AGING, DEMOGRAPHICS AND MEMORY STUDY (ADAMS)

Sample Design, Weighting and Analysis for ADAMS

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This technical report describes the sample design, design-based weighting and analysis procedures for the Aging, Demographics and Memory Study (ADAMS), a national study that recruited Health and Retirement Study (HRS) panel members to undergo a psychometric evaluation and clinical assessment visit. Langa et al. (2005) describe the general design and methods for the ADAMS including relevant background on the HRS longitudinal sample. This document provides additional detail on the sample design for the ADAMS including a description of survey sample selection, sample attrition and nonresponse, population weights, design-based variance estimation and related topics of importance to analysts of the ADAMS data.

1. The ADAMS Study Design and Sample – Wave A

The nationally representative HRS sample (Heeringa and Connor, 1995; Juster and Suzman, 1995; Willis, 2006) provided the sample frame for ADAMS. From this larger nationally representative sample of approximately 7000 HRS respondents age 70 and older, a stratified, random subsample of 1770 individuals was selected for participation in ADAMS. The ADAMS goal was to obtain clinical assessments on 850 individuals. ADAMS sample selection, initial consent and final data management for the project were conducted by staff of the University of Michigan Survey Research Center, Ann Arbor. In-home cognitive tests and related assessments and consensus conferences to establish final diagnoses were directed by experienced teams at the Duke University Dementia Epidemiology Research Center (Langa et al., 2005).

Early in the design stage of the ADAMS project, the investigators recognized that a field period of two or more years would be required to complete 850 in-home assessments with the nationally-distributed subsample of HRS panel members. The initial assessments with the final sample of n=856 individuals (Wave A) actually occurred between August 2001 and December 2003. To maximize efficiencies in the field and to minimize the elapsed time between an HRS cognitive assessment and the ADAMS evaluation, the ADAMS sample was drawn in two phases. Each phase was based on a random ½ sample of the full HRS multi-stage sample design. In the sixteen largest metropolitan statistical areas that form the self-representing primary stage strata of the HRS sample design, eligible HRS panel members in a random ½ of the second stage units (area segments) were included in the pool for ADAMS Phase 1 or 2 sample selection. For the remaining 71 nonself-representing (NSR) primary stage strata, the complete sample of HRS individuals from the selected primary stage unit (PSU) was allocated to either the Phase 1 or 2 sample partition.

The stratified sample for ADAMS Phase 1 areas was selected based on HRS 2000 cognition scores. A final stratified sample for the Phase 2 areas was selected based on updated cognition measures obtained in the HRS 2002 interview. A small number of exceptions to this original Phase 1/Phase 2 randomization of sample areas was permitted during actual field period

to avoid gross inefficiencies in the travel schedules for the Duke University assessments teams; however, these exceptions were limited and not expected to seriously affect the randomization to time that was inherent in the original Phase 1/Phase 2 assignments.

1.A Study Population and Eligibility

All HRS respondents age 70 and older at the time of the HRS 2000 interview were eligible for the initial ADAMS selection in Phase 1 sample areas. Likewise, all HRS respondents in Phase 2 areas who were age 70 and older at the time of the 2002 HRS interview were eligible for Phase 2 sample selection. As a consequence of this two-phase randomization, respondents in Phase 2 areas who died between the HRS 2000 and 2002 interview contacts were not eligible for ADAMS sample selection. By the same turn, Phase 2 area HRS panel members who turned 70 between the 2000 and 2002 interview contacts became eligible for ADAMS. Analysts should recognize that the implication of the time offset in the randomized selection of the ADAMS Phase 1 and 2 sample members is that when properly weighted the pooled sample remains representative of the 70+ population over the two year data collection window. Due to the average time lapse between the HRS baseline interview and the ADAMS follow-up, the effective lower age bound for the ADAMS sample is actually closer to 71 years. (See Section 3 below).

1.B Sample Stratification, Sample Allocation and Selection

In order to achieve a sufficient number of ADAMS respondents across the full range of cognitive ability, the Phase 1 and 2 samples were stratified based on cognitive test scores, gender and age (see Tables 1 and 2). Respondents were classified into major cognitive strata based on their performance on the cognitive measures in the designated HRS interview (either 2000 or 2002, depending on the ADAMS Phase assignment). Self-respondents were classified into cognition strata based on the full set of HRS cognitive tests (aggregate scores ranging from 0-35). Herzog, et al. (1997) and Ofstedal et al. (2005) provide a detailed description of these HRS cognition measures. Proxy respondents were classified based on scores ranging from 1.0 to 5.0 on the IQCODE scale (Jorm, 1994).

Three major cognitive strata were initially defined for selection of the Phase 1 sample: low functioning, borderline impaired, and normal functioning. The normal functioning group was further stratified by age (age 70-79 versus 80 or older) and gender in order to ensure adequate numbers of ADAMS observations in each of these demographic subgroups.

For selection of the Phase 2 sample, the normal functioning stratum was divided into three substrata: 'low normals,' 'moderate normals,' and 'high normals.' The primary objective of this change was to increase the sample size in the portion of the distribution of HRS cognitive scores over which the probabilities of dementia and of cognitive impairment, not dementia (CIND) change most rapidly. To that end, Phase 2 respondents in the low normal group were given a higher probability of selection into the ADAMS sample than the high or moderate normals. The final combined ADAMS sample of n=1770 persons consists of 414 low

functioning, 381 borderline impaired, 347 low normal and a combined 628 moderate and high functioning respondents.

The combination of stratification criteria—HRS self or proxy interview status, cognition stratum, age and gender—yielded 18 explicit strata for the ADAMS Phase 1 and Phase 2 sample selection. Tables 1 and 2 describe these eighteen strata, the total number of ADAMS sample cases selected for each phase, and the empirical sampling rate by phase for cases in each stratum.

Table 1: ADAMS Self-report Sample Selection. Phase 1 and 2.

ADAMS Stratum	Stratum Function Classification	Cognitive Score	Age Range	Gender	Phase 1		Phase 2	
					n	Sample Rate	n	Sample Rate
1	Low Function	0-8	70+	M,F	72	1.0000	80	1.0000
2	Borderline	9-11	70+	M,F	97	1.0000	128	1.0000
3	Normal: Low	12-16	70+	M,F	38	0.0812	262	0.6469
4	Normal: Med	17-20	70-79	M	8	0.0400	33	0.1737
5	Normal: Med	17-20	70-79	F	15	0.0593	37	0.1616
6	Normal: Med	17-20	80+	M	19	0.1557	35	0.2713
7	Normal: Med	17-20	80+	F	12	0.0597	44	0.2378
8	Normal: High	20-35	70-79	M	34	0.0594	62	0.1176
9	Normal: High	20-35	70-79	F	39	0.0498	91	0.1220
10	Normal: High	20-35	80+	M	15	0.0949	34	0.2012
11	Normal: High	20-35	80+	F	38	0.1271	45	0.1475
				Total	387		851	

Table 2: ADAMS Proxy Report Sample Selection. Phase 1 and 2.

ADAMS Stratum	Stratum Function Classification	Cognitive Score JORM	Age Range	Gender	Phase 1		Phase 2	
					n	Sample Rate	n	Sample Rate
12	Low Function	3.90-5.00	70+	M,F	175	1.0000	87	0.5206
13	Borderline	3.35-3.89	70+	M,F	77	1.0000	79	1.0000
14	Normal: Low	3.10-3.34	70+	M,F	7	0.0972	40	0.8163
15	Normal: Med	1.00-3.10	70-79	M	6	0.0576	20	0.2105
16	Normal: Med	1.00-3.10	70-79	F	3	0.0789	8	0.1905
17	Normal: Med	1.00-3.10	80+	M	6	0.2222	10	0.3704
18	Normal: Med	1.00-3.10	80+	F	4	0.0930	10	0.2564
				Total	278		254	

2. Disposition of the ADAMS Sample – Wave A

The ADAMS study design called for initial assessments with the full sample to take place between August 2001 and December 2003 (wave A), and for follow-up assessments with a subsample of 340 respondents approximately 18 months after the initial visit (Wave B). Wave A assessments were completed with a total of 856 respondents, representing an unweighted response rate (among non-deceased sample members) of 56 percent. Wave B follow-up visits began in November 2002 and continued through March 2005. The analyses and results presented here focus exclusively on recruitment experience and diagnostic assessments associated with the initial assessments of ADAMS sample members. Please refer to Section 8 for information about prospective, longitudinal analyses for Waves A-C.

Table 3 summarizes the final disposition of the full sample of n=1770 ADAMS cases. In the total sample, ADAMS clinical evaluations and diagnostic assessments were completed with a total of n=856 sample individuals (48.4% of the sample, 55.6% of persons known to be alive at the time the ADAMS contact was attempted). In the time window between the 2000 or 2002 HRS interview and the subsequent ADAMS assessment attempt, 228 (12.9%) of the designated sample members died. An additional 59 (3.3%) sample members were believed to be alive but could not be located at the time of the scheduled assessment. A total of 499 (28.2%) sample individuals refused to participate in ADAMS Wave A and an additional 128 (7.2%) could not participate for other reasons (including health and lack of a suitable proxy).

Table 3 illustrates the very different pattern of ADAMS sample dispositions for persons who were self respondents or proxy respondents in the 2000 and 2002 HRS interviews that determined their sample stratum and sample selection status. The percentages of original sample cases that proved to be no contact, other non-interview or refusals are very similar for the two respondent type groups but short-term mortality rates were much higher for persons who required a proxy respondent in the preceding HRS interview.

Table 3: ADAMS Wave A Sample Dispositions by Respondent Type

Sample Disposition	Total	Self R	Proxy R
	n=1770	n=1238	n=532
Assessed	48.4%	53.1%	37.3%
No Contact	3.3%	2.8%	4.7%
NI Other	7.2%	7.8%	6.0%
Refused	28.2%	28.6%	27.2%
Deceased	12.9%	7.8%	24.8%

The following two sections more closely examine the patterns of mortality and nonresponse attrition in the original ADAMS sample of 1770 persons.

3. Time to Assessment and Survival of ADAMS Sample Members – Wave A.

The majority of researchers who will analyze the ADAMS data set will approach it as a cross-sectional survey, ignoring the fact that the Wave A in-home assessments spanned a time window of almost 28 months.   Population estimates generated from cross-sectional survey data typically ignore short-term variation in the dates of the actual observations. For example, an HRS analyst interested in estimating the proportion of the population age 70 and older hospitalized in the past year typically ignores the fact that subjects were interviewed as early as March or as late as December of a data collection year.   Therefore, the point estimate produced from the survey data is a time weighted average of individual respondent experiences. Barring extremes of seasonal variation or other time sensitivity such estimates are satisfactory representations of the population experience over the survey period.

