Non-observation of Recurrent Biomeasures Collected in Longitudinal Panel Surveys

by

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DEDICATIONS

To my eternal companion, Megan

To my loving parents, Mike and Cindy

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ABSTRACT

Biomeasure collection in surveys has increased substantially in the last two decades, but little focus has been given to the recurrent nature of this collection in longitudinal panel surveys. The purpose of this dissertation is to explore various sources of biomeasure non-observation in a population-based longitudinal survey, identify predictors of missingness, ascertain if bias results from these different sources, and address approaches to imputation for this kind of data. These studies utilize interview, biomeasure, and interviewer data from the Health and Retirement Study (HRS) encompassing the 2006 through 2014 cycles.

The first study defines and investigates five primary sources of non-observation for longitudinal biomeasure collection: mortality, nonresponse/attrition, health-related and non-health-related ineligibility, and biomeasure non-consent. The first component of this study examines the common sociodemographic and health predictors of the five non-observation sources for dried blood spot (DBS) collection in HRS. After controlling for natural panel losses due to mortality, significant predictors of non-observation (nonresponse, ineligibility, and biomeasure non-consent) are respondent race/ethnicity, chronic conditions, physical activity, and cognitive functioning. The second component examines the successive impacts each of the five non-observation sources has on the final observed distributions of the five DBS biomarkers. Most DBS biomarkers see little change in their distributions after controlling for censoring due to mortality. Cystatin C and HbA1c see significant changes when excluding health-related ineligible respondents and wave nonrespondents, respectively.

The second study builds on previous biomeasure consent work (e.g., Sakshaug, Couper, & Ofstedal, 2010) by looking specifically at the second biomeasure consent request for both DBS and physical measurements (PM) separately. This analysis expands past work by looking at recent changes in physical and mental health, a wider array of wave- and mode-specific survey resistance measures, interviewer continuity, and reason for non-consent to see how each of these impact consent to PM and DBS conditional on previous biomeasure consent behavior. Recent health changes such as increased number of functional limitations or less frequent physical activity reduce the likelihood of future consent to PM and DBS, but only for previous consenters. Interviewer continuity appears to reduce the likelihood of future consent to DBS for previous non-consenters, but also for future consent to PM for previous consenters. Using survey resistance measures from the prior face-to-face wave of data collection lead to better predictions of consent than survey resistance measures from the most recent telephone wave.

The third study compares three different applications of sequential regression multivariate imputation (SRMI) for the imputation of longitudinal biomarker data. This study also looks at the effects of imputing for all biomeasure eligible cases instead of only biomeasure consenting respondents. Focusing on two biomarker outcomes (Cystatin C and C-reactive protein), each approach is evaluated using multiple univariate and multivariate analyses to observe shifts in estimates, reduction in variability, and recovery of statistical information. The results are generally mixed as to which SRMI approach is best for longitudinal biomarker data. Imputing all biomeasure eligible cases does result in noticeable changes for Cystatin C with large changes in the distribution and substantive changes in the proportion at risk.

CHAPTER 1

Introduction

Over the last two decades, the collection of biomeasures has increased substantially in surveys (Beebe, 2007; Sakshaug, 2013; Sakshaug, Ofstedal, Guyer, & Beebe, 2015). Biomeasures collectively refer to any kind of physical or biological measurement or sample (Jaszczak, Lundeen, & Smith, 2009; Sakshaug et al., 2015), including but not limited to anthropometric measures (e.g., height/weight, waist-to-hip ratio), physical performance measures (grip strength, spirometry), and biological material including blood (dried blood spot, whole blood draw), saliva (passive drool, oral swab), and urine.

The driving force behind the collection of biomeasures in population-based social research is to understand the interaction of human behavior (social science) and biological forces (Harris, Gruenewald, & Seeman, 2007; see also Finch, Vaupel, & Kinsella, 2001; Weinstein, Vaupel, & Wachter, 2007). Weinstein and Willis (2001) provide four key uses and benefits of collecting biomeasures in conjunction with traditional, self-reported survey data (see also Sakshaug, Ofstedal, Guyer, & Beebe, 2015): (1) obtaining population-representative data from nonclinical samples; (2) the ability to calibrate self-reports with self-reported measures of health and disease; (3) the ability to explore and better define the causal connections between health and social research; and (4) the ability to link genetic information with surveys.

While each of these four uses has an important role in research, the third benefit – explore causal connections – is the only one that is strongly dependent on the collection and use of longitudinal data (Crimmins & Seeman, 2001). Repeated collection of biomeasures in large-scale, population-based surveys has been on-going on for over a decade, but few investigations have been made into the issues related to non-observation associated with recurrent collection of biomeasures in a longitudinal context.

The purpose of this dissertation is to explore various forms of biomeasure non-observation in population-based longitudinal surveys, to identify various sources of missingness along with its predictors, to ascertain the biases incurred in biomeasures by these different missing data mechanisms, and investigate how to best address missingness for analyses directly and indirectly focused on those more causal connections between human behavior and biological forces.

1.1 Methods of biomeasure collection in population-based longitudinal surveys

There are a wide variety of surveys that collect biomeasures and each conducts that collection in different and distinctive ways. Harris, Gruenewald, and Seeman (2007) and Sakshaug et al. (2015) both discuss a variety of community and population-based studies that collect biomeasures. A number of studies are highlighted to illustrate differences in how the biomeasures are collected.

The largest and most prominent of these studies is the National Health and Nutrition Examination Survey (NHANES) (Johnson, Dohrmann, Burt, & Mohadjer, 2014). NHANES serves many as a gold standard for population health statistics in the United States, especially in relation to biomeasure-related factors. NHANES collects a wide range of biomeasures through

the use of a Mobile Examination Center (MEC) which houses all of the necessary equipment to collect biomeasures under identical conditions at every survey location. NHANES has been able to maintain over a 90% examination rate from 1999 to 2016 for those households interviewed. While there is no question related to the quantity and quality of data NHANES collects, such a detailed and expansive collection of data is expensive. In addition, such a collection requires a large and well-trained medical operation involving trained doctors, nurses, and expensive medical equipment. For social research surveys, achieving this level of biomeasure collection and quality is virtually unattainable. NHANES is a repeated cross-sectional study as opposed to a panel study and thus does not collect data repeatedly for the same group of individuals. A simplification of the MEC model is to make use of local established health clinics similar to the Irish Longitudinal Study on Ageing (TILDA; Cronin et al., 2013) or the Midlife in the United States study (MIDUS; Love et al., 2010). However, coordination for a large-scale national panel study across all participants could prove a daunting task.

A middle ground approach employed by some surveys, particularly of those using nurses for biomeasure data collection, are the English Longitudinal Study of Ageing (ELSA; Marmot & Steptoe, 2007), Understanding Society (UKLHS; McFall, Booker, Burton, & Conolly, 2012), the Irish Longitudinal Study on Ageing (TILDA; Cronin et al., 2013), the 1999 National Long Term Care Survey (NLTCS; Research Triangle International, 2002), and a pilot for the UK Millennium Cohort Study (Calderwood, Rose, Ring, & McArdle, 2014). This approach allows for the benefit of having a medically trained nurse perform the collection of select biomeasures in the respondent's home including whole blood draws. This reduces respondent burden by removing unnecessary travel, but does necessitate a secondary visit from the original interview with a third party. The combined consent rate to the nurse visit with the biomeasure consent rate

produce a much smaller sample of final cases for these studies. For example, of the eligible respondents in Wave 2 of Understanding Society, 74% agreed to participate in the nurse visit and only 77% of those agreed to venipuncture resulting in only about 57% of the eligible sample with available biomeasures for analysis (McFall et al., 2012).

A fairly inexpensive alternative to collect biomeasures viable in any survey mode is the mail-back approach. Here participants self-collect the biological material (e.g., dried blood spot, saliva) and mail the sample back to the study team. This has proven somewhat successful for a variety of different studies including the 2003 HRS Diabetes Mailout Study (65% return rate; Heisler et al., 2007) and the Wisconsin Longitudinal Study (54% return rate; Dykema, DiLoreto, Croes, Garbarski, & Beach, 2017). However, the overall success of this approach is highly dependent on the sampled population, the original survey mode, and the nature of the greater study itself (Gatny, Couper, & Axinn, 2013). Self-collection also limits what types of biomeasures can be collected, usually restricted to those deemed minimally invasive (Lindau & McDade, 2007).

A large remainder of population-based surveys today that collect biomeasures use non-medically trained field interviewers to perform a majority of this collection. These studies include the Health and Retirement Study (HRS; Weir, 2008; Guyer, Ofstedal, Lessof, Cox, & Jürges, 2009); the National Social Life, Health, and Aging Project (NSHAP; Jaszczak et al., 2009; O'Doherty et al., 2014); the National Longitudinal Study of Adolescent to Adult Health (Add Health; Harris, 2013); the Survey of Health, Ageing and Retirement in Europe (SHARE; Weiss, Sakshaug, & Börsch-Supan, 2019; Korbmacher, 2014); and a pilot study for Understanding Society (UKLHS; McFall, Conolly, & Burton, 2014). This collection is more economically feasible for most studies rather than other large-scale operations or requiring travel

to a collection center. Anthropometrics, dried blood spots (DBS), and saliva are all minimally invasive collections that are routinely completed in this setting (Lindau & McDade, 2007). The interviewer can perform the collection of these biomeasures during the survey interview. The collection procedures are for the most part cognitively simple and low risk and the corresponding samples are easily transportable and stored.

Collection of biomeasures using non-medically trained field interviewers has proved to be generally quite effective. In general, the consent rates for physical measurements, DBS, and various saliva-based collections see average rates around or above 85% (see Jaszczak et al., 2009; Crimmins et al., 2013; Jaszczak et al., 2014; Crimmins et al., 2015; Weiss et al., 2019). Notable exceptions to these high rates are vaginal swab samples from NSHAP at 74% (Jaszczak et al., 2014) – understandable given the overly sensitive and intrusive nature of the collection – and the DBS collection in SHARE ranging from 34.6% in Greece to 83.5% in Denmark during Wave 6 (Weiss et al., 2019). Overall, these consent rates are strongly encouraging for studies considering whether to include biomeasures.

The major disadvantage of this form of collection, similar to the mail-back approach, is that these procedures are minimally invasive. A simple example is the difference in collecting DBS versus whole blood via venipuncture. Blood serum or plasma contains a vast array of health biomarkers making it a gold standard in health research. DBS restricts you to a limited number of assays and excludes the study of some analytes because of the requirement for larger volumes of blood (Lindau & McDade, 2007). DBS assay values are strongly correlated with whole blood levels on a number of biomarkers including HbA1c, Cystatin C, and C-reactive protein, but not as strongly with others such as lipid levels (Crimmins et al., 2014). In addition, there are differences in scale making direct comparisons problematic.

With the context of these various forms of biomeasure collection in mind, this dissertation focuses on longitudinal panel studies using non-medically trained field interviewers to collect biomeasures recurrently.

1.2 Overview

This dissertation examines the sources, predictors, and treatment of non-observation in recurrently collected biomeasures in longitudinal panel surveys using non-medically trained field interviewers for biomeasure collection. Non-observation from wave to wave can be attributed to a number of sources including, but not limited to, mortality, attrition, ineligibility, and consent. Each of these mechanisms are impacted by different factors (e.g., declining health, respondent-interviewer interaction) and could influence multiple mechanisms. Understanding the interplay between factors associated with obtaining a biomeasure and the bias incurred in the biomarker outcome by different forms of non-observation helps to balance the benefit or harm of potential interventions.

Chapter 2 investigates a variety of non-observation mechanisms in relation to recurrent collection of DBS samples. The first part of the study examines the common sociodemographic and health predictors of each non-observation mechanism on DBS collection and looks for patterns across mechanisms. The second half of the chapter examines the successive impacts of these mechanisms on the distributions of five DBS biomarkers.

While there are many sources of non-observation for biomeasure data, consent is one of the more direct forms of non-observation as the respondent makes an explicit decision in relation to the collection of the measure. Biomeasure consent has received some attention in recent years (e.g., Sakshaug et al., 2010; Korbmacher, 2014), but has always focused on cross-sectional

consent. Collection of biomeasure data in a longitudinal panel survey means that previous experiences and interactions can have a meaningful impact on decisions in a future wave. The role of changing health, interviewer continuity, and previous consent choices all play a role in whether biomeasure data will be collected in subsequent waves.

Chapter 3 reviews known predictors associated with single wave biomeasure consent and postulates factors related to the longitudinal nature of the biomeasure collection. The analyses explore the role of recent physical and mental health changes for the respondent, reluctance by wave and mode, and interviewer continuity as factors impacting future consent to physical measurements and DBS samples conditional on previous biomeasure consent behavior.

Understanding the sources of non-observation in biomeasures is important for making future design decisions, but there is always the inevitability that biomeasure data will not always be available for all cases. This loss in precision and potential for bias can be potentially mitigated by recovering statistical information through imputation. Depending on the imputation approach, imputation models can harness the power of historical observations of biomarker values to better inform imputed values.

Chapter 4 investigates three different approaches using sequential regression multivariate imputation (SRMI) to impute missing biomeasure data. The cross-sectional approach ignores the longitudinal nature of the collection. The sequential approach uses only past waves of interview and biomeasure data for the imputation model. The wide approach includes all available waves of data collection, past and future, to inform the imputation model. Focusing on two DBS biomarker outcomes, each imputation approach is evaluated using multiple univariate and

multivariate analyses to measure the benefit (or detriment) each approach can have on missing biomarker outcomes.

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CHAPTER 2

Understanding the Impact of Sequential Non-observation Sources on Longitudinal Panel Study Biomeasures

2.1 Introduction

There are many sources of non-observation that impact biomeasures collected in a longitudinal panel study. Each source is an opportunity to lose respondents and systematically bias the final distribution of key biomarker outcomes. While consent to biomeasure collection is often typically the first and likely the most salient given the direct relationship to biomeasure missingness, the numerous non-observation sources preceding consent can potentially be just as, if not more, troublesome. These additional sources include mortality, unit nonresponse, and operational eligibility.

Each of these non-observation sources are impacted by different factors and some factors may effect multiple sources. If these effects are consistent across sources, the cumulative effect can bias population estimates. When considering a possible intervention to address a single form of non-observation, it is important to understand how addressing one source of non-observation could have an adverse effect on other sources of non-observation if they are not independent mechanisms. In order to balance the benefit and harm of a potential intervention decision on obtaining a biomeasure estimate with as little bias as possible, the interplay between the impact

of obtaining the outcome itself and the bias caused by the different sources of non-observation on the outcome must be understood.

The purpose of this chapter is to examine the competing risks and associated bias from each source of non-observation. There are two overarching goals: identifying covariates associated with the propensity of removal at each source of non-observation and measuring the cumulative effect of sequential sources of non-observation on bias in biomeasure estimates.

2.2 Non-observation sources

Errors of non-observation refer to anything that excludes eligible respondents or sample records (Lavrakas, 2008). Sampling, coverage, and nonresponse error are all forms of non-observation in the total survey error framework (Groves, Fowler, Couper, Lepkowski, Singer, & Tourangeau, 2009). This survey error framework can also be associated with the Heckman concept of sample selection bias popularized in the late 1970s, where nonrandom participant self-selection or nonrandom researcher decisions alter sample composition (Heckman, 1979).

"Nonrandom self-selection by the participant" is nonresponse error in the survey framework. In the context of panel studies, it is referred to as attrition. This notion includes a participant's conscious decision to not participate (e.g., hard refusal) as well as a possibly unconscious decision to not participate (e.g., unavailable or inaccessible). More commonly consent or permission to collect data would fall into this participant self-selection problem.

"Nonrandom decisions by a researcher" is not discussed as often in the literature, as it is commonly an assumption or a feature of the research design. In the context of biomeasure collection, though, researchers can make administrative decisions – practical or theoretical, subjective or objective – about who is considered eligible to provide biomeasures. For example,

a common administration decision is based on age, including for instance only those younger than 65 years old. But the decision may also appear as a medical safety criterion (those not taking an anticoagulant, or blood thinner) or a survey design-based criterion (a particular mode of data collection). The impact of these less often considered dimensions of non-observation are also examined.

In a longitudinal panel survey the sources include mortality, unit nonresponse, eligibility, and consent. Multiple factors can have an effect on the source and the size of bias in biomeasure estimates.

2.2.1 Mortality

Mortality is a natural source of non-observation or censoring especially for an aging population. Given the strong relationship between health and mortality (e.g., Idler & Benyamini, 1997), and the relationship of biomeasures to health, it is an important non-observation source to understand in the longitudinal survey. The relationship between health and mortality is a well-studied relationship for many populations (e.g., Hurd & McGarry, 1995; Luo, Hawkley, Waite, & Cacioppo, 2012). Mortality removes subjects from the sample and so it is important to capture when considering sources of non-observation. Death does attenuate many sources of longitudinal bias.

However, mortality does not result in biased estimates, because estimates are for the population of the living unless mortality is not captured for all eligible sample members. Accuracy of mortality ascertainment can be problematic with both false positives (i.e., reported deceased but available) and false negatives (believed alive but deceased) resulting in biased findings, especially as it relates to mortality as an outcome. This is most often the case with long-

term unit nonrespondents where mortality may not be systematically observed. Longitudinal studies of aging need accurate sources of information or the ability to verify informant reports of mortality. For example, the Health and Retirement Study (HRS) documents mortality through two primary sources: 1) deaths reported during attempts at subsequent wave interviews resulting in an exit interview with next-of-kin and 2) the National Death Index. Over 95% of deaths are reported in both sources. HRS retains those lost to attrition for mortality observation and overall has found the mortality ascertainment is accurate and representative (Weir, 2016).

2.2.2 Unit nonresponse

Survey response generally has two distinct mechanisms: contact and cooperation (or in other words, non-contact and refusal) (Groves & Couper, 1998). Contact relates to the ability to find or locate (or relocate) the participant, while cooperation is the process of convincing the participant to participate and is conditional on contact. Lepkowski and Couper (2002) further divide contact in the context of panel studies into location and contact (see also Amaya & Harring, 2017). Many studies have shown that these mechanisms are generally different in both cross-sectional and panel studies (Groves & Couper, 1998; Lepkowski & Couper, 2002; Olson, 2006; Olson, Smyth, & Wood, 2012; Amaya & Harring, 2017). In panel studies, a single wave of nonresponse following the initial wave (also known as attrition) can occur due to noncontact or a lack of cooperation for any given wave. Attrition is a permanent state of nonresponse since a participant is never found again or requests to be removed from the panel permanently.

Survey nonresponse and panel attrition are well documented in the literature and a full discussion is not necessary here. Some key predictors of nonresponse and attrition in face-to-face panel surveys include impediments to entry (Groves & Couper, 1998), employment status

(Groves & Couper, 1998; Lepkowski & Couper, 2002), housing tenure (Groves & Couper, 1998), urbanicity (Groves & Couper, 1998), civic engagement (Groves, Singer, & Corning, 2000), social integration (Lepkowski & Couper, 2002; Amaya & Harring, 2017), and previous survey enjoyment (Laurie, Smith, & Scott, 1999; Lepkowski & Couper, 2002; Olsen, 2005). In addition, surveys of older adult populations are likely to see nonresponse predictors like age, cognitive impairment, and physical limitations (Kelfve, Thorslund, & Lennartsson, 2013). While there are clear relationships with the nonresponse mechanism, it is unclear how these factors might influence estimated biomarker values.

2.2.3 Operational eligibility

A source of non-observation preceding consent is eligibility. A respondent may not have a particular attribute (e.g., questions regarding pregnancy are not asked of men) or may have characteristics that exclude subjects through study protocols. This latter form of eligibility is sometimes referred to as operational eligibility. It is not discussed often in the literature, though it is a major concern for survey practitioners and research teams. Often operational eligibility involves screening (identifying and excluding) selected respondents from participating on the basis of some characteristic in order to protect respondents or minimize risk to them. This may include location constraints, respondent limitations, survey conditions, or external factors.

This concept can also be linked to following ethical practices in line with the Belmont Report and its principle of beneficence (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1978): (1) do no harm and (2) maximize possible benefits while minimizing possible harms. In biomeasure research it would be inappropriate and unsafe to ask a participant receiving anticoagulants (blood thinners) to provide

a blood sample due to increased risk of uncontrolled bleeding and perhaps even death. Similarly, one would not ask a respondent in a wheelchair to perform a walking test, exposing them to the risk of falls. Operational eligibility does not mean that a study participant does not have the desired attribute or that the measure could not feasibly be obtained given appropriate safeguards, controls, and conditions. In many cases, it is a necessary form of censoring that could induce bias in estimates.

The researcher essentially redefines the population of interest by specifying that only a particular subset of all potential subjects is to be examined. Conclusions can only be made in relation to the redefined population to ensure that conclusions are not extrapolated to populations other than those studied. However, the exclusion of respondents whose levels of biomeasures are related to the outcomes of interest generates a systematic and potentially sizable bias in biomeasure estimates toward (most likely) healthier outcomes.

In the context of an in-person, non-medically trained interviewer biomeasure collection, there are multiple forms of operational eligibility that exempt individuals from participating in biomeasure collection. Four forms of operational eligibility are explored here: (1) using a proxy respondent, (2) living in a nursing home, (3) completing collection in an out-of-scope survey mode, and (4) incomplete or partial interviews. These are not mutually exclusive states; a respondent could belong to any (or all) of these states.

Study protocol may require data collection from a proxy informant to complete the survey interview. Most often, this is due to the respondent being too ill or disabled, cognitively or physically, to complete the survey on their own (Moore, 1988; Nelson, Longstreth Jr, Koepsell, & van Belle, 1990; Weir, Faul, & Langa, 2011). In some cases, a proxy respondent

may be used because interviewers are unable to contact the respondent and, in accordance with survey protocols, the research team seeks out a knowledgeable proxy (e.g., spouse, parent, adult child) to provide the relevant information (Moore, 1988; Cobb, 2018). Proxy respondents are allowed for some surveys to increase response rates and reduce data collection costs (Weir et al., 2011; Cobb, 2018). However, proxies can also increase measurement error depending on the proxy's familiarity with the selected respondent's characteristics (Cobb, 2018).

Switching from self to proxy interviews in a panel study of older adults is associated with age and declining physical and mental health (Weir et al., 2011). Cognition, physical limitations, and age-related chronic conditions are highly correlated with health status. As a result, proxy data collection may lead to bias toward healthier levels of some biomarker values.

A second form of operational eligibility is living in nursing homes or other institutionalized facilities. Their placement in such a facility suggests an inability to complete daily or routine tasks due to diminishing physical and/or mental health. Depending on the condition of the respondent, these individuals may choose or even require that a proxy responds in their place. Given the respondent is being closely monitored due to their compromised mental and/or physical health, it is a sensible and necessary precaution to avoid collecting biomeasures as these individuals are at increased risk for injury and complications related to the collection procedures and may be inappropriately allowed or coerced to participate, compromised by an impaired cognitive state. In addition to safety, most facilities would not allow biomeasure collection by research study personnel, especially with non-medically trained interviewers. Again, cognition measures and physical limitations should be highly correlated covariates (Kelfve et al., 2013). These concerns are heightened by great disparities in placement into nursing home across racial groups (Stevens, Owen, Roth, Clay, Bartolucci, & Haley, 2004).

One factor related to declines in cognition ultimately resulting in the need for a proxy or placement in a nursing home is education. Higher education is generally attributed as a protective factor against cognitive decline, showing a decreased risk of dementia or Alzheimer's disease (Stern et al., 1994; Cobb et al., 1995; Ott et al., 1995; Karp et al., 2004; Rapp et al., 2013). However, higher education is also associated with steeper cognitive decline once diagnosed with dementia or Alzheimer's disease (Stern, Albert, Tang, & Tsai, 1999; Wilson et al., 2004; Scarmeas, Albert, Manly, & Stern, 2006; Rapp et al., 2013). This more rapid decline may be related to delayed detection and onset of clinical symptoms (Stern et al., 1994). More education could manifest as either a positive effect denoting the protective aspect of education or as a negative effect denoting the rapid decline following onset. Similar to proxy status, the exclusion of nursing home respondents is also likely to bias biomarker estimates toward healthier levels.

The third form of ineligibility is response in a survey mode other than one where biomeasure collection can occur. This specifically occurs in a multi-mode survey where biomeasure collection can only occur in a single or a subset of modes. For purposes of in-person, non-medically trained interviewer biomeasure collection, this would be any mode other than face-to-face (FTF). For example, the Health and Retirement Study (HRS) since 2006 has alternated between FTF and computer-assisted telephone interviews (CATI) every two year survey wave in order to reduce burden on respondents (Fisher & Ryan, 2018). Respondents are only eligible to provide biomeasures when they participate in a FTF wave. As such, interviewers cannot conduct any of the biomeasure collections if a respondent assigned to complete a FTF interview is responding via CATI. Other biomeasure collection studies which utilize a mail-back, self-collection approach for simple, non-invasive collections (e.g., Gatny, Couper, & Axinn,

2013; Dykema, DiLoreto, Croes, Garbarski, & Beach, 2017) may not observe this mode impact as acutely, depending on specific collection protocols by mode.

The decision to participate in a mode other than one assigned may be due in part to a number of factors. Smyth, Olson, and Millar (2014) suggest four reasons why a respondent may choose one mode over another: (1) familiarity with and access to the mode, (2) physical and cognitive demands of the mode, (3) self-presentation, and (4) personal safety concerns. All of these reasons are relevant in interviewer biomeasure collection in a longitudinal panel study. A FTF survey requires that the respondent be physically present and available when the interviewer makes contact. Factors like employment status and barriers to entry then influence the choice of survey mode (Groves & Couper, 1998; Tourangeau, 2004), though some of this choice may ultimately be due to the interviewer and not the respondent. Though FTF and CATI collections are both interviewer administered modes, the CATI interview for some respondents could prove to be more convenient and less cognitively demanding as it increases the social distance between the respondent and the interviewer. Interviews may be shortened, removing social pressures of FTF interaction, and ensuring one's personal safety and wellbeing (Groves, 1990; Schwarz, Strack, Hippler, & Bishop, 1991; Holbrook, Green, & Krosnick, 2003). Health related factors (e.g., chronic diseases, physical limitations) could account for some reasons to opt for a different mode, though there are potentially more factors related to the respondent and their living situation which may have more leverage in that decision.

The fourth and final eligibility form is a partial interview (i.e., survey breakoff) and do not receive the biomeasure module. This is most likely to occur if biomeasure collection occurs near or at the end of the interview. Studies like HRS (Weir, 2008) and the National Social Life,

Health, and Aging Project (NSHAP) (O'Doherty et al., 2014) attempt to avoid this problem by placing the biomeasure collection in the middle of the interview.

The general nonresponse framework established by Groves and Couper (1998) is useful for examining survey breakoffs (e.g., Peytchev, 2009; McGonagle, 2013). The framework repeatedly examines the respondent's motivations, desire, and ability to complete the survey as each new question is presented. Survey characteristics like the questionnaire content and length certainly play a role in this decision. Situational factors related to the respondent characteristics or the respondent-interviewer interaction could also lead a respondent to breakoff prematurely. It is possible that in surveys of older adults that health-related factors related to things like physical or mental exhaustion could play a role in continuing the survey. The choice to prematurely halt the survey as opposed to choosing not answer a question (i.e., item nonresponse) could be due to increasing cognitive burden comprehending questions, difficulty retrieving relevant information, and making appropriate judgments necessary to respond accurately (Loosveldt, Pickery, & Billiet, 2002; Yan & Curtin, 2010; see also Tourangeau, Rips, & Rasinski, 2000; Beatty & Herrmann, 2002).

While this overview of eligibility exclusions has tried to generally link different forms of ineligibility with health conditions (both physical and mental), there are a number of other factors that could result in exclusion under any of these situations. The connection between eligibility and overall health is important, because sample selection bias due to health yields systematic differences in health measure estimates, particularly biomeasures of interest.

These non-observation sources are not successive in nature, generating additional levels of missingness. In order for these states to be more useful in understanding the systematic loss of

data, it is necessary to classify each state as taking precedence over another. For example, while presence in a nursing home temporally precedes whether or not a subject (or proxy) respond to the survey, a nursing home respondent can provide data while a nonrespondent cannot. From a data perspective, nonresponse determines data presence, while nursing home residency does not. These issues are discussed further in reference to specific analyses conducted in this paper in Section 2.3.2.

2.2.4 Biomeasure consent

Biomeasure collection requires secondary consent from the respondent in addition to the consent to conduct the survey interview due to the invasive nature of collection (Weir, 2008; Jaszczak et al., 2009). Consent is the direct form of non-observation for biomeasures since the respondent must make a conscious decision to participate in the collection of biomeasures. Other mechanisms discussed above were indirect, since they involve survey participation generally.

A number of common sociodemographic factors have not been found to be significant predictors of biomeasure consent, including age, gender, and education (Gavrilova & Lindau, 2009; Sakshaug, Couper, & Ofstedal, 2010; Korbmacher, 2014). African Americans have been found to be less likely to consent to biomeasure collection (Gavrilova & Lindau, 2009), though this is not always a strong association (Sakshaug et al., 2010). Dykema and colleagues' (2017) found that more religious persons, as measured by weekly church attendance, are less likely to participate in biomeasure collection. However, after controlling for sociodemographic, health, and other factors, weekly church attendance led to higher rates of consent than those who did not attend or attended infrequently.

In general, healthier individuals are more likely to consent to biomeasure collection. More functional limitations (physical functioning where one needs assistance) as well as difficulty performing daily activities correspond to lower rates of biomeasure consent (Sakshaug et al., 2010; Korbmacher, 2014). Chronic conditions like diabetes are associated with higher levels of biomeasure consent, especially with dried blood spot assays (Sakshaug et al., 2010; Korbmacher, 2014). McClain et al. (2015) found higher levels of a word recall measure of cognition resulted in greater rates of consent to physical measurements (e.g., blood pressure, height, weight).

2.2.5 Research questions

The first research goal is to identify covariates associated with the propensity of participating in each eligibility state (living, response, biomeasure eligible, and consent) in opposition to the sources of non-observation (mortality, nonresponse, biomeasure ineligibility, and non-consent). Interest is in determining whether there are consistent sets of predictors that could result in a cumulative bias for key biomarker estimates. Existing research suggests that cognitive impairment, physical limitations, and chronic conditions are likely candidates for a survey of older adults. Thus, the first research question is:

(1) Are there common covariate predictors between each source of between-wave non-observation that could result in a bias for biomeasure estimates?

Individual respondent or household characteristics need to be examined, as well as potentially powerful predictors like knowing a respondent's previous eligibility state when predicting their future eligibility state. For example, a respondent who fails to complete the interview in one wave may be less likely to respond in the next wave (Watson & Wooden, 2009).

An older respondent experiencing increasing physical or cognitive difficulty and refusing biomeasure collection could be more likely to need a proxy interview, be admitted into a nursing home, or be deceased in a future wave. These considerations lead to a second research question:

(2) Does a previous source of non-observation predict a future eligibility state conditional on known covariate predictors of that future state?

The second research goal of measuring the effect of the sequential sources of non-observation bias on biomeasure outcomes focuses on the biomeasures themselves as they relate to each source of non-observation. While one might expect nonresponse or non-consent to represent major sources of non-observation for biomeasures, non-random associations of eligibility and health outcomes with consent could also be a source of systematic bias in biomarker estimates. Thus, two additional research questions posed are:

(3) What is the size of the bias of each non-observation source on biomeasure estimates, and which source results in the largest bias?

(4) How does the size of non-observation bias due to ineligibility compare to nonresponse or non-consent?

2.3 Methods

2.3.1 Data

The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the Institute for Social Research (ISR) at the University of Michigan. HRS is a longitudinal survey of adults over the age of 50 living in the United States that collects various measures related to health, medical care, employment, income, and cognition. HRS began in 1992 with a cohort of preretirement-aged individuals born

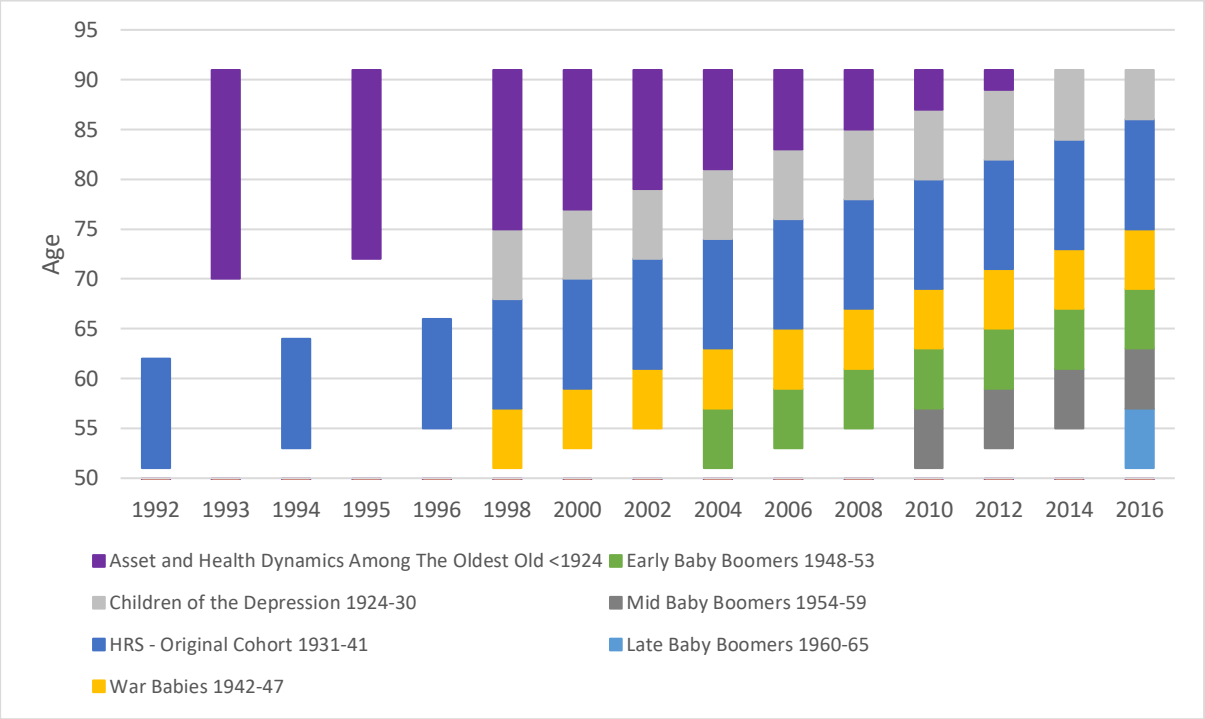

Figure 2-1. Longitudinal cohort design of the Health and Retirement Study. Adapted from Figure A-4 of "The Health and Retirement Study: Aging in the 21st Century: Challenges and Opportunities for Americans," by Survey Research Center, Institute for Social Research, 2017, p. 13.

between 1931 and 1941. New birth cohorts are enrolled every 6 years (e.g., 1998, 2004, 2010) to refresh the sample at younger ages (see Figure 2-1). The HRS conducts about 20,000 interviews every 2 years with response rates between 65 and 85 percent in the baseline wave and between 85 and 95 percent in follow-up waves.

In 2006, HRS began alternating respondents between face-to-face and telephone interviews, with a random half sample of the full panel being assigned to each mode (see Figure 2-2). Every two years each half-sample switches to the other mode[1]. In face-to-face interviews, noninstitutionalized, non-proxy respondents are asked to provide measures of physical

[1] Respondents over the age of 80 alternate between FTF and E-FTF interviews unless they specifically request a telephone interview.

functioning (i.e., blood pressure, hand grip strength, a walking test, height, weight, etc.), a one-time saliva sample (for DNA extraction and storage), and a dried blood spot assay (for measuring Hemoglobin A1c, cholesterol, and other biochemical measures.). Saliva and blood samples have different collection, storage, and analysis procedures. Respondents are given three consent forms for each of the biomeasure components. HRS refers to this face-to-face interview with biomeasure collection and self-administered questionnaire on psychosocial topics as the enhanced face-to-face (E-FTF) interview.

This study uses the 2006, 2010, and 2014 E-FTF waves of HRS. Biomeasure eligible respondents to the 2006 wave are included (n = 7,954). Analyses focus on biomarkers collected from the dried blood spot (DBS) assays in 2006. All respondent-level data was obtained from the HRS Public Release data available at http://hrsonline.isr.umich.edu/index.php?p=avail. Biomarker data, denoted as sensitive health data, were obtained through an application process (see http://hrsonline.isr.umich.edu/index.php?p=healthdat for details).

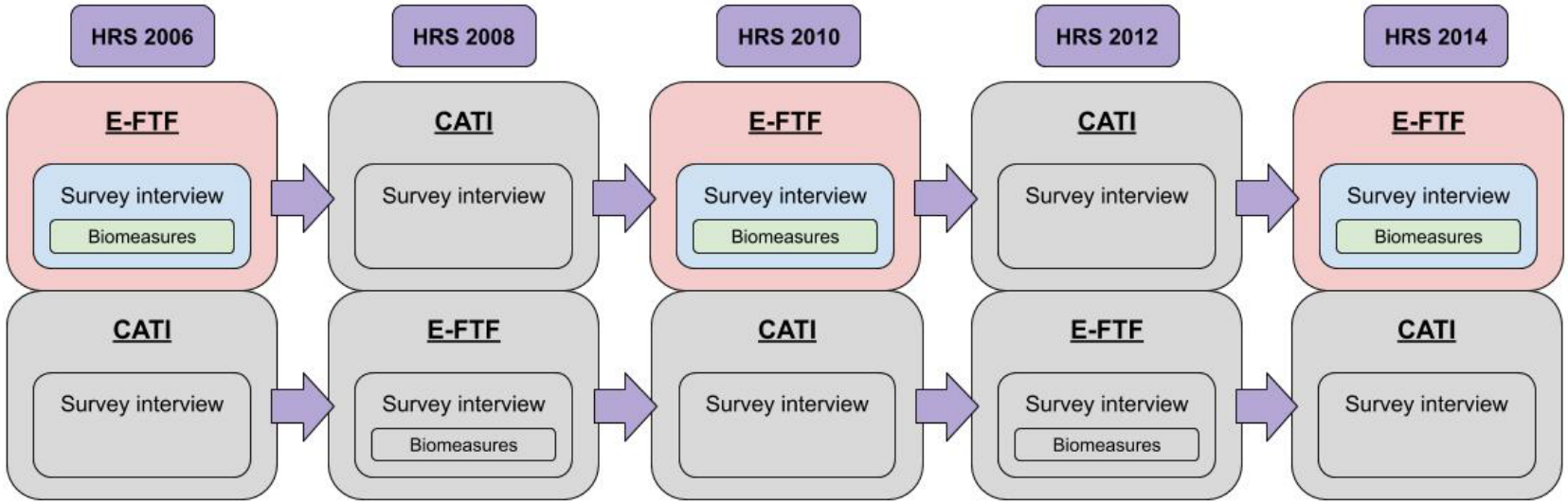

Figure 2-2. HRS alternating wave design highlighting biomeasure collection. Each row represents a random half-sample in the alternating survey mode design. Colored boxes represent data used for the analyses in this chapter. Gray boxes are not included in this analysis.

2.3.2 Disentangling eligibility states

In order to better disentangle the reasoning behind a biomeasure ineligible state and reduce the number of possible non-observation sources, one has to understand whether the reason for a respondent's ineligibility is related to their health or other circumstances. Health-related reasons would be more likely to cause bias in biomarker estimates.

Reasons for ineligibility can be examined by reviewing interviewer observations from the HRS 2010 interview of those who were biomeasure eligible in 2006. HRS interviewers were asked on up to two separate occasions to assess the mental or physical state of the respondent relative to ability to respond. For proxy interview respondents, interviewers were asked item MA011, "Do you have reason to think that [FIRST NAME] would have difficulty completing this interview because of cognitive limitations?" Response options include "No reason to think" this, "the respondent may have some cognitive limitations", and "the respondent has cognitive limitations that prevent him/her from being interviewed." While these reasons are all related to the mental condition of the selected respondent, and not physical condition, the latter two responses are considered health reasons for purposes of this analysis. After the interview is complete, the interviewer answers item M011: "Did the (respondent have/informant report that the respondent has/proxy report that the respondent has) any of the following impairments making it difficult to respond?" Response options that deal with more permanent physical or mental health issues include "mentally handicapped", "hard of hearing", "physically handicapped", and "speech impediment". Other potential, non-health related responses include "poor spoken English", "under the influence of alcohol or drugs", and "some other impairment". While being under the influence of alcohol or drugs is a temporary physical/mental condition, it

Table 2-1. Interviewer reported physical or mental difficulties for HRS 2010 biomeasure ineligible respondents who were biomeasure eligible in HRS 2006

Reason for ineligibility	Biomeasure Ineligible Respondent	Proxy Respondent	Nursing Home Respondent	CATI Respondent	CATI, not Proxy/Nursing Home
Health reason	42.2%	82.2%	84.5%	36.5%	9.3%
Not health reason	57.8%	17.8%	15.5%	63.5%	90.7%
Sample size	699	292	161	561	347
% of total sample	100.0	41.8	23.0	80.3	49.6

Note. Reason for ineligibility in 2010 is based off of MA011 and M011 asked of the interviewer.

is not indicative of a permanent state of compromised health. "Some other impairment" is too vague for categorization as health-related or not.

For those classified as ineligible in 2010 (n = 699), 42.2% were classified as ineligible due to health-related reasons (see Table 2-1). Of all proxy respondents (41.8% of ineligible respondents), over 82% were recorded as having health problems that made them ineligible. Of nursing home respondents (23.0% of ineligible respondents), 84.5% were recorded as having health-related problems. Among CATI respondents (80.3% of ineligible respondents), nearly 36% had health problems related to their response. However after excluding telephone respondents who used a proxy or were in a nursing home (nearly 50% of the total ineligible sample), there are only 9.3% with health-related impairments. The number of partial interviews is less than 10 cases, and most were proxy interviews. That is, proxy interview and nursing home respondents primarily identify health reasons for their biomeasure ineligibility, while CATI non-nursing home and CATI self-respondents primarily do not identify health reasons for ineligibility.

