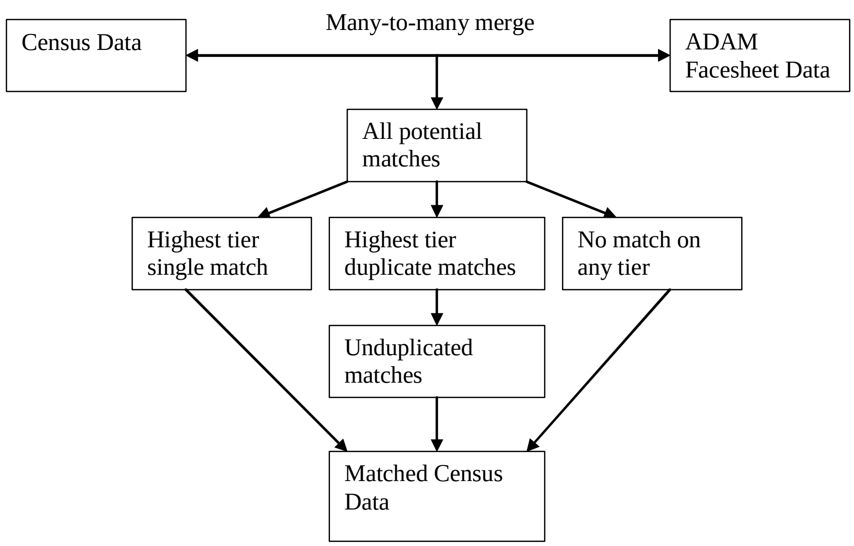
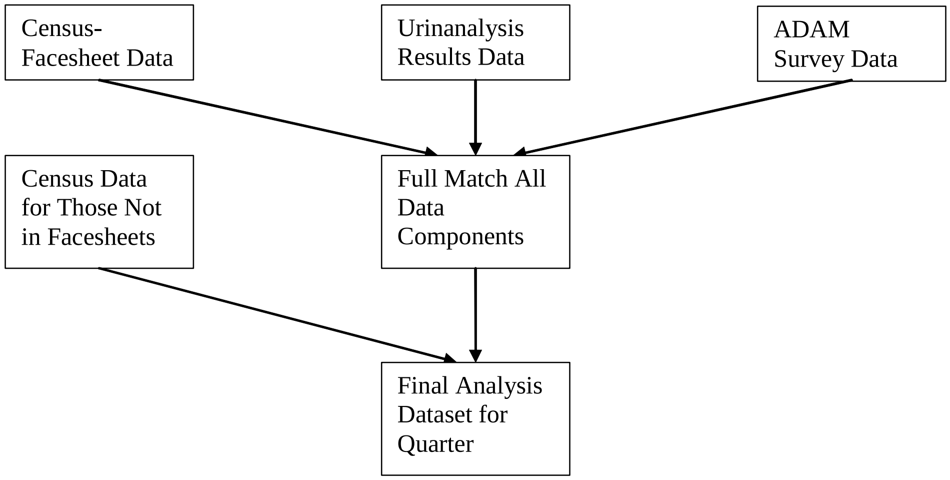


Figure 3 demonstrates the last step in the construction of the analysis file for each site and each data collection quarter. The linked census-facesheet data are merged with the appropriate urinalysis and survey record using unique identification numbers recorded in barcoded labels on the facesheet, interview and urine specimen. The result is the final analysis dataset for each quarter for each particular ADAM site.

Figure 3: Creation of Final Analysis File



3. Weighting the ADAM II Sample

The original ADAM program (2000–2003) used post-stratification weighting of cases. This meant that after the data have been assembled, analysts stratified the sample in each site according to jail, stock and flow, day-of-the-week and charge. The sampling probability was the number of interviews completed within each stratum divided by the number of bookings that occurred in that same stratum. Weights were the inverse of the achieved sampling probabilities. Although post-stratification may seem straightforward, weighting was time-intensive and uncertain. The resulting strata sometimes had empty cells or so few observations that one stratum had to be merged with one or more other strata. How this merging affected the validity of the weights is unknowable.

To increase the validity of the weights and to reduce standard errors of the estimates, ADAM II adopted **propensity score weighting**. This section explains the logic of using propensity scores to weight survey data.

ADAM II requires two sets of weights, one pertaining to interview questions, and the other pertaining to urine test results. This dual set of weights is needed because some arrestees who agree to interviews are unable or unwilling to provide urine specimens. The illustration presented in this section describes the weights for urine tests, but the weighting procedure for interviews is identical.

3.1. The Logic of Weighting with Propensity Scores

As mentioned earlier, ADAM II data are not derived from a simple random sample. Rather, sampling probabilities vary systematically with features of the data: arrest charge, number of bookings, and time of the booking. Logistic regression is used to estimate the probability of appearing in the sample conditional on these salient features of the data. Consistent with the professional literature, predictions based on the logistic regression are called the *estimated propensity scores*. The inverse of the estimated propensity score provides a weight that, when applied to sample data, provides consistent estimates of drug use and other behaviors for the population of arrestees.[3] Ignoring these weights may lead to biased and inconsistent population estimates.

The use of propensity scores dates to influential work such as Rosenbaum (1984) and Rosenbaum and Rubin (1984). Rotnitzky and Robins (1995), among others, proposes using "inverse probability weighting" as a solution for missing data problems, of which sampling provides an illustration. Wooldridge (2003) proposes a generalized two-step estimation method, which produces consistent and asymptotically normal estimates. This method estimates propensity scores (i.e., probabilities of being sampled) in the first step, and uses inverses of the estimated propensity scores as weights when estimating the parameters of interest in the second step. Several studies (e.g. Wooldridge 2003; Hirano et al. 2003) argue that using the inverse of the estimated propensity score as weights is more efficient than weighting by the inverse of the "true" selection probability, in the sense that it leads to smaller standard errors and narrower confidence intervals.

[3] This assumes selection on observables. This means that inclusion in the sample is random, conditioned on the estimated propensity score. One cannot be sure this condition holds, but nearest neighbor replacement sampling helps assure that the condition is met, and the use of propensity score weighting reduces bias when the condition is not met exactly.

However, estimating standard errors is complicated using the two-step estimators. In ADAM II, relying on Wooldridge, standard errors are programmed in STATA and SAS and the results from that programming are used when estimating preliminary ADAM II population statistics. The ADAM II experience is that the adjustment to the sampling variance is immaterial, and users can apply these weights without fear that the sampling variance is too high.[4]

The use of propensity scores is a rapidly developing research topic, and some authors consider the methods for estimating standard errors as unsettled. Most survey applications currently in use appear to ignore the apparently minor variance inflation that occurs because of two-step estimation, and that is the ADAM II approach. As noted, however, the risk of materially understating standard errors appears minor, and estimators will be modified as estimation routines evolve.

3.2. Development of Propensity Scores

The following discussion uses original ADAM data from Portland for 2000 and 2001 as an illustration of estimating and testing propensity score weights for a single jail. The 2002/2003 contractor was unable to provide the census data for those years, so only 2000 and 2001 data were originally included. Because the 2000/2001 data were readily available, they were originally used to develop estimation routines, including diagnostic tools, that were then adapted to each of the other nine sites. As explained later, those estimation routines and diagnostic tools are used to reweight the original ADAM data for 2000/2001 and to weight all ADAM II data going forward. The diagnostic routines are repeated for each site each quarter. The diagnostic output for ADAM II sites is voluminous and not reported here, but, as noted in the Introduction, electronic documentation is available upon request.

Throughout the notation used in this section, the subscripts reference the i^{th} arrestee who was booked during the k^{th} half-hour on the j^{th} day of year t. The index k runs from 1 to 48 beginning at the thirty-minute period immediately after midnight.

S_{ijkt} This is a dummy variable coded 1 if the i^{th} arrestee who was booked during the k^{th} half-hour of the j^{th} day of year t was included in the sample. It is coded zero otherwise.

ST_{ijkt} This is a dummy variable denoting that the arrestee was booked during the stock period.

FL_{ijkt} This is a dummy variable denoting that the arrestee was booked during the flow period.

H_{ijkt} This is a dummy variable representing the half-hour during which the arrestee was booked.

FEL_{ijkt} This is a dummy variable coded 1 if the arrestee was charged with a felony and coded 0 otherwise.

MIS_{ijkt} This is a dummy variable coded 1 if the arrestee was charged with a misdemeanor and coded 0 otherwise.

OTH_{ijkt} This is a dummy variable coded 1 if the arrestee was charged with neither a felony nor misdemeanor and coded 0 otherwise.

4 Although Wooldridge offers one approach to adjusting standard errors, other authorities offer alternative approaches, and according to Morgan and Winship (2007), there is no universal standard. As statistical theory and statistical software evolve, future versions of ADAM II will incorporate improved standard error estimation. Fortunately, current ADAM II testing using the Wooldridge approach suggests that standard errors are not seriously biased, so correcting them at this time is not critical.

NS_{jt} This is the number of bookings that occurred during the entire stock period of the j_{th} day of year t.

NFH_{jkt} This is the number of bookings that occurred during the k_{th} half-hour on the j_{th} day of year t.

Q_{qt} This is a dummy variable coded 1 if the arrestee was booked during the q_{th} quarter of year t.

To estimate the propensity score, a logistic regression is estimated with the logit:

$$[1]\quad P(S_{ijkt} = 1) = \frac{1}{1 + e^{-X_{ijkt}}}$$

where X_{ijkt} is defined as:

$$X_{ijkt} = \sum_{k=1}^{48} \alpha_k ST_{ijkt} H_{ijkt} / NS_{jt} + \sum_{k=1}^{48} \beta_k FL_{ijkt} H_{ijkt} / NFH_{jkt} + \delta_1 FEL_{ijkt} ST_{ijkt} +$$
$$\delta_2 MIS_{ijkt} ST_{ijkt} + \delta_3 OTH_{ijkt} ST_{ijkt} + \delta_4 FEL_{ijkt} FL_{ijkt} + \delta_5 MIS_{ijkt} FL_{ijkt} + \sum_{t=2000}^{2001} \sum_{q=1}^{4} \theta_{qt} Q_{qt}$$

This model is used to estimate weights for the ADAM II samples (2007, 2008, 2009), and to estimate new weights for the 2000 and 2001 ADAM sample. The reason for estimating new weights for 2000 and 2001 is that the propensity score estimator is an improvement over the post-stratification weighting procedure used previously. Since the propensity score is estimated using all available data, computing new weights for 2000 and 2001 is not an additional burden. In trend estimations (discussed in a Section 5), ADAM II utilizes the reweighted data (2000-2001) and the only weights available for 2002-2003, the original ADAM weights.

The model specification requires some explanation. While [1] is the general specification used across the sites, site-specific changes are often made to this specification. Typically, the specification is modified because offenses appeared to be coded differently across the years, so the felony/misdemeanor/other distinction can not always be identified. When data allow, race and age are included in the construction of propensity scores. Some sites—Washington, DC is an example—present unique problems, so that the propensity score model has to be simplified. The special case of Washington will be discussed later.

