PROFILE OF ANTI-DRUG LAW ENFORCEMENT

IN URBAN POVERTY AREAS IN MASSACHUSETTS

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The author is entirely responsible for any remaining errors in the data presented and speaks for himself in drawing conclusions.

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Organization of this Report

The Summary and Discussion presents the study results in brief and outlines some of their implications for criminal justice policy. The Findings section presents the study results in much more depth. The lengthy Methodology section explains the derivation of the study results in complete detail. Most readers will use the Methodology section primarily as a reference for understanding findings of particular interest to them.

Summary and Discussion

This study uses newly available information technology to provide new insights into crime and law enforcement in the state of Massachusetts. To our knowledge, it is the first study to apply geographic information systems to map the neighborhood-level distribution of the residences of criminals. It offers quantitative answers to several basic questions central to public debate about criminal justice policy in Massachusetts:

- To what extent are criminals (especially drug dealing criminals) concentrated in urban poverty areas?
- Within the highest poverty areas, what are the rates of serious involvement in the criminal justice system?
- What portion of criminal justice system involvement arises from drug offending?
- Are the offenders punished for drug crimes typically offenders with records for violent and other serious crime?

The data on concentration of criminal careers raised an additional question: How do prison commitment rates vary by race and ethnicity when neighborhood poverty variables are held constant? The Findings section details the answers that our Massachusetts data provide to each of these questions.

The findings tend to support the concept that ***crime problems and the need for crime prevention efforts are greatest in poverty areas:***

- State prison commitments for drug offenses are 56 times more frequent in the poorest 10% of neighborhoods in the state than in the wealthiest 10%; state prison commitments for non-drug offenses are 14 times more frequent. See page 8.
- Juvenile commitments for drug offenses are 84 times more frequent in the poorest 10% of neighborhoods in the state than in the wealthiest 10%; juvenile commitments for non-drug offenses are 15 times more frequent. See page 8.

- Poverty neighborhoods account for over half (57.1%) of state prison commitments for drug offenses and over one third (39.7%) of state prison commitments for non-drug offenses. See page 6.

- The wealthiest *50*% of all neighborhoods in the state account for only 8.9% of state prison drug commitments and 17.9% of state prison non-drug commitments. See page 8.

For non-drug offenses, these neighborhood contrasts in prison commitment rates appear to be driven by underlying contrasts in offending rates (as opposed to being driven by neighborhood differences in the way the criminal justice system responds to offenses). The neighborhood distributions of other indicators of non-drug crime volume parallel the neighborhood distribution of non-drug state prison commitments:

- Weapons related injuries, i.e., shootings and stabbings, are as concentrated in poverty areas as prison commitments for corresponding violent offenses. They are 26 times more frequent in the poorest 10% of neighborhoods in the state than they are in the wealthiest 10%. See page 9.

- The poorest 10 cities in the state have roughly the same share of state prisoners (66.0%) as would be predicted based on their crime rates. See page 10.

Our finding that offenders reside disproportionately in poverty areas suggests the need for additional poverty area programs to help steer offenders and potential offenders back to the main stream. However, not only additional helping resources, but also additional enforcement resources may be needed in poverty areas. While the poorest 10 cities in the state account for 66.0% of the state prisoners they have only 40.6% of the municipal police officers. See page 10.

At the same time, our study findings amplify the concern that ***incarceration rates in poverty areas, particularly among African-Americans and Hispanics, are damagingly high:***

- Even within poverty areas, Black and Hispanic state prison commitment rates are over five times higher than White rates. See page 17.

- In poverty areas, at current state prison commitment rates, 1 in 6 young adult minority men will experience state prison incarceration before the age of 40. Among Whites in non-poverty areas, the projected rate is only 1 in 100. See page 21.

- Although our data on House of Corrections experience rates are incomplete, they suggest that as many as half of young minority males in poverty areas will experience House of Corrections incarceration before the age of 40. See page 22.

- Roughly 1 in 20 minority males in poverty areas in Massachusetts are incarcerated on any given day. See page 24.

The high exposure of poverty-area minority males to incarceration suggests that the currency of punishment is being devalued. When incarceration becomes routine, it cannot deter crime and may even be seen as a positive rite of passage. The findings also highlight the significance of incarceration experience as a potentially corrosive social phenomenon in poverty areas. They emphasize the importance, especially in poverty areas, of anti-crime measures that do not increase incarceration – many forms of community policing, violence and drug prevention efforts, drug treatment and community-based approaches to corrections. They also emphasize the appeal of rehabilitative programming in prison and of post-release services and supervision.

Our findings also tend to amplify ***concerns often raised about the impact of heavy sentencing for drug offenses, especially mandatory sentencing, on African-Americans and Hispanics:***

- The relative rates of prison commitment for drug offenses in poverty areas and among minorities are disproportionate to (much higher than) relative rates of admission to publicly funded drug treatment. See pages 11 and 20.

- Minorities make up 84.9% of state prison commitments for drug offenses; Hispanics alone make up over half – 54.4%. See page 28.

- Hispanics are committed to state prison for drug offenses at a rate 81 times higher than Whites. See page 18.

- For Hispanics, drug offenses account for roughly half of the state prison incarceration experience; for Blacks they account for roughly one fifth; and for Whites under one tenth. See page 25.

Our findings also tend to confirm that ***many of those incarcerated for drug offenses have no criminal records or relatively light, non-violent records :***

- Almost half of state prison level drug offenders have never been charged with a violent offense in Massachusetts. Only 1 in 3 has a prior conviction for a violent offense. Only 1 in 12 has been previously convicted for a serious violent offense. See page 29.

- Over half of drug offenders have "no/minor" or "moderate" records (applying labels defined by the Massachusetts Sentencing Commission). Traffickers, those sentenced to longer terms for distributing 14 grams or more of cocaine or heroin, tend to have *less* serious records. See page 32.

- State Prison drug sentences – even for non-traffickers, i.e, those guilty of retailing of minor quantities – compare to or exceed sentences for serious violent crimes like voluntary manslaughter or armed robbery. See page 31.

As discussed above, the project data show strong relationships between race, poverty and state prison commitment rates. It is important to emphasize that this study was not designed to measure the effects of racism in criminal justice system decision-making. It measures primarily the end product of the criminal justice system process – incarcerations. It does not trace and compare the processing of matched individual cases as would be necessary to measure racism.

Our data suggest that much of the disproportionality in racial/ethnic commitment rates for non-drug offenses may be related to poverty rate differences. See page 18. However, the contrasts in commitment rates for drug offenses are too wide to be explained either in this way or with reference to drug use patterns. The contrasts suggest race-related differences, either in anti-drug enforcement or in drug-dealing involvement. Our data do not allow us to distinguish these possibilities.

Regardless of the causes, the importance of a firm response to drug dealing must be balanced against concerns about high incarceration rates in minority communities. The high state prison experience rates in poverty-area minority communities suggest that the deterrence value of long incarcerations is not great. The lack of a known history of violence for many drug offenders means that use of prison resources to house them reduces resources available to incapacitate violent offenders. Mandatory penalties for drug offenses lead to the inflexible over-application of harsh punishment, further diminishing its deterrence value, misallocating scarce resources and exacerbating high incarceration rates. Our main conclusions from this report are that we need to moderate our mandatory drug sentencing policies and to invest more heavily in approaches to controlling drug dealing in poverty areas that do not rely primarily on long incarcerations.

FINDINGS

To what extent are criminals (especially drug dealing criminals) concentrated in urban poverty areas?

Background - "Poverty Areas"

The Census Bureau divides each county in the country into "tracts." Tracts are intended to roughly coincide with neighborhoods in the sense of being homogeneous in demographic characteristics, economic status and living conditions. There are 1,331 census tracts in Massachusetts with an average of 4,520 persons in each.

The Census Bureau defines "poverty" tracts as those in which more than 20% of the residents live in households with incomes below the poverty line. Scholars of urban poverty tend to agree that this criterion includes many neighborhoods that do not seem severely distressed. Tracts with poverty rates over 40% tend to exhibit more visible indicators of poverty – idling adult males, abandoned housing, dirty streets.[1] The Census Bureau distinguishes these poverty tracts as "extreme" poverty tracts. Many refinements of these basic Census Bureau definitions merit consideration. One could for example focus on poverty tracts in urbanized or metropolitan areas only. In Massachusetts, however, essentially all poverty tracts are urban and possible refinements have little effect on the aggregates reported in this study. For simplicity and comparability, we have followed the basic Census Bureau definitions except where otherwise noted. See Methodology, pages 35 and following, for further discussion of these definitions and alternative poverty area definitions that we considered.

Chart 1 shows the relative sizes of the populations living in tracts classified as non-poverty, poverty (over 20% poor but under 40% poor) and extreme poverty (over 40% poor). From Chart 1, it is clear that extreme poverty areas are quite small in Massachusetts. In this report the phrase "poverty tracts" refers to both poverty and extreme poverty tracts except where extreme poverty tracts are explicitly distinguished, as, for example, in Chart 1.

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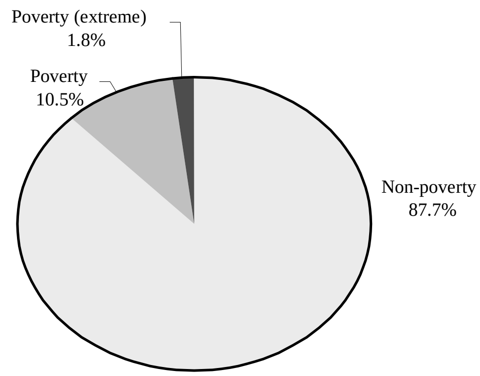
[1] See, for example, Jargowsky, Paul (1996) *Poverty and Place: Ghettos, Barrios and the American City* (New York, Russell Sage). See also Wilson, William J. (1996) *When Work Disappears* (New York, Knopf).

Chart 1: Massachusetts Population by Poverty of Residence Tract (1990)



In Massachusetts, contiguous poverty tract clusters with over 10,000 total population account for 82.9% of the total population in poverty tracts. These clusters occur in 11 large cities (listed in descending order of poverty cluster size): Boston, Springfield, Lawrence (with part of Methuen), Worcester, Lowell, Holyoke, Lynn, New Bedford, Brockton, Chelsea, Fall River. Smaller clusters in these same cities account for 4.4% of the population in poverty areas, and smaller clusters in 19 other cities and towns for 8.4%. The partially rural area around Amherst, with an apparent concentration of statistically poor students, accounts for the balance (4.4%) of the poverty area population. The poverty tract clusters with over 10,000 population include 93.9% of the population in extreme poverty tracts. See Appendix of Maps.

Table 1 provides socioeconomic characteristics of the persons living in the several categories of poverty area. The table shows that areas with higher poverty rates have higher concentrations of less educated persons, families headed by females, households with public assistance income, and men over 16 who are not participating in the labor force. See page 37 under Methodology for detail on individual poverty clusters.

Table 1: Characteristics of Persons in Massachusetts Poverty and Non-Poverty Tracts (1990)

POVERTY AREA	Persons	% Poor	% over 25 with no HS Diploma	% of Households with Children Female Headed	% of Households with Public Assistance	% of Males not in Labor Force
Non-poverty	5,277,220	6.2%	17.9%	15.6%	5.9%	22.5%
Poverty	630,011	26.3%	36.2%	45.8%	19.2%	31.5%
Poverty (extreme)	109,194	47.6%	51.8%	61.2%	37.0%	45.5%
Statewide	6,016,425	8.9%	20.0%	19.7%	7.7%	23.8%

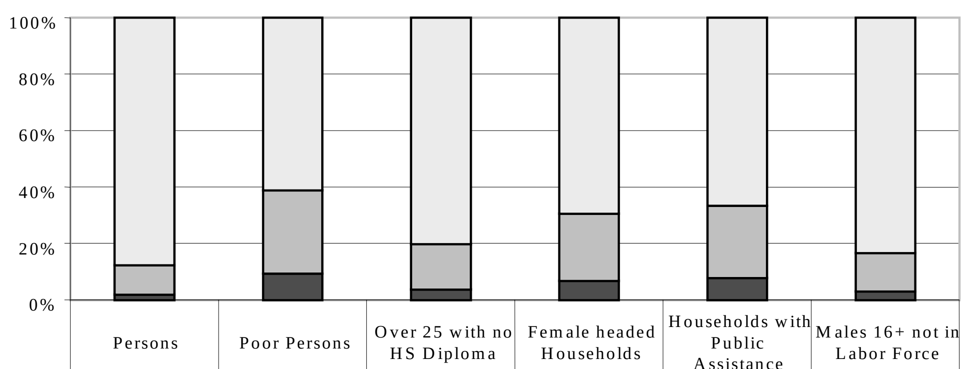
It is worth emphasizing that poverty areas contain only a small share of the categorically disadvantaged persons in Massachusetts. Chart 2 shows the large share of several categories of disadvantaged persons resident *outside* poverty areas.

In summary, extreme poverty areas, the areas which are most recognizably troubled (poverty rate over 40%), are small in Massachusetts, including only 1.8% of the population (as compared to 4.5% in the United States). Other poverty areas (poverty rate over 20% to 40%) are a somewhat larger group, including a full 10.5% of the population (as compared to 17.2% in the United States). The majority (61.1%) of poor persons in Massachusetts reside in non-poverty areas (as compared to 49.2% in the United States). In Massachusetts, the overall poverty rate, 8.9%, is below the U.S. poverty average of 13.1%. Of course, this reflects 1989 income data and poverty rates fluctuate with the economy, but relative rates and neighborhood poverty patterns change more slowly. See Methodology at page 34.

Concentration of Criminals

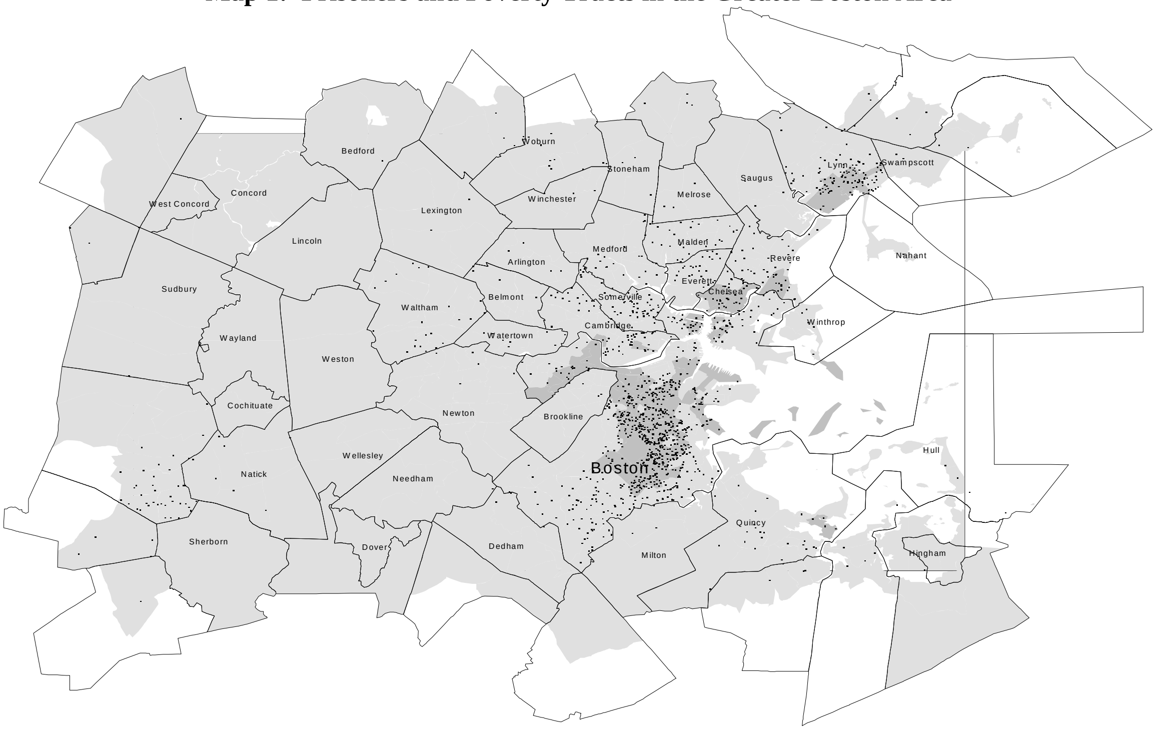
With the assistance of the Department of Correction (DOC), the project team mapped the pre-incarceration addresses of newly committed state prisoners (i.e. incoming prisoners) in fiscal years 1995 and 1996. With the assistance of the Department of Youth Services (DYS), the project team also mapped the legal custody addresses of minors committed to DYS from fiscal years 1992 through fiscal 1996.

Chart 2: Distribution of Massachusetts Persons by Poverty of Residence Tract (1990)



	Persons	Poor Persons	Over 25 with no HS Diploma	Female headed Households	Households with Public Assistance	Males 16+ not in Labor Force
Non-poverty	5,277,220	317,168	635,314	95,418	115,907	450,044
Poverty	630,011	154,128	128,351	32,833	44,615	72,750
Poverty (extreme)	109,194	48,043	28,992	9,137	13,380	16,242

Map 1: Prisoners and Poverty Tracts in the Greater Boston Area

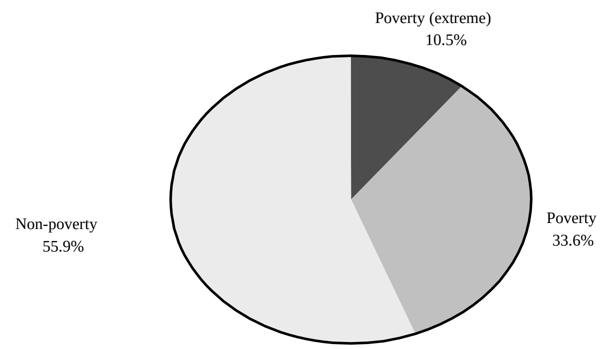


Except as noted, all commitment rate data presented in this report are based on annual averages derived from these subject periods; DYS commitments include both males and females; among state prisoners, only males are included. Female state prisoners in our sample are concentrated in poverty areas to roughly the same degree as male prisoners, but our sample is not fully representative of female prisoners. For a full description of the data see pages 41 ff. under Methodology. Regarding the geocoding process and accuracy considerations in the geocoding process, see pages 52 ff.

The DOC and DYS datasets provide a unique view of the geographical distribution of more serious criminals. The state prisoners constitute roughly half of the just over 20,000 adult prisoners in Massachusetts; the balance of the prisoners are in county Houses of Correction. The state prisoners are generally the more serious adult offenders. Males incarcerated in state prison have been (a) selected for prosecution in Superior Court[2]; (b) convicted of a felony; and (c) sentenced by a Superior Court judge to

[2] In Massachusetts, the trial court system is bifurcated into lower "District Courts" and higher "Superior Courts". The Superior Courts have jurisdiction over all criminal offenses. The district courts have jurisdiction only over offenses with a maximum penalty of five years in state prison and certain other offenses. For the many offenses within the concurrent jurisdiction of both courts, prosecutors exercise discretion in choosing which court a case should be brought in. Since District Courts may not impose a

Chart 3: State Prison Commitments by Poverty of (Pre-Incarceration) Residence Tract



state prison instead of a House of Correction (usually implying a longer term and possibly a higher security level). Those committed to the Department of Youth Services represent the more serious juvenile offenders who have earned DYS supervision (which may entail residential detainment).

Map 1 shows the results of mapping state prisoners in the greater Boston area. Each dot on the map represents the pre-incarceration residence of a single state prisoner. The dots are randomly placed within each census tract to fully protect anonymity while accurately reflecting the density of prisoners in each tract. Poverty tracts are shaded. Chart 3 quantifies statewide the reality apparent in Map 1 – that prisoners are heavily concentrated in poverty areas. Poverty areas account for 44.1% of state prison commitments.

Chart 4 compares, by poverty and non-poverty area of residence, the concentrations of poor persons and of DOC and DYS Commitments broken down as drug and non-drug. It is striking that drug offenders, especially youth drug offenders, are considerably more concentrated in poverty areas than non-drug offenders. Note that at the State Prison level, 99.2% of drug offenses are dealing offenses as opposed to possessory offenses.

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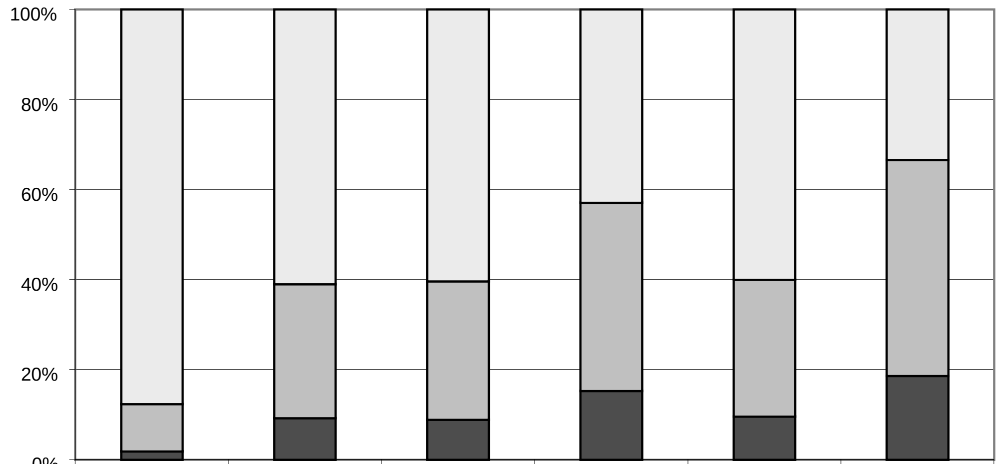
term of incarceration greater than two and one-half years in a House of Corrections, prosecutors bring the cases which they judge to be more serious in Superior Court.

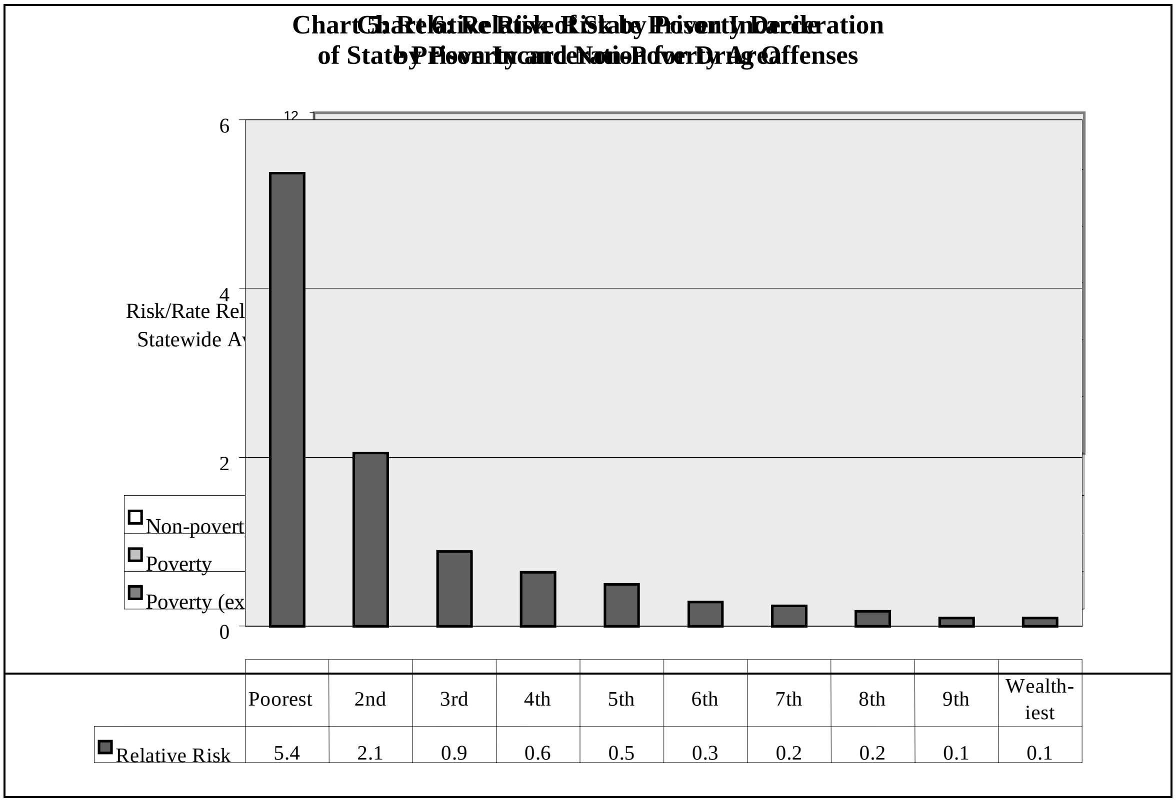
Chart 4: Poor Persons and Commitments by Poverty of Residence Tract



	Total Persons	Poor Persons	State Prison Non-Drug	State Prison Drug	DYS Non-Drug	DYS Drug
Non-poverty	87.7%	61.1%	60.4%	42.9%	60.0%	33.4%
Poverty	10.5%	29.7%	30.8%	41.8%	30.4%	48.0%
Poverty (extreme)	1.8%	9.3%	8.9%	15.3%	9.6%	18.6%

Extreme poverty areas (with poverty rates over 40%) include only 1.8% of the population, and turn out to be too small to account for the bulk of the state prison or DYS commitments. Poverty areas (broadly defined with poverty rates over 20%), do account for roughly half of the offenders (more of the drug offenders and less of the non-drug offenders). Yet, with half of offenders coming from *non*-poverty areas in Massachusetts, it does not seem realistic or analytically useful to think of criminal careers as primarily *confined* to poverty areas.

That said, it does seem useful to recognize the significant contrasts between poverty areas, and the wealthier areas of the state. Chart 5 compares the “relative risk” of incarceration in non-poverty areas, poverty areas and extreme poverty areas. “Relative risk” means the ratio of the local rate to the statewide average; it gives a measure of the degree of contrast between areas. Chart 5 shows that the relative-risk spread for incarceration for non-drug crime is comparable to that for poverty itself. Chart 5 also shows that the relative risk for incarceration for drug crime is considerably more skewed – it is 19 times higher (9.7/0.5) in extreme poverty areas than outside poverty areas. That is, males living in extreme poverty areas are 19 times more likely than males in non-poverty areas to be incarcerated for a drug offense.



Additional contrasts emerge if we momentarily put aside the non-poverty/ poverty/ extreme-poverty classification of tracts and group all of the Massachusetts tracts into deciles by percent of persons in poverty as in Chart 6. To group by "deciles," we ranked the tracts by poverty rate and then divided them into progressively lower poverty-rate groups with each group containing ten percent of the state's population. The first (highest poverty rate) decile is a subset of the poverty (greater than 20% poverty rate) tracts. It includes 177 of the 212 poverty tracts. The effect of using a decile approach is to further differentiate the non-poverty tracts into nine groups.