For operational eligibility, any or all of the non-observation sources can apply to a respondent. For example, a nursing home respondent could have a proxy respondent who completes the interview over the phone even though the respondent is assigned to E-FTF for a particular wave. In order for these states to be useful and interpretable in these analyses, a hierarchy of mutually exclusive eligibility states was established.

Sixty-eight percent of nursing home respondents use a proxy respondent while of all proxy respondents only 38% live in a nursing home. Thus, nursing home status is strongly influenced by the need for a proxy. Two exploratory logistic regression models (see Appendix A) predicting nursing home response and proxy response found a number of similarities in the demographic and health predictors for each non-observation source, including age, education, cognition, and physical activity. The largest differences are in home ownership and current work status with nursing home respondents less likely to own a home or currently hold a job. Given the relationship between these two sources of non-observation and the health-related reasons for each, **proxy and nursing home interviews are considered as a single source of non-observation associated with health-related issues**.

After excluding the proxy and nursing home interviews, the majority of the remaining biomeasure ineligible respondents completed CATI interviews and do not cite health-related issues as an impairment to response. The small remainder of ineligible respondents are survey breakoffs. Those who chose CATI over E-FTF and those who did not complete the interview are linked to increased survey resistance generally. **Breakoff interviews are grouped with CATI respondents as a single source of non-observation associated with survey resistance and not health-related concerns.**

Lastly, location, contact, and cooperation are usually modeled and examined separately for nonresponse (see Lepkowski & Couper, 2002). Due to small sample sizes, **location, contact, and cooperation are considered as non-observation due to nonresponse**. The analyses that follow consider five mutually exclusive and hierarchical sources of non-observation for biomeasure collection:

(1) Mortality,

(2) Nonresponse,

(3) Proxy/nursing home respondent (i.e., health ineligible respondent),

(4) Telephone/partial complete respondent (i.e., non-health ineligible respondent), and

(5) Biomeasure non-consenting respondent.

Including biomeasure consenting respondents, a total of six eligibility outcomes are considered (see Figure 2-3). Conversely, there are nested eligibility states representing the mathematical complements of the five non-observation sources above (i.e., living, respondent, non-nursing home self-respondent, biomeasure eligible respondent, and biomeasure consenting respondent).

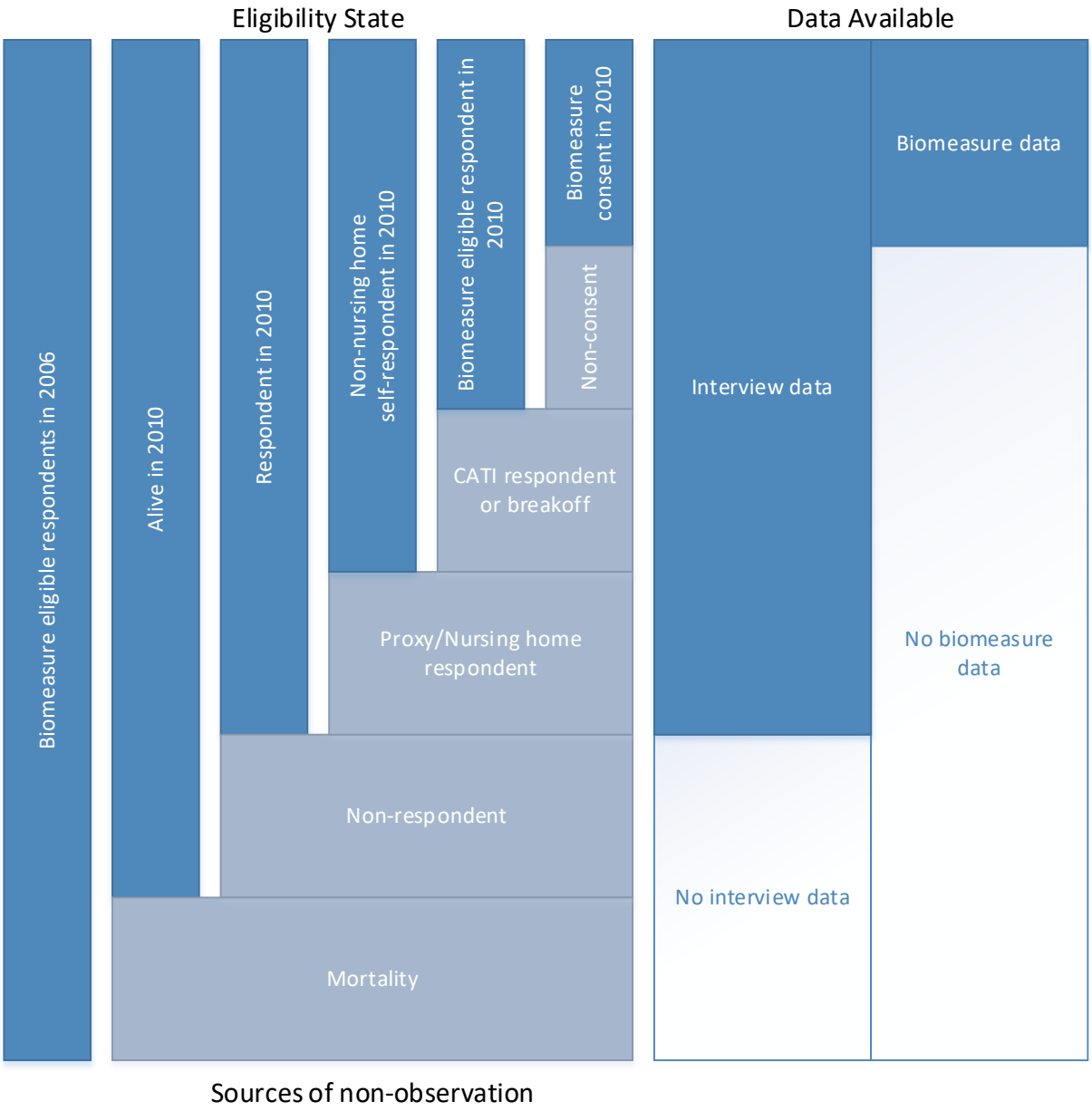

Figure 2-3. Sources of non-observation and eligibility states for HRS 2006 biomeasure eligible respondents in HRS 2010. This figure illustrates the relationship between successive sources of non-observation and final eligibility states for biomeasure collection in HRS 2010 and the impact on observable data. The right-hand side depicts the interview and biomeasure data available for each eligibility state. Eligibility state sizes are not reflective of actual proportions per non-observation source.

2.3.3 Part 1 – Sources of non-observation propensity model

The two research questions related to the sources of non-observation, a continuation ratio ordinal multinomial regression model (Fullerton & Xu, 2016), also known more simply as the continuation ratio logit model (Agresti, 2002) or the sequential logit model (Tutz, 1991), will be applied simultaneously to each of the successive non-observation source. The continuation ratio model is equivalent to conditional logistic regression models used in previous studies (e.g., Lepkowski & Couper, 2002; Olson, 2006) when the covariate set for each conditional model is the same.

Given known covariate differences across some of the non-observation models (e.g., Lepkowski & Couper, 2002; Olson, 2006), the non-parallel slopes continuation ratio model will be used. Covariance matrices are estimated assuming no covariance between models allowing for statistical testing of slopes across non-observation models. In addition, the parallel slopes assumption can be tested to assess whether a constrained or unconstrained partial model might be appropriate (Fullerton & Xu, 2016).

The non-parallel slopes continuation ratio model can be written as

$$\log\left(\frac{\pi_{j+1}+\cdots+\pi_J}{\pi_j}\right) = \boldsymbol{X}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j}}, j = 1, \ldots, J-1 \qquad (2.1)$$

where $\{\pi_1, \ldots, \pi_J\}$ denotes the response probabilities of each non-observation source plus consent (i.e., eligibility outcomes) satisfying $\sum_j \pi_j = 1$, j represents each of the eligibility outcomes (*mortality, nonresponse, proxy/nursing home, biomeasure ineligible, non-consenters, and consenters)*, $\boldsymbol{X}$ denotes the matrix of regressors, and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{j}}$ denotes the estimated regression

parameter vectors for the J-1 models. Expanding this model into its five sub-models, the outcomes are modeled as follows:

$$\log\left(\frac{\pi_{survived}}{\pi_{deceased}}\right) = \log\left(\frac{\pi_{consent} + \pi_{nonconsent} + \pi_{ineligible} + \pi_{proxy/nursing} + \pi_{nonrespondent}}{\pi_{deceased}}\right)$$

$$\log\left(\frac{\pi_{respondent}}{\pi_{nonrespondent}}\right) = \log\left(\frac{\pi_{consent} + \pi_{nonconsent} + \pi_{ineligible} + \pi_{proxy/nursing}}{\pi_{nonrespondent}}\right)$$

$$\log\left(\frac{\pi_{self-respondent}}{\pi_{proxy/nursing}}\right) = \log\left(\frac{\pi_{consent} + \pi_{nonconsent} + \pi_{ineligible}}{\pi_{proxy/nursing}}\right)$$

$$\log\left(\frac{\pi_{biomeasure\ eligible}}{\pi_{biomeasure\ ineligible}}\right) = \log\left(\frac{\pi_{consent} + \pi_{nonconsent}}{\pi_{biomeasure\ ineligible}}\right)$$

$$\log\left(\frac{\pi_{consent}}{\pi_{nonconsent}}\right)$$

Two separate sets of models are considered here: a two-wave model predicting the second wave of biomeasure collection (i.e., 2010) and a three-wave model predicting the third biomeasure collection (2014).

The base two-wave model is

$$\log\left(\frac{\pi_{j+1,10}+\cdots+\pi_{J,10}}{\pi_{j,10}}\right) = \boldsymbol{Z}\widehat{\boldsymbol{\gamma}}_j + \boldsymbol{X_{06}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,06}} \qquad (2.2)$$

where $\{\pi_{1,10}, \ldots, \pi_{J,10}\}$ denotes the response probabilities to the six eligibility outcomes in HRS 2010, $\boldsymbol{Z}$ denote a time-independent covariate matrix, $\widehat{\boldsymbol{\gamma}}_{\boldsymbol{j}}$ denotes the estimated regression parameter vectors of the time-independent covariates, $\boldsymbol{X_{06}}$ denotes the matrix of wave-specific

HRS 2006 covariates, and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,06}}$ denotes regression parameter vectors of the wave-specific covariates from HRS 2006.

To capture the impact of the previous wave eligibility outcome, an expanded version of model 2.2 is

$$\log\left(\frac{\pi_{j+1,10}+\cdots+\pi_{J,10}}{\pi_{j,10}}\right) = \boldsymbol{Z}\widehat{\boldsymbol{\gamma}}_j + \boldsymbol{X_{06}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,06}} + \boldsymbol{W_{06}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,06}} \quad (2.3)$$

where $\boldsymbol{W_{06}}$ denotes previous wave non-observation source and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,06}}$ denotes estimated regression parameters of previous wave non-observation source. Thus, model 2.2 is nested within model 2.3. For the two-wave model, because the sample is restricted to those who were biomeasure eligible in 2006, the only previous wave eligibility outcome available is whether they have consented to DBS collection.

The three-wave model expands model 2.2 to include a second wave of time dependent variables:

$$\log\left(\frac{\pi_{j+1,14}+\cdots+\pi_{J,14}}{\pi_{j,14}}\right) = \boldsymbol{Z}\widehat{\boldsymbol{\gamma}}_j + \boldsymbol{X_{06}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,06}} + \boldsymbol{X_{10}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,10}} \quad (2.4)$$

where $\{\pi_{1,14}, \ldots, \pi_{J,14}\}$ denotes the response probabilities to the six eligibility outcomes in HRS 2014, $\boldsymbol{X_{10}}$ denotes a matrix of wave-specific covariates from HRS 2010, and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,10}}$ denotes the estimated regression parameters of the wave-specific covariates from 2010. Model 2.4 is nested within an expanded model including eligibility states from 2010:

$$\log\left(\frac{\pi_{j+1,14}+\cdots+\pi_{J,14}}{\pi_{j,14}}\right) = \boldsymbol{Z}\widehat{\boldsymbol{\gamma}}_j + \boldsymbol{X_{06}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,06}} + \boldsymbol{X_{10}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,10}} + \boldsymbol{W_{06}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,06}} + \boldsymbol{W_{10}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,10}} \quad (2.5)$$

where $\boldsymbol{W_{10}}$ denotes previous wave non-observation source in 2010 and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,10}}$ denotes the estimated regression parameters of previous wave non-observation source for 2010. Model 2.5 requires that cases deceased in 2010 that are part of model 2.4 be excluded from the model 2.5 sample estimation. Thus, model 2.4 is subset to cases that allows it to be nested within model 2.5.

The sample used in the two-wave model is all age-eligible and biomeasure eligible respondents from 2006 HRS (n = 7,954), while the three-wave model is further reduced following the exclusion of those deceased in 2010 (n = 6,990). In order to confirm the non-parallel slopes assumption in the above models, a formal parallel slope test for variable k across the j = 5 continuation ratio logit sub-models will be conducted:

$$H_0\colon \beta_{1,k} = \beta_{2,k} = \beta_{3,k} = \beta_{4,k} = \beta_{5,k} \tag{2.6}$$

where $\beta_{j,k}$ is a regression parameter from $\widehat{\boldsymbol{\gamma}}_{\boldsymbol{j}}, \widehat{\boldsymbol{\beta}}_{\boldsymbol{j,06}}, \widehat{\boldsymbol{\beta}}_{\boldsymbol{j,10}}, \widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,06}}$, or $\widehat{\boldsymbol{\beta}}_{\boldsymbol{j,W,10}}$ in sub-model j corresponding to covariate k. The parallel slope test is a Wald chi-square test with j-1, or 4, degrees of freedom. Failing to reject this hypothesis suggests the possibility of simplification of the analytic models, although such simplification could lead to an overfitted model.

Demographic predictor variables included in the above models are age (continuous), gender, education (less than high school, high school graduate, some college, college graduate), race/ethnicity crossed by language of interview (non-Hispanic other, non-Hispanic black, Hispanics interviewed in English, and Hispanics interviewed in Spanish), current employment status, and religious service attendance (at least once a week vs. less than once a week).

In addition to individual sociodemographic variables, a number of household characteristics are included in the model, including whether the home is owned, if there are impediments to entry (based an interviewer observation), whether the respondent lives in a rural area, and if there is another eligible HRS participant in the household. These household variables are dichotomies and are included as factors associated primarily with contact and cooperation in nonresponse models. When impediments to entry was missing, previous values

In relation to cognition and health, a variety of measures are included to capture mental and physical ailments and limitations. To measure cognitive functioning, two indices were created based on constructed variables developed by the HRS Health Working Group (Ofstedal, Fisher, & Herzog, 2005; Fisher, Hassan, Faul, Rodgers, & Weir, 2017). The first index measures memory through two word recall tasks including 10 immediate word recall items and 10 delayed word recall items totaling to a maximum score of 20. The second index measures the respondent's overall mental status assessing knowledge, language, and orientation, and is comprised of three cognitive measures which combine the results from a test to count backwards from 20 (score of 2), eight naming tasks (each with a score of 1), and a five-stage subtraction task known as the Serial 7's test (each stage with a score of 1). This combination of three measures results in an index with a maximum score of 15. In the event the respondent was not asked to complete the naming tasks, the most recent score available was used to calculate the mental status score.

To measure physical health and wellness, self-rated health (four levels, combining fair and poor), mild vigorous activity (at least once a week, one to three times a month, or hardly ever/never), a functional limitation index, and a chronic disease index are included as covariates in the model. The functional limitation index is the summation of three separate scales: the six

item basic activities of daily living (BADL) (Katz et al., 1963), the seven item instrumental activities of daily living (IADL) (Lawton & Brody, 1969), and the 10-point NAGI impairment scale (Nagi, 1976). (Additional details about the inclusion of these measures in HRS is available in Fonda and Herzog (2004)). With each item in the three scales categorized as dichotomous responses, the functional limitation index has a maximum score of 23. The chronic disease index was the sum of indicators for hypertension, coronary heart disease, stroke, diabetes, cancer, arthritis, and lung disease resulting in a maximum score of seven. The list of chronic diseases used in the index was based on available variables presented in Ward et al. (2012).

To indicate change in the three-wave models from initial wave observations, covariate differences were added for whether the condition or state began or ended. For indices like word recall, mental status, functional limitations, and chronic diseases this is simply the difference between 2006 and 2010 values, with a positive value meaning the value increased (e.g., number of functional limitations increased). For the remaining health measures (e.g., self-rated health and mild vigorous activity), an indicator for whether the condition improved (e.g., fair/poor self-rated health to good), or worsened (e.g., one to three times a month mild vigorous activity to hardly ever/never) was included where “no change” is the reference category. For the household measures (e.g., impediments, urbanicity), an indicator for each change was included.

The final indicator in the two-wave model is previous DBS non-consent coded as 1 = non-consent. For the three-wave model, the 2006 DBS non-consent is included in addition to four non-observation source indicators for 2010: nonrespondent, nursing home or proxy respondent, biomeasure ineligible respondent, and non-consent.

For the two-wave continuation ratio logit model, there are up to 24 predictors in the model. The corresponding Bonferroni correction for a single sub-model or the parallel slope tests is $\alpha = 0.05/24 = 0.0021$. For the three-wave continuation ratio logit model, there are up to 47 predictors in the model resulting in a corresponding Bonferroni correction of $\alpha = 0.05/47 = 0.0011$.

Item missingness was less than 5% for most variables[2] and was imputed by the nearest-neighbor hot deck approach using the R package 'HotDeckImputation' (Joenssen, 2015).

2.3.4 Part 2 – Bias evaluation across eligibility states

The second part of the analysis focuses on bias in biomarker estimates across the sources of non-observation. DBS biomarkers with the following characteristics are considered (Crimmins et al., 2013):

(1) Glycosylated hemoglobin (HbA1c) – an indicator of blood glucose, or blood sugar, levels over a longer period of time (approximately 120 days) commonly used to measure the level of control for diabetics, or as a screening tool for diabetes

(2) High-Density-Lipoprotein cholesterol (HDL) – an indicator of lipid levels related to "good cholesterol"

(3) Total cholesterol – an indicator of overall lipid levels

(4) C-reactive protein (CRP) – an indicator of systemic inflammation within the body related to infections, inflammatory diseases, and injury

(5) Cystatin C – an indicator of kidney functioning and healthy aging.

[2] Impediment to entry had approximately 17% item missingness due to nonresponse from the interviewer. Using household move data in conjunction with data available from adjacent waves, impediment to entry was able to be logically imputed for a majority of cases and item nonresponse was reduced to under 5% for 2006.

Table 2-2. Dried blood spot biomarker thresholds for high or at risk levels

Dried blood spot biomarker	High/At risk level
Glycosylated Hemoglobin (HbA1c)	>= 6.4%
HDL cholesterol	< 40 mg/dL
Total cholesterol	>= 240 mg/dL
C-Reactive Protein (CRP)	>= 3.0 ug/mL
Cystatin C	> 1.55 mg/L

Note. Thresholds consistent with those defined by Crimmins et al. (2013).

Distributions of these five DBS biomarker measures from the 2006 HRS will be examined as cases for each 2010 non-observation source are deleted. The distribution of the surviving sample is the population of interest, serving as the primary sample, although the change in distributions due to mortality are examined as well.

Analysis will compare percentiles (1st, 5th, 10th, 25th (Q1), 50th (median), 75th (Q3), 90th, 95th, and 99th), means, and a proportion of those with high or at risk levels (see Table 2-2) for each of the five biomeasures. NHANES adjusted values based on whole blood values are the HRS recommended values for analysis (Crimmins et al., 2013, 2015).

The 2006 biomeasure weights, and stratum and cluster variables, are used to estimate population values. The biomarker weight is the product of the core respondent weight[3] and a nonresponse adjustment based on a propensity model predicting the probability of completing the biomeasure portion of the interview. The nonresponse propensity model uses predictors including age, sex, race/ethnicity, education, marital or partner status, and health factors (including self-rated health, number of physical limitations, hypertension, heart conditions, myocardial infarction, angina, congestive heart failure or stroke). The biomeasure nonresponse

[3] The core respondent weight is the product of the inverse of the probabilities of selecting a household and the individual respondent within households. A second post-stratification adjustment is also used, based on the American Community Survey, for differential nonresponse for the HRS survey based on age, gender, race/ethnicity, and geography. For more details on the creation of this weight, see Ofstedal, Weir, Chen, and Wagner (2011).

adjusted weights are post-stratified by age, gender, and race of the HRS sample (Crimmins et al., 2013).

Bias, after an initial adjustment for mortality, for each non-observation source is estimated as follows:

$$Outcome\ adjustment\ for\ mortality(\hat{y}_{BIO}) = \hat{y}_{BIO,Alive} - \hat{y}_{BIO,Sample} \quad (2.7)$$

$$Nonresponse\ bias(\hat{y}_{BIO}) = \hat{y}_{BIO,Resp} - \hat{y}_{BIO,Alive} \quad (2.8)$$

$$Proxy/nursing\ home\ bias(\hat{y}_{BIO}) = \hat{y}_{BIO,SelfR} - \hat{y}_{BIO,Resp} \quad (2.9)$$

$$Telephone/Dropout\ bias(\hat{y}_{BIO}) = \hat{y}_{BIO,Elig} - \hat{y}_{BIO,SelfR} \quad (2.10)$$

$$Non-consent\ bias(\hat{y}_{BIO}) = \hat{y}_{BIO,Consent} - \hat{y}_{BIO,Elig} \quad (2.11)$$

where $\hat{y}_{BIO,Sample}$ is the full 2006 sample distribution estimate (mean or proportion) for the selected biomarker, $\hat{y}_{BIO,Alive}$ is the 2006 biomarker estimate for those still alive in 2010, $\hat{y}_{BIO,Resp}$ is the 2006 biomarker estimate for those who responding to HRS in 2010, $\hat{y}_{BIO,SelfR}$ is the biomarker estimate for non-nursing home, self-respondents in 2010, $\hat{y}_{BIO,Elig}$ is the estimate for the biomeasure eligible respondents in 2010, and $\hat{y}_{BIO,Consent}$ is the estimate of those who consented to biomeasure collection in 2010.

Total bias due to all sources of non-observation (i.e., the sum of bias estimates in expressions (2.8) through (2.11) above) is of interest if the individual level changes are small:

$$Total\ non\text{-}observation\ bias(\hat{y}_{BIO}) = \hat{y}_{BIO,Consent} - \hat{y}_{BIO,Alive} \quad (2.12)$$

Operational eligibility is the sum of two components. An overall operational eligibility bias is also estimated to compare to overall nonresponse and non-consent:

$$Operational\ eligibility\ bias(\hat{y}_{BIO}) = \hat{y}_{BIO,Elig} - \hat{y}_{BIO,Resp} \qquad (2.13)$$

The relative bias is also examined:

$$Relative\ bias(\hat{y}_{BIO}) = \frac{\hat{y}_{BIO,(j+1)} - \hat{y}_{BIO,j}}{\hat{y}_{BIO,j}}$$

where *j* is the "full" sample estimate and *j+1* is the estimate of the desired subset.

There are a total of 35 bias estimates for means as well as for proportions. A Bonferroni correction is used for all 70 estimates: $\alpha = 0.05/70 = 0.000714$.

Table 2-3 shows the analytic sample sizes in the biomarker bias evaluations. Four of the DBS biomarkers have observations available for over 90 percent of the total consenting sample. Loss in sample is due to insufficient or improperly collected specimens. For HDL, though, only available for 76 percent of the total sample is available.

These bias estimates assume that biomarkers remain, on average, constant over time, ignoring aging, natural human variation, improvements or declines in physical health due to dietary, activity, or lifestyle changes, differences in collection and storage, and differences between laboratories used[4]. It is difficult to disentangle changes due to declines in health or laboratories used (Crimmins et al., 2014). In addition, some differences in Cystatin C and CRP may be of imputations in 2006 due to values too low for detection (Crimmins et al., 2013). This assumption of constancy across waves is examined further in Section 2.5.5.

[4] For dried blood spots, Biosafe Laboratories and the University of Vermont were used in 2006 and Heritage Laboratories and the University of Washington were used in 2010 (Crimmins et al., 2015).

Table 2-3. Dried blood spot biomarker sample sizes by eligibility state

	Full 2006 sample[2]	2010 living sample	2010 HRS Respondent	Non-nursing home, self-respondent	Biomeasure eligible respondent	Consenting DBS respondent
DBS consenters	6,570	5,833	5,581	5,321	5,068	4,669
Total sample[1]	6,203	5,537	5,309	5,062	4,817	4,447
% of consenters	94.4	94.9	95.1	95.1	95.0	95.2
HbA1c	6,101	5,445	5,218	4,976	4,735	4,374
% of total sample	98.4	98.3	98.3	98.3	98.3	98.4
HDL	4,708	4,209	4,042	3,861	3,673	3,392
% of total sample	75.9	76.0	76.1	76.3	76.3	76.3
Total Cholesterol	5,796	5,181	4,969	4,745	4,517	4,173
% of total sample	93.4	93.6	93.6	93.7	93.8	93.8
CRP	5,817	5,200	4,988	4,761	4,530	4,188
% of total sample	93.8	93.9	94.0	94.1	94.0	94.2
Cystatin C	5,724	5,121	4,911	4,685	4,454	4,120
% of total sample	92.3	92.5	92.5	92.6	92.5	92.6

Note. DBS = dried blood spot.
[1] Total is for sample with a non-zero biomeasure weight. Loss from the full set of consenters is due to insufficient or improperly collected specimens. [2] Sample sizes here are off compared to those reported in Crimmins et al. (2013) due to a match error between core interview data and biomeasure data.

2.4 Results Part 1 – Sources of non-observation propensity models

This section focuses on the transitions from one source of non-observation to another from wave to wave. Section 2.4.1 reviews the basic eligibility outcome transition probabilities from 2006 to 2010, 2010 to 2014, and 2010 to 2014 conditional on 2006. Section 2.4.2 examines the two-year continuation ratio models that predict 2010 eligibility states based on respondent and household level sociodemographics and respondent health measures. These models also expand to include consent status from 2006. Section 2.4.3 examines the three-year continuation ratio models building on the results of Section 2.4.2 including the addition of household and health change measures and expanding the non-observation source indicators to include 2010.

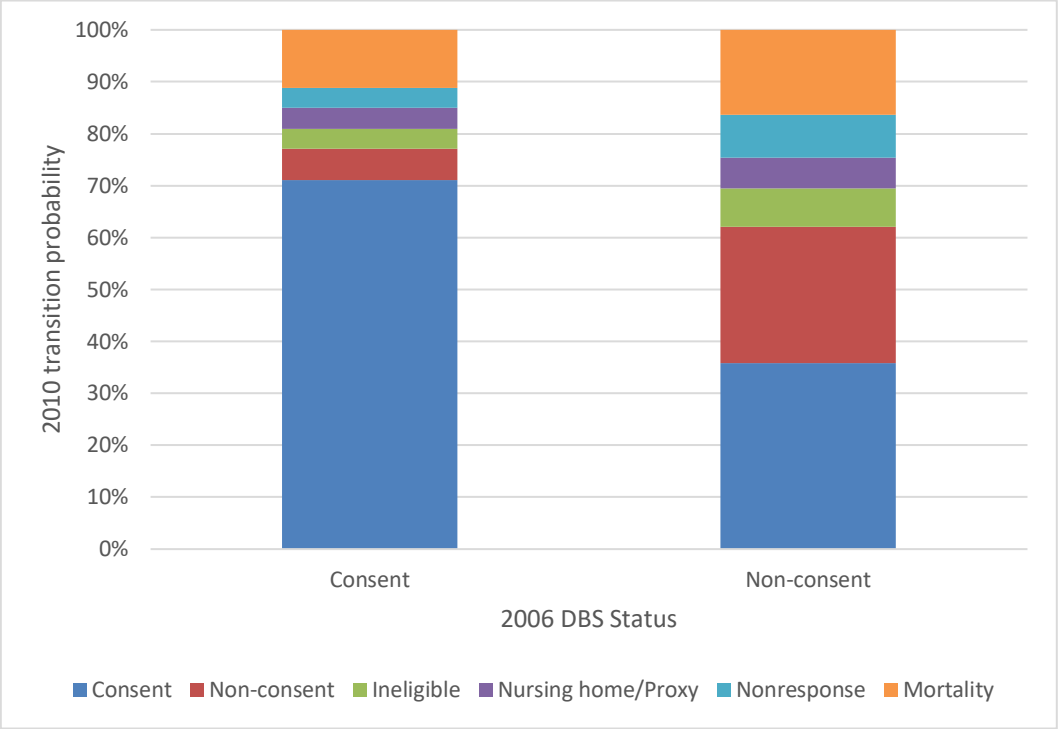

Figure 2-4. HRS 2010 eligibility outcome transition probabilities by 2006 dried blood spot consent status. This only includes biomeasure eligible respondents from HRS 2006.

2.4.1 Eligibility outcome transition

Table 2-4 displays the unweighted transition counts and probabilities for HRS 2006 biomeasure eligible respondents to 2010 for the six sources of non-observation. These results show that a quarter of the original 2006 biomeasure eligible sample is lost to mortality, nonresponse, and ineligibility. Over 12% of the 2006 biomeasure eligible sample did not survive to the next E-FTF wave.

There are large transition differences from 2006 and 2010 depending on whether the respondent consented or not to the dried blood spot (DBS) collection (see also Figure 2-4). Focusing on 2006 consenters, almost a quarter of respondents were not biomeasure eligible in 2010 with nearly half of those cases having died before 2010 data collection, accounting for 11.2% of 2006 consenters overall. Nearly 38% of 2006 non-consenters were ineligible in 2010

with just less than half of those ineligible cases having died before 2010. Comparing non-consenters to consenters, there are nearly doubled rates of nonresponse (8.2% vs. 3.8%) and out-of-mode ineligibility (7.4% vs. 3.8%). Previous consenters who remained biomeasure eligible in 2010 overwhelming consented at 92.1% while 57.6% of eligible non-consenters chose to consent in 2010 (36% of total non-consenters).

Considering the transition from 2010 to 2014 for these same biomeasure eligible respondents in 2006, there are continued differences in non-observation source trajectories (see Table 2-5 and Figure 2-5). HRS 2010 consenters and non-consenters had similar transitions to those who consented in 2006 showing similar percentages across years. There is a greater proportion of biomeasure ineligible (i.e., CATI respondent or breakoff) who remain ineligible (13.8%) or whom are likely to be nonrespondents (16.9%). Fifty-four percent of those who were biomeasure ineligible in 2010 were eligible in 2014 with 85% consenting to biomeasure collection. Nursing home and proxy respondents are most likely to be deceased before the next E-FTF wave (54.7%) with over a quarter maintaining their nursing home/proxy state (27.5%). Less than 10% become eligible in 2014, though nearly 85% do consent to biomeasure collection if they are eligible. The majority of 2010 nonrespondents remain nonrespondents into 2014 (56.4%). Nearly 14% of 2010 nonrespondents return in 2014 and provide consent to collection biomeasures (84.7% of eligible cases).

Table 2-4. HRS 2010 eligibility outcome transition counts and probabilities by 2006 dried blood spot consent status

	2010 Eligibility Outcome						
2006 DBS Status	Mortality	Nonresponse	Nursing home/Proxy	Ineligible	Non-consent	Consent	Total
Consent	737	252	260	253	399	4,669	6,570
% of Total	11.2	3.8	4.0	3.8	6.1	71.1	82.6
% of Total | Alive	-	4.3	4.5	4.3	6.8	80.0	
% of Total | Eligible	-	-	-	-	7.9	92.1	
Non-consent	227	113	82	103	364	495	1,384
% of Total	16.4	8.2	5.9	7.4	26.3	35.8	17.4
% of Total | Alive	-	9.8	7.1	8.9	31.5	42.8	
% of Total | Eligible	-	-	-	-	42.4	57.6	
Total	964	365	342	356	763	5,164	7,954
% of Total	12.1	4.6	4.3	4.5	9.6	64.9	100.0
% of Total | Alive	-	5.2	4.9	5.1	10.9	73.9	
% of Total | Eligible	-	-	-	-	12.9	87.1	

Note. This only includes biomeasure eligible respondents from HRS 2006. Eligibility outcome columns include row percentages. Total column includes column percentages. DBS = dried blood spot.

Table 2-5. HRS 2014 eligibility outcome transition counts and probabilities by 2010 eligibility outcome

	2014 Eligibility Outcome						
2010 Eligibility Outcome	Mortality	Nonresponse	Nursing home/Proxy	Ineligible	Non-consent	Consent	Total
Consent	593	229	164	160	157	3,861	5,164
% of Total	11.5	4.4	3.2	3.1	3.0	74.8	64.9
% of Total | Alive	-	5.0	3.6	3.5	3.4	84.5	
% of Total | Eligible	-	-	-	-	3.9	96.1	
Non-consent	113	66	34	28	216	306	763
% of Total	14.8	8.7	4.5	3.7	28.3	40.1	9.6
% of Total | Alive	-	10.2	5.2	4.3	33.2	47.1	
% of Total | Eligible	-	-	-	-	41.4	58.6	
Ineligible	40	60	13	49	29	165	356
% of Total	11.2	16.9	3.7	13.8	8.1	46.3	4.5
% of Total | Alive	-	19.0	4.1	15.5	9.2	52.2	
% of Total | Eligible	-	-	-	-	14.9	85.1	
Nursing home/Proxy	187	28	94	1	5	27	342
% of Total	54.7	8.2	27.5	0.3	1.5	7.9	4.3
% of Total | Alive	-	18.1	60.6	0.6	3.2	17.4	
% of Total | Eligible	-	-	-	-	15.6	84.4	
Nonresponse	53	206	26	21	9	50	365
% of Total	14.5	56.4	7.1	5.8	2.5	13.7	4.6
% of Total | Alive	-	66.0	8.3	6.7	2.9	16.0	
% of Total | Eligible	-	-	-	-	15.3	84.7	
Mortality	964	-	-	-	-	-	964
% of Total	100.0	-	-	-	-	-	12.1
% of Total | Alive	-	-	-	-	-	-	
% of Total | Eligible	-	-	-	-	-	-	
Total	1,950	589	331	259	416	4,409	7,954
% of Total	24.5	7.4	4.2	3.3	5.2	55.4	100.0
% of Total | Alive	-	9.8	5.5	4.3	6.9	73.4	
% of Total | Eligible	-	-	-	-	8.6	91.4	

Note. This only includes biomeasure eligible respondents from HRS 2006. Eligibility outcome columns include row percentages. Total column includes column percentages.

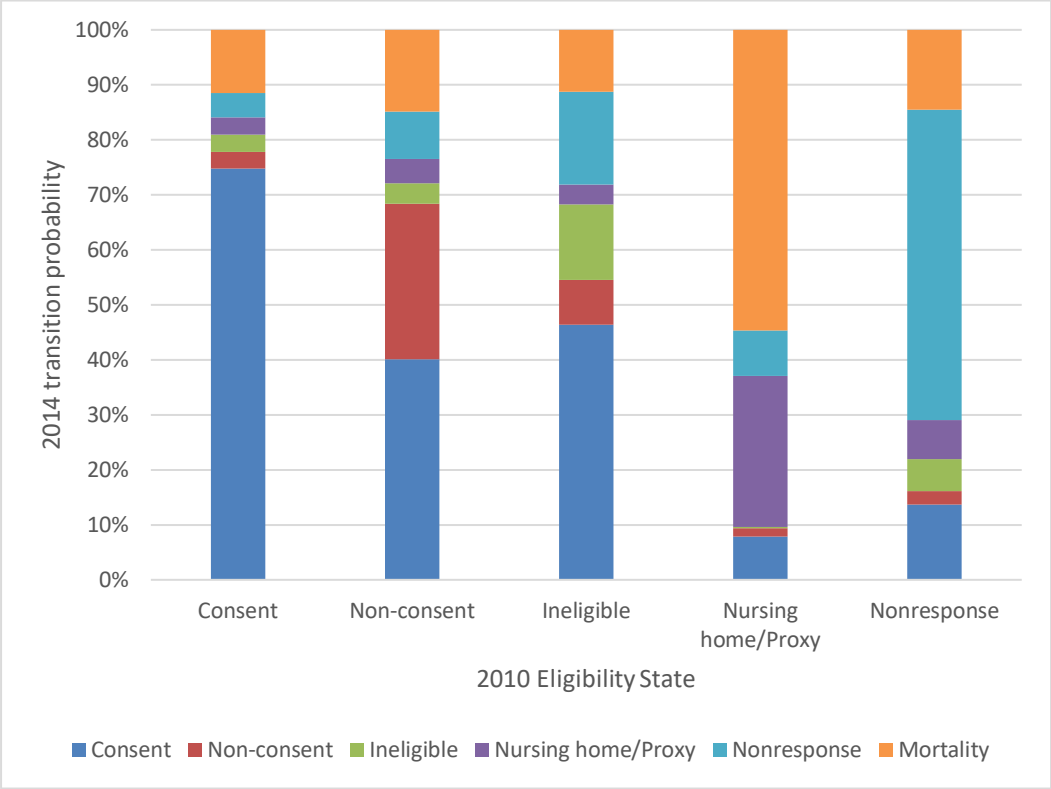

Figure 2-5. HRS 2014 eligibility outcome transition probabilities by HRS 2010 eligibility outcome. This only includes biomeasure eligible respondents from HRS 2006. The 964 respondents deceased before 2010 are excluded from this figure.

Respondents who were biomeasure ineligible in 2010 differed greatly by their 2006 consent status (see Table 2-6 and Figure 2-6). Those who consented in 2006 saw 60% who were biomeasure eligible in 2014 following their intervening wave of ineligibility with 90.7% consenting (54.2% of total) while only 41% of non-consenters became biomeasure eligible after their temporary ineligibility with only 67% consenting (27.2% of total). Non-consenters from 2006 were also more likely to remain ineligible in 2014 (19.4% vs 11.5%) or be a nonrespondent in 2014 (22.3% vs 14.6%). Eligibility state transitions for nursing home and proxy respondents shows little to no difference conditional on 2006 consent status with the majority not likely to survive into 2014 (55%) followed by maintaining their proxy/nursing home state (~27%).

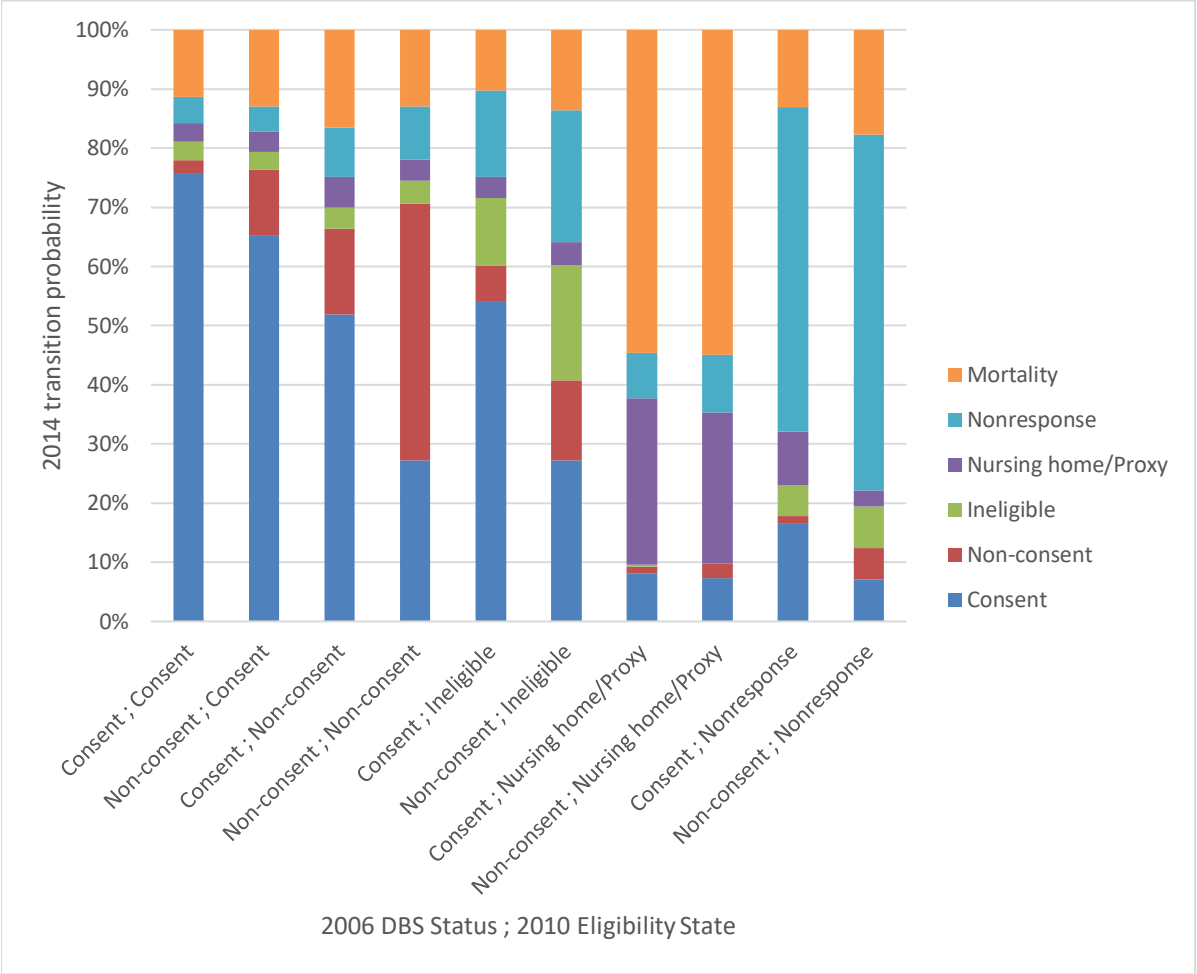

Figure 2-6. HRS 2014 eligibility outcome transition probabilities by HRS 2006 dried blood spot consent status and HRS 2010 eligibility outcome. This only includes biomeasure eligible respondents from HRS 2006. The 964 respondents deceased before 2010 are excluded. Columns are clustered by 2010 state to compare conditioned on 2006 consent status. DBS = dried blood spot.

