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HIV Among Injection Drug Users in Large US Metropolitan Areas, 1998

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ABSTRACT *This article estimates HIV prevalence rates among injection drug users (IDUs) in 95 large US metropolitan areas to facilitate social and policy analyses of HIV epidemics. HIV prevalence rates among IDUs in these metropolitan areas were calculated by taking the mean of two estimates: (1) estimates based on regression adjustments to Centers for Disease Control and Prevention (CDC) Voluntary HIV Counseling and Testing data and (2) estimates based on the ratio of the number of injectors living with HIV to the number of injectors living in the metropolitan area. The validity of the resulting estimates was assessed. HIV prevalence rates varied from 2 to 28% (median 5.9%; interquartile range 4.0–10.2%). These HIV prevalence rates correlated with similar estimates calculated for 1992 and with two theoretically related phenomena: laws against over-the-counter purchase of syringes and income inequality. Despite limitations in the accuracy of these estimates, they can be used for structural analyses of the correlates, predictors and consequences of HIV prevalence rates among drug injectors in metropolitan areas and for assessing and targeting the service needs for drug injectors.*

KEYWORDS *Epidemic modeling, HIV prevalence estimates, Injection drug users, Local epidemics, Structural analysis.*

INTRODUCTION

A notable fact about HIV epidemics among injection drug users (IDUs) is the great differences in prevalence and incidence rates in different localities. This divergence was documented by Holmberg[1] for the 96 largest metropolitan statistical areas (MSAs) in the United States. In his data on the situation in 1992, he found that prevalence rates ranged from 1 to 41% (with median 5.9% and considerable right-skewing) and that incidence rates varied from 0.2 to 4.9 per 100 person-years at risk (with two-thirds of the metropolitan areas having incidence of less than 1 per 100 PYAR).

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Estimates of HIV prevalence rates among IDUs in specific geographic areas are essential for deepening our understanding of both the etiology and effects of the HIV epidemic and for designing and implementing related public health programs and policies. Difficulties in studying probability samples of hidden populations such as IDUs, together with temporal bias processes (due to the lack of medical justification for frequent retesting of HIV positives) make such estimates difficult. In this article, we present a method of calculating HIV prevalence rates among IDUs in each of 95 large US metropolitan areas in 1998, describe the resulting estimates, and assess their validity.

Knowing HIV prevalence rates among IDUs in specific geographic areas can help policy makers in allocating resources. It is also an important prerequisite for investigating social, economic, and policy characteristics that shape HIV epidemics and thus for laying the basis for policy or structural interventions. Though considerable research has been conducted to identify the individual characteristics that predispose IDUs to be or become infected with HIV, much less research has been conducted on structural or policy determinants of HIV prevalence rates in MSAs or cities. Two studies have examined time-trajectories of HIV prevalence rates among IDUs in cities with and without syringe exchanges. Both Hurley et al.[2] and MacDonald et al.[3] found syringe exchange to be negatively associated with HIV prevalence rates. Friedman et al.[4] found (using Holmberg's earlier estimates for HIV prevalence rates in the MSAs studied in this article) that syringe laws and other MSA characteristics such as income inequality were associated with HIV prevalence rates among IDUs.

In the present analysis, the geographic units studied are 95 of the 96 US metropolitan statistical areas (MSAs) that had populations greater than 500,000 in 1993. (The San Juan-Bayamon MSA was omitted due to missing data.) MSAs are defined by the US Census Bureau as contiguous counties that contain a central city of 50,000 people or more and that form a socioeconomic unity as defined by commuting patterns and social and economic integration within the constituent counties.[5,6] The MSA was chosen as the unit of analysis for three reasons. First, it allows continuity with Holmberg's 1992 estimates.[1] Second, health data are more available for the county units that comprise MSAs than for municipalities. Third, the economic, social, and commuting unity of metropolitan areas make them a reasonable unit in which to study drug-related HIV and other epidemics. For example, many IDUs live in the suburbs but buy drugs (and perhaps get drug-related services) in the central city.