The relative rates for state prison level drug offending among the wealthier half of the tracts in the state (the five rightmost groups in Chart 6) are strikingly low. This suggests that while we cannot think of criminal careers as concentrated in a small group of urban poverty tracts, it is realistic to think of the more prosperous half of the state as relatively devoid of individuals with drug offending careers that land them in state prison. A person living in the more prosperous half of the state is relatively unlikely to have a neighbor who is dealing drugs.

Table 2 summarizes these contrasts. The contrasts for non-drug offenses are substantial but not as great as they are for drug offenses. Reading Table 2, we see that the wealthier half of the state yields only

17.9% of the non-drug state prison commitments and only 8.9% of the drug commitments. It follows that the less-wealthy half yields 82.1% of the non-drug commitments and 91.1% of the drug commitments. The second row of Table 2 shows the ratios of commitment rates between the poorest and the wealthiest deciles. Again, the contrasts are most significant for drug offenses.

Table 2: Contrasts between Wealthier and Poorer Tracts

	State Prison Non-Drug Commitments	State Prison Drug Commitments	DYS Non-Drug Commitments	DYS Drug Commitments
Share from wealthier half of tracts	17.9%	8.9%	17.8%	6.3%
Ratio of risks: (poorest decile to wealthiest decile)	14x	56x	15x	84x

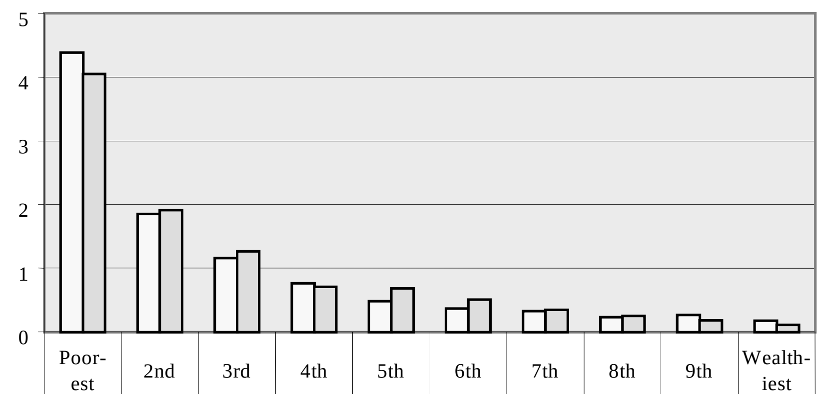
Causes of Disparity – Comparison Measures

To what extent do the high relative densities of state prisoners and DYS committed youths originating from poorer census tracts reflect the underlying density and offending frequency of criminals in those census tracts, as opposed to disparities in the way the criminal justice system operates? The data presented so far do not measure underlying crime rates, only the end product of the whole sequence of justice system decision-making.

Weapons-Related Injuries

The only statewide dataset relevant to crime which includes geocodable addresses for each incident is the Weapons Related Injury Surveillance System (WRISS) operated by the Department of Public Health. This system captures the addresses of victims of weapons injuries treated in hospital emergency rooms. If the laws are consistently enforced, one might expect the geographic distribution of state prison incarcerations of victimizers to parallel the distribution of weapons-related injuries of victims (to the extent victim and victimizer reside close to each other – see Methodology at page 44).

Chart 7: Relative Risks for Prison Commitment for Assault Offenses compared to Relative Risks for Weapons Related Injuries by Poverty Rate Decile



	Poor-est	2nd	3rd	4th	5th	6th	7th	8th	9th	Wealth-iest
Injuries	4.4	1.9	1.2	0.8	0.5	0.4	0.3	0.2	0.3	0.2
Assaults	4.0	1.9	1.3	0.7	0.7	0.5	0.3	0.3	0.2	0.1

Chart 7 shows that risk levels for weapons-related injuries actually slightly exceed risk levels for state prison incarceration for assault offenses[3] in the poorest tracts. If one believed that high incarceration rates for violent offenses in poverty areas were due to invidiously differential enforcement, one would expect the opposite divergence, with commitment rates in the poorest tracts exceeding injury rates. These results (although perhaps distorted by health care access patterns) offer some evidence of rough geographic consistency, at least as to assault crimes.

Crimes Known to the Police

Statewide crime incident reports are grouped by reporting police force. This aggregation prevents a neighborhood-level measurement of crime density by poverty and non-poverty area. However, the data do allow us roughly to compare the ten poorest cities to the rest of the state.

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[3] Assault offenses are defined here to include violations of the following sections of Massachusetts General Laws, Chapter 265: 13A, 13D, 13J, 14, 15, 15A, 15B, 16, 18, 18A, 18C, 29. These constituted 617 or 19.3% of the 3196 state prison commitments for non-drug crimes. Only the 552 of these commitments with geocodable addresses are included in the chart. This chart includes both males and females, both as victims and as state prison commitments, and for both series uses population as the denominator.

Chart 8: Poorest Ten Cities' Share of Crime
as Compared to their Share of Prisoners and their Share of Police Officers

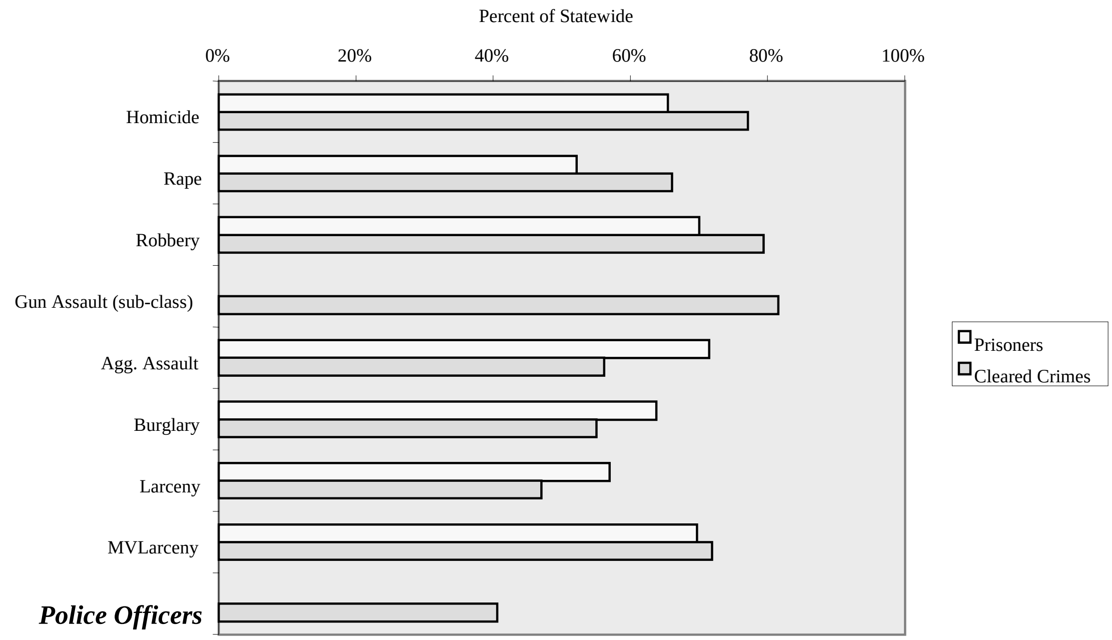

Chart 8 shows, for the 10 poorest cities in the state taken as a group, the share of prisoners originating from them compared to their shares of corresponding cleared crimes (i.e. crimes for which an arrest has been made). For the most serious crimes that are most likely to result in state prison incarceration (homicide, rape, robbery) the poorest cities' share of cleared crimes is greater than their share of prisoners. The poorest cities' share of prisoners committed for aggravated assaults is above their share of cleared aggravated assaults. However, it is well below their share of cleared gun assaults, the most serious subcategory of aggravated assault and the one most likely to result in incarceration.[4] It turns out that the poorest cities' overall share of the state prisoners is essentially the same as would be predicted from their share of cleared crimes. One gets the same answer if one uses the larger universe of reported crimes (cleared or not) to predict incarceration shares. See Methodology at page 56 for definition of the reporting universe included (which is a subset of the state) and detailed quantitative reasoning supporting these statements.

This comparison, like the preceding comparison of injuries to assault commitments, favors the view that the disproportionately high prison commitment rates for non-drug offenses in poverty areas are primarily due to disproportionately high non-drug crime rates in those areas, as opposed to disproportionate enforcement intensity in those areas. Also consistent with this view is the last bar in the chart, which shows that the poorest cities' share of full time[5] sworn police officers is well below their share of statewide crime or statewide incarcerations. In other words, there are fewer police officers per serious crime in the poorest cities, which further indicates that high incarceration rates in poor areas are unlikely to be due to excess enforcement intensity. It also indicates that urban police officers spend more of their time solving serious crimes and may be less available to attend to minor disturbances and provide ancillary community service.

Comparison Measures for Drug Offending

The comparison measures offered above speak only to non-drug offenses. Unfortunately there is no direct comparison measure for drug offenses. We can, however, say with some confidence that state prison incarcerations for cocaine and heroin dealing are more skewed to poverty areas than is abuse of cocaine and heroin.

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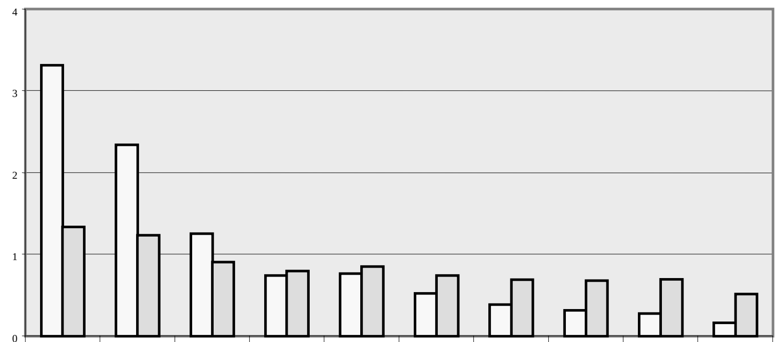
[4] Because the statutory categories of assault crimes do not correspond to the crime report categories, we cannot directly compare gun assaults to any particular statutory category of assault, so that for gun assaults the chart shows only the cleared crime share without a corresponding commitment share.

[5] The staffing data is that reported to the State Police Crime Reporting Unit. None of the poorest cities rely significantly on part-time officers.

Chart 9: Two *Alternative* Indicators of Relative Levels of Cocaine and Heroin Abuse Across Deciles of Poverty (by Zip Code) Derived from Treatment Admissions Data to Publicly Funded Treatment Programs in Fiscal 1996 (see Text)



	Poor-est	2nd	3rd	4th	5th	6th	7th	8th	9th	Weal-thiest
High Skew	3.3	2.3	1.3	0.7	0.8	0.5	0.4	0.3	0.3	0.2
Low Skew	1.3	1.2	0.9	0.8	0.8	0.7	0.7	0.7	0.7	0.5

Chart 9 presents two alternative indicators of the relative risk for heavy cocaine or heroin use according to poverty decile. Both of these indicators should be approached with caution for reasons elaborated in the Methodology at page 51. The "High Skew" represents the population relative risk of admission to a (partially or fully) publicly-funded drug treatment program (outpatient as well as detoxification and other inpatient). It includes only those presenting cocaine, crack or heroin as the primary drug of abuse – these are the drugs associated with state prison incarcerations.

The universe of treatment admissions covered includes only admissions to facilities in which at least some patients are publicly funded. Admissions to facilities accepting exclusively privately-funded patients do not appear in the data. These facilities amount to less than 10% of the formal drug treatment capacity, but most of their clients are likely to be non-poor, so that the "High Skew" understates treatment utilization in the wealthier areas. It represents a likely upper bound on the degree of contrast in treatment utilization for cocaine and heroin abuse across poverty deciles.

The "Low Skew" represents the relative risk *among clients admitted to publicly funded treatment programs* that the clients' primary drug of abuse is cocaine, crack or heroin (as opposed to alcohol, marijuana or other drugs). The "Low Skew" thus factors out the overall rate of admissions to publicly funded treatment programs. It overcorrects for the greater access to private treatment programs in wealthier areas and so represents a lower bound on the degree of contrast across poverty deciles. See further discussion under Methodology at page 51.

By either indicator, the concentration of cocaine and heroin abuse in poverty areas is less than the concentration of prison commitments for heroin and cocaine dealing. Compare Chart 6 to Chart 9 above and see Table 3 below. Anecdotal evidence suggests that targeting of anti-drug enforcement involves greater discretion than targeting of other types of law enforcement. It is thus possible that contrasts in drug commitment rates are magnified by enforcement pressure on visible street dealing operations in poverty areas. It is also possible (and consistent with anecdotal evidence) that a significant portion of the demand served by drug dealers operating within poverty areas actually originates from outside poverty areas.

Table 3: Contrasts between Wealthier and Poorer Zip Codes – Comparison of Dealing and Abuse Indicators for Heroin and Cocaine

	State Prison Drug Commitments	Admissions for Cocaine/Crack or Heroin ("High Skew")	Same as % of all Admisisons ("Low Skew")	Unique Individuals Admitted for C/C or H	Same as % of all Individuals Admitted
Share from Poorest decile of Zip Codes	44.0%	32.9%	NA	32.0%	NA
Share from wealthier half of Zip Codes	8.7%	16.5%	NA	17.4%	NA
Ratio of risks: (poorest decile to wealthiest decile)	59x	21x	2.6x	18x	3.2x

Summary of Concentration Analysis

Our analysis of state prison and DYS commitment data shows that over half of all serious criminals live outside poverty areas. Yet criminals are far more concentrated in poverty areas than outside them. The contrasts between poverty areas and the wealthier non-poverty areas are particularly wide. The quantitative fact that explains this apparent contradiction is that poverty areas account for a relatively small share of the population in Massachusetts.

Our analyses of weapons-related injury data and crime report data are offered as rough tests of the consistency of enforcement and sentencing for non-drug offenses. These analyses suggest that the observed distribution of system outputs (incarcerations) is less concentrated in poverty areas than the observed distribution of two system inputs (weapons-related injuries and crimes cleared by arrest). This suggests that high state prison commitment rates for non-drug offenses in poverty areas are due primarily to high non-drug offending rates in those areas, not to special enforcement or punishment intensity applied to those areas. However, the picture as to commitments for drug offenses (which are more concentrated in poverty areas) is less clear. Commitments for drug offenses appear to be considerably more concentrated in poverty areas than substance abuse (as indicated by treatment admissions). The difference in concentration may reflect either high relative enforcement intensity in poverty areas or a concentration of dealing in poverty areas disproportionate to the local demand.

How do prison commitment rates vary by race and ethnicity when neighborhood poverty variables are held constant?

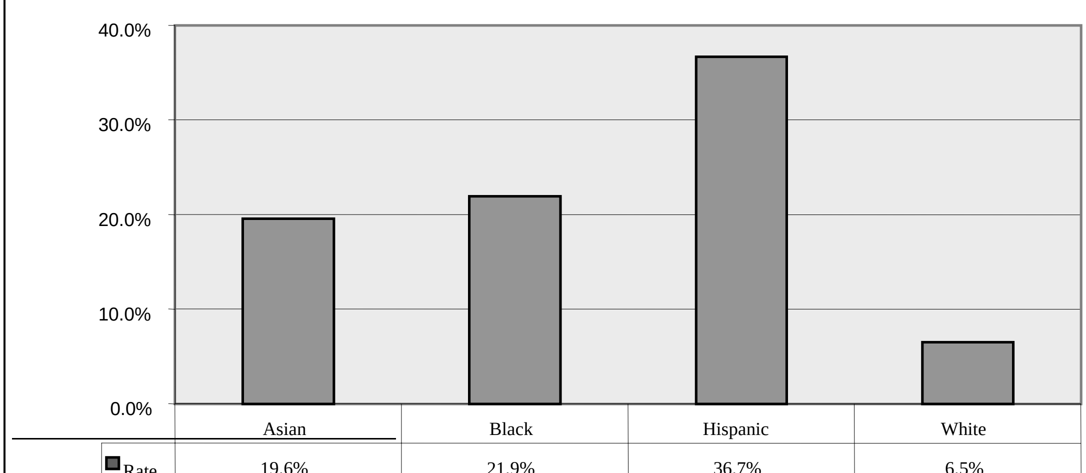
Background: Geographic Patterning of Race, Hispanic Ethnicity and Poverty

Poverty rates in Massachusetts vary significantly by race and Hispanic ethnicity, as illustrated in Chart 10. The (non-Hispanic) White poverty rate, 6.5%, is only a fifth of the Hispanic poverty rate, 36.7%. It is worth noting in passing that while Black and White poverty rates in Massachusetts are each several points below the respective national averages, the Hispanic poverty rate in Massachusetts considerably exceeds the national average of 25.3%. Asians, Whites, Blacks and Hispanics comprise 99.4% of the population in Massachusetts.

Despite these differences in the poverty rates, the poor population is 63.9% White. However, the minority poor population is much more concentrated in poverty areas than the White poor population: For example, 27.2% of poor Hispanics live in extreme poverty census tracts (where the poverty rate is over 40%) as against only 2.9% of poor Whites.

As a result of the geographic concentration of the minority poor, 49.4% of the population in extreme poverty tracts is in "ghetto" or "barrio" tracts, defined as those in which over two-thirds of the population is Hispanic or other minority[6]. The ghetto/barrio tracts are concentrated in the largest cities. Only Boston contains any heavily (two-thirds) Black census tracts (at any poverty level). Only Boston, Holyoke, Lawrence and Springfield contain any heavily Hispanic census tracts (at any poverty level).

Chart 10: Poverty Rates by Race/Ethnicity (1990)



[6] The "two-thirds" cutoff is arbitrary. We are following Jargowsky in picking this level as a cutoff representing local racial concentration. See note 1.

Chelsea, Cambridge, and Worcester contain some small mixed minority (over 2/3 minority) neighborhoods (comprising less than 4,000 persons in each city); Boston and Springfield contain larger mixed minority neighborhoods. In other cities, all poverty areas are mixed (over one third White) or heavily (over two-thirds) White. Outside poverty areas, 97.9% of the population is in tracts that are heavily White.

Table 4 makes clear, however, that, although extreme poverty areas are often heavily minority, many minorities reside outside poverty areas, and/or in heavily White areas.

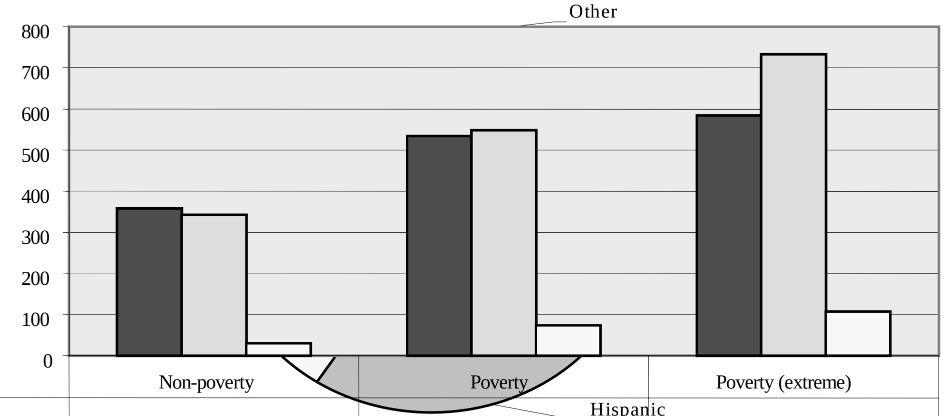
Table 4: Race/Ethnicity Groups by Neighborhood of Residence

	Black	Hispanic	Asian	White
In Poverty areas of own minority (over 2/3 of population)	22.9%	10.9%	2.9%	NA
In Poverty White areas (over 2/3 of population)	5.1%	10.2%	12.5%	4.7%
In other Poverty areas (primarily "Mixed")	25.0%	32.7%	14.3%	2.6%
In non-Poverty areas of own minority (over 2/3 of population)	3.9%	0.0%	0.0%	NA
In non-Poverty White areas (over 2/3 of population)	32.6%	41.2%	66.2%	91.6%
In other non-Poverty areas (primarily "Mixed")	10.6%	5.0%	4.1%	1.0%
TOTAL FOR RACE/ETHNICITY GROUP	100.0%	100.0%	100.0%	100.0%

Race/Ethnicity Variations in Incarceration Rate

Blacks, Hispanics and Whites account for most of those incarcerated in State Prison. For simplicity, our comparative analyses will focus on these three groups. Blacks and Hispanics each constitute 4.6% of the state's total population and respectively 11.0% and 18.7% of the state's poor population. Chart 11 shows that both groups are over-represented in the state prison population.

Chart 12: State Prison Commitment Rate (per 100,000 males over 16)
by Race/Ethnicity by Neighborhood Poverty Level



	Non-poverty	Poverty	Poverty (extreme)
Black	358	534	584
Hispanic	343	548	732
White	29	74	107

Black and Hispanic state prison commitment rates differ significantly from the White commitment rate. As Chart 12 indicates, the differences occur at all poverty levels of neighborhood. Even within extreme poverty areas, for example, the Hispanic incarceration rate is almost seven times the White rate (732/107). In non-poverty areas, the ratio is almost 12 to 1 (343/29). The greater differential in non-poverty areas is, in part, caused by the weighting of the minority population towards the poorer "non-poverty" areas where incarceration rates are higher. However, the minority-to-white commitment rate ratios diminish only slightly in a decile-by-decile analysis. See discussion in Methodology at page 64 and following for definitional issues and statistical analysis.

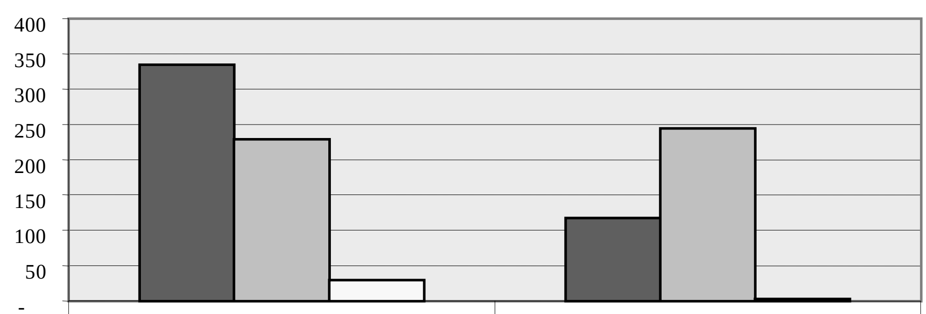
Another significant difference between the racial groups is their relative level of involvement in drug offending. As Chart 13 shows, the disproportionalities in commitment rate are much greater for drug offenses than for non-drug offenses. The Hispanic incarceration rate for drug offenses is 81 times (244/3) higher than the White rate. Drug offenses account for over half of the Hispanic commitments (244 of 473 per 100,000), but under one-tenth of the White commitments (3 of 33 per 100,000).

Because the Black and Hispanic group commitment rates are relatively high, local commitment rates in heavily minority census tracts are high relative to White neighborhoods. Heavily minority neighborhoods – 87.6% of which are in poverty areas – contain only 3.8% of the population, yet they account for 19.2% of non-drug state prison commitments and 25.3% of drug commitments. Mixed neighborhoods, which include 5.2% of the population, account for an additional 14.5% of non-drug commitments and 23.9% of drug commitments. Thus almost half of all state prison drug commitments originate from the 9% of neighborhoods which are less than 2/3 White.

Quantitative Perspective on the Race/Ethnicity Analysis

Our data indicate that significant racial and ethnic variations in state prison commitment rates persist across poverty level of neighborhood. Several points must be emphasized about the limitations of these findings. First, the data in this report primarily relate to the "impact" of the criminal justice system. Our study was not designed to measure the influence of defendant race on decision-making in the system.

Chart 13: State Prison Commitment Rate (per 100,000 males over 16) by Race/Ethnicity by Type of Offense



	Non-Drug	Drug
Black	335	117
Hispanic	229	244
White	30	3

To quantify the effects of racism, one would need to begin with a set of matched cases entering the system and compare the results of processing.

Second, our finding that racial differences in incarceration rates persist across neighborhood poverty levels is not equivalent to a finding that racial differences in offending rates persist across individual poverty levels. Our findings do not show that middle-class Blacks or Hispanics are more likely than middle-class Whites to end up in state prison. The individual poverty rate contrasts shown in Chart 10 persist even within in non-poverty areas. For example, within non-poverty areas in 1990, Black males in the high offending age range (16-39) had a poverty rate (11.3%) almost three times that of White males in the same age range (3.9%).

Further, even among those currently poor, significant differences in true socio-economic status exist. Poverty levels as used throughout this report are based on a full year of income and expenses, so that a middle-class person who is without income for several months due to job loss or divorce may appear to be poor during the reference year. The Census Bureau's Survey of Income and Program Participation is designed to measure duration of poverty. That nationwide survey showed that among those meeting the full-year poverty criterion in 1992, Blacks were 2.0 times more likely than Whites to have been poor for each of 24 consecutive months in the 1991 to 1992 study period.[7] For Hispanics the rate of sustained poverty among the poor was 1.3 times the White rate.

It is consistent with both common sense and a broad body of research to expect criminality to be most often associated with sustained as opposed to episodic poverty, although measurement problems prevent direct confirmation of this hypothesis. For non-drug state-prison commitments, if one factors out both individual poverty rate differences and differences in the rates of sustained poverty, the Black-White and Hispanic-White differences in non-drug state prison commitment rates substantially diminish.[8] This

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[7] Calculations based on revised figures from the Survey of Income and Program Participation as appearing at "Dynamics of Economic Well Being: Poverty, 1991 to 1993," http://www.census.gov/hhes/poverty/povdynam/pov91tl.html, last revised August 1996.

[8] Combining the SSIP data sustained poverty ratios with data from Chart 10 and from Chart 13, one computes as follows to get the poverty-adjusted Black to White commitment rate Ratio: 335/30, multiplied by the poverty rate ratio, 6.5%/21.9%, divided by 2.0, the sustained poverty rate differential, gives (335/30 * .148) an adjusted ratio of 1.7 . For Hispanics, the adjusted ratio comes down to 1:1 -- 229/30 * 6.5%/36.7% * 1/1.3 = 229/30 * .136 = 1.0. An omitted factor in this adjustment is the phenomenon of student poverty which may inflate White poverty rates more than minority poverty rates:

computation is offered only as an indication that socioeconomic differences not fully captured by neighborhood poverty level may make substantial contributions to the racial group commitment rate differences.