Those who consented in 2006 but failed to respond in 2010 were most likely to not respond again in 2014 (54.8%) with a similar effect for those who did not consent in 2006 (60.2%). Of the 2010 nonrespondents, only 17.9% who consented previously were biomeasure eligible in 2014 while only 12.4% of those who did not consent in 2006 were eligible. Of those eligible in 2014, previous consenters consented to biomeasure collection at 93.3% while previous non-consenters consented at only 57.1%.

Table 2-6. HRS 2014 eligibility outcome transition counts and probabilities by 2006 DBS consent status and 2010 eligibility outcome

		2014 Eligibility Outcome					
2006 DBS Status	2010 Eligibility Outcome	Mortality	Nonresponse	Nursing home/Proxy	Ineligible	Non-consent	Consent
Consent	Consent	529	208	147	145	102	3,538
	% of Total	11.3	4.5	3.2	3.1	2.2	75.8
	Non-consent	66	33	21	14	58	207
	% of Total	16.5	8.3	5.3	3.5	14.5	51.9
	Ineligible	26	37	9	29	15	137
	% of Total	10.3	14.6	3.6	11.5	5.9	54.2
	Nursing home/Proxy	142	20	73	1	3	21
	% of Total	54.6	7.7	28.1	0.4	1.2	8.1
	Nonresponse	33	138	23	13	3	42
	% of Total	13.1	54.8	9.1	5.2	1.2	16.7
	Mortality	737	-	-	-	-	-
	% of Total	100	-	-	-	-	-
Non-consent	Consent	64	21	17	15	56	323
	% of Total	12.9	4.2	3.4	3	11.3	65.1
	Non-consent	47	33	13	14	158	99
	% of Total	12.9	9.1	3.6	3.8	43.4	27.2
	Ineligible	14	23	4	20	14	28
	% of Total	13.6	22.3	3.9	19.4	13.6	27.2
	Nursing home/Proxy	45	8	21	0	2	6
	% of Total	54.9	9.8	25.6	0	2.4	7.3
	Nonresponse	20	68	3	8	6	8
	% of Total	17.7	60.2	2.7	7.1	5.3	7.1
	Mortality	227	-	-	-	-	-
	% of Total	100	-	-	-	-	-

Note. This only includes biomeasure eligible respondents from HRS 2006. Eligibility outcome columns include row percentages. DBS = dried blood spot.

2.4.2 Two-wave continuation ratio model

This section examines the respondent- and household-level demographics, respondent health measures, and previous consent status predicting 2010 eligibility state. Table 2-7a displays all five of the nested models, only examining demographics and health measures. Near the end of the section, the predictors expand to include the previous wave source of non-observation: non-consent. The full model is shown in Table 2-7b. Results deemed statistically significant are defined using a Bonferroni adjusted critical value for an overall critical value of 0.05. Results presented that are an exception to this rule are noted, but may be considered insufficiently conservative as a test criteria to assess the null hypothesis.

The first of the five models examines predictors related to mortality. Age and death are unsurprisingly related with older respondents less likely to survive to the next E-FTF wave. Females have almost 1.6 times the odds of survival between E-FTF waves over males. Compared to the non-Hispanic other race/ethnic group, non-Hispanic blacks and Hispanics interviewed in Spanish both have higher odds of survival, though not significant given the Bonferroni correction. Those employed at the previous wave as well as those who attend church weekly are also more likely to survive. Household characteristics like impediments to entry, owning a home, and living in a rural area all have no relationship with mortality when holding all other individual and household characteristics equal. As expected, a major driver of mortality is one's physical and mental health. Respondents with higher word recall and mental status scores are significantly more likely to survive. Self-rated health, as documented previously, shows a strong relationship with those rating themselves as "good" having half the odds of survival over "excellent" and those rating themselves as "fair" or "poor" with nearly one-third the odds of survival over "excellent." Individuals who are hardly ever or never active, as measured by mildly vigorous

activity, are less likely to survive as well as those with an increased number of functional limitations and chronic conditions.

In terms of wave nonresponse, very few respondent demographic and household characteristics are found to be significant predictors in these models at the Bonferroni adjusted critical value. Respondents with higher cognitive scores and larger numbers of chronic conditions both are more likely to respond. It is unclear how the lack of significant covariates may be related to the combining of contact and cooperation.

For predicting self-respondents not living in a nursing home, older respondents are more likely to have a nursing home or proxy interview. This is the only model where education is found to be predictive with those with higher education more likely to be a nursing home or proxy-respondent, consistent with the finding that higher education results in a quicker decline once diagnosed with dementia or Alzheimer's Disease (e.g., Stern et al., 1999) which are not included in this model. However, this effect is not significant with the Bonferroni correction. Non-Hispanic black respondents have nearly twice the odds of being a non-nursing home, self-respondent over non-Hispanic other respondents which shows consistency with the findings of Stevens et al. (2004). Respondents with higher cognition scores are more likely to be self-respondents not in a nursing home. Those who rated themselves as "fair" or "poor" on self-rated health had 0.55 times the odds of being a self-respondent not in a nursing home, but only at $\alpha = 0.05$. Both limited mildly vigorous activity (1-3 times/month) and no mildly vigorous activity are associated with lower rates of self-response outside of a nursing home (OR = 0.51 and OR = 0.65, respectively), though the latter is only significant at the 0.05 alpha level. Functional limitations and chronic conditions had no effect on this outcome holding all other demographic and health variables constant.

Demographic and household characteristics seem to have few associations with being a biomeasure eligible respondent after removing nursing home and proxy respondents. Non-Hispanic blacks who have 1.63 times the odds of being biomeasure eligible over non-Hispanic other while Spanish interviewed Hispanics had 0.58 time the odds over non-Hispanic other, both at only $\alpha = 0.05$. More frequent church attenders have 1.46 times the odds of being biomeasure eligible than less frequent church attenders. Respondents who rated themselves "good" on self-rated health had a lower odds of being biomeasure eligible compared to those who rated themselves "excellent" at $\alpha = 0.05$ (OR = 0.60). A non-significant effect for those rated "fair" or "poor" may be due partially to the sample loss from earlier sources (i.e., mortality, proxy/nursing home) with those who rated themselves "fair/poor".

Finally for the consent model, both non-Hispanics black respondents and Hispanic respondents interviewed in English have about 0.70 times the odds of consenting compared to non-Hispanic other respondents – a reversal from the strong positive effects seen in the previous models for non-Hispanic blacks. However, these effects are not significant when accounting for the multiple-comparisons. Weekly church attendance is also a predictor of consent at $\alpha = 0.05$ with those attending at least once a week having 1.25 times the odds over those who do not attend frequently or at all. No household characteristics seem related to consent. In relation to physical and mental health, those with higher mental status scores are more likely to consent, with no effect from word recall. Respondents who exercise very little if at all are less likely to consent to DBS over those who perform mildly vigorous activity at least once per week (OR = 0.67). Each additional chronic condition also leads to 1.10 times the odds of consenting, potentially aided in particular from those whom are diabetic. However, these last two effects are weak given the multiple-comparison correction.

Reviewing the five models with the previous consent status added (see Table 2-7b), consent refusal adds nothing significant to the mortality model and does not result in substantive changes in the previous interpretation of the respondent and household characteristics. In the nonresponse model, previous DBS non-consenters had 0.42 times the odds of responding in the current wave compared to those who had consented reflecting the earlier observation from the transition matrices showing non-consent as a strong indicator of future nonresponse. The addition of the non-consent indicator made little substantive change in the odds ratios for this model.

For the self-response model, previous DBS non-consent resulted in 0.69 times the odds of self-response, non-nursing home response over those who did consent previously, but not significant at the 0.0021 level. For the biomeasure eligibility model, non-consent results in 0.40 times the odds of being a biomeasure eligible respondent in the subsequent E-FTF wave. The only notable change in the odds ratios is weekly religious service attendance, which is no longer significant using the Bonferroni adjustment, holding previous DBS consent constant.

Unsurprisingly the inclusion of previous DBS consent is significant in predicting future DBS consent. Previous consent refusals result in nearly 0.12 times the odds of consenting in 2010 compared to previous consenters or, conversely, previous consenters have over eight times the odds of consenting over non-consenters. Looking at the demographic and health variables, a number of coefficients and standard errors change with the inclusion of previous non-consent given the strong correlated nature of the new variables and the outcome. The significant effect of chronic conditions is no longer present. More minor shifts in parameter estimates are seen for non-Hispanic blacks, church attendance, mental status score, and little/no mildly vigorous activity.

The final evaluation of the two-year model is assessing the assumption of parallel slopes. Most of the variables that were significant predictors of multiple eligibility states had some evidence that the assumption of parallel slopes was violated (e.g., age, non-Hispanic black, cognition, chronic conditions). For age, there is a consistent negative effect (i.e., odds ratios less than 1) supporting the notion that biomeasure samples are less representative of the oldest of older adults. This pattern also matches with the cognitive measures, which are highly associated with age, which indicate an over representation of the most cognitively robust respondents. Self-rated health also does this to a limited extent consistently removing the poorest in self-rated health. For non-Hispanic Blacks there is a consistent positive effect across the first four models until the final consent model where there is a negative effect though the parallel slopes test is not significant given the multiple-comparisons correction. This breakdown suggest that subsequent sources of non-observation may over-represent non-Hispanic blacks and that while they may be less likely to consent to DBS collection, this effect may not be as detrimental as it first appears. Current employment, mildly vigorous activity, and functional limitations also see weak violations of the parallel slopes assumption, but only a single model contains a significant odds ratio – employment and functional limitations in the mortality model and physical activity (1-3 times per month) for the nursing home, proxy-respondent model.

When including the previous sources of non-observation, there are some minor changes to the parallel slope assumptions in terms of level of statistical significance. Previous consent refusal appears as significantly deviating from the parallel slopes assumption with the significance across the five models strongly in the negative direction given differing degrees of reduced odds ratios in particular for the response, biomeasure eligibility, and consent models.

Table 2-7a. Continuation ratio logit model odds ratios predicting sequential 2010 eligibility states based on 2006 respondent and household characteristics

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Respondent characteristics						
Age (years)	**0.94 (0.004)******	1.00 (0.007)	**0.93 (0.007)******	1.01 (0.008)	1.00 (0.005)	****
Female	**1.58 (0.137)******	0.96 (0.114)	1.11 (0.154)	0.86 (0.104)	0.98 (0.085)	***
Education (ref: less than HS)						
High school	0.97 (0.091)	1.01 (0.152)	0.68 (0.104)*	1.13 (0.174)	0.98 (0.105)	
Some college	1.14 (0.286)	0.69 (0.185)	0.59 (0.217)	1.21 (0.364)	1.29 (0.291)	
College graduate	1.03 (0.137)	0.83 (0.153)	0.64 (0.139)*	0.92 (0.173)	0.88 (0.120)	
Race/ethnicity (ref: Non-Hispanic Other)						
Non-Hispanic black	1.44 (0.172)**	1.27 (0.224)	**2.02 (0.389)******	1.63 (0.325)*	0.72 (0.084)**	****
Hispanic (English interview)	1.17 (0.238)	1.07 (0.292)	0.66 (0.174)	0.96 (0.264)	0.69 (0.128)*	
Hispanic (Spanish interview)	1.78 (0.360)**	0.89 (0.236)	1.42 (0.426)	0.58 (0.146)*	1.44 (0.361)	**
Currently employed	**1.55 (0.205)*****	1.15 (0.160)	1.04 (0.200)	0.83 (0.111)	1.20 (0.118)	*
Attends church at least 1/wk	**1.39 (0.114)******	1.02 (0.116)	1.07 (0.136)	**1.46 (0.174)*****	1.25 (0.103)**	
Household characteristics						
Impediments to entry	1.14 (0.138)	1.35 (0.271)	1.34 (0.270)	0.92 (0.165)	0.91 (0.118)	
Own home	1.21 (0.119)	0.87 (0.140)	1.11 (0.178)	1.27 (0.191)	0.95 (0.107)	
Rural	1.18 (0.103)	1.31 (0.169)*	1.13 (0.156)	0.96 (0.119)	0.96 (0.085)	
Another eligible HH member	1.25 (0.113)*	1.07 (0.138)	0.94 (0.136)	1.00 (0.132)	1.13 (0.105)	
Cognition and health						
Word recall score	**1.08 (0.015)******	1.05 (0.021)*	**1.20 (0.027)******	1.01 (0.021)	0.98 (0.014)	****
Mental status score	**1.05 (0.016)*****	**1.08 (0.024)*****	**1.22 (0.029)******	1.04 (0.026)	**1.06 (0.019)****	****
Self-rated health (ref: Excellent)						
Very good	0.79 (0.171)	0.92 (0.166)	0.81 (0.221)	0.72 (0.144)	0.97 (0.132)	
Good	**0.50 (0.104)*****	1.00 (0.191)	0.82 (0.225)	0.60 (0.124)*	0.91 (0.129)	
Fair/Poor	**0.36 (0.077)******	0.81 (0.177)	0.55 (0.158)*	0.80 (0.196)	0.92 (0.151)	**
Mildly vigorous activity (ref: At least 1/wk)						
1-3 times/month	1.14 (0.173)	0.92 (0.200)	**0.51 (0.102)*****	1.21 (0.307)	0.77 (0.118)	*
Hardly ever/never	**0.55 (0.057)******	0.97 (0.213)	0.65 (0.117)*	0.93 (0.208)	0.67 (0.099)**	
No. of functional limitations	**0.96 (0.010)******	1.03 (0.021)	0.99 (0.018)	0.99 (0.020)	0.98 (0.013)	*
No. of chronic conditions	**0.88 (0.028)******	**1.18 (0.061)*****	0.97 (0.050)	1.09 (0.057)	1.10 (0.040)**	****

Note. The parallel slopes test is a Wald chi-square test with 4 degrees of freedom. HS = high school.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0021$ and are **bolded**.

Table 2-7b. Continuation ratio logit model odds ratios predicting sequential 2010 eligibility states based on 2006 respondent and household characteristics and 2006 dried blood spot consent status

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Respondent characteristics						
Age (years)	**0.94 (0.004)******	1.00 (0.007)	**0.93 (0.007)******	1.01 (0.008)	0.99 (0.006)	****
Female	**1.58 (0.137)******	0.94 (0.113)	1.09 (0.152)	0.84 (0.103)	0.91 (0.085)	****
Education (ref: less than HS)						
High school	0.97 (0.092)	1.02 (0.154)	0.68 (0.104)*	1.13 (0.175)	1.02 (0.118)	
Some college	1.15 (0.287)	0.71 (0.190)	0.59 (0.214)	1.20 (0.365)	1.47 (0.355)	
College graduate	1.04 (0.138)	0.85 (0.158)	0.64 (0.139)*	0.93 (0.177)	0.94 (0.137)	
Race/ethnicity (ref: Non-Hispanic Other)						
Non-Hispanic black	**1.45 (0.173)****	1.37 (0.244)	**2.05 (0.395)******	1.78 (0.358)**	0.88 (0.111)	**
Hispanic (English interview)	1.18 (0.239)	1.09 (0.300)	0.67 (0.178)	0.96 (0.263)	0.66 (0.132)*	
Hispanic (Spanish interview)	1.79 (0.365)**	0.90 (0.239)	1.45 (0.440)	0.56 (0.142)*	1.46 (0.387)	**
Currently employed	**1.55 (0.204)*****	1.13 (0.157)	1.03 (0.198)	0.79 (0.107)	1.10 (0.116)	*
Attends church at least 1/wk	**1.38 (0.113)******	0.99 (0.113)	1.06 (0.135)	1.44 (0.173)**	1.23 (0.109)*	
Household characteristics						
Impediments to entry	1.14 (0.139)	1.41 (0.285)	1.38 (0.279)	0.95 (0.171)	1.00 (0.140)	
Own home	1.21 (0.119)	0.88 (0.142)	1.11 (0.179)	1.30 (0.196)	1.00 (0.121)	
Rural	1.17 (0.103)	1.30 (0.168)*	1.13 (0.157)	0.93 (0.117)	0.90 (0.085)	
Another eligible HH member	1.24 (0.112)*	1.04 (0.135)	0.93 (0.135)	0.97 (0.129)	1.08 (0.107)	
Cognition and health						
Word recall score	**1.08 (0.015)******	1.05 (0.021)*	**1.20 (0.027)******	1.01 (0.021)	0.98 (0.015)	****
Mental status score	**1.05 (0.016)****	**1.07 (0.024)*****	**1.22 (0.029)******	1.04 (0.026)	1.05 (0.020)*	****
Self-rated health (ref: Excellent)						
Very good	0.79 (0.172)	0.92 (0.168)	0.81 (0.222)	0.73 (0.147)	1.00 (0.145)	
Good	**0.50 (0.105)*****	1.01 (0.195)	0.82 (0.225)	0.62 (0.127)*	0.95 (0.144)	
Fair/Poor	**0.36 (0.077)******	0.83 (0.184)	0.56 (0.161)*	0.83 (0.205)	1.03 (0.182)	**
Mildly vigorous activity (ref: At least 1/wk)						
1-3 times/month	1.15 (0.175)	0.97 (0.213)	**0.51 (0.103)*****	1.26 (0.321)	0.84 (0.139)	*
Hardly ever/never	**0.55 (0.058)******	1.02 (0.224)	0.66 (0.119)*	0.98 (0.222)	0.71 (0.114)*	*
No. of functional limitations	**0.96 (0.010)******	1.03 (0.021)	0.99 (0.018)	1.00 (0.020)	0.99 (0.015)	*
No. of chronic conditions	**0.87 (0.028)******	1.17 (0.061)**	0.97 (0.050)	1.08 (0.056)	1.08 (0.042)*	****
Previous non-observation source						
DBS consent refusal	0.85 (0.081)	**0.42 (0.051)******	0.69 (0.102)*	**0.40 (0.050)******	**0.12 (0.011)******	****

Note. The parallel slopes test is a Wald chi-square test with 4 degrees of freedom. HS = high school. DBS = dried blood spot.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0021$ and are **bolded**.

2.4.3 Three-wave continuation ratio model

This section expands the earlier analyses to look at predicting the third wave E-FTF eligibility state for collecting biomeasures. Two nested models are tested here. The first examines the relationship between the five eligibility states and wave one characteristics including respondent demographics, household characteristics, and cognitive and physical health as well as the change indicators for those characteristics (Table 2-8a). The full model includes the non-observation source indicators for the first (non-consent vs. consent) and the second wave (nonrespondent, nursing home or proxy respondent, biomeasure ineligible, non-consent; see Table 2-8b). Again, results deemed statistically significant are defined using a Bonferroni adjusted critical value, but results of interest that may not conservative enough to test the null hypothesis are noted.

There are a number of similarities between the demographic characteristics in the two-wave model and three-wave model for mortality including significant odds ratios for age, gender, Hispanic ethnicity, religious activity, as well as cognitive and physical health measures. Effects for non-Hispanics blacks and current employment are not seen in the three-wave model. While non-Hispanic black respondents were significantly more likely to survive from 2006 to 2010, this effect is not present for 2014. However the odds ratio for Hispanics interviewed in either English or Spanish increases dramatically (1.17 to 1.93 for English interviewed Hispanics and 1.78 to 2.78 for Spanish interviewed Hispanics) suggesting that Hispanic respondents are significantly more likely to survive into the third E-FTF wave than non-Hispanic other respondents.

Adding to these already significant health and cognition predictors, many of the change measures and indicators are also significant. Both change in word recall and mental status have

coefficients nearly identical to their baseline counterparts suggesting that the change in these cognition scores does not have a differential effect on predicting mortality, though the latter is only significant at $\alpha = 0.05$. Both self-rated health change indicators have effects on predicting E-FTF wave three mortality with a decline in self-rated health resulting in about 0.60 times the odds of survival (significant with the Bonferroni adjustment) and an improved rating resulting in 1.35 times the odds of survival controlling for baseline self-rated health (only significant at a 0.05 alpha level). Respondents who increased their mildly vigorous activity between 2006 and 2010 were unexpectedly less likely to survive into 2014 having 0.55 times the odds of surviving compared to those with no change in activity, while those who decreased their level of activity saw no significant change in their odds of survival. An increase in the number of functional limitations has a similar effect as the baseline level of functional limitations (OR = 0.92), but a similar effect is not seen for change in the number of chronic conditions. Changes in household characteristics seemed to have no effect on predicting mortality into the third E-FTF wave.

After introducing the non-observation sources from the previous two waves into the three-wave model (see Table 2-8b), there are minor shifts in the odds ratios of the respondent and household characteristics for the mortality model. The two-wave model showed previous non-consent as a significant predictor of mortality. With the 2010 non-observation sources, nonrespondents have half the odds of being alive compared to previous DBS consenters and proxy- or nursing home respondents have 0.43 times the odds of survival compared to previous consenters (an effect clearly observed in Figure 2-5).

Considering the three-wave model for nonresponse, those with some college have half the odds of responding in the third E-FTF wave compared to those with less than a high school education. There is no difference for high school graduates or college graduates. Non-Hispanic

black respondents have 1.52 times the odds of responding, but not accounting for the Bonferroni correction at 0.0011. No baseline household characteristics are significant in the three-wave response model, but a couple of household change indicators are at the 0.05 level. While changing residence alone had no impact on response, the introduction of an impediment to entry led to increased odds of obtaining an interview. However, this effect disappears with the addition of wave two non-observation sources in the model, reducing the odds ratio from 2.48 to 1.65. Similarly the end of employment in the second E-FTF wave also increases the odds of obtaining an interview (OR = 1.65) though this effect also disappears with the addition of wave two sources of non-observation (OR = 0.98).

Those with more chronic conditions are more likely to respond as in the two-wave model. The remaining health factors are only significant at the 0.05 level. The mental status score has an effect on predicting survey response, with each additional point of the scale resulting in 1.06 times the odds of responding. Unlike the two-wave model, there is no effect on response from the baseline word recall score. Respondents with the lowest baseline self-rated health were less likely to respond compared to those with "excellent" self-rated health. Those who exhibit less frequent (1-3 times/month) baseline mildly vigorous activity are also less likely to respond (OR = 0.52). However, all of these effects completely (or nearly) disappear with the addition of wave two sources of non-observation. The two-wave models had self-rated health, mildly vigorous activity, and chronic conditions strongly associated with the nonresponse and nursing home/proxy states and may explain the removal of these effects with the introduction of the wave two sources of non-observation. Many of the physical health change indicators are positively associated with response in this three-wave model. Both declining and improving self-rated health seem to result in odds ratios greater than 1 as does both declining and increasing

activity levels. An increase in the number of chronic conditions has a higher odds ratio than the baseline level. But like previous variables in the three-wave response model, all of these effects disappear or are reduced with the inclusion of wave two sources of non-observation.

Focusing on the non-observation sources related to response, nonrespondents in the most recent wave had only 0.03 the odds responding in the current wave compared to previous consenters holding all other demographic, household, and health factors constant. This translates into previous nonrespondents having over 37 times the odds of remaining a nonrespondent in the future wave compared to those who consented to DBS in the previous wave. This pattern is consistent with previous research and with what was seen in the eligibility outcome evaluation (see Figure 2-5). Both forms of biomeasure ineligibility (health-related and non-health-related) have about a quarter the odds of responding compared to previous consenters. Previous wave non-consenters had half the odds of responding compared to previous DBS consenters, holding all else constant.

The transition from the two-wave model to the three-wave model did little to change many of the significant effects for the non-nursing home, self-response model in relation to demographic and household characteristics. Age and education all maintained similar coefficients to the two-wave model though effects of race/ethnicity, specifically for non-Hispanic blacks, reduced from an odds of 2.02 to 1.57 of being a self-respondent not living in a nursing home. While the three-year model does show females are more likely to need a proxy-respondent or be in a nursing home, this effect is weak and ultimately removed with the introduction of the previous non-observation source indicators. Another temporary but weak effect is having another eligible study member in the household, but again dissipates with the inclusion of non-observation sources.

Cognition continues to play a large role in the proxy/nursing home eligibility at E-FTF wave three. Both coefficients are very similar to their two-wave counterparts with higher baseline word recall and mental status scores resulting in higher chances of being a non-nursing home, self-respondent. The change in both cognition scores between wave one and two have similar magnitudes to their baseline counterparts. For physical health, no mildly vigorous activity and the number of functional limitations each display reduced odds in completing a non-nursing home self-respondent interview, though these effects disappear with the inclusion of non-observation sources.

Nonrespondents in the previous wave have less than 0.10 odds of being a self-respondent not living in a nursing home compared to previous consenters. Nursing home or proxy-respondent in the previous wave had 0.02 odds of switching their status in the next wave compared to previous consenters (Figure 2-5). Previous wave non-health-related ineligibility and refusal to DBS collection have no effect on this state.

Non-observation related to telephone interview or partial interviews again show few significant predictors. Age increases the odds of a biomeasure eligible interview, but only at the 0.05 level. The number of baseline chronic conditions at the initial E-FTF has a positive effect on completing a biomeasure eligible interview at the third E-FTF wave ($\alpha = 0.05$) though there seems to be no relationship with a change in the number of chronic conditions from wave one to wave two.

Previous nonrespondents have one-tenth the odds of being biomeasure eligible in the upcoming wave relative to previous DBS consenters. Previous biomeasure ineligibility due to

non-health factors has 0.17 odds of being eligible in the third wave relative to previous DBS consenters.

College graduates have only half the odds of wave 3 consenting to DBS collection compared to those who did not complete high school. While the two-wave model suggested an effect for active churchgoers, the three-wave model does not show a significant effect though the odds ratio remains the same. Non-Hispanic black respondents have about 0.60 odds of consenting in the third wave compared to other non-Hispanic respondents before the inclusion of previous non-observation source measures. Baseline rural respondents are significantly more likely to consent to DBS collection than urban respondents when controlling for previous source of non-observation (OR = 1.56). Respondents who no longer owned their home between 2006 and 2010 had 0.62 times the odds of consenting to DBS in 2014, but the standard error greatly increases with the non-observation sources removing the small effect at $\alpha = 0.05$. The number of chronic conditions increases the odds of DBS consent in the three-wave-model (OR = 1.24) though the effect is weakened when previous wave non-observation source indicators are included (OR = 1.16). Mental status score and little to no mildly vigorous activity also see temporary weak significant effects before the inclusion of previous wave non-observation source indicators.

Like in the two-wave model, consent to DBS collection in 2006 has a large effect on consent in 2014. Consent refusal in 2006 has 0.17 odds of consent in 2014 while consent refusal in 2010 has 0.10 odds compared to previous consenters. Nonresponse and non-health-related ineligibility in the previous wave all result in reduced odds of consent with each having a similar 0.30 odds compared to previous consenters, though the former is not significant with the multiple-comparisons adjustment.

Table 2-8a. Three-wave continuation ratio logit model odds ratios predicting sequential 2014 eligibility states based on 2006 and 2010 respondent and household characteristics

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Respondent characteristics						
Age (years)	**0.93 (0.005)******	0.99 (0.007)	**0.93 (0.008)******	1.02 (0.010)*	1.00 (0.008)	****
Female	**1.61 (0.149)******	1.16 (0.117)	0.73 (0.112)*	0.88 (0.130)	1.00 (0.119)	****
Education (ref: less than HS)						
High school	0.93 (0.095)	0.98 (0.125)	0.68 (0.114)*	1.08 (0.198)	0.69 (0.113)*	
Some college	0.73 (0.163)	**0.50 (0.103)*****	0.87 (0.374)	2.11 (0.895)	1.03 (0.327)	*
College graduate	0.98 (0.135)	0.91 (0.144)	0.55 (0.123)**	1.15 (0.266)	**0.49 (0.093)******	**
Race/ethnicity (ref: Non-Hispanic Other)						
Non-Hispanic black	1.24 (0.151)	1.52 (0.239)**	1.57 (0.303)*	1.37 (0.305)	**0.62 (0.094)*****	***
Hispanic (English interview)	1.93 (0.469)**	1.04 (0.228)	1.17 (0.367)	1.61 (0.608)	0.88 (0.229)	
Hispanic (Spanish interview)	**2.78 (0.659)******	0.96 (0.218)	1.65 (0.539)	0.79 (0.252)	2.06 (0.804)	**
Currently employed	1.23 (0.198)	1.07 (0.135)	0.91 (0.218)	0.81 (0.143)	1.19 (0.179)	
Attends church at least 1/wk	1.19 (0.099)*	1.05 (0.098)	1.04 (0.135)	1.19 (0.164)	1.23 (0.137)	
Baseline household characteristics						
Impediments to entry	1.08 (0.163)	0.99 (0.171)	1.32 (0.335)	1.02 (0.283)	1.00 (0.208)	
Own home	1.22 (0.144)	1.14 (0.162)	1.29 (0.243)	0.91 (0.198)	0.87 (0.155)	
Rural	0.99 (0.090)	0.88 (0.088)	1.07 (0.156)	0.80 (0.114)	**1.56 (0.206)*****	**
Another eligible HH member	0.99 (0.099)	1.22 (0.134)	0.72 (0.116)*	1.27 (0.202)	1.05 (0.136)	
Baseline cognition and health						
Word recall score	**1.11 (0.019)******	1.03 (0.020)	**1.18 (0.033)******	1.01 (0.029)	1.00 (0.023)	****
Mental status score	1.04 (0.020)*	1.06 (0.023)**	**1.19 (0.035)******	1.03 (0.035)	1.06 (0.029)*	**
Self-rated health (ref: Excellent)						
Very good	0.72 (0.130)	0.93 (0.138)	1.27 (0.328)	0.71 (0.159)	0.76 (0.134)	
Good	0.58 (0.107)**	0.80 (0.131)	0.68 (0.176)	0.66 (0.166)	0.77 (0.154)	
Fair/Poor	**0.37 (0.077)******	0.66 (0.135)*	0.77 (0.239)	0.54 (0.171)	0.67 (0.170)	
Mildly vigorous activity (ref: At least 1/wk)						
1-3 times/month	1.00 (0.167)	0.52 (0.111)**	0.63 (0.166)	1.02 (0.406)	0.72 (0.184)	
Hardly ever/never	**0.49 (0.071)******	0.78 (0.176)	0.54 (0.139)*	1.48 (0.666)	0.55 (0.142)*	
No. of functional limitations	**0.94 (0.013)******	1.03 (0.019)	0.95 (0.021)*	1.01 (0.028)	0.96 (0.020)	**
No. of chronic conditions	**0.87 (0.031)******	**1.22 (0.055)******	1.02 (0.060)	1.22 (0.084)**	**1.24 (0.068)******	****

(continued)

Table 2-8a. Three-wave continuation ratio logit model odds ratios predicting sequential 2014 eligibility states based on 2006 and 2010 respondent and household characteristics (continued)

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Change in household characteristics						
Change in current work (ref: baseline)						
Now currently working	1.40 (0.538)	1.88 (0.667)	0.89 (0.432)	1.29 (0.561)	1.06 (0.339)	
No longer working	0.69 (0.131)	1.65 (0.287)**	1.12 (0.329)	1.39 (0.295)	1.05 (0.187)	*
Moved residences	1.15 (0.325)	2.02 (0.877)	0.61 (0.220)	0.78 (0.325)	0.86 (0.306)	
Change impediment (ref: baseline)						
New impediment	0.93 (0.186)	2.48 (0.922)*	0.74 (0.225)	1.20 (0.486)	1.05 (0.303)	
No longer impediment	1.34 (0.365)	1.16 (0.370)	0.93 (0.393)	1.02 (0.481)	1.03 (0.363)	
Change rural (ref: baseline)						
Move to rural residence	1.67 (0.661)	2.84 (2.077)	0.75 (0.349)	0.45 (0.206)	1.42 (0.763)	
Move to urban residence	1.22 (0.481)	0.63 (0.254)	0.65 (0.351)	3.01 (3.094)	3.81 (3.909)	
Change home ownership (ref: baseline)						
Now own home	1.24 (0.299)	1.63 (0.536)	0.71 (0.237)	1.19 (0.516)	1.21 (0.442)	
No longer own home	0.83 (0.138)	1.00 (0.236)	0.83 (0.219)	0.86 (0.266)	0.62 (0.145)*	
Change in HH member status (ref: baseline)						
Now living w/ eligible HH member	0.93 (0.379)	0.97 (0.380)	4.07 (4.370)	2.21 (1.619)	2.33 (1.416)	
No longer living w/ HH member	1.06 (0.169)	0.81 (0.147)	1.39 (0.356)	0.88 (0.236)	1.22 (0.288)	
Change in cognition and health						
Change in word recall score	**1.11 (0.018)******	1.01 (0.018)	**1.11 (0.028)******	1.05 (0.027)	1.00 (0.021)	****
Change in mental status score	1.04 (0.021)*	1.02 (0.027)	**1.17 (0.037)******	1.06 (0.043)	1.05 (0.034)	*
Change in self-rated health (ref: baseline)						
Declined	**0.59 (0.064)******	**1.50 (0.190)*****	0.74 (0.128)	0.96 (0.164)	0.85 (0.112)	****
Improved	1.35 (0.157)*	**1.69 (0.224)******	0.91 (0.156)	0.97 (0.174)	1.15 (0.180)	*
Change in mildly vigorous activity (ref: baseline)						
Declined	1.03 (0.186)	**2.33 (0.614)*****	1.94 (0.650)*	0.96 (0.419)	1.32 (0.369)	
Improved	**0.55 (0.054)******	**2.01 (0.336)******	**0.42 (0.064)******	1.27 (0.287)	0.89 (0.144)	****
Change in no. functional limitations	**0.92 (0.011)******	1.04 (0.021)	**0.93 (0.019)******	1.00 (0.028)	0.98 (0.021)	****
Change in no. chronic conditions	0.95 (0.046)	**1.42 (0.095)******	1.15 (0.092)	1.08 (0.102)	1.06 (0.079)	***

Note. The parallel slopes test is a Wald chi-square test with 4 degrees of freedom. HS = high school.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0011$ and are **bolded**.

Table 2-8b. Three-wave continuation ratio logit model odds ratios predicting sequential 2014 eligibility states based on 2006 and 2010 respondent and household characteristics and 2006 and 2010 non-observation source

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Respondent characteristics						
Age (years)	**0.93 (0.005)******	1.00 (0.007)	**0.93 (0.009)******	1.02 (0.011)*	0.99 (0.009)	****
Female	**1.65 (0.153)******	1.14 (0.128)	0.72 (0.120)	0.90 (0.136)	0.95 (0.132)	****
Education (ref: less than HS)						
High school	0.96 (0.097)	0.98 (0.138)	0.69 (0.129)*	1.04 (0.198)	0.74 (0.139)	
Some college	0.76 (0.170)	0.49 (0.113)**	1.01 (0.482)	2.11 (0.915)	1.20 (0.437)	*
College graduate	1.04 (0.144)	0.98 (0.170)	0.60 (0.148)*	1.19 (0.281)	**0.48 (0.107)*****	*
Race/ethnicity (ref: Non-Hispanic Other)						
Non-Hispanic black	1.18 (0.146)	1.57 (0.272)**	1.50 (0.326)	1.41 (0.324)	0.76 (0.137)	*
Hispanic (English interview)	2.00 (0.490)**	1.18 (0.293)	1.51 (0.547)	1.86 (0.724)	1.07 (0.317)	
Hispanic (Spanish interview)	**2.73 (0.653)******	1.05 (0.273)	1.46 (0.517)	1.00 (0.336)	2.08 (0.865)	*
Currently employed	1.28 (0.208)	1.19 (0.171)	1.05 (0.271)	0.85 (0.155)	1.01 (0.177)	
Attends church at least 1/wk	1.19 (0.100)*	0.99 (0.105)	1.04 (0.152)	1.14 (0.161)	1.18 (0.153)	
Baseline household characteristics						
Impediments to entry	1.08 (0.164)	0.97 (0.189)	1.26 (0.351)	1.01 (0.285)	1.27 (0.311)	
Own home	1.26 (0.150)	1.09 (0.173)	1.49 (0.306)	0.87 (0.192)	0.96 (0.198)	
Rural	0.98 (0.089)	0.80 (0.090)	1.05 (0.169)	0.79 (0.116)	1.61 (0.246)**	**
Another eligible HH member	0.98 (0.099)	1.28 (0.158)*	0.73 (0.129)	1.33 (0.216)	0.85 (0.131)	*
Baseline cognition and health						
Word recall score	**1.09 (0.019)******	1.02 (0.021)	**1.15 (0.035)******	1.00 (0.029)	1.00 (0.026)	***
Mental status score	1.02 (0.020)	1.02 (0.024)	**1.15 (0.037)******	1.01 (0.036)	1.06 (0.034)	*
Self-rated health (ref: Excellent)						
Very good	0.72 (0.131)	0.97 (0.162)	1.26 (0.349)	0.73 (0.167)	0.91 (0.187)	
Good	0.57 (0.107)**	0.90 (0.166)	0.66 (0.186)	0.69 (0.176)	0.95 (0.218)	
Fair/Poor	**0.37 (0.078)******	0.74 (0.171)	0.87 (0.291)	0.56 (0.179)	0.89 (0.262)	
Mildly vigorous activity (ref: At least 1/wk)						
1-3 times/month	1.10 (0.187)	0.81 (0.201)	0.78 (0.232)	1.11 (0.444)	1.17 (0.351)	
Hardly ever/never	**0.53 (0.079)******	1.26 (0.322)	1.01 (0.307)	1.76 (0.832)	0.69 (0.212)	**
No. of functional limitations	**0.95 (0.013)******	1.03 (0.021)	0.96 (0.024)	1.01 (0.029)	0.97 (0.023)	*
No. of chronic conditions	**0.86 (0.031)******	1.11 (0.056)*	0.99 (0.066)	1.20 (0.086)*	1.16 (0.074)*	****

(continued)

Table 2-8b. Three-wave continuation ratio logit model odds ratios predicting sequential 2014 eligibility states based on 2006 and 2010 respondent and household characteristics and 2006 and 2010 non-observation source (continued)

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Change in household characteristics						
Change in current work (ref: baseline)						
Now currently working	1.32 (0.509)	1.17 (0.426)	0.78 (0.402)	1.17 (0.514)	0.82 (0.306)	
No longer working	0.64 (0.122)*	0.98 (0.181)	0.80 (0.251)	1.29 (0.282)	1.13 (0.237)	
Moved residences	1.24 (0.362)	1.76 (0.780)	0.57 (0.240)	0.79 (0.333)	0.94 (0.390)	
Change impediment (ref: baseline)						
New impediment	0.93 (0.188)	1.65 (0.619)	0.73 (0.247)	0.96 (0.390)	0.83 (0.277)	
No longer impediment	1.31 (0.361)	0.81 (0.272)	1.20 (0.616)	0.99 (0.476)	0.74 (0.301)	
Change rural (ref: baseline)						
Move to rural residence	1.72 (0.686)	2.59 (1.908)	0.85 (0.467)	0.47 (0.224)	1.19 (0.701)	
Move to urban residence	1.27 (0.510)	0.49 (0.200)	0.86 (0.546)	2.74 (2.841)	2.24 (2.348)	
Change home ownership (ref: baseline)						
Now own home	1.50 (0.377)	1.37 (0.468)	1.28 (0.530)	1.14 (0.505)	1.87 (0.785)	
No longer own home	0.83 (0.140)	0.78 (0.189)	0.72 (0.215)	0.93 (0.299)	0.63 (0.174)	
Change in HH member status (ref: baseline)						
Now living w/ eligible HH member	0.88 (0.362)	0.65 (0.259)	2.31 (2.411)	2.20 (1.632)	1.82 (1.231)	
No longer living w/ HH member	1.08 (0.176)	0.58 (0.108)**	1.94 (0.629)*	0.84 (0.229)	1.35 (0.370)	**
Change in cognition and health						
Change in word recall score	**1.11 (0.018)******	1.03 (0.021)	**1.11 (0.031)******	1.05 (0.027)*	0.99 (0.024)	***
Change in mental status score	1.04 (0.021)*	1.04 (0.032)	**1.23 (0.046)******	1.07 (0.045)	1.06 (0.039)	**
Change in self-rated health (ref: baseline)						
Declined	**0.57 (0.064)******	0.88 (0.124)	0.74 (0.144)	0.88 (0.156)	0.90 (0.139)	
Improved	1.32 (0.157)*	0.86 (0.125)	0.92 (0.178)	0.84 (0.156)	1.10 (0.199)	
Change in mildly vigorous activity (ref: baseline)						
Declined	0.91 (0.167)	0.96 (0.275)	1.20 (0.441)	0.74 (0.335)	1.34 (0.446)	
Improved	**0.57 (0.058)******	1.48 (0.262)*	**0.45 (0.076)******	1.23 (0.284)	0.88 (0.163)	****
Change in no. functional limitations	**0.93 (0.012)******	1.01 (0.022)	0.97 (0.023)	0.99 (0.029)	0.97 (0.024)	*
Change in no. chronic conditions	0.92 (0.045)	1.15 (0.086)	1.02 (0.092)	1.05 (0.103)	1.01 (0.086)	

(continued)

Table 2-8b. Three-wave continuation ratio logit model odds ratios predicting sequential 2014 eligibility states based on 2006 and 2010 respondent and household characteristics and 2006 and 2010 non-observation source (continued)

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Wave 1 non-observation source						
DBS consent refusal	0.96 (0.105)	0.80 (0.101)	1.07 (0.207)	0.71 (0.125)	**0.17 (0.022)******	****
Wave 2 non-observation source (ref: DBS consent)						
Nonrespondent	**0.52 (0.098)*****	**0.03 (0.004)******	**0.07 (0.021)******	**0.10 (0.031)******	0.30 (0.123)**	****
Non-nursing home/proxy respondent	**0.43 (0.067)******	**0.24 (0.058)******	**0.02 (0.005)******	1.44 (1.499)	0.33 (0.187)	****
Biomeasure ineligible respondent	0.98 (0.194)	**0.23 (0.038)******	0.66 (0.213)	**0.17 (0.033)******	**0.27 (0.063)******	****
DBS consent refusal	0.88 (0.116)	**0.50 (0.079)******	0.67 (0.151)	0.87 (0.198)	**0.10 (0.014)******	****

Note. The parallel slopes test is a Wald chi-square test with 4 degrees of freedom. HS = high school. DBS = dried blood spot.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0011$ and are **bolded**.