The term $\sum_{k=1}^{48} \alpha_k ST_{ijkt} H_{ijkt} / NS_{jt}$ appears in this model to account for variation in the sampling rate during the stock period. Because the quota n_S is invariant while NS varies over the two-week sampling period, the probability of being interviewed during the stock period changes from day-to-day, depending on the number of bookings during that day's stock period. Hence, NS_j appears in the denominator. The parameter should not vary greatly across the stock period because ADAM replaces missing respondents with their nearest neighbor. This replacement may not work perfectly, however, so the model allows the probability of selection to vary within a given stock period. Note that α_k may be taken to be zero when k occurs during the flow period.[5]

The term $\sum_{k=1}^{48} \beta_k FL_{ijkt} H_{ijkt} / NFH_{jkt}$ appears in the model to account for variation in the sampling rate during the flow period. Because n_F is fixed while N_F varies, and because bookings are not evenly distributed over time, the probability of sample selection decreases with the number of bookings that occur during the half-hour when the arrestee is sampled. Hence NFH_{jkt} appears in the denominator. Given the way that the sample is selected, one would not expect β to vary much over time, but allowing this parameter to vary by hour increases the model's flexibility with little costs for the estimates.

The terms $FEL_{ijkt} S_{ijkt}$, $MIS_{ijkt} S_{ijkt}$, and $OTH_{ijkt} S_{ijkt}$ appear in the model to account for variation in the sampling rate due to the severity of the charge. An arrestee booked during the stock period cannot be sampled if he is released prior to being approached by an interviewer. As mentioned before, the probability of being released during the stock period depends in part on the charge. One would not expect that the probability of being sampled varies appreciably across charge types during the flow period, but it may be that arrestees charged with certain types of offenses (serious violent crimes) are comparatively inaccessible, so the terms $MIS_{ijkt} FL_{ijkt}$ and $FEL_{ijkt} FL_{ijkt}$ are introduced. The interaction term $OTH_{ijkt} FL_{ijkt}$ is the reference category.

Finally, variations in the sampling probabilities across quarters are controlled for by adding quarter dummy variables for each year in the logistic model [1]. **Table 1** (column 3) shows variability in the realized sampling proportions across quarters. Without introducing quarter dummy variables into [1] (see column 4), the average estimated sampling probabilities fail to adequately capture the average realized sampling probabilities (compare columns 3 and 4). After introducing quarter dummy variables into [1] (see column 5), the average estimated sampling probabilities capture the average realized sampling probabilities (compare columns 3 and 5). Unless these seasonal differences are controlled, it may be impossible to model arrestees' sampling probabilities correctly.

Table 1: Sampling Proportions By Quarter and Year

Year	Quarter	Realized Sampling Proportion (SP)	Estimated SP (Quarters not controlled)	Estimated SP (Quarters controlled)
2000	1	.137	.165	.137
2000	2	.149	.176	.149
2000	3	.209	.171	.209
2000	4	.216	.174	.216
2001	1	.150	.158	.151
2001	2	.152	.170	.153
2001	3	.191	.179	.192

Notes: Quarter 4 is missing in 2001 since ADAM interviews were not conducted in Portland in this quarter.

5 The starting time H and the stopping time H+S are not always constant from day-to-day. Therefore, one can not precode this summation to start at the beginning of the stock period and end at the termination of the stock period.

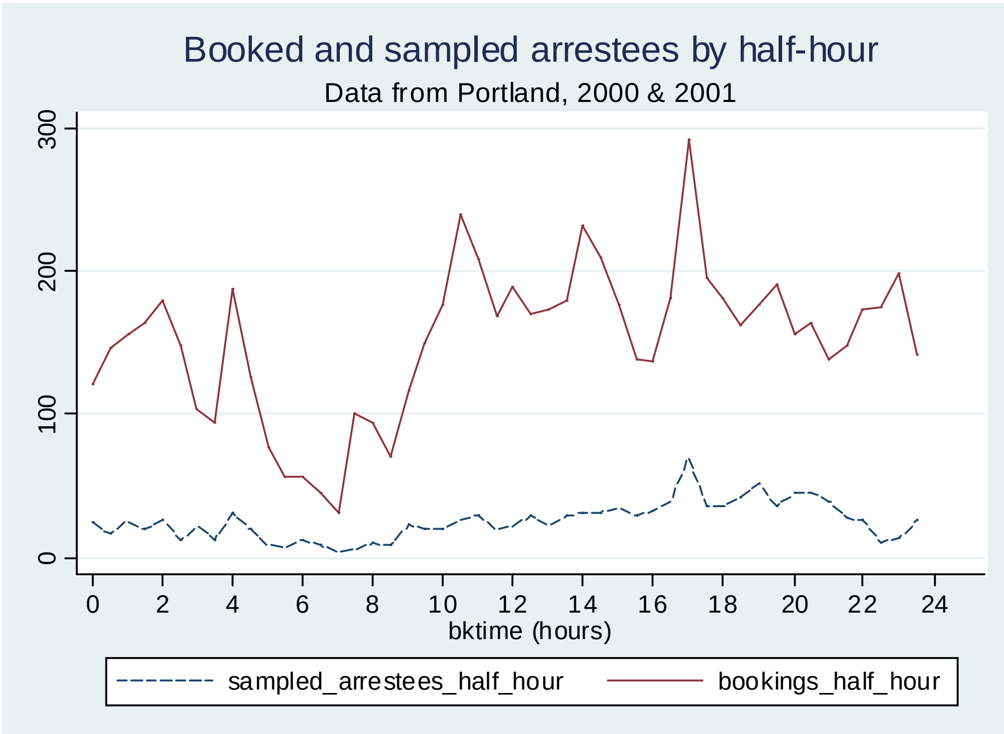
Figure 4 (panel a) shows the number of bookings and the number of arrestees in the sample by half-hour period; **Figure 4** (panel b) reports the sampling proportions by half-hour period. The figures show some differences in the sampling rates between the stock period (roughly 20/100 were sampled) and flow period (roughly 15/100 were sampled). Because these sampling rates imply weights of 5 and 6.7, respectively, the conclusion is that the sample is reasonably balanced.

Looking at **Figure 4** (panel b), there is apparent variation in the sampling rates from half-hour to half-hour. To prevent the weights from getting too large, the weights are trimmed so that the largest 5 percent of the weights have the same value, namely, the size of the smallest weight among the largest 5 percent. In **Figure 4** (panel b), this places a ceiling of about 10 on these weights. The smallest weight is about 3. Again, the sample is reasonably balanced in the sense that there are no wide disparities in the weights.

Table 2 shows the number of bookings and the number of arrestees in the sample by charge. Overall the sampling probabilities do not vary materially with the charge. They are 0.18 for felony charges, 0.19 for misdemeanor charges, and 0.15 for other charges. Both the figures and table demonstrate that ADAM II is able to achieve reasonable balance with respect to booking time and charge, the two variables that are likely to have the greatest effect on sampling rates.

Figure 4

Panel a: Number of Bookings and Number of Sampled Arrestees by Half-Hour



Panel b: Sampling Proportions by Half-Hour

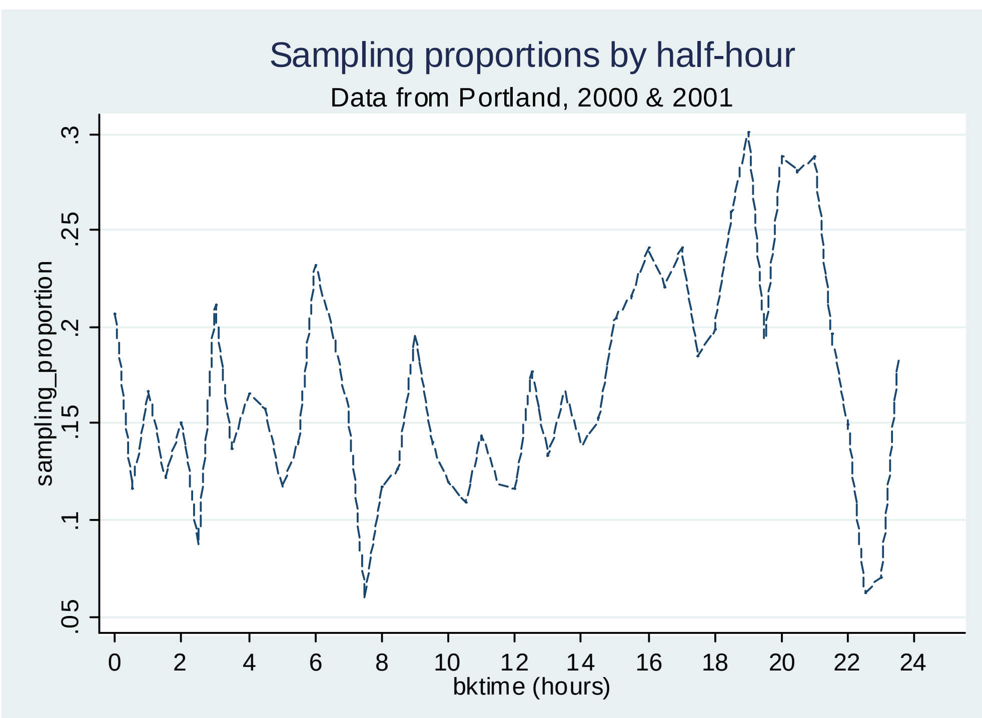


Table 2: Number of Bookings and Number of Arrestees In the Sample By Charge Portland 2000 and 2001

Charge	Number of Bookings	Number of Arrestees in the Sample	Sampling Rate
Felony	2492	456	0.18
Misdemeanor	2141	400	0.19
Other	2663	388	0.15

Table 3 presents coefficient estimates of the logit model specified by equation [1]. As would be expected, the parameter estimates are typically significantly different from zero. Although a reader cannot tell from inspection of the table (because estimated parameter covariance are not reported), the parameters do not necessarily differ from each other.

The model specification varies slightly across the sites due to variations in data availability, but departures from this generic form are never large. Variations are not detailed in this report, but as noted in the introduction, details are available in electronic form by request.