The contrasts in drug offending rates shown in Chart 13 are too wide to render proportionate using poverty statistics. Black commitment rates for drug offenses are 39 times higher than White rates and Hispanic commitments are 81 times higher. Even after adjustment for individual poverty and sustained poverty differentials the disproportions remain substantial. Nor can the differences be explained by reference to racial differences in cocaine and heroin use levels. Using the same "High Skew" and "Low Skew" measures discussed at page 12 (with White rates as the comparison base), the BSAS treatment admissions data indicate cocaine and heroin treatment utilization by Blacks and Hispanics at rates between 1.7 and 7 times higher than White rates. Cocaine and Heroin use differentials in this range are plausible given higher poverty rates among Blacks and Hispanics, but do not suffice to explain the incarceration rate differentials for drug crimes.

Summary of the Race/Ethnicity Analysis

Our data show Black/White and Hispanic/White contrasts in commitment rates that persist across neighborhood poverty levels. For non-drug offenses, these contrasts are modest enough that they can be viewed as proportionate to alternative measures of poverty. The drug offense commitment rates are so wide that one must consider other explanations, including differential enforcement intensity, differential enforcement success and differential participation in drug distribution businesses (and combinations of the foregoing). Our data do not allow us to disentangle these possibilities. Our findings as to commitment rate differentials by race parallel our findings on commitment rate differentials by neighborhood poverty level. The data in the previous section showed that non-drug prison commitment rates by neighborhood are consistent with non-drug crime rates and weapons-related injury rates,[9] while drug commitment rates are disproportionately high in poverty areas.

30.7% of the poor persons between the ages of 16 to 24 in non-poverty areas in Massachusetts are high-school graduates pursuing further education.

[9] See Chart 7 and Chart 8 above and related discussion tending to establish that commitments for non-drug offenses in poverty areas are roughly proportionate to injury and crime rates. Note that in our WRISS data, Blacks and Hispanics comprise a slightly larger share of victims of violence (34.3% and 24.4% respectively) than they do of prisoners committed to state prison for assault offenses (33.2% and

Within the highest-poverty areas, what are the rates of serious involvement in the criminal justice system?

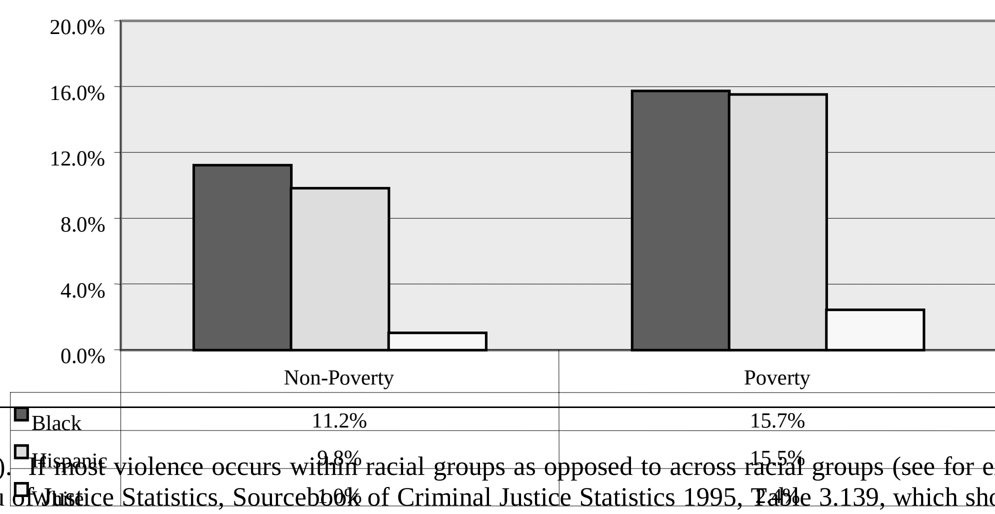
State Prison Experience

When we measure lifetime-to-age-40 state prison experience below, we are not measuring actual historical incarceration experience. We are estimating, based on current incarceration rates, the future experience of the current cohort of 16 year-old males – what percentage of them will go to state prison before age 40, assuming that age-specific crime rates and punitive response remain roughly constant. This computation is not so much a prediction as a conceptual measure of the effects of our current policies.

Chart 14 shows wide differences in lifetime-to-40 experience in state prison by race/ethnicity. These Black-White and Hispanic-White group contrasts are more pronounced than the poverty area residence contrasts. They are consistent with the commitment rate contrasts observed in the preceding section. Methodology (at page 58) provides a full explanation of the issues and uncertainties at each step of the process underlying the estimates in Chart 14.

As detailed under Methodology, our intention at each step has been to provide an estimate that is conservative – that does not overstate involvement, particularly among urban Blacks and Hispanics. On the other hand, it is important to note that there are some hard-to-measure factors that may tend to inflate these estimates modestly. Considering all uncertainties, it seems unlikely, based on the analysis detailed under

Chart 14: State Prison Experience by Age 40
by Race/Ethnicity and Poverty Level of Neighborhood



19.9%). If most violence occurs within racial groups as opposed to across racial groups (see for example, Bureau of Justice Statistics, Sourcebook of Criminal Justice Statistics 1995, Table 3.139, which shows that in 86.8% of homicides, the perpetrator and the victim were of the same race), then this comparison is further evidence of a lack of disproportionality for non-drug crimes.

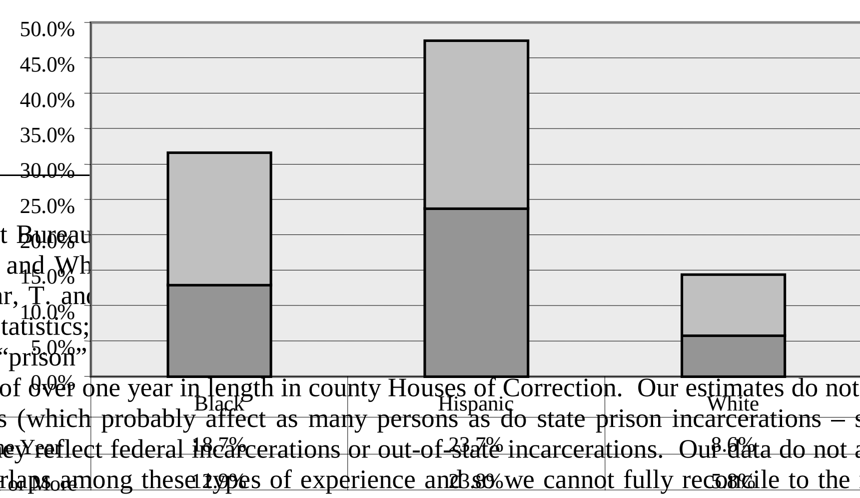
Methodology, that lifetime-to-40 state prison experience rates for Blacks and Hispanics in poverty areas should be estimated at below 9% or above 18%. It is worth noting that our estimates do not reflect out-of-state, federal or foreign incarceration experience. Our estimates are broadly consistent with national estimates of prison experience.[10]

House of Corrections Experience

We lack a statewide perspective on incarceration experience in Houses of Correction. Each county's House of Correction maintains a separate system for recording inmate commitments. Preparation of a consolidated view of the House of Correction population is well beyond the scope of our study. However, the Sheriffs of Middlesex and Norfolk counties provided us with views of the commitments to their facilities. Both of these counties are relatively prosperous. Middlesex does contain one sizeable poverty area within the City of Lowell and a smaller one in the City of Cambridge.

Chart 15 shows estimates of the lifetime-to-age-40 incarceration experience of Black, Hispanic and White males living in poverty areas in Middlesex County in the Middlesex House of Corrections. (It does not reflect those residing in Middlesex County who end up incarcerated in other counties or in state prison.) The lower portion of the bar represents those who experience incarceration for one year or more. The upper portion represents those who experience only shorter terms of incarceration. The stacked bar

Chart 15: Middlesex House of Corrections Incarceration Experience by Age 40 for Males in Poverty Areas within Middlesex County by Race/Ethnicity and Length of Sentence



[10] A recent Bureau [illegible] d 3.5% of Black, Hispanic and Wh[illegible] by the age of 40. Bonczar, T. an[illegible] Prison". Bureau of Justice Statistics; [illegible] In these national statistics, "prison" [illegible] ons are sentenced to terms of over one year in length in county Houses of Correction. Our estimates do not include these incarcerations (which probably affect as many persons as do state prison incarcerations – see next section). Nor do they reflect federal incarcerations or out-of-state incarcerations. Our data do not allow us to estimate the overlaps among these types of experience and so we cannot fully reconcile to the national estimates.

represents the total (31.6% for Blacks; 47.4% for Hispanics, 14.3% for Whites).

Several caveats should be noted: These estimates pertain to a small area – there are only 609 Black males in the relevant age range in the 14 Middlesex County poverty tracts (1,776 Hispanic, and 7,696 White). A local spike in the census undercount rate *could* cause a material overstatement in these estimates. On the other hand there are factors which tend to minimize these estimates. See Methodology at page 67. Our data do not allow us to generalize the computation to other counties, and results would undoubtedly vary considerably.

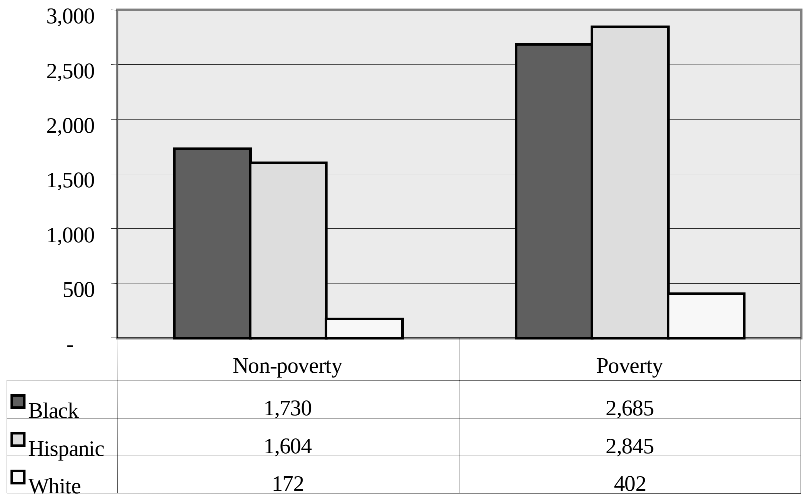
Point in time estimates of current incarceration levels

Our primary analyses in this study are "flow" analyses driven by *commitments* to state prison over a given period. The current *population* or "stock" in state prison, where sentences range up to life in length, is the result of commitments and releases over many years. Since we have only two recent years worth of commitment data, we cannot fully account for the composition of the current state prison population.

As an approximation, we can use our current flow numbers to derive an estimated "steady state" stock and then apply the proportions of subgroups in that estimate to model the composition of the current actual stock. This computation and its validity are further discussed under Methodology at page 69. The result of this computation is displayed in Chart 16.

Applying the same methods we are able to estimate current incarceration rates for Middlesex House of Corrections inmates in poverty areas in Middlesex County at 1236 per 100,000 for Blacks, 1885 for Hispanics and 330 for Whites. Because many Middlesex County residents may be incarcerated in other county facilities, these estimates may understate overall incarceration rates. Combining the State Prison and House of Corrections estimates, it appears that among Black and Hispanic males with primary residences in poverty areas in Middlesex County, and perhaps elsewhere in Massachusetts, roughly 1 in 20 are incarcerated on any given day.

Chart 16: Estimated Current (January 97) State Prison Incarceration Rates per 100, 000 Males over 16 Year of Age by Race and Poverty Level of Neighborhood



Summary of Experience/Point-Estimate Analyses

The analyses presented here suggest that, among minority males in poverty areas, roughly one in six will experience State Prison before he turns 40, roughly one in two or three will experience a House of Corrections before he turns 40, and one in 20 is incarcerated on any given day. These estimates are all subject to considerable uncertainty. However, the numbers seem high enough that the influence of incarceration experiences on convicts returning to urban communities should be a significant concern for policy makers.

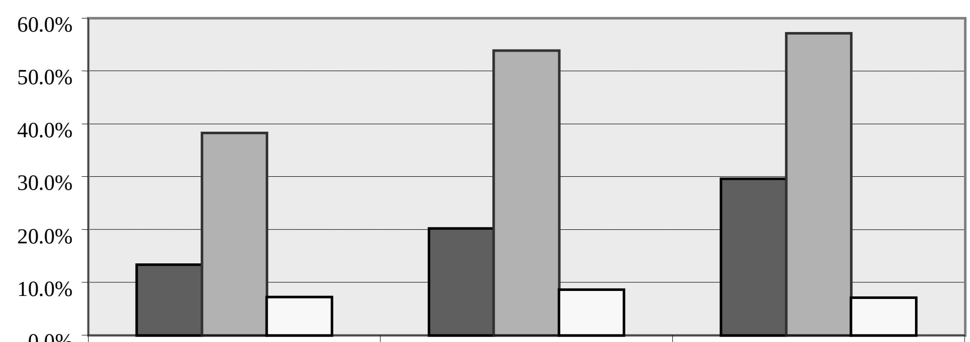
What portion of criminal justice system involvement arises from drug offending?

Alternative Measures of Drug Offending Share

Our analysis of a sample of criminal records of incoming state prisoners indicated that 64% of non-drug prisoners and 57% of drug prisoners have prior incarceration experience in Massachusetts. Some drug offenders have prior non-drug incarceration experience and some non-drug offenders have prior drug incarceration experience. It is therefore both conceptually and empirically difficult to attribute a specific portion of the lifetime-to-40 experience rates to drug offenses.

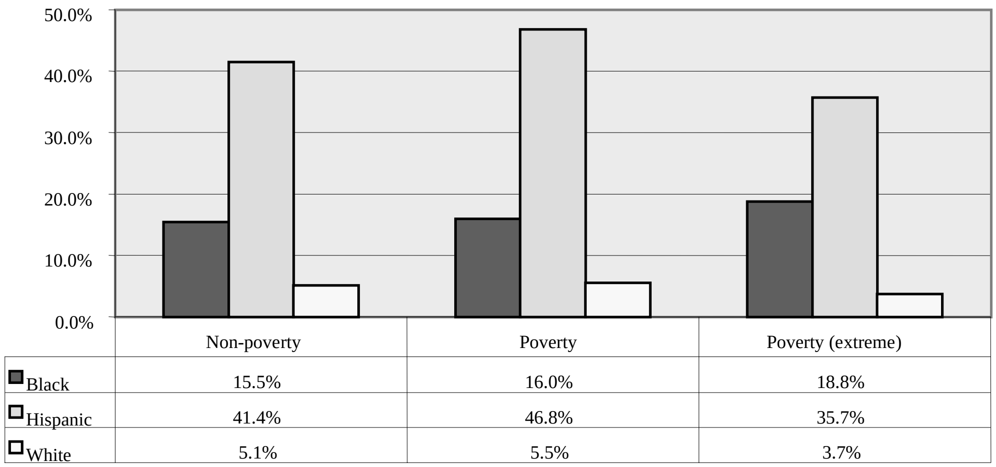
We can, however, make two types of statements. First, for Black and Hispanic men, drug offenses are frequently the basis for the first state prison level incarceration. As Chart 17 shows, this is particularly true in poverty areas. Chart 17 shows, for example, that for Hispanics in extreme poverty areas, 57.1% of first-time state prison incarcerations were for drug offenses.

Chart 17: First-Time State Prison Incarcerations for Drug Offenses as Percent of All First Time State Prison Incarcerations



	Non-poverty	Poverty	Poverty (extreme)
Black	13.4%	20.1%	29.6%
Hispanic	38.2%	53.8%	57.1%
White	7.2%	8.6%	7.1%

Chart 18: Committed Man-years to State Prison due to Drug Offenses as Percent of All Committed Man-years to State Prison



Second, we can compute the overall share of incarcerated man-years due to drug offenses. Essentially this computation represents the prison population share attributable to drug offenses. Chart 18 shows, for example, that among Hispanics committed from extreme poverty areas, drug offenses account for 35.7% of all their man-years sentenced to state prison; non-drug offenses thus account for 64.3%. The population shares in Chart 18 are below the first-time commitment percentages in Chart 17 because, notwithstanding the long sentences for some trafficking offenses, at the state prison level, the average length of sentences for drug offenses is only slightly over half the average length of sentences for non-drug offenses.[11] For Hispanics, over-represented in the higher level trafficking categories, the difference is smaller.

We cannot reliably classify House of Corrections offenses as drug or non-drug based on the data analyzed for this study – see Methodology at page 46. Based on a rough classification, in the House of Corrections in Middlesex County, the drug/non-drug man-year proportions appear to be similar to the state prison proportions in Chart 18. However, at the House of Corrections level, drug sentences appear, on

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[11] Among males in our two-year subject group, the average maximum sentence for non-drug offenses was 10.5 years and for drug offenses 5.8 years. The average minimums were 7.6 years and 4.4 years respectively. The contrast may be somewhat overstated for those whose offenses occurred before the effective date of "truth in sentencing" on July 1, 1994, but who were sentenced in our study period. For non-drug offenders in this group, the effective sentence may be below the minimum. Our method may

average, to be longer (35% longer in our Middlesex County data), than non-drug sentences; over all, drug offenses may account for as few as 11.0% of the commitments in Middlesex County.

Summary of Drug Sentence Contribution Analysis

The analyses presented here suggest that for Whites, low drug incarceration rates contribute to relatively low overall levels of incarceration experience. For Hispanics and to a lesser extent for Blacks, sentences for drug offenses contribute materially to high overall levels of incarceration experience. The numbers in Chart 17 may be taken as an upper bound on the role of drug sentences in moving men into the category of state prison ex-convicts. If no Hispanic men were sent to state prison for drug offending, the lifetime-to-40-state-prison-experience rate for Hispanics would be reduced by at most half; for Blacks, the reduction would be at most 20%. Because many offenders commit both drug and non-drug offenses, the actual reduction would be less.

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further overstate the true proportion of man-years due to non-drug offenses through our treatment of life sentences. See Methodology at page 42.

Are the offenders punished for drug crimes typically offenders with records of violence and other serious crime?

Overview of Incarcerated Drug Offenders

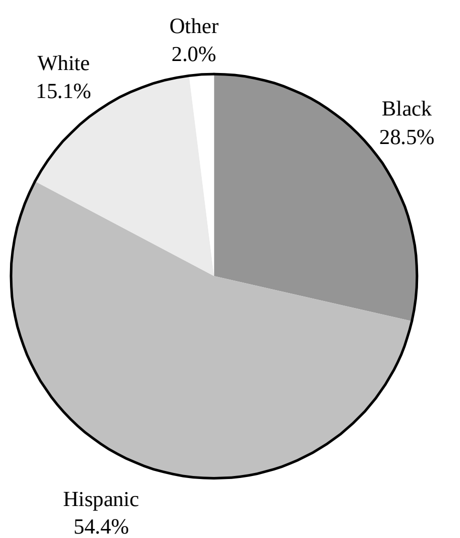
At the outset, it is important to understand the types of offenses that bring drug offenders to state prison. Mere possessory offenses almost never lead to state prison incarceration. 99.2% of state prison level drug offenders are committed for dealing (at a retail level) or trafficking (i.e., selling quantities greater than usually bought by retail users). 99.7% of the commitments involve cocaine or heroin, as opposed to marijuana.

Consistent with the data presented in Chart 11 and Chart 13 above, Chart 19 shows that Blacks and especially Hispanics are over-represented among incarcerated drug offenders. Mandatory sentences, either for "trafficking" (34.0%) or for retail dealing (30.9%), account for almost two-thirds of all of the commitments. Thus, most (54.4%) state prison level drug offenders are Blacks or Hispanics committed pursuant to a mandatory sentence for sale of cocaine or heroin. Most of the rest (28.4%) are Blacks or Hispanics committed pursuant to non-mandatory sentences for sale of cocaine or heroin.

Criminal Histories of Drug Offenders

We analyzed the criminal histories of a random sample of 151 males committed to state prison for

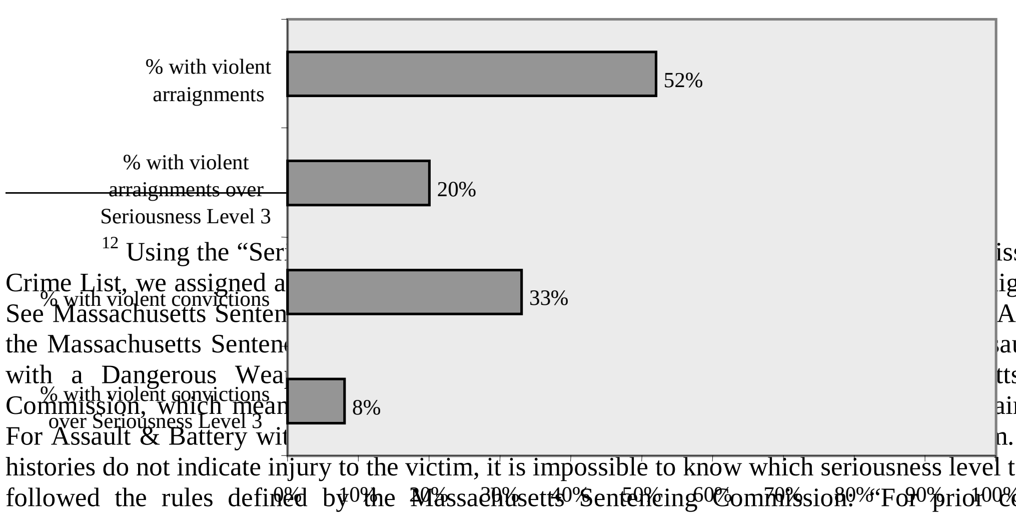
Chart 19: Male Drug Offenders by Race



drug offenses. The criminal records we obtained reflect only adult arraignments in Massachusetts courts. For information about the sample and our procedure for analyzing the criminal histories, see Methodology at page 70. Caution should be exercised in interpreting the findings in this section, because many factors can contribute to understatement of drug offenders' criminal histories. See Methodology at page 77. However, the data that we present here are derived from the official computer files commonly relied upon in Massachusetts courts for evaluation of criminal histories.

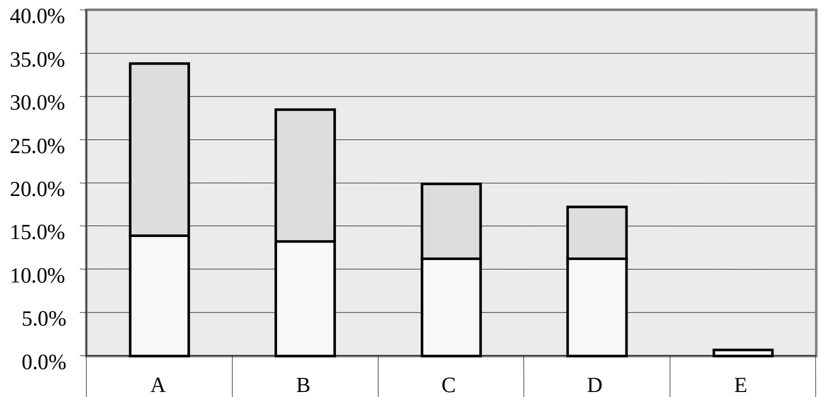
As shown in Chart 20, half of the drug offenders had a prior arraignment for a violent offense in Massachusetts, and one-third had a prior conviction for a violent offense. The majority of the violent offenses for which the drug offenders were arraigned or convicted were Level 3 charges, most of which were Assault & Battery or Assault and Battery with a Dangerous Weapon charges.[12] Only 8% of the drug offenders had a prior conviction for a violent offense above level 3.

Chart 20: Prior Violent Records of a Sample of Male Drug Offenders



[12] Using the "Ser[illegible]ission's Master Crime List, we assigned a[illegible]ignment event. See Massachusetts Senten[illegible]All citations to the Massachusetts Senten[illegible]ault & Battery with a Dangerous Wea[illegible]tts Sentencing Commission, which mean[illegible]aircase factor." For Assault & Battery wit[illegible]n. As criminal histories do not indicate injury to the victim, it is impossible to know which seriousness level to assign. We followed the rules defined by the Massachusetts Sentencing Commission: "For prior convictions of staircased offenses, there is a rebuttable presumption to count the prior conviction in the lower(est) staircased level for that offense in the Master Crime List" (p. 17).

Chart 21: Male Drug Offender Sample by Age at Incarceration (compared to Median age of 29.8) and Criminal History Group (sum of all cells = 100%)



	A	B	C	D	E
Age under Median	19.9%	15.2%	8.6%	6.0%	0.0%
Age over Median	13.9%	13.2%	11.3%	11.3%	0.7%

To derive an overall view of the caliber of offenders being sentenced for drug crimes, we used the Massachusetts Sentencing Guidelines "Criminal History Group" framework. The Massachusetts Sentencing Commission defined groups ranging from A to E (least to most serious) according to the number and severity of prior convictions. We computed the criminal history group for each person in our sample of state prison sentenced drug offenders. See Methodology at page 73 for more detail on this classification.

Chart 21 shows that most drug offenders have no/minor (A) or moderate (B) records. The meaning of an "A" record is that the offender has never been convicted or has been convicted of only minor infractions – such as motor vehicle violations, disturbances of the peace and simple drug possession – and not more than five such infractions. "B" records may have more of these minor infractions or may have one or two moderately serious offenses such as assault and battery (inflicting moderate injury), a larceny or a drug retailing offense. Even among older drug offenders, who have had more time to build a record, the majority (13.9% plus 13.2% out of 50%) have only an A or B record.[13] If drug offenses are excluded from

[13] These findings are generally consistent with the survey of sentencing practices conducted by the Massachusetts Sentencing Commission. See Table 14, "Convicted and Incarcerated Defendants by Offense Seriousness Level, Criminal History Group and Offense of Conviction – Superior Courts," in Sentencing Commission Report.

the computation of criminal history, then 78.8% have A or B records -- 49.0% of the drug offenders have "A" non-drug records and 29.8% have "B" non-drug records.

Putting aside for the moment traffickers, those receiving longer mandatory sentences for distributing 14 grams or more of cocaine or heroin, Table 5 focuses on non-traffickers. These are persons sentenced to state prison for various categories of retailing offense, predominantly (69.5%) first offense sale of cocaine or heroin. Table 5 shows the average of the minimum sentences that they received, grouped by their criminal history groups. (State prison sentences are imposed as a range from minimum to maximum). Table 5 also shows crimes that would earn equivalent sentences under the Guidelines for offenders with comparable criminal histories. The inference from Table 5 is that first offense cocaine and heroin retailing is often treated as comparable to serious non-drug offenses.