2.5 Results Part 2 – Bias evaluation across eligibility states

With a better understanding of the factors that predict various eligibility states, this paper now shifts focus to the impact that each source of non-observation has on the biomarker outcomes. Section 2.5.1 will look at the overall distribution of each biomarker outcome based on key percentiles. Section 2.5.2 will look at the difference in means across each eligibility state followed by the difference in high or at risk proportions in Section 2.5.3. An evaluation of potential confounding factors follows in Section 2.5.4. Finally, in Section 2.5.5 some of the assumptions from these analyses are evaluated.

2.5.1 Distributional changes

Looking first at the weighted percentiles for each biomarker outcome, the percentiles examined change very little for each eligibility state (see Table 2-9). Change is primarily observed in the higher percentiles, especially in the 90^{th}, 95^{th}, and 99^{th} percentiles where those values were pulled closer to the median though there is limited substantive difference. This is more likely to impact the at risk proportions for the outcomes (the one exception being HDL which has a left tail at risk value). Cystatin C saw some of the largest changes with the upper percentiles of (1.50, 1.76, 2.74) for the full sample shifting down to (1.43, 1.63, 2.28) for the living sample, and finally down to (1.37, 1.63, 2.21) for the consenting sample. CRP saw a similar drop for mortality, but minimal change in the following states. Only two biomarkers saw the median value shift across the successive sources of non-observation: total cholesterol and CRP.

These changes suggest that means and proportions are most likely to shrink as the extreme values in the upper tails are removed. Figures 2-7a through 2-7e also show how there is very little movement in the distributions with the most notable (though small) changes in Cystatin C and CRP consistent with the numerical evaluation.

Table 2-9. Percentiles of five dried blood spot assays by 2010 eligibility state

	1st	5th	10th	25th (Q1)	50th (Median)	75th (Q3)	90th	95th	99th
HbA1c									
Full sample	4.65	4.88	4.99	5.22	5.57	6.03	6.72	7.53	10.18
Alive in 2010	4.65	4.88	4.99	5.22	5.57	6.03	6.61	7.30	9.95
Respondent in 2010	4.65	4.88	4.99	5.22	5.57	6.03	6.61	7.30	9.95
Self-R in 2010	4.65	4.88	4.99	5.22	5.57	6.03	6.61	7.30	9.95
BioElig-R in 2010	4.65	4.88	4.99	5.22	5.57	6.03	6.61	7.30	10.16
Consent 2010	4.65	4.88	4.99	5.22	5.57	6.03	6.61	7.18	9.95
HDL									
Full sample	25.28	32.00	35.36	42.20	52.16	64.48	76.80	84.64	98.08
Alive in 2010	26.40	32.00	35.36	43.20	52.16	64.48	77.92	84.64	98.08
Respondent in 2010	26.40	32.00	35.36	43.20	52.16	64.48	77.92	84.64	98.08
Self-R in 2010	26.40	32.00	35.36	43.20	52.16	65.60	77.92	84.64	98.08
BioElig-R in 2010	26.40	32.00	35.36	43.20	52.16	65.60	77.92	85.76	98.08
Consent 2010	26.40	32.00	35.36	43.20	52.16	65.60	77.92	85.76	98.08
Total cholesterol									
Full sample	126.56	142.16	151.53	171.30	198.35	229.56	262.86	282.63	306.56
Alive in 2010	126.56	143.20	153.61	172.34	200.43	230.61	263.90	283.67	306.56
Respondent in 2010	126.56	142.16	153.61	172.34	199.39	230.61	263.90	283.67	306.56
Self-R in 2010	126.56	142.16	153.61	172.34	199.39	230.61	263.90	283.67	306.56
BioElig-R in 2010	126.56	142.16	152.83	172.34	200.43	230.61	264.94	283.67	306.56
Consent 2010	127.60	143.20	153.61	172.34	200.43	230.61	264.94	283.67	306.56
CRP									
Full sample	0.11	0.26	0.41	0.91	1.97	4.82	10.02	15.95	41.32
Alive in 2010	0.11	0.25	0.41	0.88	1.89	4.55	9.44	14.72	37.66
Respondent in 2010	0.11	0.25	0.41	0.88	1.89	4.55	9.44	14.85	37.66
Self-R in 2010	0.11	0.26	0.41	0.88	1.89	4.55	9.44	14.85	36.51
BioElig-R in 2010	0.11	0.25	0.41	0.88	1.89	4.55	9.48	14.85	37.71
Consent 2010	0.11	0.25	0.41	0.88	1.86	4.46	9.44	14.56	36.39
Cystatin C									
Full sample	0.52	0.65	0.71	0.84	0.97	1.17	1.50	1.76	2.74
Alive in 2010	0.52	0.65	0.71	0.84	0.97	1.17	1.43	1.63	2.28
Respondent in 2010	0.52	0.65	0.71	0.84	0.97	1.17	1.43	1.63	2.28
Self-R in 2010	0.52	0.65	0.71	0.84	0.97	1.11	1.37	1.63	2.24
BioElig-R in 2010	0.52	0.65	0.71	0.84	0.97	1.11	1.37	1.63	2.21
Consent 2010	0.52	0.65	0.71	0.84	0.97	1.11	1.37	1.63	2.21

Note. NHANES adjusted biomarker values are reported. Corresponding sample sizes are included in Table 2-3. "Self-R" refers to non-nursing home, self-respondent. "BioElig-R" refers to biomeasure eligible.

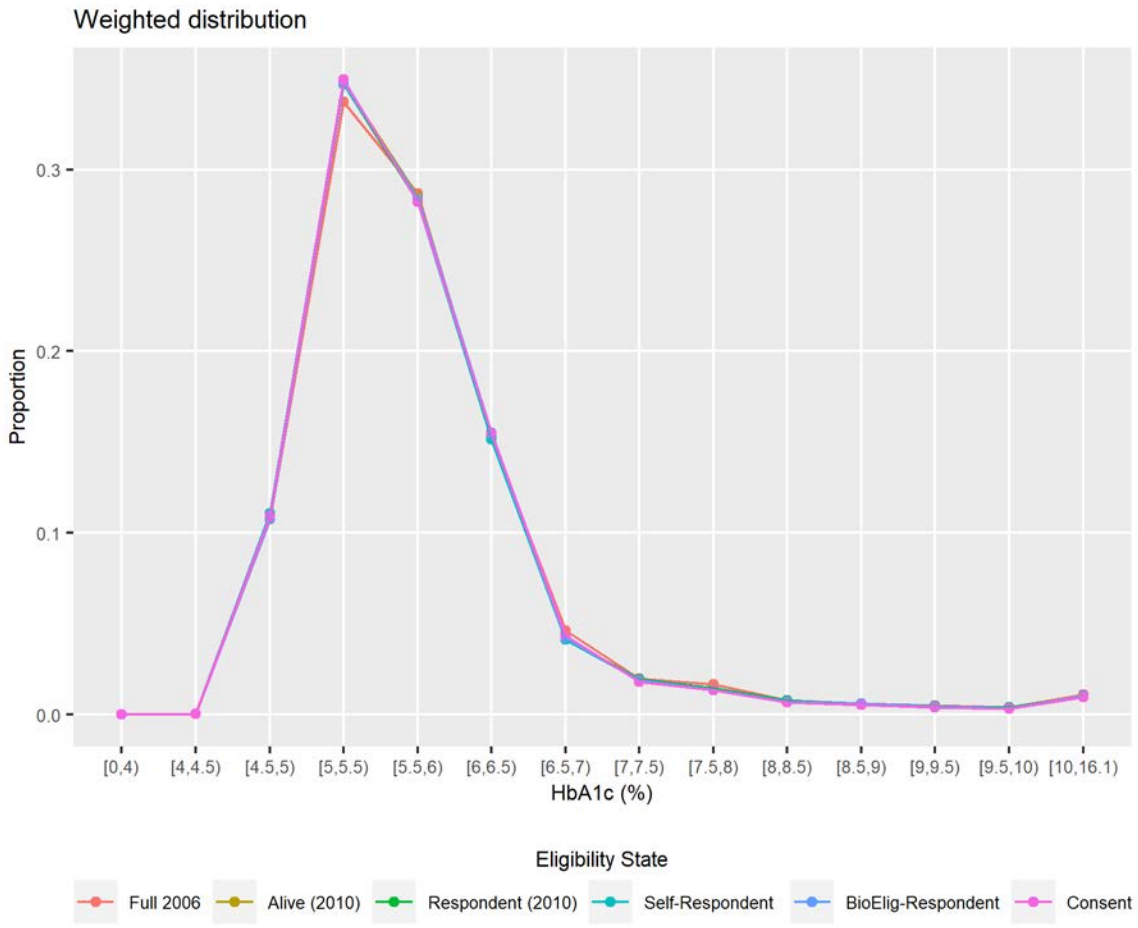

Figure 2-7a. Weighted distribution of HbA1c (NHANES adjusted) by 2010 eligibility state. "BioElig-Respondent" refers to biomeasure eligible.

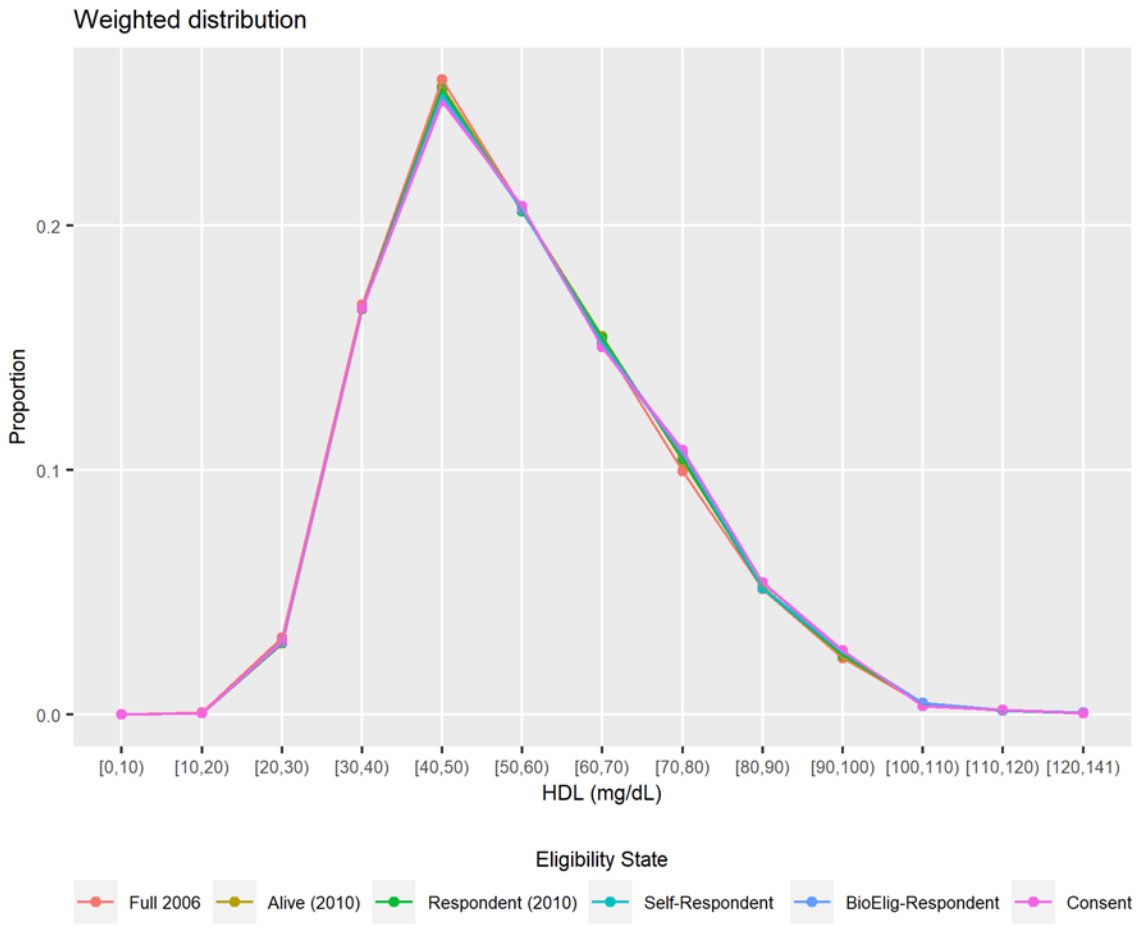

Figure 2-7b. Weighted distribution of HDL (NHANES adjusted) by 2010 eligibility state. "BioElig-Respondent" refers to biomeasure eligible.

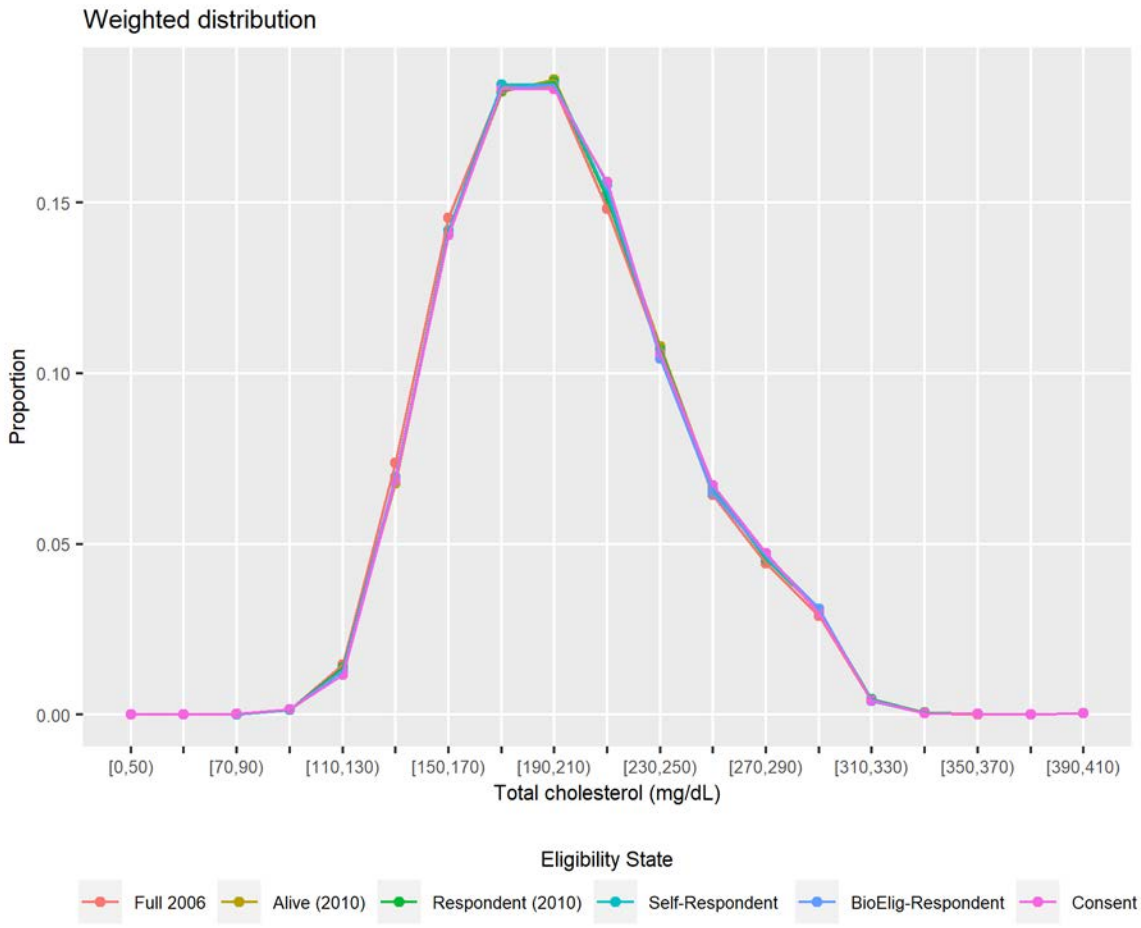

Figure 2-7c. Weighted distribution of total cholesterol (NHANES adjusted) by 2010 eligibility state. “BioElig-Respondent” refers to biomeasure eligible.

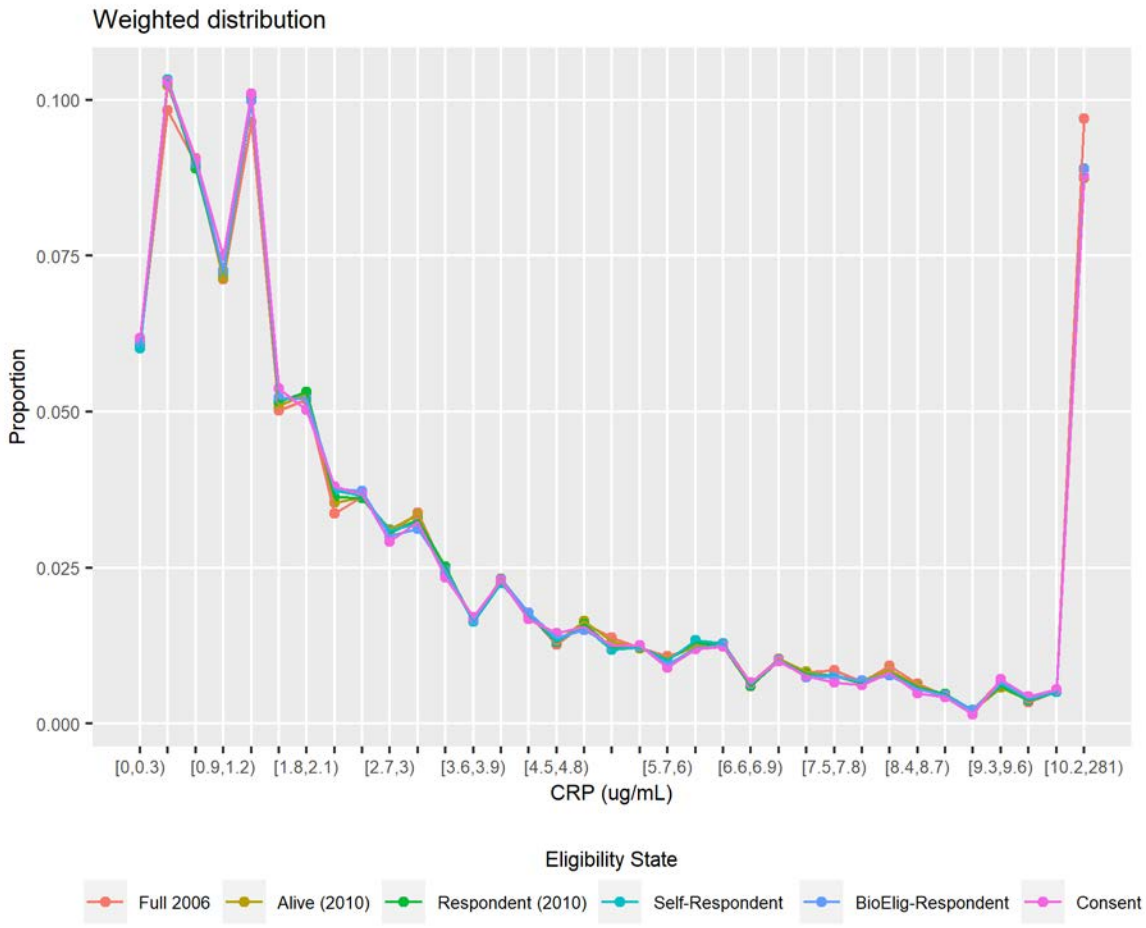

Figure 2-7d. Weighted distribution of C-reactive protein (CRP) (NHANES adjusted) by 2010 eligibility state. “BioElig-Respondent” refers to biomeasure eligible.

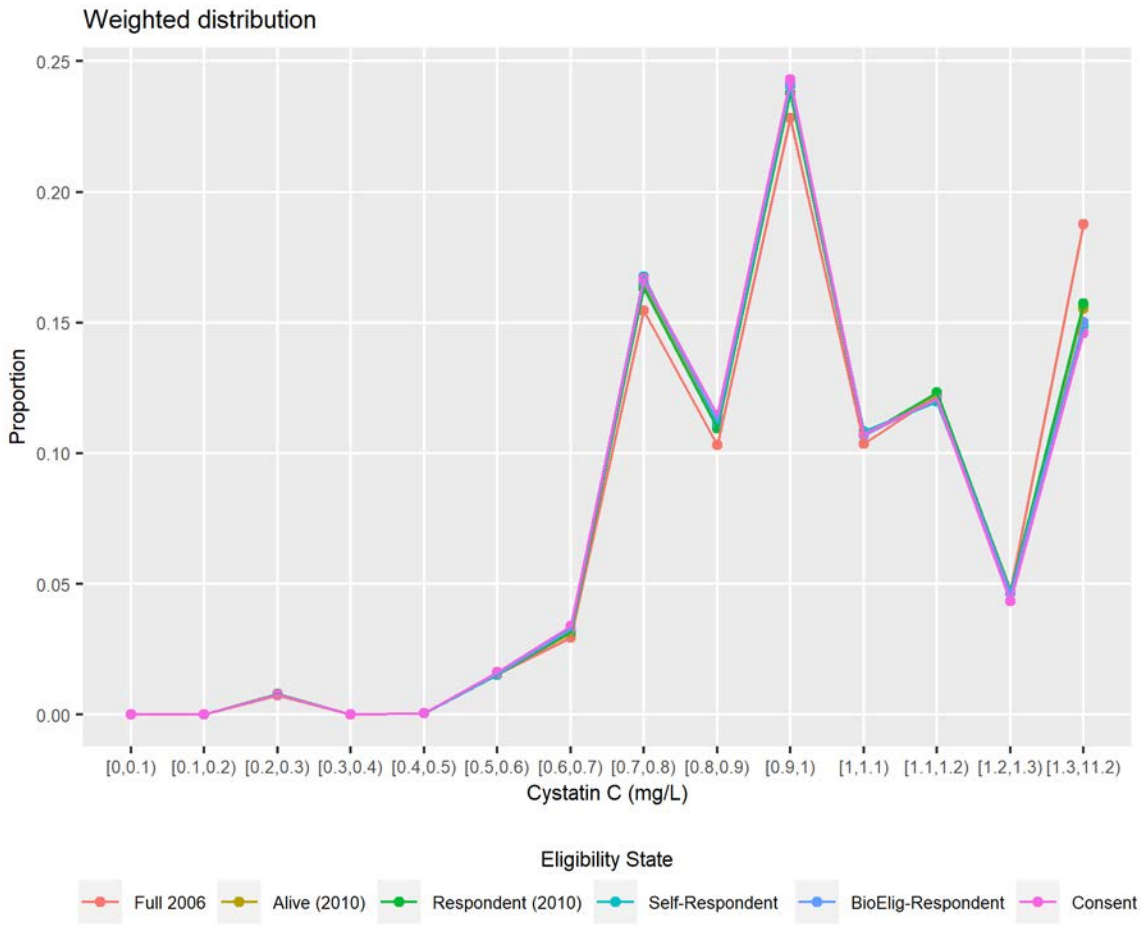

Figure 2-7e. Weighted distribution of Cystatin C (NHANES adjusted) by 2010 eligibility state. "BioElig-Respondent" refers to biomeasure eligible.

2.5.2 Bias in biomarker means

Tables 2-10a through 2-10e present the mean, bias (as specified in Equations (2.7) through (2.13)), and relative bias for each of the eligibility states. Corresponding figures (Figures 2-8a through 2-8e) display these means and their 95% confidence intervals.

For HbA1c (Table 2-10a; Figure 2-8a) there is a statistically significant shift in the mean percent HbA1c going from the full sample (5.81%) to the living sample (5.78%), though the relative bias is just over a half percent and has minimal substantive importance. Overall there is very little shift in the sample mean going from the living sample to the 2010 consenters though the general trend is negative. A positive shift is observed from the living respondents to the 2010 respondents (5.784%), however this bias is not statistically significant with the Bonferroni correction.

Similar to HbA1c, there is no significant shift in the HDL mean from the living sample to the consenting sample (Table 2-10b; Figure 2-8b). The difference from the full sample to the living sample is not significant given the Bonferroni correction though the absolute relative bias is comparable to what was seen with HbA1c (0.6%). Total cholesterol (Table 2-10c; Figure 2-8c) also shows comparable patterns to HDL and HbA1c with a larger change from the full sample (203.0 mg/dL) to the living sample (204.2 mg/dL), but no significant bias for the other eligibility state transitions.

CRP experiences the largest absolute relative difference between the full sample and the living sample across all five biomarkers at 7.1%. However, there are no other large differences across various eligibility states though the general trend is a reduction in the mean CRP (Table 2-10d; Figure 2-8d).

Cystatin C sees larger and more significant shifts in the means after removing the sources of non-observation then the previous biomarkers (Table 2-10e; Figure 2-8e). The large shift from the full sample to the living sample (1.08 mg/L to 1.03 mg/L) results in an absolute relative difference of over 4%. The difference between the all 2010 respondents and non-nursing home, self-respondents is also significant by reducing the mean Cystatin C by about 1.0%. The significant removal of proxy and nursing home respondents is reflected in both composite bias measures with the total non-observation bias (comparing the living respondents to the consenting respondents) showing an absolute relative bias of 1.2% and the total operational eligibility bias showing an absolute relative bias of 0.8%, though the latter is only marginally significant given the Bonferroni correction ($p = 0.0009$).

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Table 2-10a. Bias of mean HbA1c from HRS 2006 by 2010 eligibility state

HbA1c (%)	**Mean (SE)**	**Bias (SE)**	**Relative bias**
Full sample	5.811 (0.017)		
Alive in 2010	5.777 (0.018)	**-0.034 (0.006)******	-0.6%
Respondent in 2010	5.784 (0.019)	0.007 (0.002)**	0.1%
Self-Respondent in 2010	5.778 (0.019)	-0.006 (0.004)	-0.1%
BioElig-Respondent in 2010	5.782 (0.019)	0.005 (0.004)	0.1%
Consent 2010	5.769 (0.020)	-0.013 (0.007)	-0.2%
Operational eligibility *(Respondent vs BioElig-Respondent)*		-0.001 (0.005)	0.0%
Total non-observation *(Alive vs Consent)*		-0.007 (0.009)	-0.1%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

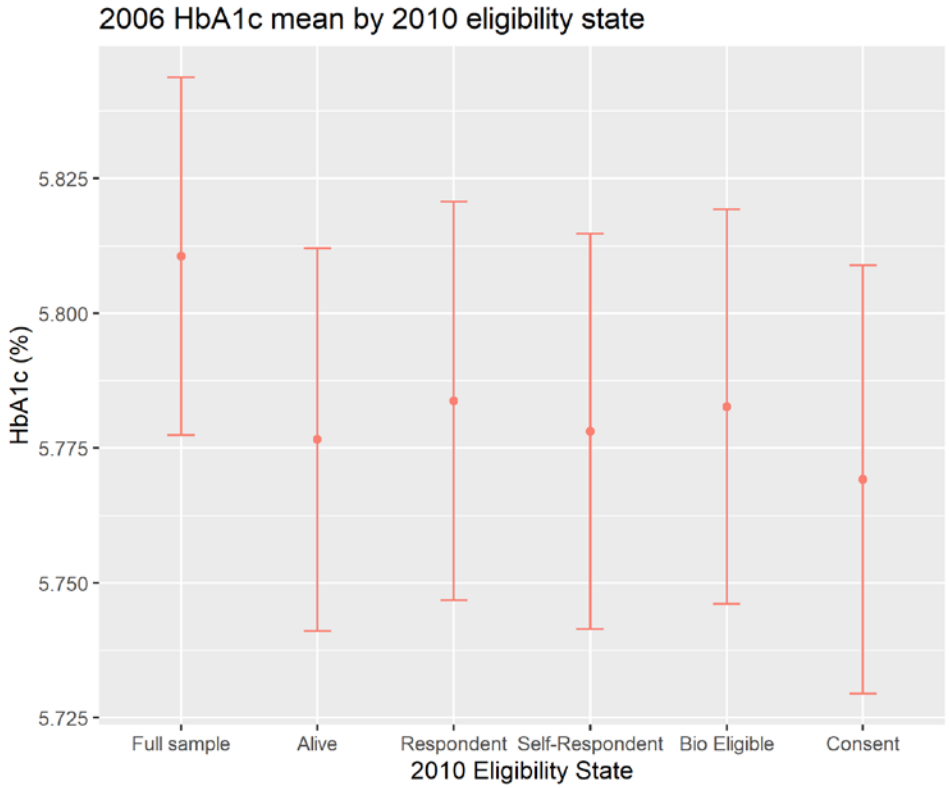

Figure 2-8a. Mean HbA1c from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-10b. Bias of mean HDL from HRS 2006 by 2010 eligibility state

HDL (mg/dL)	**Mean (SE)**	**Bias (SE)**	**Relative bias**
Full sample	54.468 (0.308)		
Alive in 2010	54.797 (0.351)	0.329 (0.099)**	0.6%
Respondent in 2010	54.814 (0.362)	0.018 (0.058)	0.0%
Self-Respondent in 2010	54.922 (0.387)	0.107 (0.056)	0.2%
BioElig-Respondent in 2010	54.941 (0.417)	0.019 (0.077)	0.0%
Consent 2010	54.977 (0.443)	0.036 (0.094)	0.1%
Operational eligibility *(Respondent vs BioElig-Respondent)*		0.127 (0.110)	0.2%
Total non-observation *(Alive vs Consent)*		0.181 (0.171)	0.3%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

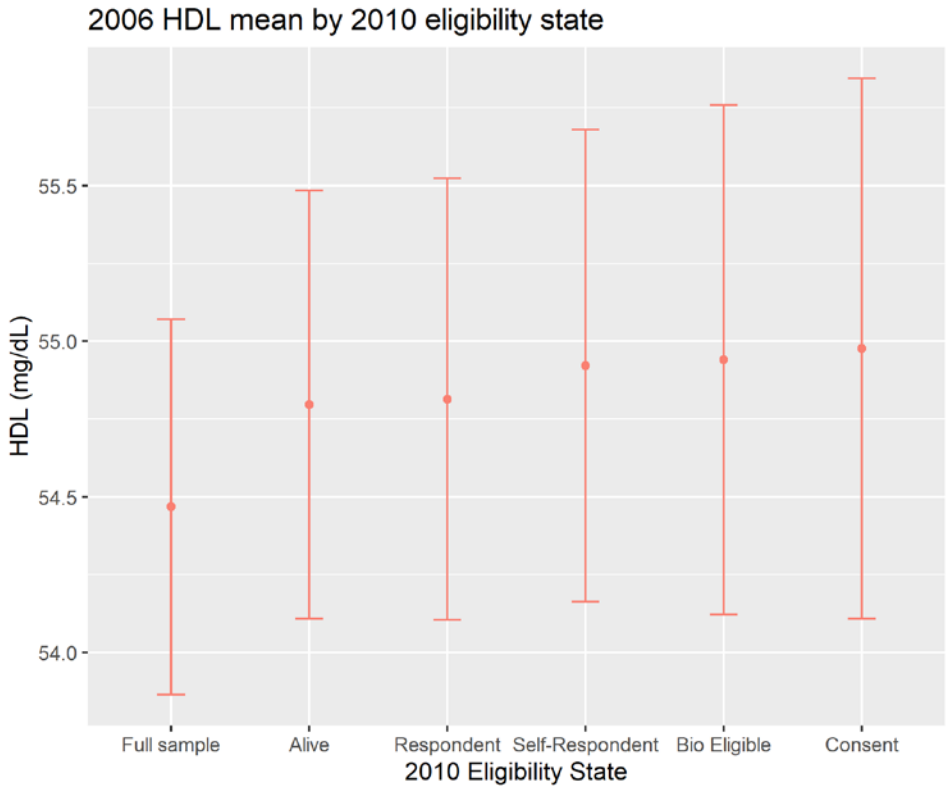

Figure 2-8b. Mean HDL from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-10c. Bias of mean total cholesterol from HRS 2006 by 2010 eligibility state

Total Cholesterol (mg/dL)	**Mean (SE)**	**Bias (SE)**	**Relative bias**
Full sample	202.984 (0.825)		
Alive in 2010	204.238 (0.886)	**1.254 (0.198)******	0.6%
Respondent in 2010	204.057 (0.897)	-0.181 (0.123)	-0.1%
Self-Respondent in 2010	204.042 (0.915)	-0.015 (0.120)	0.0%
BioElig-Respondent in 2010	204.063 (0.925)	0.021 (0.147)	0.0%
Consent 2010	204.424 (0.919)	0.361 (0.181)	0.2%
Operational eligibility *(Respondent vs BioElig-Respondent)*		0.006 (0.212)	0.0%
Total non-observation *(Alive vs Consent)*		0.186 (0.336)	0.1%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

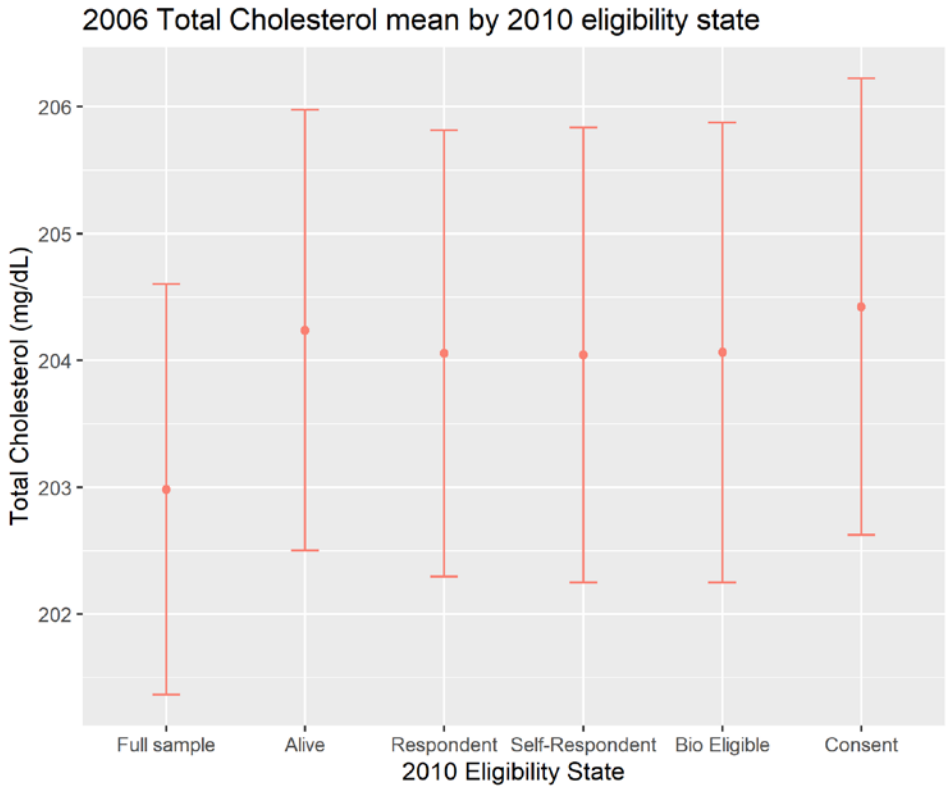

Figure 2-8c. Mean total cholesterol from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-10d. Bias of mean C-reactive protein (CRP) from HRS 2006 by 2010 eligibility state

CRP (ug/mL)	**Mean (SE)**	**Bias (SE)**	**Relative bias**
Full sample	4.472 (0.114)		
Alive in 2010	4.156 (0.113)	**-0.317 (0.069)******	-7.1%
Respondent in 2010	4.177 (0.117)	0.021 (0.017)	0.5%
Self-Respondent in 2010	4.158 (0.115)	-0.019 (0.023)	-0.5%
BioElig-Respondent in 2010	4.170 (0.122)	0.013 (0.018)	0.3%
Consent 2010	4.125 (0.129)	-0.046 (0.035)	-1.1%
Operational eligibility *(Respondent vs BioElig-Respondent)*		-0.006 (0.032)	-0.2%
Total non-observation *(Alive vs Consent)*		-0.031 (0.053)	-0.7%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

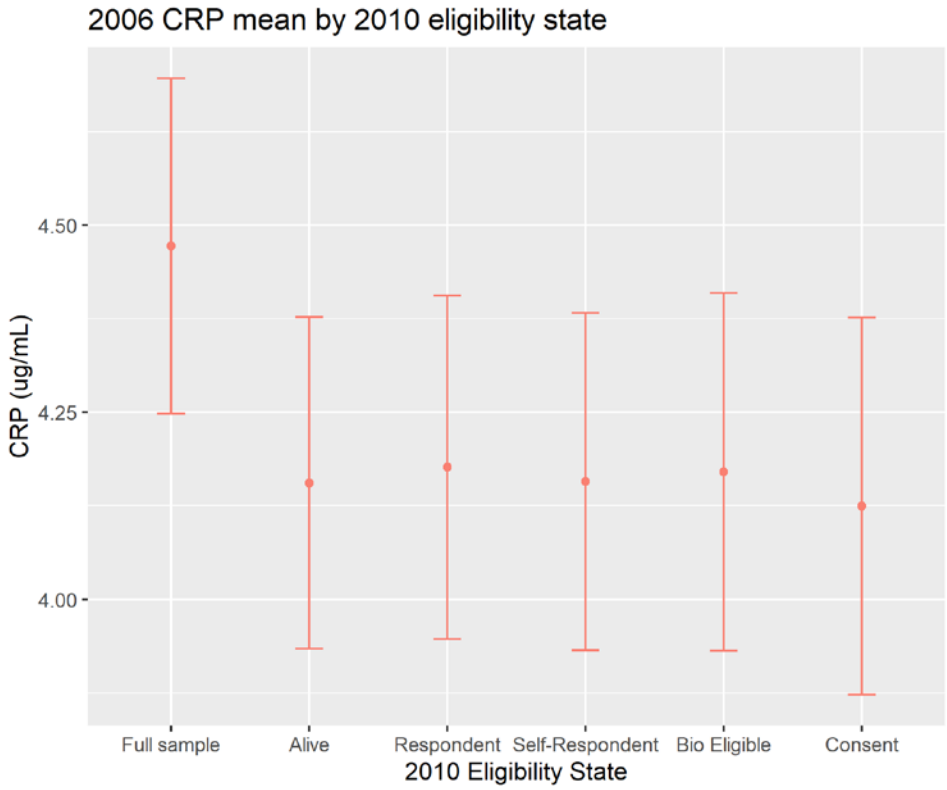

Figure 2-8d. Mean CRP from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-10e. Bias of mean Cystatin C from HRS 2006 by 2010 eligibility state

Cystatin C (mg/L)	**Mean (SE)**	**Bias (SE)**	**Relative bias**
Full sample	1.081 (0.008)		
Alive in 2010	1.034 (0.007)	**-0.047 (0.005)******	-4.3%
Respondent in 2010	1.036 (0.007)	0.002 (0.001)	0.2%
Self-Respondent in 2010	1.026 (0.007)	**-0.010 (0.002)******	-0.9%
BioElig-Respondent in 2010	1.027 (0.007)	0.001 (0.001)	0.1%
Consent 2010	1.021 (0.007)	-0.006 (0.002)**	-0.6%
Operational eligibility *(Respondent vs BioElig-Respondent)*		-0.009 (0.002)***	-0.8%
Total non-observation *(Alive vs Consent)*		**-0.013 (0.003)*** **	-1.2%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

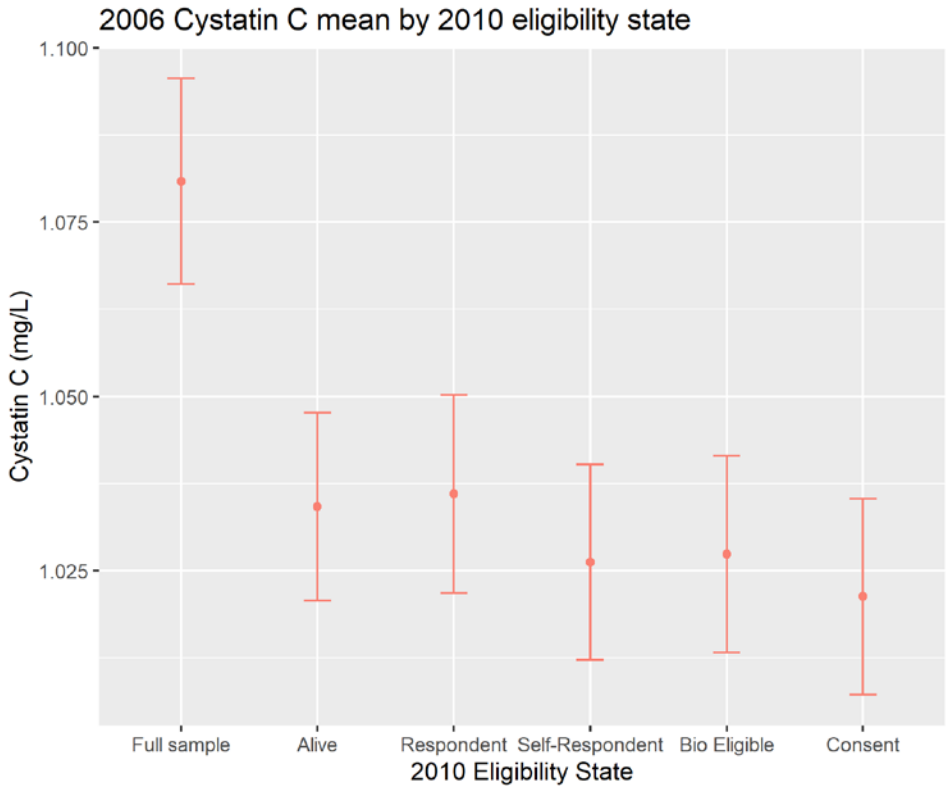

Figure 2-8e. Mean Cystatin C from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

2.5.3 Bias in proportions at risk

Following the same sequence as the estimate means, the full sample flagged 13.6% of consenting respondents as diabetic based on an HbA1c of 6.4% or greater (see Table 2-11a and Figure 2-9a). After removing the deceased respondents, the percentage of diabetics decreases to 12.4% – a significant absolute relative difference of 9%. This drop corresponds with the drop in mean noted earlier as well as the declining upper percentiles. A second significant change is seen between the living participants and the 2010 respondents. However, instead of a decrease in the high risk proportion there is a relative increase of 2.3% raising the proportion at risk to 12.6%. None of the remaining transitions experience a significant change in the proportion at risk for diabetes. The summary bias measures (in particular, the total non-observation bias) do not detect the shift for respondents as the observed effect may be mitigated by the subsequent changes related to eligibility and consent, though not individually significant themselves.