Table 3: Parameter Estimates from the Logit Model for Propensity Scores: Portland 2000 and 2001

Covariates	Coefficient	Std. Error	Z	P>|z|
Felony*Stock	-0.675	0.192	-3.52	0.000
Felony*Flow	-0.890	0.202	-4.41	0.000
Misdemeanor*Stock	0.193	0.114	1.70	0.089
Misdemeanor*Flow	-1.036	0.196	-5.28	0.000
Other*Stock	-0.136	0.116	-1.17	0.240
Stock*Half_Hour 1/NS_j	43.585	13.005	3.35	0.001
Stock*Half_Hour 2/NS_j	26.344	11.681	2.26	0.024
Stock*Half_Hour 3/NS_j	27.307	9.290	2.94	0.003
Stock*Half_Hour 4/NS_j	17.385	9.891	1.76	0.079
Stock*Half_Hour 5/NS_j	27.546	9.308	2.96	0.003
Stock*Half_Hour 6/NS_j	5.876	12.050	0.49	0.626
Stock*Half_Hour 7/NS_j	42.028	10.230	4.11	0.000
Stock*Half_Hour 8/NS_j	18.372	12.879	1.43	0.154
Stock*Half_Hour 9/NS_j	26.061	8.648	3.01	0.003
Stock*Half_Hour 10/NS_j	26.835	9.227	2.91	0.004
Stock*Half_Hour 11/NS_j	15.628	12.725	1.23	0.219
Stock*Half_Hour 12/NS_j	21.247	12.495	1.70	0.089
Stock*Half_Hour 13/NS_j	41.062	12.674	3.24	0.001
Stock*Half_Hour 14/NS_j	40.899	14.811	2.76	0.006
Stock*Half_Hour 15/NS_j	31.188	19.377	1.61	0.108
Stock*Half_Hour 16/NS_j	-12.757	18.706	-0.68	0.495
Stock*Half_Hour 17/NS_j	35.026	15.282	2.29	0.022
Stock*Half_Hour 18/NS_j	22.691	14.733	1.54	0.124
Stock*Half_Hour 19/NS_j	46.892	11.299	4.15	0.000
Stock*Half_Hour 20/NS_j	23.556	11.386	2.07	0.039
Stock*Half_Hour 21/NS_j	17.823	11.596	1.54	0.124
Stock*Half_Hour 22/NS_j	17.740	10.110	1.75	0.079
Stock*Half_Hour 23/NS_j	27.260	10.426	2.61	0.009
Stock*Half_Hour 24/NS_j	19.201	11.099	1.73	0.084
Stock*Half_Hour 25/NS_j	24.344	10.729	2.27	0.023
Stock*Half_Hour 26/NS_j	36.517	10.315	3.54	0.000

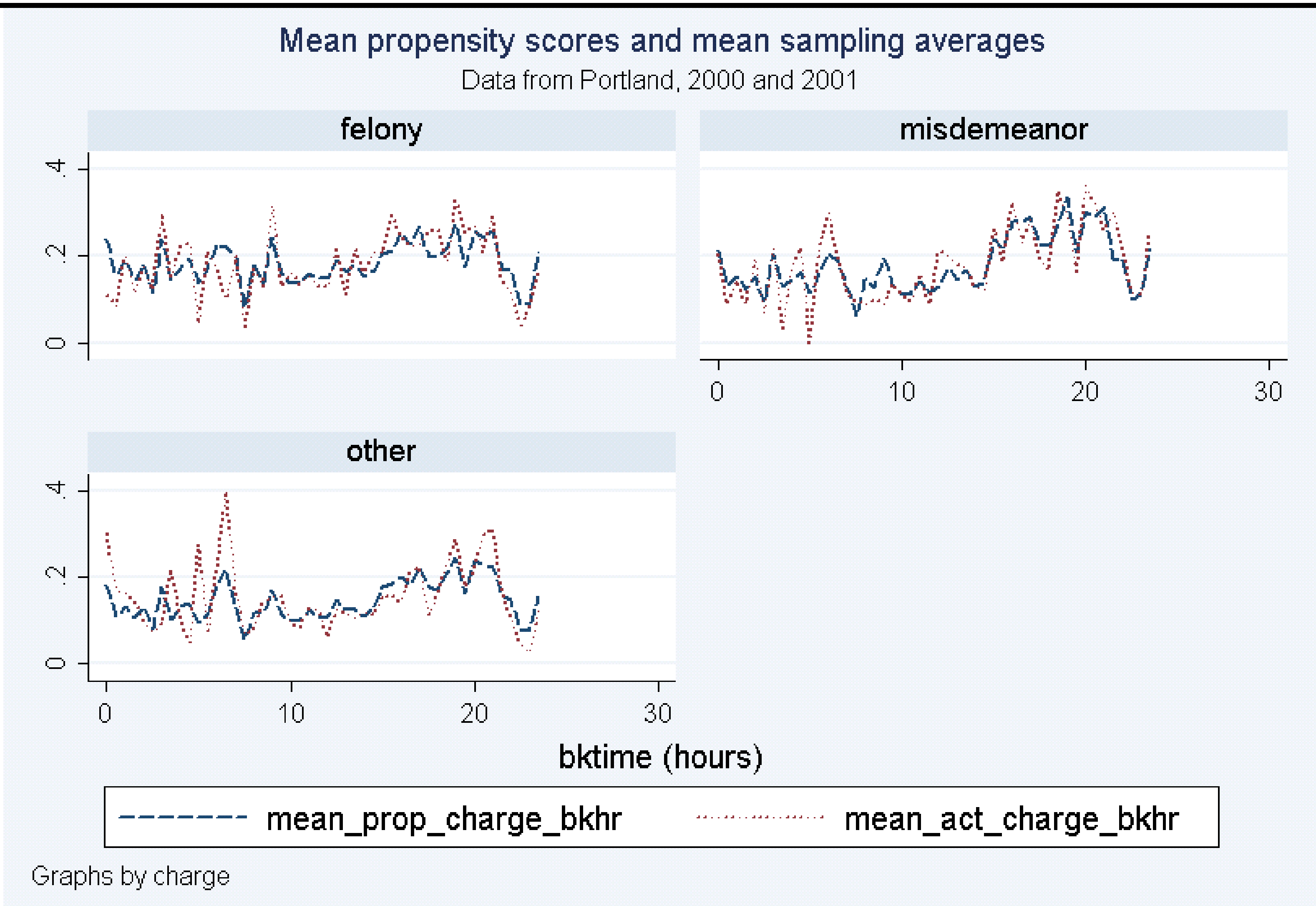
Table 3: Parameter Estimates from the Logit Model for Propensity Scores: Portland 2000 and 2001

Covariates	Coefficient	Std. Error	Z	P>|z|
Stock*Half_Hour 27/NS_j	27.684	10.536	2.63	0.009
Stock*Half_Hour 28/NS_j	32.131	10.407	3.09	0.002
Stock*Half_Hour 29/NS_j	21.347	9.837	2.17	0.030
Stock*Half_Hour 30/NS_j	29.673	10.244	2.90	0.004
Stock*Half_Hour 31/NS_j	43.304	17.492	2.48	0.013
Stock*Half_Hour 32/NS_j	34.297	19.029	1.80	0.071
Stock*Half_Hour 33/NS_j	45.035	15.906	2.83	0.005
Stock*Half_Hour 34/NS_j	43.197	15.183	2.85	0.004
Stock*Half_Hour 47/NS_j	-47.981	30.179	-1.59	0.112
Stock*Half_Hour 48/NS_j	23.942	11.696	2.05	0.041
Flow*Half_Hour 1/NFH_{jk}	0.813	0.575	1.41	0.158
Flow*Half_Hour 2/NFH_{jk}	-1.618	1.169	-1.38	0.166
Flow*Half_Hour 31/NFH_{jk}	0.461	0.421	1.09	0.274
Flow*Half_Hour 32/NFH_{jk}	0.439	0.404	1.09	0.277
Flow*Half_Hour 33/NFH_{jk}	0.840	0.370	2.27	0.023
Flow*Half_Hour 34/NFH_{jk}	0.759	0.398	1.91	0.057
Flow*Half_Hour 35/ NFH_{jk}	1.493	0.367	4.07	0.000
Flow*Half_Hour 36/NFH_{jk}	0.332	0.374	0.89	0.375
Flow*Half_Hour 37/NFH_{jk}	0.283	0.388	0.73	0.466
Flow*Half_Hour 38/NFH_{jk}	0.763	0.347	2.20	0.028
Flow*Half_Hour 39/NFH_{jk}	1.263	0.335	3.77	0.000
Flow*Half_Hour 40/NFH_{jk}	0.027	0.393	0.07	0.946
Flow*Half_Hour 41/NFH_{jk}	0.936	0.328	2.85	0.004
Flow*Half_Hour 42/NFH_{jk}	0.886	0.335	2.65	0.008
Flow*Half_Hour 43/NFH_{jk}	0.965	0.334	2.89	0.004
Flow*Half_Hour 44/NFH_{jk}	0.024	0.392	0.06	0.952
Flow*Half_Hour 45/NFH_{jk}	-0.123	0.405	-0.30	0.762
Flow*Half_Hour 46/NFH_{jk}	-1.950	0.666	-2.93	0.003
Flow*Half_Hour 47/NFH_{jk}	-0.793	0.672	-1.18	0.238
Flow*Half_Hour 48/NFH_{jk}	1.600	0.548	2.92	0.004
Quarter 1 in 2000	-0.544	0.137	-3.97	0.000
Quarter 2 in 2000	-0.507	0.123	-4.13	0.000
Quarter 4 in 2000	0.023	0.116	0.20	0.843
Quarter 1 in 2001	-0.316	0.117	-2.70	0.007
Quarter 2 in 2001	-0.396	0.118	-3.36	0.001
Quarter 3 in 2001	-0.172	0.117	-1.47	0.142
Constant	-1.289	0.136	-9.46	0.000

Notes: In this table, Half_Hour_k denotes the dummy variable for half hour k. NS_j, and NFH_{jk} are defined as in the text. Quarter 4 in 2001 and other (drug offenses in Portland)*flow are the omitted dummy variables.

The estimated coefficients are then employed to predict propensity scores for the sampled arrestees. Inverses of the estimated propensity scores are the sampling weights. **Figure 5** tabulates the mean propensity score estimates and the mean sampling averages as a function of the time of day and the charge. The largest discrepancy between the propensity score and the achieved sampling rate is for those times of the day when bookings are fewest (see **Figure 4**), but overall the figure suggests that the logistic model is successful in capturing the variation in the sampling rates by time of the day and charge.

Figure 5: Mean Propensity Scores and Mean Sampling Averages by Charge and Half-Hour



The new propensity score weights and old ADAM weights are comparable in the sense that they both sum to the population size, but beyond that there are apparent differences. The propensity score weights have a standard deviation of 2.89; the original ADAM weights have a standard deviation of 3.90. This suggests that the estimates based on the propensity score weights should have smaller sampling variances, because small variation in the weights should lead to smaller variances in the weighted estimates. In short, the ADAM II estimates are more precise than the original ADAM estimates. This additional precision improves both point estimates and trend estimates.

Figure 6 displays histograms of the propensity score weights and the old weights after discarding weights larger than 15 (less than 1% of the propensity score weights and less than 3% of the old weights). These weights are discarded to improve the resolution of the figure. A regression of the propensity score weights on the old weights produce a regression:

$$WT_{propensity} = 4.04 + 0.283 WT_{old}$$

The parameter estimates are significant at $P<0.001$. The $R^2=0.09$.

Obviously, the propensity score weights are not the same as the old ADAM weights. In part, this is because the old weights fall into discrete categories since they are based on a finite number of strata (Hunt and Rhodes, 2001). The new weights are comparatively continuous. Consequently, the old weights do not perfectly explain the new weights.

There are other distinctions. The propensity score weights are not simply distributed about the old weights because the constant is 4.04 rather than 0. This finding seems curious, but the explanation is likely that the range of the weights is small. The average weight is about 5.9. The standard error about the regression is about 2.1. Thus, the propensity score weights are not actually much smaller or much larger than the original weights.

In order to test the significance of the estimated coefficients of the charge categories and the cycle covariates, likelihood ratio and Wald tests are performed for the unweighted and weighted specifications respectively.[6] Results of these tests suggest that the coefficients on the charge categories are jointly significant, whereas the ones on the cycles are not significant at conventional levels.[7] Portland serves as an example, but similar regressions are estimated for all other ADAM II sites; and these regressions are updated as new quarters of data are added to the ADAM II sample.[8] As noted in the introduction, complete documentation for each site is available in electronic form by request.

