Intra-class Correlation Patterns of Behavioral and Cognitive Measures of Substance Use and Acquisition in Six Major Metropolitan Areas

Zhiwei Zhang¹, Michael P. Cohen¹, and Douglas Wright¹ ¹NORC at the University of Chicago, 4350 East-West Hwy, Suite 800, Bethesda, Maryland, 20814

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1. NHSDA, Clusters, and Intra-class Correlation

Through the National Household Survey on Drug Abuse (NHSDA) – the predecessor of the current National Survey on Drug Use and Health (NSDUH) – which collected national data on both illicit and licit drugs, we calculate intra-class correlations (ICC) for both cognitive and behavioral measures on drug use at the census tract and census block group and NHSDA segment¹ levels within six major metropolitan areas. We demonstrate that IC should not be overlooked in the substance abuse fields and discuss further the utility of empirical knowledge of intra-class correlations of pertinent measures in future sample design, estimations, and for policy oriented preventions and interventions.

We deliberately focus on two types of outcome measures – cognitive and behavioral in light of their implications on health care interventions and preventions. The behavior measures are behaviors reported by household respondents about their uses in the month prior to the survey interviews of various substances such as alcohol, cigarette, marijuana, cocaine, any illicit drug except marijuana, and any illicit drug. The cognitive measure is perceived difficulties of getting illicit drugs in the month prior to interview.

Estimating components of variance from large-scale observational data has the advantage that large numbers of clusters may be included, leading to more precise estimates of intra-class correlations. Given that NHSDA/NSDUH are surveys at the national level and considering that sub-national level of ICC estimations may enrich our understanding of the differentiated ICCs across metropolitan areas, we estimated ICCs for six metropolitan areas separately so that the results can better inform the localized community interventions. Comparable information and findings from a national survey may be considered more generalizable than data obtained through interventions in a single locality.

Ignoring intra-class correlation can greatly inflate the chances of making Type I errors, resulting in many more findings of significance. Similarly, small intra-class correlations in large groups

¹ A segment can vary from one to several hundred individual census blocks. It might overlap with, but was different from, Census block groups although they were very similar in terms of population size and especially the numbers of respondents.

can also inflate the alpha level. For variance component models (without randomly varying slopes), the sample design question of how many subjects and units are needed is analogous to that addressed by Kish (1965) in computing effective sample size in two-stage cluster sampling. For a given intra-class correlation, adding numbers of units, for example, from 20 to 100 (with 20 subjects per unit), produces an effective sample size almost four times as large as a similar study with 20 units and 100 subjects per unit.

		Cluster Size		
Cluster Level	Number of Clusters	Mean	CV	
Metro	6	7448.67	0.036	
Segment	3893	11.48	0.627	
Tract	2842	15.73	0.856	
Block-Group	3857	11.59	0.712	

Table 1: Cluster Sizes in the NHSDA 1991-1993 (Sample Size=44,692)

Note: CV is the coefficient of variation which is the ratio of the standard deviation to the mean.

Table 1 shows the number of different types of clusters in the pooled NHSDA 1991-1993 surveys, and the mean numbers of the respondents in each type of the cluster. The six metropolitan areas held an average of close to 7,500 respondents per metro area. Among the census tract, NHSDA segment, and the census block group clusters, the tract held an average of about 16 respondents each, and the segment and block groups held an average of 11 to 12 respondents.

 Table 2: Intra-class Correlations for the Perceptions of the Difficulties of Getting Illicit Drugs

 within Major Metropolitan Areas

Metropolitan Areas	Segment	Block-Group	Tract
All 6 metropolitan areas	13	13	10.6
Miami	17.8	16.4	13.2
Chicago	14.2	16.2	14.1
New York	13.4	15.4	13.8
Washington, D.C.	9.4	7.3	5.8
Denver	7.8	7.1	4.1
Los Angeles	6.9	7.1	5.4

A set of intra-class correlations were calculated on the NHSDA respondents' self-reported perceptions of the difficulties of getting drugs, presumably in or from their neighborhoods. In general, intra-segment and intra-block-group correlations were higher than the intra-tract correlations, reflecting the fact that Census tracts are considerably larger, and the greater diversity with these larger areas leads to smaller interclass correlations. Table 2 also reveals that

regardless of the type of clusters, the intra-class correlations were not uniformly distributed across the six metropolitan areas investigated. Miami, Chicago, and New York had much higher intra-class correlations than Los Angeles, Denver, and Washington, D.C.

