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National Survey of Midlife Development in the United States (MIDUS), 1995-1996

Technical Report on Methodology

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National Survey of Midlife Development in the United States (MIDUS), 1995-1996

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METHODOLOGY OF THE NATIONAL SURVEY OF MIDLIFE DEVELOPMENT IN THE UNITED STATES (MIDUS)

Field Procedures

The National Survey of Midlife Development in the U.S. (MIDUS) was based on a nationally representative random-digit-dial sample of noninstitutionalized, English-speaking adults, aged 25 to 74, selected from working telephone banks in the coterminous United States. Field procedures lasted approximately one year, with all data collected during 1995. Predesignated households were selected in random replicates, one-fourth of which included a special enhanced nonrespondent incentive component and the other not. Contact persons were informed that the survey was being carried out through Harvard Medical School and was designed to study health and well-being during the middle years of life. They were told that participation would entail completing a telephone interview and two mail questionnaires.

After explaining the study to the informant, a household listing was generated of people in the age range 25-74 and a random respondent was selected. Oversampling of older people and of men was achieved by varying the probability of carrying out the interview at this stage as a joint function of the age and sex of the randomly selected respondent. No other person in the household was selected if the selected respondent did not complete the interview.

Once it was determined that we wanted to include the random respondent in the survey, an attempt was made to talk with this person and recruit them to be a participant. A study fact brochure was mailed to respondents who asked for more information before deciding and a recontact telephone appointment was made after the time they received the brochure. Senior study staff were also made available to respondents requesting information not contained in the brochure before deciding to participate.

Once random respondents decided to participate we carried out a telephone interview that lasted an average of thirty minutes and mailed questionnaires that we estimated took an average of an additional two hours to complete. The questionnaire mailing also included a boxed pen and a check for $20. A reminder postcard was mailed to all respondents three days after the initial questionnaire. A second questionnaire with a cover letter urging respondents to return the questionnaire was mailed two weeks later to all respondents who had not returned the questionnaire by that time. Reminder telephone calls were made two weeks later to all respondents who had still not returned the questionnaire. In the subsample of replicates designated for participation in the nonrespondent survey, interviewers in these final calls offered respondents an additional financial incentive to complete and return the questionnaires.

The Response Rate

We cannot compute an exact response rate for MIDUS because we only wanted to interview about half of people we contacted, and it is only the latter who should be in the denominator of the response rate. We have no way of knowing how many of the refusers would have been selected for interview, which means that we cannot compute the denominator exactly. However, it is possible to make an estimate of the number of people in the denominator and, based on this, an estimate of the response rate. This estimate, the calculation of which is described below, is 70.0% for the telephone interview, 86.8% for the completion of the main questionnaire among the telephone respondents, and 60.8% for the overall response rate (.700 x .868).

The sample disposition (Table 1) shows that 3323 respondents completed telephone interviews in the national random sample before we carried out the refusal conversion. In the refusal conversion of one-in four refusers who were offered a financial incentive ($100) to complete the interview, 162 initial refusers gave us a telephone interview based on this incentive. (See Table 2.) We gave each of these 162 a weight of four to adjust for the fact that we only made this offer to one-fourth of respondents. The weighted numerator of the response rate for the telephone interview, then, is:

$$\mathbf{3323 + 4 \times 162 = 3971.}$$

Table 1. MIDUS Sample Disposition in the National RDD Prior to Refusal Conversion[1]

Screening Completed	Total	Sample 1	Sample 2
Completed Telephone Interview			
Usable	3323	881	2442
Unusable	2	0	2
Ineligible			
No one 25-74 yrs	988	240	748
Selected R-Age terminate	2473	540	1933
Language problem	71	23	48
Circumstantial	104	27	77
	3636	830	2806
Appointment Not Completed			
R selected, interview not started	111	18	93
After R began interview	20	9	11
	131	27	104
Refused			
R selected, interview not started	932	238	694
After R began interview	78	24	52
	1008	262	746
Screening Not Completed			
Ineligible			
Language problem	362	80	282
Circumstantial	154	46	108
	516	126	390
Appointment Not Completed	66	2	64
Refusal	2087	582	1505
Maximum Calls-No Contact	1246	327	919
Non-household	2743	632	2111
Non-working Number	5242	1331	3911
Total Numbers	20000	5000	15000