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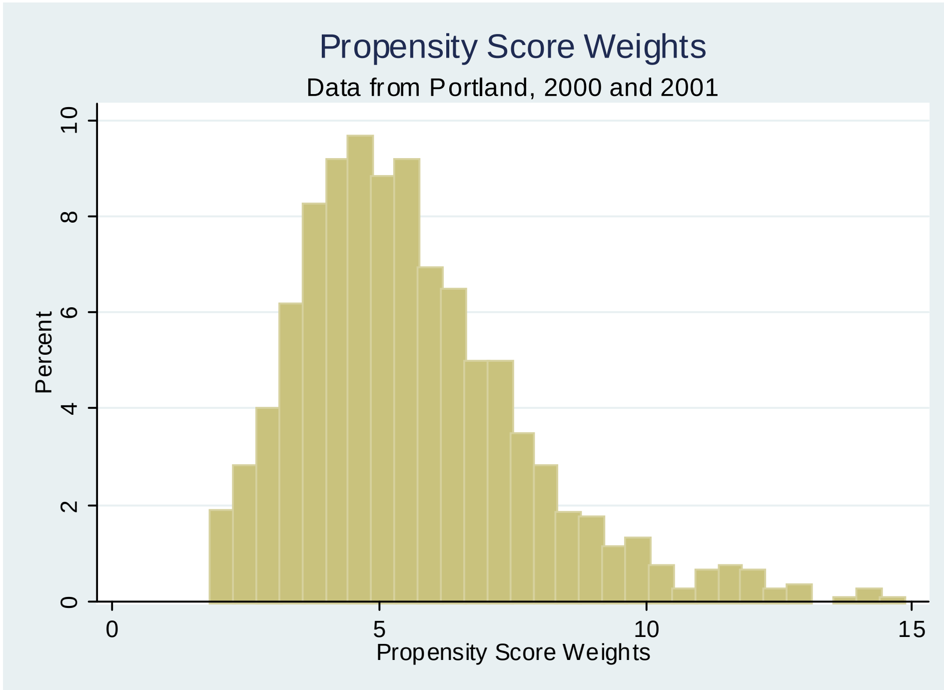
6 Note that when weights are employed, it is not appropriate to use a likelihood ratio test.

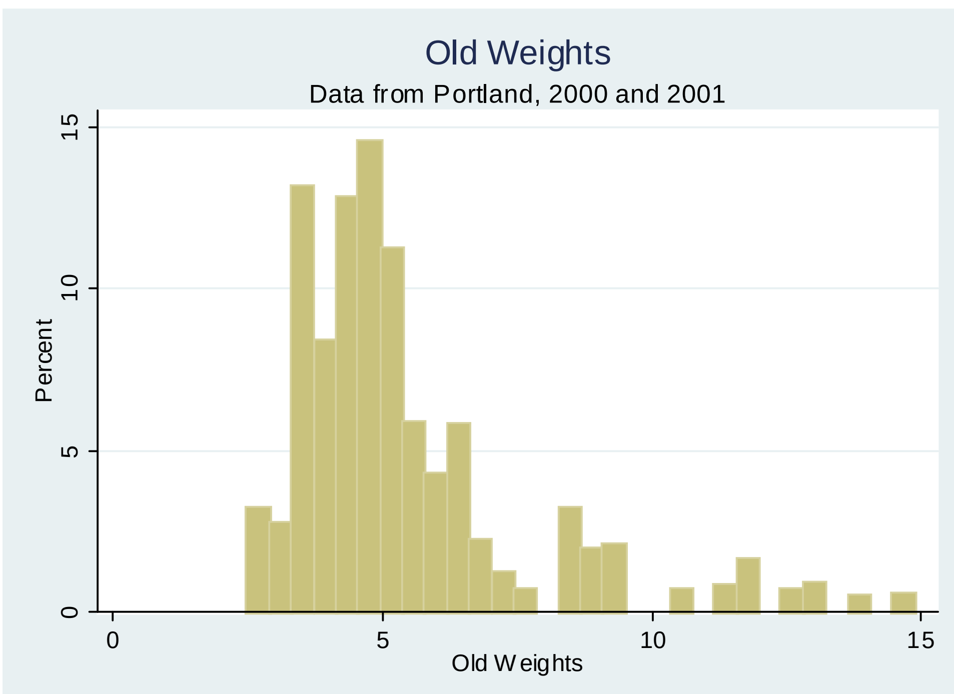
7 In the unweighted specification, the chi-squared test statistics for the charge categories and cycle covariates are 21.04 (6) and 4.76(4), respectively. When propensity score weights are employed, these values become 35.72 and 1.99 with the same degrees of freedom. Corresponding chi-squared critical values at the 5% level are 12.59 and 9.49 respectively.

8 The regression specification varies slightly from site-to-site because analysts could not always distinguish violent, property and other offenses or, felony offenses from misdemeanor offenses. The cycles are statistically significant for some sites; they are not significant for others.

Figure 6

Propensity Score Weights and Old Weights





3.3. Estimating Propensity Scores for 2007 and Later Years

Formula [1] pertains to estimating propensity scores using data from Portland for 2000 and 2001.[9] The model described by formula [1] applies to 2007, 2008 and 2009 with model modification. Referring to formula [1], the last term is:

$$\sum_{t=2000}^{2001} \sum_{q=1}^{4} \theta_{qt} Q_{qt}$$

To extend the formula to 2007 and beyond, this term is replaced with:

$$\sum_{t=2000}^{2001} \sum_{q=1}^{4} \theta_{qt} Q_{qt} + \sum_{t=2007}^{20XX} \sum_{q=1}^{4} \theta_{qt} Q_{qt}$$

20XX represents the most recent year of ADAM II data.

This formulation means that the propensity scores are updated for each site every time that ADAM II is administered. Potentially, then, earlier ADAM estimates could be changed with each administration of ADAM II. This periodic updating was felt to be confusing, and it was decided to "freeze" estimates once reported. This decision has implications for estimates going forward, which are discussed in section 5.

9 Again, ADAM II is not able to reweight data from 2002–2003, as the development of propensity scores requires each site's census data for each quarter. These data are not available from the prior ADAM contractor. Census data from 2000–2001 were kept in-house by Abt Associates, the contractor for those years.

4. Imputation of Missing Test Data

For a variety of reasons, some of the ADAM II sites have higher than expected levels of missing urine test results. The consequences of high missing urine rates and how they are dealt with are discussed here. The way missing data in Washington, DC are handled is different from the way missing data in all other sites are handled, so the Washington, DC approach is discussed separately.

4.1. Dealing with Missing Test Data

Missing data are a frequent problem in social science research. Perhaps the most common way of dealing with missing data is to discard cases in which data are missing and only work with data that are not missing. The original ADAM project took this approach. Whatever the merits of this approach generally, discarding survey data when the urine test result is missing is problematic when missing data comprise a material proportion of the sample. First, there is the prospect of introducing bias, because those arrestees who fail to provide a urine specimen may differ systematically from those who provide a urine specimen, and the propensity score may fail to control for those differences. Second, when missing data are material, sampling variances will be larger than is intended by the planned sampling design.

Statisticians have developed sophisticated approaches for dealing with missing data problems (Rubin, 1987; Schaefer, 1997). While the ADAM II team explored some complicated approaches, ADAM II estimation relies on an approach that is simple. To provide some intuition for the approach, an imputation example is presented here for recent cocaine use. The ADAM II interview asks all respondents the question: Did you use cocaine within the last three days? The answer is either "yes" or "no." In subset A of those respondents, ADAM II also obtains a drug test result, which indicates that the offender is either positive or negative for cocaine use in the prior three days. For subset B, ADAM II fails to obtain a test result, and imputations are done exclusively for subset B.

Using data from subset A, the probability of a positive urine test is P_1 when the respondent says that he used cocaine in the last three days, and the probability of a positive urine test is P_2 when the respondents says that he did not use cocaine in the last three days. P_1 is typically close to 1; P_2 is larger than 0 but much lower than 1 because (1) many respondents who deny use are being truthful so $P_2 < 1$, but (2) many respondents who deny recent drug use are being untruthful, so $P_2 > 0$. Turning to imputations for subset B, the best estimate is that a proportion P_1 of those offenders who answered "yes" to the 3-day question would in fact have tested positive for cocaine had they in fact been tested, and the best estimate is that a proportion P_2 of those offenders who answered "no" to the 3-day question would have tested positive for cocaine had they in fact been tested. **Nothing in the approach assumes truthful reporting.** This logic provides the basis for data imputation, although in practice (discussed below) the statistical underpinnings of this approach are complicated.[10]

[10] There is an important assumption: Failure to provide a urine test must not be correlated with recent drug use conditional on the response to the 3-day question. Put another way, among those respondents who denied using cocaine, those who did and those who did not use cocaine must be equally likely to provide a urine test. This assumption is not testable. Even if the assumption is incorrect, Schaefer (1997) argues that imputation will reduce bias that will otherwise arise from discarding data for arrestees who fail to provide urine specimens.

Deriving an imputation uses the following steps. First, the probability that a urine test result would be positive when an arrestee said that he had used a drug during the last three days is estimated. In fact, the probability is close to 1. Second, the probability that a urine test result would be positive when an arrestee said that he had not used a drug during the last three days is estimated. In fact, the probability is positive, but much closer to 0. Basically, the approach is to estimate these probabilities, draw a random sample from a Bernoulli distribution, and thereby assign a value of 1 or 0 to replace the missing value.

Although the basics of the imputation are simple, using the imputation when estimating the proportion of arrestees who tested positive for each drug is more complicated. Although a value of 1 or 0 based on the above procedure can be imputed, subsequent statistical analysis would not reflect two forms of sampling error without additional steps. First, the estimates of the probability of testing positive conditional on a self-report of recent drug use are, in fact, an estimate with its own sampling variance. Second, the random draw from the Bernoulli distribution is only one possible realization of a random process. Estimation must take additional sampling variation into account. A step-by-step explanation is provided below. *These steps are taken separately for each site and for each drug.*

1. According to current analysis, the probability of testing positive conditional on admission of use in the last three days does not vary much over time. Consequently, estimation is based on a simple model. Conditional on the respondent saying "YES" to the three day use question, the estimated probability of testing positive when the urine test is known is estimated as P_1. Conditional on the respondent saying "NO," the estimate is P_2.
2. Of course P_1 and P_2 are estimates, but the distribution of the estimates is known—they are asymptotically normal with estimated variances of $\sigma_1=P_1(1-P_1)/N_1$ and $\sigma_2=P_2(1-P_2)/N_2$ respectively, where N_1 and N_2 are the number of observations with self-reports of "YES" and "NO" that have corresponding urine test results.
3. The distributions of σ_1 and σ_1 are distributed as inverted Chi-square with N_1 and N_2 degrees of freedom, respectively. Using a Baysian logic (Lancaster, 2004), a realization of σ_1 and $\sigma_{1\ a}$ is drawn from the inverted Chi-square. These realizations are used in the next step.[11]
3. Continuing to apply a Baysian logic, estimates of P_1 and P_2 are drawn from the normal distribution conditional on the previous draws of σ_1 and σ_2.
4. The previous draws of σ_1 and σ_1 and of P_1 and P_2 define two independent normal distributions.
   A. Conditional on an offender saying that he used the drug in the last three days, random draws are made from the normal with P_1 and σ_1. Missing responses for urine test results are replaced with these random draws. No non-missing reports for urine test results are replaced.
   B. Conditional on an offender saying that he did not use the drug in the last three days, random draws are made from the normal with P_2 and σ_2. Missing responses for urine test results are replaced with these random draws. No non-missing reports for urine test results are replaced.