Time of interview or more specifically, elapsed time between sample selection and interview, takes on greater importance in the ADAMS since the sample is older and much more frail than general population samples commonly observed in cross-sectional surveys. Under the ADAMS research protocol in which respondents are selected to the sample based on HRS 2000 or 2002 interview data and then assessed at variable lengths of time in the future, mortality is an important "selection" or censoring force. Most ADAMS analysts will assume that conditional on observed characteristics of selected sample cases, mortality imposes a Type I (random censoring) on the observed ADAMS sample. The question is not whether persons who are older, sicker or more frail at baseline are less likely to survive—over any window of time their mortality is higher. The question is whether the elapsed time between the baseline HRS interview and the ADAMS assessment for the 856 observed Wave A cases is a function of the survival probability

Figure 1.a Distribution of Dates of ADAMS Assessments: Phases 1 and 2
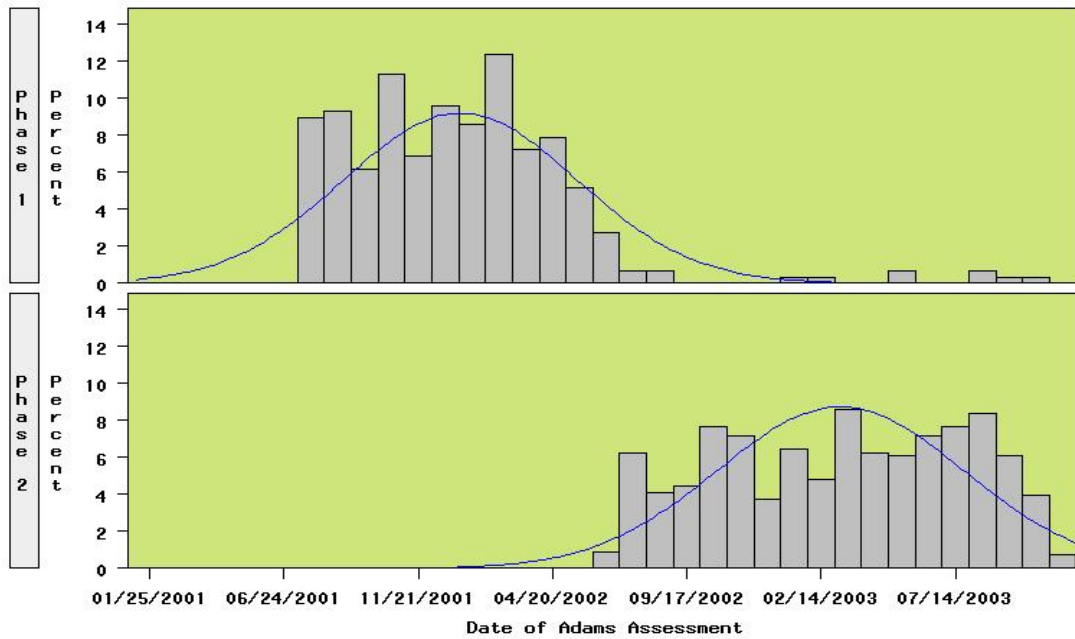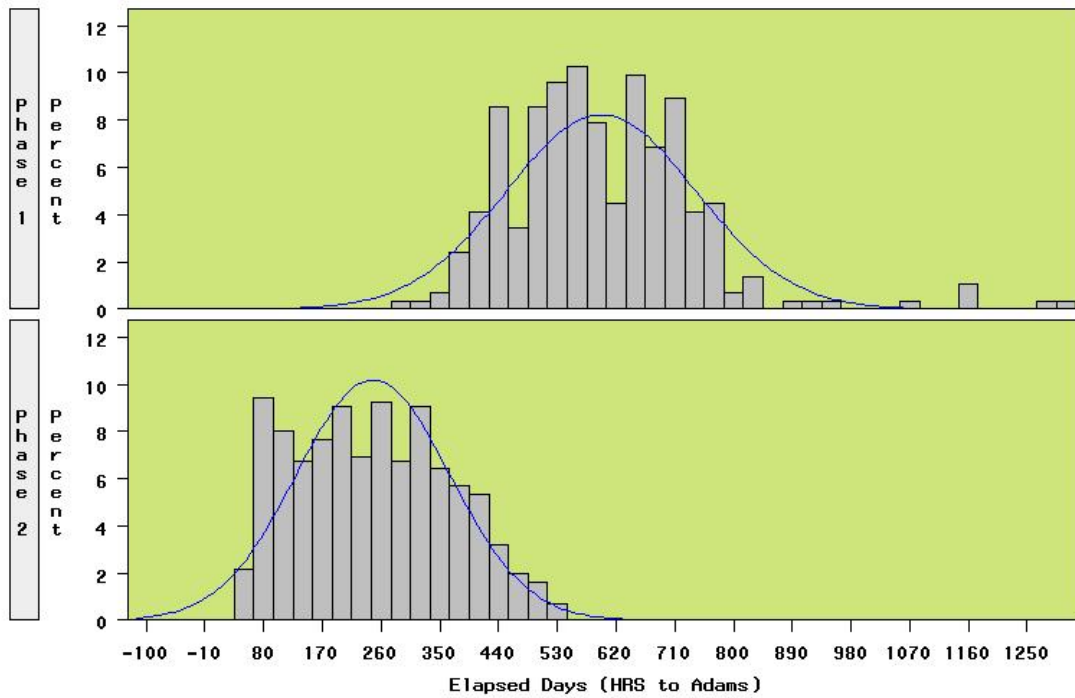

Figure 1.b Elapsed Days from HRS Interview to ADAMS Assessment

of the respondent.   If for some administrative or other reason the times to assessment for older, less healthy ADAMS sample members were longer than their younger, healthier counterparts the observed sample would be expected to be healthier than the steady state population of interest. The opposite would be true if time to assessment was shorter for older, less healthy sample members.

Figure 1a illustrates the month-by-month frequency of the Phase 1 and 2 ADAMS assessments. Figure 1b shows the corresponding distribution of elapsed times between the date of the HRS interview used to establish the cognition stratum and sample inclusion for the case and the date on which the initial Duke assessment actually occurred. University of Michigan Survey Research Center staff controlled the ADAMS sample selection, initial consent and sample release to the Duke University project director and study teams. SRC staff selected the Phase 1 sample after the HRS 2000 interview data collection was complete. Therefore, the delivery of the Phase 1 sample to Duke occurred in several large batches. Phase 2 ADAMS selections were based on the HRS 2002 interview; with cognitive scoring, sample selection, and the ADAMS consent process typically occurred within 1-2 months after the HRS 2002 interview. This difference in the Phase 1 and Phase 2 sampling protocol—one post-survey selection vs. a continuous, short-delay procedure—explains the large difference seen in Figure 1b in average elapsed times to assessment for the two phases. Subject to time required to obtain initial consent, SRC staff generally scheduled the release of ADAMS sample cases to Duke in a balanced manner, proportionately distributed by age, gender and cognitive status. A minor exception to this balanced release policy occurred in August 2002 when a periodic review of the ADAMS sample progress led to the decision to increase the Phase 2 allocation for persons in the "moderate" and "low" normal cognition strata. The selection of the supplemental sample was randomized for eligible HRS 2002 respondents in this stratum; however, this late release of additional normal sample could have led to a different distribution of elapsed times to assessment for these cases.

The Duke University assessment teams received contact information for each consenting ADAMS sample member from SRC but were blind to the initial cognitive scores or sample stratum to which the case was assigned. Once the contact information for consenting ADAMS sample individuals was delivered to the Duke assessment teams, actual visits were scheduled in geographic clusters to balance weekly work loads and maximize travel efficiency (e.g. collecting three Chicago area cases before flying a team in).   Elapsed times to assessment were therefore not strictly randomized across ADAMS subjects, but by the same turn there was no aspect of the Duke assessment protocol other than geographic location and proximity to other respondents that would be expected to produce a systematic bias in the time to assessment for major demographic, cognition or physical health groupings of the ADAMS sample members.

There are a number of approaches that can be used to test the assumption that the mortality of sample members prior to ADAMS assessment does not bias the general population representation of the data for the window of time in which the assessments were actually conducted.   The most direct approach, a formal survival analysis based on exact dates of death for deceased sample members and interview for observed ADAMS cases, cannot be conducted at this time due to lack of necessary data on precise dates of death for cases in the ADAMS sample.

However, a two-step indirect approach can be used to investigate the potential for mortality-based or "frailty-based" selection bias in the ADAMS data.

Table 4 summarizes the results from the first of the two steps, a logistic regression analysis of the probability that ADAMS sample members survived to the date when they would be contacted for the Duke team's cognitive assessment visit. These models do not account for the timing of the death, simply that the respondent died before an ADAMS assessment could be completed. Table 3 has already demonstrated that mortality rates for HRS self-report sample members were significantly less than for HRS proxy-respondents selected for ADAMS. Initial models for combined self report and proxy report respondents demonstrated that the predictors of mortality also were significantly different for the two groups. The propensity modeling exercise considered a substantial set of predictors including age (linear and quadratic), gender, nursing home status, health conditions (cancer, stroke, psychiatric disorder, diabetes, etc.), cognitive stratum and self-reported health status. As shown in Table 4, older age, nursing home residency and poorer self-reported health status were the significant predictors of mortality for HRS self-reporters selected to the ADAMS sample. For HRS proxy reporters, residence in a nursing home and a previous diagnosis of a psychiatric disorder proved marginally significant in predicting survival to contact for the ADAMS assessment. Better general health status as reported by the subject's proxy was also predictive of survival; however, the relationship is not as strong as observed in the ADAMS self-report sample.

Table 4: Final Survival Propensity Models for Self and Proxy Respondents

Model	Self R Model (n=1237)			Proxy R Model (n=533)		
Parameter	β	$Se(\beta)$	$p>X^2$	β	$Se(\beta)$	$p>X^2$
Intercept	6.16	1.74	<.001	-0.26	1.28	0.83
Age	**-.04**	**0.13**	**.001**	-0.001	0.11	.0.99
Age^2	**-.008**	**0.002**	**.001**	-0.001	-.002	0.61
Gender: Male	-.57	0.42	0.18	-0.326	-0.36	0.36
CogStrat1:Low	-0.98	0.49	0.04	-0.329	0.66	0.61
CogStrat2:Border	-0.96	0.49	0.05	0.06	0.72	0.93
Cog Strat3: Low Norm	-0.13	0.56	0.82	0.52	0.67	0.44
CogStrat4: Med Norm	-0.28	0.56	0.62	na	-	-
NursHome: Yes	**-1.34**	**0.44**	**.002**	*0.64*	0.32	*.04*
PreCancer: Yes	-0.90	0.50	0.07	-0.51	0.52	0.33
PreStroke: Yes	-0.01	0.36	0.97	-0.22	0.29	0.45
Prepsych: Yes	0.47	0.46	0.30	*0.63*	*0.31*	*.04*
Prehlth 1: exc	**2.53**	**0.58**	**<.001**	*1.29*	*0.56*	*.02*
Prehlth 2: vgood	*1.25*	*0.60*	*0.04*	0.75	0.72	0.30
Prehlth 3: good	**1.25**	**0.39**	**.001**	**1.37**	**0.45**	**.002**
Prehlth 4: fair	0.49	0.49	0.32	0.28	0.50	0.58

For self-reporters, the model summarized in Table 4 presents a very logical explanation for the mortality of panel members—increasing with age and declining health. The lack of significant predictors in the model for ADAMS proxy sample cases is very likely due to the

generally advanced age of these subjects and the pre-existing health conditions that necessitated a proxy interview in the HRS baseline wave.