[1]This disposition reflects the status of all sample numbers given one refusal conversion attempt. A total of 844 numbers (238 + 24 + 582) were classified as final refusals from Sample 1. These numbers then became eligible for inclusion in the refusal conversion study. The final disposition for these numbers is given on me following page

Table 2. MIDUS Sample disposition in the National RDD Prior to Conversion Sample

Screening Completed	Total
Completed Telephone Interview	162
Completed Short Form	14
Screening Not Complete	
Ineligible	
No one 25-74 yrs	23
Selected R-Age terminate	50
Language problem	0
Circumstantial	6
	79
Refusal	
R selected, interview not started	174
After R began interview	15
	189
Ineligible	
Language problem	2
Circumstantial	9
Refusal	383
Non-household	6
Total Numbers	844

The denominator of the telephone response rate is the number of people we wanted to interview. Our best estimate of the latter for the total sample is:

3323	(initial interviews usable prior to refusal conversion)
2	(unusable interviews)
131	(selected for interview but appointment never kept)
1008	(selected for interview but refused)
A	(66 people had appointments but never kept, so we do not know if we would have wanted interview them or not)
B	(2087 people refused before we determined if we wanted to interview them)

The uncertainty in computing the response rate involves the number of people in A and B who we wanted to interview. It is impossible to know. However, we estimated from the people who were screened that the percent eligible is 56.3%. This estimate is based on the fact that the people for whom screening was completed prior to refusal conversion included 3323 + 2 + 131 +

1008 eligible and 3636 ineligible minus 71 with language problems and 104 circumstantial. The ratio of eligible to total here is 4464/(4464 + 3461) = 56.3%. If we apply this same percent to A and B, we estimate that 1212 of the people in A and B combined were eligible, which means that a total of 5676 people were eligible overall, for a telephone response rate of 3971/5676 = 70.0%.

Once we had the telephone interview completed we developed a weight that adjusted the telephone respondents to be representative of the population. This weight was applied to the data, and then we computed empirically the weighted percent of these people who also returned the mail questionnaire. This conditional response rate is 86.8%. The overall response rate was then computed by multiplying the telephone response rate (.700) by the conditional mail response rate (.868) to get an overall response rate of 60.8%.

Sample Weights:

Representativeness of the sample was increased by using a series of weights that adjusted for differences in probability of selection and differential nonresponse. A total of six weights were developed and the product of these weights used to create a final summary weight that can be used in analysis.

Typically, MIDMAC analyses are made with weighted and also unweighted data; when outcomes differ, the analyst reports this fact and attempts to interpret the basis. Conventions by various social science disciplines prefer the use of unweighted or weighted data. MIDMAC=s convention is to present both when results warrant.

A detailed description of the procedure used to create these weights is entitled *Weighting the MIDUS Data.*

Weighting The MIDUS Data

Weight 1:

We had Census data for the telephone exchange geographic areas of the sample. This was supplied by Genesis, the company that supplied the sample of phone numbers. The universe of telephone exchange areas was mapped into the universe of Census zip code areas and aggregate data estimated for such things as percent of the telephone exchange area who are black, percent who are white, percent living in poverty, etc. As there is no one-to-one match between telephone exchange areas and zip code areas, weighted averages across all zip codes in a telephone exchange area were used to define the aggregate data for each telephone exchange area. We obtained a total of 38 items with this type of aggregate data from Genesis. In addition, we classified each telephone number by region of the country and by whether or not the zip codes connected to the exchange were in an MSA. This resulted in a total of 40 variables, which are listed in Table 1.

Table 1. Census "Neighborhood" Variables Used to Predict Success in Obtaining a Household Listing and a Subsequent Telephone Interview.