2. Cluster Size Variation and Design Effects

Design effect has often been calculated by *Design effect* = $1 + \rho(\overline{m} - 1)$, where \overline{m} is the average number of the cluster sizes, and it is assumed that cluster sizes are fairly constant. Due to cluster size variation, we calculate (adjusted) design effects based on $1 + \rho(\overline{m}^* - 1)$, where $\overline{m}^* = \overline{m}(1 + CV_m^2)$ and CV_m is the coefficient of variation of the cluster sizes. In Table 3, we juxtaposed the design effects and the adjusted design effects for each of the three levels of clusters, by the detailed behavioral and cognitive measures of substance use and illicit drug acquisition.

	Segment		Block-Group		Tract			
	Design	Design	Design	Design	Design	Design		
Measures	Effect	Effect*	Effect	Effect*	Effect	Effect*		
Behavioral								
Alcohol use	1.80	2.14	1.93	2.44	2.29	3.29		
Marijuana use	1.45	1.63	1.54	1.84	1.73	2.30		
Any illicit drug use	1.45	1.64	1.55	1.86	1.74	2.31		
Cognitive								
Difficulties of	2.36	2.95	2.38	3.14	2.56	3.78		
getting drugs								

Table 3: Design Effects and Adjusted Design Effects for Cognitive and BehavioralMeasures by Segment, Tract, and Block-group Levels

Table 4:Intra-class Correlations (ρ) and Design Effects at the Segment, Tract, and Block
Group Levels for Selected Measures of Past Month Behaviors for All Persons 12 or
Older

	Segment $(\overline{m}^*=16.00)$		Block Group $(\overline{m}^* = 17.47)$		Tract $(\overline{m}^* = 27.26)$	
Self-reported Behavioral Measures	Р	Design Effect	ρ	Design Effect	ρ	Design Effect
alcohol use	0.0763	2.1440	0.0875	2.4407	0.0873	3.2921
cigarette use	0.0478	1.7167	0.0548	1.9023	0.0542	2.4231
marijuana use	0.0425	1.6372	0.0512	1.8430	0.0496	2.3023
cocaine use	0.0193	1.2894	0.0238	1.3919	0.0236	1.6196
illicit drugs except marijuana	0.0254	1.3808	0.0318	1.5236	0.0307	1.8061
any illicit drug	0.0431	1.6462	0.0522	1.8595	0.0499	2.3102

Source: NHSDA 1991 – 1993.

Regardless of measures involved, the intra-tract correlations tend to be the highest or similar to the intra-block-groups correlations; however, the design effects for the tract clusters are much higher than those of the block-groups. This is as expected since for large average cluster size even small values of ρ can result in large increases of design effect (i.e., see Kish, 1987:42). However, what we observed here is that in the NHSDA surveys we investigated, even a slightly smaller ρ for tract clusters, relative to block-group clusters, may be likely to have a higher adjusted design effect² (see Table 4) due to a higher coefficient of variation of cluster sizes (see Table 1).

Variables with higher prevalence rates (i.e., alcohol or cigarette use as compared to marijuana, cocaine, and other illicit drug use) tend to have higher ρ as well as higher design effect values. In addition, as shown in Table 4, regardless of the level of clusters examined, ρ values have greater relative ranges of variation than design effect (DEFF) values (Kish, 1987:204). The results show that ρ values are much more "portable" to cross classes than DEFF values. Design effect values would change to a greater extent if there were considerable differences in terms of the cluster sizes.

Some researchers suggest that the ICC will be related to true cluster size rather than to the number of people sampled per cluster. If so, given the relatively fixed (assuming not time-varying) size of the geographic area groups such as counties, tracts, and block-groups, the ICCs for designated measures of interest may be relatively stable, making it suitable as a statistic with stable and portable properties across studies³.

3. Sensitivity to Cluster Levels

The NHSDA segment was usually located within tract although it could occupy portions of multiple tracts, but it was similar to block-groups in terms of size. Cognitive measures tend to have higher ICC ρ than behavioral measures. Locations of neighborhoods condition the intraclass correlations.

As shown in Table 5, whereas cluster level changes with size increasing by 37% (15.73-11.48/11.48), the ρ 's changes range from 13.3% to 22.3%; however, the design effect's changes range from 25.6% to 53.6%. Due to cluster size variation, adjusted average cluster size may be

 $^{^{2}}$ For example, the intra-tract correlation was 0.0873–similar to the intra-block-group correlation which was 0.0875, but the adjusted design effect for the tract clusters was 3.292–higher than that for the block-group clusters which was 2.441.