Across the two cholesterol measures, there are no significant changes in the proportion of those at risk for low HDL with the percent at risk for the full sample being 20.0% and the 2010 consenting sample at 19.7%, though the largest shift is to the living sample (2.3% absolute relative difference) (see Table 2-11b and Figure 2-9b). Considering total cholesterol, only one significant difference in the proportion of those with high cholesterol is found which is between the full sample and those alive in 2010 raising the proportion by a relative 3.5% from 18.6% to 19.2% (see Table 2-11c). This proportion is generally maintained across the additional non-observation transitions (see also Figure 2-9c).

The same pattern of observing a large shift from the full sample to the living sample is observed for CRP (38.1% to 36.8%) with no additional transitions exhibiting significant changes

(see Table 2-11d and Figure 2-9d). The non-observation bias shows a large negative cumulative effect across the subsequent sources of non-observation (relative bias of -1.9%), but not statistically different from the living sample.

For the high risk proportion for Cystatin C, the full sample to living sample transition is significant cutting the identified proportion at risk by a quarter from 9.1% to 6.8% (see Table 2-11e and Figure 2-9e). Like with the mean difference, the transition from all 2010 respondents to the non-nursing home, self-respondents is significant reducing the percent at risk from 6.9% to 6.3%, or an 8% absolute relative bias. However, there are no significant drops for the composite bias measures given the Bonferroni correction though the total non-observation bias and sample selection bias follow the same general pattern as before.

Table 2-11a. Bias of HbA1c proportion at risk from HRS 2006 by 2010 eligibility state

HbA1c >= 6.4%	**Proportion (SE)**	**Bias (SE)**	**Relative bias**
Full sample	0.136 (0.005)		
Alive in 2010	0.124 (0.005)	**-0.012 (0.002)******	-9.0%
Respondent in 2010	0.126 (0.006)	**0.003 (0.001)*****	2.3%
Self-Respondent in 2010	0.125 (0.005)	-0.002 (0.001)	-1.2%
BioElig-Respondent in 2010	0.125 (0.006)	0.000 (0.001)	0.1%
Consent 2010	0.123 (0.006)	-0.002 (0.001)	-1.5%
Operational eligibility *(Respondent vs BioElig-Respondent)*		-0.001 (0.002)	-1.1%
Total non-observation *(Alive vs Consent)*		-0.000 (0.002)	-0.4%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

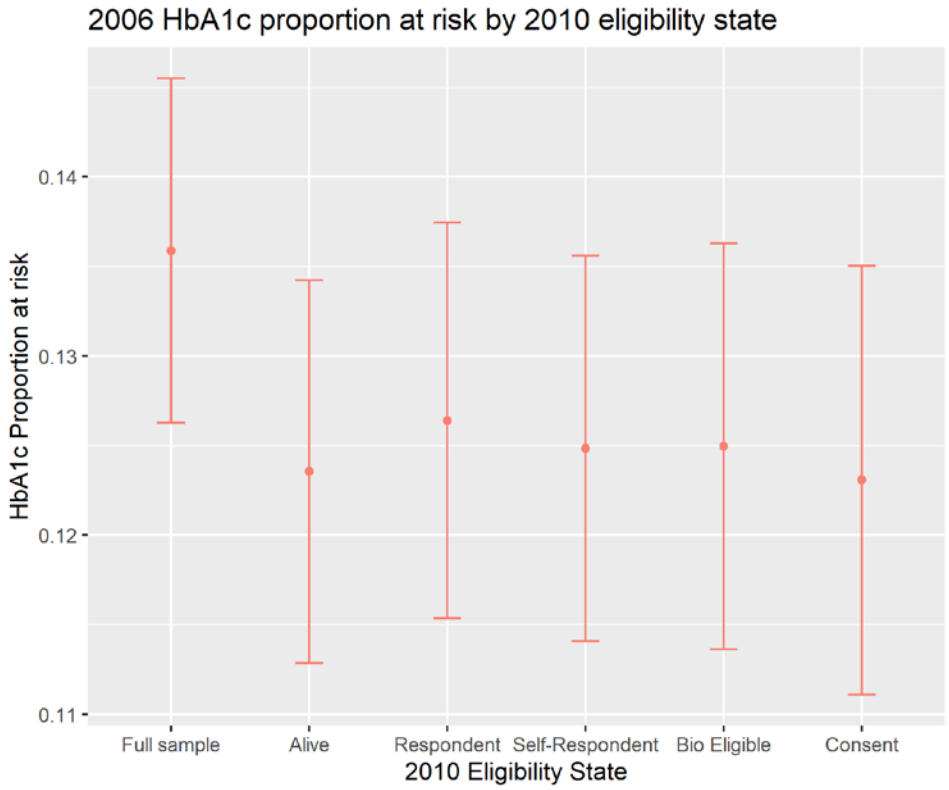

Figure 2-9a. HbA1c proportion at risk from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-11b. Bias of HDL proportion at risk from HRS 2006 by 2010 eligibility state

HDL < 40mg/dL	**Proportion (SE)**	**Bias (SE)**	**Relative bias**
Full sample	0.200 (0.006)		
Alive in 2010	0.195 (0.007)	-0.005 (0.002)*	-2.3%
Respondent in 2010	0.196 (0.007)	0.001 (0.002)	0.6%
Self-Respondent in 2010	0.196 (0.008)	-0.001 (0.002)	-0.3%
BioElig-Respondent in 2010	0.197 (0.008)	0.001 (0.002)	0.7%
Consent 2010	0.197 (0.009)	0.000 (0.002)	-0.1%
Operational eligibility *(Respondent vs BioElig-Respondent)*		0.001 (0.003)	0.3%
Total non-observation *(Alive vs Consent)*		0.002 (0.004)	0.8%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

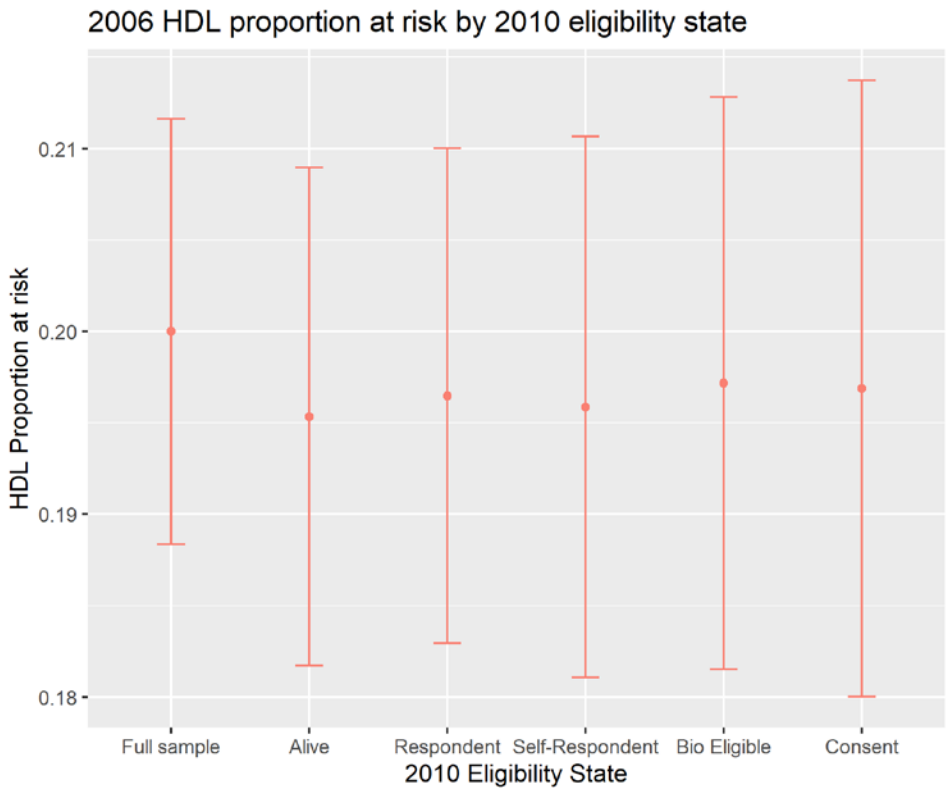

Figure 2-9b. HDL proportion at risk from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-11c. Bias of total cholesterol proportion at risk from HRS 2006 by 2010 eligibility state

Total Chol. >= 240mg/dL	**Proportion (SE)**	**Bias (SE)**	**Relative bias**
Full sample	0.186 (0.007)		
Alive in 2010	0.192 (0.008)	**0.007 (0.002)*** **	3.5%
Respondent in 2010	0.192 (0.008)	0.000 (0.002)	-0.1%
Self-Respondent in 2010	0.192 (0.008)	-0.001 (0.001)	-0.3%
BioElig-Respondent in 2010	0.192 (0.008)	0.000 (0.001)	0.2%
Consent 2010	0.195 (0.009)	0.003 (0.002)	1.6%
Operational eligibility *(Respondent vs BioElig-Respondent)*		0.000 (0.002)	-0.1%
Total non-observation *(Alive vs Consent)*		0.003 (0.003)	1.4%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

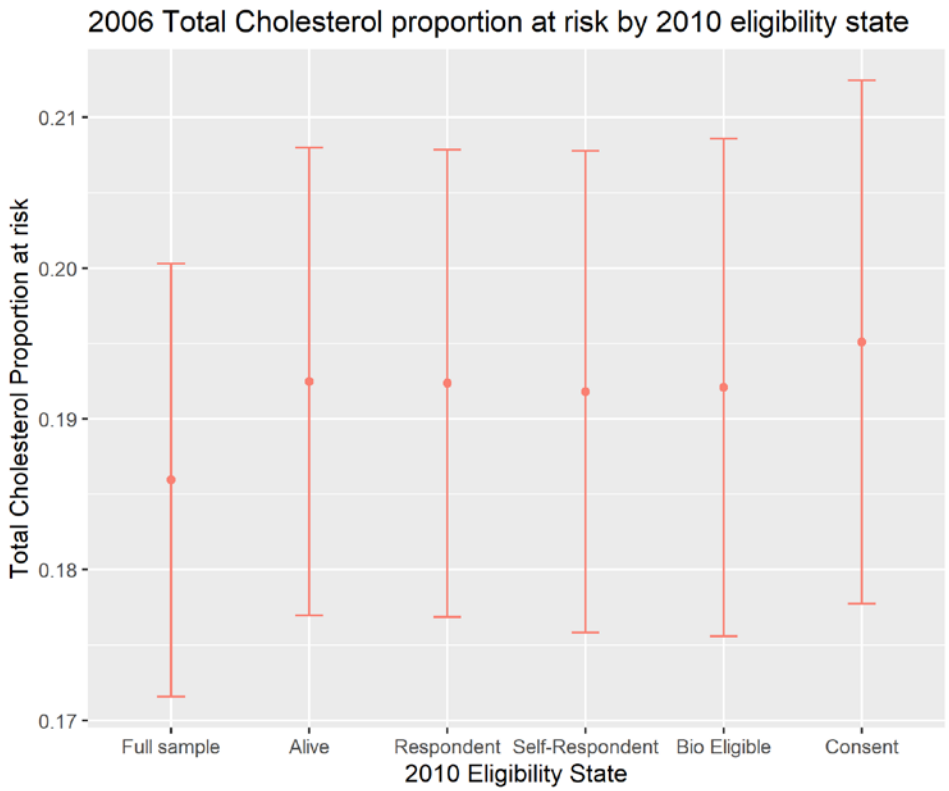

Figure 2-9c. Total cholesterol proportion at risk from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-11d. Bias of CRP proportion at risk from HRS 2006 by 2010 eligibility state

CRP >= 3.0 ug/mL	**Proportion (SE)**	**Bias (SE)**	**Relative bias**
Full sample	0.381 (0.009)		
Alive in 2010	0.368 (0.010)	**-0.013 (0.003)******	-3.3%
Respondent in 2010	0.366 (0.009)	-0.002 (0.002)	-0.4%
Self-Respondent in 2010	0.365 (0.009)	-0.001 (0.001)	-0.4%
BioElig-Respondent in 2010	0.364 (0.010)	-0.001 (0.002)	-0.2%
Consent 2010	0.361 (0.010)	-0.003 (0.003)	-0.9%
Operational eligibility *(Respondent vs BioElig-Respondent)*		-0.002 (0.002)	-0.6%
Total non-observation *(Alive vs Consent)*		-0.007 (0.004)	-1.9%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

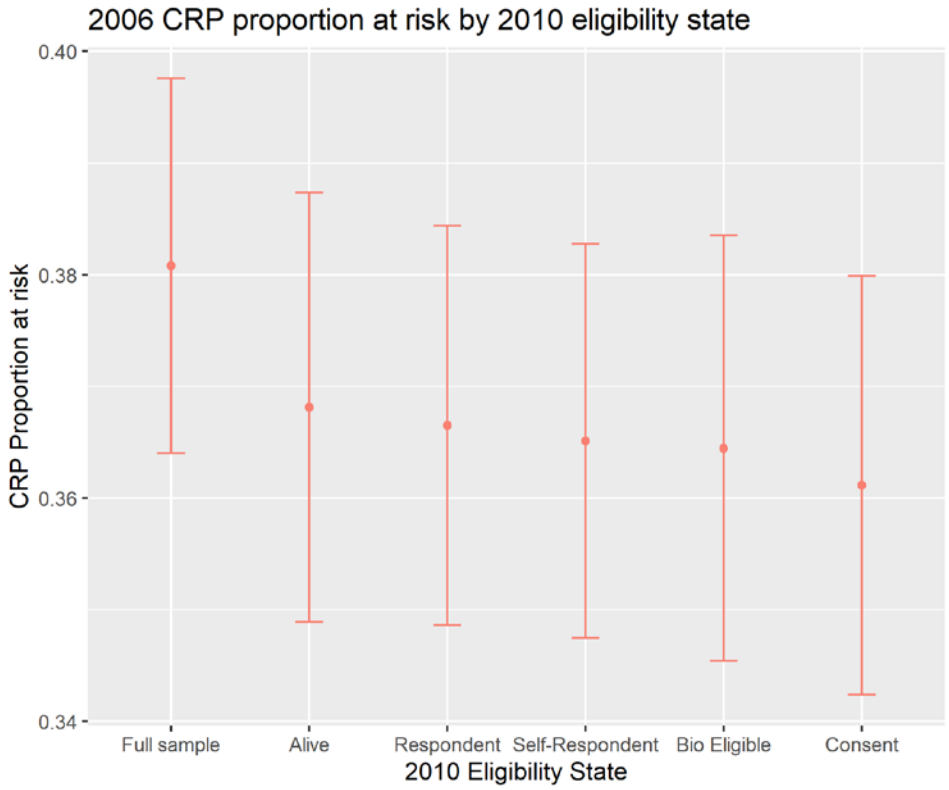

Figure 2-9d. CRP proportion at risk from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

Table 2-11e. Bias of Cystatin C proportion at risk from HRS 2006 by 2010 eligibility state

Cystatin C > 1.55mg/L	**Proportion (SE)**	**Bias (SE)**	**Relative bias**
Full sample	0.091 (0.005)		
Alive in 2010	0.068 (0.004)	**-0.023 (0.002)******	-25.4%
Respondent in 2010	0.069 (0.005)	0.001 (0.001)	1.2%
Self-Respondent in 2010	0.063 (0.004)	-0.006 (0.002)***	-8.2%
BioElig-Respondent in 2010	0.064 (0.004)	0.001 (0.001)	1.7%
Consent 2010	0.061 (0.004)	-0.003 (0.001)*	-5.2%
Operational eligibility *(Respondent vs BioElig-Respondent)*		-0.005 (0.002)*	-6.6%
Total non-observation *(Alive vs Consent)*		-0.007 (0.002)**	-10.4%

Note. Bonferroni correction suggests a significance level of 0.000714 and are **bolded**.
"BioElig-Respondent" refers to biomeasure eligible.
* p < 0.05; ** p < 0.01; *** p < 0.001; **** p < 0.0001.

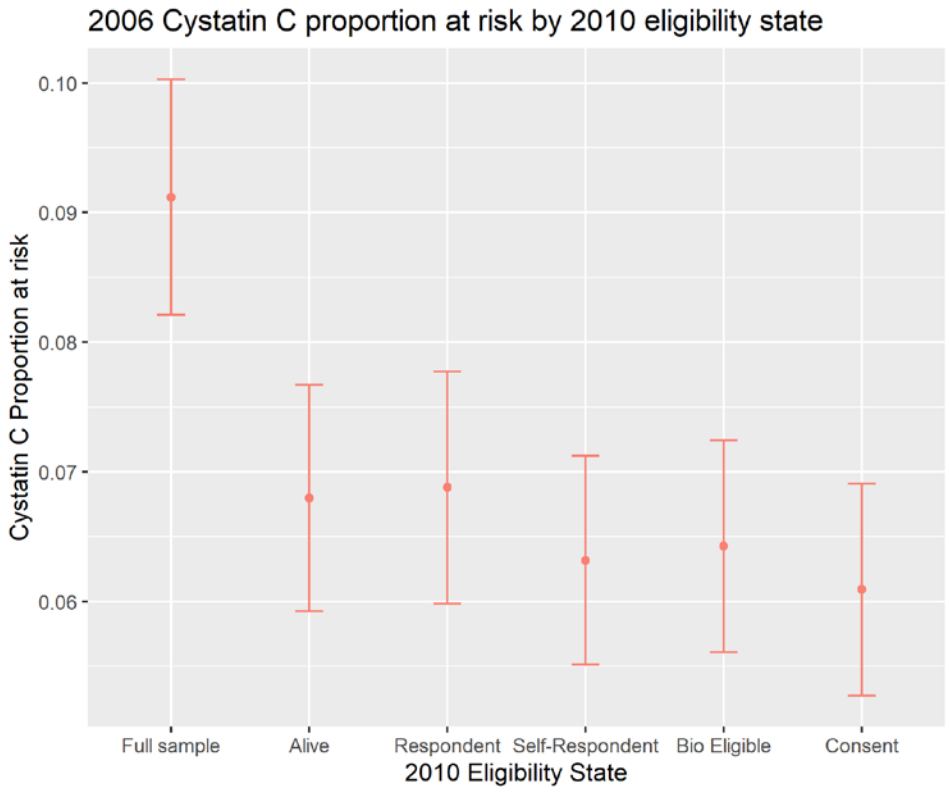

Figure 2-9e. Cystatin C proportion at risk from HRS 2006 by 2010 eligibility state with 95% confidence interval. "Bio Eligible" refers to biomeasure eligible.

2.5.4 Subgroup impact

In order to ensure that the bias analyses were not impacted by subgroups (e.g., Simpson, 1951; Blyth, 1972), regression models were run to test for any possible interaction between major demographic and health characteristics and the eligibility states on the five DBS biomarkers. A total of eight indicators were tested including age (50-74 vs. 75+), gender (male vs. female), race (non-Hispanic black vs. other), self-rated health (fair/poor vs. other), diabetes, chronic conditions (0-1 vs. 2+), mild vigorous activity (hardly/never vs. other), and functional limitations (0-4 vs. 5+). Crossing the five subgroup comparisons, the five biomeasures, and eight indicators, a total of 200 models were estimated.

Of the 200 models analyzed, only 19 interactions were found to be significant. Of those 19 significant interactions, 12 were associated with the transition from the full sample to the surviving sample and 9 were associated with Cystatin C. Using a Bonferroni adjustment for the multiple models ($\alpha = 0.00025$), only the full to living sample transitions are significant and they are all related to Cystatin C.

Overall, there is little statistical evidence to suggest that subsets of respondents have differential rates of change in the five biomeasures as the sample reduces from each successive source of non-observation. However, there are large, significant differences in the biomeasure values for the subsets, which are to be expected given the strong relationship between these health measures and the biomeasure outcomes.

2.5.5 Violation of assumptions

One strong assumption in these analyses is the consistency between the 2006 and 2010 biomarker outcomes. Observing cases where a biomarker value was collected in both 2006 and 2010, there is evidence to suggest that the biomarker values do change from wave to wave on average as the mean difference is statistically different from zero (see Table 2-12). However, the mean and median differences are practically zero and may not be substantively different based on the mean to range ratio. Some of these differences are suspect, since the minimum and maximum differences exceed the observed range of values for a particular year. For example, the absolute value of the minimum and maximum differences in HbA1c (8.73 and 8.68) exceed the range of the 2006 sample (10.18 – 4.65 = 5.53). Given the large variability and questionable extreme values, it is possible that many differences may be in fact due to differential quality in wave to wave blood sample as well as differences in collection, storage, and laboratories used.

Table 2-12. Difference in 2010 and 2006 DBS biomarker values for respondents who provided biomeasures in both waves

	Mean	$H_0: \bar{y} = 0$	Min	Q1	Median	Q3	Max	Range	Mean/Range
HbA1c (%)	0.07	****	-8.73	-0.28	0.06	0.40	8.68	17.41	0.38%
HDL (mg/dL)	-1.05	***	-73.79	-11.42	-0.21	9.87	71.56	145.35	0.72%
Total cholesterol (mg/dL)	-11.14	****	-169.55	-42.72	-10.34	21.24	199.18	368.73	3.02%
CRP (ug/mL)	-0.46	**	-217.24	-1.41	-0.16	0.73	182.25	399.49	0.11%
Cystatin C (mg/L)	0.12	****	-2.15	-0.10	0.08	0.27	5.25	7.40	1.59%

Note. Reporting $y_{2010} - y_{2006}$. NHANES adjusted biomarker values are reported. DBS = dried blood spot.

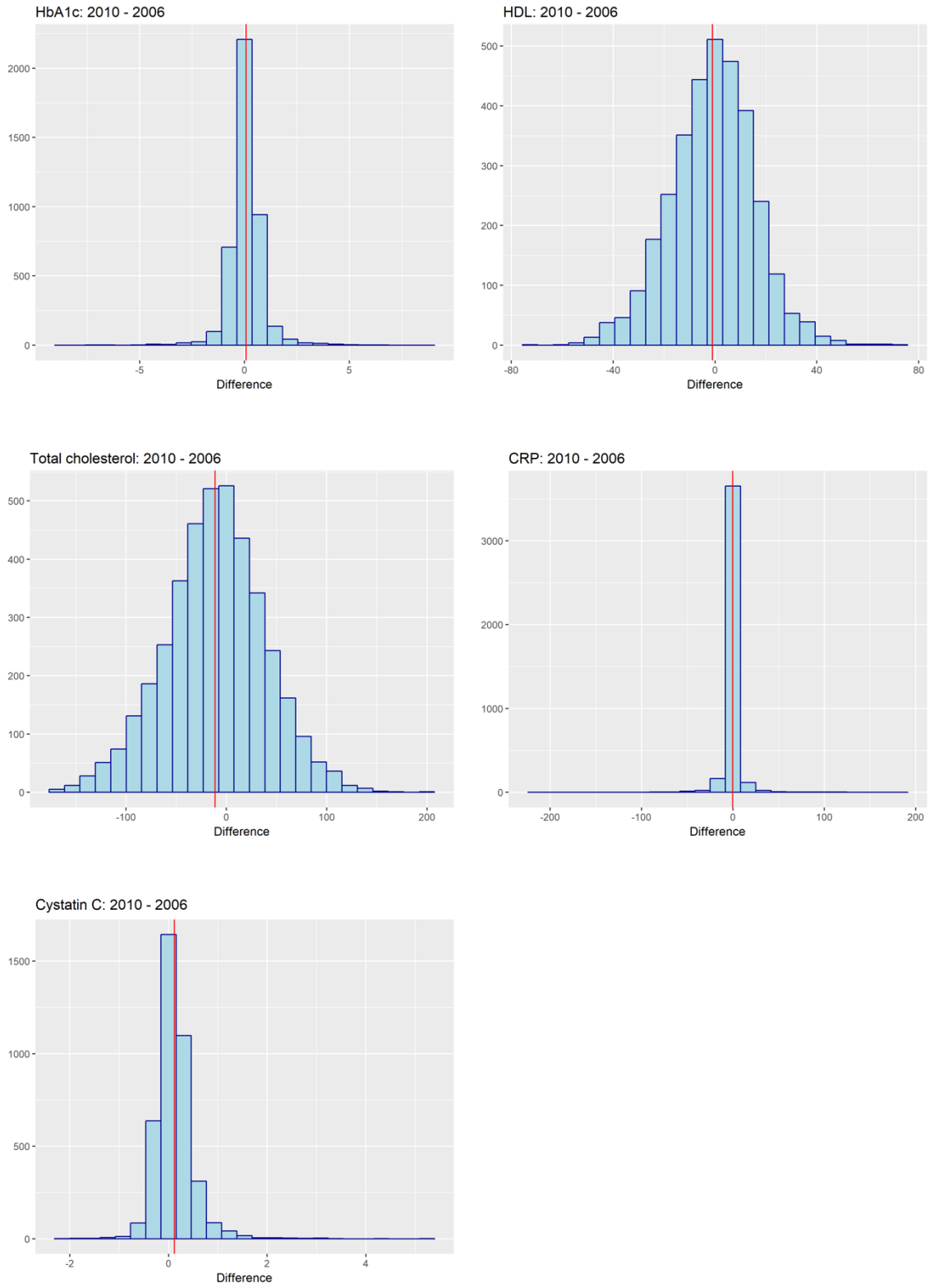

Figure 2-10. Difference in 2006 and 2010 DBS biomarker values (NHANES adjusted) for respondents who provided biomeasures in both waves. Red line is mean difference.

2.6 Discussion

The five eligibility state outcomes had similar covariates. Cognitive ability was a significant predictor in four of the five continuation ratio models with higher cognitive scores predicting an increased likelihood of being in the successive eligibility state. Change in cognitive ability also was a significant predictor in the three-wave models. Other health measures like self-rated health, physical activity (baseline and change), and number of chronic conditions appeared as significant predictors in at least two sub-models. Many of these factors are consistent with the literature reviewed previously. Regarding sociodemographic characteristics, age and race/ethnicity were significant predictors across many of the models while weekly church attendance appeared in the two-wave models and education appeared in the three-wave models. Baseline and changing household characteristics had little association with these models though they historically have a relationship with survey response. In general, these similar effects were in a consistent direction across non-observation states suggesting a cumulative biasing effect of these predictors on the final consenting sample in support of the first research question. The magnitude of those effects varied across the five models supported by the significant parallel slope tests rejecting the parallel slopes assumption for those associated variables. However, the majority of variables included in these models failed to reject the parallel slopes assumption. While a constrained partial continuation ratio logit model could be considered, many of these variables were non-significant predictors meaning that sub-models may contain too many uninformative variables.

When previous sources of non-observation were included in the predictive models, they were often predictors of their future eligibility state. Previous non-observation source indicators accounted for the significant respondent demographic and health predictors, often reducing

substantially coefficients in the three-wave models. Age and cognition often remained the only significant predictors in the expanded models. These findings emphasize the predictive power of one's previous eligibility state positively answering the second research question. However, trying to utilize the sources of non-observation in predictive models does create complications in model interpretation given the endogeneity of these non-observation sources with sociodemographic and health factors. The previous eligibility state absorbs much of the explanatory power of single wave predictors or, rather, explains their contributions to later wave eligibility. Individual models for each eligibility state could be an option to reduce challenges with interpretability, but would prove less effective with small sample sizes.

A weakness of the continuation ratio logit model is that the models cannot be viewed as causal, but rather only as descriptive due to reducing heterogeneity from eligibility outcome to eligibility outcome (Fullerton & Xu, 2016). In order to account for potential selection bias, one could alternately use sample selection models (Heckman, 1979). Heckman's original model only focuses on a single selection mechanism, though others have examined the use of two or three selection mechanisms (see Catsiapis & Robinson, 1982; Ham, 1982; Fishe, Trost, & Lurie, 1981; Maddala, 1986). However, the exploration and benefit of using such an approach is unknown, especially when extended to five selection mechanisms, and could be considered for future work.

When considering the specific biomarker outcomes, there was very little change in the means and proportions at risk for the five DBS measures after accounting for changes due to the loss of deceased sample. In reference to the third research question, these results suggest that there is minimal bias introduced for population estimates due to nonresponse, operational eligibility, and non-consent. Two notable exceptions were observed: 1) the living sample to survey respondent transition for the proportion at risk for diabetes and 2) the difference in means

for the respondent to non-nursing home, self-respondent transition for Cystatin C. While the former's bias did not seem to have a lasting impact on the proportion at risk following the effects of the other sources of non-observation, the latter's effect was still present and significant following the eligibility and non-consent exclusions. However, the relative bias is quite small and may not be substantively meaningful. In relation to the fourth and final research question exploring the impact of operational eligibility, only Cystatin C saw a larger bias due to ineligibility, primarily due to removing respondents who entered a nursing home or needed a proxy respondent. These differences are not large relative to the full sample before accounting for mortality, which for Cystatin C was less than a one percent relative change in the mean. However, operational eligibility accounted for more of the total bias than consent for Cystatin C

These are reassuring findings considering the amount of loss of sample across waves in a longitudinal study due to attrition, operational eligibility, and non-consent. However, a limitation in this analysis is related to using historical biomarker values which do not account for potentially large individual changes due to changes in health which could impact any, if not all, of the five biomeasure outcomes considered here. It is difficult to disentangle natural human variation from actual improvements or declines in physical health and differences in biomeasure collection procedures across waves.

The overwhelming difference in estimates from the full sample to the living sample in the biomarker means and proportions makes sense given the effects associated with a majority of the included health indicators. Each biomarker is related in some way to increased comorbidities, functional limitations, and poor quality of life, which are predictors of mortality. The statistically significant shift in the means and proportions estimated for HbA1c from the living to the 2010 respondent sample seems to directly correspond to the significant odds ratios for the chronic

conditions index in both the two-wave and three-wave models for the response sub-model as diabetes is one of the included chronic conditions. In addition, the significant drop in Cystatin C when excluding nursing home and proxy respondents shows the linkage of healthy aging and declining cognition, significantly observed in both the two-wave and three-wave models, is associated with increased levels of Cystatin C (Sarnak et al., 2008; Yaffe et al., 2008).

Something not examined in this paper is the impact of ineligible respondents becoming eligible in a future wave and the recruitment of new cohorts. To streamline the analysis, biomeasure ineligible cases in 2006 were excluded and not reintroduced into the analytic sample. While large shifts occurred due to mortality and (to a smaller extent) other eligibility transitions, the addition of new cohorts may serve to counterbalance some of these changes over time.

One source of non-observation not discussed in this chapter is non-observation due to failed collection or an insufficient sample. Respondents may not have been able to provide sufficient blood for all six spaces on the blood spot card resulting in only a subset of biomarkers. Alternatively, specimens could have been improperly stored during transit and thus unable to be processed. This form of non-observation is ideally small (see Table 2-3), but may also result in sporadic patterns of item missingness of biomeasures as opposed to the more monotonic missingness evaluated in this chapter. Incorporating this form of non-observation and evaluating its (small) contribution to bias is a step for future consideration.

The logic applied to divide operational eligibility into health and non-health reasons could also be applied to non-consent and could be useful in future explorations. Choosing not to participate in biomeasure collection because of general resistance to the survey or resistance to more sensitive requests could stem from very different reasoning than choosing not to participate

due to a health concern. HRS paradata does allow for these reasons to be distinguished and explored. This concept is briefly evaluated in Appendix B and expanded on in Chapter 3.

The relative absence of large significant biases in the biomarkers is potentially reassuring when considering future steps to account or correct for this loss in biomeasure sample for longitudinal analyses. Imputation of biomarkers could prove beneficial to retain sample size of responding cases especially in the later sources of non-observation where there were fewer predictors of these eligibility states.

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CHAPTER 3

Factors Influencing Recurrent Consent Requests for Biomeasures in a Longitudinal Survey

3.1 Introduction

Due to the invasive nature of biomeasure collection, human subjects review requires respondents provide written consent for collection of biomeasures in addition to general consent to participate in the survey. Consent to biomeasure collection is the most direct form of potential non-observation because the respondent is actively choosing to participate (or not). There are a number of factors that appear to affect a respondent's decision to consent to biomeasure collection. The research literature on consent to biomeasure collection by non-medically trained interviewers is still small and has only focused on consent in cross-sectional or single wave collection. For longitudinal panel surveys, the effect of recurrent consent requests on consent rates and patterns of missingness has not been explored.

The purpose of this study is to investigate informative or selective factors that may be addressed by interventions to improve consent during recurrent biomeasure requests or used as additional adjustments in post-processing. Section 3.2 reviews the known predictors associated with single wave biomeasure consent while Section 3.3 considers potential predictors of longitudinal consent. Section 3.4 outlines the study goals and research questions, while Sections 3.5 and 3.6 describe the methods and results of the analyses, respectively. Finally, Section 3.7 will discuss the findings and implications of the analyses.

3.2 Predictors of single wave biomeasure consent

The primary factors associated with single wave biomeasure consent in population-based longitudinal surveys, most of which use interviewer administered collection, are sociodemographic characteristics, health status, survey resistance, and the effect of interviewers on biomeasure consent.

3.2.1 Sociodemographic characteristics

The literature does not show a consistent effect of respondent age, gender, race, or education on biomeasure consent. One study of older adults in Germany found that the older the respondent the more likely they were to participate in a dried blood spot (DBS) assay (Korbmacher, 2014), while another study of older women asked to provide a vaginal swab experienced lower consent as the age of the female participants increased (Lindau et al., 2009). This latter example may be more indicative of the increasingly sensitive nature or the perceived needlessness of the request given advancing age.

Gender has not generally been associated with differential rates of consent to biomeasures (Gavrilova and Lindau, 2009; Sakshaug et al., 2010; Korbmacher, 2014) though some studies have found females less likely to provide saliva samples (McClain, Lee, Faul, & Barba, 2015; Dykema et al., 2017).

Blacks or African Americans have been found to be less likely to consent to biomeasure collection (Gavrilova and Lindau, 2009) though this is not always a statistically significant finding (Sakshaug et al., 2010). Research showing that deep-rooted distrust of medical research and scientific studies by blacks generally supports this finding (e.g., Gamble, 1997; Corbie-Smith, Thomas, Williams, & Moody-Avers, 1999; Corbie-Smith, Thomas, & George, 2002).

Studies that examined those who attended some college versus high school or less found no measurable effect on consent (Gavrilova & Lindau, 2009; Sakshaug et al., 2010) while a study that examined college graduates versus lower education levels did find a higher consent rate among college graduates (Dykema et al., 2017). The earlier study of older females that asked for a vaginal swab found that female participants without a high school diploma were significantly less likely to consent (Lindau et al., 2009).

One study where multiple household members could be eligible to participate in the study and provide biomeasures found that the presence of another eligible household member increased the chance of obtaining consent (Sakshaug et al., 2010). As these other household members could be a spouse, an adult child, or parent, the social expectation of another household member participating or earning the support of an intermediary may lead to another household member participating in the study. Making a gatekeeper or intermediary an ally instead of a hindrance can help facilitate a collaborative research environment as opposed to inhibiting research activities (McNeely & Clements, 1994; Porter & Lanes, 2000).

Dykema and colleagues' (2017) review of the relevant epidemiological literature suggested more religious persons – as measured by regular church attendance and belief in the Bible – would be less likely to consent to biomeasure collection. However, after controlling for sociodemographic, health, and other factors, results revealed weekly church attendance is associated with higher rates of consent than those who did not attend or attended infrequently. The authors posited that church attendance was capturing some facet of social participation (Dykema et al., 2017). Sakshaug et al. (2010) saw a similar effect size for those who attended religious services at least weekly.

3.2.2 Respondent health

Given the collection of biomeasures is directly related to the respondent's health at the time of collection, a number of physical health indicators are correlates of consent. Self-rated health is not a significant predictor of consent especially if indicators of specific health conditions are also considered (Gavrilova and Lindau, 2009; Lindau et al., 2009; Sakshaug et al., 2010; Dykema et al., 2017). Diabetic respondents are significantly more likely to consent to collection, especially DBS, perhaps because these respondents observe and manage blood glucose levels regularly through the use of blood lancets (Sakshaug et al., 2010; Korbmacher, 2014). Other chronic conditions (i.e., comorbidities) like cancer and heart disease have not been shown to be individually or collectively (e.g., comorbidity index) associated with biomeasure consent (Lindau et al., 2009; Sakshaug et al., 2010; Dykema et al., 2017). The number of functional limitations (areas of physical functioning where one needs assistance) that a respondent currently is experiencing as well as their difficulty with performing daily activities correspond to lower rates of biomeasure consent (Sakshaug et al., 2010; Korbmacher, 2014), though this effect is not always statistically significant (Dykema et al., 2017). Having had a recent physical exam or visit to the doctor corresponds with higher rates of biomeasure consent (Sakshaug et al., 2010; Dykema et al., 2017).

Cognition, as a measure of one's ability to acquire and recall knowledge, is of interest to survey researchers but has rarely been examined in the context of survey-related tasks. McClain et al. (2015) used word recall as a measure of cognition and found that higher word recall scores resulted in greater rates of consent to physical measurements (e.g., blood pressure, height, weight), but not to DBS or a saliva catch. Dykema et al. (2017) used adolescent IQ scores as a predictor of consent for a sample of older respondents and found that those with lower cognitive

ability were significantly less likely to provide consent for a saliva sample years later. These findings suggest that as cognition declines (regardless of the specific measure used) so does the likelihood of consenting to biomeasure collection.

3.2.3 Survey resistance

Because biomeasure collection is occurring within a survey, factors related to the overall survey experience may have an impact on a respondent's consent decision. Paradata collected from interviewers during the survey process gives researchers an idea of the respondent's resistance to participate both prior to and during the survey interview (Kreuter, 2013). Measures of survey resistance can include indicators such as contact difficulty (e.g., the number of contact attempts), respondent inquiries about the content or length of the survey, respondent enjoyment or cooperation, or refusal for sensitive items (e.g., household income). While interviewer-observed paradata can be a good predictor of survey participation and used to design a successful intervention strategy (Sinibaldi & Eckman, 2015; Plewis, Calderwood, & Mostafa, 2017), such paradata are not available for all sample units and are not sufficiently predictive to be used for effective nonresponse adjustment for survey weights, including biomeasure-specific weights (Biemer, Chen, & Wang, 2013; Olson, 2013; Sinibaldi, Trappman, & Kreuter, 2014; West, Kreuter, & Trappmann, 2014).

By using data from the most recent wave of data collection, both Sakshaug et al. (2010) and Dykema et al. (2017) found that those least likely to consent to biomeasures had a higher number of contact attempts for both the current and previous waves of data collection suggesting greater levels of general survey resistance. Respondents who voiced questions or concerns regarding confidentiality and the length of the interview in the previous wave were also much

less likely to consent to biomeasures. Interviewer assessments of a respondent's level of cooperation and enjoyment in the previous wave were also associated with consent to biomeasures (Sakshaug et al., 2010). Dykema et al. (2017) found that those who refused to participate in the previous wave as well as those who did not complete the last wave were both less likely to consent to a saliva collection.

Korbmacher (2014) found that respondents who failed to report their income had half the odds of consenting to a DBS assay compared to those who did report income.

3.2.4 Interviewer effects

The interviewer can also play a role in a respondent's consent decision. When considering biomeasure collection, the respondent's assessment of the interviewer's competence for collecting biomeasures might influence the decision to consent. Unfortunately, no direct measures of a respondent's perception of the interviewer's competence are routinely collected. Factors such as the interviewer's age, education, race, and interviewing experience can serve as potential correlates of perceived experience and capability. One study found that respondents with older interviewers had significantly higher consent rates than respondents with younger interviewers, while respondents with interviewers who had medium or high levels of education had over six times the odds of obtaining blood spot consent than respondents whose interviewer had lower education (Korbmacher, 2014). On the other hand, Sakshaug et al. (2010) did not find evidence of a significant interviewer age effect on a respondent's consent to biomeasures, and only a weak relationship between interviewer education and consent. Respondents whose interviewer was black were less likely to consent than those who had a white interviewer in the 2006 wave of the HRS (Sakshaug et al., 2010), but improved training reduced the effect in the

subsequent wave of collection (Ofstedal et al., 2010). In one study, respondents who were interviewed by a new hire displayed no difference in consent from respondents who were interviewed by more experienced interviewers (Sakshaug et al., 2010). A second study found that was a negative effect of years of interviewing experience on biomeasure consent rates (Korbmacher, 2014). Sakshaug et al. (2010) and Korbmacher (2014) both found significant amounts of interviewer variance still unexplained in their final biomeasure consent models after controlling for interviewer attributes.

3.3 Potential predictors of longitudinal biomeasure consent

3.3.1 Changes in health

Given the natural passage of time between waves in a panel study, there are likely to be changes in respondents' health that cause them to make changes in their lifestyle. For example, increased risk for type 2 diabetes due to impaired glucose tolerance (Tuomilehto et al., 2001) or a diagnosis of cancer (Demark-Wahnefried, Aziz, Rowland, & Pinto, 2005) could lead to changes in lifestyle. A recent diagnosis of a chronic disease or a sudden decrease in one's ability to perform daily tasks may cause additional reluctance when presented with the request to collect various biomeasures. For example, a respondent who was recently diagnosed with diabetes may be more likely to consent to a DBS assay since they have started performing regular blood glucose tests, while another respondent who has become unable to perform many basic household tasks without aid may be less likely to consent to physical measurements. Depending on the nature of the health change, one might expect either a positive or negative impact on the likelihood of consent.