METHODS

In estimating HIV prevalence rates among IDUs, we combined estimates based on regression adjustments to CDC Voluntary HIV Counseling and Testing data with estimates based on calculating the ratio of IDUs living with HIV to the IDU population of the metropolitan area.

Regression Adjustments to CDC Data

For 88 MSAs, enough IDUs went through Voluntary HIV Counseling and Testing at sites incorporated into CDC data-collection systems for us to use these data in making our estimates. As Holmberg[1] recognized, these CDC data underestimate HIV prevalence rates. The major reason is that people who have tested positive once (or twice, as a confirmation) have no reason to be tested again. Thus, those who get tested tend to be HIV negatives who have never been tested before; HIV negatives who have previously tested negative and come back to be tested again; and a relatively small proportion (except in localities with major HIV outbreaks) who have tested negative but have become infected since then. Over time, then, there is a tendency for HIV prevalence rates among those being tested to decline. This source of error is likely to be greater in MSAs with higher HIV prevalence rates and those with long-lasting epidemics of stable (or declining) prevalence rates. Thus, these data need to be adjusted before they can be used in estimating HIV prevalence rates. We used regression imputation with research-based estimates as our anchor points to accomplish this adjustment.

We reviewed published literature and conference abstracts to find HIV prevalence rate estimates among IDUs in the 95 MSAs of interest. Web-based searches and inquiries of researchers identified one or more eligible research articles or abstracts for 25 metropolitan areas. To be eligible, a study had to have been conducted between 1994 and 2002; to have determined HIV serostatus through the testing of blood, urine, or saliva samples rather than through self-report; and not to have been part of the Voluntary Counseling and Testing system. Where more than one study was available, we used the median value as the research-based estimate. Research-based estimates for one MSA were excluded because the two available estimates (12 and 25%) were considered too far apart.

The research-based estimates for these 25 MSAs were regressed on the CDC Counseling and Testing data for these metropolitan areas. The resulting predictor equation (R^2=.72) was

Research-based estimate of HIV prevalence rate (in %)=2.1%+1.83 * {C & T estimate}.

This equation, it should be noted, implies that our estimate for a metropolitan area with 0% prevalence rate on Counseling and Testing data would be 2.1%. This is not unreasonable, because the only values lower than this among the 26 metropolitan areas with research data were 0.5%, 1.75%, 1.75%, and 1.8%, and issues of sampling error, and possible sampling bias make it hard to argue that any of these MSAs has a true value lower than 2.1%. The estimates appear in Table 1.

Lieb Estimates

A second estimate was based on methods developed by Lieb et al.[7] Briefly, the total number of HIV-positive IDUs (including those who are also men who have had sex with men) living in an MSA was designated as k. The estimated numbers of IDUs (a) and the estimated HIV prevalence rates among IDUs (b) were variables related by the function, $k=ab$; thus, $b=a/k$. Data on a, the estimated number of IDUs who had injected drugs in the last year in each MSA, were available from Friedman et al.[8] To account for the fact that Lieb's period for injection drug-use behavior (since 1977, which is consistent with CDC's classification conventions for HIV exposure[9]) was considerably longer than Friedman's period (the past year), we adjusted Friedman's estimates by multiplying them by 2.47, which equals the ratio of living persons in the 91 MSAs who had injected drugs since 1977 (from estimates developed by Lieb) to the total number of persons who injected drugs in the last year as estimated by Friedman et al.[8]

To estimate the number of IDUs living with HIV (k), Lieb started with the number of persons living with AIDS (persons living with AIDS [PLWAs]) through 2001; he then applied an expansion factor of 2.4844 to the number of IDUs and MSM/IDUs living with AIDS in an MSA to estimate the number living with HIV. [This

TABLE 1. Estimated HIV prevalence rates (and imputed values*) among injection drug users (IDUs) in 95 large metropolitan statistical areas (MSAs) in the USA, 1998