The second step in the indirect analysis of potential mortality-based selection bias in the ADAMS assessment data was to model the elapsed time to the ADAMS assessment as a function of the respondent covariates. The purpose of this step was determine if time between the HRS and ADAMS interview bore any relationship to the factors that were shown in the first step to be significant in predicting survival (or conversely mortality) of ADAMS respondents. Two linear regression models were estimated—one for Phase 1 respondents and a second for Phase 2 respondents. The elapsed time (days) to the ADAMS follow-up was the dependent variable. The set of predictor variables again included: proxy status, age (linear and quadratic), gender, nursing home status, health conditions (cancer, stroke, psychiatric disorder), cognitive stratum and self-reported health status.

Table 5 presents a summary of the tests of significance for the predictors in these two models. Note that controlling for other factors, the effects that proved highly significant in predicting whether an individual survived to the ADAMS assessment (age, nursing home status, self-reported health at baseline) are generally not associated with the elapsed times to a completed ADAMS assessment. The exception is Phase 2 where there is some evidence that age has a negative relationship to the number of elapsed days to the assessment. Also in Phase 2, there is a strong, significant relationship between elapsed time to assessment and the cognitive status of the ADAMS participant (longer times for less impaired individuals). Both of these findings are a known artifact of the "sample release" schedule for Phase 2 in which late in the 2002 HRS interview period a decision was made to increase the sampling rate for persons in the "moderate" and "high" normal categories (see above). This late release in Phase 2 of substantial samples of moderate and high normal cases resulted in shorter average times to assessment for these cases.

The simple analyses presented in this section suggest that the natural process of mortality among the members of the original ADAMS sample is not introducing significant selection/attrition bias into the final sample of 856 ADAMS assessments for surviving members of the 70+ age cohort. Nevertheless, as noted at the beginning of this section, the age and relative frailty of the ADAMS survey population makes this an important issue for ADAMS analysts to consider. Once National Death Index (NDI) matches for HRS panel members are complete for the years 2002 and 2003, this issue can be revisited using a formal treatment based on survival analysis model.

Table 5: Regression Models for Elapsed Time to ADAMS Assessment.
Tests of major effects. Models are unweighted.

Model Predictor	Phase 1 Model		Phase 2 Model	
	F	p>$\mathcal{F}$	F	p>$\mathcal{F}$
Age	0.02	0.88	3.96	0.05
Age^2	0.02	0.89	*4.28*	*0.02*
Gender	0.01	0.94	0.02	0.89
Proxy	2.03	0.16	1.20	0.28
Nursing home	0.10	0.75	0.39	0.54
Pre-Cancer	0.70	0.41	*6.23*	*0.02*
Pre-Stroke	0.71	0.41	0.38	0.54
Pre-Psych	0.00	0.95	1.71	0.20
Pre-Health*	2.28	0.08	1.12	0.36
Cognition Stratum*	*3.71*	*0.01*	**9.57**	**<.001**

*These effects are represented by 4 parameters. These models are estimated with equal weight for each completed case. Test is a joint design-adjusted Wald test.

4. Nonresponse and Attrition Bias, Predictors of ADAMS Participation

The previous section addressed the potential role of mortality on the time-averaged representativeness of the ADAMS sample. This section continues the investigation of potential selection bias, focusing not on mortality but on sample attrition due to nonresponse and noncontact of surviving ADAMS sample members.

Contingency table analyses were conducted to investigate the simple association between ADAMS assessment participation (1=yes, 0=no) and a selected set of individual covariates. Since the initial results from this analysis of the total sample of n=1542 surviving ADAMS sample members suggested that respondent type status at the time of the preceding HRS interview was an important factor, the analysis was repeated separately for Self R and Proxy R cases. Figure 2 summarizes the outcome of this simple investigation. In the pooled sample, gender, proxy status, a previous stroke or previous cancer diagnosis showed evidence of association with ADAMS participation outcomes. The analysis identified important interactions of several factors with the cases' proxy or self reporter status. Among ADAMS sample members who self-reported in the previous HRS interview, male gender, previous stroke and a previous cancer diagnosis were associated with higher participation in ADAMS.   Among the complementary set of proxy respondents, low cognitive function level, female gender, nursing home residence and past poorer health rating exhibited an association with increased participation in ADAMS.

Figure 2: Predictors Considered in ADAMS Attrition Analysis.

Significance of Predictor *	Total Sample	Self R	Proxy R
Highly Significant p<.001	Gender Proxy Status	Gender	Cognition Stratum
Significant (.001<p<=.01)		Stroke-pre	
Possibly Important (.01<p<.10)	Stroke-pre Cancer-pre	Cancer-pre	Gender Nursing Home Health Status- pre
No Apparent Significance (p>.10)	Age-grouped Cognition Stratum Nursing Home Health Status- pre Health Change-pre Heart Disease-pre Hypertension-pre Lung-pre Arthritis-pre Couple Status	Age-grouped Cognition stratum Nursing Home Health Status- pre Health Change-pre Heart Disease-pre Hypertension-pre Lung-pre Arthritis-pre Couple Status	Age-grouped Health Change-pre Heart Disease-pre Stroke-pre Hypertension-pre Cancer-pre Lung-pre Arthritis-pre Couple Status

* Based on design-adjusted Rao-Scott X^2 test of independence between levels of predictor and response/nonresponse outcome. Excludes ADAMS sample members who were deceased at the time of contact.

The results of the analyses of simple association between individual predictors and ADAMS participation informed the next stage of the analysis which involved fitting multivariate logistic regression models to estimate the propensity that surviving ADAMS cases participated in the clinical assessment. Tables 6A and 6B present a summary of these models.

For surviving ADAMS sample members who self-reported in the HRS Wave corresponding to their sample phase, the strongest predictor of participation was gender. All else being equal males were more likely to consent than females. We speculate that this counterintuitive finding may be explained by the fact that due to differential mortality, male gender and younger age effects are highly confounded in this model.

These two models were used as the basis for the propensity weighting adjustment described in the next section.

Table 6A: Propensity Models for Self Respondents

Model	Full Model (n=1107)			Reduced Model (n=1107)		
Parameter	β	Se(β)	$p > X^2$	β	Se(β)	$p > X^2$
Intercept	-1.67	1.13	0.14	0.43	0.41	0.29
Age	-0.11	0.09	0.24	-0.02	0.01	0.16
Age^2	.002	.002	0.23			
Gender (Male)	**0.70**	**0.15**	**<0.001**	**0.65**	**0.16**	**<.001**
Pre-NurseHome (yes)	-0.56	0.64	0.39			
Pre-Cancer (yes)	0.18	0.15	0.22	0.21	0.15	0.15
Pre-Stroke (yes)	0.33	0.31	0.29	0.31	0.31	0.31
Pre-Psych (yes)	0.46	0.24	0.06	*0.52*	*0.25*	*0.04*
Prehlth 1 (exc)	0.28	0.47	0.36			
Prehlth 2 vgood)	0.60	0.29	0.03			
Prehlth 3 (good)	0.36	0.34	0.29			
Prehlth 4 (fair)	0.18	0.31	0.56			
Pre-NAGI	0.05	0.03	0.10			
Pre-ADL	0.09	0.08	0.25	0.14	0.07	0.04
CogStrat1:Low	-0.07	0.20	0.74			
CogStrat2:Border	0.08	0.17	0.64			
Cog Strat3: Low Norm	0.19	0.23	0.40			
CogStrat4: Med Norm	0.03	0.14	0.80			

Table 6B: Propensity Models for Proxy Respondents

Model	Full Model (n=375)			Reduced Model (n=375)		
Parameter	β	Se(β)	$p > X^2$	β	Se(β)	$p > X^2$
Intercept	-3.75	1.52	0.01	-1.47	1.10	0.18
Age	-0.13	0.12	0.27	0.17	0.03	0.51
Age^2	.002	.002	0.37			
Gender (Male)	-.36	0.31	0.25	-.38	.34	.26
Pre-NurseHome	0.20	0.36	0.40			
Pre-Cancer (yes)	0.58	0.39	0.14	0.63	0.38	0.10
Pre-Stroke (yes)	0.20	0.27	0.46	0.22	0.28	0.42
Pre-Psych (yes)	-0.05	0.29	0.87			
Prehlth 1 (exc)	-0.86	0.60	0.15	-1.15	0.61	0.06
Prehlth 2 vgood)	1.02	0.71	0.15	0.71	0.71	0.32
Prehlth 3 (good)	-0.13	0.47	0.77	-0.34	0.50	0.49
Prehlth 4 (fair)	0.54	0.08	0.48	0.44	0.42	0.28
Pre-NAGI	0.05	0.08	0.47			
Pre-ADL	0.19	0.11	0.48	0.19	0.10	0.06
CogStrat1:Low	0.99	0.52	0.06	*1.03*	*0.52*	*0.05*
CogStrat2:Border	0.17	0.47	0.72	0.28	0.43	0.51
Cog Strat3: Low Norm	0.48	0.44	0.28	0.49	0.44	0.26
CogStrat4: Med Norm	A	A	A	A	A	A
A – The surviving Proxy sample does not include any sample persons in Cogstratum 5 (high normal). Cogstrat4 is the reference category.						

5. Population Weights for ADAMS Data Analysis – Wave A

This section provides a description of the computation algorithm and assumptions used to develop a population weight for descriptive analysis of the ADAMS data set. The computation of the ADAMS weight involved a sequence of four steps: 1) determination of a weight factor to account for each case's population representation in the full HRS panel from which ADAMS cases were subsampled; 2) calculation of a weight factor to account for the stratified subsampling of ADAMS cases from the full set of eligible HRS panel respondents; 3) adjustment for nonresponse among the surviving members of the ADAMS sample; and 4) poststratification of weights to U.S. population controls.

The following sections describe the computation of each of these weight components.

5.A HRS Panel Base Weight, $W_{HRSpanel}$:

As described above, the ADAMS sample is selected from the HRS respondent samples for 2000 and 2002. Properly weighted, each of these samples is representative of the U.S. household population for the biennial data collection year. In terms of population representation, the weight for analysis of the ADAMS data begins with the HRS population weight value.

$$W_{HRSpanel,i} = \left\{ W_{HRS2000,i} \text{ for Phase } 1, W_{HRS2002,i} \text{ for Phase } 2 \right\}$$

$where$:

$W_{HRS2000,i}, W_{HRS2002,i}$ are the year 2000, 2002 HRS individual weights for case i.

The HRS weight selected as the base weight for computing the ADAMS population weight was the 2000 HRS final weight for Phase 1 sample cases and the HRS 2002 final weight for Phase 2 sample cases.

5.B ADAMS Subselection Weight Factor, $W_{ADAMSsub}$:

As described in Section 1.B above, the ADAMS sample was a stratified random subsample of cases from the HRS panel members age 70 and older. Tables 1 and 2 provide the sample size and sample selection rates, f_h, for eligible persons in each of the 18 ADAMS design strata. Two alternative approaches for computing the ADAMS subsampling weight factor were considered.

5.B.1 Phase-specific option: The first was simply to compute the factors separately for Phase 1 and 2. Under this phase-specific option, the subsampling weight is the reciprocal of the probability of selection within each stratum (see sampling rates in Tables 1 and 2):

$$W_{ADAMSsub, phase} = \left(\frac{m_{h, phase}}{M_{h, phase}} \right)^{-1} = \left(f_{h, phase} \right)^{-1}$$

where:

$M_{h,phase}$ = the total number of HRS Panel members assigned to ADAMS stratum h=1,…,18 in sample areas assigned to the phase;

$m_{h,phase}$ = the total number of ADAMS sample cases selected from stratum h=1,...,18 by phase 1 and 2—See table 1 and 2 ; and

$f_{h,phase}$= the phase-specific sampling rate for ADAMS cases selected in stratum h.