[11] In early applications of the imputation methodology, the analysis team applied step 4, but failed to apply step 3. This caused the standard errors to be slightly underestimated. This error is corrected in the current estimation methodology.

5. Steps 2 through 4 are repeated twenty times. Schaefer (1997) argues that five to ten repetitions are usually adequate for computing standard errors, but computing time is insignificant for the ADAM II problem, so the computing algorithm uses a conservative twenty repetitions. (Testing shows that more repetitions [50] are unnecessary because results do not change.) This leads to twenty data sets that have the same responses when the urine test result is known and potentially different imputed responses when the urine test result is otherwise missing.
6. Each of these data sets yields parameter estimates and a variance.
    A. These estimates are averaged to produce the grand estimate. This is reported as *the estimate*.
    B. Twenty variance estimates are computed for each of the 20 point estimates. These are averaged to produce a grand estimate of the variance. Call this V1.
    C. The variance of the 20 point estimates is computed. Call this V2.
    D. The variance estimates used for reporting is V=V1+V2. The square-root of V is reported as the *standard error*.

One might improve the imputation by using multiple imputation procedures—for example, by adding age, race and other variables to the imputation model. Although this improvement is possible, the imputations are applied in computing loops across drugs and over sites, and simplicity is desirable.[12]

4.2. Dealing with Missing Data in Washington, DC

In Washington, DC, arrestees submit to drug testing prior to arraignment as a standard part of criminal justice processing. There would be little reason for doing ADAM II drug testing in DC except that not all arrestees go on to arraignment. An appropriate estimator is to use Pretrial Service Agency (PTS) test results for offense types that typically go on to arraignment, and to use ADAM II drug test results for arrest types that typically do not go on to arraignment.[13] Because pre-arraignment drug test results are common, this estimation strategy greatly reduces the standard errors for drugs that are part of the PTS testing procedures. Unfortunately, pre-trial testing excludes marijuana and methamphetamine; for these two drugs, all estimates are based on standard ADAM II data.

[12] The imputations could be done with a logistic regression, but especially when dealing with drugs whose use is infrequent, the logistic regression is increasingly unstable as more variables are added as conditioning variables. The reason is that unique combinations of variables result in a probability of 1 or 0, in which case no estimate is possible. Dealing with this problem is straightforward for a single regression, but is problematic in an automated estimation procedure.

[13] One might object to this approach on two grounds. The first is that PTS might uses a different threshold to declare a urine test as positive; the second is that the time between arrest and the PTS urine specimen might differ from the time between arrest and ADAM II urine specimen. In fact, ADAM urine testing and PTS urine testing use the same test thresholds and yield similar results. During 2007 and 2008 the ADAM II project tested 106 respondents who were also tested by PTS. About 60 percent of those tests agreed that the arrestee was positive for cocaine; about 30 percent of the tests agreed that the arrestee was negative for cocaine. About 3 percent of the arrests were positive according to the PTS but negative according to ADAM, and about 7 percent were negative according to the PTS but positive according to ADAM II. Some of this discrepancy may result from imprecision matching ADAM records with PTS records, so the agreement rate is likely higher than is reported here. In addition, pretrial testing is done at a point longer than 48 hours post arrest, when the detection window for many drugs of interest begins to close. Given that standard errors are greatly reduced by using the PTS data, whatever limited bias arises from using the PTS data is dwarfed by the reduction in mean-squared error.

What follows is the step-by-step estimation procedure used for Washington, DC:

1. Given the availability of PTS data, the DC census data are divided into two partitions: arrestees whose urine tests are reported by PTS data and arrestees whose urine tests are not reported by PTS data. The estimation methodology differs for these two partitions.
   a. The first partition comprises all arrestees who are represented in the PTS data. Establishing this partition is judgmental, based on an inspection of the offense types that appear in the PTS data and the offense types that appear in the census data.
   b. The second partition comprises all arrestees who are not represented in the PTS data.
   c. A total of N1 census records have a corresponding record in the PTS data. A total of N2 census records have no corresponding record in the PTS data.
2. The proportion of adult males who test positive for a month according to the PTS data is computed as P1.
3. Otherwise the probability of testing positive during the sampling period is P2. It has a sampling variance of S2. P2 and S2 are estimated exactly the same way that drug test results are estimated in every other ADAM II sites.
4. The grand estimate of the probability of testing positive in DC is:

$$P = \left(\frac{N1}{N1+N2}\right)P1 + \left(\frac{N2}{N1+N2}\right)P2$$

   The sampling variance is:

$$VAR = \left(\frac{N2}{N1+N2}\right)^2 S2$$

This explains the estimation procedure for Washington, DC. P is an estimate of the proportion of arrestees who test positive for a specified drug. P1 comes from analysis of the PTS data and P2 comes from analysis of the ADAM II data that do not have corresponding records in the PTS data. The two are weighted by the proportion of census records that do and do not have corresponding PTS records.

VAR is the sampling variance. There is no variance when the estimate is based on the PTS data because the sample equals the population. The only component of the variance comes from the ADAM II records that are used in the estimation of P2.

5. Developing Estimates

ADAM II reports two types of estimates. One is a **point prevalence estimate** such as the *proportion of arrestees who test positive for cocaine*. The second is a **trend estimate** such as *the change in the proportion of arrestees who test positive between each of the years 2000-2003, 2003/2007, and the current collections, 2007-2009.*

5.1. Point Prevalence

As the term is used here, a "point prevalence" estimate is an estimate of the proportion of arrestees who would have tested positive for a specific drug had all arrestees been tested for that drug during the two-week period when ADAM II samples arrestees. Three methods for calculating the point-prevalence estimate of the proportion of arrestees testing positive for methamphetamine were first developed using data from Portland as a prototype. The methods were then extended to all 10 sites and each of the drugs of interest.

The **first method** uses an *unweighted* logit regression to model the probability of a sampled arrestee's testing positive for a particular drug. This regression uses the results from urine testing as the dependent variable and variables that appear in the census data as independent variables. These independent variables will be described subsequently. Then, estimation uses the coefficient estimates from this model to estimate the probability of testing positive for every arrestee appearing in the census data. (The prediction applies to arrestees for whom there are no drug test results. Otherwise the drug test results rather than the predictions are used.) Finally, these predicted probabilities are averaged over the population of all arrestees to compute the point-prevalence estimate.

The **second method** is very similar to the first one, except it employs inverses of the propensity scores as *weights* when estimating the logit model for testing positive for a particular drug. The second method is used in developing trends over time.

Lastly, using the inverses of the propensity scores, the **third method** estimates the *weighted* proportion of arrestees who tested positive for a drug in the survey sample.[14] Since the weights are an important element in the analysis, the third method is used for estimating point prevalence.

These three approaches are asymptotically equivalent, provided models are correctly specified. That is, the first two approaches will produce estimates that are consistent, provided the regression of urine test results on census variables is correctly specified. The second and third approaches will produce estimates that are consistent, provided the propensity score regression is correctly specified. All three estimates will be consistent, if both the propensity score regression and the urine testing regression are correctly specified.

This report previously explained the estimation of the propensity scores. To explain the first two estimators identified above, logistic regression is used to regress the outcome from a drug test onto variables that appear in the census data. The illustration comes from Portland and is based on ADAM

[14] Note that this is the second step of the two-step estimator that Wooldridge (2003) proposes in the presence of nonrandom selection.

data for 2000 and 2001, which was historically the first test site. However, the exercise was repeated in each of the other sites and similar results were obtained in all. Portland is simply used here as the example.

When regressing the test results onto the census variables, let index i denote an arrestee booked on the j^{th} day of year t. In addition, let N_{jt} be the number of bookings occurred on the j^{th} day of year t and n_{jt} be the number of arrestees selected into the sample on day j. The data are arranged in such a way that for the j^{th} day of year t, the index i runs from 1 to n_{jt} for members of the sample and it runs from 1 to N_{jt} for members of the population, where $N_{jt} > n_{jt}$. Using these indexes, the following variables are defined:

M_{ijt}	This is a dummy variable coded one if the ith arrestee, who was booked and sampled on the j^{th} day of year t tested positive for methamphetamine. It is coded zero if he tested negative. Note that this variable is available for $i \leq n_{jt}$. It is unobservable, and therefore missing for $n_{jt} < i \leq N_{jt}$.
$P(M_{ijt}=1)$	This is the probability that the ith arrestee booked on day j tested positive for methamphetamine. It is estimated from available data.
FV_{ijt}	This is a dummy variable coded one if the ith arrestee booked on day j was charged with a violent felony and coded zero otherwise.
FP_{ijt}	This is a dummy variable coded one if the ith arrestee booked on day j was charged with a property felony and coded zero otherwise.
FO_{ijt}	This is a dummy variable coded one if the ith arrestee booked on day j was charged with a felony that cannot be categorized as a violent, property related or drugs related offense and coded zero otherwise.
MV_{ijt}	This is a dummy variable coded one if the ith arrestee booked on day j was charged with a violent misdemeanor and coded zero otherwise.
MP_{ijt}	This is a dummy variable coded one if the ith arrestee booked on day j was charged with a property misdemeanor and coded zero otherwise.
MO_{ijt}	This is a dummy variable coded one if the ith arrestee booked on day j was charged with a misdemeanor that cannot be categorized as a violent, property related or drugs related offense and coded zero otherwise.
YD_t	This is a dummy variable coded one for the observations from 2000 (t=2000) and zero otherwise.

Using the sample data ($i \leq n_{jt}$), estimate the following logistic regression:

$$[2]\quad P(M_{ijt}=1) = \frac{1}{1+e^{-Z_{ijt}}}$$

where Z_{ijt} is defined as:

$$Z_{ijt} = \theta_0 + \theta_1 FV_{ijt} + \theta_2 FP_{ijt} + \theta_3 FO_{ijt} + \theta_4 MV_{ijt} + \theta_5 MP_{ijt} + \theta_6 MO_{ijt} + \theta_7 YD_t + \sum_{c=1}^{C} \theta_{8c} Cycle_{cj}$$

Note that this model specification captures any differences of drug use across charge categories defined by the severity (felony, misdemeanor, other) and the nature (violent, property, other) of the charge. A dummy variable is included that estimates the yearly trend in the overall drug use between years. Finally, the last term in [2], which is based on Fourier transformations, represents half-yearly and yearly cycles, which control for periodicity in drug use.

This logistic model is estimated first without using any weights; this is the basis for the first estimation method. Then the logistic regression is estimated using propensity score weights. This is the basis for the second regression. Coefficient estimates and standard errors are displayed in **Table 4**. As would be expected given that the sample is balanced, the parameter estimates are similar for the weighted and unweighted regressions.

Estimates reported for ADAM II use the ADAM data for 2000-2003, as well as the ADAM II data. Additional year dummy variables control for the year and provide the means to test for trends.[15] **Table 4** is just an illustration of the approach.