Metropolitan area	Research-based estimate (%)	Estimate by regression adjustment to CDC data (%)	Estimate by Lieb formula (%)	Estimated HIV prevalence rate (%)*	HIV prevalence rate rank	Estimated number of injectors who injected drugs in prior 12 months‡
Akron, Ohio		4.00	2.37	3.19	86	1994
Albany–Schenectady–Troy, New York		5.22	15.62	10.42	22	2340
Albuquerque, New Mexico	0.5[16]	3.08	1.63	2.36	95	6457
Allentown–Bethlehem–Easton, Pennsylvania		5.21	5.14	5.18	57	5936
Ann Arbor, Michigan		6.54	3.95	5.25	56	1067
Atlanta, Georgia	13[17]	20.88	15.01	17.95	7	15007
Austin–San Marcos, Texas		3.33	5.67	4.50	66	10087
Bakersfield, California		3.03	3.97	3.50	80	8110
Baltimore, Maryland	24.85[18–22]	17.82	10.49	14.16	11	40306
Bergen–Passaic, New Jersey		23.58	16.48†	20.03	5	6383
Birmingham, Alabama		9.00†	7.60	8.30	33	2906
Boston, Massachusetts–New Hampshire	10.6[18]	6.68	7.89	7.29	37	36889
Buffalo–Niagara Falls, New York		5.48	5.45	5.47	52	5601
Charleston–North Charleston, South Carolina		2.10	2.95†	2.53	94	1806
Charlotte–Gastonia-Rock Hill, North Carolina–South Carolina		9.18	8.13	8.66	29	5199
Chicago, Illinois	17.3[18,23]	11.22	9.42	10.32	23	33432
Cincinnati, Ohio–Kentucky–Indiana		3.63	3.09	3.36	82	4426
Cleveland–Lorain–Elyria, Ohio		4.79	4.88	4.84	62	8903
Columbus, Ohio		6.22	5.55†	5.89	49	6962
Dallas, Texas		3.81	15.86	9.84	25	20693
Dayton–Springfield, Ohio		4.77	0.39	2.58	92	2517
Denver, Colorado	1.8[18,24]	9.17	3.46	6.32	42	13684
Detroit, Michigan	5.7[18]	6.24	4.07	5.16	58	26872
El Paso, Texas		4.16	2.14	3.15	87	5912

TABLE 1. ***Continued***

Metropolitan area	Research-based estimate (%)	Estimate by regression adjustment to CDC data (%)	Estimate by Lieb formula (%)	Estimated HIV prevalence rate (%)*	HIV prevalence rate rank	Estimated number of injectors who injected drugs in prior 12 months‡
Fort Lauderdale, Florida		18.56	20.05	19.31	6	6902
Fort Worth–Arlington, Texas		4.57	3.51	4.04	72	18153
Fresno, California	5.9[25]	4.97	1.49	3.23	85	15072
Gary, Indiana		10.13	1.86	6.00	46	5478
Grand Rapids–Muskegon–Holland, Michigan	2.6[26]	8.66	2.55	5.61	50	2752
Greensboro–Winston-Salem–High Point, North Carolina		7.40	4.88	6.14	44	5081
Greenville–Spartanburg–Anderson, South Carolina		2.10	9.76	5.93	47	2322
Harrisburg–Lebanon–Carlisle, Pennsylvania		10.13	5.81	7.97	36	5112
Hartford, Connecticut	18[27,28]	12.17	13.59	12.88	14	9602
Honolulu, Hawaii		7.60†	6.10	6.85	38	4727
Houston, Texas	5.3[18]	7.58	4.48	6.03	45	41570
Indianapolis, Indiana		7.12	3.87	5.50	51	6644
Jacksonville, Florida		14.53	9.47	12.00	19	6989
Jersey City, New Jersey		32.93	20.68	26.81	2	5113
Kansas City, Missouri-Kansas		5.37	4.57	4.97	59	8740
Knoxville, Tennessee		7.71	2.19	4.95	60	3943
Las Vegas, Nevada-Arizona		5.26	3.29	4.28	70	14172
Little Rock–North Little Rock, Arkansas		9.26†	7.90	8.58	30	4818
Los Angeles–Long Beach, California	3.5[18,25,29–31]	6.98	3.92	5.45	53	66430
Louisville, Kentucky–Indiana		4.38	2.55	3.47	81	7823
Memphis, Tennessee–Arkansas–Mississippi		9.91	7.09	8.50	31	4648
Miami, Florida	19[32]	24.16	24.07	24.12	3	10529
Middlesex–Somerset–Hunterdon, New Jersey		12.92	13.66	13.29	13	4299
Milwaukee–Waukesha, Wisconsin		4.99	4.51	4.75	63	4716
Minneapolis–St. Paul, Minnesota–Wisconsin		5.84	3.86	4.85	61	7205