The phase-specific computation of $W_{ADAMSSub}$ is the most direct approach but results in substantial weight variability due to the phase-specific dichotomy of the weight values for each stratum.

5.B.2 Pooled computation option: A second approach to the computation of $W_{ADAMSSub}$ is to pool the computation of the stratum-specific subsampling weights across the two phases:

$$W_{ADAMSsub, pool} = \left(\frac{m_{h, pool}}{M_{h, pool}} \right)^{-1} = \left(f_{h, pool} \right)^{-1}$$

where:

$M_{h,pool}$ = the total number of HRS Panel members assigned to ADAMS stratum h=1,…,18 in both sample phases;

$m_{h,pool}$ = the total number of ADAMS sample cases selected from stratum h=1,...,18; phase 1 and 2—See Tables 1 and 2 ; and

$f_{h,pool}$= the pooled sampling rate for ADAMS cases selected in stratum h.

Table 7 provides the stratum-specific values of $W_{ADAMSSub,phase}$ and $W_{ADAMSSub, pool.}$

As described in Section 6 (below), the pooled option for computing the ADAMS subselection factor was the method chosen for development of the final ADAMS analysis weight.

Table 7. ADAMS Subsampling Weight Factors, Phase-specific and Pooled Options.

ADAMS Stratum	Phase-Specific Calculation				Pooled Calculation	
	m_h	$W_{ADAMSSub, Phase 1}$	m_h	$W_{ADAMSSub, Phase 2}$	m_h	$W_{ADAMSSub, pool}$
1	72	1.0000	80	1.0000	152	1.0000
2	97	1.0000	128	1.0000	225	1.0000
3	38	12.31	262	1.54	300	2.91
4	8	25.00	33	5.75	41	9.51
5	15	16.86	37	6.19	52	9.27
6	19	6.42	35	3.68	54	4.65
7	12	16.75	44	4.20	56	6.89
8	34	16.82	62	8.50	96	11.45
9	39	20.07	91	8.20	130	11.76
10	15	10.53	34	4.97	49	6.67
11	38	7.86	45	6.78	83	7.23
12	175	1.00	87	1.91	262	1.31
13	77	1.00	79	1.00	156	1.00
14	7	10.28	40	1.22	47	2.57
15	6	17.33	20	4.75	26	7.65
16	3	12.66	8	5.25	11	7.27
17	6	4.5	10	2.7	16	3.38
18	4	10.75	10	3.9	14	5.86
Total	665	-	1105	-	1770	-

5.B.3 Combined ADAMS Sample Selection Weight, $W_{ADAMSSel}$:

The final sample selection weight factor for ADAMS cases is the product of the two factors $W_{HRSpanel}$ and $W_{ADAMSsub}$:

$$W_{ADAMSsel} = W_{HRSpanel} \times W_{ADAMSsub}$$

Table 8 (column 2) provides a univariate summary of the original distribution of the sample selection weights for all 1770 ADAMS cases. The selection weight is based on the "pooled" option for computing the ADAMS subsampling factor. The final column in Table 8 provides the distribution of the final sample selection weights for the 1542 surviving ADAMS sample cases. Properly computed, the sum of selection weight factors for sample cases is an expansion estimator (Kish, 1965) of the number of individuals in the corresponding survey population. Note in the final row of this table that the sum of sample selection weights for surviving members in the ADAMS sample is 23.52 million. For comparison purposes, an external estimate of the July 1, 2002 U.S. population age 71+ is approximately 24.19 million persons (U.S. Census Bureau, 2007, BLS, 2007). Section 5.E.4 (below) describes a final post-stratification step in which the ADAMS weights are controlled to the July 2002 Census

population estimates for gender and five-year age groupings. The source of the Census population estimates that were used for the post-stratification is http://www.census.gov/popest/national/asrh/NC-EST2006-sa.html.

Table 8. Distribution of ADAMS Sample Selection Weight Variables.

Weight Distribution Descriptive Statistic	Distribution of $W_{ADAMSsel}$	
	Total Sample	Survivors Only
n	1770	1542
mean	14258	15253
standard deviation	15873	16282
coefficient of variation	1.11	1.06
Min	545	545
1%-tile	1073	1073
5%-tile	1652	1710
10%-tile	2025	2057
25%-tile	3221	3460
Median	6694	8192
75%-tile	21,554	23,566
90%-tile	37,975	38,688
95%-tile	46,707	48,112
99%-tile	61,428	61,428
Max	134,766	134,766
Sum of Weights	25.24×10^6	23.52×10^6

5.C Nonreponse Adjusted Weight, $W_{ADAMSnr}$:

The next factor in the construction of the ADAMS population analysis weight is a nonresponse adjustment. Two related methods for nonresponse adjustment were developed and evaluated—a simple weighting class adjustment method and a propensity score weighting approach.

5.C.1 Weighting class approach, $W_{ADAMSnr,wc}$: The weighting class adjustment method assigned each of ADAMS sample cases to an adjustment cell based on the original 18 ADAMS sample strata (See Tables 1 and 2). Cases that died before the ADAMS evaluation could take place represent natural attrition in the survey population (see Section 3) and were excluded from the nonresponse adjustment calculation. Using the final sample selection weight factors for each case, weighted response rates were computed for each of the 18 weighting class cells, c=1,...,18. The weighting class nonresponse adjustment was then computed as the reciprocal of the weighted response rate for the cell c=1,...,C to which the case was assigned:

$$W_{ADAMSnr,wc,i} = \frac{1}{rrate_c}$$

$where: rrate_c = $ the weighted response rate for weighting class c=1,..., 18.

Table 9 provides the definitions of the 18 nonresponse weighting class cells, the weighted response rate for each cell and the value of the adjustment factor for cases in that cell. Note that when the adjustment factors shown in the final column are applied to the sample selection weights for respondents in each cell, the respondent sample is reweighted to the estimated surviving population count for that cell.

Table 9. Cognitive Strata Weighting Class Nonresponse Adjustment Factors for the ADAMS Sample, $W_{ADAMSnr,wc}$.

Cell	Functional Classification	Cognitive Score *	Age Range	Sex	Resp + Nonresp	Resp Only	Weighting Cell Adjust Factor, $W_{ADAMSnr,wc}$
	Nonresponse Weighting Cell Definition				Sum of Weights. $W_{ADAMSSel}$		Weighting Cell Adjust Factor,
1	Low Function	0-8	70+	M,F	395667	213311	1.855
2	Borderline	9-11	70+	M,F	574465	331940	1.733
3	Normal: Low	12-16	70+	M,F	2643349	1571786	1.681
4	Normal: Med	17-20	70-79	M	1256578	817920	1.536
5	Normal: Med	17-20	70-79	F	1873246	978504	1.916
6	Normal: Med	17-20	80+	M	649807	462155	1.406
7	Normal: Med	17-20	80+	F	1188118	613110	1.938
8	Normal:High	20-35	70-79	M	3613246	2262243	1.597
9	Normal: High	20-35	70-79	F	5617695	2451299	2.294
10	Normal: High	20-35	80+	M	1061406	723997	1.466
11	Normal: High	20-35	80+	F	2142943	1258749	1.704
12	Low Function	3.90-5.00	70+	M,F	722824	441044	1.639
13	Borderline	3.35-3.89	70+	M,F	381152	165281	2.304
14	Normal: Low	3.10-3.34	70+	M,F	337771	129133	2.618
15	Normal: Med	1.00-3.39	70-79	M	484992	111010	4.367
16	Normal: Med	1.00-3.39	70-79	F	261552	114396	2.288
17	Normal: Med	1.00-3.39	80+	M	132447	27992	4.739
18	Normal: Med	1.00-3.39	80+	F	184585	57986	3.185
				Total	23.52×10^6	12.73×10^6	

5.C.2 Propensity cell adjustment approach, $W_{ADAMSnr,prop}$: The propensity cell weighting approach also assigns each respondent sample selection weight an adjustment factor that is equal to the reciprocal of the estimated probability that they participated in the survey. However, in the propensity adjustment method, the assignment of cases to adjustment cells is based on individual response propensity values estimated (via logit transform) from a logistic model.

$$\hat{p}_{ADAMS,resp,i} = prob(respondent = yes \mid X_i) = \left(\frac{e^{X_i\hat{\beta}}}{1+e^{X_i\hat{\beta}}} \right)$$

$where:$

X_i is a vector of values of response predictors for i=1,...,n;

$\hat{\beta}$ the corresponding vector of estimated logistic regression coefficients.

The predictor variables and coefficient estimates for the logistic models used to estimate response probabilities and weights for the ADAMS propensity adjustment models are provided

in Tables 6A and 6B above. Based on the final models for Self R and Proxy R cases, the estimated response propensity was determined for all respondent and nonrespondent cases. Ten adjustment cells were then defined based on the deciles of the combined distribution of response propensities (Little and Rubin, 2002). Using the final sample selection weight factors for each case, weighted response rates were then computed for each of the 10 propensity score cells. The propensity score nonresponse weighting adjustment was then computed as the reciprocal of the weighted response rate to the cell d=1,...,D to which the case was assigned:

$$W_{ADAMSnrprop,i} = \frac{1}{rrate_d}$$

$$where: rrate_d = \text{ the weighted response rate for propensity cell d=1,...,D}$$

Table 10 provides the definitions of the 10 propensity score weighting cells, the weighted response rate for each cell and the value of the adjustment factor for cases in that cell.

Table 10: Propensity Cell Definitions, Weighted Response Rates, Adjustment Factors.

Cell	Propensity Range	Weighted Response Rate	$W_{ADAMSnr,prop}$
1	0-.431	.294	3.401
2	.431-.468	.457	2.188
3	.468-.496	.484	2.066
4	.496-.536	.422	2.370
5	.536-.592	.555	1.802
6	.592-.620	.597	1.675
7	.620-.649	.706	1.416
8	.649-.688	.563	1.776
9	.688-.738	.759	1.318
10	.738-1.000	.679	1.473

Note that the actual value of the weighted response rate for cases in a modeled propensity decile does not always fall within the range of scores for the decile. This is a reflection of lack of fit in the propensity model. Given the relatively poor fit of the nonresponse propensity model, a decision was made to use the simpler weighting cell adjustment approach for nonresponse adjustment in the final ADAMS analysis weights.

5.C.3 Prelimnary nonresponse adjusted weight, $W_{ADAMSnr}$:

A preliminary final analysis weight was computed as the product of the sample selection and nonresponse adjustment weight factors:

$$W_{ADAMSnr,i} = W_{ADAMSsel,pool,i} * W_{ADAMSnr,wc,i}$$

where:

$W_{ADAMSnr,i} = $ Preliminary population weight for case i=1,...,n;

$W_{ADAMSsel,pool,i} = $ ADAMS sample selection weight for case i;

$W_{ADAMSnr,wc,i} = $ ADAMS weighting cell nonresponse adjustment factor

5.D Final Post-stratification of ADAMS Analysis Weight:

Once the computation of the ADAMS sample selection weight and nonresponse adjustment factors was complete, the construction of the final weight values for individual ADAMS cases involved three additional computation/adjustment steps.