NAMED	DESCRIPTION
COLGRDN	Number of college graduates. (Based on population, 25+ years)
COLGRDP	Percent of population with college degree (Based on population, 25+ years)
EDMEDYR	Median number of years of education. (Based oh population, 25+ years)
AG0_17N	Number of people age 0 - 17.
AG0_17P	Percent of people age 0 - 17.
AG15_24N	Number of people age 15 - 24.
AG15_24P	Percent of people age 15 - 24.
AG25_34N	Number of people age 25 - 34.
AG25_34P	Percent of people age 25 - 34.
AG35_44N	Number of people age 35 - 44.
AG35_44P	Percent of people age 35 - 44.
AG45_54N	Number of people age 45 - 54.
AG45_54P	Percent of people age 45 - 54.
AG55_64N	Number of people age 55 - 64.
AG55_64P	Percent of people age 55 - 64.
AG65PLN	Number of people age 65 plus.
AG65PLP	Percent of people age 65 plus.
IN0_10N	Number of households with income 0 - 10K.
IN0_10P	Percent of households with income 0-10K.
IN10_15N	Number of households with income 10-15K.
IN10_15P	Percent of households with income 10-15K.
IN15_25N	Number of households with income 15-25K.
IN15_25P	Percent of households with income 15-25K.
IN25_35N	Number of households with income 25-35K.
IN25_35P	Percent of households with income 25-35k.
IN35_5ON	Number of households with income 35-50K.
IN35_5OP	Percent of households with income 35-50K.
IN5O_75N	Number of households with income 50-75K.
IN5O_75P	Percent of households with income 50-75K.
IN75PLN	Number of households with income 75K plus.
IN75PLP	Percent of households with income 75K plus.
MEDINC	Median income of households.
RACWN	Number of people/race = white.
RACWP	Percent of people/race = white.
RACBN	Number of people/race = black.
RACBP	Percent of people/race = black.
RACHN	Number of people/race = hispanic.
RACHP	Percent of people/race = hispanic.
MSA	Metropolitan Statistical Area.
REGION	Census Region

This is all the information we had to help us predict variation in the first stage survey cooperation. We did this by using each of these variables, one at a time, to predict whether we were able to get a household listing. A HU listing is information from someone in the HU about the age-sex composition of the people living there that is used to select a respondent. Included in this analysis were all households contacted, whether eligible or not, in the subsample that used enhanced refusal conversion procedures. This subsample, which makes up 25% of all original numbers, is described in more detail below along with a rationale for limiting the analysis to this subsample. Excluded were phone numbers where we never got an answer to our calls and phone numbers where we got an answer and discovered that we did not want to talk to this number prior to listing (e.g., the phone number was for a business or the people who answered the phone could not speak English)

We discovered that a small number of Census variables are significant predictors of getting a listing. We then looked for nonlinearities in these associations and for interactions among the different predictors in multivariate equations. We did not cross-validate in half samples because we were not concerned about overfitting due to the fact that we were dealing with a small number of predictors and we were working with Census population data. The results of the final model are presented in Table 2, where we see that success in getting a listing is. negatively associated with neighborhood percent of Hispanics, positively associated with neighborhood percent of people ages 0-17 and 18-24, and lower in the Northeast than other areas of the country.

Table 2. Final Model to Predict Success in Obtaining a Household Listing

PREDICTOR	OR	(95% CI)
Intercept	1.43	(0.73-2.80)
Percent Hispanic in Telephone Area	0.98	(0.97-0.98)
Percent Ages 0-17 in Telephone Area	1.04	(1.02-1.07)
Percent Ages 18-24 in Telephone Area	1.04	(1.01-1.08)
Northeast	0.54	(0.43-0.67)
$X^2_4 = 85.0$		

We computed WT1 to adjust for differential probability of success in listing. This was done in three steps. First, we assigned a predicted probability of getting a listing to each HU where we did get a listing based on the equation in Table 2. (Note: The equation was used for every HU that was listed in the sample, not just those in the replicates used to estimate the equation.) Second, we computed the inverse of this predicted probability as the raw version of WT1, which is identified as RWT1 in your data file. RWTI ranges from a low of 1.05 to a high of 2.56~and has a mean of 1.24 in the subsample of 8290 HUs where we got a listing. Third, in order to stabilize the estimated weight, we computed the median of RWT1 in quintiles of the sample and assigned this median value to everyone in the quintile. This is the final version of WT1, which is also on your data file. Note that WTX has only five values, which are 1.15, 1.17, 1.20,. 1.29, and 1.41.

What was being done here? In a nutshell, we weighted to make sure the distribution of "neighborhood" (defined as telephone exchange area) characteristics of listed Errs is the same as of the population of all telephone Errs in the country. Then we stabilized the weight in an effort to minimize the impact of overfitting on parameter estimates and significance tests. There is no guarantee that this adjustment will improve the representativeness of the sample. In the absence of complete information about differences between listed and non-listed HUs, though, it seems reasonable to think that we're better off having a sample that reflects the distribution of neighborhoods than one that does not.

Weight 2:

Once we had the age-sex composition of the HO, we selected a random respondent if there was someone 25-74 in the HU and we selected no one if the MU was made up exclusively of people under age 25 or over age 74. The selection of only one person per RU no matter the number of people in the MU introduces a differential probability of selection that leads to an over-representation of people from small HUs in the sample. We corrected this in WT2.