TABLE 1. *Continued*

Metropolitan area	Research-based estimate (%)	Estimate by regression adjustment to CDC data (%)	Estimate by Lieb formula (%)	Estimated HIV prevalence rate (%)*	HIV prevalence rate rank	Estimated number of injectors who injected drugs in prior 12 months‡
Monmouth–Ocean, New Jersey		15.09	10.61	12.85	15	4581
Nashville, Tennessee		5.37	7.25	6.31	43	6927
Nassau-Suffolk, New York		21.05	10.47	15.76	8	11779
New Haven–Bridgeport–Waterbury–Danbury, Connecticut		11.05	13.77	12.41	17	13760
New Orleans, Louisiana		8.99	7.47	8.23	35	11914
Newark, New Jersey	36[18,31]	34.83	20.02	27.43	1	15384
New York, New York	29[14,18,19,31]	26.35	20.96	23.66	4	108515
Norfolk–Virginia Beach–Newport News, Virginia-North Carolina		15.04†	14.20	14.62	10	9555
Oakland, California	6[25,33§]	8.04	3.75	5.90	48	20038
Oklahoma City, Oklahoma		6.16	4.64	5.40	55	4679
Omaha, Nebraska–Iowa		6.68	4.17	5.43	54	2047
Orange County, California		4.36	3.38	3.87	75	15465
Orlando, Florida		14.45	13.00	13.73	12	6750
Philadelphia, Pennsylvania-New Jersey	15¶	15.98	9.25	12.62	16	49837
Phoenix–Mesa, Arizona		9.59	3.51	6.55	40	17893
Pittsburgh, Pennsylvania		3.47	2.14	2.81	90	11981
Portland-Vancouver, Oregon-Washington		5.44	2.14	3.79	76	18321
Providence–Fall River–Warwick, Rhode Island–Massachusetts	18.5[34,35]	5.71	7.77	6.74	39	5234
Raleigh–Durham–Chapel Hill, North Carolina		8.65	7.93	8.29	34	4556
Richmond–Petersburg, Virginia		15.31†	14.50	14.91	9	6655
Riverside–San Bernadino, California		3.91	4.44	4.18	71	21682
Rochester, New York		5.60	13.82	9.71	26	4221
Sacramento, California	4.3[25]	4.05	2.43	3.24	84	15342
Saint Louis, Missouri-Illinois		4.37	3.14	3.76	77	11495

TABLE 1. *Continued*

Metropolitan area	Research-based estimate (%)	Estimate by regression adjustment to CDC data (%)	Estimate by Lieb formula (%)	Estimated HIV prevalence rate (%)*	HIV prevalence rate rank	Estimated number of injectors who injected drugs in prior 12 months‡
Salt Lake City–Ogden, Utah		4.31	3.03	3.67	78	9124
San Antonio, Texas	2.8 [36]	5.49	3.15	4.32	69	13062
San Diego, California	1.15 [25,37]	4.68	4.36	4.52	65	21326
San Francisco, California	9.15 [18,25,38,39]	9.26	10.09	9.68	27	24582
San Jose, California	1.75 [19,40]	5.81	2.86	4.34	68	8740
Sarasota–Bradenton, Florida		3.64	5.18	4.41	67	3510
Scranton–Wilkes-Barre–Hazelton, Pennsylvania		3.49	6.00	4.75	63	1739
Seattle-Bellevue–Everett, Washington	1.75 [18,31,41]	2.57	3.36	2.97	88	16644
Springfield, Massachusetts		10.57	7.66	9.12	28	6320
Stockton–Lodi, California		3.47	1.60	2.54	93	8210
Syracuse, New York		6.08	10.79	8.44	32	2326
Tacoma, Washington		4.78	2.33	3.56	79	6282
Tampa-St. Petersburg–Clearwater, Florida		6.37	6.72	6.55	40	14265
Toledo, Ohio		3.13	3.55	3.34	83	1723
Tucson, Arizona		5.91	1.98	3.95	73	11025
Tulsa, Oklahoma		3.09	2.72	2.91	89	4353
Ventura, California		3.65	1.78	2.72	91	3675
Washington, D.C., Maryland-Virginia, West Virginia	16 [18]	7.78	13.42	10.60	21	29576
West Palm Beach-Boca Raton, Florida		11.49	11.22	11.36	20	6165
Wichita, Kansas		12.56†	11.50	12.03	18	1599
Wilmington–Newark, Delaware–Maryland		9.53	10.81	10.17	24	5730
Youngstown–Warren, Ohio		4.82†	3.07	3.95	73	2030