Table 5: Average Minimum Sentences for Non-Traffickers in Sample by Criminal History Group and Comparison to Guidelines for Other Crimes

Criminal History Group	**Count in Sample**	**Average Minimum Sentence (months)**	**Representative Offenses which would earn same minimum sentence under Sentencing Guidelines for offenders in same Criminal History Group**
A	27	37.4	Armed Robbery or Involuntary Manslaughter
B	32	40.7	Armed Robbery or Involuntary Manslaughter
C	23	37.7	Unarmed Robbery or Larceny over $50K
D	22	42.3	Unarmed Robbery or Larceny over $50K
E	1	48.0	Unarmed Robbery or Larceny over $50K

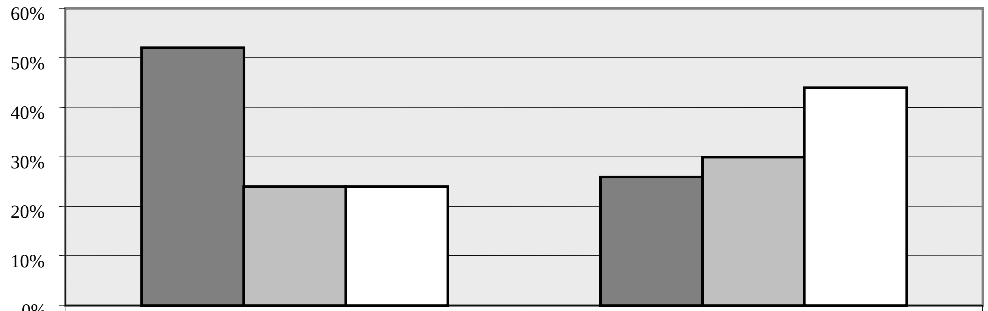
Comparison of Traffickers and Non-Traffickers

We explore here the issue of how traffickers, those receiving longer mandatory sentences for distributing 14 grams or more of cocaine or heroin, compare to other drug offenders.[14] Methodology at page 78 provides additional detail on this comparison.

Using criminal history groups in Chart 22, we see that the traffickers have significantly less serious criminal pasts. Over half of the traffickers fall into Criminal History Group A ("No/Minor Record"), while the same is true for only one-quarter of the non-traffickers. 24% of the traffickers as against 44% of the non-traffickers are classified as having a serious record falling into Groups C through E.

[14] Note that the category "other drug offenders" includes roughly equal portions of offenders serving mandatory and non-mandatory sentences. Among the mandatory sentenced charges, 39.9% are for second offense retailing, 42.7% for cocaine retailing (charged by prosecutorial decision under an enhanced penalties statute), and 16.5% for school zone offenses.

Chart 22: Comparison of Traffickers and Non-Traffickers by Criminal History Group

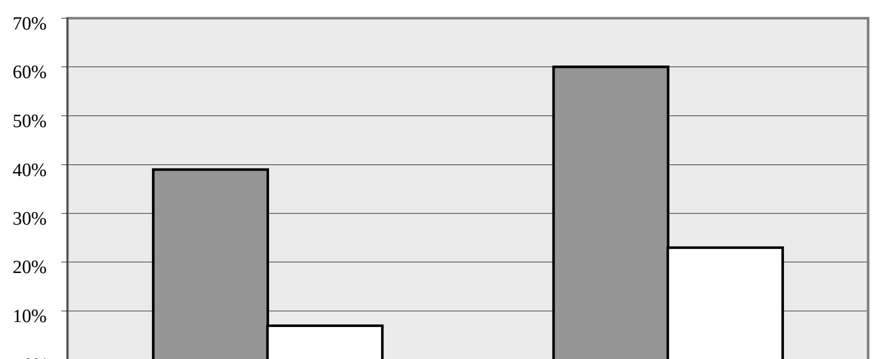


	Traffickers	Non-Traffickers
A	52%	26%
B	24%	30%
C-E	24%	44%

Chart 23 illustrates that the traffickers have significantly lower percentages of prior incarceration both in Houses of Corrections and State Prison.

Especially given the traffickers' generally lighter Massachusetts records, to receive sentences as stiff as their longer mandatory sentences they would have to commit very serious non-drug crimes. Table 6 shows the average of the minimum sentences that they received, grouped by their criminal history groups with comparable crimes from the sentencing guidelines as in Table 5.

Chart 23: Comparison of Traffickers and Non-Traffickers by Prior Incarceration



	Traffickers	Non-Traffickers
Prior HOC	39%	60%
Prior State Prison	7%	23%

Table 6: Average Minimum Sentences for Traffickers in Sample by Criminal History Group and Comparison to Guidelines for Other Crimes

Criminal History Group	Count in Sample	Average Minimum Sentence (months)	Representative Offenses which would earn same minimum sentence under Sentencing Guidelines for offenders in same Criminal History Group
A	24	103.0	Voluntary Manslaughter or Rape of Child with Force
B	11	42.6	Armed Robbery (no gun) or Involuntary Manslaughter
C	7	89.1	Voluntary Manslaughter or Rape of Child with Force
D	4	54.0	Unarmed Robbery or Larceny over $50K
E	0		

Summary of Drug Offender Characteristics Analysis

The analyses presented here suggest that, while the records of state prison drug offenders cannot be readily typified, a majority of them are light or moderate. Many of the offenders have no known record of violence. Therefore, we cannot say that our heavy mandatory penalties for drug offenses are usually operating to incapacitate individuals who are dangerous apart from their drug-dealing. The value of our drug sentencing policies, particularly for trafficking offenses, must be judged on their fairness and their direct effectiveness in deterring drug dealing, not, for the most part, on their indirect value in incapacitating generally dangerous individuals.

METHODOLOGY

Concentration Analyses – Alternative Measurement Frameworks

Use of 1990 Census Data

Except as noted, all of the sociodemographic data used in this study are derived from the 1990 Census.[15] There is, of course, no real alternative to decennial census data for detailed socio-demographic analysis. However, we considered the possibility that the date mismatch between our census data and our other mid-decade datasets might introduce some distortion or bias. In general, given our primary use of the census data to select and characterize *neighborhoods*, we saw no risk of meaningful inaccuracy. While neighborhoods may move from just below a given cutoff to just above it in a span of five years, they are unlikely to completely change in character. Similarly, comparisons to national averages change slowly. The Massachusetts poverty rate in 1989 was 8.9% as compared to the national average of 13.1%. Five years later, in 1994, the poverty rate in Massachusetts was again roughly two-thirds the national average – 9.7% as against 14.5%.[16]

One significant change occurred with some local predictability between 1990 and 1995: The age structure moved forward 5 years. The only place in this study where it seemed important to correct for the changing age structure was in our comparisons of incarceration rates and experience by racial groups. These adjustments are flagged in the appropriate sections.

Census Undercount

One factor that may tend to bias our estimates of commitment and incarceration rates upwards is the undercount of minority males in poverty areas. The magnitude of this undercount is a controversial question. According to an unpublished Census Bureau memorandum, provided by Alan Zaslavsky of Harvard Medical School, the undercount rate is 15.83% in urbanized areas in the Northeast for non-home-owning Black males in the 18 to 29 age range. Homeowner rates, Hispanic rates and rates for older males are lower, according to the Census memorandum. However, in any given city, the undercount rate may be considerably higher. In part for this reason, in most charts, we present only aggregates combining areas in Massachusetts. Most other uncertainties tend to down-bias our estimates, so that we do not believe that our estimates of minority incarceration rates are materially inflated.

The Basic Hypothesis

Our basic hypothesis in the concentration analysis was that the state prison population would be dense in urban poverty areas relative to other areas of the state. Our concern was not so much to validate this widely received hypothesis, but to measure the magnitude of the contrast. Our concentration analysis was a descriptive exercise. This section describes our measurement approach.

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[15] Specifically, Summary Tape File 3A on CD-ROM prepared by the Bureau of the Census, Data User Services Division as Reissued in November 1995. Except as noted, all definitions of terms are as they appear on the technical documentation for that file. Note that most definitions of Census Bureau terms may be found in the standard appendices to any publication of the 1990 decennial census. In a few instances special cross-tabulations (for example, poverty status by race by age) are derived from SSTF 17, see note 18.

[16] See Bureau of the Census, Current Population Reports Series P-60/189, "Income, Poverty and Valuation of Non-Cash Benefits," 1994.

Basic Definitions

We used the standard Census Bureau definition of "poverty" (household income below a set of levels that vary as a function of household composition).[17] We followed the Census Bureau in defining poverty *tracts* as those in which over 20% of the persons live in households with incomes below the poverty line. We also followed the Census Bureau in referring to tracts in which over 40% live in households with incomes below the poverty line as "extreme" poverty tracts.[18]

We considered narrowing our focus to urban poverty tracts, as possibly differing from rural tracts. However, in Massachusetts, this distinction is largely irrelevant. Table 7, shows the results of applying alternative urbanicity concepts.

Table 7: Comparison of Poverty Area Urbanicity Definitions

	Count of Tracts[19]	Population	Poverty Rate	Commitment Rate per 100,000 Males
State Total	1,331	6,016,425	8.9%	78
Non-Poverty Areas	1,119	5,277,220	6.2%	50
Urban	771	3,495,614	7.1%	63
Rural	348	1,781,606	4.5%	24
Poverty Areas	212	739,205	29.4%	294
Urban	209	723,085	29.5%	301
Urban in Urbanized Area	202	695,311	29.6%	312
Metropolitan	200	694,263	29.6%	313
Clusters over 1,000	196	692,537	29.6%	314
Clusters over 10,000	173	612,635	29.9%	321
Elder Areas excluded	170	599,955	30.2%	322
Student Areas excluded	143	464,361	30.5%	386

In Table 7, we classified tracts as "urban" if 100% of the population in them was classified by the Census as living in an urban place – i.e., a Census place (city, town, village, borough or other designated place) with more than 2,500 persons. Similarly we classified tracts as in an urbanized area if 100% of the

[17] The Census Bureau defines persons in poverty as persons in households with incomes below a set of nationally defined levels specific to household size and structure. The levels are derived from a definition originally developed by the Social Security Administration in 1964 and subsequently refined through federal interagency committees. For example, the poverty line in 1989 for a family of four, two adults and two children, was $12,575. Household income includes public assistance benefits. Poverty status is not determined for institutionalized persons, personnel living in military group quarters, students living in college dormitories, or "unrelated individuals" under 15 years old, e.g., foster children. All poverty rate statistics exclude these groups. For example, in 1989, the Massachusetts poverty rate was 8.9% – i.e., 8.9% of the persons for whom poverty status was determined in Massachusetts had incomes below the poverty line.

[18] For Census Bureau discussion of poverty tracts see "Statistical Brief: Poverty Areas," http://www.census.gov/socdemo/www/povarea.html (as last revised on March 13, 1997). For complete data on poverty areas nationwide see Census of Population and Housing, 1990: Special Subject Tape File (SSTF) 17 on CD-ROM, *Poverty Areas in the United States* [machine-readable data files], prepared by the Bureau of the Census, Data Users Services Division, 1994. We also follow a Census Bureau convention in rounding the poverty rate to the nearest integer before applying the definitional inequality. So that, in effect, poverty tracts are those with a poverty rate greater than 19.5% and extreme poverty tracts are those with a poverty rate greater than 39.5%.

[19] The total of 1331 includes 4 "Block Numbering Areas" or "BNA's." In some sparsely populated non-metropolitan counties, the Census Bureau has not established tracts. In these counties, the Census Bureau reports on BNA's, which are statistical subdivisions created in 1990 for untracted counties. These statistical subdivisions are delineated according to guidelines similar to those for delineating tracts. In Massachusetts, the only untracted county is Nantucket. On Nantucket, there are 4 block numbering areas, which we treated as if they were census tracts for all purposes in this report.

population in them was living in “urbanized” area – an “urbanized area” is a central urban place together with a densely settled fringe with at least 50,000 persons. Tracts were classified as “metropolitan” if they fell in Metropolitan Areas, federal statistical areas designed to represent population nuclei together with their socially and economically integrated suburbs. Note that census tracts can straddle Metropolitan Area boundaries, but that no poverty tracts do in Massachusetts; similarly, while Metropolitan Areas can include rural or non-urbanized areas, all metropolitan poverty tracts in Massachusetts are urban and in urbanized areas.

Table 7 also shows the effect of excluding “elder” and “student” areas. “Elder” areas in this chart are areas where exclusion of the elder population in the poverty rate computation changes the classification from poverty to non-poverty. There are four such tracts, three of which fall in poverty clusters over 10,000. (There are no tracts for which exclusion of elderly population moves the tract from extreme to non-extreme poverty.) “Student” areas are tracts in which either there is a dormitory or other housing dedicated to college students or over 20% of the persons in non-college-dedicated housing are enrolled in college. This is a reasonable definition intended to be inclusive.[20] Among statistically poor tracts, it captures the Amherst area (5 tracts), the Allston-Brighton-Kenmore area (15 tracts) and 15 other scattered tracts. It captures 89 tracts in non-poverty areas.

It is clear from Table 7 that the various reasonable definitions of urbanicity result in largely overlapping groups of census tracts.

The gradient in state prison commitment rates apparent as one progresses down narrower definitions of urbanicity in Table 7 arises from a combination of three phenomena. First, the larger clusters include more extreme poverty areas that have higher commitment rates. Second, the smaller clusters include some significant student areas that have lower commitment rates. Third, there appears to be a modest commitment rate gradient associated with urbanicity or cluster size.

Table 8 is intended to disentangle these influences by showing the matrix of census tracts classified on each of these three dimensions – poverty rate, student population and urbanicity/cluster size. In Table 8, “student areas” are areas meeting the criteria above and “small clusters” are clusters which are either under 10,000 in size *or* not in urban areas.

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[20] Since 1950, the Census Bureau has enumerated college students in the tracts in which they reside while attending college, as opposed to in their parental homes. Calculations based on Table PB18 in Special Subject Tape File 17 indicate that in poverty areas, among persons in the 18-24 age group who are high school graduates and enrolled in school and not resident in a dormitory (i.e., are likely off-campus resident college or graduate students, although not necessarily full time), the poverty rate is 49%. In extreme poverty areas, the non-dormitory student poverty rate is only slightly higher: 53%. Our criteria for student areas select 34 poverty tracts. As a test of the reasonableness of these criteria, we tried adjusting the poverty rate downwards by subtracting from the numerator (persons below poverty) half of the non-resident college-student population (as suggested by the analysis of Table PB18). This test adjustment would move 24 tracts of the 34 student poverty tracts below the poverty rate cutoff; in 5 of the other 10, the bulk of the population is resident in dormitories. Applying the same adjustment to poverty tracts not selected as student tracts by our criteria moves an additional 41 tracts below the poverty rate cutoff (20%). All of these tracts have unadjusted poverty rates just slightly above the poverty rate cutoff of 20% – none have of poverty rates over 24%. In most instances, the test adjustment moves most of them just below the poverty cut off – 36 of the 41 have adjusted poverty rates over 15%. Thus our criteria seem to select fairly well the poverty tracts most affected by the presence of students.

Table 8: State Prison Commitment Rates per 100,000 Males as Related to Classification of Census Tract by Poverty, Student/Population and Cluster Size over 10,000 in Urbanized Area or Not

	Tracts	Population	Poverty Rate	Commitments per 100,000	
				Annualized	½ of 95% C.I.
Poverty Areas – 20 to 39%	170	630,011	26.3%	259	10
Student areas in small clusters	7	40,777	26.1%	18	14
Student areas in large clusters	23	120,556	27.4%	139	22
Non-student areas in small clusters	25	79,160	24.3%	253	42
Non-student areas in large clusters	115	389,518	26.4%	339	22
Extreme Poverty Areas – Over 40%	42	109,194	47.6%	524	37
Student areas in small clusters	0	-	-	-	N/A
Student areas in large clusters	4	15,038	43.0%	289	69
Non-student areas in small clusters	7	6,633	60.2%	261	90
Non-student areas in large clusters	31	87,523	47.4%	605	46
NON POVERTY AREAS	1,119	5,277,220	6.2%	50	2

Inspection of Table 8 makes clear that there are statistically significant differences in commitment rates between most of the appropriately comparable subcategories (95% confidence intervals do not overlap). Within levels of poverty and cluster sizes, student areas differ significantly from non-student areas. Within levels of poverty and student/non-student areas, cluster size is significant. Overall, however, the widest differences are between non-poverty, poverty and extreme poverty areas.[21] It is this perspective, together with the fact that most poverty areas are in large non-student areas anyway, which made us comfortable with simplifying the presentation in the body of the text by distinguishing only by poverty level.

Table 9 presents sociodemographic data for each of the state's 13 urban poverty clusters with population over 10,000 by city containing them. (Recall that as noted in the Findings text, some of these cities also contain some unclustered poverty tracts.) The Allston/Brighton/Kenmore student area is recognizably different from the other clusters.

Table 9: Characteristics of Persons in Massachusetts Large Poverty Clusters (1990) by City/Town Containing Them

Location of Urban Poverty Area	Total Persons	% Poor	% of over 25 without HS degree	% of families with children headed by females	% of households with public assistance income	% of males over 16 not in labor force
Allston/Brighton/Kenmore	82,290	28.64%	14.14%	27.48%	6.54%	34.36%
Boston	170,307	28.57%	37.53%	56.28%	24.00%	29.74%
Brockton	22,617	25.02%	34.70%	43.93%	25.05%	29.96%
Chelsea	20,441	27.25%	41.42%	46.76%	24.98%	24.69%
East Boston	10,533	26.78%	47.69%	45.11%	23.12%	32.61%
Fall River	19,667	22.11%	66.90%	31.36%	23.00%	32.34%
Holyoke	17,950	46.99%	50.80%	60.40%	41.32%	41.66%
Lawrence-Methuen	61,215	32.12%	46.17%	44.72%	23.80%	30.56%
Lowell	34,922	33.38%	51.03%	42.37%	26.95%	35.21%
Lynn	26,833	28.26%	38.36%	46.40%	20.60%	32.20%
New Bedford	24,848	25.93%	51.75%	43.22%	24.42%	36.46%
Springfield	65,692	35.79%	41.71%	58.61%	29.29%	38.23%
Worcester	55,320	28.07%	41.30%	48.59%	22.45%	35.16%
Unclustered/Non-Urban	126,570	26.39%	32.50%	42.42%	18.27%	35.44%

[21] The attentive reader may notice the wide difference between small and large non-student extreme poverty clusters. This is an artifact. Five of the seven small non-student extreme poverty clusters consist primarily of populations in institutional or other group quarters.

Alternative Measurement Approaches

One can vary one's approach to defining poverty areas in three other ways beyond the urbanicity/cluster-size variations considered above. First, one can vary cutoff levels, either for the poverty line itself or for the concentration of poverty constituting a poverty area. Second, one can look at attributes other than income level in defining poverty. Third, one can adjust geographical boundary definitions to reflect edge effects.

Cutoff Variations

In varying income cutoff levels for the poverty line, the only readily feasible approach is to use Census-Bureau-supplied rates of households having incomes below fractions and multiples of the poverty line. Of course, these rates are highly correlated with each other. Since our use of the poverty level is to select tracts with concentrated poverty, varying the poverty level cutoff has roughly the same effect (inversely) as varying the required concentration level. See Table 10.

Table 10: Offsetting Effects of Alternative Cutoff Levels

Income Cutoff	Concentration Cutoff	Number of Tracts Selected	Overlap between Selected Tracts and Poverty Tracts
Standard Poverty Line	20.0%	212	100.0%
50% of Standard Poverty Line	7.4%	212	82.5%
200% of Standard Poverty Line	41.6%	212	80.2%

Our approach in this study is to hold the poverty level cutoff fixed, but to present results using several alternative poverty concentration cutoffs in defining poverty areas. The main variations presented in the body of the text are the 20 and 40% cutoffs chosen by the Census Bureau and the poverty rate decile groupings.

The decile groupings were derived by sorting all tracts by poverty rate and then picking cutoff levels that grouped the tracts into ten groups, each including 10 percent of the population. In the highest poverty decile, the lowest tract poverty rate in the group is 21.6%. This decile includes 177 tracts, all of which, of course, are among the 212 poverty tracts (poverty rates greater than 20%).

The second highest-poverty-rate decile of tracts consists primarily of working class neighborhoods in larger cities. The lowest poverty rate in this decile is 12.9%, and 58.9% of the population in this decile comes from the 12 cities in the state which include clusters of poverty tracts with over 10,000 persons. The lower-poverty-rate deciles represent gradations of increasingly homogeneous non-poverty with the lowest-poverty-rate deciles corresponding to upper income suburbs.

Poverty Related Attributes

Income below the poverty line is statistically correlated with many other variables measured by the Census Bureau – for example, education level, family formation, labor force participation, receipt of public assistance income. One could use one or more of these variables to select "poverty" tracts. For example, one could define poverty tracts as tracts in which there are high concentrations of both female-headed households and males outside the labor force.[22]

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[22] Or, one could combine variables *before* measuring concentration – i.e., one could select tracts having a high concentration of individuals who are simultaneously poor, outside the labor force and undereducated. Some experimentation with pre-comparison combination of variables suggests that it leads

A basic poverty line approach captures most of the relevant nuances of more complex approaches. Table 11 summarizes some observations about the correlation of several poverty-related variables with the rate of state prison commitments among males.

Table 11: Correlations of Tract Concentrations of Selected Variables from 1990 Census with Rate of Commitments to State Prison

Variable	Correlation with Commitment Rate
Poverty Rate (persons below poverty among person for whom poverty status is determined)	.659
Poverty Rate (adjusted down by of half of college students not resident in dormitories)[23]	.679
Incomes below 50% of Poverty (among persons for whom poverty status is determined)	.599
Female Headed Households (among households with children)	.760
Labor Force Non-Participation (among men over 16)	.266
Lack of High School Degree (among persons over 25)	.582
Public Assistance Income (among households)	.803

All of the correlations are statistically significant at or below the .01 level. The public assistance rate is the strongest predictor of the rate of DOC commitments. However, using public assistance concentrations to select tracts does not result in a selection of tracts substantially different from our poverty selection. 79.4% of the tracts in the decile of tracts with the highest public assistance rates are also included in the highest poverty rate decile of tracts. The difference in selection looks even less meaningful when one looks examines the share of state prison commitments in the alternative tract groupings:

Table 12: Comparison of High Public Assistance Tracts to High Poverty Tracts

	Number of Tracts	Percentage of Total Population	Share of Total DOC Non-Drug Commitments	Share of Total DOC Drug Commitments
Highest Poverty Rate Decile of Tracts	177	10.0%	34.7%	50.1%
Highest Public Assistance Rate Decile of Tracts	176	10.0%	37.8%	53.5%

A linear regression model entering all of the variables in Table 11 (entering the non-dormitory college student rate on its own along with the unadjusted poverty rate) explains only 4% more of the variance in commitment rates than does a one-variable model using public assistance rate as the independent variable. (The public assistance rate explains 64% of the variance.) Thus, combinations of variables can add little to the predictive power of the public assistance rate. And the import of Table 12 is

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to a similar selection of tracts. See Kasarda, JD, 1992, "The Severely Distressed in Economically Transforming Cities," in Harrell AV and Petersen GE in Drugs, Crime and Social Isolation (Washington, Urban Institute Press) at page 57.

[23] See note 20.

that for our purposes of subject tract selection, use of the public assistance rate adds little precision over the use of the standard poverty rate measure.

The absolute concentration of state prison commitments only modestly exceeds the concentration of prisoners in poverty areas:

Table 13: Comparison of High State Prison Commitment Rate Tracts to Poverty Tracts

	Number of Tracts	Percentage of Total Population	Share of Total DOC Non-Drug Commit-ments	Share of Total DOC Drug Commit-ments
Highest Poverty Rate Decile of Tracts	177	10.0%	34.7%	50.1%
Highest State Prison Commitment Rate Decile of Tracts	172	10.0%	44.2%	59.6%

Since grouping by rate of state prison commitments results in the maximal concentration of commitments in the top decile, Table 13 shows the limited potential for more parsimonious explanation of the concentration of prison commitments through any alternative method of tract selection.

Given the foregoing, given the value of simplicity, and given the modest difference in tract selection by poverty rate and tract selection by public assistance rate, we elected to rely on poverty rate for most purposes.

Geographic Boundaries of Neighborhoods

Generally, the census tract is the geographic unit of analysis chosen in most studies of neighborhoods. Tract boundaries, when established, represented relatively homogeneous neighborhood groupings. Tract homogeneity may have declined over time in some tracts. The Census Bureau does offer socio-demographic breakdowns at a geographic level finer than the tract – the block group. There are, on average, 4.2 block groups per census tract in Massachusetts. Early in the study, we explored use of block group data as a way to refine our definitions of troubled "neighborhoods."

We observed that most high-poverty-rate block groups tend to occur in high-poverty-rate census tracts. We further observed that the marginal refinements possible in poverty neighborhood boundaries resulted in little net change in the share of state prison commitments included in those neighborhoods. Also, the use of block groups introduced a patchiness to the patterning of poverty areas which was inconsistent with a commonsense understanding of neighborhoods. For these reasons, and given the general acceptance of tract level analysis, we used census tracts as our units of analysis throughout this study.

We also were concerned with the issue of edge effects around the natural clusters of urban poverty tracts. Do tracts around the edges of poverty areas, influenced by those areas, include an important share of the state prison commitments? We conducted two analyses to explore this issue.

First, we mapped tracts for which the poverty decile ranking was more than two levels different from the state prison rate decile ranking. No pattern was evident on inspection of these maps (except that many tracts in the rural western part of the state tended to have lower state prison rates in relation to their poverty rates).

Second, we tested an alternative hybrid area construct – reflecting not only poverty but incarceration rates. This is a circular construct for the purposes of analyzing how poverty relates to incarceration rates, but has some heuristic value in understanding how incarceration rates vary around the edges of poverty areas. We appended to our existing urban poverty areas two groups of tracts, those surrounded on more than 50% of their perimeter by the poverty area (measured roughly by inspection) and those tracts in the highest state prison rate decile which were to any extent contiguous to an urban poverty area. For the second group of additional tracts, but not for the first, we iterated along chains of contiguous tracts to include additional tracts. This construct, while capturing more of the high commitment rate tracts, also turned out to have a patchy effect – adding edge tracts inconsistently. In the end we saw little analytic or descriptive value in the expanded construct. The exercise did assure us, however, that there were not consistent edge effects that we were missing in our basic definition of Poverty areas.

Except as noted in this study, we used the basic definitions of poverty and extreme poverty areas outlined under Basic Definitions above.

Data Acquisition and Quality Issues

Department of Correction

Selection of Study Population

The Department of Correction (DOC) began maintaining home street addresses for prisoners in early 1994. These addresses are acquired at the time of admission so that only recently admitted prisoners have street addresses; addresses were consistently acquired beginning in June 1994. We began our study in December 1996. We selected prisoners admitted in the two-fiscal-year period, July 1, 1994 through June 30,1996, as our study population.

DOC maintains records on all individuals admitted to its facilities. In addition to individuals actually sentenced to state prison following conviction for a felony offense, the records include prisoners transferred from other correctional systems, prisoners awaiting trial, persons committed for alcohol rehabilitation and persons committed for observation or detoxification at the Bridgewater facility. We selected only those individuals actually committed to state prison per se after conviction for a crime.