In addition, as you know, we tried to get roughly equal numbers of men and women in each of five decades of age and, to this end, we did not attempt to interview all people who were selected as the random MU respondent. If the random respondent was a man in the age range 65-74 we attempted to interview this person 100% of the time because this was the rarest subsample. In all other cases, though, we used a randomization procedure to decide not to interview a probability subsample of the other random household respondents. The probability of us rejecting the respondents varied depending on how easy it was to fill the quota cell. So, for example, women ages 25-34 are so numerous in relation to men ages 65-74 (in the sense that there are a lot of these young women in the population and they tend to live in small HUs where they have a high probability of selection) that we got almost twice as many as we wanted by time we got enough older men. As a result, we turned down nearly half these young women rather than interview them.

The approach used to carry out this procedure was as follows: (i) We went to the Current Population Survey and carried out an analysis that told us the expected proportion of men and women in the population in each decade of life we would get in our sample if we used a random household selection procedure. (ii) We then used this as an initial way of setting targets for the percent of predesignated respondents to turn down in each age-sex cell. (iii) But we knew that this was not the only consideration.

Men have a different probability of agreeing to be in surveys than women and there might be differences between the CES and our telephone sample. As a result, we wanted to allow for midcourse correction. In doing this, though, we also wanted to make sure we had a probability sample at the end of the day rather than a quota sample. In order to achieve these goals we divided our initial sample of phone numbers into 400 random subsamples and only used the initial selection probabilities in the first 50 replicates. These 50 were used to carry out the first interviews and additional phone numbers were not releases to the interviewers until these numbers had been worked through. Based on the empirical results found in these initial replicates we adjusted the within-cell probabilities of turning down respondents. This procedure was continued throughout. the field period to that we were able to adjust selection probabilities in such a way as to get as close as possible to the target numbers of interviews in each age-sex cell, 50 replicates at a time at first and then 25 replicates at a time near the end of the field period.

It is important to note that a selection probability was never changed inside a replicate.

For example, if the selection-probability of a particular age-sex cell was .725 in the first 50 replicates but it took us a number of months to track down and finally get a listing with a particular household in one of those replicates, the selection probability stayed .725 even if we had already released new replicates to the field and changed the selection probability in these replicates to .80. This consistency within replicates guaranteed that easy-to-reach and hard-to-reach respondents had the same probability of being recruited into the sample. This would not have been the case if we had used a nonprobability quota design in which we interviewed everyone in every cell and then stopped taking any new cases in a cell once the quota of interviews was reached.

A five-step procedure was used to create WT2. First, if the only people in the HU were men or only women, the first part of the weight received a value of 1.0. If there were both eligible men and eligible women in the HU, this part of the weight was 2.0. This was because the first part of the selection procedure in sampling was to decide either to ask for men or women and to take a person of that sex unless there was none in the HU.

Second, we computed a component of the weight that is equal to the number of people in the HU with there same sex as the predesignated respondent. The reason for this is that the second part of the sample selection process was to select one random respondent of the designated sex out of whatever number of eligible respondents of that sex there were in the RU. If there were four eligible women in the HU,. the respondent who was finally selected had only a one-in-four chance of being selected after the point of deciding that a woman rather than a man would be interviewed. So that women would receive a weight of 4.0 in the second part of the weight.

Third, the selection probability of the age-sex cell specified in the replicates was assigned as the final part of WT2. Even though this third component differed across replicates, we used the mean of the selection probability within each age-sex cell as the basis for computing the weight because replicates were randomized. The inverse of this probability was the weight component.

The 10 values of this component of WT2 are shown in Table 3.

Table 3. The Proportions to Predesignated Respondents (at the Point of Household Listing) Who were Selected for Recruitment in the Telephone Interview by Age and Sex.

AGE	MEN	WOMEN
25-34	.589	.546
35-44	.581	.470
45-54	.754	.797
55-64	1.000	.979
65-74	.860	.678

Fourth, these three components were multiplied together to construct the raw version of WT2 (RWT2). which is on your data analysis file. The mean on RWT2 is 2.91 and the range is between 1.00 and 17.20. Some examples: A 55-64 year old man who lived with his wife and their 30 year old son would receive a weight of 4.0 because he would be the designated respondent only once out of every four households with this composition and would be accepted for interview 100% of the time. The wife in this HU would receive a raw weight of 1.96 because she would have been selected half the time and would have a .989 chance of being accepted.