*The HIV prevalence rate was determined by averaging the Counseling and Testing-based regression adjustment estimate and the Lieb estimate.

†Imputation methods were used here to create an imputation estimate as described in the text.

‡These estimates of numbers of persons who injected drugs in each metropolitan area in the prior 12 months are from Table 1 in Reference [7]. They are estimates with considerable uncertainty, as is described in Reference [7]. As discussed in the text of the this article, the prior 12 months" estimates of numbers of injectors were adjusted by multiplication by 2.47 to estimate the number of living injectors who injected drugs since 1977.

§Personal communication with Alex Kral (May 2002). May 2, 2002: Qualitative interview covering local trends in HIV epidemiology among injection drug users.

¶Personal communication with David Metzger (December 2002). December 5, 2002: Qualitative interview covering local trends in HIV epidemiology among injection drug users.

expansion factor used Centers for Disease Control and Prevention (CDC) data[10] to generate a national expansion factor = 2.4844 = 900,000/362,261, where 900,000 is the national HIV prevalence point estimate,[11] and 362,261 is the total number of people living with AIDS in the United States at the end of 2001.][10]

The estimated number of HIV-infected IDUs (k) in each MSA was then divided by the adjusted number of IDUs in this MSA (a) to obtain the second estimate of HIV prevalence rates (b).

Combined Estimates

There were 85 MSAs for which we had both regression adjustment estimates and Lieb estimates for HIV. For these 85 MSAs, the two estimates differed somewhat (Lieb method: mean = 6.93; SD = 5.28; regression estimate mean = 8.36, SD = 6.35); they were correlated at $r = 0.76$. There were 3 MSAs for which we had data from CDC Counseling and Testing but not a Lieb estimate; and 7 for which we had a Lieb estimate but not Counseling and Testing data. In these cases, we used regression imputation methods to calculate each estimate as a function of the other. If the Lieb data were missing, we used the Counseling and Testing data to impute an estimate for the missing data and vice versa if the Counseling and Testing data were missing. In general, the imputed value and the data-based estimate were quite close: In 9 cases, the difference was less than 2%; in the other case, the Bergen-Passaic MSA, the difference was 7.1% (with the adjusted Counseling and Testing estimate equal to 23.6% and the imputed value for the Lieb formula equal to 16.5%).

Given that both the adjusted Counseling and Testing estimates and the Lieb estimates (including their imputed values) have considerable error but that the sources of these errors seem to be different, one way to attempt to minimize error is to combine the estimates into one value. The final estimate is the simple average of these data for each of 95 MSAs.

Statistical analyses were conducted using SAS version 9.1 (SAS Institute, Cary, NC) including Procs Corr, Reg and Univariate.

RESULTS

Table 1 presents the estimates of HIV prevalence rate levels among IDUs in 95 metropolitan areas in 1998 and highlights the imputed values for MSAs that lacked data on one of the sub-estimates. Table 2 compares the means, medians, and quartiles for these estimates to those for Holmberg's estimates for 1992. Estimated HIV prevalence rates in 1998 varied from 2.4 to 27.4% with mean 7.9% and median 5.9%. Most MSAs continue to have prevalence rates among IDUs less than 10% and approximately 40% have prevalence less than 5%.