Table 4: Determinants of Methamphetamine Use in Portland: Weighted and Unweighted Logistic Regression

	Unweighted Logistic		Weighted Logistic	
Covariates	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Felony-Violent	-0.269	0.231	-0.258	0.218
Felony-Property	0.293	0.236	0.233	0.217
Felony-Other	-0.033	0.199	-0.046	0.177
Misdemeanor-Violent	-1.038***	0.254	-0.941***	0.247
Misdemeanor-Property	-0.829***	0.28	-0.836***	0.279
Misdemeanor-Other	-0.728**	0.35	-0.848***	0.316
Sin Year	-0.075	0.131	-0.199	0.125
Cos Year	-0.037	0.11	-0.02	0.109
Sin Half-Year	-0.174	0.313	-0.48	0.319
Cos Half-Year	0.061	0.379	0.363	0.392
Year 2000	-0.059	0.182	-0.071	0.170
Constant	-0.952***	0.152	-0.84***	0.140
N	1242			

Notes: *** p<0.01, ** p<0.05, * p<0.1.

In order to test the significance of the estimated coefficients of the charge categories and the cycle covariates, the Abt team performed likelihood ratio and Wald tests for the unweighted and weighted specifications respectively.[16] Results of these tests suggest that the coefficients on the charge categories are jointly significant, whereas the coefficients for the cycles are not significant at

15 As noted earlier, census data for 2002 and 2003 are not available. In these analyses, the propensity score weights calculated for 2000 and 2001 and the original ADAM weights for 2002 and 2003 are used (because census data for those years is not available). All ADAM II estimates (2007-2009) use the new propensity score weights.

16 Note that when weights are employed, it is not appropriate to use a likelihood ratio test.

conventional levels.[17] At least for Portland during the period studied, it appears important to take offense category into account, but unimportant to take seasonality into account. These findings can change as ADAM II data are added to the study and when the regressions are applied to other sites. Most importantly, the analysis shows how offense and seasonality are taken into account without prejudging if offense and seasonality must be taken into account by the analysis. The electronic documentation for specifics across each of the sites is available by request.

These results emphasize why weighting is potentially important for estimation. Each of the misdemeanor categories predicts a lower rate of testing positive than does the omitted drug category. (The felony categories do not differ significantly from the omitted drug category). Consequently, in this example, unweighted statistics would produce biased estimates of methamphetamine use, if the sampling probabilities differed by felony and misdemeanor charges. As noted previously, the sampling probabilities do vary by charge category during the stock and flow periods. And failing to weight is a potential problem for estimation.

It may not be a large problem, however. The ADAM sample is reasonably balanced, meaning that the sampling probabilities are roughly constant for all members of the sample. If the sampling probabilities were exactly equal, there would be no need to weight. The fact that they are close to equal implies that unweighted estimates will not depart greatly from weighted estimates. However, one cannot be sure that this balance will be maintained as additional data are assembled over time; nor is it certain that this high level of balance will be preserved across the ADAM II sites. Consequently, weighting is an important step.

The first two estimation methods use the coefficient estimates reported in **Table 4**. The third uses only the propensity score weights. Results using each method are presented and compared below.

Method 1

Method 1 uses results from the unweighted logistic regression [2] to estimate in this example the proportion of arrestees who would have tested positive for methamphetamine had all arrestee been tested. Using these coefficient estimates, the probability of testing positive for methamphetamine is estimated for every member of the population. Call this:

$$\hat{P}_u\left(M_{ijt} = 1\right)$$

where the subscript u shows that this is the unweighted probability estimate. Using $\hat{P}_u\left(M_{ijt} = 1\right)$, the point prevalence value (proportion of arrestees testing positive) is estimated by:

$$[3] \quad \hat{P}_u(M = 1) = \frac{\sum_{t=2000}^{2001} \sum_{j=1}^{J} \sum_{i=1}^{N_j} \hat{P}_u(M_{ijt} = 1)}{N}$$

17 Joint significance means a test of the null hypothesis that the offense category does not affect the probability of testing positive (the first test) and a test of the null hypothesis that seasonality does not affect the probability of testing positive (the second test).

where N denotes the number of arrestees in the census and J represents the number of days in the sample. (i.e. $N = \sum_{t=2000}^{2001} \sum_{j=1}^{J} N_{jt}$). The standard error of this proportion is derived using a standard Taylor approximation. Let D^l be the derivative of $P_u(M_{ij}=1)$ with respect to the l^{th} parameter in the logistic model in [2]:

$$[4]\ D^l = \frac{1}{N} \sum_{t=2000}^{2001} \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} P_u(M_{ijt} = 1)\left[1 - P_u(M_{ijt} = 1)\right] X^l$$

Note that here, X^l denotes the l^{th} covariate in the model. There are L of these D^l terms (l=1, 2,…, L) so that D is defined as the $Lx1$ column vector:

$$D = \begin{bmatrix} D^1 \\ D^2 \\ . \\ . \\ D^L \end{bmatrix}$$

Let V_u denote the variance-covariance matrix for the parameters from the unweighted logistic regression. Then the sampling standard error for the proportion P (M=1) is calculated by:

$$[5]\ \sigma_{P(M=1)} = \sqrt{D^T V_u D}$$

where D^T is the transpose of D. For example, using this approach, the unweighted point-prevalence estimate of the proportion of arrestees testing positive for methamphetamine is 0.221 with a standard error of 0.012.

Method 2

The second method for calculating the point-prevalence estimate also employs the logistic model represented by equation [2]. Here, the only difference is that inverses of the propensity score estimates from equation [1] are used as weights when estimating this logistic regression. Resulting parameter estimates and standard errors are presented in **Table 4**. Note that here, when estimating the standard errors, estimation takes into account the fact that the propensity scores have been estimated. Otherwise the second and first estimation procedures are the same. Utilizing this second method, the point-prevalence estimate is 0.226 with a standard error of 0.011 for methamphetamine. The extensions to other drugs for this site are found in **Tables 5** and **6** in the Appendix.

Method 3

The third method for the point-prevalence estimate uses the inverses of the propensity scores to weight the arrestees who tested positive for methamphetamine. Let:

$PS(U_{ijt}=1)$ This is the estimated propensity score of the i^{th} arrestee's (booked on the j^{th} day of year t) providing a urine sample.

Then the point-prevalence estimate is calculated by:

$$[6]\quad \frac{\sum_{t=2000}^{2001}\sum_{j=1}^{J}\sum_{i=1}^{n_{jt}}\frac{1}{PS(U_{ijt}=1)}M_{ijt}}{\sum_{t=2000}^{2001}\sum_{j=1}^{J}\sum_{i=1}^{n_{j}}\frac{1}{PS(U_{ijt}=1)}} = \frac{\sum_{t=2000}^{2001}\sum_{j=1}^{J}\sum_{i=1}^{n_{jt}}\frac{1}{PS(U_{ijt}=1)}M_{ijt}}{N}$$

Recall that n_{jt} denotes the number of arrestees sampled on day j. Using this formula, the point-prevalence estimate is found to be 0.226 with a standard error of 0.013 for methamphetamine.[18]

Discussion of the Three Methods

All three methods are consistent for the true rate of testing positive for methamphetamine provided the propensity score model and the drug test model are correctly specified. The three estimates are virtually indistinguishable. These three estimates can be compared with the estimate that results from using the previous ADAM weights and with unweighted estimates. For instance, when the previous ADAM weights are used in place of the propensity score weights in the second method, the point-prevalence estimate becomes 0.225 with a standard error of 0.012, which is very close to the previous three estimates. Finally, the unweighted proportion of sampled arrestees testing positive for methamphetamine is 0.220 with a standard error of 0.012. Given the balance in this sample, the unweighted estimates do not depart materially from the weighted ones.

Extending the Estimators to Other Drugs and Other Variables

The illustration has focused on a single drug (methamphetamine) in a single ADAM site (Portland) for each of three estimators. **Table 5** and **Table 6** (in the appendix) show comparable estimates for three other drugs (cocaine, heroin, and marijuana) for the same years in Portland.[19]

As was true for methamphetamine in Portland, **Table 6** shows that each of the three estimation procedures produces similar point estimates and standard errors. Method 2 is preferred, because the estimates are consistent, provided either equation [1] or [2] is correctly specified. Nevertheless, all three estimation procedures produce good estimates, and provided a user ignores the complicated variance calculations, method 3 is the easiest to apply. The cost of ignoring the complicated variance calculations is slightly inflated standard errors, but experience is that the inflation factor is small and acceptable.

When estimating prevalence using ADAM II data, the following rules apply:

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18 As noted in footnote 4, statistical theory and software to improve standard error estimation in models such as those used in ADAM II are still evolving. The analytic team follows this literature and will incorporate improved estimation techniques as they develop.

19 The same estimation procedures and diagnostic steps described here are conducted with all sites each quarter.

- When estimating the proportion of offenders testing positive for a drug of interest, typically the second method is used.
- Some drugs have very low prevalence, and for them the third method is used. This approach is required because it is not possible to estimate equation [4] for rare outcomes.
- For prevalence estimates other than the proportion of arrestees testing positive for drugs, the third method is used.

In practice, the methodology described by the first two bullets is slightly modified to deal with missing drug test results. This modification is described in subsection 4.1.

Extending the Estimators to Other Drugs and Other Variables

The example in formula [2] pertains to Portland for 2000 and 2001. Extending the estimator to other sites and other years is straightforward. Returning to formula [2], replace the term:

$$\theta_7 YD_t$$

with the term:

$$\sum_{t=2001}^{20XX} \theta_{7t} YD_t$$

This is an obvious extension. The YD are year dummy variables.

Formula [2] in both its original and modified forms pertains to urine test results. For some purposes, it is useful to modify the estimation procedure and extend it to other variables including self-reports, offender characteristics, and so on. Specifically, a modification of [2] provides:

$$Y_{ijt} = F\left(Z_{ijt}\right)$$

Here Y_{ijt} is a generic outcome variable, F(…) represents some appropriate link function, and Z_{ijt} is defined as:

$$Z_{ijt} = \sum_{t=2001}^{20XX} \theta_{7\mathrm{k}} YD_t + \sum_{k=1}^{4} \theta_{8\mathrm{k}} Q_{kt}$$

This model only uses quarters and years. The more complicated model (with offenses and Fourier transformations) is used for all estimates based exclusively on the urine tests. The simpler model (with just the year and quarter) is used to annualize all statistics that involved self-reports in any form.[20] The process of annualizing the statistics is discussed in the next section.

[20] For ADAM II, all statistics are annualized. This is necessary because yearly reports (2000-2003, 2007-2009) are based on different quarters of data; e.g., three or four quarters for sites in 2000-2003 and two quarters in 2007, 2008 and 2009. Estimating variation over the quarters allows annualization, removing the

5.2. Trends and Annualizing the Statistics

The logistic regression model estimates the probability of testing positive for a specified drug conditional on the offense, season, and the year. This regression can be extended to all years of data using the propensity score weights for 2000/2001, the original ADAM II weights for 2002/2003, and the propensity score weights for later years (2007, 2008, 2009). The year parameter is especially useful for testing the null hypothesis that drug use has not changed between any two years (i.e., 2000-2001, 2002-2003, 2003 and 2007, etc.) or between any clusters of years (i.e., 2000 through 2003 and 2007 through 2009).