In reaching our final study population tally of 4,486, we excluded 29 commitments that were last-name/first-name/date-of-birth duplicates of other commitments in the database.[24] In all analyses presented in the study, we further selected the 4,202 (93.7%) prisoners committed in the study period who were male. Since most county Houses of Correction have limited facilities for females, most female convicts in the state are housed in the DOC facility in Framingham. This facility thus houses a mixed female population including many inmates serving short sentences which, for males would normally be served in a House of Corrections. Only 284 (6.3%) out of 4486 commitments in the study period were females. However, some additional committed female inmates are booked as transfers from Houses of Corrections. Our data on transfers is incomplete. We focussed on male inmates.

Except in Chart 14 and Chart 16, in all charts and tables that present data by geographic area (e.g., Urban Poverty area), subjects whose addresses were missing, out-of-state or otherwise could not be geocoded are excluded. Among in-state offenders, the exclusion of missing or non-geocodable street addresses, results in an absolute understatement of commitment rates by 9.4%, but creates only minor distortions in relative rates among categories displayed. See Methodology at page 62.

The data as maintained by DOC does not distinguish prisoners committed immediately following conviction from prisoners initially placed on probation and committed after a violation of probation. Prisoners committed for violations of probation are booked as if they were directly committed for the

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[24] Inspection of these duplicates suggested that: 6 possibly involved bad records; 9 were possibly on-and-after sentences booked as separate commitments; and 14 were possibly actual second commitments in the two year period. In 26 instances we chose the earlier of the two commitments; in 3 instances, the data on the earlier record was incomplete and we chose the later. It is possible that exclusion of these duplicate commitments contributed to a slight understatement of overall sentencing impact.

underlying crime for which they were originally placed on probation. In our analyses, we made no effort to differentiate probation violators. [25] It was unnecessary to differentiate parole violators – state prison parolees whose parole is revoked come back under their original commitment number, so that our commitment records only include new commitments.[26]

Data Quality Issues

All of the DOC prisoner data used in this study originates from the routine booking and record-keeping activities of DOC personnel (the only exception being the criminal history research conducted by the study team for a subset of the study population).

The critical variables used in most analyses in this study are age, race, sex, address, charge and sentence. Data quality issues around the address are discussed in the section on geocoding. Age and race may not be completely reliable, but we have no reason to suspect any systematic bias in these fields.

Given the complexity of statutory charge and sentencing data, our principal concerns for accuracy were in this area.

Charge, i.e. statutory violation leading to conviction, was present on all but 11 records (of which only 7 were geocodable). These records are grouped as "non-drug" in analyses which divide drug and non-drug offenders. Minimum and maximum sentences were present for all but 17 offenders.

For averaging purposes in Chart 18, 168 life-sentenced offenders (regardless of parole eligibility) were treated as having been sentenced to a minimum of 50 and a maximum of 60 years. This probably overstates actual years served especially for parole eligible lifers, and so tends to overstate the role of non-drug sentences in Chart 18. Because, using this rule, life sentences amount to 34.8% of the aggregate of minimum sentences for non-drug offenses (among male prisoners in our sample with geocodable addresses), the effective overstatement could be material. Unfortunately, we do not have data that would allow us to estimate actual averages for life sentences. The actual averages are a function of historically variable parole and pardon policies.

DOC records clerks capture charge and sentencing data at the time of admission from the "mittimus" (in effect, the routing/instruction slip from the sentencing court which the prisoner arrives with). DOC provided us only the lead charge in the database, usually the first charge listed on the mittimus, which is also usually the most serious charge (i.e., the one carrying the longest sentence).

The research staff at DOC compiles a second database of commitments for purposes of preparing annual statistics. In this process, an effort is made to independently identify the most serious charge at commitment. In order to verify the quality of the booking system data we were using, we compared our data to the latest calendar year of data then available from the research staff – 1995.

The agreement rates were high: Among 1,664 commitments for non-drug offenses in 1995 according to the booking system data, 99.4% had a non-drug offense as most serious offense on the research database. Among 643 drug commitments, 97.3% had a drug offense as most serious offense on

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[25] While it is unclear whether any differentiation is merited in principle, it is clear that differentiation would not affect our results significantly. In the course of examining criminal histories of 153 in-state males from within the study population who, according to DOC data, were committed for drug offenses, we determined that 2 (1.0%) were committed for violations of probation. Among 187 who, according to DOC data, were committed for non-drug offenses, we determined that 16 (or 8.6%) were committed for violations of probation.

[26] Our examination of criminal histories confirmed this. We were generally able to match a commitment on the criminal history to the current DOC commitment (see further discussion of this issue in the section on analysis of criminal histories).

the research database. Among the 17 of the 643 that had a non-drug offense as most serious, 10 had a secondary drug offense.

We took a closer look at the 643 drug offenses in the booking/intake data:

Table 14: Comparison Between Lead Offense Recorded at Intake and Most Serious Offense identified by Research Staff

Intake Data Drug Offenses as Compared to Research Data	% of Intake Drug Offenses
Exact matches	91.0%
"Close matches"	5.4%
Non-match with drug offense	0.9%
Non-drug offenses (non-match)	2.6%

In the above table, close matches are those in which the charges were highly similar, e.g., the databases differed only as to whether the drug involved was heroin or cocaine, while agreeing on the weight sold.

As to sentence lengths, we found that minimum sentences agreed within 6 months in 95.7% of the 2,307 comparisons, and maximum sentences agreed within 6 months in 94.9%. In almost every instance of a greater difference, the research database had a longer sentence. In the analyses in this study, the sentence length always is treated as a proportional quantity (e.g., total years sentenced for drug offenses as a percent of total years sentenced for all offenses), so a small consistent down bias in reported sentence should not affect any of our results materially.

Given the high agreement rates and the more complete availability of the booking data, we elected to rely solely on that data.

Weapons Related Injury Surveillance System

Acquisition and Processing Issues

The Weapons Related Injury Surveillance System WRISS is a data collection system operated by the Department of Public Health. Hospital emergency rooms admitting patients for weapons related injuries are required to collect a quite complete set of facts about the injury, including the residential address of the victim.

The project team, serving as unpaid consultants to the WRISS unit, geocoded the most recent full year of incidents available (1995), using our Standard Procedure for geocoding detailed below. After creation of aggregations by census tract, all information relating to individual victims was returned to the WRISS unit (supplemented with latitude and longitude geocoding for the victims).

Table 15 provides a summary accounting for our processing of the WRISS data.

Table 15: WRISS Data Processing

Initial 1995 Records Provided by WRISS Unit	2,624
Duplicates (patients transferred among hospitals) eliminated	-59
Self-inflicted and accidental injuries (identified based on hospital reports and WRISS unit analysis) eliminated	-215
Missing and out-of-state addresses	-154
Geocoding attempted:	2,196
Geocoding successful (89.9% of attempted)	1,975

Accuracy Issues

The completeness of the WRISS data depends on hospital consistency in reporting the data. The WRISS unit conducts a compliance audit process. The 17 larger hospitals, that provide most of the data, are audited annually, while the roughly 70 smaller hospitals are grouped in a pool, and are individually audited only on a three-year cycle. The audit of each hospital is based on a sample of cases, so compliance rates are estimates. The WRISS unit estimates 1995 statewide compliance at 75% with a 95% confidence interval of 71 to 80%.

Estimates of individual hospital compliance rates range from 58 to 97%, but the confidence intervals around those estimates are large enough that only one hospital is statistically different from the statewide average. In particular, the compliance rate of the pool of 70 smaller hospitals (typically serving less urbanized, less poor populations) is slightly lower, but statistically indistinguishable from the compliance rate of the larger urban hospitals as a group. Based on these facts, we made no effort to adjust our geographic analysis for hospital specific compliance rates.

Use of WRISS Victim Data as Validation of Location of Offender Residence

Another issue in using the WRISS data is the possible variance between the census tract of the victim's residential address and the census tract of the offender's residential address. The WRISS files include no location for the offender and no exact location for the incident. However, they do include the city in which the incident occurred. Table 16 shows, for 20 larger cities which include poverty areas as defined in this study, the percentage of victims resident in each city who were injured in that city (where the denominator excludes injuries for which location was unknown). The average for these 20 cities[27] was 87.1%, roughly consistent with a view that most injuries occur close to home.

[27] Note that the 20 cities shown account for 77.0% of all victims whose addresses we were able to geocode.

Table 16: Victims Living in City of Injury
(for 20 Cities including Poverty areas)

Victim Residence City	Total Victims	Total Injured in Residence City	Unknown Injury Location	Residence City as % of Known Injury Locations
Boston	596	356	177	85.0%
Brockton	118	88	18	88.0%
Cambridge	26	17	1	68.0%
Chelsea	49	35	3	76.1%
Fall River	29	24	0	82.8%
Fitchburg	15	13	1	92.9%
Haverhill	18	15	3	100.0%
Holyoke	45	41	1	93.2%
Lawrence	73	22	48	88.0%
Leominster	6	4	1	80.0%
Lowell	35	31	4	100.0%
Lynn	78	64	4	86.5%
New Bedford	70	63	0	90.0%
Northampton	2	0	0	0.0%
Pittsfield	9	7	0	77.8%
Quincy	11	4	2	44.4%
Revere	29	19	2	70.4%
Salem	9	8	0	88.9%
Springfield	197	185	3	95.4%
Worcester	106	92	4	90.2%
TOTAL	1,521	1,088	272	87.1%

In summary, the WRISS data provide a comparison point of modest but material weight in considering the geographic distribution of offenders.

Youth Corrections Data

The Department of Youth Services (DYS) maintains a database of all youths that have been committed to its custody. This database consolidates repeat commitments of youths so that each record reflects a unique individual and contains a history of the individual's repeated commitments.

DYS provided us an extract from their database including 10,249 records of youths committed or recommitted after January 1, 1986. The data were current as of November 21, 1996. The data did not include a sex field, but included both males and females.

The data included an address field for the legal custodian of the youth – i.e., the parent or foster parent. DYS youths may be physically housed with their custodians or in DYS facilities. The custodian's address was used for geocoding. Geocoding was completed according to the standard process described below. See Table 25 for geocoding results.

From this database, we sub-selected 5017 records with initial commitments in the five most recent fiscal years (i.e., between July 1, 1991 and June 30, 1996). Of these records, 4496 had census tracts assigned as a result of successful geocoding.

DYS maintains fields representing the offenses for which the youths were committed. They extracted for us the most serious initial offense and the most serious overall offense (across the initial commitment and any recommitments). Seriousness was ranked according to a DYS hierarchy in descending order as follows: Offenses against the person, weapons offenses, drug offenses involving class B (cocaine), property offenses, other drug offenses, motor vehicle offenses and public order offenses.

Among the 4496 geocoded offenders, 446 or 9.9%, had a drug offense as either their most serious initial offense or their most serious overall offense. In the text (Chart 4 and Table 2), these are described as "drug commitments."

House of Corrections Data

The Norfolk and Middlesex County Sheriffs provided us data on commitments to their Houses of Corrections. Because commitments to Houses of Corrections are relatively short and the periods of data provided were relatively long, many individuals appeared more than once. We consolidated commitment records that had the same last name, first name and date of birth. (Alternative consolidation approaches did not lead to widely different consolidation rates.)

Table 17: Commitments Data Supplied by Norfolk and Middlesex County Sheriffs

	Middlesex	Norfolk
Period provided	1990-1997	1988-1997
Period selected as apparently complete (calendar years)	1992-1996	1991-1996
Commitments in selected period	14,326	7,114
Unique individuals	10,667	5,329
Individuals with first commitment address in county	72.5%	48.8%

In both Middlesex and Norfolk counties, a significant portion of the inmates with addresses had addresses outside the counties (in Norfolk a majority were outside) – see Table 17. This indicates that one would need to get data from all of the counties in a single metropolitan area to have confidence that one was fairly reflecting the incarceration experience of men in that area. This effort was beyond the scope of our project. We made limited use of the House of Corrections data as a result.

We had limited confidence in our reading of the data on charges (crime leading to commitment) in both databases. The charge data was freeform (not coded) and therefore not consistent. We made no use of the charge data in the study (except speculatively at page 26).

Another issue in the House of Corrections data pertained to the annual counts of commitments. The Department of Corrections collects monthly commitment data from the Houses of Corrections and produces a report of annual commitments to the Houses of Corrections. Our annual commitment counts, derived directly from the Middlesex and Norfolk Houses of Corrections' databases, ran 5 to 10% higher than the DOC reported numbers. Because of the freeform ambiguity of the commitment reason (charge) data, we were unable to precisely reconcile these differences, but it appeared that they related to the exclusion of parole violators from the DOC reports.

Bureau of Substance Abuse Services Treatment Admissions Data

The Data Source

The Massachusetts Bureau of Substance Abuse Services (BSAS) operates a Management Information System on admissions to treatment.[28] This system covers all admissions to treatment programs receiving any public funding. Many publicly funded treatment programs also accept clients with private funding. These clients are included in the data. Some programs accept no clients with public funding.

[28] For a general description and history of this system, see Joy Camp, Milly Krakow, Dennis McCarty and Miton Argeriou (1992), "Substance Abuse Treatment Management Information Systems: Balancing Federal, State and Service Provider Needs," *The Journal of Mental Health Administration*,19(1): 5-20.

These programs are not covered in the system. The admissions statistics include detoxification, other acute, and longer-term inpatient treatment as well as outpatient treatment settings.

BSAS provided us with a dataset of all admissions in Fiscal 1996. Health and Addictions Research, Inc. assisted us in understanding the dataset. The dataset included a unique random identifier for each individual, allowing individuals with multiple treatment episodes to be identified. There were 102,862 admissions for 65,456 individuals on the file -- 17,430 had two or more admissions. The identifying information captured and reported to BSAS at the time of admission is very limited, so as to protect confidentiality. The unique random identifier provided to us is a synthetic identifier not used by the people actually inputting the coding data. It is the product of the application of matching algorithms to the universe of admissions. Thus, in a minority of instances it may falsely merge different individuals and in other instances, it may provide more than one identifier for admissions of the same individual.[29] As it turns out, the limited analysis presented in this report is not very sensitive to whether the unit of analysis is admissions or individuals. See Table 3.

Demographic Data on Admissions and Individuals

The file included basic demographic and substance abuse related information. For our limited purposes in this study, we used only race category (non-Hispanic Black, non-Hispanic White, Hispanic and other) and primary substance of abuse. The only tests we were able to perform on these variables were to compare the coding across those individuals with multiple admissions. For 11.1% of individuals with multiple admissions, the race was coded in more than one category. This variation may in part be due to variations in how the same individual is identified at admission, but also may be caused by necessary imprecision in the matching process. For 30.7% of individuals with multiple admissions, the primary drug of abuse varied across admissions. This variation is unsurprising given the prevalence of polysubstance abuse. Both of these fields are routinely used by researchers familiar with the data[30], and we relied on them without further scrutiny.

Geographic Data on Admissions and Individuals

For our analysis, we sought to make use of the geographic information available in the BSAS dataset. Those data consist of a 3 digit city/town code (with values for the 351 cities and towns in Massachusetts, 11 specific neighborhoods within Boston, certain correctional institutions and certain out-of-state locations). In addition, the file includes a zipcode for each record. BSAS staff familiar with the data have doubted the reliability of the zipcode data and we accordingly scrutinized them carefully before making use of them.

(1) Validity of Zip Codes

BSAS provided us a table decoding the 3-digit city/town code. For the 351 Massachusetts cities/towns and the 11 Boston neighborhoods, we supplemented the table with a listing of valid Zip Codes.[31] We then tested the validity of the city/town code and Zip Code combinations appearing on the treatment database. In the table below, the key finding is that of records with city/town code referring to

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[29] Unpublished manuscript, Health and Addictions Research, Inc. (1997), "Developing the MIS Data Set of Distinct Individuals," Boston, MA.

[30] E.g., Joy Camp, Milly Krakow and Dennis McCarty (1995), "Substance Abuse Treatment Admissions, FY1988-1993, a Changing Profile," Health and Addictions Research, Inc., Boston (prepared for Bureau of Substance Abuse Services, Department of Public Health).

[31] In creating this table, we used the 1996 Zip Code Directory, Dome Publishing Company, Warwick, R.I. In addition, for Boston zipcodes, and in a number of other specific instances, we verified the directory data by referring to the United States Postal Service Zip Code database as available online at http://www.usps.gov/ncsc.

non-institutional in-state locations (i.e., the 351 city/towns and the 11 Boston neighborhoods), 88.7% of the records had valid zipcodes.

Table 18: Analysis of Zip Code Validity on BSAS Records

	City/Town Code and Zip Code Combinations	Record Count
Full Database		102,862
Memo: Missing City/Town codes (actually blank)		0
Memo: Missing Zips (actually blank)		0
Memo: Collateral Clients		1,778
Full Database	6,331	102,862
City/Town Code Valid	6,331	102,862
City/Town Code in 400's (Out of State)	449	1,282
City/Town Code in 500's (County correctional)	55	1,378
City/Town Code 600 up (State correctional)	26	271
City/Town Code under 400 (MA Cities and Towns)[32]	5,801	99,931
Zips 00000	171	799
Zips 99999	117	615
Zips other not 01000 through 02800	453	501
Zips 01000 through 02800 (01001-02795)	5,059	98,015
Zip/Town combination valid (88.7% of Under 400)	590	88,614
Town Code in Boston Range (21.6%)	61	19,132
Town Code not in Boston Range (78.4%)	529	69,482
Zip/Town combination invalid	4,469	9,401
Town Code in Boston Range (24.1%)	553	2,264
Town Code not in Boston Range (75.9%)	3,936	7,137
Zip/Town combination valid	590	88,614
ZipCode on STF3B (98.9%) (see below)	510	87,609
ZipCode not on STF3B (1.1%)	80	1005
Zip/Town combination valid	590	88,614
Primary Admissions		87,003
Collateral Admissions		1,611

Given our primary use of the data to map treatment admissions into poverty areas, we were concerned to see how the validity rate varied by size and poverty level of municipality (municipality determined by the city/town code). It follows from Table 19 that Zip Codes for smaller towns are somewhat less likely to be valid and that the validity rate is slightly higher in the 12 large cities with poverty clusters than it is elsewhere. This may tend to skew the concentration of admissions in poverty areas slightly upwards.

Table 19: Zip Code Validity Rates by Types of Cities/Towns on BSAS Records

Unweighted Average Validity Rate for Cities/Towns	76.9%
Percentage of All from Cities/Towns with above Average Validity	94.5%
Percent Valid Among Cities/Towns with above Average Validity	90.3%
Percent Valid Among Cities/Towns with below Average Validity	61.4%
Percent Valid Among 12 Cities with Large Poverty Clusters	90.6%
Percent Valid Outside 12 Cities with Large Poverty Clusters	86.8%

Note the last distinction in Table 18, between primary and "collateral" clients. Collateral clients are dependents and others who are admitted with the primary client but are not receiving treatment for substance abuse themselves. We omitted these clients in the analyses presented in Findings and as noted in the additional tables presented below.

In assessing validity we lastly examined the database to determine if the rate at which the zipcode was valid varied by race and/or primary drug of abuse. As is apparent in Table 20, there is some variation

[32] Massachusetts cities and towns and 11 Boston Neighborhoods.

cell by cell. Some of this variation is statistically significant, but none of it is large enough to materially affect our results.

Table 20: Zip Code Validity on BSAS Records (Collateral Clients Excluded) by Exclusive Race Categories and Primary Drug of Abuse

%Valid	White	Black	Hispanic	Other	Total
Alcohol	89.0%	86.5%	88.0%	88.9%	88.6%
Cocaine	87.5%	87.2%	86.6%	89.5%	87.4%
Crack	90.1%	89.4%	90.3%	90.7%	89.8%
Marijuana	91.2%	90.5%	88.0%	88.2%	90.5%
Heroin	88.0%	88.2%	89.3%	87.7%	88.3%
Other	88.4%	83.9%	95.8%	83.0%	88.4%
	88.8%	87.7%	88.7%	88.5%	88.6%

Given the high overall validity rates and lack of wide variation among the categories we are concerned with, we subselected for the database all records with valid city/town code and Zip Code combinations and conducted our further analysis on this universe.

(2) Accuracy of Zip Codes

We had no direct ability to assess the accuracy of zip-coding by the personnel capturing Zip Codes at admission to treatment facilities. Concerns about Zip Code accuracy expressed by BSAS staff arose from ad hoc analyses of Zip Code assignment in the Boston area.

Boston is the only city in which some neighborhoods have their own codes. The BSAS MIS form lists city/town code "35" for Boston and then gives specific city/town codes for 11 neighborhoods underneath it. It seems likely that data entry personnel use the 35 code in two circumstances -- when none of the neighborhood codes are appropriate and when they are unsure or the client is homeless.

We first note that with the exception of West Roxbury, all of the Boston town codes had Zip Code validity rates near the average.

Table 21: Boston City/Town Codes on BSAS Records – Validity of Zipcodes Associated

City/Town Code	City/Town Name	Invalid Zip Codes	Valid Zip Codes	Valid %
35	BOSTON	568	5,299	90.3%
352	ALLSTON-BRIGHTON	69	520	88.3%
353	CHARLESTOWN	54	430	88.8%
354	DORCHESTER	573	4,150	87.9%
355	EAST BOSTON	134	946	87.6%
356	HYDE PARK	91	363	80.0%
357	JAMAICA PLAIN	195	1,676	89.6%
358	MATTAPAN	183	1,916	91.3%
359	ROSLINDALE	73	401	84.6%
360	ROXBURY	422	2,314	84.6%
361	SOUTH BOSTON	151	940	86.2%
362	WEST ROXBURY	127	177	58.2%
	ALL TOWN CODES	11,317	88,614	88.7%

We next compared Zip Codes associated with the general Boston city/town code (35) and with the individual neighborhoods. Table 22 compares the distribution of Zip Codes associated with city/town code 35 (using our Zip Code table to map back to neighborhoods) with the distribution of neighborhoods directly coded. The Zip Codes for Roxbury are distinctly over-represented among the Zip Codes associated with city/town code 35.

Table 22: Distribution of BSAS Records (Admissions) by Neighborhood within Boston

	Town Code 35 (Boston General)		Neighborhood Town Codes	
	Classed by Zip	% of Nbhd	Direct Code	% of Nbhd
Allston-Brighton	56	1%	520	4%
Charlestown	14	0%	430	3%
Dorchester	668	17%	4,150	30%
East Boston	108	3%	946	7%
Hyde Park	26	1%	363	3%
Jamaica Plain	129	3%	1,676	12%
Mattapan	84	2%	1,916	14%
Roslindale	43	1%	401	3%
Roxbury	2,605	68%	2,314	17%
South Boston	108	3%	940	7%
West Roxbury	7	0%	177	1%
All Other	1,451			
Only Neighborhoods	3,848		13,833	
All Boston	5,299			

The disproportion between the second and fourth columns shown in Table 22 – the disproportionate assignment of the Roxbury Zip Codes, 68% among Town Code 35 while 17% among the other Town Codes – is surprising. A closer look at admissions assigned to Roxbury Zip Codes alleviates some of this concern.

Table 23: Admissions with Town Code 35 and Roxbury Zip Codes by Exclusive Race Category

	White	Black	Hispanic	Other
02118	896	905	323	64
02119	65	191	50	11
02120	24	53	19	4
Admissions from 02118, % distribution by race	41.0%	41.4%	14.8%	2.9%
Population of 02118, % distribution by race (1990)	36.1%	31.7%	17.5%	14.8%

Table 23 shows that most of the admissions using city/town code 35 and Roxbury Zip Codes use Zip Code 02118. It shows further that in that Zip Code, many of the admissions are White and that the racial distribution of admissions is similar to the population distribution (except that the Other category, mainly Asian in the population, is underrepresented). 02118 is the zipcode of the Pine Street Inn, a shelter which many homeless persons may list as an address on admission to treatment. The data available do not allow us to identify admissions by street address. It seems very likely, however, that for persons who do not identify one of the listed neighborhoods as their home and so end up with city/town code 35, 02118 is disproportionately often the correct Zip Code.

The only other test we were able to perform on the Zip Code data was to compare Zip Codes for the same individuals listed on multiple admissions. We found that 51.4% of 17,430 individuals having multiple admissions were assigned different Zip Codes on some of their admissions. Persons admitted more than once for treatment in any given year may be living unstable lives and may, in fact, be homeless or reside at more than one address.

Clearly, the Zip Code data are likely frequently to be inaccurate. Many persons admitted to treatment are homeless (12.6% statewide and 18.8% in the Metropolitan Region)[33]. Treatment personnel assigning Zip Codes on intake forms may have difficulty ascertaining an accurate Zip Code. Apart from

[33] David Cavanagh and Lee Panas (1996), "Socio-Demographic Characteristics of Admissions to Publicly Funded Substance Abuse Treatment by Region and CHNA for Fiscal Year 1995," Health and Addictions Research, Inc., Boston (prepared for Bureau of Substance Abuse Services, Department of Public Health).

the disproportion noted in Table 22, which we discount, nothing we have seen suggests a systematic bias in the data.

Concern about Zip Code accuracy is further diminished when the use of the Zip Code is limited as it is in our analysis. We use the Zip Code only to classify admissions into poverty and non-poverty areas. Most of the poverty areas in the state are clustered in the centers of larger cities. Many errors in Zip Code assignment will have no effect on this analysis. See, for example, Table 24, which shows that 10 of 29 Boston Zip Codes appearing on the Bureau of the Census file for 1990 are ranked in the highest poverty rate decile. Errors across these Zip Codes will not affect the accuracy of our analysis.

Table 24: Poverty Decile Classification of Boston Zip Codes with Non-Zero Population on 1990 Census Zip Code File (STF3B)

POVERTY RATE DECILE	Total Persons	Number of Zip Codes
0 (Poorest)	238,340	10
1	181,723	6
2	53,601	6
3	36,745	2
4	23,922	1
5	805	1
6	26,655	1
7	914	1
8	0	0
9 (Wealthiest)	0	1
TOTAL	562,705	29

In summary, while the Zip Code data should be treated with caution, it is probably serviceable for our limited purposes. Possible bias towards poverty areas in the coding process would tend to undercut rather than reinforce the principal conclusion we draw from the data – that treatment admissions are materially less concentrated than incarcerations for drug offenses.

Census Zip Code Data – Comparability Issues

To assign poverty rates to Zip Codes, we used Census Bureau Summary Tape File 3B (CD-ROM Version supplied by Bureau of the Census, Data Users Services Division), which provides 1990 Census data summarized at the Zip Code level. This file tiles the state of Massachusetts with 474 Zip Codes. The actual number of Zip Codes used in Massachusetts by the Postal Service is much greater. Some Zip Codes refer to post office address only or to specific buildings or have been recently added and do not appear on the STF3B file. We found, however, that 98.9% of the BSAS treatment records with valid Zip Codes used Zip Codes appearing on the STF3B file, and we made no effort to allocate the remaining 1.1% of the population.