Fifth, RWT2 was stabilized in the same way as RWT1, by dividing the sample into quintiles and assigning the median of the quintile to all cases in that one-fifth of the sample; These medians are 1.26, 1.83, 2.33, 3.08, and 4.26.

Weight 3:

Once a decision was made to accept a predesignated respondent for interview, an attempt was made to interview that respondent. Standard procedure was to make a refusal conversion attempt if the respondent would not agree to be interviewed. As noted above, in a random one-fourth of cases, an enhanced refusal convention approach was attempted. Specifically, an additional refusal conversion attempt was made in which we offered the respondent $100 to complete the interview. In order to take into consideration the fact that only one-fourth of refusers were offered this substantial incentive, the people who completed the interview only after this incentive were given a weight of 4.0. This is WT3. That is also why we confined the analysis of WT1 to this 25% of the sample, as we wanted to define WT1 in terms of total conversion and then give a weight of 4.0 to the enhanced subsample in the third stage of weighting.

Weight 4:

The same sort of modeling procedure used to construct WT1 was used to see it there are any systematic between-neighborhood differences in the probability of obtaining a completed interview in the subsample of HUs where we got a listing. There were not. A total of 9519 eligible HUs were listed and selected for tan interview, of which 3485 yielded a complete telephone interview. None of the 40 variables listed in Table 1 was significantly related to obtaining a complete telephone interview in this subsample of 9519. It should be noted that we examined the predictors of success in conventional recruitment in the total sample as well as the predictors of success in conventional and enhanced recruitment in the 25% subsample where enhanced recruitment was attempted. We failed to find significant predictors in either analysis. As a result, our original plan to construct a WT4 was abandoned.

Weight 5:

The product of WT1 x WT2 x WT3 was assigned to all cases where we obtained a complete telephone interview. This weighted sample was subjected to further analysis to see if there is a systematic difference between the 3032 telephone respondents who returned a completed mail questionnaire and the 453 who did not.. To study this we used all Census "neighborhood" variables and all variables in the telephone survey as predictors of obtaining a mail questionnaire in the subsample of 3485 telephone interview respondents.

In the first step, we went through the interview and selected 28 variables that we examined as possible predictors of questionnaire completion. These are listed in Table 4. In addition, all the neighborhood variables in Table 1 were used as predictors. For each potential predictor, we estimated a pair of logistic regression equations. One was a linear equation and the second was an equation in which we included both the linear term and the square of the predictor.

Table 4. Telephone Interview Variables Used to Predict Success in Obtaining a Questionnaire in the Subsample of Respondents who Completed the Interview

NAME	DESCRIPTION
QA4	Physical Health
QA5	Mental\Emotional Health
QA6	Health Compared to Most People Your Age
QA7	Totally Unable to Work Because of Health
QA8	Cut Back on Work Because of Health
QA11	Heart Trouble
QA13	Heart Attack Risk
QA36	Cancer
QA40	Smoke Cigarettes
QA53	Drink
QA57	Sad, Blue, or Depressed
QA80	Worry
QA87a	Panic Attack
QB1	Education
QB3	Work
QB17	Marital Status
QE1	Living in Institutional Setting
QE2	Homeless
QE3	No
QD1	Satisfaction with Life
QD2	Control Over Life
QD3	Satisfied with Self
QD4	Outgoing
QD5	Worrying
QD6	Curious
QD7	Optimistic
QD8	Contribution to Others
QD9	Disappointment with Achievements

In the second step, we discretized each predictor with a nonlinear effect into ten categories and examined the ten-by-two cross-classification with a dichotomous measure of completion of the mail questionnaire. Inspection of this cross-classification led to a reduction of the number of categories, usually with a final number of two or three categories.

Third, we used the TREE program in S+ to predict completion of the questionnaire. The TREE program is a sequential orthogonal partitioning program that uses a search strategy to general a nonhierarchical n-way analysis of variance "tree" structure to predict the outcome of interest. Subsample cross-validation was used to select the correct level of partitioning and then a final solution was estimated in the total sample at the appropriate level.

Fourth, the tree solution was used to generate predicted probabilities of completing the questionnaire for every telephone interview respondent based on the profile of predictors specified in Figure 1. The inverse of these predicted probabilities was used to define RWT5. The latter was divided into quintiles and median values of these quintiles were used to define WT5.