5.D.1 Trimming of Extremes in the Preliminary Weight Distribution:

To minimize the influence of extreme weight values on the variances of ADAMS sample estimates, the full distribution of nonresponse adjusted weights was trimmed to the 5%-tile and 95%-tile values. Within each stratum, the full vector of trimmed weights was then linearly rescaled to the original stratum total weight to preserve the population weight total. For example, prior to trimming the sum of the weighting class nonresponse adjustment weights for cases in Stratum 11 was 2,142,943. In the trimming step, weight values less than $Q_{.05}$= 3165 were increased to 3165 and weight values greater than $Q_{.95}$= 89,416 were reduced to that 95th %-tile value. Following the trimming step, the sum of weights for the truncated distribution totaled 2,138,124. To restore the total weight in Stratum 11 to its original value, each weight in Stratum 11 was multiplied by 2,142,943/2,138,124=1.02254—thereby redistributing the weight lost in the trimming of a few extreme cases across all respondent cases in Stratum 11.

Table 11 provides a descriptive summary of the distribution of the preliminary ADAMS weights after the trimming and rescaling step.

Table 11. Distribution of ADAMS Trimmed, Nonresponse Adjusted Weight.

Weight Distribution Statistic	Trimmed Nonresponse Adjusted Weight $W_{ADAMSnr,wc,trimmed}$
n	856
mean	27480
standard deviation	30087
coefficient of variation	1.09
Min	3097
1%-tile	3097
5%-tile	3158
10%-tile	3634
25%-tile	5900
Median	13744
75%-tile	39728
90%-tile	75660
95%-tile	98783
99%-tile	112011
Max	112011
Sum of Weights	23.52×10^6

5.D.2 Update of Weights for ADAMS Nursing Home Residents

Prior to May of 2006, the intent of standard releases of the household- and person-level weights for the HRS longitudinal data was to provide weighted representation for the U.S. household population. HRS panel members who entered a nursing home or nursing facility therefore received a zero population weight for those waves in which they were technically not in the "household population".   In the process of finalizing the population weights for the ADAMS sample data, a decision was made to formally develop a 2000 and 2002 analysis weight for all HRS panel members who had entered a nursing facility at some point after their baseline interview.   The revised HRS 2000 and 2002 weights for nursing home residents (an all other cases) were used as the value of $W_{HRSpanel}$ in determining the ADAMS sample selection weight.

Data from the 2000 Census and the Centers for Medicare and Medicaid Services (CMMS) Minimum Data Set (MDS) were used to establish poststratification population controls for developing the final 2000 and 2002 HRS weights for the nursing home population. Since accurate population representation of the age 70+ nursing home population is particularly important in ADAMS, these same poststratification controls were applied to develop the ADAMS final weight.   Table 12 provides a numerical summary of the post-stratification step.

The 109 ADAMS respondents who were nursing home residents were assigned to four post-strata based on age category (70-79, 80+) and gender. It is important to note that the ADAMS expansion estimate of the total nursing home population is approximately 87% of the external control value; however, the estimated totals for age by gender grouping—especially males, 70-79 – can differ substantially from the established control totals. The sample size for the male, 70-79 adjustment cell (n=4) is smaller than desired for a post-stratification cell (20-25 cases minimum is a rule of thumb). However, given the importance of each age x sex group, a decision was made not to further collapse cells across gender or age.

For these four post strata, a post-stratification factor was computed as the ratio of the HRS nursing home population control to the sum of the ADAMS nonresponse adjusted weights for nursing home residents in that cell. These computed post-stratification factors were then applied to the values of the nonresponse-adjusted weights for the nursing home cases.

Table 12: ADAMS Nursing Home Post-Stratification.

Post-Stratum	Age	Gender	n	Nursing Home Residents		
				Population Control	Sum of Weights, $W_{ADAMSnr,wc,tr}$	Post-Stratification Factor
1	70-79	M	4	135,992	26,837	5.067
2	80+	M	23	221,315	171,692	1.289
3	70-79	F	26	243,475	303,004	0.804
4	80+	F	56	870,232	785,361	1.108
Total			109	1,471,014	1,286,894	na

5.D.3 Final Post-stratification of ADAMS Weights to Census 2002 Population Estimates

As discussed in Section 3 above, the ADAMS sample was recruited from eligible persons in both the 2000 HRS and 2002 HRS. With ADAMS in-home evaluations occurring as soon as three months or as long as three years after the qualifying HRS interview, it was difficult to specify a specific reference time point for the representation of the ADAMS samples. The ADAMS Public Use data set was initially released without additional post-stratification controls to U.S. population estimates. In early Fall of 2007, a decision was made to post-stratify the ADAMS weights to July 1, 2002 U.S. Census population estimates for age and gender groupings.

Table 13 provides a summary of the post-stratification factors that were used to compute the updated ADAMS Wave A analysis weights. Note that the post-stratification controls for the youngest male and female age groups are restricted to ages 71-74, reflecting the roughly one year average lag in time from initial HRS eligibility for the ADAMS sample (at age 70) to the actual ADAMS assessment. In February, 2009 we discovered an error in the application of the post-stratification for those age 90+. For men age 90+, the revised post-stratification factor for 90+

males is 407,246/414,346=0.9829. For 90+ females the revised factor is 1,201,074/1,227,645=0.9784.

Table 14 provides the distribution of the revised, final weights for ADAMS Wave A after the Census-based post-stratification adjustment was applied to the preliminary weight that included only the sample selection, weighting cell nonresponse adjustment and nursing home adjustment.

Table 13: Final ADAMS Sample Post-stratification.

Post-strata Criteria		Post-stratification
Age	Gender	Factor
71-74	Male	.9902
71-74	Female	.9607
75-79	Male	.9617
75-79	Female	.9066
80-84	Male	1.1626
80-84	Female	1.1662
85-89	Male	1.3054
85-89	Female	1.3270
90+	Male	0.9829
90+	Female	0.9784

Table 14. Distribution of ADAMS Wave A Final Analysis Weight Variable.

Weight Distribution Descriptive Statistic	Final Weight: With Census 2002 Post-stratification
N	856
mean	28263.08
standard deviation	29252.47
coefficient of variation	103.50
Min	2548
1%-tile	2633
5%-tile	3264
10%-tile	3844
25%-tile	6466.5
Median	14586
75%-tile	44071
90%-tile	80207
95%-tile	95276
99%-tile	108034
Max	118178
Sum of Weights	24.19×10^6

6. Direct Estimation of Dementia/CIND Prevalence in the HRS/ADAMS Survey Population – Wave A

The analyses summarized in the preceding sections of this technical report suggest that factors such as proxy status, gender, pre-existing cancer and stroke diagnoses, and cognition and overall health status may have influenced surviving ADAMS sample members' participation in the clinical assessment. It is impossible to say whether or not these analyses have fully identified the true underlying model of ADAMS participation. It is highly likely that there remain unidentified and possibly unmeasured variables that further explain the patterns of participation in ADAMS. Nevertheless, the set of demographic and health variables examined certainly includes many, if not most, of the best candidate predictors of selection bias in the ADAMS data.

Given that there appears to have been some selectivity in individuals' ability or willingness to participate in ADAMS, an important question is: If we apply the weighting adjustments described in Section 5 that correct for the modeled selection bias, do these adjustments have an important impact on the population estimates and associated inferences from the ADAMS data? What is the effect of the several components of the ADAMS sample selection and nonresponse adjustment weighting calculations? Which weight should be the recommended standard for direct analysis of the ADAMS data?

To explore the answer to this question, a simple sensitivity analysis was conducted. In this analysis, direct estimates of population proportions and means were computed for a selected set of dementia diagnostic variables, physiological measures and demographic characteristics. Table 15 presents the results of this exercise. The estimates and standard errors (in italics) reflect the effects of each successive stage in the development of the final ADAMS weight. All standard errors shown in this table reflect the complexities of the ADAMS sample and the underlying HRS sample design.

The first series of estimates in Table 15 columns (1) and (2) are included only for comparison purposes. The first includes no adjustment for sample selection probabilities or nonresponse. Since the original HRS sample is disproportionately allocated to persons of African-American and Hispanic ancestry and the ADAMS oversamples persons of limited cognitive function, this naïve series of estimates is by design highly biased for the population values. The second series of estimates (2), weights each of the respondent cases by its HRS sample selection weight. It therefore adjusts for initial sample inclusion probabilities in HRS but does not adjust for the highly disproportionate sampling rates used to selected HRS panel members for ADAMS participation. These weighted estimates that do not account for the ADAMS subselection are therefore also expected to be biased for population statistics estimated using only the ADAMS data.

The next series of estimates, (3) and (4), are weighted by a full ADAMS sample selection weight. The estimates in column (3) are based on the pooled ADAMS subselection probability and the those in column (4) incorporate the phase-specific values for the subsampling rates. Barring the effect of differential nonresponse, these series of estimates should yield unbiased or nearly unbiased estimates of population statistics. The estimates have numerically different

values; however, if the standard errors of the estimates are considered, none of the observed differences in these two series is significant at a reasonable (e.g. α=.05) decision level. Since standard errors of key ADAMS estimates (% dementia, %CIND) based on the pooled ADAMS subselection weight (see Section 5 above) are lower than the alternative weight that incorporates phase-specific subsampling factors, the "pooled" alternative was chosen as the basis for further ADAMS weight development.

The final series of estimates in columns (5)-(6) are based on weights that are the product of the final pooled ADAMS sample selection weight,a nonresponse adjustment and post-stratification to U.S. population controls for July 2002. Columns (5) and (6) display estimates that incorporate the simpler weighting class adjustment for ADAMS nonresponse—the second of this pair includes the further step of post-stratification of the weight counts for nursing home residents.   The final column (7) provides estimates based on the final Census 2002 post-stratified weights. When the Census July, 2002 population controls are incorporated into the ADAMS weights, the point estimates of dementia and Alzheimer's Disease (AD) prevalence increase over 1% point compared to the estimates that only incorporate sample selection and nonresponse adjustment factors. This increase in estimated prevalence for dementia and AD can be attributed to the increase in total weight that the Census-based post-stratification applies to respondents age 80 year and older.

Taking into account the sampling variability of the estimates, this difference is not statistically significant; however, analysts should note the sensitivity of these prevalence estimates to age changes in the weighted population distribution. The difference in estimates compared in columns (5)-(7) of Table 15 reflect the effect of the post-stratification step and the associated "upweighting" of under-represented persons age 80+ to match the Census 2002 population controls. Over time, similar changes in the actual U.S. population can be expected as the proportion of the population over age 70 that survives to their 80s and 90s increases.

The final weight that is included in the February 2009 updated public release version of the ADAMS data set is the weight that includes: the pooled ADAMS subselection factor, the simpler weighting cell adjustment for nonresponse and the post-stratification to July 2002 U.S. population counts. ***This weight variable is called AASAMPWT_F.***

Table 15: Sensitivity of Selected ADAMS Sample Estimates to Stages of ADAMS Weight Development.