Several procedures were used to validate these estimates. We compared them with Holmberg's[1] estimates for 1992 as a long-term test–retest reliability study—which is justifiable because all evidence suggests relatively slow change in HIV prevalence rates in most MSAs. The two estimates were correlated ($r = 0.86$), which is a quite respectable reliability estimate for this test, and the constant (5.9%) median value (Table 2) was not unexpected. Second, the estimates were correlated with two other theoretically related characteristics of the MSAs as a way to investigate construct validity. As expected from previous articles, HIV prevalence rates correlated significantly and positively ($r = 0.23$), with laws against over-the-counter purchase of syringes and with income inequality ($r = 0.26$).[4,12]

TABLE 2. HIV prevalence rates among injection drug users in 95 large metropolitan areas of the United States, 1992 and 1998

	1992*	1998
Median (range)	5.9% (1.0–41.0%)	5.9% (2.4–27.4%)
Mean (standard deviation)	9.1% (8.5%)	7.9% (5.5%)
First quartile	3.0%	4.0%
Third quartile	12.5%	10.2%
HIV prevalence range	Percentage of metropolitan areas in that range	
0–4.99%	41%	40%
5–9.99%	24%	35%
10–19.99%	22%	20%
20–29.99%	8%	5%
30–39.99%	3%	0
40–49.99%	1%	0

*These statistics were compiled from data from Holmberg (1996) and supporting materials (available upon request).[1]

DISCUSSION

Despite our efforts to validate the estimates of HIV prevalence rates, serious limitations undoubtedly exist concerning their accuracy. The research data for 25 metropolitan areas use samples that in most cases have little claim to be representative of all IDUs and, in addition, used inconsistent criteria for sample eligibility. Inaccuracies based on these sample characteristics undoubtedly affect the accuracy of the regression adjustments made to the CDC Voluntary HIV Counseling and Testing data, as do a range of local variations in Counseling and Testing site locations and other characteristics that affect which IDUs do and do not get tested. The Lieb equations are limited by inaccuracies in our estimates of numbers of drug injectors living with HIV and in our estimates of the number of IDUs in each metropolitan area (see Friedman et al.[8] for detailed discussion of related limitations). As was true in estimating the numbers of IDUs, the data are further limited by social desirability biases on the part of people being tested when they report on whether they have ever injected drugs and, if so, when they last did so. Efforts to construct-validate the results by examining their correlates are limited by the paucity of research about what metropolitan area characteristics are associated with HIV prevalence rates among IDUs.

MSA-specific estimates should be used cautiously. Our construct validation procedures provide estimates of overall reliability of the entire set of 95 estimates and are thus less meaningful for any given metropolitan area. We particularly want to caution against MSA-specific comparisons of *change* in HIV prevalence rate estimates based on comparing our data to Holmberg's[1] estimates because such subtractions can compound the errors at the two periods to produce very misleading conclusions.

Despite their limitations, these estimates will be useful for policy planning and as supporting data in seeking funding for prevention and care of HIV. They also have considerable scientific utility. They can be used to study what metropolitan area characteristics are associated with HIV prevalence rates among IDUs. Such analyses might usefully inform urban or policing policy as well as assist in assessing the large-scale impacts of programs for promoting access to sterile syringes.[4,13]

It appears that HIV prevalence rates have declined in those MSAs with the highest rates in the early 1990s, probably as a result of deaths of infected injectors (for whatever cause) not being matched by new infections as appears to be the case with New York City and as Holmberg had suggested was occurring in his 1996 article.[1,14,15] The decreases in new infections may be due to the success of prevention efforts such as syringe exchange and to other sources such as decreases in the proportion of drug-use events in which the drugs are injected.[1,14,15]

As presented here, between these data for 1998 and Holmberg's[1] for 1992, we have some capacity to study change over time. Given the extent of noise in these data, however, two points in time may well be insufficient to analyze causation. We are planning to create annual estimates for the period since 1992 and then to analyze what structural and policy factors are associated with changes in HIV seroprevalence among IDUs.

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