3.3.2 Factors influencing panel attrition and reengagement

In the context of recurrent consent requests in longitudinal studies, a new perspective is needed. With the exception of Chapter 2 of this dissertation, no research to date has investigated the similarities between biomeasure consent and other sources of panel attrition. Biomeasure collection can be a time consuming and uncomfortable experience for respondents within an already long interview session. Factors associated with panel attrition may also be associated with failure to consent to biomeasure collection in a future wave. Thus, unit nonresponse may be a competing risk with consent (Loosveldt, Pickery, & Billiet, 2002; Mason, Lesser, & Traugott, 2003; Yan & Curtin, 2010).

Consent to a recurrent within-survey request may be closely tied to panel engagement itself. A respondent who is showing signs of resistance or panel fatigue may not choose to completely refuse the interview request, but instead turn down a module of the survey (e.g., biomeasure collection). Failure to consent to biomeasure collection at an earlier wave could correlate with future attrition, viewing consent as another measure of survey resistance (Loosveldt, Pickery, & Billiet, 2002). Factors associated with multiple mechanisms of survey attrition are might inform a model of recurrent biomeasure collection requests.

Watson and Wooden (2009) provide a detailed overview of factors that are associated with panel attrition. With the goal of identifying correlates that can be applied to recurrent biomeasure consent, factors related to contact are not discussed here. In addition to the standard respondent characteristics, many of the factors Watson and Wooden (2009) discussed can be summarized into two main categories discussed previously: interview resistance and interviewer effects.

Respondents who enjoyed a survey interview are much less likely to dropout in subsequent waves (Laurie et al., 1999; Olsen, 2005; etc.). Respondents who refuse to answer survey items, especially more sensitive items like income, are much more likely to drop out in later waves of the survey (Laurie et al., 1999; Loosveldt et al., 2002; etc.). Both of these findings are consistent with what was discussed previously as factors for consent to biomeasure collection. Respondents who provide a straight refusal to a survey request as opposed to indirect reasons are significantly less likely to reengage in the study at a later wave (Watson & Wooden, 2014). Applying this finding to recurrent biomeasure consent, a reasonable hypothesis is that those who did not provide a straight refusal at the previous consent request are more likely to provide biomeasure consent in future interviews.

For face-to-face surveys, interviewer continuity has been found to have mixed results on attrition, with some studies supporting a positive retention effect (i.e., panelist responds, does not drop out of the study), while others observe no effect at all (Laurie et al., 1999; Campanelli & O'Muicheartaigh, 2002; Olsen, 2005; Lynn et al., 2014; etc.). Watson and Wooden (2014) looked at re-engagement in four different longitudinal studies and found that interviewer continuity lowered the chance of re-engaging a respondent if they had not responded in the previous wave. Such an effect could suggest that respondent-interviewer rapport is poor and changing the interviewer would result in increased chances of subsequent panel participation. This finding could be applied to biomeasure collection suggesting that interviewer continuity may hurt the chances of converting a previously non-consenting respondent.

3.3.3 Previous consent

A strong predictor of future consent to a survey request (e.g. biomeasure) is previous consent to the same request. In addition to prediction of future behavior, previous consent is an excellent candidate when considering where to apply a design intervention to try to help improve future consent (for an example in the data linkage consent literature, see Sala, Knies, & Burton, 2014). However, when trying to understand the mechanisms influencing the current consent decision, previous consent is a poor explanatory variable since factors like sociodemographics and health predict both previous as well as future consent (see Figure 3-1). In other words, previous consent absorbs most of the explanatory power of single wave predictors or explains their contributions to later wave consent. Second, previous consent is likely to be related to various survey resistance indicators for that wave. For example, when a respondent refuses to provide consent for biomeasures the interviewer may label the respondent as less cooperative in their post-interview debrief. Modeling future consent using both previous consent and paradata related to resistance as predictors is likely to generate findings that are difficult to interpret. Alternatively, one could condition the analysis on previous consent status, the approach followed in this chapter.

As discussed in Chapter 2 regarding operational eligibility, the reason a classification of non-observation due to ineligibility was helpful in distinguishing different types of respondents. Consent to biomeasures is quite similar. The choice to not participate in biomeasure collection because of general resistance to surveys or resistance to sensitive requests could stem from very

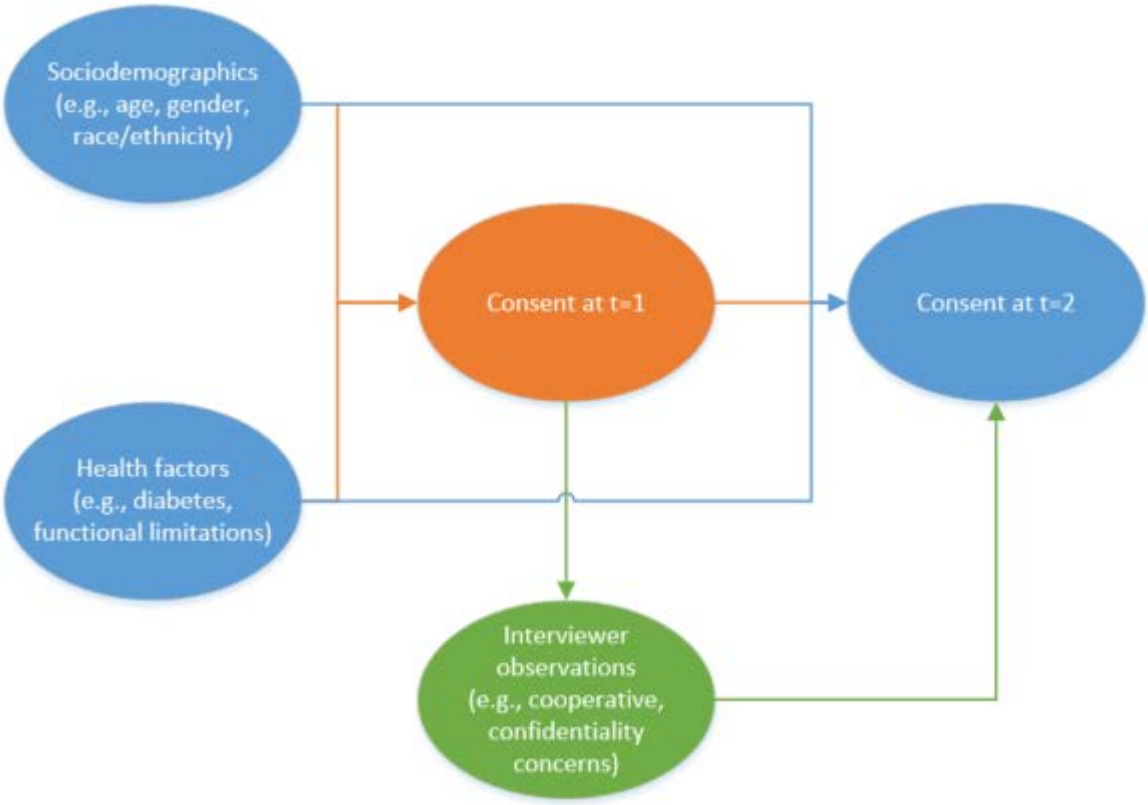

Figure 3-1. Sample diagram of the endogeneity problem of previous consent in models of recurrent consent. Orange item and lines show how consent at time 1 is endogenous to consent at time 2. Green item and lines shows how consent influences interviewer observations which, in turn, impact consent at time 2.

different reasons than those choosing not to participate due to health concerns. For non-consenters, including the reason for non-consent could help to disentangle different types of respondents helping in prediction.

3.4 Research questions

This paper considers four fundamental questions to understand recurrent biomeasure consent in the context of operational considerations, causal relationships, and post-survey adjustment:

(1) What are the similarities and differences in factors that predict future biomeasure consent for previous biomeasure consenters and non-consenters?

(2) Do changes in a respondent's physical and cognitive health effect a respondent's likelihood to participate in biomeasure collection?

(3) How does interviewer continuity affect the likelihood of biomeasure consent at the second request? Does the effect of interviewer continuity differ depending on whether the respondent originally consented or not?

(4) Does a respondent's reason for refusing to consent in a previous wave predict consent at a later wave?

3.5 Methods

3.5.1 Data

The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the Institute for Social Research (ISR) at the University of Michigan. HRS is a longitudinal survey of adults over the age of 50 living in the United States that collects various measures related to health, medical care, employment, income, and cognition. HRS began in 1992 with a cohort of preretirement-aged individuals born between 1931 and 1941. New birth cohorts are enrolled every 6 years (e.g., 1998, 2004, 2010) to refresh the sample at the younger ages. The HRS conducts about 20,000 interviews every 2 years with response rates between 65 and 85 percent in the baseline wave and between 85 and 95 percent in follow-up waves.

In 2006, HRS began alternating respondents between face-to-face and telephone interviews, with a random half sample of the full panel being assigned to each mode. Every two

years each half-sample switches to the other mode[5]. In face-to-face interviews, noninstitutionalized, non-proxy respondents are asked to provide measures of physical functioning (i.e., blood pressure, hand grip strength, a walking test, height, weight, etc.), a one-time saliva sample (for DNA extraction and storage), and a dried blood spot assay (for measuring Hemoglobin A1c, cholesterol, and other biochemical measures). Saliva and blood samples have different collection, storage, and analysis procedures. Respondents are given three consent forms for each of the biomeasure components. HRS refers to this face-to-face interview with biomeasure collection and self-administered questionnaire on psychosocial topics as the enhanced face-to-face (E-FTF) interview. As the request for the saliva sample was not repeated over E-FTF interviews (i.e., saliva was only collected once per respondent), only the physical measurements (PM) and dried blood spot (DBS) samples are explored here.

This study focuses on age-eligible respondents (50 years and older) who were eligible to provide biomeasures in two successive E-FTF waves: the HRS biomeasure eligible respondents in 2006 and 2010 (one half-sample) as well as 2008 and 2012 (a second half-sample; see Figure 3-2). There were initially 7,954 eligible respondents in the 2006 E-FTF sample and 6,991 in 2008. Approximately 12 percent of these respondents across both half samples died before the corresponding E-FTF interview four years later. Again, across half samples about 6 percent of the surviving sample members refused to respond to the second E-FTF wave, while an additional 9 percent were ineligible for biomeasure collection. Further, E-FTF respondents were considered ineligible for biomeasure collection if they currently lived in a nursing home, had a proxy complete the interview on their behalf, preferred to be interviewed by telephone, or if they broke

[5] Respondents over the age of 80 alternate between FTF and E-FTF interviews unless they specifically request a telephone interview.

off the interview before the physical measures and biomarker collection. Deletions for mortality, attrition, and ineligibility of various types leaves about 75 percent of the original samples (5,927 for the 2006 half-sample and 5,193 for 2008) as eligible for biomeasure collection in the second E-FTF wave.

Biomeasure eligible participants are analyzed here, with two removals: 13 HRS 2010 and 9 HRS 2012 cases were excluded due to missing interviewer ID needed for determining interviewer continuity status. Three interviewers refused consent to using their sociodemographic data for research purposes, which led to a further loss of 131 HRS 2006 and 118 HRS 2008 cases. The final analytic sample size consists of 5,783 HRS 2006 and 5,066 HRS 2008 cases.

In order to draw broader conclusions on recurrent consent, the two half-samples are combined for this analysis for a total sample size of 10,849. In order to combine the two half-samples, variables were matched corresponding to first E-FTF wave, or Wave 1 (W1). The most recent telephone[6] wave (2008 for the 2006 E-FTF half-sample and 2010 for the 2008 E-FTF half-sample) is denoted as Wave 2 (W2). The follow-up E-FTF wave (2010 and 2012, respectively) is denoted as Wave 3 (W3). A visual depiction of this half-sample matching is shown in Figure 3-2.

Two independent sets of models were explored for W1 consenters and W1 non-consenters. This is to help disentangle the confounding with respondent predictors related to measures of survey resistance and biomeasure consent in W1. The combined 2006 and 2008 E-FTF half-samples results in 10,268 PM consenters and 581 PM non-consenters, 9,424 DBS consenters and 1,425 DBS non-consenters (see Table 3-1).

[6] Not all respondents participate via telephone in W2. See footnote 5.

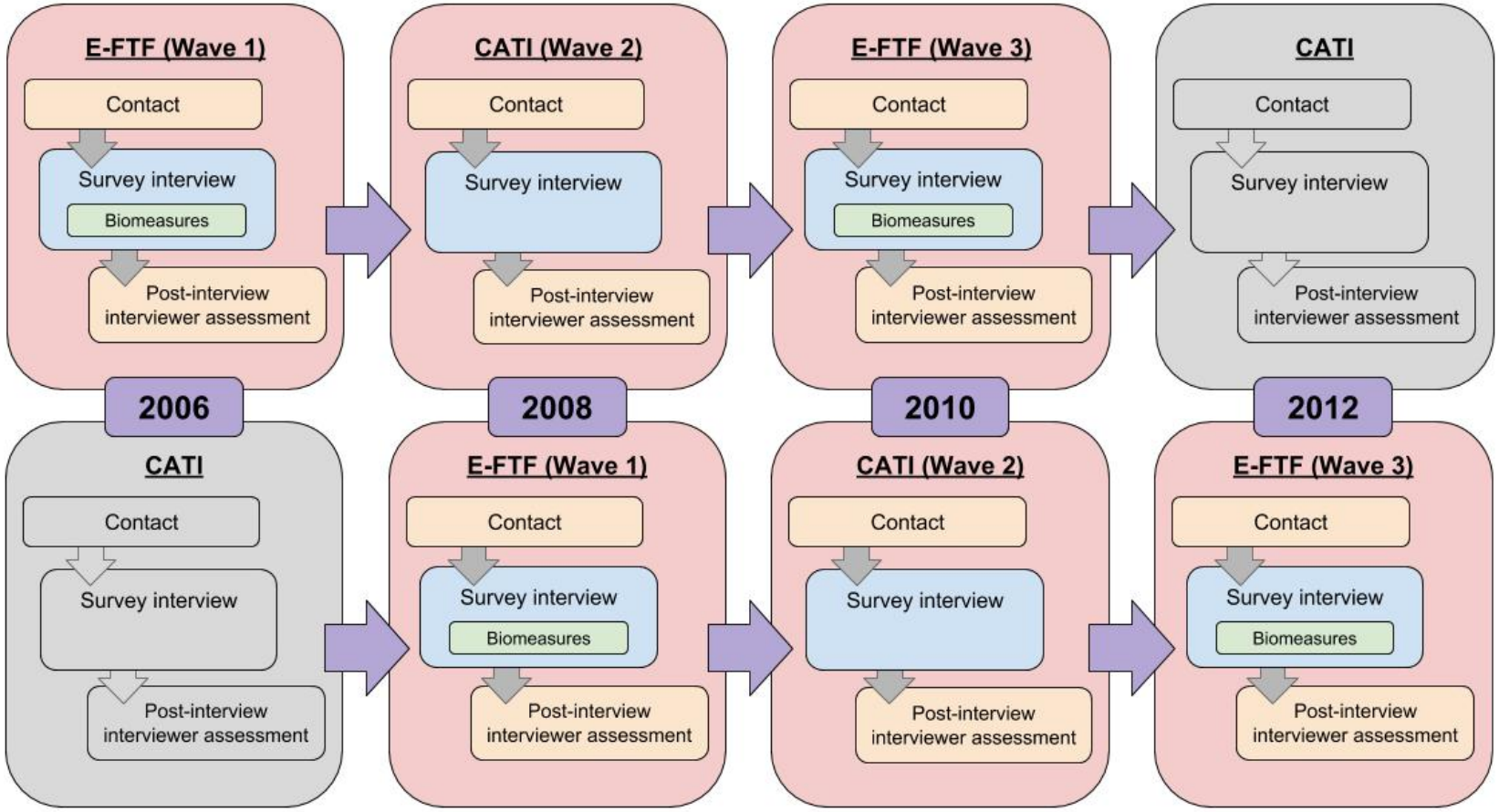

Figure 3-2. Wave matching of the Health and Retirement Study half-samples for combined analysis. Each row represents a random half-sample in the alternating survey mode design. Blue boxes represent data collected from the respondent. Orange boxes represent paradata from the interviewer about the interview or collected about the survey process. Gray boxes are not included.

Table 3-1. Wave 1 consent status of Wave 3 biomeasure-eligible respondents (combined 2006/2008)

Wave 1 Consent	Physical measurements	Dried blood spot
Yes	10,268 (94.6%)	9,424 (86.9%)
No	581 (5.4%)	1,425 (13.1%)
Total	10,849	10,849

All of the respondent-level data was obtained from the HRS Public Release data available at http://hrsonline.isr.umich.edu/index.php?p=avail. Interviewer characteristic data is controlled data obtained with permission from the Senior Staff Advisory Committee (SSAC) at the Survey Research Center (SRC) at the University of Michigan.

3.5.2 Outcome measures

The outcomes of interest are the consent at W3 to PM and DBS. Because respondents could refuse to complete any particular measure after signing the consent form (e.g., consent to the collection of physical measurements but later refusal to be weighed), this analysis examines whether or not survey respondents signed consent forms, assessing initial willingness to complete the biomeasure collection.

3.5.3 Predictors

For this analysis a standard set of demographic variables are included to serve as control variables and well as predictors of consent. These variables include age at W3, gender, the interaction of race/ethnicity and language of interview (classified as non-Hispanic other, non-Hispanic black, Hispanics interviewed in English, and Hispanics interviewed in Spanish), and education (classified as less than high school, high school graduate, some college, college graduate). Attending church service at least once a week will also be added to the model based

on findings from Dykema et al. (2016). This analysis also includes an indicator for whether there is another interviewed HRS respondent in the household.

To test the hypothesis relating consent to a respondent's physical health, self-rated physical health (excellent, very good, good, fair/poor), how often they performed mildly vigorous activities (at least once a week, 1-3 a month, hardly ever/never), and a medical diagnosis of diabetes are included in the models of consent. All of the single wave static health indicators are taken from the W1 survey interview. Body mass index (BMI), calculated from self-reported height and weight, is categorized into three groups: underweight/normal weight (BMI less than 25)[7], overweight (BMI between 25 and 30), and obese (BMI of 30 or greater). Respondents who refused to provide either their height or weight were retained in the sample and were classified as a fourth group, not reporting BMI, serving as an indicator of item nonresponse. A functional limitation index is included as a summation of three separate scales: the six item basic activities of daily living (BADL) (Katz et al., 1963), the seven item instrumental activities of daily living (IADL) (Lawton & Brody, 1969), and the 10-point NAGI impairment scale (Nagi, 1976). (Additional details about the inclusion of these measures in HRS is available in Fonda and Herzog (2004)). With each item in the three scales categorized as dichotomous responses, the functional limitation index has a maximum score of 23. Finally, an indicator of whether the respondent went to the doctor at all in the last two years is included.

In order to measure if changes in health (e.g., development of disease, increase in physical limitations) influence future consent, responses from W1 were compared to those on the same measure in W3. For dichotomous indicators like diabetes, the change indicator denotes the

[7] Underweight and normal weight are combined due to small sample sizes for the underweight (BMI < 18.5) group.

development of the condition since W1 (e.g., did not have the condition in 2006, did have the condition in 2010)[8]. For ordinal health variables (i.e., self-rated health, BMI, performing mildly vigorous activity) a three-category indicator has categories of improvement, decline, or no change (i.e., the reference group) from W1 to W3. The indicator does not differentiate increase from normal weight to overweight or normal weight to obese. For number of functional limitations the change value is simply the W1 value subtracted from the W3 value, with positive values denoting more limitations and negative values fewer. There is an observed range of -16 to +19 for the change in functional limitations with a median of zero. While not directly a change indicator, a companion indicator of whether the respondent went to the doctor in the two years prior to W3 is included along with the W1 indicator of a prior doctor visit.

Two cognitive status indices were created based on constructed variables developed by the HRS Health Working Group (Ofstedal, Fisher, & Herzog, 2005; Fisher, Hassan, Rodgers, & Weir, 2011). The first index measures memory through two word recall tasks including 10 immediate word recall items and 10 delayed word recall items totaling to a maximum score of 20. The second index measures the respondent's overall mental status assessing knowledge, language, and orientation. It is comprised of three cognitive measures: a test to count backwards from 20 (score of 2), eight naming tasks (each with a score of 1), and a five-stage subtraction task known as the Serial 7's test (each stage with a score of 1). This combination of three measures results in an index with a maximum score of 15. Participants under age 65 were not

[8] There are inconsistencies when a previous wave recorded a respondent giving an affirmative response to having a condition and in the new wave them refuting that assertion (e.g., in HRS 2010, there were a total of 107 across both the E-FTF and CATI interviews who reversed a previous diagnosis of diabetes). For purposes of this analysis, cases that go from having a condition (e.g., diabetes) to not having a condition are not flagged as having a change and the original affirmative response in wave 1 is maintained.

asked to complete the naming tasks in W3; the most recent available score (typically the initial wave when they entered the study) was used when calculating the under 65 mental status score[9].

As a dimension of changes in health and how that may impact changing a consent decision, change in cognition was also computed for each of these cognitive functioning indices. The simple difference of the W1 cognition score from the W3 cognition score yields a range of values from -16 to +15 for word recall (median of -1) and -13 to +9 for mental score (median of 0).

Contact before and behavior during the interview are also considered predictors of future consent. Multiple waves of interview paradata are used due to the nature of the alternating survey mode design of HRS. The number of contact attempts from the current wave is included as it precedes the consent decision (Sakshaug et al., 2010). In addition, survey resistance measures from the most recent wave are included. Respondents may behave differently during face-to-face interviews than during telephone interviews, or interviewers may differentially perceive respondent engagement in each interview mode (for more details, see Appendix C). In addition, there is interviewer variation across these measures, and respondents are not guaranteed to have the same interviewer across waves. Given the W2 interview was primarily conducted over the telephone, the inclusion of interviewer observations from the last E-FTF interview (W1) provides additional insights to the W2 observations given the similarities in the environment and circumstances between W1 and W3.

[9] This choice results in a slightly conservative measure of mental status change for those under 65 because they are guaranteed a change score of 0 for the 8 item naming task. The justification for retaining mental status score in this analysis comes from the retained backwards count from 20 and the Serial 7's task which account for the remaining 7 points of the score.

The number of call attempts is included for W1, W2, and W3 separately. In order to measure resistance to the survey itself, a number of questions regarding various aspects of the interview experience are asked of interviewers after the completion of the interview. Indicators were created for seven of the post-survey interviewer observations in order to form two indices: a confidentiality concern index and uncooperativeness index. These indices were adapted from earlier work by Sakshaug et al. (2012) on record linkage consent. Adaptations were necessary as to include items available in HRS 2006 and 2008. The confidentiality concern index includes:

- "During the interview, how often did the respondent express concern about whether his/her answers would be kept confidential?" (never, **seldom**, **often**)
- "During the interview, how often did the respondent ask you why you needed to know the answer to some questions" (never, **seldom**, **often**)
- "How truthful do you believe the respondent was regarding his/her answers on financial questions?" (completely truthful, mainly truthful, **about half and half**, **mainly untruthful**)

The uncooperativeness index includes:

- "How was the respondent's cooperation during the interview?" (excellent, **good**, **fair**, **poor**)
- "During the interview, how often did the respondent ask how much longer the interview would last?" (never, **seldom**, **often**)
- "How much did the respondent seem to enjoy the interview?" (a great deal, quite a bit, **some**, **a little**, **not at all**)
- "How attentive was the respondent to the questions during the interview?" (**not at all attentive**, **somewhat attentive**, very attentive)

This final item in the uncooperativeness index replaces an earlier item in Sakshaug et al. (2012) that was only collected in HRS 2006: "How would you describe the level of resistance from the respondent?" Sakshaug et al. (2012) originally tested attentiveness as a separate covariate to measure acquiescence, but ultimately found it to be a non-significant predictor. As attentiveness encompasses the focus and relative interest a respondent may have during the survey interview, its inclusion in the uncooperativeness index is consistent with the other indicators like enjoyment and asking how much longer the interview would last. For both indices, a value of 1 was assigned if the interviewer recorded a negative response (i.e., expressing concern about confidentiality or displaying uncooperative behavior, which are denoted by the bold underlined responses above). This results in a confidentiality index range of 0 to 3 and an uncooperativeness index range of 0 to 4. These indices are included for both W1 and W2. Further exploration of these indices is included in Appendix C.

In addition to wave specific resistance variables, variables corresponding to the longitudinal nature of the study are included to capture resistance due to panel fatigue and previous nonresponse: an indicator of whether a respondent was ever a nonrespondent before W1 and an indicator if they were a nonrespondent in W2.

As the interviewer is the one who administers consents and actually collects the biomeasures, a number of interviewer characteristics are included in this analysis including age (continuous), education (divided into high school graduate, some college, college graduate, and advanced degree), race/ethnicity (same breakdown as the respondent race/ethnicity), and if a new hire. In order to test whether interviewer continuity helps or harms the possibility for consent, an indicator was included that identified if the same interviewer made the biomeasure requests in

both W1 and W3. However, it does not account for interviewer continuity between W1 and W2 or W2 and W3; it only denotes E-FTF interviewer continuity.

For non-consenters, the respondent's logic for refusing to consent to either PM or DBS could reflect concerns related to their health or current situation as opposed to general resistance to surveys or the nature of the biomeasure request itself. Someone willing to participate but concerned about compromising their health further may be differentially willing to participate at a future time if their health or situation improves. Thus, the reason for refusal could be informative for both explanatory and predictive purposes.

When a respondent refuses to consent in HRS, interviewers immediately record the reason for the non-consent. Possible reasons include the respondent (or the interviewer) did not feel it safe to complete the collection, the respondent did not understand the instructions, the respondent had hemophilia or was taking a blood thinning medication (anticoagulant; unique to DBS), no suitable location for the collection, and respondent refusal or unwillingness to complete the measurement. The final reason is the only one that does not have an explicit situational or health related factor as a reason for the non-consent. These cases could be considered straight refusals, while the preceding reasons are health-related refusals.

The reason for refusal to DBS collection was included in both 2006 and 2008, while the reason for refusal for PM was included in 2008. Because the reason for refusing PM is missing in 2006, it was necessary to impute PM refusal. Using consent and reason for refusal data available in 2008 and 2010, proportions of straight refusals were estimated based on consent status to DBS in those years (see Table 3-2). Of DBS consenters, nearly two-thirds provided a straight refusal to PM. Straight refusals to DBS resulted in almost 90% also providing straight refusal to PM.

Table 3-2. Straight refusal to physical measurements based on consent status to dried blood spots

	Straight refusal to PM given…		
HRS	Consent to DBS	Straight refusal to DBS	Health-related refusal to DBS
2008	66.7%	89.9%	7.1%
2010	65.6%	87.6%	7.2%
Average	66.2%	88.8%	7.2%

Note. PM = physical measurement. DBS = dried blood spot.

Health-related refusals to DBS had around 7% straight refusal to PM. Reason for PM refusals in 2006 were imputed from random draws from a uniform distribution based on the observed rates of PM refusal.

Item missingness for sociodemographic, health, cognition, and survey resistance variables was less than two percent over all items combined. A nearest-neighbor hot deck approach using the R package 'HotDeckImputation' (Joenssen, 2015) was used to impute these missing values. Imputation was not used for W2 survey variables for 122 respondents who did not respond in W2. The number of contact attempts is set to the maximum number of attempts for that wave and half-sample[10]. The missing interviewer attributes for the three interviewers in 2010 and the two interviewers in 2012 were also not imputed.

3.5.4 Statistical analyses

Two-level random effects logistic regression models were used to estimate the respondents' likelihood of consenting to the biomeasure request, conditional on respondent- and interviewer-level covariates. The primary unit of analysis is the respondent with respondents

[10] Follow-up analyses found that use of the median or a higher percentile (e.g., 90th) of contact attempts made no difference in the W2 contact attempts estimate for any of the models. Number of contact attempts is available for non-respondents as restricted data.

nested within interviewers. The regression was performed using the MELOGIT procedure in Stata 15. Wald tests were used to evaluate the model fit of various analytic variable sets given the complex sample survey design (Heeringa, West, & Berglund, 2010).

HRS uses a complex sample survey design that needed to be incorporated into this analysis to properly estimate standard errors for this model. The sample consists of 56 sampling strata with a pair of primary sampling units (PSUs) within each strata resulting in a total of 112 PSUs. A jackknife variance estimation procedure with 112 replications (JKn)[11] was performed to compute appropriate standard errors. Final sample weights accounting for selection and nonresponse were not incorporated into this analysis as the goal of this analysis was not to generalize to the overall HRS population.

The first two models are identical for both W1 consenters and non-consenters. The first model includes time independent sociodemographic characteristics, previous wave health and cognition (W1 in this analysis), survey resistance indicators from the most recent wave (W2 for this analysis), and current wave (W3) contact attempts and interviewer characteristics. This model is comparable to those used in Sakshaug et al. (2010) and Korbmacher (2014) for single wave consent. Model 1 is

$$\ln\left(\frac{p(Y_{ij}=1|\boldsymbol{X_1},\boldsymbol{u})}{p(Y_{ij}=0|\boldsymbol{X_1},\boldsymbol{u})}\right)=\boldsymbol{X_1}\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}+\boldsymbol{u} \tag{3.1}$$

where Y_{ij} denotes the consent outcome for PM or DBS of respondent *i* interviewed by interviewer *j*, $\boldsymbol{X_1}$ represents the matrix of single wave first and second level covariates (including

[11] While the two PSU per strata design of the HRS would allow for a JK2 estimator to be used, JK2 is not theoretically supported for non-linear estimators like logistic regression coefficients (Valliant, Dever, & Kreuter, 2013). Initial analyses using the JK2 estimator suggested there was an unstable covariance matrix. Instability may also be related to available degrees of freedom and the number of predictors in the model.

sociodemographics, W1 health and cognition measures, W2 survey resistance measures, W3 contact attempts, and W3 interviewer attributes), $\widehat{\boldsymbol{\beta}}_{\mathbf{1}}$ is the estimated regression parameter vector, and $\boldsymbol{u}$ is the vector of random interviewer effects distributed as $N(0, \sigma^2)$.

The second model addresses the longitudinal changes expected to influence recurrent consent decisions by expanding on the first model to include the longitudinal and change measures including changes in health and cognition (W1 to W3), previous E-FTF wave survey resistance indicators (W1) as well as previous wave nonresponse, and continuity between E-FTF interviewers.

$$\ln\left(\frac{p(Y_{ij}=1|\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{u})}{p(Y_{ij}=0|\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{u})}\right) = \boldsymbol{X_1}\widehat{\boldsymbol{\beta}}_{\mathbf{1}} + \boldsymbol{X_2}\widehat{\boldsymbol{\beta}}_{\mathbf{2}} + \boldsymbol{u} \tag{3.2}$$

where $\boldsymbol{X_2}$ represents the additional first level covariates (including W1 to W3 health and cognition change indicators, W1 survey resistance measures, and W1 to W3 interviewer continuity) and $\widehat{\boldsymbol{\beta}}_{\mathbf{2}}$ is the additional estimated regression parameter vector. These two models are the only models considered for previous consenters.

For previous non-consenters, two additional models are considered. The third model for non-consenters expands the second model by including previous reason for refusal (the vector $\boldsymbol{X_3}$) to see how this impacts consent, holding all other health, survey resistance, and interviewer effects constant.

$$\ln\left(\frac{p(Y_{ij}=1|\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{u})}{p(Y_{ij}=0|\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{u})}\right) = \boldsymbol{X_1}\widehat{\boldsymbol{\beta}}_{\mathbf{1}} + \boldsymbol{X_2}\widehat{\boldsymbol{\beta}}_{\mathbf{2}} + \boldsymbol{X_3}\widehat{\boldsymbol{\beta}}_{\mathbf{3}} + \boldsymbol{u} \tag{3.3}$$

The fourth and final model for non-consenters includes an interaction between previous refusal and interviewer continuity (summarized as vector $\boldsymbol{X_4}$) posing the question of whether interviewer continuity has a differential impact on consent for previous non-consenters.

$$\ln\left(\frac{p(Y_{ij}=1|\boldsymbol{X_1},\boldsymbol{X_2},\boldsymbol{X_3},\boldsymbol{X_4},\boldsymbol{u})}{p(Y_{ij}=0|\boldsymbol{X_1},\boldsymbol{X_2},\boldsymbol{X_3},\boldsymbol{X_4},\boldsymbol{u})}\right)=\boldsymbol{X_1}\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}+\boldsymbol{X_2}\widehat{\boldsymbol{\beta}}_{\boldsymbol{2}}+\boldsymbol{X_3}\widehat{\boldsymbol{\beta}}_{\boldsymbol{3}}+\boldsymbol{X_4}\widehat{\boldsymbol{\beta}}_{\boldsymbol{4}}+\boldsymbol{u} \quad (3.4)$$

In order to better understand the impact of reasons for non-consent with interviewer continuity, a single post-hoc linear combination was performed to examine if the effect of interviewer continuity for those who provided a straight refusal to PM or DBS is different than 0. This post-hoc test is expressed as a test of log-odds with a null hypothesis of the form:

$$H_0: \beta_{Continuity}+\beta_{Continuity\times Refusal}=0 \quad (3.5)$$

The sum of these two coefficients is the log-odds of interviewer continuity when straight refusal to PM or DBS is provided. Alternatively, this hypothesis can be expressed as an odds ratio:

$$H_0: \exp^{(\beta_{Continuity}+\beta_{Continuity\times Refusal})}=\exp^{(\beta_{Continuity})}\exp^{(\beta_{Continuity\times Refusal})}=\exp^{0}$$

$$H_0: OR_{Continuity}\times OR_{Continuity\times Refusal}=1$$

The primary reason for building these models this way is to illustrate the need for including more longitudinal information in consent models where the request is repeated across waves and specifically measure the impact of reason for refusal.

3.6 Results

Section 3.6.1 looks at PM and DBS consent from W1 to W3 and breaks down the bivariate relationships between both W3 consent indicators and the explanatory variables. Section 3.6.2 reviews the two models for previous consenters for physical measurements

followed by dried blood spots. Section 3.6.3 reviews the multiple models for previous non-consenters. Any results cited in these sections as having a higher or lower rate are statistically significant at the $\alpha = 0.05$ level. Given there are as many as 64 predictors in each model, a recommended Bonferroni correction for these models is $\alpha = 0.05/64 = 0.0008$. Bonferroni adjusted critical values are denoted as statistically significant in this section. Additional results are also presented, but may be deemed insufficiently conservative as a test criterion to assess the null hypothesis.

3.6.1 Outcome and sample characteristics

Across the two half-samples, 94.1% of the eligible 2006 and 2008 W1 E-FTF respondents consented to the collection of physical measurements (PM) in W3 (see Table 3-3). Of those who consented to PM in W1, over 95% consented to collect PM at W3. Of those who did not consent to PM (for health or other reasons) at W1, over 72% consented in W3. This is a reassuring finding. With minimal wave-to-wave intervention, almost three-fourths of non-consenting individuals eligible for biomeasure collection are likely to consent in the following E-FTF wave. For DBS consent, nearly 88% of eligible respondents consented in W3. Over 92% of respondents who had consented previously consented in the subsequent E-FTF wave. Fifty-eight percent of W1 DBS non-consenters consented in W3.

For PM consenters (see Table 3-4), college graduates have 2.22 odds of PM consent compared to those with less than high school with high school graduates and those with some college education having odds ratios higher than 1. Both non-Hispanic black and English interviewed Hispanic respondents have significantly lower odds of consent than non-Hispanic other respondents though Hispanic respondents interviewed in Spanish are quite similar. A

Table 3-3. Wave 3 biomeasure consent rates for physical measurements and dried blood spots across two E-FTF waves

	W3 PM Status		
W1 PM Status	Consent	Non-consent	Total
Consent	9,788 (95.3%)	480 (4.7%)	10,268
Non-consent	420 (72.3%)	161 (27.7%)	581
Health reason	*81 (75.0%)*	*27 (25.0%)*	*108*
Non-health reason	*339 (71.7%)*	*134 (28.3%)*	*473*
Total	10,208 (94.1%)	641 (5.9%)	10,849

	W3 DBS Status		
W1 DBS Status	Consent	Non-consent	Total
Consent	8,697 (92.3%)	727 (7.7%)	9,424
Non-consent	827 (58.0%)	598 (42.0%)	1,425
Health reason	*174 (71.0%)*	*71 (29.0%)*	*245*
Non-health reason	*653 (55.3%)*	*527 (44.7%)*	*1,180*
Total	9,524 (87.8%)	1,325 (12.2%)	10,849

Note. Italicized values are subsets of non-consent based on reason for non-consent. E-FTF = enhanced face-to-face interview. PM = physical measurements. DBS = dried blood spot.

respondent living in a household with another eligible study member improved the odds of consenting to PM in W3. Regarding a respondent's health status, the least healthy or physical active categories had low odds of PM consent. Respondents classified as having fair/poor self-rated health have less than half odds of PM consent as do those who perform mildly vigorous activity hardly ever or never. Obese respondents have 0.66 odds of PM consent in W3, but respondents who refused height and weight only have 0.40 odds of consent. Respondents diagnosed with diabetes, hardly ever or never exercise, and have more functional limitations were less likely to consent to PM. Health status change indicators do not appear to be as important as W1 measures, though reductions in mildly vigorous activity (OR = 0.59) and increases in functional limitations (OR = 0.92) are significant predictors of W3 non-consent. Baseline cognition scores are significant predictors of W3 PM consent. Increases in the mental status cognition score resulted in higher odds of consent at W3. Both W1 and W2 survey

resistance indices are significant predictors. W2 and W3 contact attempts are also important. Those who kept the same interviewer between E-FTF waves had 0.77 odds of consenting to PM at W3 relative to those with a different interviewer at W1 and W3, though this effect is only significant at 0.05. Respondents interviewed by non-Hispanic black interviews had half odds of PM consent in W3 compared to respondents interviewed by non-Hispanic other interviewers.

For PM non-consenters, few variables are significant given a multiple-comparisons adjustment and so that criterion is relaxed for purposes of discussion for this group. Those who originally performed mildly vigorous activity less than once a week were less likely to consent at W3 (OR = 0.51). In addition, the number of functional limitations at W1 has a negative relationship with W3 PM consent (OR = 0.95). The W1 survey resistance indices both predict W3 non-consent with those who were more uncooperative and concerned about confidentiality less likely to consent. Only the W2 confidentiality index has an effect on W3 consent. Interviewer continuity has a negative effect on future PM consent with those maintaining the same interviewer having half the odds of consenting in W3. Interviewer age and hire status also play a role for previous non-consenters. The reason for a W1 PM refusal (health-related or otherwise) does not show a relationship with future consent.

DBS consenters have similar bivariate effects to PM consenters with the exceptions of respondent education, religious activity, diabetes, and change in BMI. In addition, interviewer continuity does not have an effect on W3 DBS consent. Unlike PM consent, changes in word recall scores from W1 to W3 do lead to increased odds of DBS consent and respondents who were a nonrespondent before W1 had 0.65 odds of DBS consent, both at the 0.05 level. Respondents with newly hired and more educated interviewers were less likely to consent.

DBS non-consenters (using a similar relaxation of the multiple-comparisons critical value) with higher education are less likely to consent to W3 DBS. No health or health change measures, except the W1 cognition scores, are significant predictors of W3 PM consent for previous DBS non-consenters. Among W2 survey resistance measures only the confidentiality index and both W1 resistance indices predict W3 consent. The reason for DBS refusal at W1 does have an effect on W3 DBS consent with those refusing for non-health-related reasons having half the odds of consenting compared to those who did so for health-related reasons. Interviewer continuity is not significant at the 0.05 level, though there is a negative effect observed with continuity with those who had the same interviewer in both waves less likely to consent to DBS, similar to the result for PM consent. Respondents with older interviewers were less likely to consent to DBS in W3. Respondents interviewed by a non-Hispanic black interviewer were less likely to consent to DBS (OR = 0.79) while those interviewed by a Hispanic interviewer were more likely to consent (OR = 1.32) compared to those interviewed by non-Hispanic other interviewers.