Interpretation of Treatment Utilization Data

The findings in the text of high relative rates of utilization of treatment in poverty areas and the inference that these increased utilization rates reflect relative rates of substance abuse should be treated with caution for several reasons.

First, as discussed above, the zip-code data are not highly reliable, although adequately so for our purposes.

Second, treatment services receiving any public funding represent only a portion, although a substantial portion of all drug treatment services. In Massachusetts, according to the major federal survey of specialty drug treatment providers (“NDATUS”) 7.8% of the treatment population is served by specialty drug treatment providers who receive no public funding (based on a one-day census).[34] The universe of "specialty drug treatment providers" in NDATUS includes inpatient and outpatient facilities with some dedicated personnel and space set aside for treatment services.

There is, however, a larger universe of care givers including primary mental health providers, self-help organizations and others who do not receive public substance abuse treatment funding. Treatment capacity in this universe is less well understood, but it is likely to disproportionately serve wealthier clients. For this reason, we refer to the "High Skew" measure in the text as an upper bound for the relative concentration of substance abuse in poverty areas.

Third, treatment utilization is an imperfect indicator of substance abuse prevalence. It reflects not only underlying substance abuse levels, but treatment seeking patterns which may vary significantly across economic groups.

Our "Low Skew" measure of the differences between poor and non-poor areas is the relative share of clients (in the data universe) who are being treated for cocaine and heroin problems among all clients in the data universe who are being treated for substance abuse problems. There is a six fold (5.78x) differential in the rate at which persons in the lowest poverty rate decile appear in the treatment dataset as compared to the rate at which persons in the highest poverty rate decile appear. In order for the Low Skew measure to overstate the underlying substance abuse contrast across areas, all of that six fold difference would have to be explained away by differences in public treatment availability, treatment-seeking behavior and differences in utilization of exclusively private treatment facilities. Given the fairly broad acceptance of public funding by treatment facilities in Massachusetts noted above, this seems an unlikely scenario. For this reason, we refer to the "Low Skew" as a lower bound measure of the contrast.

While the present study may be the first to present treatment utilization data by poverty of geographic area in this form, it is consistent with other studies of substance abuse indicators. See for example, McCarty, D. (1992), Indicators of Substance Use in Massachusetts, prepared by Health and Addictions Research, Inc. This study compared results by size of city. Substance abuse indicators were higher in the larger cities (which are disproportionately poor). Our results show somewhat larger contrasts, but this is to be expected since Zip Codes are smaller units that further differentiate poverty from non-poverty areas. See also Substance Abuse and Mental Health Services Administration (1997), Advance Report Number 12: National Admissions to Substance Abuse Treatment Services: The Treatment Episode Data Set (TEDS) 1992-1995. This nationwide study of individuals admitted to substance abuse treatment shows that individuals admitted to substance abuse treatment are more likely than the general population not only to be unemployed (possibly reflecting their current disease), but to lack a high school diploma (more likely to indicate long term poverty).

Geocoding of Data Sets

Standard Procedure

The project used geographic information software to transform street addresses into map points. For each incident or prisoner with an address within the state of Massachusetts, we attempted to derive a latitude and longitude and from that to assign the incident or prisoner to a census tract. In every instance, the same Standard Procedure was followed:

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[34] Substance Abuse and Mental Health Services Administration, Office of Applied Studies (1995) Advance Report Number 9A: Overview of the FY94 National Drug and Alcoholism Treatment Unit Survey: Data from 1993 and 1980-1993, SAMSHA, Washington. Note that patient turnover rates tend to be lower in private facilities, so that the wholly private facilities' annual admissions share may be below the 7.8% reflected based on one-day census. See Figure C.1 in TEDS Advance Report Number 12 cited in the text.

1. First, we set the incident/prisoner records up in a Microsoft Access 95/97 database including fields which we could use to maintain an audit trail of the geocoding process.

2. Second, we scanned the data, manually and/or using Access queries, to mark as non-geocodable out-of-state and fatally incomplete addresses (mostly blank, but also some non-addresses such as "homeless," "unknown," or "shelter"). Unambiguous omissions were corrected (e.g., the state would be supplied for records having a street address in a Massachusetts city but lacking a state field).

3. Third, we used Group One Software's StreetRite product, version 5.1 with the Zip Code tables Group One provides, to "scrub" the addresses to (a) remove common misspellings; (b) standardize street designators; and (c) most importantly, to supply missing zipcodes.

4. Fourth, we ran MapInfo's MapMarker product, version 2.1 with geographic tables supplied by MapInfo, to convert the scrubbed addresses into latitude and longitude coordinates. This was a two step process. In the first step, we ran MapMarker in its automatic mode requiring exact number/street/zipcode matches between the sample addresses and the addresses in MapMarker's database of addresses. In this mode, MapMarker matches addresses in a batch process without manual intervention; any record for which MapMarker cannot recognize an exact match is bypassed.

5. In a second MapMarker step, we ran MapMarker in its "interactive" mode. In this mode, MapMarker supplies a set of imperfectly matching addresses from its database and the operator either selects the best match or marks the address as non-geocodable.

6. Fifth, we used MapInfo's MapInfo product, version 4.1, to convert the latitude/longitude coordinates into census tract identifiers. In this step, we used MapInfo's census tract boundary files.

We developed this procedure after quality control experimentation with the several software products. In theory, all of the geocoding could have been done using MapMarker. However, we found by experimentation that in the absence of a correct zipcode, MapMarker had much lower match rates and sometimes produced unpredictable results, generating locations several cities away from the true location. This motivated our use of the more robust StreetRite as a prior clean-up step to supply zipcodes. We also found that although MapMarker is capable of supplying a census tract code as it assigns latitude and longitude coordinates, due to internal table errors MapMarker occasionally miscomputes the county portion (positions 4 through 6) of census tract codes. For this reason we used MapInfo to assign census tracts based on latitude and longitude.

Geocoding Success Statistics

We were fortunate that most of the potentially geocodable addresses matched using our automated tools in all five of our datasets. Relatively little manual intervention was required:

Table 25: Geocoding Success Rates

			Percentages of In-State Records with Addresses			
Data Set	Selected Records	In State with Addresses	StreetRite Scrubbed	MapMarker Geocoded	Manually Geocoded	Not Geocoded
DOC Prisoners	4,486	3,999	84.7%	83.9%	9.9%	6.2%
Middlesex HOC Inmates	14,326	13,812	83.7%	84.3%	10.0%	5.7%
Norfolk HOC Inmates	7114	6,964	86.5%	86.0%	9.1%	4.8%
DYS Committed Youths	10,249	9,714	85.8%	86.6%	7.0%	6.4%
WRISS Victims	2,350	2,196	84.2%	84.2%	5.7%	10.1%

In Table 25, "In State with Addresses" includes all records not excluded in Step 2 above. "StreetRite scrubbed" means that StreetRite was able to recognize the address on the record and assign a five digit zipcode in Step 3 above. "MapMarker Geocoded" means that latitude/longitude coding was achieved in step 4 above. This column represents the percentage of geocodable records that were geocoded automatically based on an exact match between the record address and an address in MapMarker's database of street addresses.

Note that, in the Department of Correction dataset, MapMarker automatically geocoded 3,319 or 98.0% of the 3,386 addresses successfully scrubbed by StreetRite. MapMarker was able to geocode only 35 additional records or 5.7% from the 613 records that StreetRite was unable to scrub. The statistics were similar for the other datasets.

"Manually Geocoded" means that manual intervention in Step 5 was necessary to identify a matching address for which MapMarker could assign latitude/longitude coordinates. "In State, Not Geocodable" includes all those records with in-state addresses for which geocoding was not possible regardless of the reason. The sum of the rightmost three columns equals 100% of all in-state records with addresses.

Procedural Reliability Issues

Given the high automated-match rates, the accuracy of the procedure outlined above depends primarily on the accuracy of the several address processing software tools. In addition, the interactive geocoding process creates opportunities for error. As a quality control on the overall accuracy of the procedure (a composite of the accuracy of the individual tools), we submitted our list of DOC prisoner addresses (together with only an identifying code) to Geographic Data Technologies. GDT, using its own suite of tools, geocoded these addresses.

We compared two different aspects of our procedure's performance as against GDT's performance. First, we compared the overall share geocoded among in-state records with addresses. Second, we compared the results on a record by record basis. As to overall share geocoded, the results were similar, as Table 26 illustrates.

Table 26: Comparison of Geocoding Success on DOC Dataset

	Standard Procedure	GDT Outsourcing
Automated Match Rate	83.9%	94.1%
Manual Match Rate	9.9%	0.0%
Total Match Rate	93.8%	94.1%
Exact Matches among Matches	92.3%	89.1%

In Table 26 'exact' matches are matches where (a) a very close or truly exact match for the record address was found in the underlying geographic database and (b) an exact location was assigned based on that address. In other instances locations were assigned based on approximate zip-4, zip-2 or Zip Code area "centroids," a "centroid" being the rough center of an area.

As to agreement, for the 3,623 records that both GDT and the standard procedure had geocoded, the gross agreement rate on tract assignment was 92.3%. However, many of the differences involved cases where the two procedures placed points very close to each other but on opposite sides of a tract boundary.

92.7% of all the point pairs generated by the two measures are less than one quarter mile[35] apart; and 96.2% are less than one mile apart. Of the 264 points over one quarter mile apart, 149 were instances

[35] To resolve the issue of how far apart the points generated by the two procedures typically were, we defined a rough Euclidean distance measure as follows: the square root of the sum of the square of the latitude difference and the square of the longitude difference, i.e., symbolically: $((LAT_{gdt} - LAT_{std})^2 + (LON_{gdt} - LON_{std})^2)^{1/2}$. This is an approximation because the ground distance of one degree of longitude

in which GDT used a zip-centroid (approximate) match instead of an exact street match. A handful of the remaining records appeared to involve differences in the interpretation of addresses, but most appeared to involve differing geographic placements of closely agreed interpretations of addresses. This observation gave us confidence that our mixed automated and manual procedure was rarely *misinterpreting* addresses in a material way – rather, most differences have to do with the underlying database and geographical computations used by GDT's software as opposed to MapInfo's software.

The ultimate issue in the comparison is how often points are being assigned to different census tracts other than in boundary cases. (In cases where the points are placed just across a boundary from each other, there is no reason to expect that the disagreement has any significance for the analytic purposes of this study.) Of the 279 instances in which census tracts differed, 89 were explainable as cross-boundary breaks (distance less than one quarter mile), bringing the agreement rate up to 94.8%.

In summary, our geocoding procedure is somewhat inexact, but a different method gave essentially the same answer in 95% of the individual instances. The remaining instances appeared to involve underlying geographic database differences that we have no reason to expect would bias the results of our analysis. The comparison to GDT showed that very few differences were due to manual address interpretation decisions through which an operator involved in the study might inadvertently introduce a bias.

Missing and Non-geocodable Addresses – Potential Biases

Prior to beginning the study we were concerned that missing and/or non-geocodable addresses might be a significant source of distortion in our results. This concern was significantly diminished when we achieved geocoding rates close to or over 90% for all of our datasets.

Several additional observations on the primary DOC dataset further diminished our concern about this issue:

Non-geocodable rates (in-state-non-geocodable as a percentage of all in-state) were similar across major racial/ethnic groups within the prisoner sample – see Table 27. The Black and White rates are statistically identical. The Hispanic rate is slightly higher and statistically different from both the Black rate and the White rate. The higher Hispanic rate may reflect language barriers in the intake process. The rate at which addresses are provided is the same among all three groups; the variation comes from the rate at which addresses provided were recognizable. The groups shown constitute 96.9% of the in-state prisoners:

Table 27: Non-Geocodable Rates: Percent of Addresses not Geocodable for Male Prisoners with Full or Partial Addresses Indicating in-state Residence (All Ages)

Race	Non-Geocodable Rate for In-State
Black	4.8% (N=1,073)
Hispanic	9.4% (N=1,054)
White	5.6% (N=1,553)

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varies from 51 to 52 miles according to how far south one is in the state of Massachusetts and the ground distance of one degree of latitude is roughly 69 miles. One unit of the measure thus varies from 51 miles to 69 miles in ground distance depending on the location and orientation of the points being compared. .02 units of the measure is thus between 1.02 miles and 1.34 miles of ground distance. For simplicity .02 units of the measure will be referred to below as a "mile."

To better measure the possible influence of address-present-but-non-geocodable records on statewide comparisons of poverty and non-poverty neighborhoods, we grouped these records according to the poverty rate of their communities.

Table 28: In-State Males with Addresses by Poverty Level of Municipality and Geocoding Result

	% of those with Non-Geocodable Addresses (N=223[36])	% of those with Geocodable Addresses (N=3,558)
10 Highest Poverty Rate Cities	60.5%	60.1%
Cities and Towns with Middle Range Poverty Rates	36.8%	35.8%
100 Lowest Poverty Rate Cities and Towns	2.7%	4.1%
All Cities and Towns	100.0%	100.0%

The comparisons in Table 28 indicate that there is little systematic difference between the distributions by poverty level of municipality of the geocodable and non-geocodable addresses. Thus our statewide poverty area analyses are unlikely to be distorted by failures in the geocoding of addresses.[37] Of course, given the high geocoding success rates, if there were any distortion at all, the distortion could not be great.

Summary Perspective on Geocoding Process

The foregoing discussion suggests three conclusions. First, our geocoding process is fairly reliable and the few erroneous assignments it may make are apparently unbiased. Second, the missing and non-geocodable addresses are distributed fairly evenly by race. Third, present-but-non-geocodable addresses are distributed fairly evenly by poverty level of municipality and thus unlikely to create any systematic bias.

It seems clear that our only likely source of systematic bias related to geocoding is in the 6.1% (234 blanks and 8 "homeless" or similar addresses) of the records which are entirely missing addresses. Many of those persons not providing addresses at the time of admission to state prison may be homeless or transient. These persons may be more likely to live in poverty areas than those providing addresses. Our various findings of high concentrations of prisoners in poverty areas are most likely to be slightly understated.

Details of Crime Rate to Commitment Rate Comparison

In the Findings section, the statement is made that "the state prison incarceration rate in the poorest cities is equal to or lower than the rate that the reported or cleared crime rates in those cities would

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[36] We were able, resolving city naming problems, to include 235 of 249 such records in this analysis; of the 249, 12 were females and were excluded. None were duplicated. Thus 223 records were compared.

[37] The non-geocodable addresses are also not concentrated in any large particular communities (a situation which might be indicative of a particular mapping problem for those communities which could distort local analyses of incarceration rates in and around them). Among individual communities in which over 10% of the addresses were non-geocodable, the only communities contributing over 10 prisoners were Chelsea, Revere, and Framingham and their non-geocodable rates were modest – respectively, 14.3%, 15.4% and 13.6%. The other communities with higher non-geocodable rates (over 10%) are scattered smaller communities. In any event, analyses of particular areas do not play a major part in this study.

predict." Chart 8 visually suggests this conclusion. This section provides a quantitative analysis. Essentially the method was to calculate statewide ratios by Uniform Crime Report category of cleared-crimes to state prison incarcerations, to apply those ratios to the cleared crimes within the poorest cities and so to derive a "predicted" number of incarcerations in those cities.

The steps of our analysis were as follows:

1. The State Police Crime Reporting Unit provided to us a dataset of uniform crime reports for the last 17 years by reporting agency and category of crime. These reports are furnished by police agencies around the state, including municipal police forces, college police forces, State Police units and other units including the MBTA police. (We were able to verify for a test year, 1994, that summary statistics we derived from the dataset coincided closely with official FBI uniform crime reports derived from the same sources with minor adjustments.[38])

2. We selected calendar 1994 and 1995 as our reference years for comparison to State Prison commitments in Fiscal 1995 and 1996 (building in a six month apprehension and court processing lag).

3. We dropped from the dataset non-municipal police forces because we lacked a reliable way to allocate the crimes they reported to municipalities. The agencies omitted included 5 county-level MBTA Police Units, 12 county-level State Police units, and the security forces of 14 educational institutions. We also dropped 50 (mostly smaller) municipal agencies not reporting in all 24 months of the two-year period. These two overlapping groups of omissions taken together resulted in a loss of only 9.5% of reported crimes.[39] The resulting count of subject agencies was 202.

4. We tabulated statewide the non-drug offenses for which males were incarcerated in the study period and associated them with uniform crime categories. The most significant ambiguity in this process involves assaults. The Uniform Crime Report (UCR) categories of assault crime do not cleanly correspond to Massachusetts statutory categories of assault. An aggravated assault, as opposed to a simple assault, for the UCR is an assault involving a weapon or causing or intended to cause serious injury. We classified all 587 assault commitments (including 4 apparently simple assault and battery commitments) as aggravated assaults. On the other hand, it is clear that most UCR "aggravated assaults", even those cleared by arrest, do *not* result in state prison commitment. See Table 29.

5. We merged municipal level census data and the state prison incarceration data (disaggregated by UCR categories) with the crime rate data. This was possible for only 194 agencies. For 8 small municipal agencies, the census tracts including the relevant municipalities also included other municipalities.

6. In the resulting universe of 194 municipalities, we selected the 10 cities (not towns) with highest poverty rates. The actual 10 poorest cities are Boston, Chelsea, Fall River, Holyoke, Lawrence, Lowell, Lynn, New Bedford, Springfield, and Worcester. (The exclusion of towns ranking high on poverty rate omits North Amherst, Stockbridge, West Dennis and Provincetown.) Chelsea and Holyoke did not make full crime reports in 1994 and 1995 and so they were excluded and the next two poorest cities, Fitchburg and Brockton were included. These 10 cities also are the cities including poverty clusters with a population over 10,000

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[38] Our comparison was to Table 3.111, "Estimated number and rate of offenses known to the police," in Maguire, K. and Pastore A. (ed.), 1996, Sourcebook of Criminal Justice Statistics, 1995. Washington, Bureau of Justice Statistics.

[39] In this computation of the loss rate, we used 1994 reported totals in the denominator except where 1994 agency data was absent, in which case we used 1995 rates in the numerator, slightly overstating the loss rate.

(losing Chelsea and Holyoke, for which reporting was incomplete, and adding Fitchburg, which includes a smaller poverty area).

Table 29: Prediction of Incarceration Rate from Cleared Crimes

	Cleared Crimes in 194 Reporting Cities	DOC Comm's in 194 Cities	Comm's as % of Cleared Crimes in 194 Cities	Cleared Crimes in 10 Poorest Cities	Predicted 10 Poorest City Comm's	Actual 10 Poorest City Comm's	Actual 10 Poorest Comm's as % of Cleared Crimes
Total Part I[40]	97,113	2,036	2.10%	53,900	1,370	1,344	2.49%
Homicide	249	188	75.50%	192	145	123	64.06%
Rape	1,770	305	17.23%	1,169	201	159	13.60%
Robbery	4,690	677	14.43%	3,723	537	474	12.73%
Gun Assault (sub-class)	2,111			1,721			
Agg. Assault	30,583	483	1.58%	17,162	271	345	2.01%
Burglary	12,477	262	2.10%	6,864	144	167	2.43%
Larceny	37,159	65	0.17%	17,474	31	37	0.21%
MVLarceny	10,185	56	0.55%	7,316	40	39	0.53%

7. Table 29 shows actual combined two-year crimes-cleared-by-arrest and state prison commitments for the 194 reporting cities (and towns) and for the 10 poorest cities (not towns) among them. The third column is a computed ratio of state prison commitments to cleared crimes (by category of Part I crime) *for all 194 cities*. The fifth, shaded "Predicted" commitments column for the 10 poorest cities is based on applying these ratios to the actual cleared crimes from those cities.

The key comparison to note in support of the statement in the text is that the predicted Total Part I commitments in the 10 poorest cities (1,370) works out to be comparable, in fact, slightly higher than the actual (1,344). This is consistent with the view that prosecutorial and punishment intensity are not higher in poverty areas and that the contrasts in incarceration rates between urban and non-urban areas have to do with underlying offense rates as opposed to variations in criminal justice system response.

Note that our analysis turns out not to be sensitive to whether we use cleared or reported crimes as our unit of analysis. In Table 29, we have used cleared crimes – crimes solved by arrests. If we use reported crimes, we get essentially the same predicted total incarcerations in the poorest cities – 1,343, instead of 1,370. Using reported crimes would factor in both the intensity of police work in solving crimes and the rates at which crimes are reported to the police. The former factor makes sense to factor in for an overall comparison of intensity; the latter is an uncontrollable, unknown distortion factor. As it turns out, the net effect of these two factors is nil.

Estimates of State Prison Experience

This section discusses the issues involved in each step of the basic state prison lifetime experience model. Throughout, we limited our analysis to males. The group of females admitted in our two-year subject period is much smaller (only 284 of 4,486 unique individuals) and so our capacity to conduct statistically meaningful analyses of subcategories was less. In addition, we limited our analysis to Black, White and Hispanic males, because all other groups taken together amounted to only 134 prisoners.

We further limited our analysis to those under age 40. Our reasons for this limitation were as follows.

[40] Part I crimes are the major crimes tracked by the FBI nationwide for computation of crime rates.

- All ages over 40 together constituted only 15.6% of our Black, Hispanic and White male commitments. In many analyses, cell sizes became too small for accurate estimation.

- The national BJS study[41], with a larger subject group estimated that lifetime odds of going to prison for the first time after age 40 are only 0.8% for Whites and 2.1% for Blacks.

- We lacked confidence in our ability to estimate mortality rates for over-40 minority males in poverty areas, but believed that they might be different enough from standard life tables to affect our analysis.

- Exploratory analysis confirmed that inclusion of the over-40 group would not materially change the comparisons among subgroups shown.

Starting from our universe of 4486 unique individuals committed to state prison in Fiscal 1995 and 1996 and applying the above criteria, we ended up with the universe of prison commitments shown in Table 30:

Table 30: Universe of Commitments in State Prison Experience Analysis – Males under 40 Committed in Fiscal Years 1995 and 1996

Age Range	Total	Black	Hispanic	White	Not Poverty	Poverty	Non-Drug	Drug
16-19	340	129	127	83	126	175	281	58
20-24	912	351	261	300	386	394	641	271
25-29	907	272	269	366	453	325	642	265
30-34	769	210	222	337	380	284	547	222
35-39	504	114	134	256	262	158	345	159
TOTAL	3431	1076	1013	1342	1607	1336	2456	975

Note that the total of "Not Poverty" and "Poverty" (2943) is only 85.8% of the grand total. This reflects the fact that we were not able to geocode addresses for all offenders (some addresses missing, not geocodable or out of state). The relevant universe for geographic commitment rate analysis is the geocodable universe. We used the larger universe only to adjust for geocoding failures and for estimating prior experience rates in the second step.

Mathematics of the Estimate

For clarity in the discussion that follows, we define the following variables:

V_n = the members our notional birth cohort who are alive but have never been to prison at their n^{th} birthday. We will express V_n in normalized terms imagining a cohort of 100,000 living on their 16^{th} birthday. So, V_{16} = 100,000 since no one goes to state prison before the age of 16.

E_n= the percent of the members of V_n who experience state prison in the year following their n^{th} birthday.

D_n= the percent of all individuals who die in the year following their n^{th} birthday (which is assumed to be the same for members of V_n as for non-members).

$\boldsymbol{D}_n$= the percent of all individuals who have already died by their n^{th} birthday (sum of previous deaths).

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[41] See foot note 10.

Σ will be used to refer to the sum from 16 to 39 of subscripted variables. So, for example, $\Sigma(E_{n.} * V_n)/100000$ is the lifetime-to-40 percentage estimate we are trying to derive.

From these definitions, it follows that

$$V_{n+1} = V_n - (E_n * V_n) - (D_n * V_n)$$

(There is a negligible second order error term omitted in this equation – the group who both go to prison and die in the same age period.)

Real world known quantities we use to estimate the parameters of model include:

P_n population (actual living) of age n

C_n number of commitments to state prison of age n

i_n percentage of commitments to state prison of age n who have never previously been to state prison.

Important intermediate computations include:

$FC_n = (i_n * C_n)$ number of first-time commitments to state prison at age n (real world known quantity for our reference years)

RV_n = the estimated real world population of age n that has not already been to prison.

Our first key estimating assumption is:

Assumption I: $RV_n / P_{n.} = V_n/[V_{16} * (1-\boldsymbol{D}_n)]$

Based on this assumption, we can estimate RV_n iteratively as:

$RV_n = P_{n.} * V_n/[V_{16} * (1-\boldsymbol{D}_n)]$

Our second key estimating assumption is also a proportionality assumption:

Assumption II: $E_n = FC_n / RV_n$

Our method of computing our ultimate answer, $\Sigma(E_{n.} * V_n)$, is iterative, starting with V_{16} = 100,000, estimating E_{16}, computing V_{17} and so on, and then summing.

Understanding the Assumptions

Our estimate of lifetime-to-40 experience is best seen as an estimate of the future experience of the current cohort of 16 year olds assuming crime rates and policies do not change much. At the same time, however, Assumptions I and II are flip sides of a basic assumption that the current pattern of prison experience in the real world population, the result of the last couple of decades of prison commitment rates, is not too inconsistent with current commitment rates.

Assumption II, in words, is the assumption that the rate at which real world men of age n who have never been to prison are going to prison is representative of future experience. However, since current incarceration rates are historically high, more older men may be first timers in our sample than would be the case in future. In the future, even if the rate of incarcerations (C_n/P_n) stays constant, the percentage of those incarcerated who have never been incarcerated before (i_n) may decline.

The actual magnitude of this effect is modest for state prisoners in Massachusetts for two reasons: First, we are already assuming very low values for i_n for older males. See discussion below at page 62 as to our assumptions regarding i_n. Second, state prison commitments in Massachusetts have been at or above their current levels for roughly a decade, having peaked in 1990.

Assumption I is the cumulative version of Assumption II. It assumes that the percentage of all young men of age n in the real world who have never been to prison is the same as that percentage predicted for men of age n based on current commitment rates. That model percentage is computed based on the assumed first-time incarceration rates of men up to age n-1. So that Assumption I for men of age n is really just the result of Assumption II applied to that cohort when they were younger.

Assumption I also builds in a more modest implicit assumption that the population of real world young men is consistent with our measured mortality rates and not too affected by net migration. The mortality assumption is not difficult. The issue of migration raises some definitional problems but probably does not distort our analysis much. [42]

The sensitivity of our model results to these assumptions is discussed below.