In order to represent how drug use changes over the years, the point-prevalence estimates of drug use are calculated for each year of interest using two approaches. The *unconditional approach* calculates the point-prevalence estimates for each year using the second method as described above. Using Portland data as the example, **Figure 7** plots the point prevalence estimate for each year and provides a 95 percent confidence interval about the point estimates. In the *conditional approach*, the estimated regression equation [2] is evaluated at the mean values of the independent variables (setting the cycle values to zero) for each year. **Figure 8** plots the corresponding conditional point prevalence estimate and provides a 95 percent confidence interval.

The first (**Figure 7**) and second (**Figure 8**) methods of estimating trends differ both conceptually and numerically. If arrest practices change over time, so that, for example, a larger proportion of arrestees are booked for drug-law violations, then the unconditional estimate will differ from the conditional estimate because the conditional estimates hold arrest practices constant and annualize the estimates. The conditional estimate is a better reflection of trends in drug use because arrest practices are partly a political decision. For example, a jurisdiction's decision to place renewed emphasis on making arrests for public order offenses (as occurred in Manhattan during the ADAM era) would change the distribution of charges in the booking population and the positive drug test rates without there really being a change in drug use. Another example is a political or legal change in pretrial detention practices, for example, by expanding the use of field citations.

Estimating the probability of testing positive at a fixed mix of charges controls for these political and administrative changes. Furthermore, when there are annual cycles in drug use, the unconditional estimate is sensitive to when the survey was actually conducted. The conditional estimate, in contrast, can be seen as annualized because it sets the cyclical variables to their mean values for the year (namely, zero). When the regression includes quarters instead of Fourier transformations, the estimates are annualized by setting the estimates equal to the average over the quarters.

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quarter effects. Consequently, data from 2007, 2008 and 2009 are annualized. The annualization process is described in Section 5.2.

Figure 7

Trends in Cocaine Use Based on the Unconditional Approach

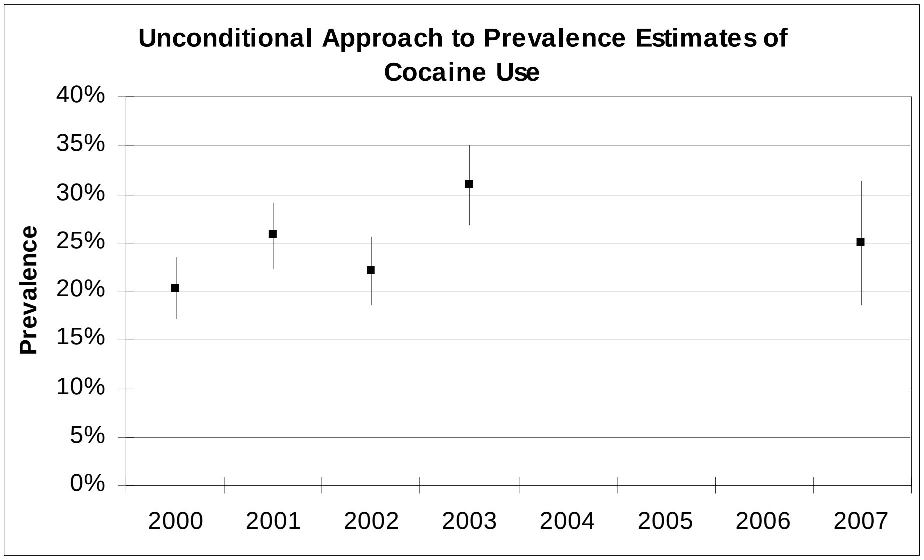
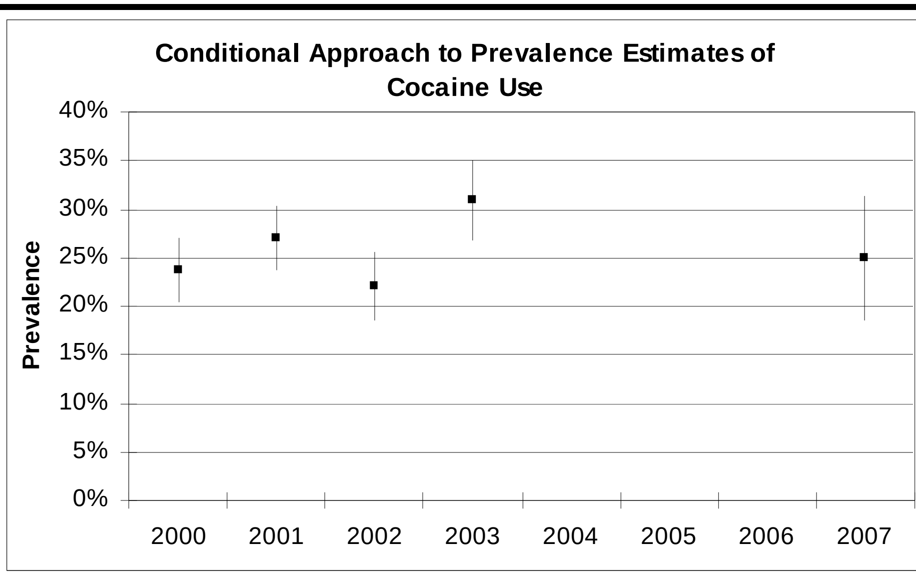


Figure 8

Trends in Cocaine Use Based on the Conditional Approach



However, a change in drug use may itself result in changes in the booking populations; this would happen, for example, if increased drug use caused more drug-law violators to come to the attention of police. On balance, political and legal decisions are of greater concern, but for public policy purposes, it seems worthwhile to report trends based on both measures.

It is important to know if there was a statistically significant change in drug use between any two years. One cannot answer this question by inspecting **Figure 7** or **Figure 8**, because the estimates are not independent, so the simple overlap of the confidence intervals is not a reliable guide to whether two estimates differ. However, the differences between any two years (such as 2003 and 2007) or clusters of years (such as 2000/2001 and 2002/2003) can be tested using the estimated covariance matrix from the logistic regression. When figures comparable to **Figures 7** and **8** appear in the ADAM II annual reports, the report indicates when the estimates for two sequential years are statistically significant.

Confidence Intervals for Trend Analysis

Because the trend estimates are based on a regression model that uses all the data from across the ADAM and ADAM II years (both data weighted with propensity scores and data weighted with the original ADAM method), the parameter estimates for the yearly trends are not independent, a fact that complicates the development of confidence intervals.

Let V represent the parameter covariance matrix for the year dummy variables in the logistic regression with dependent variable "testing positive for drug D". If there were four years of data, the covariance matrix would be a symmetric 4x4 matrix:

$$V = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ & \sigma_2^2 & \sigma_{23} & \sigma_{24} \\ & & \sigma_3^2 & \sigma_{34} \\ & & & \sigma_4^2 \end{bmatrix}$$

The terms in this matrix represent the variances and covariances for the four parameter estimates pertaining to year dummy variables, and one of the four year dummy variables is the omitted category. The terms below are not shown for below the diagonal, because the matrix is symmetric.

Let B represent a row vector with the parameter estimates for the four year dummy variables:

$$B = \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 \end{bmatrix}$$

Let P represent a second row vector that records the average probability of testing positive for each of the four years.

$$P = \begin{bmatrix} P_1 & P_2 & P_3 & P_4 \end{bmatrix}$$

The difference between the parameter estimates for year i and year j has an approximately normal distribution with a sampling variance of:

$$\sigma_{\beta_i - \beta_j}^2 = \begin{bmatrix} 1 & -1 \end{bmatrix} \begin{bmatrix} \sigma_i^2 & \sigma_{ij} \\ \sigma_{ij} & \sigma_j^2 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \sigma_i^2 + \sigma_j^2 - 2\sigma_{ij}$$

This sampling variance can be used to test the null hypothesis that the probability of testing positive for drug D has changed between year i and year j.

Confidence Intervals for Point Estimates

For ADAM II data, the delta method is used to estimate a confidence interval for a point estimate. This approach requires no new notation, because the discussion surrounding equations [3], [4] and [5] presented earlier already introduced suitable notation when explaining how to estimate the standard error for the confidence interval for testing positive for drug use. See equation [5].

Estimating the confidence interval for the estimate of testing positive for drug use conditional on a fixed set of covariates is actually a simplification. First, in equation [3], the probability of testing positive during a year for the *average arrestee* is estimated. The average arrestee is a hypothetical arrestee who has an average value on all variables that enter into the logistic regression used to estimate the probability of testing positive for a specified drug, except that the year dummy variable is not averaged. Second, the estimate for each year is computed for the average arrestee, allowing only the year variable to change from year to year. This approach is a simplification compared with equations [3], [4] and [5] because calculations require no summations. All calculations are specific to the average offender.

Estimating Trends Beyond 2007

From 2000 through 2003, ADAM used poststratification to estimate sampling probabilities and to calculate weights. Data were stratified by jail, stock and flow, and day of the week. Within each stratum, the sampling probability was estimated as the number sampled per number booked. Although conceptually simple, the approach was operationally difficult. The principal operational difficulty was that strata sometimes had no or few members of the sample. This meant that strata had to be merged, and it often resulted in heterogeneous strata being combined.

To avoid these complications, ADAM II adopted propensity scores as an alternative device for estimating sampling probabilities and computing weights. The propensity score approach does not require stratification, because the sampling probability can be modeled as a continuous function of factors that affect the sampling rate. As mentioned earlier, because 2000 and 2001 ADAM data provided the necessary census data, the survey team replaced the original weights for the 2000 and 2001 ADAM data with new weights based on propensity scores. That is, the survey team replicated the ADAM II weighting procedure using the 2000 and 2001 ADAM data.

This replication was not possible for the 2002 and 2003 ADAM data because the ADAM contractor did not retain the census data for those years. Thus, for purposes of reporting trend statistics, the ADAM II survey team:

- Uses the reweighted ADAM data for 2000 and 2001;
- Uses the ADAM data for 2002 and 2003 without changing the weights; and
- Uses the propensity score weights for the ADAM II data.

It is important to note that there was nothing *wrong* with the original ADAM weights. They simply led to sampling variances that were larger than necessary, so the ADAM II study team improved the weights when possible. Because there was nothing wrong with the original sampling weights, there is nothing misleading about mixing the reweighted data for 2000-2001, the 2002-2003 data with their original weights, and the new ADAM II data in producing trend estimates.

However, this reweighting has two consequences. The first is that the 2000- 2001 estimates changed slightly from those reported earlier. The second is that estimates from year-to-year in reweighted years are no longer independent. Consequently, to test for trends, an analyst requires an estimate of the parameter covariance matrix.

As anticipated, this has the result of potentially slightly changing the prior years' estimates that appeared first in the 2007 report. Although this approach improves the efficiency of the estimates, there is concern that yearly revisions going forward, regardless how slight, would be confusing. Consequently, 2008 and 2009 estimates are developed holding earlier estimates at their previously reported levels.

In this procedure, the 2007 and earlier estimates for parameters and standard errors are treated as fixed for subsequent estimation. There are five steps for estimation procedures for 2008 and beyond data.