Table 3-4. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 PM consent

	W1 PM Consenters (*n*=10,268)				W1 PM Non-consenters (*n*=581)			
	Estimate	W3 consent	Odds Ratio	LR p-value	Estimate	W3 consent	Odds Ratio	LR p-value
Respondent characteristics								
Age	71.89 (0.088)	-	0.977	< 0.0001	71.29 (0.389)	-	0.988	0.2278
Gender								
Male	0.409	0.955	ref.		0.439	0.690	ref.	
Female	0.591	0.952	0.943	0.5373	0.561	0.749	1.336	0.1201
Education								
Less than HS (<12 years)	0.203	0.930	ref.		0.275	0.681	ref.	
High school (12 years)	0.336	0.957	1.703		0.329	0.717	1.187	
Some college (13-15 years)	0.225	0.954	1.572		0.213	0.782	1.681	
College grad (16+ years)	0.236	0.967	2.217	< 0.0001	0.182	0.726	1.242	0.2988
Race/ethnicity								
Non-Hispanic other	0.778	0.960	ref.		0.658	0.723	ref.	
Non-Hispanic black	0.137	0.928	0.549		0.248	0.694	0.875	
Hispanic (English interview)	0.042	0.915	0.439		0.059	0.794	1.300	
Hispanic (Spanish interview)	0.042	0.956	0.919	< 0.0001	0.036	0.810	1.637	0.6059
Religious activity								
Less than 1/week	0.564	0.948	ref.		0.632	0.703	ref.	
At least 1/week	0.436	0.960	1.293	0.0071	0.368	0.757	1.316	0.1581
Other eligible household member								
No	0.364	0.940	ref.		0.441	0.742	ref.	
Yes	0.636	0.961	1.587	< 0.0001	0.559	0.708	0.841	0.3555
Health status (W1)								
Self-rated health								
Excellent	0.116	0.967	ref.		0.093	0.704	ref.	
Very good	0.321	0.965	0.935		0.251	0.760	1.335	
Good	0.321	0.953	0.684		0.301	0.743	1.216	
Fair/Poor	0.243	0.931	0.459	< 0.0001	0.355	0.685	0.913	0.3948
Body mass index (BMI)								
Underweight/Normal (<25)	0.282	0.962	ref.		0.258	0.753	ref.	
Overweight (25-29.9)	0.385	0.957	0.885		0.368	0.734	0.902	
Obese (>30)	0.317	0.944	0.665		0.336	0.697	0.755	
Refused	0.016	0.909	0.395	0.0003	0.038	0.636	0.573	0.5255

(continued)

Table 3-4. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 PM consent (continued)

	W1 PM Consenters (*n*=10,268)				W1 PM Non-consenters (*n*=581)			
	Estimate	W3 consent	Odds Ratio	LR p-value	Estimate	W3 consent	Odds Ratio	LR p-value
Mildly vigorous activity								
At least 1/week	0.872	0.956	ref.		0.811	0.745	ref.	
1-3 times/month	0.060	0.961	1.131		0.069	0.600	0.513	
Hardly ever/never	0.068	0.908	0.453	< 0.0001	0.121	0.643	0.615	0.0469
Diabetes								
No	0.798	0.956	ref.		0.790	0.736	ref.	
Yes	0.202	0.942	0.749	0.0090	0.210	0.672	0.734	0.1639
No. of functional limitations	3.39 (0.034)	-	0.937	< 0.0001	4.30 (0.182)	-	0.947	0.0079
Visited the doctor in the last 2 years (W1)								
No	0.045	0.950	ref.		0.072	0.667	ref.	
Yes	0.955	0.953	1.069	0.7621	0.928	0.727	1.333	0.4061
Change in health status								
Self-rated health change								
No change	0.563	0.953	ref.		0.556	0.697	ref.	
Declined	0.253	0.957	1.080		0.238	0.732	1.189	
Improved	0.184	0.949	0.921	0.5316	0.207	0.783	1.575	0.1780
BMI change								
No change	0.788	0.955	ref.		0.794	0.703	ref.	
Declined	0.097	0.961	1.160		0.093	0.796	1.653	
Improved	0.115	0.937	0.710	0.0207	0.114	0.803	1.724	0.0940
Mildly vigorous activity change								
No change	0.788	0.958	ref.		0.725	0.746	ref.	
Declined	0.145	0.929	0.585		0.191	0.676	0.710	
Improved	0.067	0.955	0.943	< 0.0001	0.084	0.633	0.587	0.1222
Diabetes change								
No change	0.940	0.953	ref.		0.926	0.719	ref.	
Developed	0.060	0.956	1.072	0.7279	0.074	0.767	1.288	0.4904
Functional limitation change	0.84 (0.027)	-	0.918	< 0.0001	0.84 (0.119)	-	0.983	0.5966
Visited the doctor in the last 2 years (W3)								
No	0.0685	0.935	ref.		0.086	0.620	ref.	
Yes	0.9315	0.955	1.473	0.0209	0.914	0.733	1.679	0.0985

(continued)

Table 3-4. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 PM consent (continued)

	W1 PM Consenters (*n*=10,268)				W1 PM Non-consenters (*n*=581)			
	Estimate	W3 consent	Odds Ratio	LR p-value	Estimate	W3 consent	Odds Ratio	LR p-value
Cognition indices								
Word recall score (W1)	10.09 (0.031)	-	1.101	< 0.0001	9.23 (0.131)	-	0.999	0.9603
Mental status score (W1)	13.04 (0.022)	-	1.125	< 0.0001	12.17 (0.113)	-	1.048	0.1574
Change in word recall	-0.84 (0.029)	-	1.020	0.2222	-0.49 (0.127)	-	1.038	0.2157
Change in mental status score	-0.55 (0.019)	-	1.114	< 0.0001	-0.50 (0.087)	-	1.075	0.1023
Survey resistance (W1)								
No. of contact attempts	5.40 (0.042)	-	0.989	0.2621	6.80 (0.280)	-	1.018	0.2349
Uncooperative index (range: 0 - 4)	0.66 (0.010)	-	0.731	< 0.0001	1.71 (0.055)	-	0.855	0.0260
Confidentiality index (range: 0 - 3)	0.40 (0.007)	-	0.685	< 0.0001	0.90 (0.040)	-	0.712	0.0003
Survey resistance (W2)								
W2 Respondent								
No	0.009	0.880	ref.		0.017	0.600	ref.	
Yes	0.991	0.954	2.811	0.0050	0.983	0.725	1.758	0.3982
No. of contact attempts	6.66 (0.122)	-	0.990	0.0010	9.17 (0.683)	-	0.998	0.7322
Uncooperative index (range: 0 - 4)	0.85 (0.011)	-	0.851	< 0.0001	1.30 (0.052)	-	0.982	0.8063
Confidentiality index (range: 0 - 3)	0.35 (0.006)	-	0.805	0.0016	0.56 (0.033)	-	0.753	0.0119
Survey resistance (W3)								
No. of contact attempts	5.76 (0.051)	-	0.967	< 0.0001	6.85 (0.274)	-	0.996	0.7497
Panel status								
Ever a nonrespondent before W1								
No	0.935	0.954	ref.		0.852	0.735	ref.	
Yes	0.065	0.941	0.759	0.1177	0.148	0.651	0.672	0.1142
Interviewer continuity								
E-FTF interviewer continuity								
No	0.839	0.955	ref.		0.850	0.745	ref.	
Yes	0.161	0.943	0.769	0.0295	0.150	0.598	0.509	0.0060
Reason for non-consent (W1)								
Straight refusal for non-consent								
No, health-related	-	-	-		0.186	0.750	ref.	
Yes	-	-	-	-	0.814	0.717	0.843	0.4818

(continued)

Table 3-4. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 PM consent (continued)

	W1 PM Consenters (*n*=10,268)				W1 PM Non-consenters (*n*=581)			
	Estimate	**W3 consent**	**Odds Ratio**	**LR p-value**	**Estimate**	**W3 consent**	**Odds Ratio**	**LR p-value**
Interviewer attributes								
Age	50.93 (0.125)	-	1.003	0.3601	50.81 (0.511)	-	0.984	0.0361
Gender								
Male	0.166	0.938	ref.		0.155	0.778	ref.	
Female	0.834	0.956	1.453	0.0014	0.845	0.713	0.709	0.1973
Race/ethnicity								
Non-Hispanic other	0.759	0.959	ref.		0.725	0.751	ref.	
Non-Hispanic black	0.147	0.925	0.519		0.196	0.649	0.615	
Hispanic	0.094	0.949	0.792	< 0.0001	0.079	0.652	0.623	0.0579
Education								
High school graduate	0.110	0.953	ref.		0.134	0.756	ref.	
Some college	0.337	0.949	0.910		0.308	0.704	0.766	
College graduate	0.294	0.950	0.940		0.267	0.742	0.926	
Advanced degree	0.259	0.962	1.256	0.0611	0.291	0.710	0.789	0.7556
New hire								
No	0.563	0.953	ref.		0.571	0.687	ref.	
Yes	0.437	0.954	1.008	0.9328	0.429	0.771	1.536	0.0237

Note. Mean estimates include standard errors in parentheses. PM = Physical measurements. LR = likelihood ratio. W1 = Wave 1. W3 = Wave 3. HS = high school.

Table 3-5. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 DBS consent

	W1 DBS Consenters (*n*=9,424)				W1 DBS Non-consenters (*n*=1,425)			
	Estimate	W3 consent	Odds Ratio	LR p-value	Estimate	W3 consent	Odds Ratio	LR p-value
Respondent characteristics								
Age	71.99 (0.092)	-	0.990	0.0147	70.98 (0.238)	-	1.013	0.0347
Gender								
Male	0.409	0.929	ref.		0.421	0.585	ref.	
Female	0.591	0.919	0.868	0.0746	0.579	0.577	0.968	0.7616
Education								
Less than HS (<12 years)	0.207	0.911	ref.		0.208	0.625	ref.	
High school (12 years)	0.338	0.922	1.156		0.323	0.613	0.986	
Some college (13-15 years)	0.224	0.929	1.279		0.225	0.545	0.719	
College grad (16+ years)	0.231	0.928	1.244	0.1426	0.244	0.520	0.650	0.0059
Race/ethnicity								
Non-Hispanic other	0.783	0.930	ref.		0.698	0.566	ref.	
Non-Hispanic black	0.131	0.897	0.666		0.224	0.586	1.102	
Hispanic (English interview)	0.043	0.869	0.494		0.044	0.619	1.279	
Hispanic (Spanish interview)	0.043	0.934	1.066	< 0.0001	0.034	0.792	2.916	0.0111
Religious activity								
Less than 1/week	0.561	0.918	ref.		0.612	0.572	ref.	
At least 1/week	0.439	0.929	1.153	0.0683	0.388	0.593	1.090	0.4361
Other eligible household member								
No	0.362	0.911	ref.		0.411	0.573	ref.	
Yes	0.638	0.930	1.284	0.0016	0.590	0.586	1.055	0.6231
Health status (W1)								
Self-rated health								
Excellent	0.116	0.940	ref.		0.106	0.517	ref.	
Very good	0.321	0.930	0.847		0.290	0.559	1.188	
Good	0.319	0.922	0.757		0.321	0.593	1.364	
Fair/Poor	0.243	0.907	0.627	0.0026	0.284	0.611	1.472	0.1609
Body mass index (BMI)								
Underweight/Normal (<25)	0.283	0.925	ref.		0.267	0.558	ref.	
Overweight (25-29.9)	0.382	0.930	1.076		0.392	0.572	1.058	
Obese (>30)	0.319	0.915	0.869		0.314	0.603	1.202	
Refused	0.016	0.850	0.458	0.0025	0.027	0.667	1.585	0.3765

(continued)

Table 3-5. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 DBS consent (continued)

	W1 DBS Consenters (*n*=9,424)				W1 DBS Non-consenters (*n*=1,425)			
	Estimate	W3 consent	Odds Ratio	LR p-value	Estimate	W3 consent	Odds Ratio	LR p-value
Mildly vigorous activity								
At least 1/week	0.874	0.927	ref.		0.837	0.581	ref.	
1-3 times/month	0.059	0.919	0.886		0.074	0.524	0.794	
Hardly ever/never	0.068	0.872	0.535	< 0.0001	0.089	0.622	1.187	0.3195
Diabetes								
No	0.796	0.922	ref.		0.808	0.571	ref.	
Yes	0.204	0.925	1.031	0.7479	0.192	0.620	1.229	0.1331
No. of functional limitations	3.40 (0.036)	-	0.958	< 0.0001	3.65 (0.102)	-	1.015	0.2909
Visited the doctor in the last 2 years (W1)								
No	0.044	0.928	ref.		0.063	0.596	ref.	
Yes	0.956	0.923	0.927	0.6914	0.938	0.579	0.935	0.7644
Change in health status								
Self-rated health change								
No change	0.562	0.922	ref.		0.568	0.581	ref.	
Declined	0.254	0.920	0.963		0.241	0.558	0.911	
Improved	0.185	0.929	1.098	0.5378	0.191	0.607	1.112	0.4794
BMI change								
No change	0.787	0.925	ref.		0.802	0.578	ref.	
Declined	0.098	0.926	1.026		0.087	0.637	1.280	
Improved	0.116	0.909	0.817	0.2047	0.111	0.551	0.894	0.3241
Mildly vigorous activity change								
No change	0.790	0.927	ref.		0.749	0.576	ref.	
Declined	0.143	0.898	0.689		0.174	0.617	1.184	
Improved	0.067	0.924	0.947	0.0015	0.077	0.536	0.850	0.3149
Diabetes change								
No change	0.941	0.922	ref.		0.926	0.577	ref.	
Developed	0.059	0.931	1.139	0.4439	0.074	0.623	1.210	0.3568
Functional limitation change	0.85 (0.028)	-	0.948	< 0.0001	0.76 (0.074)	-	1.014	0.4673
Visited the doctor in the last 2 years (W3)								
No	0.069	0.923	ref.		0.072	0.602	ref.	
Yes	0.931	0.923	0.997	0.9826	0.928	0.579	0.908	0.6440

(continued)

Table 3-5. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 DBS consent (continued)

	W1 DBS Consenters (*n*=9,424)				W1 DBS Non-consenters (*n*=1,425)			
	Estimate	W3 consent	Odds Ratio	LR p-value	Estimate	W3 consent	Odds Ratio	LR p-value
Cognition indices								
Word recall score (W1)	10.05 (0.033)	-	1.035	0.0048	9.95 (0.084)	-	0.939	0.0002
Mental status score (W1)	13.03 (0.023)	-	1.059	0.0006	12.72 (0.064)	-	0.949	0.0208
Change in word recall	-0.84 (0.030)	-	1.040	0.0027	-0.66 (0.080)	-	1.014	0.4286
Change in mental status score	-0.56 (0.019)	-	1.075	0.0003	-0.49 (0.052)	-	0.983	0.5279
Survey resistance (W1)								
No. of contact attempts	5.37 (0.043)	-	0.994	0.4692	6.17 (0.156)	-	0.999	0.8798
Uncooperative index (range: 0 - 4)	0.61 (0.010)	-	0.779	< 0.0001	1.43 (0.034)	-	0.920	0.0485
Confidentiality index (range: 0 - 3)	0.37 (0.007)	-	0.737	< 0.0001	0.80 (0.024)	-	0.784	< 0.0001
Survey resistance (W2)								
W2 Respondent								
No	0.009	0.838	ref.		0.015	0.500	ref.	
Yes	0.992	0.924	2.345	0.0112	0.985	0.582	1.390	0.4445
No. of contact attempts	6.59 (0.125)	-	0.992	0.0014	8.09 (0.399)	-	0.996	0.2692
Uncooperative index (range: 0 - 4)	0.83 (0.011)	-	0.898	< 0.0001	1.17 (0.032)	-	0.927	0.0797
Confidentiality index (range: 0 - 3)	0.34 (0.006)	-	0.822	0.0007	0.53 (0.020)	-	0.800	0.0016
Survey resistance (W3)								
No. of contact attempts	5.70 (0.052)	-	0.965	< 0.0001	6.55 (0.160)	-	0.989	0.2140
Panel status								
Ever a nonrespondent before W1								
No	0.937	0.925	ref.		0.888	0.583	ref.	
Yes	0.064	0.890	0.653	0.0029	0.112	0.556	0.895	0.5130
Interviewer continuity								
E-FTF interviewer continuity								
No	0.840	0.921	ref.		0.839	0.592	ref.	
Yes	0.161	0.931	1.144	0.2119	0.161	0.522	0.753	0.0501
Reason for non-consent (W1)								
Straight refusal for non-consent								
No, health-related	-	-	-		0.172	0.710	ref.	
Yes	-	-	-	-	0.828	0.553	0.506	< 0.0001

(continued)

Table 3-5. Unweighted univariate descriptors of analysis variables with bivariate comparisons to wave 3 DBS consent (continued)

	W1 DBS Consenters (*n*=9,424)				W1 DBS Non-consenters (*n*=1,425)			
	Estimate	**W3 consent**	**Odds Ratio**	**LR p-value**	**Estimate**	**W3 consent**	**Odds Ratio**	**LR p-value**
Interviewer attributes								
Age	50.96 (0.131)	-	1.002	0.5733	50.72 (0.335)	-	0.989	0.0071
Gender								
Male	0.165	0.887	ref.		0.166	0.536	ref.	
Female	0.835	0.930	1.692	< 0.0001	0.834	0.589	1.242	0.1298
Race/ethnicity								
Non-Hispanic other	0.764	0.930	ref.		0.716	0.586	ref.	
Non-Hispanic black	0.143	0.889	0.598		0.196	0.527	0.786	
Hispanic	0.094	0.915	0.809	< 0.0001	0.088	0.651	1.315	0.0496
Education								
High school graduate	0.111	0.949	ref.		0.116	0.667	ref.	
Some college	0.335	0.916	0.581		0.333	0.561	0.639	
College graduate	0.295	0.915	0.576		0.277	0.587	0.712	
Advanced degree	0.259	0.929	0.703	0.0006	0.274	0.560	0.637	0.0850
New hire								
No	0.565	0.935	ref.		0.552	0.597	ref.	
Yes	0.435	0.908	0.687	< 0.0001	0.448	0.560	0.861	0.1658

Note. Mean estimates include standard errors in parentheses. DBS = dried blood spot. LR = likelihood ratio. W1 = Wave 1. W3 = Wave 3. HS = high school.

3.6.2 Two-level random effects models for previous consenters

Within the multiple logistic regression model, sociodemographic characteristics like education, race/ethnicity and having another eligible household member show no effects for previous consenters on W3 PM consent though significant in bivariate associations. Respondent age is significant with older respondents less likely to consent at W3. Hispanic respondents who were interviewed in English had half the odds of consenting to PM compared to non-Hispanic other respondents, though this effect is not significant using the Bonferroni correction. Attending religious services at least once a week results in around 1.4 odds of W3 PM consent, slightly greater than the corresponding bivariate odds ratio, but only at the 0.05 level.

Regarding wave 1 health indicators, obese (BMI > 30) respondents have about 0.70 odds of consenting to PM at W3 compared to those who are underweight or have a normal BMI. Those who refused to provide height and weight to calculate BMI had nearly half the odds of consent, but this effect is not significant with the multiple-comparison correction. Respondents who do little to no mildly vigorous activity are also less likely than those who are active at least once a week to consent again to PM at W3 (OR = 0.67 in Model 1). This activity-related effect is strengthened once accounting for longitudinal factors like changes in health status (OR = 0.52). While significant in bivariate analyses, self-rated health, diabetes, and the number of functional limitations all have no effect on consent to PM at W3.

Considering the longitudinal and change indicators introduced in Model 2, an increase in the number of functional limitations also results in a reduction in the odds of consent (OR = 0.93) when holding the original number of limitations constant. A decline in mildly vigorous

activity from W1 to W3 results in 0.73 odds of consent to PM at W3 compared to no change in activity, but the effect is weak.

In Model 1, neither cognition index is a significant predictor of W3 PM consent. With the introduction of the cognition change variables in Model 2, both the mental status score and the change in mental status score are found to be significant with 1.06 and 1.07 odds for a unit shift (positive) in the change scores, respectively, but only at the 0.05 level.

None of the W2 survey resistance measures explain W3 PM consent, but both the W1 confidentiality and uncooperative indices do explain W3 consent, with about 0.80 odds of PM consent in W3 PM consent per unit on the index. Number of contact attempts in the current wave (W3) is also significant in both models with 0.97 odds of W3 PM consent for each additional contact attempt. Nonresponse, whether before W1 or during W2, did not predict PM consent in W3.

Three W3 interviewer attributes for previous PM consenters were significant predictors in Model 2. Respondents with non-Hispanic black interviewers had nearly half the odds of PM consent compared to respondents with other non-Hispanic interviewers. Respondents with female interviewers had 1.45 odds of PM consent compared to those with male interviewers holding all respondent and interviewer attributes constant in Model 2 at the 0.05 alpha level. E-FTF interviewer continuity from W1 to W3 results in about 0.60 odds of future PM consent, though not quite significant accounting for the Bonferroni correction. There is a significant amount of interviewer variance not explained by the interviewer attributes included in the model.

Table 3-6. Predictors of wave 3 physical measurement consent for wave 1 physical measurement consenters

	Model 1	Model 2
	Odds Ratio (95% CI)	**Odds Ratio (95% CI)**
Respondent Characteristics		
Age (years)	**0.97 (0.96, 0.98)******	0.98 (0.96, 0.99)**
Female	1.08 (0.89, 1.29)	1.07 (0.88, 1.30)
Education (ref: less than HS)		
High school	1.26 (0.96, 1.66)	1.19 (0.91, 1.55)
Some college	1.04 (0.75, 1.44)	0.97 (0.71, 1.34)
College graduate	1.28 (0.86, 1.92)	1.17 (0.79, 1.74)
Race/ethnicity (ref: Non-Hispanic other)		
Non-Hispanic black	0.91 (0.64, 1.29)	1.01 (0.71, 1.45)
Hispanic (English interview)	0.47 (0.30, 0.75)**	0.51 (0.32, 0.82)**
Hispanic (Spanish interview)	1.87 (1.00, 3.49)	2.30 (1.21, 4.36)*
Attends religious services at least 1/wk	1.42 (1.08, 1.85)*	1.35 (1.02, 1.78)*
Another eligible HH member	1.27 (0.98, 1.66)	1.23 (0.94, 1.61)
Health status indicators (W1)		
Self-rated health (ref: Excellent)		
Very good	1.02 (0.68, 1.53)	1.07 (0.69, 1.64)
Good	0.83 (0.52, 1.32)	0.90 (0.53, 1.53)
Fair/Poor	0.73 (0.49, 1.10)	0.87 (0.52, 1.45)
BMI (ref: Underweight/Normal)		
Overweight	0.90 (0.72, 1.14)	0.87 (0.68, 1.11)
Obese	**0.70 (0.56, 0.86)*****	**0.67 (0.53, 0.85)*****
Did not report	0.52 (0.30, 0.91)*	0.49 (0.29, 0.84)**
Diabetes	1.03 (0.79, 1.34)	1.12 (0.85, 1.47)
Mildly vigorous activity (ref: At least 1/wk)		
1-3 times/month	1.43 (0.89, 2.32)	1.18 (0.64, 2.18)
Hardly ever/never	0.67 (0.50, 0.90)**	**0.52 (0.37, 0.74)*****
No. of functional limitations	0.99 (0.96, 1.02)	0.98 (0.95, 1.01)
Ever visited doctor in last 2 years (W1)	1.10 (0.69, 1.76)	1.03 (0.63, 1.69)
Change in health status		
Self-rated health (ref: No change)		
Declined		1.05 (0.83, 1.31)
Improved		0.91 (0.68, 1.22)
BMI (ref: No change)		
Declined		1.02 (0.67, 1.55)
Improved		0.97 (0.76, 1.23)
Developed diabetes		1.13 (0.68, 1.87)
Mildly vigorous activity (ref: No change)		
Declined		0.73 (0.54, 0.98)*
Improved		1.47 (0.85, 2.54)
Change in no. functional limitations		**0.93 (0.90, 0.96)******
Ever visited doctor in last 2 years (W3)		1.30 (0.88, 1.93)

(continued)

Table 3-6. Predictors of wave 3 physical measurement consent for wave 1 physical measurement consenters (continued)

	Model 1	Model 2
	Odds Ratio (95% CI)	**Odds Ratio (95% CI)**
Cognition indices		
Word recall score (W1)	1.03 (0.99, 1.08)	1.02 (0.96, 1.08)
Mental status score (W1)	1.04 (1.00, 1.08)	1.06 (1.01, 1.11)*
Change in word recall score		1.00 (0.96, 1.05)
Change in mental status score		1.07 (1.01, 1.13)*
Survey resistance (W1)		
No. of contact attempts		1.01 (0.99, 1.03)
Uncooperative Index		**0.80 (0.72, 0.88)******
Confidentiality Index		**0.77 (0.69, 0.87)******
Survey resistance (W2)		
Nonrespondent in W2	0.57 (0.11, 2.94)	0.49 (0.09, 2.63)
No. of contact attempts	1.00 (0.98, 1.01)	1.00 (0.98, 1.01)
Uncooperative Index	0.90 (0.81, 1.01)	0.96 (0.86, 1.08)
Confidentiality Index	0.86 (0.71, 1.03)	0.91 (0.75, 1.11)
Survey resistance (W3)		
No. of contact attempts	**0.97 (0.96, 0.99)******	**0.97 (0.96, 0.99)******
Panel status		
Ever a nonrespondent before W1		0.98 (0.65, 1.48)
Interviewer continuity		
E-FTF interviewer continuity		0.59 (0.40, 0.87)**
Interviewer attributes (W3)		
Age (years)	1.00 (0.99, 1.00)	1.00 (0.99, 1.01)
Female	1.33 (1.00, 1.78)	1.45 (1.09, 1.94)*
Race (ref: Non-Hispanic other)		
Non-Hispanic black	**0.56 (0.42, 0.74)******	**0.56 (0.42, 0.74)******
Hispanic	1.04 (0.70, 1.55)	1.00 (0.64, 1.55)
Education (ref: HS graduate)		
Some college	0.93 (0.63, 1.38)	0.96 (0.64, 1.43)
College graduate	1.13 (0.72, 1.79)	1.19 (0.75, 1.90)
Advanced degree	1.46 (0.91, 2.34)	1.51 (0.92, 2.46)
New hire	0.81 (0.63, 1.04)	0.76 (0.57, 1.01)
Interviewer variance	**3.17 (2.17, 4.63)******	**3.31 (2.21, 4.95)******

Note. Confidence intervals are based on jackknife standard errors from a two-level random effects logistic regression model. CI = confidence interval. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. HS = high school.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0008$ and are **bolded**.

For DBS consent in wave 3, few sociodemographics have an effect when controlling for the other variables (see Table 3-7). Hispanics who completed an English interview had 0.55 odds of consenting to DBS while Hispanics who completed a Spanish interview had 1.96 odds of consenting in Model 2 (OR = 1.70 in Model 1), though the latter effect is not significant given the Bonferroni correction. Older respondents are somewhat less likely to consent in Model 1, but accounting for health changes and W1 resistance eliminates that effect.

Regarding wave 1 health indicators, having a doctor's diagnosis of diabetes resulted in 1.41 odds of DBS consent in Model 2 (OR = 1.29 in Model 1). Respondents who do little to no mildly vigorous activity are also less likely to consent to DBS at W3 compared to those who are active at least once a week (OR = 0.64), similar to the PM model. This effect is amplified in Model 2 (OR = 0.48). Previous DBS consenters who failed to provide height and weight data for BMI at W1 had 0.52 odds of consenting to DBS collection in W3, but this effect is not significant given the Bonferroni correction.

When introducing the health change indicators in Model 2, a decline in mildly vigorous activity from W1 to W3 results in 0.76 odds of consent to W3 DBS compared to no change in activity. Increased mildly vigorous activity also was significant in Model 2 resulting in 1.67 odds of DBS consent in W3, an effect not observed in the PM model. However, both of these effects are not significant at the Bonferroni correction level of 0.0008. Similar to the PM model, a one unit increase in the number of functional limitations between W1 and W3 also results in a significant reduction in the odds of consent (OR = 0.96) though the original number of functional limitations has no measurable effect despite a large difference in the bivariate comparison.

The cognition indices, significant in the bivariate relationships, are not significant for W3 DBS consent (similar to the PM model). However, with the introduction of the change variables in Model 2, the change in word recall score is found to be 1.04 times the odds of DBS consent in W3 at the 0.05 level.

Examining the survey resistance variables, a one-unit change in the W2 uncooperative index reduces the odds of W3 DBS consent by 0.89. Again, the number of previous wave contact attempts and the confidentiality index for W2 add nothing to the understanding of DBS consent. When adding the W1 survey resistance indicators, the W2 uncooperative index does not remain significant, but both the W1 confidentiality and uncooperative indices are significant each resulting in 0.81 and 0.88 the odds of W3 DBS consent, respectively. The number of contact attempts in the current wave (W3) is also significant in both versions of the model with 0.97 the odds of DBS consent for each additional contact just like PM consent. Any nonresponse before W1 and W2 nonresponse were not predictive of DBS consent in W3.

Like PM consent, respondents with female and non-Hispanic black interviewers were more likely to DBS consent in W3 at the 0.05 level. In addition, respondents with older interviewers were less likely to consent (OR = 0.99) while respondents interviewed by new hires had 0.60 odds of DBS consent. Interviewer continuity remains unassociated for follow-up DBS consent, consistent with the bivariate results. Like the PM model, there is a significant amount of interviewer variance not explained by the interviewer attributes included in the model.

Table 3-7. Predictors of wave 3 dried blood spot consent for wave 1 dried blood spot consenters

	Model 1	Model 2
	Odds Ratio (95% CI)	**Odds Ratio (95% CI)**
Respondent Characteristics		
Age (years)	0.98 (0.97, 0.99)**	0.99 (0.98, 1.01)
Female	0.91 (0.79, 1.06)	0.87 (0.74, 1.02)
Education (ref: less than HS)		
High school	1.01 (0.78, 1.29)	0.97 (0.75, 1.24)
Some college	1.07 (0.79, 1.46)	1.02 (0.74, 1.39)
College graduate	0.97 (0.69, 1.36)	0.88 (0.63, 1.23)
Race/ethnicity (ref: Non-Hispanic other)		
Non-Hispanic black	0.86 (0.64, 1.16)	0.93 (0.68, 1.27)
Hispanic (English interview)	**0.54 (0.40, 0.72)******	**0.55 (0.41, 0.75)******
Hispanic (Spanish interview)	1.70 (1.04, 2.77)*	1.96 (1.19, 3.23)**
Attends church at least 1/wk	1.19 (0.99, 1.44)	1.15 (0.94, 1.39)
Another eligible HH member	1.04 (0.87, 1.23)	1.01 (0.85, 1.20)
Health status indicators (W1)		
Self-rated health (ref: Excellent)		
Very good	0.89 (0.67, 1.19)	0.88 (0.66, 1.19)
Good	0.84 (0.62, 1.13)	0.81 (0.59, 1.11)
Fair/Poor	0.80 (0.57, 1.10)	0.77 (0.54, 1.11)
BMI (ref: Underweight/Normal)		
Overweight	1.07 (0.88, 1.30)	1.05 (0.85, 1.29)
Obese	0.91 (0.74, 1.12)	0.87 (0.69, 1.08)
Did not report	0.54 (0.34, 0.88)*	0.52 (0.32, 0.84)**
Diabetes	1.29 (1.06, 1.57)**	**1.41 (1.16, 1.72)*****
Mildly vigorous activity (ref: At least 1/wk)		
1-3 times/month	0.92 (0.70, 1.21)	0.72 (0.52, 0.98)*
Hardly ever/never	0.64 (0.47, 0.86)**	**0.48 (0.34, 0.66)******
No. of functional limitations	0.99 (0.96, 1.01)	0.99 (0.96, 1.02)
Ever visited doctor in last 2 years (W1)	0.93 (0.63, 1.38)	0.96 (0.66, 1.40)
Change in health status		
Self-rated health (ref: No change)		
Declined		0.92 (0.74, 1.14)
Improved		1.11 (0.88, 1.41)
BMI (ref: No change)		
Declined		0.94 (0.70, 1.25)
Improved		0.97 (0.77, 1.23)
Developed diabetes		1.24 (0.90, 1.72)
Mildly vigorous activity (ref: No change)		
Declined		0.76 (0.61, 0.95)*
Improved		1.67 (1.14, 2.43)**
Change in no. functional limitations		**0.96 (0.94, 0.98)*****
Ever visited doctor in last 2 years (W3)		0.97 (0.75, 1.27)

(continued)

Table 3-7. Predictors of wave 3 dried blood spot consent for wave 1 dried blood spot consenters (continued)

	Model 1	Model 2
	Odds Ratio (95% CI)	**Odds Ratio (95% CI)**
Cognition indices		
Word recall score (W1)	1.00 (0.97, 1.03)	1.01 (0.98, 1.06)
Mental status score (W1)	1.01 (0.97, 1.05)	1.01 (0.97, 1.06)
Change in word recall score		1.04 (1.01, 1.07)**
Change in mental status score		1.04 (0.99, 1.08)
Survey resistance (W1)		
No. of contact attempts		1.01 (0.99, 1.04)
Uncooperative Index		0.88 (0.81, 0.96)**
Confidentiality Index		**0.81 (0.72, 0.90)*** **
Survey resistance (W2)		
Nonrespondent in W2	0.45 (0.15, 1.40)	0.42 (0.13, 1.32)
No. of contact attempts	1.00 (0.99, 1.01)	1.00 (0.99, 1.01)
Uncooperative Index	0.89 (0.81, 0.97)**	0.93 (0.85, 1.01)
Confidentiality Index	0.90 (0.77, 1.06)	0.93 (0.79, 1.09)
Survey resistance (W3)		
No. of contact attempts	**0.97 (0.95, 0.98)**** **	**0.97 (0.95, 0.98)**** **
Panel status		
Ever a nonrespondent before W1		0.82 (0.60, 1.14)
Interviewer continuity		
E-FTF interviewer continuity		0.81 (0.61, 1.08)
Interviewer attributes (W3)		
Age (years)	0.99 (0.98, 1.00)**	0.99 (0.98, 1.00)**
Female	1.41 (1.12, 1.78)**	1.43 (1.13, 1.82)**
Race (ref: Non-Hispanic other)		
Non-Hispanic black	0.65 (0.50, 0.84)**	0.65 (0.50, 0.85)**
Hispanic	0.91 (0.64, 1.30)	0.89 (0.62, 1.29)
Education (ref: HS graduate)		
Some college	0.78 (0.54, 1.13)	0.80 (0.55, 1.16)
College graduate	0.87 (0.61, 1.26)	0.91 (0.62, 1.32)
Advanced degree	1.00 (0.69, 1.43)	1.04 (0.72, 1.51)
New hire	**0.61 (0.50, 0.76)**** **	**0.59 (0.47, 0.74)**** **
Interviewer Variance	**1.91 (1.49, 2.44)**** **	**1.94 (1.50, 2.52)**** **

Note. Confidence intervals are based on jackknife standard errors from a two-level random effects logistic regression model. CI = confidence interval. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. HS = high school. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0008$ and are **bolded**.

3.6.3 Two-level random effects models for previous non-consenters

As noted with the bivariate associations, there are few significant predictors for the W3 consent models for previous non-consenters. Results from the PM and DBS non-consenters are in Tables 3-8 and 3-9, respectively. Full results from the fourth model, which includes the interaction of continuity and consent refusal type, are not displayed in these tables, but are included in Appendix D. The relevant variables, along with the post-hoc test, are included for both PM and DBS in Table 3-10. Table 3-11 compares previous consenters (see Section 3.6.2) and non-consenters for PM. Table 3-12 does the same for DBS.

Consistent with the bivariate breakdown, W1 PM non-consenters had very few informative predictors in the W3 model (see Table 3-8). No respondent characteristics were significant. While the odds ratio for Spanish interviewed Hispanics is quite large (10.56 in Model 2), the variance is also quite large. Only two W1 health status or health change indicators are associated with W3 PM consent at the 0.05 level. Each functional limitation at W1 resulted in about 0.92 odds of consenting to PM in W3. Improving one's BMI classification (e.g., obese to overweight, overweight to normal) had 2.50 odds of obtaining W3 PM consent compared to those with no change in their BMI classification. For cognition, W1 PM non-consenters with higher scores on their baseline word recall index had 0.90 odds to consent to PM in W3 for each point on the word recall scale.

Survey resistance factors are also not as strong in the PM non-consenters model. The W2 confidentiality index sees 0.67 the odds of W3 PM consent with each unit increase in the confidentiality index, but the effect disappears with the inclusion of W1 resistance measures for which the W1 confidentiality index is significant at the Bonferroni correction level (OR = 0.65 in Model 2). While there is a small odds ratio for W2 nonrespondents (OR = 0.22) in Model 2, the

standard error results in a very wide confidence interval: (0.01, 4.27). Unlike previous consenters, the number of contact attempts has no effect on PM consent in the current wave.

Race of the interviewer is the only significant interviewer attribute predictor at 0.05. In Model 1, respondents with Hispanic interviewers had 0.25 odds of W3 PM consent compared to those with non-Hispanic other race interviewers. Respondents with non-Hispanic black interviewers have 0.46 odds of PM consent after introducing the longitudinal factors in Model 2. The variables included in this model do not leave a significant amount of interviewer variance unexplained by the interviewer attributes, though the magnitude is on par with the PM consenters model. Interviewer continuity is also not a significant predictor, though the 0.59 odds ratio is similar to what was seen with the PM consenters.

When considering Model 3 which adds the type of refusal to the W1 PM collection, the effect is not significant, though the odds ratio is 0.62. The addition of refusal reason only results in some minor changes across the wider model. The inclusion of the interaction effect of interviewer continuity and previous refusal type is also not significant in Model 4 meaning there is no difference in the odds of consent for interviewer continuity between those who provided a straight refusal and those who provided a health-related refusal (see Table 3-10 or Appendix D). For PM non-consenters who gave a health-related refusal to PM in W1, interviewer continuity results in virtually no effect on the odds of PM consent in W3 (OR = 1.01). For those who gave a straight refusal to PM in W1, interviewer continuity results in 0.54 odds of PM consent in W3 (OR = 1.01*0.53 = 0.54). The linear combination specified in Equation (3.5) to test this latter effect results in a Wald chi-square of 2.48 which is not significant at the 0.05 level (see Table 3-10). Thus, the odds ratio of interviewer continuity for those who provided a straight refusal to PM consent in W1is not statistically different from one.

Table 3-8. Predictors of wave 3 physical measurement consent for wave 1 physical measurement non-consenters

	Model 1	Model 2	Model 3
	Odds Ratio	**Odds Ratio**	**Odds Ratio**
Respondent Characteristics			
Age (years)	0.97 (0.95, 1.00)	0.98 (0.94, 1.01)	0.98 (0.94, 1.01)
Female	1.39 (0.91, 2.13)	1.31 (0.86, 2.01)	1.28 (0.84, 1.95)
Education (ref: less than HS)			
High school	1.20 (0.67, 2.15)	1.13 (0.60, 2.13)	1.17 (0.61, 2.26)
Some college	1.74 (0.83, 3.64)	1.54 (0.67, 3.55)	1.59 (0.69, 3.68)
College graduate	1.20 (0.54, 2.70)	1.10 (0.45, 2.69)	1.10 (0.45, 2.68)
Race/ethnicity (ref: Non-Hispanic other)			
Non-Hispanic black	0.78 (0.40, 1.52)	0.77 (0.39, 1.51)	0.78 (0.41, 1.50)
Hispanic (English interview)	1.28 (0.38, 4.33)	1.29 (0.36, 4.59)	1.27 (0.36, 4.48)
Hispanic (Spanish interview)	7.06 (0.95, 52.26)	10.56 (0.99, 112.5)	10.28 (0.87, 121.3)
Attends church at least 1/wk	1.28 (0.80, 2.04)	1.33 (0.81, 2.17)	1.35 (0.82, 2.22)
Another eligible HH member	0.76 (0.48, 1.20)	0.73 (0.46, 1.16)	0.73 (0.46, 1.15)
Health status indicators (W1)			
Self-rated health (ref: Excellent)			
Very good	1.22 (0.52, 2.89)	1.01 (0.36, 2.84)	1.03 (0.36, 2.93)
Good	1.35 (0.55, 3.34)	1.19 (0.41, 3.51)	1.22 (0.42, 3.52)
Fair/Poor	1.32 (0.55, 3.17)	1.14 (0.36, 3.63)	1.16 (0.36, 3.69)
BMI (ref: Underweight/Normal)			
Overweight	0.87 (0.42, 1.82)	0.77 (0.37, 1.61)	0.79 (0.38, 1.64)
Obese	0.80 (0.41, 1.55)	0.71 (0.36, 1.41)	0.73 (0.37, 1.46)
Did not report	0.44 (0.12, 1.58)	0.55 (0.13, 2.42)	0.59 (0.13, 2.57)
Diabetes	0.75 (0.38, 1.47)	0.87 (0.43, 1.77)	0.89 (0.43, 1.81)
Mildly vigorous activity (ref: At least 1/wk)			
1-3 times/month	0.52 (0.23, 1.16)	0.64 (0.25, 1.61)	0.59 (0.23, 1.51)
Hardly ever/never	0.81 (0.36, 1.83)	0.91 (0.29, 2.90)	0.86 (0.28, 2.63)
No. of functional limitations	0.94 (0.88, 1.00)*	0.93 (0.86, 1.00)*	0.91 (0.85, 0.99)*
Ever visited doctor in last 2 years (W1)	1.91 (0.80, 4.58)	1.46 (0.58, 3.72)	1.50 (0.58, 3.88)
Change in health status			
Self-rated health (ref: No change)			
Declined		1.15 (0.64, 2.05)	1.10 (0.62, 1.94)
Improved		1.56 (0.63, 3.88)	1.54 (0.62, 3.82)
BMI (ref: No change)			
Declined		1.49 (0.52, 4.27)	1.52 (0.51, 4.49)
Improved		2.49 (1.19, 5.18)*	2.50 (1.19, 5.25)*
Developed diabetes		1.79 (0.63, 5.12)	1.86 (0.67, 5.17)
Mildly vigorous activity (ref: No change)			
Declined		0.84 (0.50, 1.42)	0.81 (0.47, 1.39)
Improved		0.72 (0.24, 2.14)	0.75 (0.25, 2.19)
Change in no. functional limitations		0.96 (0.88, 1.04)	0.95 (0.88, 1.04)
Ever visited doctor in last 2 years (W3)		1.69 (0.69, 4.17)	1.68 (0.68, 4.17)

(continued)

Table 3-8. Predictors of wave 3 physical measurement consent for wave 1 physical measurement non-consenters (continued)

	Model 1	Model 2	Model 3
	Odds Ratio	**Odds Ratio**	**Odds Ratio**
Cognition indices			
Word recall score (W1)	0.91 (0.84, 0.99)*	0.90 (0.81, 0.99)*	0.90 (0.82, 0.99)*
Mental status score (W1)	1.06 (0.96, 1.17)	1.11 (0.98, 1.25)	1.10 (0.97, 1.25)
Change in word recall score		1.00 (0.89, 1.12)	0.99 (0.88, 1.11)
Change in mental status score		1.09 (0.94, 1.26)	1.08 (0.93, 1.25)
Survey resistance (W1)			
No. of contact attempts		1.02 (0.98, 1.06)	1.02 (0.98, 1.06)
Uncooperative Index		0.98 (0.82, 1.17)	0.96 (0.80, 1.16)
Confidentiality Index		**0.65 (0.51, 0.82)*** **	**0.66 (0.52, 0.83)*** **
Survey resistance (W2)			
Nonrespondent in W2	0.32 (0.02, 5.20)	0.22 (0.01, 4.27)	0.20 (0.01, 4.43)
No. of contact attempts	1.01 (0.99, 1.03)	1.01 (0.98, 1.04)	1.01 (0.98, 1.04)
Uncooperative Index	1.11 (0.91, 1.35)	1.12 (0.92, 1.38)	1.13 (0.93, 1.39)
Confidentiality Index	0.67 (0.51, 0.89)**	0.74 (0.55, 1.01)	0.73 (0.54, 1.00)
Survey resistance (W3)			
No. of contact attempts	0.99 (0.96, 1.02)	0.99 (0.95, 1.02)	0.99 (0.95, 1.02)
Panel status			
Ever a nonrespondent before W1		0.64 (0.32, 1.29)	0.66 (0.33, 1.33)
Interviewer continuity			
E-FTF interviewer continuity		0.59 (0.29, 1.21)	0.60 (0.29, 1.24)
Previous biomeasure consent			
Straight refusal to PM sample (W1)			0.62 (0.34, 1.13)
Interviewer attributes			
Age (years)	0.99 (0.96, 1.02)	0.99 (0.97, 1.02)	0.99 (0.97, 1.02)
Female	0.55 (0.30, 1.04)	0.55 (0.30, 1.02)	0.53 (0.28, 1.00)
Race (ref: Non-Hispanic other)			
Non-Hispanic black	0.52 (0.26, 1.01)	0.46 (0.22, 0.97)*	0.45 (0.22, 0.95)*
Hispanic	0.25 (0.09, 0.73)*	0.25 (0.08, 0.82)*	0.26 (0.08, 0.85)*
Education (ref: HS graduate)			
Some college	0.84 (0.38, 1.85)	0.88 (0.40, 1.93)	0.88 (0.39, 1.96)
College graduate	0.83 (0.36, 1.92)	0.85 (0.38, 1.87)	0.84 (0.38, 1.88)
Advanced degree	0.64 (0.28, 1.43)	0.62 (0.29, 1.32)	0.63 (0.29, 1.35)
New hire	1.23 (0.66, 2.31)	1.18 (0.65, 2.14)	1.20 (0.67, 2.17)
Interviewer variance	2.02 (0.46, 8.85)	1.81 (0.38, 8.75)	1.79 (0.38, 8.41)

Note. Odd ratios 95% confidence intervals are based on jackknife standard errors from a two-level random effects logistic regression model. CI = confidence interval. PM = physical measurements. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. HS = high school.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0008$ and are **bolded**.