Measuring Commitments -- C_n

The first step in the analysis was to estimate commitments. We averaged our two-subject-year universe to get annual counts in cells by age, race, and poverty area residence. For the purposes of computing C_n in each cell, we did not divide offenders into drug and non-drug groups. This classification was used only in estimating prior experience rates, i_n, below.

Missing addresses and geocoding failures bias downwards our commitment rates slightly. Table 31 shows the rates at which these problems occur by racial group within our sample.[43] We adjusted

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[42] To the extent that young males originating from poverty areas leave the state or move to non-poverty areas within the state, and to the extent that motion occurs in the opposite direction as well, our conceptual cohorts of 16 year-olds lose their integrity. We have no knowledge of how long a state prisoner committed from an urban poverty area resided in the area. Given that juvenile commitments are slightly more concentrated in poverty areas than adult state prison commitments (see Chart 4), it seems unlikely that that net in-migration of criminals is a reason for higher commitment rates in poverty areas. The more subtle problem is that in Assumption I, the denominator on the left hand side (i.e., actual population) reflects net migration but the denominator on the right hand side does not. 10 of the 12 poorer cities identified in this report as containing large poverty clusters have experienced net out-migration recently, with Lawrence experiencing the most rapid out-migration at 6.5% in from 1990 to 1995. See Massachusetts Institute for Social and Economic Research (1997), "Population Estimates for Massachusetts Cities and Towns for 1995," University of Massachusetts, Amherst. It seems most likely that poverty areas in Massachusetts have experienced a modest out-migration of young males. Mathematically in our model, a failure to adjust for out-migration looks identical to an understatement of mortality rates. The model is not very sensitive to variations in this parameter. Even setting five-year combined mortality and out-migration rates at 12 percent at all ages (effectively assuming five-year out migration of roughly 10 percent) moves our bottom line estimate for blacks in poverty areas downwards by only 2.3 points. At the same time, five-year out-migration rates of 10 percent would mean that another set of inputs to the model, our population estimates, P_n, should be adjusted downwards by 10 percent, proportionately increasing our bottom line estimates, partially offsetting the first error and bringing the net effect under one point.

[43] The Black/White difference as to not-geocodable rates (i.e. % of in-state addresses provided which are not geocodable) is not statistically significant, but the Hispanic non-geocodable rate is significantly different at the .01 level from the other rates. The Black and White group's not-geocodable rates do not significantly vary by age range. Younger Hispanics' addresses geocode better than older Hispanics' addresses, consistent with a language theory of their lower geocoding rate: 4.1% of 16-19 year old Hispanics' addresses failed to geocode as against 13.8% of the 35-39 year olds. This could also be explained by residence in a more stable parental home. In any event, no other geocoding rate for Hispanics

commitment rates upwards (only for the life-time-to-40 experience, not elsewhere in the report) using the product of the reciprocals of these rates. The resulting adjustment factor is shown in the right column of Table 31. Thus, for example, for Blacks, 1/[(1-.028)(1-.047)] = 1.079.

Table 31: Address and Geocoding Related Understatement of Commitment Rates by Race – Males with Ages 16-39 and Correction Applied

	No Address (% of all)	Not Geocodable % with MA Address	Factor to Correct Address-Related Understatement
Black	2.8% (N=1,076)	4.7% (N=976)	107.9%
Hispanic	3.1% (N=1,013)	8.7% (N=924)	112.9%
White	2.5% (N=1,342)	5.2% (N=1,240)	108.1%

Estimating Prior Experience Rates, i_n

The principal element of uncertainty in our model enters in the estimation of prior state prison experience rates. However, prior experience is hard to measure. Determination of whether a new commitment has previously been to state prison depends on accurate identification. Many criminals seek to hide their identities precisely to avoid being labeled recidivists and punished more harshly.

We had two data sources from which to estimate prior state prison experience rates. First, the DOC booking process does attempt to identify previously committed inmates and record their prior commitment number, a field that was provided to us on our database. DOC staff believed that this field was not reliable.

We derived a second perspective by retrieving and analyzing the criminal records of 322 of the commitments – 171 non-drug offenders and 151 drug offenders. (See the methodology on CORI analysis for more detail on this sample.) In the sample we studied, the booking process turned out to be more accurate than we had hoped in identifying prior commitments. Of the 64 prior commitments identified either in our records sample or in the booking process, the booking process identified 81.3% (82.1% if one weights drug and non-drug offender rates to reflect their proportions in the full universe of commitments).

In the sample, age-range cell sizes were too small to allow any testing of variation among subgroups. Given the finding that the booking process was fairly reliable, we used the full data set to conduct a full set of comparison tests of experience rates on subgroups (overall and by age range) by race, drug or non-drug current offense, and by poverty or non-poverty residence. Table 32 summarizes those comparisons.

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in any age range differed significantly from the average for Hispanics for all ages. Thus, it seemed unnecessary to further differentiate correction factors by age.

Table 32: Significance of Differences in Experience Rates (i_n) averaged by Age[44]

	Variable Held Constant						
	Race/Ethnicity			Poverty Area		Drug Offense	
Comparison	Black	Hisp.	White	Not	Poverty	No	Yes
BW						*	
BH				***	***	***	**
HW				***	***	***	
Urban/Not							*
Drug/Not	*			***	*		

***=p<.001; **=p<.01; *=p<.05

Differences in the experience rate by race (Hispanics having significantly lower rates than either Blacks or Whites as shown in the next table) persist when poverty rate and offense-type are isolated and held constant. However, when race is isolated and held constant, (with one modest exception) the other variables lose significance as predictors of average experience rates. There were no instances where more than one age range cell (significance of individual age cells not shown in Table 32) significantly differed without the average across ages significantly differing (significance of differences in cross-age averages shown in Table 32). However, in subcategories, there was apparent small cell noise – e.g., non-urban Hispanics 30 to 34 year olds have experience rates half of those of both non-urban Hispanic 25-29 year olds and non-urban Hispanic 30-39 year olds.

Accordingly, for simplicity and to avoid small cell noise, we used the experience rates based on race/ethnicity alone as shown in Table 33 as a starting point for our analysis.

Table 33: Prior Experience Rates based on Booking Data and Comparison to Sample Record Review

	Black	Hispanic	White
16-19 Booking Data	2.8%	0.0%	1.3%
20-24 Booking Data	10.3%	5.5%	6.6%
25-29 Booking Data	23.3%	13.1%	16.9%
30-34 Booking Data	37.8%	15.2%	30.5%
35-39 Booking Data	37.4%	25.0%	30.8%
AVERAGE for Booking Data across Age Ranges	21.1%	11.2%	19.6%
Drug Offender Sample	15.8%	19.3%	14.3%
Non-Drug Offender Sample	28.3%	14.3%	20.9%
Weighted Samples Average	22.4%	16.6%	17.8%

[44] This analysis (except for poverty/non-poverty area of residence comparisons) was conducted using the full universe of Black, White and Hispanic Males (including those providing no addresses and out of state addresses). There were no significant differences among racial groups in the rate at which they provided null or out of state addresses. The poverty area definition used in these comparisons includes 172 tracts and corresponds most closely (89.9% overlap) to the 173 tracts in the "clusters over 10,000" line in Table 7, plus 18 tracts in smaller clusters, less 19 tracts with significant group quarters populations (of which 11 are student tracts).

95% confidence intervals vary from ±3% to ±9% in the booking data cells for age ranges over 20 (the 16-19 cells are undersize). Only for Hispanics do the *average* booking data rates and the weighted sample averages differ significantly.

Our exercise in record review left us with a sense of the fragility of our systems for tracking criminal records. See our discussion of our sampling process documenting the inconsistencies and lacunae we encountered. The booking data appear to miss as many as 18.8% of prior commitments. See page 77. It also seems likely that there are some prisoners who manage to claim different identities so that both the official criminal records and the booking data omit the prior commitment. Anecdotal evidence indicates that for Hispanics, whose surnames are often confused by English speaking clerks, the confusion may be greater.

An underestimate of prior experience among committed prisoners would contribute to an overestimate of experience-by-40 in our method. We sought to avoid overstatement. We adopted the arbitrary but probably conservative assumptions that our experience estimates omitted 20% of Blacks' and Whites' prior commitments and 50% of Hispanic's prior commitments. We adjusted the rates in the upper half of Table 33 to reflect these assumptions and used them in our estimation. See variations discussed below under sensitivity analysis.

Table 34: Values of i_n (First Time Commitments as share of All Commitments) for Males by Age Range (Poverty and Non-poverty areas not Statistically Different) as Used in State Prison Experience Estimate.[45]

	Black (Experience inflated 20%)	Hispanic (Experience inflated 50%)	White (Experience inflated 20%)
16-19	96.6%	100.0%	98.3%
20-24	87.1%	89.1%	91.8%
25-29	70.9%	73.8%	78.8%
30-34	52.8%	69.6%	61.9%
35-39	53.3%	50.0%	61.5%

Measuring Population -- P_n

The STF3-A census file only tabulates sex/race cells by age ranges, not by individual years. So, we were constrained to use five-year age ranges instead of individual years in our analysis, as shown in Table 30. Further subdivision would, in any event, have created some unacceptably small cell sizes. There were no state prison commitments below the age of 16.

The minority populations and poverty populations have younger age structures, as shown in Table 35, consistent with population expansion.

Table 35: Percent of Total Population Subgroup by Age (1990)

	BLACK	HISPANIC	WHITE

[45] This is derived as described above. So for example, for Blacks, 16-19, the share, 96.6% is derived as 1 – 2.8%/(1-20%).

	NOT	Poverty	NOT	Poverty	NOT	Poverty
0-15	26%	31%	30%	39%	21%	18%
16-19	7%	8%	7%	9%	5%	8%
20-24	9%	10%	12%	11%	8%	16%
25-29	11%	10%	13%	10%	9%	12%
30-34	11%	9%	11%	8%	9%	9%
35-39	9%	7%	7%	7%	8%	7%
40-44	7%	6%	6%	5%	8%	5%
45-49	5%	4%	4%	4%	6%	4%
50+	14%	15%	9%	7%	25%	21%

Accordingly, it seemed likely that if we failed to adjust our age structure to reflect mid-decade changes, we would underestimate the number of young Black and Hispanic men and so overstate their commitment rates. Consistent with our desire to make a conservative estimate of commitment and experience rates, we rolled each of these cells forward five years. (The 0-15 cell is broken down in the STF3-A data, allowing a roll forward with little estimation, only a split of the 10-11-year-old range.)

In rolling forward ages, we did not attempt to adjust downwards for mortality. Five year mortality rates for males under 40 are under 1 percent, although they may be higher among young minority men in poverty areas. Not adjusting here for mortality results in a slight understatement of commitment and incarceration rates, perhaps most pronounced in poverty areas and among minorities. (See discussion below under "Mortality Rates and the Computation of Total Experience.")

Note that the P_n quantities that we derived from the STF3-A files include incarcerated persons *by census tract where they are incarcerated*. In the STF3-A data, 83.2% of the incarcerated population is in *non*-poverty areas. So incarcerated minority males originating in poverty areas may be reported as resident in non-poverty areas. This understates the population of minority males with their homes in poverty areas and so overstates their commitment rates. The amount of this overstatement is on the order of 5 to 8%.[46]

Lastly note that the Census Bureau data available for population at the tract level by age and sex do not distinguish non-Hispanic from Hispanic ethnicity among persons of White, Black or Asian race. In our analyses of race specific incarceration rates, we use racial categories – Asians, Blacks, Whites – which include Hispanic persons, but will refer to them and Hispanics as if they represented distinct groups. The overlap is modest: 2.1% of Asians, 8.5% of Blacks, and 2.3% of Whites are of Hispanic Ethnicity in Massachusetts. The prisoner data for Blacks and Whites includes only non-Hispanic Blacks and Whites. The Hispanic incarceration rates are not distorted, but non-Hispanic Black and White rates are slightly understated by the overlap.

Note that these age-shifted by-race population counts are used in Chart 12 and Chart 13 as well as in the lifetime-to-40 experience analysis.

[46] The census includes jails and police lock-ups in its count of the correctional population, many of which tend to be in urban (often poverty) areas. Thus, probably well over 83.2% of the population actually committed to State Prison or a House of Corrections are enumerated in non-poverty areas. The STF3-A files do not provide a breakdown of incarcerated persons by age and race, so that we cannot adjust for this factor. However, using our commitment data, in the manner described under "point in time" estimation (see page 23), we can estimate the worst case distortion. Our estimate is that in poverty areas, roughly 5% Black and Hispanics males are incarcerated at any given time. If all of them are incarcerated in non-poverty areas, then the population of minority males with their homes in the poverty areas may be understated by that amount. If all of the incarcerated males are in the 16-39 age range (not true, but worst case), then the understatement in that age range would be roughly 8.3%, since roughly 60% of the adult minority male population in poverty areas is in that age range. This population understatement would result in an overstatement of our bottom-line estimate by the same proportion.

Memo Computation: Commitment Rates (C_n/P_n)

Table 36 shows the commitment rates (prior to adjustment for geocoding failures) based on the above analysis.

Table 36: Annual State Prison Commitment Rates per 100,000 Males by Age Ranges from 16 to 39

	Non-Poverty			Poverty		
	Black	Hispanic	White	Black	Hispanic	White
16-19	399	466	24	762	623	126
20-24	985	654	61	1290	960	167
25-29	749	563	72	933	850	82
30-34	556	341	54	687	873	107
35-39	251	334	40	449	450	113
Avg. ½ length of Age Specific 95% C.I.'s	133	118	7	150	141	36

The rate differences between Blacks and Hispanics are not consistently significant. The differences between Whites and both Blacks and Hispanics are significant at well below the .001 level at all age levels. Note that these differences remain significant if one analyzes Extreme poverty areas alone (not shown). The poverty/non-poverty comparisons are generally significant, but not so at all levels when race and age-group are broken out.

Table 37: Statistical Significance of Racial Differences in Commitment Rates in Preceding Table Computed Using Age-Specific Confidence Intervals

	Non-Poverty			Poverty			Poverty/Non		
Age Range	BW	BH	HW	BW	BH	HW	BB	HH	WW
16-19	***		***	***		***	**		***
20-24	***	**	***	***	**	***	*	**	***
25-29	***		***	***		***		**	
30-34	***	**	***	***		***		***	***
35-39	***		***	***		***	**		***
AVG	***	**	***	***		***	***	***	***

***=p<.001; **=p<.01; *=p<.05

Mortality Rates and the Computation of Total Experience

The computation of lifetime-to-age-40 experience is iterative. For a full implementation of the model mathematics we would need to have age-specific mortality rates by race and poverty or non-poverty status. The best data available[47] were age-specific by race for White and Black males, with no poverty adjustment. We used the Black rates for the Hispanic group. The model is not very sensitive to this parameter – see below.

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[47] The data are compiled but not published by the U.S. National Center for Health Statistics. They appear in Table 120 of the Statistical Abstract of the United States: 1996. Bureau of the Census, Washington.

Sensitivity Analysis

The numbers presented in the text follow from the assumptions above. The chart below summarizes the possible influence of various factors on our bottom-line estimates.

Table 38: Sensitivity of Lifetime-to-40 State Prison Experience Estimates for Minority Males in Poverty Areas to Estimating Assumptions and Measurement Problems

Factor	Effect on Lifetime-to-40 State Prison Experience Estimate
Understatement of prior experience, either due to historic commitment rate trends or due to misidentification of offenders.	Possible overstatement, but unlikely to be more than 5 points for poverty-area minorities. Model already assumes high prior experience rates for older prisoners.
Overstatement due to lack of mortality adjustment in age roll-forward	Understatement for minorities in poverty areas, but minor – well under ½ point effect.
Census undercount of urban minority males	Could lead to up 1.5 point overstatement for urban minority males in poverty areas
Net migration to or from poverty areas	Possibly as large as one point either direction (see note 42).
Misclassification of population as poverty or non-poverty due to incarceration leading to overcount in poverty areas	Up to 1 point overstatement for minorities in poverty areas (less if simultaneously assuming overstatement due to prior experience)
Understatement of mortality rates for poverty area minority group members	Effect is nil. Tripling of rates used does not change estimate by a full point.

The numbers are very insensitive to mortality rates, since first time incarcerations occur most frequently among the young.

The principle uncertain term in the model is i_n – the share of new commitments of age n who have not previously been incarcerated. As discussed above, overstatement of this term could occur either because of high non-identification of previously committed inmates in our sample, or because of a rising historical commitment rate trend. Assuming that no one is incarcerated for the first time after the age of 30, and also that we miss 60% of previous commitments for Blacks and 75% for Hispanics in the under-30 age groups lowers the lifetime-to-40 estimates to 10.2% and 9.2% respectively for poverty area Blacks and Hispanics. The net of the several Census error terms could take another two points off of each of these. Thus 8% (roughly) represents the far low-side of the possible range of estimates of lifetime-to-40 experience for urban minority males.

High side estimates, varying the assumptions in our model, do not go much above 18% for poverty area minority males, but it should be remembered that our model does not include out-of-state or federal prison experience.

Estimates of House of Corrections Experience

We geocoded commitment databases from the Houses of Corrections in Middlesex and Norfolk Counties. These counties are both relatively prosperous. Table 39 shows how Middlesex and Norfolk counties compare to the rest of the state. It groups poverty tracts by statewide decile of neighborhood poverty rate and shows the population of those groupings as a percentage of the county population.

Given the steep gradient in commitment rates by decile shown in the text, it is clear that any overall computation of House of Corrections commitment rates based on these counties would be misleading. There is only one poverty tract in Norfolk County (a housing project in Quincy) and it includes only 3306 persons. Thus, the only estimates we make are for the Poverty tracts in Middlesex County.

There is every reason to believe that these estimates are *not* necessarily representative of any other particular poverty area as incarceration rates do vary considerably among areas.

Table 39: Population of Middlesex and Norfolk Counties by Poverty Rate Decile of Residence Tract (Poorest to Wealthiest Left to Right)

	0	1	2	3	4	5	6	7	8	9
Middlesex	2.7%	5.8%	8.5%	12.2%	9.2%	8.9%	8.1%	12.6%	14.4%	17.5%
Norfolk	0.5%	0.8%	3.7%	8.4%	8.9%	15.4%	15.7%	13.1%	15.4%	18.2%
All other	14.0%	12.9%	11.5%	9.5%	10.5%	9.5%	9.8%	8.7%	7.6%	6.2%

Our estimation processes for House of Corrections incarceration rates in poverty areas in Middlesex County differed from those we used for State Prison in the following respects:

Computing Population (P_n)

Our population totals for minority males in this estimate are particularly vulnerable to the census undercount problem. In effect, this computation includes the poverty areas in a single city, Lowell. (There are 14 poverty tracts in Middlesex County; 11 are in Lowell, and 2 of the other 3 are not student or hospital areas.) Thus, it is very possible that small area deficiencies in the accuracy of the census could be pushing our numbers up considerably – possibly doubling them. The most likely overstatement is more modest – on the order of 15%. See discussion above at page 34.

Computing Commitments (C_n)

Of necessity, we considered only commitments of Middlesex County residents to the Middlesex House of Corrections. These exclude time spent held on bail awaiting trial. They do include commitments for violations of probation and parole, and these commitments are not consistently distinguishable from other commitments and are therefore included.

At the county level, many inmates cross county lines – individuals residing outside Middlesex County accounted for 30.0% percent of commitments to the Middlesex County House of Corrections in our subject reference period, 1992 to 1996. At Norfolk County House, 49.9% came from outside the county between 1991 and 1996. Presumably, therefore, many individuals with a primary address in Middlesex County had House of Corrections experience in other counties. *We made no adjustment for cross-county traffic, resulting in a probably significant understatement of the house of corrections level experience of Middlesex County residents. Nor did we make any up adjustment for geocoding failure rates.* The no-address rate was 0.9% in the Middlesex House of Corrections sample, and the in-state not-geocodable rate was 6.4%.

Estimating Experience Rates (i_n)

The Middlesex data did allow us to identify, among inmates committed in 1996, those who had prior *Middlesex* House of Corrections experience *since 1992*. In addition, we had as a comparison our state prisoner criminal record samples (described below at pages 70 and following) for which we identified prior House of Corrections experience. State prisoners, generally having more serious records, should be more likely to have prior house experience than House of Corrections inmates.

Because the state prison samples were too small to be the basis of race specific estimates and the House of Corrections sample was temporally incomplete we took the following conservative strategy: We used the *maximum* of the available prior House experience rates (an approach which minimizes our bottom line experience estimate). This approach may slightly down-bias the bottom-line estimate for the Hispanic group relative to the others. As in the State Prison population, the Hispanic Group has lower prior House experience as shown in Table 40. We did not additionally apply an inflation factor for "missed" prior experience as we did for the state prison population.

Table 40: Prior House of Corrections Experience Rates

	Middlesex Past Five Years			State Prison Sample		USED
	Black	Hispanic	White	DRUG	NON-DRUG	Maximum for Age
16-19	35%	10%	28%	25%	8%	35%
20-24	36%	34%	43%	57%	63%	63%
25-29	45%	41%	46%	50%	72%	72%
30-24	50%	36%	48%	50%	79%	79%
35-39	57%	34%	44%	65%	61%	65%

Note that the Middlesex prior experience estimates reflect any prior commitment to the House of Corrections regardless of length (although they do not include time spent in Jail awaiting trial). This is a factor that operates to minimize our number of first time prisoners and understate our bottom-line estimate of significant lifetime incarceration experience.

Estimates of Point-in-Time Incarceration Rates

Our method of estimating local point-in-time incarceration rates was as follows:

1) Derive a race-by-poverty-area cross tabulation of the total man-years sentenced (i.e., the sum of all the sentences) for all of the male commitments during our study period, including those without geocodable addresses. Note that, because below we are concerned with the proportions, not the absolute magnitudes of sentences, it turns out to make almost no difference whether one bases this computation on minimum or maximum sentences (no cell proportion changes by more than one percent).

2) Model the total "steady state" population as the sum of all cells in the cross-tabulation in the preceding step.

3) Compute the ratio of the actual total population to this modeled total population. (We used an "actual" population of 10,000, which is the level around which DOC has recently fluctuated; it was 9411 males on January 2, 1997.) Note that this ratio, when based on minimum sentences is, 70.1%. This reflects the fact that inmates sentenced under pre-July-1994 policies often may be released prior to their minimum sentence.

4) Apply this ratio to the cells in the cross-tabulation to deflate them to levels consistent with the actual population. This, in effect, adjusts for parole.

5) Adjust these adjusted man-year sums in the (geocodable) race/poverty-area cells upwards by the percentages in Table 31 (to adjust for non-geocoded addresses).

6) Divide the resulting estimated race/poverty-area population counts by the estimated mid-decade counts of males over 16 used in the experience modeling.

From basic stock/flow modeling, we know that the sum of the total sentenced years in a single year's worth of commitments provides an estimate of the population *if and only if* annual flow continues at the same rate. We know that this is at best a partially valid assumption. Historically, based on DOC publications, the offense type mix has fluctuated and the overall volume of commitments has risen.

For our present purpose of race by poverty-area estimation, the mix need remain constant only on those dimensions. We have no way to test the constancy of the poverty-area mix; however, the race mix predicted by our model is not far off the actual historical race mix.

Table 41: Actual vs. Modelled Race Mix of State Prison Population

	MODEL RATIOS	Actual as of 1/1/95	Actual as of 1/1/94
BLACK	29%	29%	29%
HISPANIC	24%	20%	19%
WHITE	45%	50%	51%
OTHER	2%	1%	1%
	100%	100%	100%

Historical DOC population breakdowns indicate a steadily increasing proportion of Hispanic inmates.[48] The discrepancy between historical proportions and our model output based on the period 7/1/94 through 6/30/96 may reflect that the continuation of that long-term trend. Thus our model may overstate the point-in-time incarceration of Hispanics and so may overstate current relative levels in Poverty areas generally, but may accurately reflect trends.

This computation is subject to the population size issue mentioned above on page 64.

Methodology for Criminal History Analysis

We conducted two categories of criminal history analysis. First, we thoroughly reviewed the criminal records of a sample of incarcerated drug offenders so as to be able to statistically characterize their histories. Second, we evaluated the criminal records of a sample of incarcerated non-drug offenders with the more limited goal of ascertaining prior incarceration experience for our analysis of lifetime incarceration experience. The methodology for each phase will be described separately.

First Phase: Criminal History Analysis of a Sample of Drug Offenders

Sample Selection and Acquisition of Criminal Offender Record Information (CORI)

From our Department of Corrections database, we generated a random sample of 200 drug offenders from the 1290 offenders incarcerated for drug crimes in Fiscal 1995 and 1996. We submitted to the Criminal History Systems Board (CHSB) the names and dates of birth of the 200 incarcerated drug offenders in order to access their criminal records.

The CHSB found a probable match for all but six of the offenders. Since all of these offenders have been committed to State Prison in Massachusetts, all of them should have criminal records that, at the very least, include the arraignment for the offense for which they were incarcerated.

The primary reason for unretrieved histories appears to be use of aliases and incorrect dates of birth by offenders. The CHSB does "soundex" matching to catch spelling variations. In most cases, an offender's aliases are identified and linked to his/her true name in the Probation Database, so that the CHSB can find a person either by true name or by alias. However, when aliases have not yet been recorded in the Probation Database, prior history may be impossible to retrieve.

Universe of Drug Offenders Included in Analysis

Of the random sample of 200 incarcerated drug offenders originally submitted to the CHSB, 151 were ultimately included in the CORI analysis. The reasons for excluding 49 offenders are as follows:

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[48] Massachusetts Department of Correction. 1996. "A Statistical Description of the Sentenced Population of Massachusetts Correctional Institutions as of January 1, 1995." Note that the DOC statistic combines males and females whereas ours only reflects males.

Table 42: Offenders Excluded from Criminal History Analysis

CORI Problems (n=14)	• No CORI found by CHSB (n=6) • Possible match, but either it's the wrong person or there's too much information missing (i.e., no arraignments or convictions for drug offenses) (n=8)
Excluded from Analysis (n=35)	• Female offenders (n=18)[49] • Offenders with out-of-state addresses on their CORI (n=14) • History indicates that offenders not committed for a drug offense (includes those committed for a violation of probation) (n=3)

We excluded offenders with out-of-state addresses on their CORI, since an out-of-state address indicates the distinct possibility that the Massachusetts CORI includes only a fraction of the offender's criminal activity. [50]

After these exclusions, the sample consists of 151 males incarcerated for a drug offense between July 1, 1994 and June 30, 1996[51] with Massachusetts addresses on their criminal histories.

Representativeness of Sample of Drug Offenders

Using variables in the DOC database, we tested the representativeness of the sample of male drug offenders against the population of male drug offenders in the DOC database. The first column of Table 43 shows the sample proportions of those 151 offenders included in the analysis. The 95% confidence intervals around the sample proportions contain the population proportions.

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[49] See above under "Selection of Study Population."