Statistic		No Weight (1)	HRS Wgt Only (2)	ADAMS Sel Wgt, Pooled (3)	ADAMS Sel Wgt, Not Pooled (4)	ADAMS WC NR Wgt, Pooled (5)	ADAMS WC NR Wgt, Pooled NH Post (6)	ADAMS Final Weight (7)
Weighted by:		*None*	$W_{HRSPanel}$	$W_{ADAMSsel, pool}$	$W_{ADAMSSel,,phase}$	$W_{ADAMS,nr,wc}$	$W_{ADAMS,nr,wc,nh}$	$W_{ADAMS,final}$
Dementia %	est	**35.98%**	**34.81%**	**12.70%**	**13.50%**	**12.48%**	**12.61%**	**13.67%**
	se	*2.61%*	*2.74%*	*1.23%*	*1.45%*	*1.14%*	*1.14%*	*1.19%*
CIND %	est	**28.15%**	**26.14%**	**22.13%**	**22.14%**	**21.64%**	**21.46%**	**22.03%**
	se	*1.51%*	*1.73%*	*1.49%*	*1.72%*	*1.75%*	*1.75%*	*1.70%*
Alzheimers %	est	**26.75%**	**25.62%**	**8.76%**	**8.89%**	**8.63%**	**8.65%**	**9.51%**
	se	*2.00%*	*2.07%*	*1.03%*	*1.06%*	*0.96%*	*0.93%*	*1.02%*
ApoE4 allele %	est	**27.97%**	**28.48%**	**26.13%**	**25.59%**	**26.15%**	**26.47%**	**26.43%**
	se	*1.41%*	*1.65%*	*2.70%*	*2.27%*	*2.50%*	*2.53%*	*2.44%*
Age 70-74 %	est	**19.98%**	**19.96%**	**29.13%**	**29.61%**	**30.95%**	**30.83%**	**28.46%**
	se	*1.59%*	*1.48%*	*2.11%*	*2.36%*	*2.27%*	*2.27%*	*2.12%*
Male %	est	**41.47%**	**40.06%**	**42.87%**	**41.76%**	**38.71%**	**39.02%**	**39.36%**
	se	*1.49%*	*1.74%*	*2.47%*	*2.35%*	*2.25%*	*2.24%*	*2.18%*
College %	est	**25.47%**	**27.65%**	**38.39%**	**36.38%**	**37.22%**	**37.27%**	**37.08%**
	se	*1.55%*	*1.85%*	*2.59%*	*2.54%*	*2.43%*	*2.43%*	*2.35%*
Nursing Home %	est	**12.73%**	**12.99%**	**5.42%**	**6.01%**	**5.47%**	**5.96%**	**6.34%**
	se	*1.36%*	*1.50%*	*0.82%*	*0.94%*	*0.92%*	*0.98%*	*1.01%*
Mean DSRS Severity	est	**10.83**	**10.52**	**5.2**	**5.5**	**5.2**	**5.24**	**5.47**
	se	*0.68*	*0.71*	*0.37*	*0.39*	*0.41*	*0.4*	*0.42*
Mean CDR Score	est	**0.83**	**0.81**	**0.39**	**0.41**	**0.39**	**0.40**	**0.42**
	se	*0.05*	*0.06*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*

7. Sampling Error Estimation in Design-based Analysis of the ADAMS Data.

ADAMS was based on a probability sample of HRS panel members and therefore shares many of the primary stage sample stratification and clustering features of the parent sample design. The HRS/ADAMS sample design is very similar in its basic structure to the multi-stage designs used for major survey programs such as the U.S. Health Interview Survey (HIS), the National Survey of Family Growth (NSFG) or the other national scientific surveys. The survey literature refers to the these samples as complex designs, a loosely-used term meant to denote the fact that the sample incorporates special design features such as stratification, clustering and differential selection probabilities (i.e., weighting) that analysts must consider in computing sampling errors for sample estimates of descriptive statistics and model parameters. Standard programs in statistical analysis software packages assume simple random sampling (SRS) or independence of observations in computing standard errors for sample estimates. In general, the SRS assumption results in underestimation of variances of survey estimates of descriptive statistics and model parameters. Confidence intervals based on computed variances that assume independence of observations will be biased (generally too narrow) and design-based inferences will be affected accordingly. Likewise, test statistics (t, X^2, F) computed in complex survey data analysis using standard programs will tend to be biased upward and overstate the significance of tests of effects.

This section of the ADAMS sample design description focuses on sampling error estimation and construction of confidence intervals for survey estimates of descriptive statistics such as means, proportions, ratios, and coefficients for linear and logistic regression models.

7.A Sampling Error Computation Methods and Programs

Over the past 50 years, advances in survey sampling theory have guided the development of a number of methods for correctly estimating variances from complex sample data sets. A number of sampling error programs that implement these complex sample variance estimation methods are available to ADAMS data analysts. The two most common approaches (Rust, 1985; Wolter, 1985) to the estimation of sampling error for complex sample data are through the use of a Taylor Series linearization of the estimator (and corresponding approximation to its variance) or through the use of resampling variance estimation procedures such as Balanced Repeated Replication (BRR) or Jackknife Repeated Replication (JRR).

7.B Taylor series linearization method:

When survey data are collected using a complex sample design with unequal size clusters, most statistics of interest will not be simple linear functions of the observed data. The linearization approach applies Taylor's method to derive an approximate form of the estimator that is linear in statistics for which variances and covariances can be directly and easily estimated. STATA Release 9 and 10, SAS V8-V9, SUDAAN Version 9 and the most recent releases of SPSS are commercially available statistical software packages that include procedures that apply the Taylor series method to estimation and inference for complex sample data.

Stata (StataCorp, 2007) is a more recent commercial entry to the available software for analysis of complex sample survey data and has a growing body of research users. STATA includes special versions of its standard analysis routines that are designed for the analysis of complex sample survey data. Special survey analysis programs are available for descriptive estimation of means (SVY, MEAN), ratios (SVY, RATIO), proportions (SVY, TAB) and population totals (SVY, TOTAL). STATA programs for multivariate analysis of survey data include linear regression (SVY, REGRESS), logistic regression (SVY, LOGIT) and probit regression (SVY, PROBIT). STATA program offerings for survey data analysts are constantly being expanded. Information on the STATA analysis software system can be found on the Web at: http://www.stata.com.

Programs in SAS versions beginning with Version 9 (SAS, 2004; www.sas.com) also use the Taylor Series method to estimate variances of means (PROC Surveymeans), proportions and cross-tabular analysis (PROC SurveyFreq, SAS V9.1.3), linear regression (PROC SurveyReg) and logistic regression (PROC SurveyLogistic).

SUDAAN (RTI, 2004) is a commercially available software system developed and marketed by the Research Triangle Institute of Research Triangle Park, North Carolina (USA). SUDAAN was developed as a stand-alone software system with capabilities for the more important methods for descriptive and multivariate analysis of survey data, including: estimation and inference for means, proportions and rates (PROC DESCRIPT and PROC RATIO); contingency table analysis (PROC CROSSTAB); linear regression (PROC REGRESS); logistic regression (PROC LOGISTIC); log-linear models (PROC CATAN); and survival analysis (PROC SURVIVAL). SUDAAN V9.0 and earlier versions were designed to read directly from ASCII and SAS system data sets. The latest versions of SUDAAN permit procedures to be called directly from the SAS system. Information on SUDAAN is available at the following web site address: www.rti.org .

SPSS Version 14.0 (http:// www.spss.com) users can obtain the SPSS Complex Samples module which supports Taylor Series Linearization estimation of sampling errors for descriptive statistics (CSDESCRIPTIVES), cross-tabulated data

(CSTABULATE), general linear models (CSGLM) and logistic regression (CSLOGISTIC).

7.C Resampling methods:

BRR, JRR and the bootstrap comprise a second class of nonparametric methods for conducting estimation and inference from complex sample data. As suggested by the generic label for this class of methods, BRR, JRR and the bootstrap utilize replicated subsampling of the sample database to develop sampling variance estimates for linear and nonlinear statistics. WesVar PC (Westat, Inc., 2000) is a software system for personal computers that employs replicated variance estimation methods to conduct the more common types of statistical analysis of complex sample survey data. WesVar PC was developed by Westat, Inc. and is distributed along with documentation to researchers at Westat's Web site: http://www.westat.com/wesvarpc/ . WesVar PC includes a Windows-based application generator that enables the analyst to select the form of data input (SAS data file, SPSS for Windows data base, ASCII data set) and the computation method (BRR or JRR methods). Analysis programs contained in WesVar PC provide the capability for basic descriptive (means, proportions, totals, cross tabulations) and regression (linear, logistic) analysis of complex sample survey data. WesVar also provides the best facility for estimating quantiles of continuous variables (e.g. 95%-tile of a cognitive test score) from survey data. WesVar Complex Samples 4.0 is the latest version of WesVar. Researchers who wish to analyze the ADAMS data using WesVar PC should choose the BRR or JRR (JK2) replication option.

STATA V9/V10 has introduced the option to use JRR or BRR calculation methods as an alternative to the Taylor Series method for all of its svy command options. SUDAAN V9.0 also allows the analyst to select the JRR method for computing sampling variances of survey estimates.

IVEWare is another software option for the JRR estimation of sampling errors for survey statistics. IVEWare has been developed by the Survey Methodology Program of the Survey Research Center and is available free of charge to users at: http://www.isr.umich.edu/src/smp/ive/ .   IVEWare is based on SAS Macros and requires SAS Version 6.12 or higher. The system includes programs for multiple imputation of item missing data as well as programs for variance estimation in descriptive (means, proportions) and multivariate (regression, logistic regression, survival analysis) analysis of complex sample survey data (Raghunathan, et al., 2001).

These new and updated software packages include an expanded set of user-friendly, well-documented analysis procedures. Difficulties with sample design specification, data preparation, and data input in the earlier generations of survey analysis software created a barrier to use by analysts who were not survey design specialists. The new software enables the user to input data and output results in a variety of common

formats, and the latest versions accommodate direct input of data files from the major analysis software systems.

7.D Sampling Error Computation Models

Regardless of whether the linearization method or a resampling approach is used, estimation of variances for complex sample survey estimates requires the specification of a *sampling error computation model.* ADAMS data analysts who are interested in performing sampling error computations should be aware that the estimation programs identified in the preceding section assume a specific sampling error computation model and will require special sampling error codes. Individual records in the analysis data set must be assigned sampling error codes that identify to the programs the complex structure of the sample (stratification, clustering) and are compatible with the computation algorithms of the various programs. To facilitate the computation of sampling error for statistics based on ADAMS data, design-specific sampling error codes will be routinely included in all public-use versions of the data set. Although minor recoding may be required to conform to the input requirements of the individual programs, the sampling error codes that are provided should enable analysts to conduct either Taylor Series or Replicated estimation of sampling errors for survey statistics. In programs that use the Taylor Series Linearization method, the sampling error codes (stratum and cluster) will typically be input as keyword statements (SAS V9.1, SUDAAN V9.0) or as global settings (STATA V9/V10) and will be used directly in the computational algorithms. Programs that permit BRR or JRR computations will require the user supplied sampling error codes to construct "replicate weights" that are required for these approaches to variance estimation.

Two sampling error code variables are defined for each case based on the sample design stratum and primary stage unit (PSU) cluster in which the sample respondent resided: Sampling Error Stratum Code (SESTRAT) and Sampling Error Cluster Code (SECLUST). The sampling error SESTRAT variable for ADAMS contains a unique code for each of 26 sampling error strata formed by combining 52 matched pairs of sampling error strata in the parent HRS design.