³ The ICC ρ is tied in part to the variable itself, and could thus change if a number of blocks become heavier users of drugs over time. Also, when builders tear down old houses and instead put in, say, more condensed residential units, this might change the variability in cluster size.

used in calculating the design effects. An inverse relation between cluster size and the degree of between-cluster variation has been well described (Smith, 1938), but this is not a pure norm and there are exceptions.

	% Change: (Block Group - Segment)*100 / Segment		% Change: (Tract -Segment)*100 / Segment		
Self-reported Behavioral		Design		Design	
Measures	ρ	Effect	ρ	Effect	
alcohol use	14.68%	13.84%	14.42%	53.55%	
cigarette use	14.64%	10.81%	13.38%	41.15%	
marijuana use	20.47%	12.57%	16.71%	40.62%	
cocaine use	23.32%	7.95%	22.28%	25.62%	
illicit drugs except	25.20%	10.33%	20.87%	30.80%	
marijuana					
any illicit drug	21.11%	12.96%	15.78%	40.33%	

Table 5: Percentage of Changes of ρ and DEFT across Segment and Tract and across Segment and Block Groups for Selected Measures for All Persons 12 or Older

Source: NHSDA 1991 – 1993.

4. Utility of Intra-class Correlation in Sample Design

Existing publications (including NHSDA/NSDUH) usually do not publish ICC. Values of ρ from surveys already done could be used for more accurate design-effect estimates in new surveys. Assumed ρ values (including $\rho = 0$) rather than ascertained values based on prior empirical studies are not infrequently used for power analysis in local community survey designs. Design effects from other surveys would be of less use since it may include effects other than clustering such as from unequal weights, and the average cluster size may not be available.

5. Implications for Cost-based Sample Design

The ICC is a key element in cost-efficient sample design. It is typically the case that a survey has a fixed sum of money *C* for sampling. There are costs associated with each level of sampling that must be taken into account. As a simple but illustrative example, consider a twolevel design: neighborhoods and households. Suppose there is one key variable and, based on similar surveys, we have an estimate ρ of its ICC. It costs C_{nb} to sample from a neighborhood and an additional C_{ho} to sample each household. Suppose we have decided to sample the same number *m* of households per neighborhood, and let *n* be the number of neighborhoods sampled. Then Hansen, Hurwitz, and Madow (1953, pp. 172-173) determined that the most efficient

sample design will sample (approximately) $n_{opt} = \sqrt{\frac{C_{nb}}{C_{ho}} \times \frac{1-\rho}{\rho}}$ neighborhoods and

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 $m_{\text{opt}} = \frac{C}{C_{nb} + C_{ho} n_{\text{opt}}}$ households per neighborhood. The central role of ρ in this calculation

continues to hold in more complicated situations.

6. Cross Level Interaction Example — Adolescents' Perceived Difficulties of Getting Illicit Drugs

To determine community-level factors affecting the prevalence rates of drug abuse and drugrelated beliefs and attitudes in the National Household Survey of Drug Abuse (NHSDA), we merged the pooled 1991-1993 NHSDA with the Census small area estimation data. The goal was to test various explanatory models and to illuminate how socioeconomic and other differences among census tract groups and block groups might influence the distribution of individual drug use attitudes and behaviors within neighborhoods and communities. We formulated and tested hypotheses about cross-level effects (e.g., how community SES may affect the relationship between adolescents' lifetime marijuana use and adolescents' drug use attitudes and behavior). The analyses were conducted for six metropolitan areas separately. In the following, we present our analysis for 1752 adolescents (aged 12-17) who lived in 111 tract groups in the Miami metropolitan area.

The contribution of living in neighborhoods with high levels of drug availability and the pressure to become involved in distribution are of great interests in systematic research. We examined data concerned with the perceived difficulty of obtaining drugs using hierarchical modeling. For this analysis, a scale was constructed using items concerning respondents' perceptions of the difficulties obtaining marijuana and cocaine. The perceived difficulty of getting drugs is a good indicator of opportunity structure for drug use in the respondents' neighborhood.