Weight 6:

Finally, a post-stratification weight was applied to the data. A post-stratification weight is a weight that adjusts for differences between the sample and the population on a series of variables for which we have population values. In this case, our colleague supplied us with data from the October, 1995 Current Population Survey on the variables listed in Table 5. The TREE program was used once again to complete this step. We began by combining the 3032 MIDUS respondents with complete data and the CPS respondents into a single data file in which the sum of weights of the CPS was set to be equal to the sum of weights of MIDUS. We then created a dichotomous outcome variable for each person in this pooled data file that defined whether the person came from MIDUS (coded 1) or the CPS (coded 0) and used this as the dependent variable in a tree analysis. The CFS variables, which were also defined in the MIDUS data, were used as the predictors. As in the construction of WT5, we cross-validated the level of complexity of the model in half-samples and then estimated the final model in the total sample.

Table 5. Current Population Survey (October 1995) Variables Used for Post-Stratification

NAME	DESCRIPTION
REGION	1=Northeast, 2=Midwest, 3=South, 4= West
MSA	1=Non-MSA/PMSA, 2=MSA/PMSA
SEX	1=Male, 2=Female
RACE	1=White, 2=Black, 3=Others
AGE	1=25 - 34, 2=35 - 44, 3=45 - 54, 4=55 - 64, 5=65 - 74
EDUCATION	1=Less than 12, 2=12, 3=Greater than 12
MARITAL STATUS	1=Married, 2=Not Married

Table 5.1 Distribution of Current Population Survey (October 1995) Variables used for Post-Stratification

NAME	POPULATION	UNWEIGHTED	WEIGHTED
REGION			
Northeast	20.6	18.0	18.7
Midwest	23.7	27.4	25.1
South	34.1	35.2	37.7
West	21.6	19.5	18.4
MSA			
Non-MSA/PMSA	25.3	23.3	23.1
MSA/PMSA	74.7	76.7	76.9
SEX			
Male	48.3	48.5	43.5
Female	51.7	51.5	56.5
RACE			
White	84.8	87.3	84.1
Black	11.2	6.1	10.8
Others	4.0	6.5	5.1
AGE			
25-34	27.6	20.8	26.0
35-44	27.0	24.2	27.8
45-54	19.2	24.0	19.1
55-64	13.9	19.9	15.2
65-74	12.2	11.1	11.8
EDUCATION			
Less than 12	15.8	10.0	13.2
12	36.4	29.3	38.3
Greater than 12	47.8	60.8	48.5
MARITAL STATUS			
Married	67.5	64.0	68.1
Not married	32.5	36.0	31.9

The final classes defined by the TREE program were used as the post-stratification classes. These are shown in Table 6. WT6 was defined for each class as the ratio of the proportion of the CBS in that class to the proportion of the weighted (WT1 x WT2 x WT3 x WT5} MIDUS sample in that class. For example, the CPS showed that 1.48% of the population is in Class 1 while 1.61% of the weighted MIDUS cases are in that class. The post-stratification weight 1.48/1.61 = 0.92 adjusted the MIDUS data so that the
final weighted proportion of cases in class 1 is identical to the proportion in the CPS.

Table 6. Final Post-Stratification Classes and Their Proportions in both the Weighted (WT1 x WT2 x WT3 x WT5) MIDUS Data and in the Current Population Survey

CLASS	MIDUS	CPS
Class 1	1.61	1.48
Class 2	1.54	0.43
Class 3	18.97	25.80
Class 4	9.91	9.12
Class 5	4.04	7.69
Class 6	2.74	8.30
Class 7	57.66	42.65
Class 8	3.53	4.53

Final Weight::

The product of WT1 x WT2 x WT3 x WT5 x WT6 was used to define raw final weight (RFNWT), which is on your data file. The distribution of RFNWT is shown in Table 7.