In variance estimation for complex sample designs, the sampling error clusters represent the "ultimate clusters" (Kalton, 1977) of the sample selection process. The SECLUST code reflects the geographic clustering of sample observations based on the PSUs to which they are assigned. Sampling variances for survey estimates will therefore be estimated under the assumption that two combined PSU sampling error clusters were selected from each stratum. Combining two HRS strata to form one ADAMS sampling error stratum and combining the PSU clusters ensures a minimum number of ADAMS observations per cluster. This combined stratum approach protects against the occurrence of "sampling zeros" in clusters for those analyses where the researcher is focusing only on a subpopulation (e.g. women age 80 and older) of the respondents. Combining strata to form sampling error clusters in this fashion is a standard practice. Estimates of

variance computed under this sampling error calculation model remain unbiased (Kalton, 1977).

Table 16 summarizes the distribution of ADAMS respondent cases to the assigned sampling error calculation strata and clusters.

Table 16: Distribution of ADAMS Respondents by Sampling Error Stratum and Cluster

SESTRAT	SECLUST	
	1	**2**
1	24	10
2	12	5
3	12	6
4	12	12
5	14	14
6	8	8
7	4	3
8	2	7
9	9	7
10	10	7
11	17	16
12	4	9
13	16	9
14	25	13
15	22	13
16	23	13
17	38	20
18	27	6
19	18	5
20	25	28
21	35	16
22	30	7
23	27	41
24	47	29
25	24	32
26	25	10
Total	510	346

7.E Syntax for ADAMS Design-based Variance Estimation Using STATA and SAS

The following two sections provide a short overview of the general syntax and command file structure for computing sampling errors using STATA and SAS programs that have been designed for the analysis of complex sample survey data. Analysts are referred to the user guides and the on-line help facilities of these two software systems for documentation of the individual programs.

7.E.1 STATA command syntax

As described above, ADAMS data analysts who are familiar with the STATA software system can utilize STATA's "svy" commands for the analysis of complex sample survey data. STATA Version 10 syntax for some of the more commonly used analysis programs is illustrated below :

.svyset seclust [pweight=aasampwt_f], strata(sestrat)

This statement defines the sample design variables for the duration of the analysis session. SVY commands issued after this statement will automatically incorporate these design specifications.

To conduct analyses, the following STATA commands and syntax are used (please refer to STATA v9/V10 Reference Manual for specific command syntax and output options):

.svy, vce(linearized): mean *vars*

[estimates, standard errors, design effects for means]

.svy, vce(linearized): tab *v1 v2*

[estimates, standard errors for proportions of single variable categories, or crosstabulations of two variables with tests of independence]

.svy, vce(linearized): regress dep x1 ...

[simple linear regression model for a continuous dependent variable]

.svy, vce(linearized): logit dep x1…

[simple logistic regression model for a binary dependent variable]

To estimate simple desriptive statistics or regression models for subpopulations of the survey population in STATA, the following optional syntax is used (illustrated for svy, tab):

.svy, vce(linearized): tab *v1 v2*, subpopulation*(var)*

where *var* is a binary variable that equals "1" for the subpopulations for which separate estimates are desired (e.g. males) and "0" for all other cases.

7.E.2 SAS Version 9 Command Syntax

SAS Version 9 includes four programs for the analysis of complex sample survey data: PROCS Surveymeans, SurveyFreq, SurveyReg and SurveyLogistic. The general syntax for specifying the ADAMS design structure in the SAS system is as follows:

PROC SurveyXXXX data=libname.filename;
STRATUM SESTRAT;
CLUSTER SECLUST;
WEIGHT AASAMPWT_F
program specific statements here;
RUN;
Users are referred to the current SAS/STAT® *User's Guide* or SAS On-line Help for documentation on program specific statements, keywords and options

8. Sample Weights for Analyzing ADAMS Data Waves A-C

8.A Recapitulation of Wave A design and analysis

Properly weighted, analyses of the ADAMS Wave A data provide a representative cross-sectional "snap shot" of the measured diagnostic states and other related characteristics of the U.S. population as of approximately July 1, 2002. The July 1, 2002 date is labeled approximate since the actual ADAMS Wave A assessments were conducted over a time period spanning August, 2001 to December, 2003 (see Figure 1.a on p. 9).   Section 3 earlier within this report addresses the issue of this "time averaging" and its implication for data analysis. The conclusion is that there is no evidence that the extended time frame for the Wave A data collection precludes treating the Wave A data as a cross-sectional representation of the July 1, 2002 adult population age 71 and older.
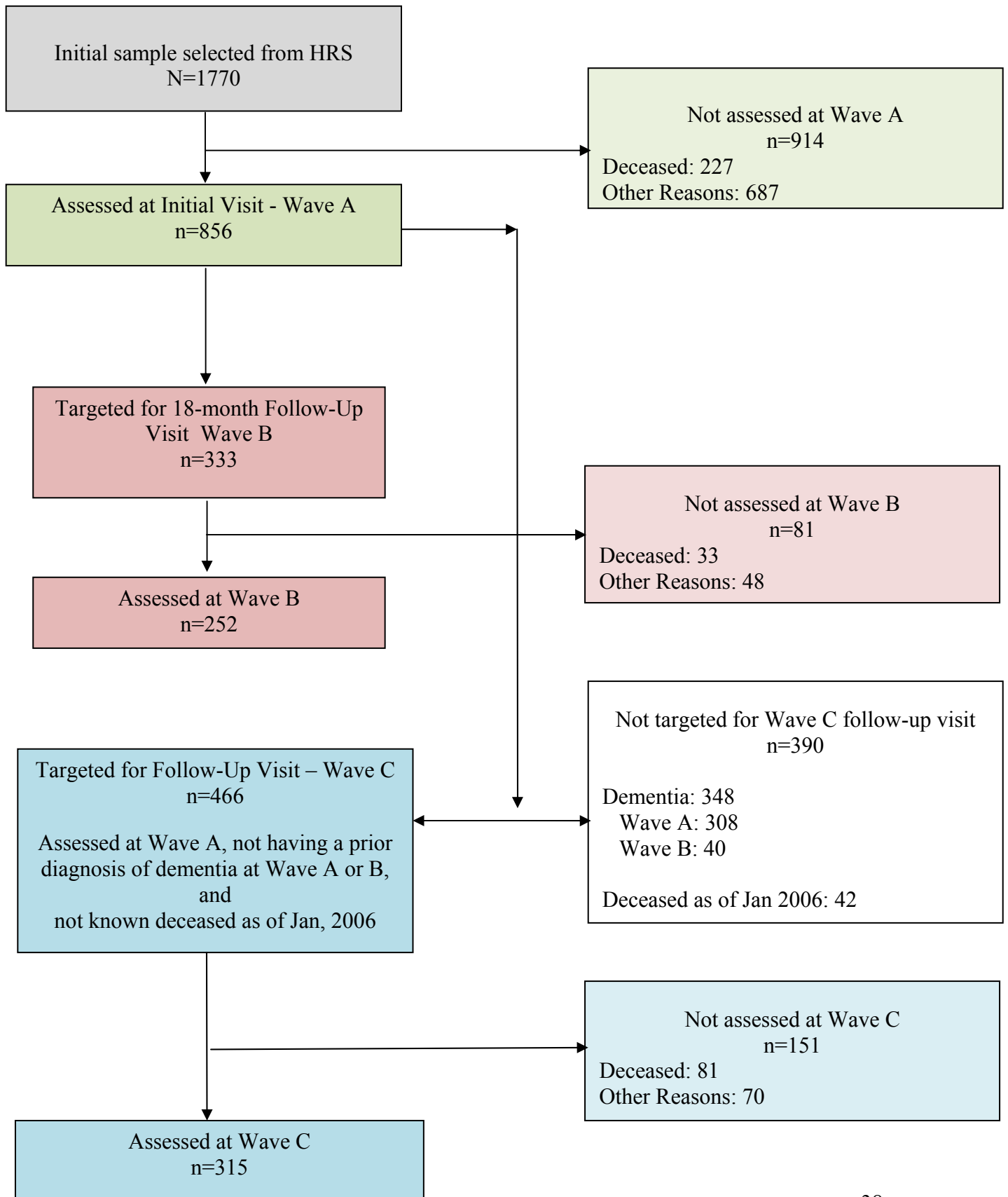
Users may analyze the ADAMS Wave A data in any software system that supports weighted estimation (e.g. through the "Weight   *vname* ;" statement in SAS or through the "pweight" specification in Stata). The appropriate weight for cross-sectional analyses of the ADAMS Wave A data is the variable labeled AASAMPWT_F. Since the

application of weights affects not only the estimates of survey statistics but also the standard errors of these estimates, users should analyze the ADAMS Wave A data in a software package that includes programs that have been adapted to complex sample designs. The previous section provides an explanation and examples of analyzing ADAMS Wave A data using appropriate complex sample analysis software.

Analysis of the ADAMS Wave A data is therefore a fairly straight forward exercise in the application of statistical techniques for complex sample survey data. However, the ADAMS public use data represent more than just a single cross-sectional picture of the cognitive status of U.S. older adults. The ADAMS is also a prospective cohort study that follows the Wave A baseline sample for over five years, capturing deaths of sample members, transitions to new diagnostic classifications of disease and in a small number of cases, "loss to follow-up." However, the data analyst must understand that the prospective follow-up of the Wave A ADAMS respondents is not always systematic; it is not repeated for all sample members at specific time points.

Figure 3 is a flow diagram that summarizes the schema of follow-up data collection activities for the Wave A baseline sample.   The top three boxes in this flow chart represent the development of the initial ADAMS cohort and the completion of assessments for n=856 cohort members in ADAMS Wave A.   As noted above, when properly weighted using the ADAMS variable, AASAMPWT_F, the data for these 856 Wave A assessments should provide a cross-sectional picture of the U.S. adult population 71+ as of July 1, 2002.   Moving down the flow chart, the next series of boxes is the schema for Wave B data collection activities. Note that the follow-up sample for Wave B includes a non-random 1/6th share of Wave A "Normal" cases, all of Wave A "CIND" cases, and about a 1/10th non-random share of the Wave A cases that had been assigned an initial "Dementia" diagnosis. ADAMS Wave B data are not representative of the full ADAMS cohort. Wave B data are useful in that they provide interim data (between Wave A and C) on mortality and updated diagnosis for a highly selective subsample of the ADAMS cohort but they should not be analyzed as a standalone data set. The lower third of the flowchart in Figure 2 summarizes the sample assignment and outcomes for the ADAMS Wave C data collection. With January 2006 as a reference date, ADAMS Wave C attempted to reassess all non-deceased Wave A sample cohort members that had not received a dementia diagnosis at the baseline or during the Wave B follow-up.