Because survey questionnaire items concerning the perceived difficulty of getting drugs were neighborhood-oriented, we expected that a significant amount of variance would be explained by the tract group factors (Wright and Zhang 1998). In this study, we constructed means as outcomes models by introducing variables with tract group aggregated statistics as covariates in the level 2 equation. These variables – all from the US Census – at level 2 included: racial heterogeneity as indicated by the percentage of blacks; and measures of social economic status including the percentage of families below poverty level, female-head of household with no spouse and a child under 18, the median household income; total population size of level 2 unit; and average number of persons per room. To evaluate the most important community factor(s) explaining the effects of the tract groups, the conditional variances were compared with the unconditional variances, and the proportion of variation explained by the tract group factors was examined

Table 6 provides estimates and hypothesis tests for the fixed effects and the variances of the random effects on adolescents' perceived difficulty of getting drugs. The results indicate that the

estimated mean tract group score of the perceived difficulty of getting drugs among adolescents is 5.83 on a 10 point scale where a higher scores means that it is less difficult to get drugs. Higher neighborhood socioeconomic status is associated ($\gamma_{04} = -.15$, t = -2.90) with greater perceived difficulty getting drugs after controlling for the effects of other tract group level variables. Adolescents living in relatively affluent neighborhoods are more likely to perceive drugs as difficult to get. A considerable proportion (41.88%) of the variation in perceived difficulty getting drugs among tract groups is explained by neighborhood characteristics such as average persons per room, percent non-Hispanic blacks in the tract group, and the population size of the tract group. Adding information concerning adolescents' age, race, and lifetime marijuana use as predictors of the perceived difficulty of getting drugs reduced the within-tract group variance by 11.39%.

Fixed effect	Coefficient	se	<i>t</i> -ratio	<i>p</i> -value	
Tract Group Mean Perception Score					
BASE, γ_{00}	5.83	0.075	77.56	0.000	
Average persons per room, γ_{01}	-0.30	0.11	-2.78	0.006	
Percentage of blacks, γ_{02}	0.17	0.064	2.74	0.007	
Total population size, γ_{03}	-0.000018	0.000013	-1.40	0.163	
SES scale, γ_{04}	-0.15	0.051	-2.90	0.004	
Adolescent age slope, γ_{10}	0.44	0.038	11.67	0.000	
Black slope, γ_{20}	0.27	0.25	1.09	0.28	
Hispanic slope, γ_{30}	-0.48	0.22	-2.14	0.033	
'Ever used marijuana slope', γ_{40}	1.89	0.25	7.29	0.000	
Random Effect	Variance Component	df	χ^2	<i>p</i> -value	
Mean tract group perception, u_{0j}	0.1447	106	150.39	0.003	
Level 1 effect, r_{ij}	6.9630				
Model	Level 1 variance: σ^2	Mean Tract Group: Perception of Drug Acquisition Difficulties, $Var(\beta_{0j})$			
Unconditional model	7.8580	0.2490			
Conditional model	6.9630	0.1447			
Proportion of variance explained (in percentage)	11.39	41.88			

 Table 6: Estimated Fixed and Random Effects on Adolescent Perceptions of the Difficulties of Getting (Illicit) Drugs

Source: NHSDA, 1991-1993, OAS, SAMHSA

Our analysis illustrates that an understanding of the local residents' perceived opportunity structure of getting drugs would be limited without considering how the socio-economic condition of the wider environment mediates the individual level effects. The results reveal significant neighborhood variations in the outcomes of adolescents' perceived opportunity structure of obtaining drugs and significant statistical interaction between aggregate- and individual-level variables, suggesting that the impact of individual-level variables is not uniform across different neighborhoods or communities, and that the socioeconomic status of neighborhoods accounts for considerable proportion of these between neighborhood variations.

ICC has implications on analysis. Measure-specific intra-class correlations help to identify appropriate models such as random coefficient models which in turn could be a good way to test grand theories – for example, the significant structural contributing factors for drug acquisitions found in the Miami metropolitan area appear to support that neighborhoods in urban areas in the U.S. are generally differentiated simultaneously in terms of three characteristics of their residents: economic status, family stage, and race and ethnicity (Fischer, 1976, pp. 45-46).

7. Conclusions

ICC and design effects, varying from variable to variable, are often large and cannot be ignored. ICC is more generalizable and preferred compared to design effect or variance inflation factor since the latter are dependent on the clusters. Future studies – especially large scale surveys – should make ICC information available because of their utilities and implications on sample design and analysis.

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