1. The first step uses the regression results that are part of the 2007 report. Recall from equation [2] that these are a function of the offense, the Fourier transformations, and the year dummy variables. All the θ parameters and the covariance matrix are retained for those θ parameters V_θ. For convenience, equation [2] is repeated as equation [7].

$$[7]\ P(M_{ijt}=1)=\frac{1}{1+e^{-Z_{ijt}}}$$

$$Z_{ijt}=\theta_0+\theta_1 FV_{ijt}+\theta_2 FP_{ijt}+\theta_3 FO_{ijt}+\theta_4 MV_{ijt}+\theta_5 MP_{ijt}+\theta_6 MO_{ijt}+\sum_{t=2}^{2007}\theta_{7t}YD_t+\sum_{c=1}^{4}\theta_{8c}Cycle_{cj}$$

2. Following Bayesian logic, analysts sample the covariance matrix V_θ from an inverted Wishert distribution. Conditional on that sampled V_θ, analysts sample θ from a multivariate normal distribution.
3. Conditional on the θ in the previous step, a new regression is estimated with the specification described by equation [8]. Note that this regression has a single free parameter α.

$$[8]\ P(M_{ijt}=1)=\frac{1}{1+e^{-Z_{ijt}}}$$

$$Z_{ijt}=\theta_0+\theta_1 FV_{ijt}+\theta_2 FP_{ijt}+\theta_3 FO_{ijt}+\theta_4 MV_{ijt}+\theta_5 MP_{ijt}+\theta_6 MO_{ijt}+\sum_{t=2}^{2007}\theta_{7t}YD_t+\sum_{c=1}^{4}\theta_{8c}Cycle_{cj}+\beta\mathrm{YD}_{2008}$$

The β could be estimated using just the 2008 ADAM II data, but using the entire set of ADAM II data is a programming convenience.

4. Steps 3 and 4 are cycled through 100 iterations. Each iteration provides a somewhat different estimate of β (100 β estimates β_1 through β_{100}) and somewhat different estimates of σ_β^2 (100 σ_β^2 estimates $\sigma_{\beta 1}^2$ through $\sigma_{\beta 2}^2$). The final estimate of β and σ_β^2 are:

$$[9] \quad \begin{aligned} \hat{\beta} &= \frac{1}{100}\sum_{k=1}^{100}\beta_k \\ \sigma_\beta^2 &= \frac{1}{100}\sum_{k=1}^{100}\sigma_{\beta k}^k + \frac{1}{100-1}\sum_{k=1}^{100}\left(\hat{\beta}_k - \bar{\hat{\beta}}\right)^2 \end{aligned}$$

5. The above steps provide everything needed for trend estimation except the covariances between β and the θ_{7t}. To estimate the covariance estimates for β and any selected θ, the formula is:

$$[10] \quad \sigma_{\beta\theta} = \frac{1}{100}\sum_{k=1}^{100}\left(\hat{\theta}_k - \bar{\hat{\theta}}\right)\left(\hat{\beta}_k - \bar{\hat{\beta}}\right)$$

Given estimates of the variance and covariance for the parameters associated with the year dummy variables, the statistical significance of any pair of years can be tested.

Annualizing Point Prevalence Estimates Beyond 2007

Most of the statistics appearing in the ADAM II reports are point prevalence estimates. A point prevalence estimate is straightforward, because it only requires weighting the desired variable by the propensity score weights. The statistics reported in the 2007 ADAM II report use this estimator.

As mentioned above, in preparation for the 2007 ADAM II report, it was determined that the prevalence estimates should be annualized to account for the fact that the ADAM sample was collected at different times during the year (3 or 4 quarters versus 2 quarters in ADAM II). This complicates the estimation explained in the previous subsection.

Annualizing the prevalence estimates requires applying the same five steps as above, except that equation [7] is replaced with equation [11]:

$$[8] \quad Y_{ijt} = F\left(Z_{ijt}\right)$$

F(…) is a link function that depends on the context. When the variable of interest is binary, for example, F(…) represents the logit. Also Z is simplified:

$$Z_{ijt} = \sum_{k=1}^{4}\lambda_k Q_k + \sum_{t=2}^{2007}\theta_{7t} YD_t + \beta \mathrm{YD}_{2008}$$

The Q are dummy variables representing quarters of the year. The λ parameters are estimated using data from before 2008. The β parameter is estimated using 2008 data. The parameter covariance matrix is estimated by following steps 1 through 5 from the previous subsection.

When making the estimates, each Q is set equal to 0.25 and each year before 2008 is set equal to 0. This gives an annualized estimate of every variable reported in the 2008 and beyond ADAM II reports except for estimates based purely on drug test results. For estimates based purely on drug test results, the formulation described in the previous subsection is used.

5.3. Special Issues

Special issues arise in different sites. To reweight the ADAM II data, the methodology requires consistent reporting of charge codes during 2000, 2001, 2007 and later. (Again, the 2002 or 2003 data can not be reweighted because the census data for those years are lacking). Tabulations of specific charge codes over the years suggest that the offense categories were not always reported consistently. There appeared to be no problem with consistently identifying the four broad offense types (violent, property, drugs and other), but there were problems with distinguishing severity levels (felony, misdemeanor and "other"). Frequently misdemeanor and "other" categories have to be merged in analyses and sometimes it is necessary to ignore the severity categories altogether. As a result, the propensity scores may be based on fewer offense categories than are identified earlier in equation [1].

Washington, DC also poses a special problem. In Washington, DC there are seven booking facilities, and each receives so few arrestees that interviewers are sometimes idle waiting for arrestees to arrive at the jails. Jail-specific propensity scores can not be estimated reliably because the sample size is too small. In Washington, DC the sampling design samples arrestees in the smaller jails on two randomly selected days during the study period, and samples arrestees in the larger jails on three randomly selected days during the study period. Because interviewers have to wait for arrestees in all jails, this sampling design produces sampling probabilities that are about the same in each of the small jails, about the same in each of the larger jails, but different between the small and larger jails. Therefore, the approach is to combine the data from the small jails and to estimate a propensity score for arrestees booked into those jails, and to combine the data from the larger jails and to estimate a propensity score for arrestees booked into those larger jails.

6. Concluding Comments

In summary, developing estimates for ADAM II poses several challenges.

In reviving ADAM in 2006, the program faced the challenge that ADAM had not been operational since 2003, and for some sites the layoff had been longer. As of data collection beginning in 2007, many of the old ADAM sites had undergone changes. New jails had opened; some old jails had closed. Even when the jails remained the same, they are sometimes now used for different purposes than was true for ADAM. Furthermore, law enforcement practices often change, so that the jail populations represented by the ADAM sample can differ from the jail populations represented by the ADAM II sample. Consequently, sampling and estimation procedures used in ADAM did not necessarily transfer into suitable procedures for ADAM II.

In addition, for reasons not yet fully understood, ADAM II respondents in two of the ADAM II sites (New York and Washington DC) have been less willing than those in ADAM to provide urine samples. The resulting bias and inflated standard errors are of concern, so procedures for imputing values for missing drug test results are implemented in ADAM II. After experimentation, a simple provisional method was developed. However, every ADAM II site seems to pose a new challenge, and it is anticipated that this imputation methodology will change over time as the best way to analyze these data is found.

Both the Drug Use Forecasting system and ADAM provided yearly estimates of drug use. But neither DUF nor ADAM attempted to provide a probability basis for estimating trends. Estimating meaningful trends is deceptively difficult because of changes that have happened since 2000. As noted, jails and the populations they house have gone through changes, and failing to account for those changes confuses trends attributable to changes in law enforcement and judicial practices with changes attributable to the frequency of drug use. The process of developing trend estimates is especially challenging because problems could not be identified and solutions explored until ADAM II data had been collected and weighting undertaken. Given three years of ADAM II data, the Abt team continues to make modifications of estimation procedures and refine our analyses.

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Appendix

Tables 5 and 6

Table 5: Determinants of Cocaine, Heroin and Marijuana Use in Portland: Weighted and Unweighted Logistic Regression

Drug	Cocaine		Heroin		Marijuana		Methamphetamine	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
Covariates								
Felony-Violent	-1.069***	-1.093***	-0.902***	-0.819**	0.195	0.269	-0.269	-0.258
	(0.25)	(0.21)	(0.32)	(0.27)	(0.20)	(0.17)	(0.231)	(0.218)
Felony-Property	-0.927***	-0.698**	-0.662**	-0.727**	0.130	0.243	0.293	0.233
	(0.28)	(0.27)	(0.33)	(0.30)	(0.22)	(0.20)	(0.236)	(0.217)
Felony-Other	-0.393**	-0.273	-0.354	-0.353	-0.0188	0.0287	-0.033	-0.046
	(0.19)	(0.17)	(0.24)	(0.22)	(0.18)	(0.16)	(0.199)	(0.177)
Misdemeanor-Violent	-1.179***	-1.118***	-1.842***	-1.964***	-0.110	-0.218	-1.038***	-0.941***
	(0.23)	(0.20)	(0.41)	(0.35)	(0.18)	(0.16)	(0.254)	(0.247)
Misdemeanor-Property	-0.444*	-0.422*	0.146	-0.0918	-0.169	-0.0527	-0.829***	-0.836***
	(0.23)	(0.20)	(0.25)	(0.23)	(0.21)	(0.19)	(0.28)	(0.279)
Misdemeanor-Other	-1.042***	-0.999***	-0.603	-0.698*	-0.908***	-0.780**	-0.728***	-0.848***
	(0.35)	(0.31)	(0.38)	(0.38)	(0.31)	(0.33)	(0.35)	(0.316)
Sin Year	-0.221*	-0.278**	-0.0952	-0.103	0.0617	0.0170	-0.075	-0.199
	(0.13)	(0.11)	(0.16)	(0.13)	(0.11)	(0.101)	(0.131)	(0.125)
Cos Year	0.0547	0.0924	-0.0928	-0.0517	0.0234	0.0253	-0.037	-0.02
	(0.10)	(0.10)	(0.13)	(0.12)	(0.093)	(0.085)	(0.11)	(0.109)
Sin Half-Year	0.174	0.119	-0.0759	-0.227	0.244	0.218	-0.174	-0.48
	(0.31)	(0.28)	(0.38)	(0.33)	(0.27)	(0.249)	(0.313)	(0.319)
Cos Half-Year	-0.224	-0.116	0.0545	0.183	-0.236	-0.244	0.061	0.363
	(0.37)	(0.34)	(0.46)	(0.41)	(0.32)	(0.30)	(0.379)	(0.392)
Year 2000	-0.327*	-0.308	0.325	0.377	-0.146	-0.189	-0.059	-0.071
	(0.18)	(0.16)	(0.22)	(0.21)	(0.15)	(0.14)	(0.182)	(0.170)
Constant	-0.473***	-0.525***	-1.616***	-1.637***	-0.458***	-0.473***	-0.952***	-0.84***
	(0.14)	(0.13)	(0.18)	(0.17)	(0.13)	(0.12)	(0.152)	(0.140)
N	1242							

Notes: Standard errors are in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.

Table 6: Point-Prevalence Estimates for Cocaine, Heroin, and Marijuana Use in Portland			
Drug	**Method 1**	**Method 2**	**Method 3**
Cocaine	0.252 (0.013)	0.248 (0.01)	0.243 (0.013)
Heroin	0.143 (0.01)	0.135 (0.009)	0.132 (0.010)
Marijuana	0.376 (0.014)	0.371 (0.012)	0.365 (0.015)
Methamphetamine	0.221 (0.012)	0.226 (0.011)	0.226 (0.013)

Notes: Standard errors are presented in parentheses