Figure 3: ADAMS Fieldwork Flow Chart

Initial sample selected from HRS
N=1770

Not assessed at Wave A
n=914
Deceased: 227
Other Reasons: 687

Assessed at Initial Visit - Wave A
n=856

Targeted for 18-month Follow-Up
Visit Wave B
n=333

Not assessed at Wave B
n=81
Deceased: 33
Other Reasons: 48

Assessed at Wave B
n=252

Not targeted for Wave C follow-up visit
n=390

Dementia: 348
   Wave A: 308
   Wave B: 40

Deceased as of Jan 2006: 42

Targeted for Follow-Up Visit – Wave C
n=466

Assessed at Wave A, not having a prior
diagnosis of dementia at Wave A or B,
and
not known deceased as of Jan, 2006

Not assessed at Wave C
n=151
Deceased: 81
Other Reasons: 70

Assessed at Wave C
n=315

8.B Prospective longitudinal design and measurement conventions for ADAMS

To correctly incorporate the ADAMS Wave B and C data in a longitudinal analysis (e.g. prospective estimation of dementia or CIND incidence over the five year period July 2002 through July 2006), researchers must build an analytic file from the components that correctly identify the events of interest (e.g. incident dementia) and also ideally attribute a date to that event. Maybe the easiest way to frame this analysis is to begin with the n=856 members of the Wave A cohort sample. Properly weighted, the Wave A sample serves to determine initial (baseline) status of the ADAMS survey population and for prospectively analyzing changes in the population that occur during a window of time that begins at Wave A and continues through Wave C. Some sample members will die—their death representing normal mortality in the population. Other members will survive but transition among disease states. A small number of the Wave A cohort will be lost to follow-up before the close of the prospective time window and their status will be uncertain.

Figure 4 illustrates the prospective tracks that Wave A sample cohort members may take. The vertical lines in this figure represent a time window beginning immediately after the Wave A assessment is complete and ending at the time of the Wave C assessment.

Beginning with the Wave A, the ADAMS cohort is divided into two groups each with different following rules: Group 1 is the set of cases diagnosed with dementia at Wave A; Group 2 are the cases with Wave A CIND or normal diagnoses. Although a small, selected number of Wave A dementia cases were followed up at Wave B, for all practical purposes the longitudinal trajectory for these cases follows two general paths. They either die (MX) prior to the end of the time window or they survive and their baseline dementia diagnosis is assumed to still hold (Dem, A). For Wave A normal and CIND cases, there are five general dispositions that can occur in the ADAMS "observation window" spanning Wave A to Wave C. The Wave A normal or CIND case may die prior to Wave C without any further observation after Wave A. The case may be observed to transition to a dementia diagnosis through the Wave B follow-up observation and either: survive to Wave C or subsequently die prior to Wave C. The Wave A normal or CIND case may be lost to follow-up (non contact, nonresponse) at or before Wave C with no observation of their diagnostic state after the Wave A assessment. Finally, a full wave C assessment may be completed and a consensus diagnosis of: 1) dementia; 2) CIND or 3) normal assigned to the case at Wave C.

8.C. Population Weight Variables for the Analysis of the ADAMS Longitudinal Data

Three weight variables are currently included on the public use file for the ADAMS. Each of these weight variables is designed for specific types of analyses and each represents a very specific population of inference.

8.C.1 AASAMPWT_F (n=856) – Wave A cross-sectional analysis weight.

The ADAMS weight variable, AASAMPWT_F, should be used for all cross-sectional analysis of the ADAMS Wave A data. The reference population for this weight is the July 1, 2002 U.S. adult population age 71+. Table 17 below provides a summary of key statistics for this weight variable. A full description of the methodology used to develop AASAMPWT_F is presented earlier in this report. Users are encouraged to run a simple descriptive summary of this weight variable from their own version of the ADAMS public use data set and compare the key statistics to those in Table 17 to ensure that they have the correct weights assigned to each Wave A observation.

8.C.2 ACLONGWT (n=786) – ADAMS Longitudinal Weight

The ADAMS weight variable, ACLONGWT, has been constructed specifically for prospective analysis of the Wave A ADAMS sample cohort (U.S. adults, age 71+ on July 1, 2002). ACLONGWT is designed to allow the analyst to look forward from July 1, 2002 and track each Wave A sample member to a final disposition at Wave C. The weight variable includes a non-zero weight value for each Wave A case that: 1) survived to Wave C and was assessed; 2) received a dementia diagnosis prior to Wave C (and therefore was not reassessed at Wave C); or 3) died prior to Wave C. The n=70 Wave A cases that survived with no prior dementia diagnosis to Wave C but were nonrespondents in that final assessment (see Figure 3) have a zero value for ACLONGWT. The explanation for the zero weight value is that the status of these cases in "censored" by loss to follow-up (nonresponse) at Wave C.
The value of ACLONGWT is therefore dependent on the disposition of each ADAMS case as of Wave C and is constructed as shown in Table 18. Data users who are conducting a longitudinal analysis of the ADAMS data are encouraged to use ACLONGWT for estimating transitions over time.

8.C.3 OUTCOMEC (n=1,770) - Status as of ADAMS Wave C

The variable, OUTCOMEC, indicates the respondent's status as of Wave C and can be used for longitudinal tracking. It permits quick determination of the longitudinal disposition of each sample case across Waves A-C, including whether the individual was assessed in Wave C, the primary research diagnosis code assigned in Wave C if assessed, and reasons for not being assessed in Wave C (e.g., prior diagnosis of dementia at Wave A or B, or having died prior to Wave C).

8.C.4 CCOHORTWT (n=315) - ADAMS Wave C Adjustment Weight

The ADAMS variable, CCOHORTWT, was used to create ACLONGWT as a necessary input to adjust for the differential probabilities of selection for the ADAMS Wave C sample cases and non-response among survivors to Wave C. **Users of the ADAMS data should recognize that the reference population for this weight is non-random, and we DO NOT advocate analysis of the Wave C data on its own.** The reference population includes only members of the original ADAMS cohort who were eligible for Wave C sample selection. As shown in Figure 2 this includes ADAMS cohort members who were eligible for assessment at Wave A, survived to Wave C **and** did not receive a dementia diagnosis prior to Wave C.

Because the Wave C sample includes only a subset of Wave A individuals who survived, a full analysis of Wave A to Wave C transitions for cohort members surviving to Wave C should also include Wave A dementia cases who survive to Wave C and Wave A Normal and CIND cases who were diagnosed with dementia in the Wave B follow-up but also survive to Wave C (see Figures 3 and 4).

For most prospective, longitudinal analyses of the ADAMS data, we encourage data analysts to use the weight variable, ACLONGWT, described above in Section 8.C.2.

Figure 4. Prospective View of ADAMS Longitudinal Outcomes
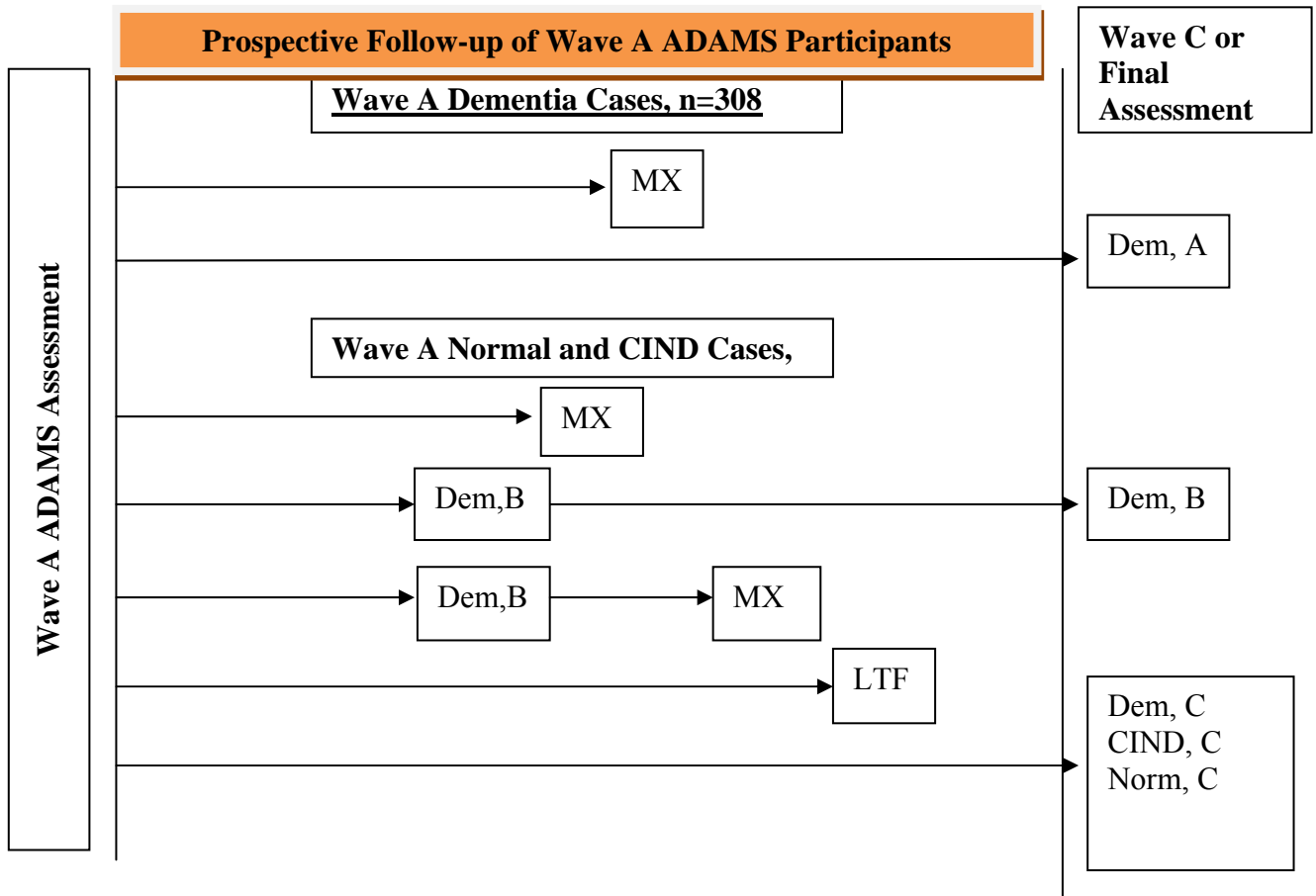
Legend	
Dem, A|B|C	Dementia diagnosed at waves A,B,C
CIND, C	CIND diagnosis at Wave C
Norm, C	Normal diagnosis at Wave C
MX	Death in observation period
LTF	CIND, Normal case, Wave C no contact or nonresponse

Table 17: Descriptive Statistics for ADAMS Weight Variables

	ADAMS Weight Variable	
Statistic or Property	AASAMPWT_F	ACLONGWT
Application	Cross-sectional	Longitudinal
Reference Population	U.S. Adults Age 71+ on July 1, 2002	Prospective Cohort Outcomes for U.S. Adults, Age 71+ Alive Beginning July 1, 2002
Total Non-zero Weights	n=856	n=786
Mean Weight Value	28,263	30,780
Minimum Value	2548	2548
Maximum Value	118,178	161,517
Sum of Weights (Estimated Size of Reference Population)	24,193,100	24,193,100

Table 18: Construction of the ADAMS Longitudinal Weight

Longitudinal Disposition of Wave A Case	Value of ACLONGWT
Wave A Dementia Diagnosis	AASAMPWT_F
Wave B Dementia Diagnosis	AASAMPWT_F
Deceased Prior to Wave C	AASAMPWT_F
Assessed at Wave C*	CCOHORTWT
Nonresponse at Wave C*	0 value is assigned

* ACLONGWT values for Wave C assessed cases include a nonresponse adjustment for the Wave C sample cases that were lost to follow-up.

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