[50] In fact, 79% (11 of 14) of the out-of-state offenders had no arraignments in Massachusetts' courts prior to the arraignments for the drug offenses for which they were incarcerated, as compared to only 15% (23 of 151) of the in-state offenders. To include the out-of-state offenders would be to understate the average extent of those offenders' criminal records.

[51] On their criminal records, six of the offenders had commitment dates earlier than 7/1/94, the beginning of our study period. In these six cases, the offender was convicted and sentenced for a "School Zone" offense (Ch. 94C Section 32J) in addition to another drug charge. School Zone offenses carry two-year mandatory sentences to be served on and after another drug charge. It is quite clear that, in these six cases, the commitment date prior to 7/1/94 is for the original drug charge and the new DOC commitment date after 7/1/94 is for the school zone charge. In another two cases, the offenders' CORI also indicated commitment dates earlier than 7/1/94. In these two cases, however, there were no school zone charges or any other on and after charges that could explain why the DOC's commitment date was significantly later. Given that all 8 of the offenders appeared unambiguously to be drug offenders and to otherwise meet our criteria for inclusion, we included them despite the ambiguity about commitment date, because commitment date is not in itself a critical variable in our analysis.

Table 43: Representativeness of Sample of Male Drug Offenders

	SAMPLE after all exclusions	5% C.I.	POPULATION (Commitments)
TOTAL N	151 males		1175 males
RACE			
% Black	25%	6.9%	29%
% Hispanic	55%	7.9%	54%
% White	19%	6.3%	15%
% Other	1%	1.6%	2%
% out-of-state place of birth	62%	7.7%	66%
AGE RANGES			
16-19	7%	4.1%	5%
20-24	23%	6.7%	24%
24-29	23%	6.7%	23%
30-34	20%	6.4%	19%
35-39	15%	5.7%	14%
40-44	8%	4.3%	7%
45-49	3%	2.7%	4%
50+	3%	2.7%	4%
% charged with trafficking	30%	7.3%	34%
% with prior commitment number on DOC database	16%	5.8%	15%

Coding Procedure

Following the Massachusetts Sentencing Guidelines Commission, we used arraignment events as our primary unit of analysis in analyzing criminal records. An arraignment event is a criminal charge or set of charges arraigned on a single day, and tends to correspond to a single criminal incident.[52]

In our measures of criminal history, we included only those arraignment events that reached final disposition (either by dismissal or sentencing) prior to the day on which the offender was sentenced to State Prison for the drug offense (commitment date).[53] For a number of offenders, more than one arraignment event reached final disposition on the offender's commitment date. We did not include those other arraignment events as history because they do not constitute prior history for the purpose of sentencing on the drug charge.

For each arraignment event, we identified the most serious convicted offense in the arraignment, or, in the absence of a conviction, the most serious offense among all of the charges. In identifying convictions, we followed the Massachusetts Sentencing Commission's definition:

> "Examples of convicted dispositions are: Guilty Filed; Guilty; Probation; Fine; House of Correction Commitment; State Prison Commitment; Split Sentence; and Suspended Sentence. Examples of dispositions that were not considered convictions are: Continued Without Finding; Filed (absent a finding of guilty); Dismissed; and Not Guilty." (p. 59-60)

[52] Where cases moved from court to court as a result of indictment or appeals to a jury of six, we combined successive arraignments to avoid double-counting. In some cases, the charges from multiple district court arraignments were brought together in a single superior court arraignment. In those instances, we recorded a separate entry in our database for each of the original district court arraignments.

[53] In the event of a disposition of "Continued Without Finding" (CWOF), we included that arraignment event only when the CWOF was dismissed or otherwise disposed of before the offender's commitment date.

When more than one conviction (or more than one offense, in the absence of convictions) shared the highest seriousness level, we recorded the drug offense, if any. Rarely did a violent offense and a drug offense vie for the most serious charge in an arraignment event.

For the most serious offense in each arraignment event, we recorded five facts.

First, we recorded the seriousness level of the most serious offense from 1 to 9 (least to most serious) based on the Massachusetts Sentencing Commission's Master Crime List. Some offenses on the Master Crime List are "staircased" in that they have different seriousness levels depending on a "staircase factor." For Assault & Battery with a Dangerous Weapon, for example, the staircase factor is injury to the victim. A&B DW is a level 3 offense with a staircase factor of "no/minor injury" and is a level 6 offense with "significant injury." Criminal history data often do not indicate the staircasing factors. We followed the Sentencing Commission's approach, and in ambiguous cases recorded the lowest seriousness level for staircased offenses.

Second, we recorded whether the most serious offense was violent or not. We followed the Uniform Crime Reports approach, considering murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault to be violent crimes – those involving force or threat of force." We also counted all assaults as violent whether or not the record gave explicit indication that they were aggravated assaults. Restraining order violations were not considered violent.

Third, we recorded whether the most serious offense was a drug offense or not. Any offense falling under G.L. Chapter 94C was considered a drug offense. If the most serious offense was not a drug offense, but another offense in that arraignment date was a drug offense, then we made a note of a "secondary drug charge."

Fourth, we recorded whether the offender was convicted for the offense.

Fifth, we recorded whether the offender was incarcerated for the offense. When the *initial* disposition included the terms "CMTD" or "SPS" (split sentence) followed by "CMTD," we considered that an incarceration. A suspended sentence "SS" is not considered incarceration.

Massachusetts Sentencing Commission's Criminal History Groups

At several points in our analysis it seemed useful to use the Massachusetts Sentencing Commission's Criminal History Groups as labels characterizing offenders. Our methods (described above) were designed to allow us to faithfully follow the Commission's group definitions[54] while also giving us flexibility to generate other measures. Table 44 summarizes the Sentencing Commission's Criminal History Groups.

[54] Our only deviation from the Sentencing Commission's procedures for determining an offender's Criminal History Group resulted from our not having access to the offenders' juvenile, out-of-state, and Federal criminal records. The Commission included all convictions from out-of-state and Federal criminal records, as well as adjudications of delinquency for offenses in level 7 through 9.

Table 44: Massachusetts Sentencing Commission Criminal History Groups

E – Serious Violent Record
Two or more prior convictions for offenses in level 7 through 9

D – Violent or Repetitive Record
One prior conviction for offenses in level 7 through 9, or
Two or more prior convictions for offenses in levels 5 or 6, or
Six or more prior convictions for offenses in levels 3 or 4

C – Serious Record
One prior conviction for offenses at levels 5 or 6, or
Three to five prior convictions for offenses in levels 3 or 4

B – Moderate Record
One or two prior convictions for offenses in levels 3 or 4, or
Six or more prior convictions for offenses in levels 1 or 2

A – No/Minor Record
One to five prior convictions for offenses in levels 1 or 2, or
No prior convictions of any kind

Table 45, combines several types of information. It gives illustrative examples of offenses at for levels three through eight of the Sentencing Commission's nine seriousness levels. It shows the sentence ranges recommended for each combination of offense-level and history group (the table does not show non-incarceration sentences, which are an option in cells in the lower left area of the grid). Lastly it shows how our sample of incarcerated drug offenders fell on the grid (100% fall in the cells shown).

Table 45: Massachusetts Sentencing Guidelines Grid with Percent of Offenders from Random Sample of State Prison Drug Offenders in Appropriate Cells (N=151)

Level	Illustrative Offenses	Sentence Range				
8	Manslaughter (voluntary) Armed Burglary Cocaine Trafficking (200g+)	96-144 months **5%**	108-162 months	120-180 months **1%**	144-216 months	204-306 months
7	Armed Robbery (Gun) Rape Cocaine Trafficking (100-200g) Heroin Trafficking (28g+)	60-90 months	68-102 months	84-126 months	108-162 months	160-240 months
6	Manslaughter (Involuntary) Armed Robbery (No gun) Cocaine Trafficking (28-100g) Heroin Trafficking (14-28g)	40-60 months **8%**	45-67 months **3%**	50-75 months **5%**	60-90 months **3%**	80-120 months
5	Unarmed Burglary Larceny ($10,000 to $50,000) Cocaine Trafficking (14-28g)	12-36 months **5%**	24-36 months **8%**	36-54 months **3%**	48-72 months **4%**	60-90 months
4	A&B DW (Moderate injury) B&E (Dwelling) Distribute Cocaine or Heroin Drug Violation Near School	0-24 months **16%**	3-30 months **15%**	6-30 months **12%**	20-30 months **10%**	24-36 months **1%**
3	A&B (No or minor injury) Larceny ($250 to $10,000) Posses Hypodermic (2^{nd} Off.)	0-12 months	0-15 months	0-18 months	0-24 months **1%**	6-24 months
	Criminal History Scale	A No/Minor Record	B Moderate Record	C Serious Record	D Violent or Repetitive Record	E Serious Violent Record

Second Phase: Determining Prior Incarceration Experience

For the purposes of estimating lifetime incarceration experience, we conducted a second phase of the criminal history analysis including the sample of drug offenders (n=151) described above and a sample of non-drug offenders. A description of the selection, universe, and representativeness of the sample of non-drug offenders follows.

Universe of Non-Drug Offenders Included in Analysis

Using the Department of Corrections database, we generated a random sample of 200 male non-drug offenders from the 3027 males incarcerated for non-drug crimes in Fiscal 1995 and 1996. Of the random sample of 200, 171 were ultimately included in the analysis. The reasons for excluding 29 offenders are as follows:

Table 46: Offenders Excluded from Criminal History Analysis

CORI Problems (n=6)	•No CORI found by CHSB (n=3) •Possible match, but either wrong person or too much information missing (n=3)
Excluded from Analysis (n=23)	•Offenders with out-of-state addresses on their CORI (n=6) •Offenders committed for violations of probation (n=16) •Offender committed for a drug crime (n=1)

The reasons for excluding the 23 offenders from the analysis are the same as in the first phase of the analysis (explained above).

Representativeness of Sample of Non-Drug Offenders

Using variables in the DOC database, we tested the representativeness of the sample of male non-drug offenders against the population of male non-drug offenders in the DOC database.

The first column of Table 47 shows the sample proportions of those offenders included in the analysis. In both cases, the 95% confidence intervals around the sample proportions contain the population proportions, except for the proportion of 24-29 year olds in the sample after exclusions. The samples cannot be said to be statistically different from the population at the 5% level.

Table 47: Representativeness of Sample of Male Non-Drug Offenders to Population

	SAMPLE after all exclusions	5% C.I.	POPULATION
TOTAL N	171 males		3027 males
RACE			
% Black	27%	6.7%	28%
% Hispanic	16%	5.5%	17%
% White	53%	7.5%	51%
% Other	4%	2.9%	4%
% out-of-state place of birth	33%	7.0%	36%
AGE RANGES			
16-19	10%	4.5%	10%
20-24	19%	5.9%	22%
24-29	30%	6.9%	22%
30-34	14%	5.2%	18%
35-39	13%	5.0%	12%
40-44	6%	3.6%	7%
45-49	4%	2.9%	4%
50+	4%	2.9%	4%
% with prior commitment number on DOC database	18%	5.8%	20%

Coding Procedure

In this phase of our analysis of the offenders' criminal histories, we simply wanted to record for each offender whether he had, prior to his current incarceration in State Prison, been incarcerated in State Prison or in a House of Correction (HOC).

We considered only those State Prison or HOC sentences that were imposed prior to the day on which the offender was sentenced to State Prison for his current offense (commitment date). We did not count prison or HOC sentences imposed on the same day as his current commitment date. While we did not include offenders *currently* committed for violations of probation, we counted *prior* commitments resulting from violations of probation the same as any other prior incarceration. [55]

[55] In most cases, criminal histories do not explicitly indicate whether the sentence is to be served in a State Prison or a HOC. Two rules made the answer clear in most cases: any sentence greater than 2½ years is a State Prison sentence; any sentence from a District Court arraignment is a HOC sentence. The only sentences not covered by these two rules are sentences of less than 2½ years from Superior Court arraignments. In this category, there were ten non-drug offenders and seven drug offenders. In none of the 17 instances was the sentence in question given as a range of time (i.e., "1 to 2 years") which would have

Table 48: Prior State Prison and HOC Experience for Both Samples of Offenders

	JUST PRIOR HOC	JUST PRIOR STATE PRISON	BOTH PRIOR HOC AND STATE PRISON	NEITHER PRIOR
NON-DRUG (n=171)	43%	4%	18%	36%
DRUG (n=151)	39%	3%	15%	43%
Weighted Average (based on the proportion of male offenders in the whole DOC population) 72% non-drug and 28% drug	42%	4%	17%	38%

Comparison of two sources of prior State Prison incarceration information: DOC prior commitment number and prior State Prison commitment on Criminal History

We had two indicators of prior state prison experience to work with: First, a field on our DOC database of commitments ("prior commitment number" or "PCN"); second the results of our criminal history analysis for our two samples. We compared them to evaluate their reliability.

Of 322 drug and non-drug offenders, all 55 offenders with PCNs on the DOC database had prior State Prison experience on their criminal histories.

We also wanted to examine potential errors in the other direction. From the sample of non-drug offenders (n=171), 37 offenders were found to have prior State Prison experience on their histories. 6 of the 37 (16.2%) had no PCNs. From the sample of drug offenders (n=151), 27 offenders were found to have prior State Prison experience on their CORI. 6 of the 27 (22.2%) had no PCNs. The rates of omission are not significantly different between the drug and non-drug offenders. The blended omission rate is 18.8%.

In our lifetime experience analyses, where prior-experience was a critical variable factor we used the DOC PCN field to study prior-experience variations by category of prisoners. (The larger database was essential to avoid small cell problems in our sample.) We then applied rough inflation factors to adjust upwards for the probable missing experience. See the discussion above under "Estimating Experience Rates (in)."

Potential for Bias/Inaccuracy in Criminal History Analysis

There are three potential sources of bias or inaccuracy in our analysis of offenders' criminal histories. All of these tend to understate the criminal histories of our subjects.

Criminal History Problems

For various reasons detailed above we had to exclude some prisoners selected from our random samples. Our comparisons of the samples after exclusions to the underlying population suggested that little distortion was introduced by these exclusions.

Also, data entry errors and omissions in criminal records are inevitable. It seems likely that errors (particularly omissions) create a slight general down-bias in our evaluation of histories. A related problem

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suggested a State Prison sentence. As a result, we decided to count these 17 sentences as HOC sentences. The effect of this decision, if at all incorrect, would be to slightly underestimate prior State Prison experience.Of the 17, only three had other prior State Prison experience. If all 17 were in fact State Prison sentences (unlikely), then we would be underestimating prior State Prison experience by 14/322 or 4.3% at most. The converse, that we might be overestimating prior HOC experience, is less likely as 12 of the 17 had other prior HOC experience. If all 17 were in fact State Prison sentences, then we would be overestimating prior HOC experience by, at most, 5/322 or 1.6%.

is that by changing identities, offenders can fragment their histories. This also creates a down-bias in perceived histories. Any analysis of criminal histories (for research or in the courtroom) is subject to these problems, and there is no good way to correct for them. We do not believe that these effects are large -- all of the data we are relying on are data that are relied on by criminal justice professionals in their daily work.

Staircased Offenses

As noted above, the Massachusetts Sentencing Commission assigns multiple seriousness levels to certain offenses based on "staircase factors." Only occasionally are staircase factors specified in the descriptions of offenses on CORI. When the staircase factor is not given, we adopted the Commission's approach by recording the lowest seriousness level for the particular offense. The effect of this approach is to understate, in some cases, the seriousness of offenses, which may create an additional source of down-bias in evaluating histories.

Lack of Access to Offenders' Juvenile, Out-Of-State, and Federal Criminal Records

As we did not have access to the offenders' juvenile, out-of-state, and Federal criminal records, we are missing parts of some offenders' criminal histories. This again creates a source of down-bias.

The absence of juvenile records simply forced us to analyze only the offenders' adult criminal activity.[56]

In an effort to minimize the down-bias arising from out-of-state records, we removed from our analysis the offenders with out-of-state addresses on their criminal histories. Among the drug offenders, 11/14 (79%) of the out of state offenders had no prior arraignments, while only 23/151 (15%) of the in-state offenders had no prior arraignments – strongly suggesting that the out-of-state offenders have criminal records in other states. While removing those with out-of-state address has reduced the distortion from our lack of access to out-of-state criminal records, even those with in-state addresses on their criminal histories could have spent a significant portion of their adult life outside of Massachusetts.

Summary on Issues of Bias and Inaccuracy in History Information

There is no good way to accurately estimate the magnitude of the potential down-biases itemized above. It is certain that our characterizations of drug offenders records are understated as a result. However, we do not believe the down-biases are so severe as affect the basic conclusion that some significant proportion of drug offenders have light, non-violent records.

Supplementary Analyses of Characteristics of Drug Offenders

Traffickers vs. Non-Traffickers

Table 49 compares traffickers to the rest of the drug offenders according to basic demographic variables.

Table 49: Demographic Comparison of Traffickers and Non-Traffickers (among all State Prison drug offenders – not subsample)

	Traffickers (N=400)	Non-Traffickers (N=775)
Race		

[56] As noted above, in the classification of offenders under the Massachusetts Sentencing Guidelines, very serious juvenile offenses count towards the adult criminal history group. It is unlikely that any offenders in our sample had offenses on their juvenile record which were serious enough to count – only 4 (2.6%) had offenses of the requisite seriousness level (over level 6) on their adult records.

Black	21%	32%
Hispanic	60%	51%
White	17%	14%
Place of Birth		
Out of State	70%	63%
Average Age at Commitment	31.6	30.0

Along demographic lines, the traffickers and non-traffickers are fairly similar. While the non-traffickers include a significantly higher percentage of Blacks and a slightly lower percentage of Hispanics, the differences are not of obvious import. The difference in the out of state place of birth percentages is primarily a function of the ethnic differences, as the vast majority (89%) of the male Hispanic drug offenders were born outside Massachusetts.

Using our analysis of the criminal histories of a sample of the offenders, we compared the prior criminal activity of the traffickers to that of the non-traffickers.

Table 50: Comparison of Prior Court Contact for Traffickers and Non-Traffickers

	Traffickers (N=46)	Non-Traffickers (N=105)
No prior arraignments	20%	13%
Average annual arraignment rate as an adult	0.52	0.77

Using court contact as a basic proxy of criminal activity, the traffickers appear to have slightly less serious records. A slightly higher percentage of the traffickers had no arraignments prior to the arraignment for the drug offense that resulted in incarceration. Similarly, the average annual arraignment rate for all of the traffickers is lower as compared to the rest of the drug offenders. There is no statistically significant difference between the traffickers and non-traffickers as to their prior history of violence.

Table 51: Comparison of Prior Drug Activity for Traffickers and Non-Traffickers

	Traffickers	Non-Traffickers
Drug arraignments		
One to two	33%	32%
Three or more	15%	39%
Drug convictions		
One to two	30%	30%
Three or more	9%	36%
Drug convictions (Seriousness Level)		
Maximum of Level 2	17%	13%
Maximum of Level 4 and over	22%	53%

Far larger than the difference in prior violent activity is the difference in prior involvement in drug crime. It follows from Table 51 that nearly two-thirds of the traffickers (61%) had no prior drug convictions as compared to one-third (34%) of the non-traffickers. Significantly higher percentages of the non-traffickers had three or more arraignments or convictions for drug offenses. Moreover, a much larger percentage of the non-traffickers had been convicted of more serious drug offenses: 53% had a conviction at Seriousness Level 4 (primarily cocaine or heroin distribution) or higher, while 22% of the traffickers had a prior conviction at those same levels.

One of the reasons that traffickers have shorter and less severe criminal records could be that more of the traffickers have criminal records outside of Massachusetts that are not included in our analysis. One way to try to test that hypothesis is to compare the two groups based on whether the offenders were born in

Massachusetts or not. In our sample of 151 male drug offenders, 65% of the traffickers had out-of-state places of birth compared to 61% of the non-traffickers. This is not a statistically significant difference. In the larger DOC database of 1,175 male drug offenders, 70% of the traffickers had out-of-state places of birth compared to 63% of the non-traffickers. This difference is significant ($p<0.05$), but not nearly great enough to explain the contrasts show in Table 51.

Analysis of All High-Weight Cocaine Traffickers

Selection of Sample and Acquiring CORI

In addition to the random sample of 200 drug offenders, we compiled the names of all of the remaining high-weight cocaine traffickers (trafficking over 100 grams). Of the 72 total high-weight cocaine traffickers, 10 were selected in the random sample, thus leaving 62 additional names. As for the additional 62 high-weight cocaine traffickers, no CORI match could be found for four offenders.

Universe of High-Weight Cocaine Traffickers in the Analysis

Of the full sample of 72 high-weight cocaine traffickers committed to State Prison over the two-year period (charged with trafficking over 100 grams or over 200 grams), 56 fit the criteria for the criminal history analysis.

Table 52: High-Weight Cocaine Traffickers Excluded from Criminal History Analysis

CORI Problems (n=7)	• No CORI found by CHSB (n=4) • Possible match, but either it's the wrong person or there's too much information missing (n=3)
Excluded from Analysis (n=9)	• Female offenders (n=5) • Offenders with out-of-state addresses on their CORI (n=4)

Table 53 presents a demographic breakdown of these high-weight cocaine traffickers compared to lower-weight cocaine traffickers (trafficking from 14 up to 100 grams) and to all of the non-traffickers. The table presents information from the DOC database.

Table 53: Demographic Snapshot of High-Weight Cocaine Traffickers

	High-Weight Cocaine Traffickers N = 56 males in analysis	Lower-Weight Cocaine Traffickers N= 316 males	All Non-Trafficking Drug Offenders n= 775 males
Race			
Black	14%	24%	32%
Hispanic	70%	55%	51%
White	13%	19%	14%
Place of Birth			
Out of State	77%	67%	63%
Average Age at Commitment	32.2	31.3	30.0

As compared to the other groups, the high-weight cocaine trafficking group has an even larger percentage of Hispanics which, in part, accounts for the higher percentage of offenders born out-of-state.

Based on our criminal history analysis, Table 54 illustrates the prior criminal activity of the high-weight cocaine traffickers as compared to the lower-weight cocaine traffickers and to the non-traffickers.

Table 54: Prior Criminal Activity of High-Weight Cocaine Traffickers

	High-Weight Cocaine Traffickers n = 56 males	Lower-Weight Cocaine Traffickers n = 36 males	All Non-Trafficking Drug Offenders n= 105 males
No prior arraignments	34%	14%	13%
Average annual adult arraignment rate	.28	.59	.77
Violent			
% with prior arraignments	18%	50%	55%
% with prior convictions	5%	31%	36%
Drug			
% with prior arraignments	39%	56%	71%
% with prior convictions	29%	44%	66%
Criminal History Group			
% in A	73%	42%	26%
% in B	20%	31%	30%
% in C-E	7%	28%	44%
% with prior State Prison experience	5%	6%	23%
% with prior HOC experience	18%	44%	60%

Though the sample sizes of the cocaine traffickers are quite small, the results point to the conclusion that the high-weight cocaine traffickers have significantly less serious criminal records than the lower-weight cocaine traffickers and especially the non-traffickers. Looking at the broader measures of past criminal activity, nearly three-quarters of the high-weight cocaine traffickers are in Criminal History Group A (No/Minor Record) and only 7% of them have “serious” criminal records in Groups C-E. Compared to the lower-weight cocaine traffickers and the non-traffickers, the traffickers have less serious records.

Distinctions Among Non-Traffickers

Among the non-traffickers, some were incarcerated for a drug crime with a mandatory sentence and some were not. The non-trafficking mandatory sentences include second offense cocaine and heroin charges and special penalties for cocaine (as against other Class B substances) as well as school zone charges. We will refer to these as “discretionary mandatory” sentences, because they differ from the mandatory sentences for trafficking in terms of the level of prosecutorial discretion involved. Anecdotal evidence indicates that persons arrested with quantities over the trafficking weights are usually indicted and prosecuted under the trafficking statutes. Prosecutors rarely consider the exercise of discretion in this context. By contrast, for distribution of lesser quantities, dealers may or may not be indicted and may or may not be indicted under provisions mandating state prison incarceration.

From our criminal history analysis, we found that the non-mandatory category had less serious criminal pasts. The histories of the groups looked very similar as to violent offenses, but the mandatory category group had more serious drug offendeing records. Since over one-third of the discretionary mandatory category is comprised of offenders incarcerated for a second offense charge, this is unsurprising.

Perhaps the most striking finding about the discretionary mandatory as compared to the non-mandatory groups is the variation in their proportions across counties. This variation may reflect prosecutorial variations in the use of discretionary mandatory charges, or it may reflect variations in the rate which judges sentence to state prison under non-mandatory charges.

Table 55 shows the differing rates at which state prisoners from different counties are sentenced under the general class B statute (a non-mandatory sentence) or the cocaine clause (a mandatory sentence).

Essentially all class B retailing offenses are cocaine retailing offenses and the decision to charge under the mandatory clause is entirely a discretionary one for prosecutors.

Table 55: State Prison Sentences under First Offense Class B and First Offense Cocaine Statutes (Actual Counts, Fiscal 1995 and 1996)

County	Class B Statute	Cocaine Statute	% Cocaine Statute
Barnstable	0	4	100%
Berkshire	3	12	80%
Bristol	6	13	68%
Essex	25	4	14%
Franklin	2	1	33%
Hampden	21	14	40%
Hampshire	0	1	100%
Middlesex	11	13	54%
Norfolk	3	0	0%
Plymouth	2	5	71%
Suffolk	36	42	54%
Worcester	44	6	12%

Table 56 illustrates some of the demographic differences between the offenders in the discretionary mandatory and non-mandatory categories. The two counties with the largest number of first offense Class B and Cocaine state prison commitments – Suffolk and Worcester have significantly different mixes of the two.

Table 56: Demographic Comparison of Offenders Convicted of Crimes Carrying Discretionary Mandatory and Non-Mandatory Sentences

	Discretionary Mandatory	Non-Mandatory
Race		
Black	45%	21%
Hispanic	42%	60%
White	13%	16%
Average Age at Commitment	28.7	31.1

A larger percentage of the offenders in the Discretionary Mandatory category is Black and a smaller percentage is Hispanic. The higher Black percentage in Table 56 can be explained by the county-level variations in the rate at which discretionary mandatory statutes are used, shown in Table 55. The largest of the high cocaine-indictment rate counties, Suffolk, also has the largest Black population. Interpreting this relationship requires data beyond the scope of this study. The data could be read as suggesting *either* harsher or more lenient treatment of Blacks (or of drug offenders generally in higher Black population counties). It could suggest more lenient treatment if one read the non-mandatory-but-sentenced-to-state-prison group as low *not* because relatively many were indicted under discretionary mandatory statutes, but rather because relatively many were indicted under non-mandatory statutes and not sent to state prison.