Table 7 Distribution of the Untrimmed Final Weight (RFNWT)

RFNWT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0.136160416	8.0	0.3	8.0	0.3
0.214644576	3.0	0.1	11.0	0.4
0.239958	9.0	0.3	20.0	0.7
0.333959473	11.0	0.4	31.0	1.0
0.360737319	406.0	13.4	437.0	14.4
0.44832475	9.0	0.3	446.0	14.7
0.445812431	60.0	2.0	506.0	16.7
0.496524531	11.0	0.4	517.0	17.1
0.56867054	234.0	7.7	751.0	24.8
0.625840478	23.0	0.8	774.0	25.5
0.635733995	336.0	11.1	1110.0	36.6
0.663245578	115.0	3.8	1225.0	40.4
0.706744393	7.0	0.2	1232.0	40.6
0.707513179	19.0	0.6	1251.0	41.3
0.790090935	10.0	0.3	1261.0	41.6
0.790950383	63.0	2.1	1324.0	43.7
0.884777301	455.0	16.0	1809.0	59.7
0.928299969	77.0	2.5	1886.0	62.2
0.986582269	10.0	0.3	1896.0	62.5
1.045548107	69.0	2.3	1965.0	64.8
1.099602234	15.0	0.5	1980.0	65.3
1.100798364	89.0	2.9	2069.0	68.2
1.10293016	18.0	0.6	2087.0	68.8
1.168849854	143.0	4.7	2230.0	73.5
1.315469898	282.0	9.3	2512.0	82.8
1.463382957	10.0	0.3	2522.0	83.2
1.477281989	25.0	0.8	2547.0	84.0
1.534993525	22.0	0.7	2569.0	84.7
1.62673669	165.0	5.4	2734.0	90.2
1.634867483	7.0	0.2	2741.0	90.4
1.635960072	22.0	0.7	2763.0	91.1
1.636645866	54.0	1.8	2817.0	92.9
2.2768333	37.0	1.2	2854.0	94.1
2.282195891	26.0	0.9	2880.0	95.0
2.328804651	9.0	0.3	2889.0	95.3
2.418600867	82.0	2.7	2971.0	98.0
2.60344116	21.0	0.7	2992.0	98.7
3.385152022	8.0	0.3	3000.0	98.9
3.62331675	19.0	0.6	3019.0	99.6
5.387077754	13.0	0.4	3032.0	100.0

This weight was trimmed. Trimming is an operation that pulls in the tails of the distribution of a weight by assigning weights for extreme cases to be equal to those of less extreme cases. If, say, the top and bottom 1% of cases are trimmed, the weights for all cases below the 1st percentile are redefined as equal to the weight for the case at the 1st percentile, while the weights for all cases above the 99th percentile are redefined as equal to the weight for the case at the 99th percentile. Trimming is done in an effort to reduce the variance of the weight in order to make sure a small number of cases with high weights do not unduly influence parameter estimates. The rule of thumb -- and there is nothing more than this to guide the decision about trimming -- is to seek a range of weights no greater than about ten to one. We decided to trim the bottom and top 5% of cases to do this and the range is about 6.5 to one when this is done. NFNWT is the trimmed final weight with a correction factor added so that the sum of weights equals 3032, the number of people who complete the telephone interview and mail questionnaire. PFNWT is the trimmed final weight with a correction factor added so that the sum of weights equals 152,614,000, the number of people in the U.S. in the age range 25-74 Parameter estimates will be the same whether you use NFNWT or PFNWT, but weighted n=s will project to the total sample if you use NFNWT and to the total population is you use PFNWT. Significance tests should be the same whether you use NF, NWT or PFNWT, but check to make sure this is the case in the program you use. There are some programs where this is not true, in which case you will not be able to use PFNWT. The distribution and values of NFNWT is shown in Table 8. The values of PFNWT are simply an inflation of those in NFNWT by the ratio 152,614,000/3032.

Table 8. Distribution of the Final Trimmed Weight

RFNWT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0.370805	437.0	14.4	437.0	14.4
0.460836	9.0	0.3	446.0	14.7
0.461338	60.0	2.0	506.0	16.7
0.510381	11.0	0.4	517.0	17.1
0.584541	234.0	7.7	751.0	24.8
0.643306	23.0	0.8	774.0	25.5
0.653476	336.0	11.1	1110.0	36.6
0.681755	115.0	3.8	1225.0	40.4
0.726468	7.0	0.2	1232.0	40.6
0.727258	19.0	0.6	1251.0	41.3
0.81214	10.0	0.3	1261.0	41.6
0.813024	63.0	2.1	1324.0	43.7
0.909469	485.0	16.0	1809.0	59.7
0.954207	77.0	2.5	1886.0	62.2
1.014115	10.0	0.3	1896.0	62.5
1.074727	69.0	2.3	1965.0	64.8
1.130289	15.0	0.5	1980.0	65.3
1.131519	89.0	2.9	2069.0	68.2
1.13371	18.0	0.6	2087.0	68.8
1.20147	143.0	4.7	2230.0	73.5
1.352181	282.0	9.3	2512.0	82.8
1.604222	10.0	0.3	2522.0	83.2
1.518509	25.0	0.8	2547.0	84.0
1.577831	22.0	0.7	2569.0	84.7
1.672135	165.0	5.4	2734.0	90.2
1.650493	7.0	0.2	2741.0	90.4
1.681616	22.0	0.7	2763.0	91.1
1.682321	54.0	1.8	2817.0	92.9
2.340374	37.0	1.2	2854.0	94.1
2.345889	26.0	0.9	2880.0	95.0
2.393796	152.0	5.0	3032.0	100.0

Comparison of MIDUS data with population (CPS) data:

The results in Table 9 show the distributions of the unweighted and weighted MIDUS data on the post-stratification variables in comparison to the nationally representative data in the CPS. You will see that the weighted MIDUS data generally are more similar to the population than the unweighted data. To take the most dramatic example, 47.8% of the population have more than 12 years of education compared to 60.8% in the unweighted MIDUS data. The weighted MIDUS data correct this over-representation to 48.5%. Note that the correction is not perfect. This is because we are trying to balance the competing threats of bias (which we try to correct by weighting) and inefficiency (which is increased by high variance in the weights).

Table 9. Comparison of MIDUS and Current Population Survey (October 1995) Data

		MIDUS	
NAME	CPS	UNWEIGHTED	WEIGHTED
REGION			
Northeast	20.6	18.0	18.7
Midwest	23.7	27.4	25.1
South	34.1	35.2	37.7
West	21.6	19.5	18.4
MSA			
Non-MSA/PMSASA	25.3	23.3	23.1
MSA/PMSA	74.7	76.7	76.9
SEX			
Male	48.3	48.5	43.5
Female	51.7	51.5	56.5
RACE			
White	84.8	87.3	84.1
Black	11.2	6.1	10.8
Others	4.0	6.5	5.1
AGE			
25-34	27.6	20.8	26.0
35-44	27.0	24.2	27.8
45-54	19.2	24.0	19.1
55-44	13.9	19.9	15.2
65-74	12.2	11.1	11.8
EDUCATION			
Less than 12	15.8	10.0	13.2
12	36.4	29.3	38.3
Greater than 12	47.8	60.8	48.5
MARITAL STATUS			
Married	67.5	64.0	68.1
Not married	32.5	36.0	31.9

Does the weighting adjust for the fact that the 10% of people in the MIDUA sample having less than 12 years of education may not be representative of the 15.8% of the population with this same amount of education? No. The weighting does, however, adjust for the possibility that the low educated people in the sample differ from those in the population on the weighting variables listed in Tables 1 and 4. Is this better than nothing? We don't know, but the intuition is that it is better to make the sample as representative as possible on the variables we can.

JRR Replicates:

There are two methods you can use to estimate design-based significance tests. The first is the Taylor series linearization method, which is implemented in the popular SUDDAN program. If you are a SAS user, you might want to buy a copy of SUDDAN for PC because SUDDAN is based on SAS and it is easy to move back and forth between the two programs. If so, all you need to do it stipulate a simple random sample option in SUDDAN and use either NFNWT or PFNWT.

An alternative is to use the method of Jackknife Repeated Replication (JRR), the most efficient of the several different pseudoreplication methods for estimating standard errors. This method requires the sample to be divided into random subsamples. We have created 100 random subsamples for this purpose, each containing either 30 or 31 respondents. The subsamples were constructed by randomizing respondents within each of the post-stratification classes and selecting a systematic sample across these classes so that we, in effect, took advantage of this0 stratification in selecting the 100 probability subsamples. The variable JRR is coded between 0 and 100 and defines membership in the 100 JRR probability subsamples. We have JRR macros that can be used in SAS to implement this procedure, although we recommend that you use the Taylor series method in SUDAAN if you are not familiar with this sort of estimation.

We understand that STATA has an option for using Jackknife and Bootstrap estimation. Complete Jackknife is computationally intensive and should be avoided unless you have a big computer. Bootstrap requires using half samples formed on the basis of multistage area probability sampling, so we have not created Bootstrap replicates. Your best bet is to use JRR in this case if STATA supports it. An alternative is incomplete Jackknife, but you will not get as much precision with this method as with JRR unless you use a much larger number of simulated runs (several hundred rather than the 100 used in JRR).