The non-consenter DBS model produces very similar findings to those in the non-consenter PM model. Only one health variable, obesity, is significant with previous DBS non-consenters classified as obese having 1.33 odds of DBS consent in W3. No health change variables appear in the final models. While both W1 cognition indices were significant in the bivariate associations, neither is significant in the multivariate models.

In Model 1, the confidentiality index is a significant predicator of W3 DBS consent with an odds ratio of 0.77. In Model 2 when the longitudinal factors are introduced, W1 confidentiality index is resulting in 0.78 odds of DBS consent in W3 for each point in that index. None of the remaining W1, W2, or W3 survey resistance variables are significant in the latter models.

Interviewer attributes do appear in the W3 DBS consent model for previous non-consenters. Interviewer age and hire status have a negative effect on DBS consent with respondent interviewed by new hires having about 0.70 odds of obtaining W3 DBS consent. Respondents with non-Hispanic black interviewers have 0.72 odds of W3 DBS consent once the longitudinal factors are included in Model 2. Like the PM non-consenters, the variables included in this model do not leave a significant amount of interviewer variance unexplained by the interviewer attributes, though the magnitude is much less than the DBS consenters and the PM non-consenters. Interviewer continuity has no effect in these models.

When introducing the reason for previous refusal in Model 3, those who provided a straight refusal to DBS in W1 had half the odds of future consent compared to those who declined for health reasons and is significant with the Bonferroni correction. The inclusion of this variable makes some minor changes in the broader model, but does not change coefficients

for previously identified factors. The interaction of interviewer continuity and reason for refusal is not significant similar to the PM model. For DBS non-consenters who gave a health-related refusal to DBS in W1, interviewer continuity does not result in a statistically significant effect on DBS consent in W3 (OR = 1.39). DBS non-consenters who gave a straight refusal in W1 had 0.63 odds of DBS consent in W3 when they had the same interviewer in W1 as in W3 (OR = 1.39*0.45 = 0.63). While the difference in interviewer continuity between the reasons for refusal may not be significant, the post-hoc linear combination does show that the odds ratio for interviewer continuity for straight refusals at 0.63 is different from 1 at the 0.05 level (Wald χ^2 = 5.89).

Table 3-9. Predictors of wave 3 dried blood spot consent for wave 1 dried blood spot non-consenters

	Model 1	Model 2	Model 3
	Odds Ratio	Odds Ratio	Odds Ratio
Respondent Characteristics			
Age (years)	1.01 (1.00, 1.02)	1.01 (1.00, 1.03)	1.01 (0.99, 1.02)
Female	0.91 (0.70, 1.17)	0.93 (0.72, 1.21)	0.92 (0.71, 1.18)
Education (ref: less than HS)			
High school	1.23 (0.87, 1.74)	1.19 (0.83, 1.71)	1.19 (0.82, 1.73)
Some college	0.90 (0.62, 1.31)	0.90 (0.60, 1.35)	0.91 (0.60, 1.36)
College graduate	0.92 (0.60, 1.41)	0.93 (0.59, 1.47)	0.90 (0.57, 1.43)
Race/ethnicity (ref: Non-Hispanic other)			
Non-Hispanic black	1.05 (0.71, 1.56)	1.03 (0.69, 1.53)	1.04 (0.71, 1.54)
Hispanic (English interview)	1.29 (0.70, 2.40)	1.29 (0.70, 2.40)	1.32 (0.69, 2.51)
Hispanic (Spanish interview)	2.69 (1.10, 6.58)*	2.72 (1.10, 6.73)*	2.71 (1.11, 6.62)*
Attends religious services at least 1/wk	1.06 (0.82, 1.37)	1.05 (0.81, 1.38)	1.02 (0.78, 1.32)
Another eligible HH member	1.13 (0.87, 1.46)	1.08 (0.84, 1.38)	1.06 (0.83, 1.36)
Health status indicators (W1)			
Self-rated health (ref: Excellent)			
Very good	1.12 (0.74, 1.71)	1.05 (0.66, 1.66)	1.04 (0.66, 1.65)
Good	1.24 (0.83, 1.85)	1.17 (0.73, 1.86)	1.12 (0.70, 1.81)
Fair/Poor	1.29 (0.84, 2.00)	1.15 (0.66, 1.99)	1.08 (0.62, 1.88)
BMI (ref: Underweight/Normal)			
Overweight	1.01 (0.76, 1.35)	1.08 (0.79, 1.47)	1.11 (0.81, 1.52)
Obese	1.18 (0.93, 1.49)	1.31 (1.02, 1.70)*	1.35 (1.04, 1.74)*
Did not report	1.36 (0.67, 2.75)	1.51 (0.74, 3.07)	1.57 (0.76, 3.26)
Diabetes	1.14 (0.91, 1.43)	1.19 (0.95, 1.49)	1.20 (0.96, 1.50)
Mildly vigorous activity (ref: At least 1/wk)			
1-3 times/month	0.73 (0.49, 1.08)	0.80 (0.54, 1.19)	0.74 (0.49, 1.12)
Hardly ever/never	0.99 (0.64, 1.54)	1.17 (0.69, 1.98)	1.12 (0.66, 1.90)
No. of functional limitations	0.98 (0.95, 1.02)	0.98 (0.94, 1.02)	0.97 (0.93, 1.01)
Ever visited doctor in last 2 years (W1)	1.01 (0.61, 1.65)	0.95 (0.57, 1.58)	0.95 (0.56, 1.59)
Change in health status			
Self-rated health (ref: No change)			
Declined		0.89 (0.67, 1.20)	0.87 (0.65, 1.16)
Improved		1.09 (0.75, 1.56)	1.11 (0.77, 1.59)
BMI (ref: No change)			
Declined		1.42 (0.93, 2.17)	1.37 (0.91, 2.06)
Improved		0.81 (0.59, 1.11)	0.79 (0.57, 1.09)
Developed diabetes		1.21 (0.74, 1.98)	1.19 (0.72, 1.97)
Mildly vigorous activity (ref: No change)			
Declined		1.18 (0.87, 1.61)	1.16 (0.86, 1.57)
Improved		0.83 (0.49, 1.39)	0.88 (0.52, 1.49)
Change in no. functional limitations		1.00 (0.96, 1.04)	1.00 (0.96, 1.04)
Ever visited doctor in last 2 years (W3)		1.05 (0.72, 1.55)	1.06 (0.73, 1.56)

(continued)

Table 3-9. Predictors of wave 3 dried blood spot consent for wave 1 dried blood spot non-consenters (continued)

	Model 1	Model 2	Model 3
	Odds Ratio	**Odds Ratio**	**Odds Ratio**
Cognition indices			
Word recall score (W1)	0.96 (0.92, 1.00)	0.96 (0.92, 1.00)	0.96 (0.92, 1.00)
Mental status score (W1)	0.99 (0.93, 1.04)	0.98 (0.92, 1.05)	0.99 (0.92, 1.05)
Change in word recall score		1.00 (0.96, 1.04)	1.00 (0.96, 1.04)
Change in mental status score		0.99 (0.90, 1.08)	0.99 (0.90, 1.08)
Survey resistance (W1)			
No. of contact attempts		1.01 (0.99, 1.03)	1.01 (0.99, 1.03)
Uncooperative Index		1.00 (0.90, 1.11)	1.02 (0.91, 1.14)
Confidentiality Index		**0.78 (0.68, 0.90)*** **	0.80 (0.69, 0.91)**
Survey resistance (W2)			
Nonrespondent in W2	0.67 (0.14, 3.31)	0.65 (0.14, 3.00)	0.62 (0.13, 2.95)
No. of contact attempts	1.00 (0.99, 1.01)	1.00 (0.99, 1.01)	1.00 (0.99, 1.01)
Uncooperative Index	0.97 (0.88, 1.08)	0.97 (0.88, 1.07)	0.98 (0.89, 1.08)
Confidentiality Index	0.77 (0.64, 0.92)**	0.81 (0.68, 0.98)*	0.82 (0.68, 0.99)*
Survey resistance (W3)			
No. of contact attempts	0.99 (0.97, 1.01)	0.99 (0.97, 1.00)	0.99 (0.97, 1.01)
Panel status			
Ever a nonrespondent before W1		0.83 (0.59, 1.18)	0.84 (0.59, 1.19)
Interviewer continuity			
E-FTF interviewer continuity		0.71 (0.49, 1.01)	0.70 (0.49, 1.01)
Previous biomeasure consent			
Straight refusal to DBS sample (W1)			**0.50 (0.36, 0.69)**** **
Interviewer attributes			
Age (years)	0.98 (0.97, 0.99)**	0.99 (0.97, 1.00)*	0.98 (0.97, 1.00)**
Female	1.23 (0.91, 1.66)	1.28 (0.92, 1.78)	1.29 (0.92, 1.79)
Race (ref: Non-Hispanic other)			
Non-Hispanic black	0.74 (0.56, 0.99)*	0.72 (0.53, 0.96)*	0.71 (0.53, 0.95)*
Hispanic	0.91 (0.59, 1.40)	0.91 (0.59, 1.41)	0.95 (0.62, 1.45)
Education (ref: HS graduate)			
Some college	0.84 (0.56, 1.27)	0.84 (0.55, 1.26)	0.80 (0.53, 1.22)
College graduate	0.94 (0.63, 1.40)	0.95 (0.64, 1.43)	0.92 (0.61, 1.38)
Advanced degree	0.86 (0.56, 1.32)	0.84 (0.54, 1.30)	0.84 (0.53, 1.30)
New hire	0.74 (0.55, 1.00)*	0.70 (0.53, 0.91)**	0.68 (0.53, 0.88)**
Interviewer variance	1.21 (0.91, 1.61)	1.18 (0.87, 1.59)	1.17 (0.87, 1.56)

Note. Odd ratios 95% confidence intervals are based on jackknife standard errors from a two-level random effects logistic regression model. CI = confidence interval. DBS = dried blood spot. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. HS = high school.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0008$ and are **bolded.**

Table 3-10. Subset of predictors of wave 3 consent and post-hoc test on interviewer continuity and reason for wave 1 non-consent for physical measurements and dried blood spots

	Model 2	Model 3	Model 4
	Odds Ratio	**Odds Ratio**	**Odds Ratio**
Physical measurements			
Interviewer continuity			
E-FTF interviewer continuity	0.59 (0.29, 1.21)	0.60 (0.29, 1.24)	1.01 (0.14, 7.08)
Previous biomeasure consent			
Straight refusal to PM sample (W1)		0.62 (0.34, 1.13)	0.69 (0.36, 1.30)
Continuity and consent interactions			
Interviewer continuity * PM refusal			0.53 (0.07, 4.09)
Continuity | Health-related refusal to PM			1.01
Continuity | Straight refusal to PM			0.54
			Wald $X^2 = 2.353$
Dried blood spots			
Interviewer continuity			
E-FTF interviewer continuity	0.71 (0.49, 1.01)	0.70 (0.49, 1.01)	1.39 (0.49, 3.93)
Previous biomeasure consent			
Straight refusal to DBS sample (W1)		**0.50 (0.36, 0.69)******	0.56 (0.40, 0.80)**
Continuity and consent interactions			
Interviewer continuity * DBS refusal			0.45 (0.16, 1.26)
Continuity | Health-related refusal to DBS			1.39
Continuity | Straight refusal to DBS			0.63*
			Wald $X^2 = 6.065$

Note. Wald X^2 test corresponds to the post-hoc test of coefficient for interviewer continuity given straight refusal to PM or DBS being equal to zero (see Equation (3.5)). Full models 95% odds ratio confidence intervals (in parentheses) are based on jackknife standard errors from a two-level random effects logistic regression model. PM = physical measurements. DBS = dried blood spot. W1 = Wave 1.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0008$ and are **bolded**.

Table 3-11. Model summary by predictor set for wave 3 physical measurement consent

		PM Consenters		PM Non-consenters			
		Model 1	Model 2	Model 1	Model 2	Model 3	Model 4
Predictor set	**df**	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}
Respondent characteristics	10	50.39****	39.54****	12.99	11.69	11.15	10.83
Health status	11	30.02**	33.32***	16.51	10.12	12.69	11.43
Change in health status	9		40.12****		12.46	12.76	12.38
Cognition W1	2	8.35*	9.17*	5.11	5.39	5.25	5.06
Change in cognition	2		5.91		1.38	1.08	1.01
Survey resistance W1	3		66.42****		18.54***	18.17***	17.99***
Survey resistance W2	3	18.82***	4.04	8.88*	4.37	4.45	4.47
Survey resistance W3	1	15.20****	16.36****	0.42	0.53	0.48	0.45
Panel status	2		0.70		2.65	2.53	2.40
Interviewer attributes	8	38.90****	36.49****	21.04**	17.12*	17.07*	16.76*
Interviewer continuity	1		7.26**		2.08	1.92	0.00
Previous PM consent	1					2.42	1.33
Continuity * Reason for refusal	1						0.37
Log-likelihood		-1726.45	-1676.491	-309.2918	-292.4817	-291.3514	-291.0438
Likelihood ratio test			99.91****		33.62	2.26	0.62
ICC		0.260	0.267	0.176	0.153	0.150	0.152

Note. Likelihood ratio test compares current model to the preceding model (e.g., Model 3 vs. Model 2). Panel status predictor set includes nonresponse before W1 and W2 nonresponse. PM = physical measurements. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. ICC = intraclass correlation.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

Table 3-12. Model summary by predictor set for wave 3 dried blood spot consent

		DBS Consenters		DBS Non-consenters			
		Model 1	Model 2	Model 1	Model 2	Model 3	Model 4
Predictor set	**df**	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}	χ^2_{Wald}
Respondent characteristics	10	59.73****	57.88****	18.17	14.92	13.72	14.07
Health status	11	34.26***	59.70****	8.77	13.30	15.68	14.96
Change in health status	9		39.29****		10.63	10.71	11.52
Cognition W1	2	0.22	0.90	3.77	3.49	3.51	3.48
Change in cognition	2		9.02*		0.14	0.17	0.13
Survey resistance W1	3		42.74****		15.33**	12.99**	13.33**
Survey resistance W2	3	27.44****	11.01*	13.99**	8.19*	6.97	7.17
Survey resistance W3	1	27.92****	28.31****	1.54	2.18	1.81	1.79
Panel status	2		3.33		1.24	1.25	1.16
Interviewer attributes	8	39.19****	40.77****	17.12*	20.86**	22.61**	22.57**
Interviewer continuity	1		2.02		3.58	3.66	0.38
Previous DBS consent	1					16.78****	10.32**
Continuity * Reason for refusal	1						2.32
Log-likelihood		-2383.61	-2342.82	-929.95	-916.54	-907.78	-906.25
Likelihood ratio test			81.59****		26.81	17.52****	3.06
ICC		0.164	0.168	0.054	0.048	0.045	0.044

Note. Likelihood ratio test compares current model to the preceding model (e.g., Model 3 vs. Model 2). Panel status predictor set includes nonresponse before W1 and W2 nonresponse. DBS = dried blood spot. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. ICC = intraclass correlation.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

3.7 Discussion

This analysis has examined the impact of various factors on recurrent consent to biomeasures in a panel study. Change in health status, additional waves of survey resistance variables, and interviewer continuity were examined. Separate models were estimated for consent to PM and DBS.

For previous consenters, there are a number of similar predictors between PM and DBS, including mildly vigorous activity, change in functional limitations, number of contact attempts in the current wave, and interviewer observed concerns regarding confidentiality and uncooperativeness. These common predictors, in support of the first research question, can be summarized into two general factors associated with recurrent biomeasure consent, regardless of the type of collection: physical wellbeing and survey resistance. One's ability to be physically active and complete daily tasks is likely a constant barometer for older adults in gauging their ability to complete new, exertive undertakings. Limited capability for the usual and essential priorities of the day are likely to outweigh more demanding within-survey requests. While current survey resistance (measured by contact attempts) directly plays a role, a respondent's reticence during a previous interview seems to carry forward into future waves of the survey. Even though a more recent survey interaction had taken place in the years between biomeasure requests, confidentiality concerns and uncooperative behavior in the previous E-FTF wave had a more salient impact in these analyses than anything from the intervening CATI interview. Additional negative effects observed for age and obesity with respect to PM consent agree with our expectations that increased difficulty with advancing age and unhealthy weight lead to reduced consent to more physically taxing tasks like the walking test. The connection between diabetes and frequent blood glucose testing makes the positive effect on DBS consent relatively

unsurprising (though a bivariate effect was not observed). Reduced consent to DBS for respondents interviewed by new hires may stem from the respondent questioning whether or not they trust the interviewer's ability to safely collect a blood sample whether by some direct observation regarding the interviewer or some intuitive sense through the survey interaction.

For previous non-consenters, the W1 confidentiality index (a measure of survey resistance) was the only significant predictor in both the PM and DBS models using the multiple-comparison correction. This means in addition to the lack of previous consent, previous concerns and resistance to the survey have an enduring impact on future waves the survey, specifically in relation to biomeasure collection. The lack of significant predictors in the previous non-consent models is likely related to small sample sizes, due to the general success of biomeasure collection in HRS, as many significant factors in the previous consenter models had similar magnitudes of odds ratios as the non-consenters models, but increased variability. Given the differences observed across consent requests and the previous consent status, future examinations need to consider separating out previous consenters and non-consenters as they seem to have differential trajectories when it comes to recurrent consent.

The majority of the evidence presented here suggests that participants who have decreasing activity levels or are experiencing more daily limitations are increasingly less likely to consent to future biomeasure collection for both PM and DBS for previous consenters in support of the second research question. These particular factors align with expectations, especially for PM, as the respondent's ability to perform the various physical tasks are diminished due to increasing physical restrictions and thus respondents may be more cautious to avoid these potentially strenuous or harmful activities. Improvements in BMI classification (e.g., obese to overweight, overweight to normal weight) were also associated with a higher likelihood

of future PM consent for previous non-consenters. Healthy weight loss can result in increased energy and greater mobility reducing possible negative side effects such atypical physical exertion. The recent development of chronic diseases like diabetes have no measurable effect on the likelihood of obtaining future biomeasure consent suggesting that one's general health as opposed to any one specific condition has the largest influence on future consent. These effects lead credence to the idea that there may be a causal relationship with changing health status and consent, especially in relation to the collection of physical measurements. The development of alternate protocols for older and more physically limited respondents could be investigated exploring the tradeoffs of obtaining less or simpler measures without any loss in measurement accuracy. Given the likely relationship between physical limitations and the outcomes of interest (specifically PM outcomes), the inclusion of physical limitations (the more recent the better) is important for adjustment models to help avoid nonresponse bias given the relationship to both consent and the outcome (Little & Vartivarian, 2005) which is currently accounted for in the HRS biomarker analysis weights (Crimmins et al., 2013).

Interviewer continuity led to some interesting findings in relation to the third research question. Interviewer continuity between biomeasure requests was related to lower odds of DBS consent for previous non-consenters who had refused for non-health-related reasons (i.e., a straight refusal). This finding in particular is consistent with previous research from Watson and Wooden (2014) suggesting that respondents who have demonstrated previous resistance or refusal are less willing to cooperate at the survey or within survey level when the interviewer remains the same across waves. The difference in this effect was notable compared to those who refused DBS collection for health-related reasons, but the subsequent increase in odds compared to those who did not have the same interviewer in both E-FTF was not significant. While no

significant effect was seen for previous PM non-consenters, the effect was in the same direction as DBS. Given the constant turnover of interviewers, this is a potentially useful finding that a lack of interviewer continuity may help increase longitudinal biomeasure consent. However survey managers should be wary in directly reassigning interviewers as an intervention as the respondent/interviewer interaction is clearly accomplishing part of its purpose by obtaining a completed survey interview.

Perhaps the larger concern is that interviewer continuity was related to lower odds of PM consent for previous consenters. Even previously established relationships that would be considered "good" given the previously affirmative consent request may not be sufficient to result in a repeated success for consent. It is also possible that interviewer continuity is associated with geographic factors. The fact that this effect persists after controlling for multiple survey resistance indicators across multiple waves is a concern. It is unclear if concerns regarding the respondent-interviewer interaction are not adequately accounted for in the survey resistance measures included in these models. Future research is needed to understand why this effect is present. One area that could be considered for previous consenters is what impact informing the interviewer of the respondent's previous consent decision might have to encourage future consent or how it might be used as an intervention to remind the respondent of their previous affirmation (see Sala, Knies, & Burton, 2014).

A straight refusal to DBS does result in nearly half the odds of future consent compared to those with a health-related refusal to DBS in support of the fourth research question. Future E-FTF requests could enact interventions targeted at these more resistant respondents. While there was no evidence for this effect with PM, the odds ratio was in the same direction and may have been diminished due to the missing reason data that was imputed for 2006.

One finding not explicitly related to the stated research goals was the use and effect of mode equivalent, survey resistance indicators. In all of the models considered, the previous E-FTF resistance indicators for confidentiality and cooperativeness indices (but only in the previous consenters model for the latter) were far more effective at predicting future consent than the most recent wave (W2), though the W2 confidentiality index was still significant for some models. The similarities in mode (e.g., type and length of social interaction, number and relative burden of within survey requests) likely play a large role in these stronger effects even though they are four years apart. Understanding the benefits and limitations of using one wave and mode's interviewer observations over another, or using them in tandem, would enhance the general understanding of the utility such measures have in response models and potentially for adjustment. In general, researchers investigating paradata in similar kinds of panel surveys may also consider how consent to biomeasures (or similar consent measures like administrative data linkage) could be a good indicator of capturing multiple facets of survey resistance.

Generalization of these results is limited given the unique data collection design of HRS. Four-year gaps between biomeasure collections may suggest large memory effects especially for an older adult population. Requests that are more frequent may result in a different set of relevant predictors. Again, reminders of previous consent behavior may also benefit recurrent consent requests (see Sala, Knies, & Burton, 2014). HRS also contains a rich source of interviewer-observation paradata that may not be available for all studies to be able to consider.

Panel health surveys play a critical role in helping us understand the causal connections between human behavior and biological forces – especially when linked with biomeasure collection. This study is one of the first to help us better understand some of the human and survey design factors that influence our ability to obtain consent for recurrent biomeasure

requests key in drawing those causal links. Using data collected from previous panel waves – especially previous biomeasure consent and refusal, interviewer continuity, interviewer observation paradata, and overall respondent health and health changes – can help researchers ensure that subsequent waves of biomeasure collection are successful as the application of such methods continues to expand.

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CHAPTER 4

Evaluating Different Applications of Sequential Regression Multivariate Imputation for Imputing Longitudinal Biomarker Measures

4.1 Introduction

Even with some knowledge of the missing data mechanisms that could potentially reduce unit and item nonresponse rates for biomeasure collection, it is inevitable that biomarker measurements will be missing for some survey respondents. Analysts experience in analytic models a loss in precision (i.e., sample size reduction) and a potential for bias due to missing cases. To recover the statistical information present in cases with item missing data requires that some form of post-survey compensation like imputation be completed. Imputation ultimately results in a "rectangular" data set where all analytic variables are complete, allowing for consistent sample sizes across analyses, and possibly achieving increased precision and reduction in bias. The purpose of this chapter is to evaluate three imputation approaches for addressing missing data in longitudinal studies with biomarker measures.

Imputation, as a well-studied area in statistics, is unnecessary in this setting to cover most of the methods available. The focus here is on imputation methods generally associated with addressing bias under a missing at random (MAR) assumption[12]. MAR missing data mechanisms

[12] The exclusion of methods to address the missing completely at random (MCAR) assumption is justified by results in Chapter 2 showing that there are demographic patterns to various forms of biomeasure missingness.

only depend on observed values within the survey, not on the missing values themselves. Item missing data for biomeasures may also result from a mechanism that implies the data are not missing at random (NMAR) where missingness depends on the values of the unobserved measures. Under a generalized pattern of missing data, treatment of NMAR item missing data typically involves simulation of potential outcomes over a reasonable range of assumptions concerning the true mechanism (Little and Rubin, 2002).

There are two important factors to consider when evaluating potential imputation methods for biomeasures: (1) many biomarker measures (e.g., concentrations) have skewed distributions, and (2) in longitudinal studies, past and/or future values may be known for some biomarkers.

4.1.1 Imputing skewed variables

Parametric imputation methods, such as the multivariate normal (MVN) imputation, require that distributional assumptions be met to avoid potentially unreliable or biased imputations. Von Hippel (2013) found that conditionally normal imputation of skewed variables can produce acceptable estimates for means, variances, and regression parameters, but not for distribution shape parameters like percentiles and coefficients of skewness. Von Hippel (2013) and Lee and Carlin (2017) suggested non-normal distributions for use in imputation including Tukey's gh distribution (He & Raghunathan, 2006), the beta or Weibull density (Demirtas & Hedeker, 2008a), the generalized lambda distribution (Demirtas, 2009), and Fleishman power polynomials (Demirtas & Hedeker, 2008b; Demirtas, 2009).

Some (e.g., White, Royston, & Wood, 2010) recommend transforming skewed variables to better approximate normality, but such transformations can result in bias if the transformed

variable does not achieve normality (von Hippel, 2013). In addition, both the imputation model and analysis model should be consistent, or congenial, to capture the relationship between important X and Y variables or risk bias in analyses (von Hippel, 2009, 2013; Bartlett et al., 2015; Heeringa, West, & Berglund, 2017; Lee & Carlin, 2017). If the analysis uses $X^* = g(X)$, then X^* should be included in the imputation model. Von Hippel (2009) found that the best parametric approach for skewed variables is to "transform, then impute," which produces unbiased regression estimates. However, imputed values were not always consistent with the observed distribution, because the imputation is attempting to maintain the relationship between X^* and Y. "The point of imputation is not that the imputed values should look like observed values. The point is that the imputed variable should act like the observed variable when used in analysis" (Von Hippel, 2013, p. 106).

While direct parametric imputation techniques can be used to impute skewed data, alternative imputation approaches do not need to rely on a specific parametric model (e.g., multivariate normal). These methods rely on imputing from an observed distribution or a posterior predictive distribution. Two of the most frequently used of these imputation methods are predictive mean matching and sequential regression multivariate imputation.

Predictive mean matching (PMM) is a hot deck imputation method that draws values or residuals from a set of observed values (i.e., donors) to retain the original distribution among observed values (Little, 1988) – a desirable property when dealing with skewed distributions. PMM implicitly avoids issues related to model misspecification (Little & Rubin, 2002; Andridge & Little, 2010; van Buuren, 2012). It also performs well when there are many possible donors for each recipient and large number of predictors are available (Andridge & Little, 2010). PMM focuses on a univariate distribution and has been found to perform well with skewed data

(Marshall, Altman, Royston, & Holder, 2010; Vink, Frank, Pannekoek, & van Buuren, 2014; Lee & Carlin, 2017).

Sequential regression multivariate imputation (SRMI; Raghunathan, Lepkowski, Van Howeyk, & Solenberger, 2001), also known as multivariate imputation by chained equations (MICE; van Buuren & Groothuis-Oudshoorn, 2000) or fully conditional specification (FCS; van Buuren et al., 2006), employs a sequence of multiple regressions, handling a wide variety of variable types – continuous, binary, categorical, counts, and mixed (semi-continuous with a probability mass at zero). It uses all observed and imputed values for all available variables as potential covariates. Imputed values are ultimately treated as draws from the joint posterior predictive distribution, which is approximated by the sequence of draws from the conditional distributions for each variable as specified by the selected regression models.

SRMI has been recommended for skewed data (White et al., 2011). Under SRMI, PMM may also replace regression as the mechanism to generate imputed values (He & Raghunathan, 2009; White et al., 2011). The SRMI approach will be used in this paper to take advantage of the relationships among biomarkers and health measures, as well as its strength with skewed data.

4.1.2 Longitudinal imputation

Given the focus on repeated biomeasure collection in longitudinal studies, there is a good chance of having at least one successful biomeasure collected for most panel members in either a previous or a future wave. This means that there may be readily available biomarker values – temporally distinct but still highly correlated with the missing biomarker of interest for a given individual.

There are common imputation methods used for longitudinal health or clinical data, such as the last observation carried forward (e.g., Kenward & Molenberghs, 2009; Lachin, 2016) or hot deck imputation (e.g., Andridge & Little, 2010). However, SRMI – mentioned in the previous section – also functions well in this framework. The approach of the SRMI model can use multiple waves of data (Raghunathan, Berglund, & Solenberger, 2018).

A cross-sectional, or single wave, approach ignores the longitudinal nature of the data altogether and may not preserve individual correlations between biomarkers or their related covariates over time. Cross-sectional imputation is done in conjunction with timely data release since it is not dependent on past or future waves of data collection. Given timeliness goals, cross-sectional imputation for item missing data or nonresponse is a common practice in longitudinal surveys (Ferro, 2014).

Imputations can instead be performed consecutively as more waves of data are collected. While a preliminary wave of data collection ($w = 1$) would default to a cross-section imputation as previously described, imputations performed at $w > 1$ would use all $w = 1, 2, \ldots W - 1$ waves within the imputation model. This preserves the "complete" data set from previous waves without the need to impute them again given the newly available data. From a practical standpoint, this can be done in tandem with individual wave data management, but does require greater resources as the number of available waves increases. Studies with a large number of planned waves need to consider the impact of over-fitting in later waves given the large number of data points and variables potentially available (Nevalainen, Kenward, & Virtanen, 2009). A fixed lag of waves (e.g., two) can be included in the imputation model at later time points.

A third approach – used by Raghunathan et al. (2018) – is to create a "wide" data file that allows an imputation model to include all available time points. This means that time w can be imputed using past (e.g., $w-1, w-2$) as well as future (e.g., $w+1, w+2$) values. This approach thereby requires having all waves of data available at once. This is advantageous for earlier waves of data collection that do not benefit from future values in the previous approaches. Depending on the missingness pattern, the final wave of data collection may be equivalent to the consecutive, or sequential, imputation discussed previously assuming the missingness was more monotonic over time. Again, as the number of waves increase, so does the likelihood of over-fitting the regression models (Nevalainen et al., 2009).

4.1.3 Study goals

Each of these approaches (cross-sectional, sequential, wide) uses differing amounts of information to inform imputation models for each variable. This choice among them may be based on the analytic needs of the researcher. This study examines all three using SRMI to compare the nature of the imputed values under each approach.

4.2 Methods

4.2.1 Data

The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the Institute for Social Research (ISR) at the University of Michigan. HRS is a longitudinal survey of adults over the age of 50 living in the United States that collects various measures related to health, medical care, employment, income, and cognition. HRS began in 1992 with a cohort of preretirement-aged individuals born between 1931 and 1941. New birth cohorts are enrolled every 6 years (e.g., 1998, 2004, 2010) to

refresh the sample at the younger ages. The HRS conducts about 20,000 interviews every 2 years with response rates between 65 and 85 percent in the baseline wave and between 85 and 95 percent in follow-up waves.

In 2006, HRS began alternating respondents between face-to-face and telephone interviews, with a random half sample of the full panel being assigned to each mode. Every two years each half-sample switches to the other mode[13]. In face-to-face interviews, noninstitutionalized, non-proxy respondents are asked to provide measures of physical functioning (i.e., blood pressure, hand grip strength, a walking test, height, weight, etc.), a one-time saliva sample (for DNA extraction and storage), and a dried blood spot assay (for measuring Hemoglobin A1c, cholesterol, and other biochemical measures). Saliva and blood samples have different collection, storage, and analysis procedures. Respondents are given three consent forms for each of the biomeasure components. HRS refers to this face-to-face interview with biomeasure collection and self-administered questionnaire on psychosocial topics as the enhanced face-to-face (E-FTF) interview.

This study uses the 2006, 2010, and 2014 E-FTF HRS. Biomeasure eligible respondents to the 2006 HRS are included (n = 7,954). These analyses focus on biomarkers collected from the dried blood spot (DBS) assays. All respondent-level data was obtained from the HRS Public Release data available at http://hrsonline.isr.umich.edu/index.php?p=avail. Biomarker data, denoted as sensitive health data, were obtained through an application process (see http://hrsonline.isr.umich.edu/index.php?p=healthdat for details).

[13] Respondents over the age of 80 alternate between FTF and E-FTF interviews unless they specifically request a telephone interview.

The focus in this investigation is on two DBS biomarkers: C-reactive protein (CRP) and Cystatin C. These biomarkers were chosen because of their statistical and distributional properties. CRP measures have right-skewed distribution, which allows investigation of the "transform and impute" approach, while Cystatin C has a more symmetric distribution. These measures are also related to important health outcomes: CRP is associated with liver function and inflammation, and Cystatin C with kidney functioning as well as healthy aging (see Sarnak et al., 2008). Beyond their direct clinical utility, both CRP and Cystatin C have also been found to be related to cardiovascular disease (e.g., CRP: Ridker, Hennekens, Buring, & Rifai, 2000; Blake & Ridker, 2002; Ridker, Rifai, Rose, Buring, & Cook, 2002; Ridker, 2003; Ridker, Rafai, Cook, Bradwin, & Buring, 2005; Cystatin C: Shlipak et al., 2005; Taglieri, Koenig, & Kaski, 2009; Battistoni, Rubattu, & Volpe, 2012). The cardiovascular connection allows a consolidation of analytic models to be explored. While results for other variables are not specifically discussed here, the remaining DBS biomarkers (HbA1c, HDL, and total cholesterol) are imputed along with CRP and Cystatin C.

Given the skewed distribution of CRP, the natural logarithm transformation, a common transformation for CRP in psychological and sociological analyses (e.g., Demakakos, Nazroo, Breeze, & Marmot, 2008; Luchetti, Barkley, Stephan, Terracciano, & Sutin, 2014; Sutin, Stephan, Luchetti, & Terracciano, 2014; Stephan, Sutin, & Terracciano, 2015; Köhler-Forsberg et al., 2017; Chiang et al., 2019), is included in the imputation models. No transformation is used for Cystatin C.

4.2.2 Analysis plan

Each of the descriptive and multivariate analyses use the stratum and cluster variables as part of the estimation. Details on the analysis weights used are described below.

To evaluate the univariate distributions of both biomarkers (Cystatin C and natural log transformed CRP), the descriptive analyses examine estimates of the means, the proportion at risk (specified in Table 4-1), and five percentiles – 5^{th}, 25^{th} (Q1), 50^{th} (median), 75^{th} (Q3), and 95^{th}. Descriptive analyses used PROC SURVEYMEANS in SAS 9.4 to compute weighted estimates.

The two selected biomarkers are also examined as predictor variables in multivariate (MV) regression models. The biomarker is specified as an independent variable: cross-sectional and longitudinal. A cross-sectional MV model will only utilize one wave of data for analysis, while a longitudinal MV model will use multiple waves.

Both Cystatin C and CRP have been found to be associated with cardiovascular disease, though this is not their primary or intended purpose as a blood biomarker. Using a common health outcome not directly associated with either biomarker (e.g., kidney disease and Cystatin C) allows for a common analytic model with the same covariates. It also avoids confounding findings with the model being tested. In HRS, cardiovascular disease is measured with the question: "Has a doctor ever told you that you had a heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems?"[14] Hence logistic regression is used for each MV model.

[14] This is the question wording when the respondent is participating for the first interview. In reinterviews, respondents who previously reported "No" are asked: "Since we last talked to you [last] has a doctor told you that you have had a heart attack, have coronary heart disease, angina, congestive heart failure, or other heart problems?" Respondents who previously reported "Yes" are asked to confirm the previous response: "Our records from your interview in {INTERVIEW MONTH, YEAR} show that you had a heart problem."

Table 4-1. Dried blood spot biomarker thresholds for high or at risk levels

Dried blood spot biomarker	High/At risk level
Total cholesterol	>= 240 mg/dL
HDL cholesterol	< 40 mg/dL
Glycosylated hemoglobin (HbA1c)	>= 6.4%
C-reactive protein (CRP)	>= 3.0 ug/mL
Cystatin C	> 1.55 mg/L

Note. Thresholds consistent with those defined by Crimmins et al. (2013).

In addition to Cystatin C and CRP as predictors of cardiovascular disease, demographic, health condition, and health behavior risk factors associated with cardiovascular disease[15] were selected as model covariates including age, gender, race/ethnicity, diabetes, hypertension, obesity, physical exercise, and smoking status. Distributions of these predictors (e.g., continuous or categorical) are included in Table 4-2.

For this model, age is centered at its mean (68.5 years). Gender is parameterized as 1 for females, 0 for males. Race/ethnicity is categorized as Hispanic, non-Hispanic black, and non-Hispanic other (reference category). Obesity is a three-category Centers for Disease Control (CDC) specification of body mass index (BMI)[16]: BMI < 25 (underweight or normal; reference category), BMI ≥ 25 but < 30 (overweight), and BMI >= 30 (obese). Diabetes and hypertension are indicators based on self-reported doctor's diagnosis. Mild vigorous activity is a self-reported measure with scale categories of: weekly (reference category), 1-3 times per month, and hardly ever/never. Current smoking status also uses three categories: current smoker, former smoker, and non-smoker (reference category).

[15] The Centers for Disease Control and Prevention (CDC) provide a list of common health conditions, health behaviors, family history and other characteristics that increase the risk of cardiovascular disease at https://www.cdc.gov/heartdisease/risk_factors.htm.
[16] https://www.cdc.gov/obesity/adult/defining.html

Table 4-2. Imputation and analytic variables for multivariate analyses

Imputation variable	Detail	Analytic variable
Demographics		
Age (centered at age 68.5), Age (centered, squared)	Continuous	Yes
Gender (female)	Categorical (2)	Yes
Age by gender interaction	Continuous	Yes
Race/ethnicity	Categorical (3): Hispanic, non-Hispanic black, non-Hispanic other	Yes
Health conditions		
Body mass index	Categorical (3): Underweight/normal weight (<25), overweight (25≤,<30), obese (>=30)	Yes; change
Diabetes	Categorical (2)	Yes; change
Heart disease	Categorical (2)	Yes – outcome
Hypertension	Categorical (2)	Yes; change
Arthritis	Categorical (2)	No
Cancer	Categorical (2)	No
Chronic pain	Categorical (2)	No
Lung disease	Categorical (2)	No
Self-rated health	Categorical (4): Excellent, very good, good, fair/poor	No
Stroke	Categorical (2)	No
Health behaviors		
Mild vigorous activity	Categorical (3): Weekly, 1-3 times/month, hardly ever/never	Yes; change
Smoking status	Categorical (3): Current smoker, former smoker, non-smoker	Yes; change
Biomeasures		
C-reactive protein (natural log transform)	Continuous	Yes; change
Cystatin C	Continuous	Yes; change
HbA1c	Continuous	No
HDL	Continuous	No
Total cholesterol	Continuous	No

Note. Analytic variables are those used in the models detailed in Section 4.2.2.3 and 4.2.2.4. "Change" refers to between-wave change variables used in Section 4.2.2.4.

For this model, age is centered at its mean (68.5 years). Gender is parameterized as 1 for females, 0 for males. Race/ethnicity is categorized as Hispanic, non-Hispanic black, and non-Hispanic other (reference category). Obesity is a three-category Centers for Disease Control (CDC) specification of body mass index (BMI)[17]: BMI < 25 (underweight or normal; reference category), BMI ≥ 25 but < 30 (overweight), and BMI >= 30 (obese). Diabetes and hypertension are indicators based on self-reported doctor's diagnosis. Mild vigorous activity is a self-reported measure with scale categories of: weekly (reference category), 1-3 times per month, and hardly ever/never. Current smoking status also uses three categories: current smoker, former smoker, and non-smoker (reference category).

The cross-sectional MV model is also a logistic regression model where the dependent variable is cardiovascular disease at wave *w*, *w = 2006, 2010, 2014*. In addition to the variables described previously, the model also includes age-squared and an age-by-gender interaction. The final cross-sectional model is specified as:

$$logit\big(p(CVD_w)\big) = Age_w + Age_w^2 + Gender + Age_w \times Gender + Race/Ethnicity + Diabetes_w + HBP_w + Obesity_w + Activity_w + Smoking_w + lnCRP_w + CystatinC_w \quad (4.1)$$

The longitudinal MV model examines the development of cardiovascular disease between 2006 and 2014, with confirmed cardiovascular disease in 2014 as the dependent variable. The analysis is subset to include panel members without a cardiovascular disease diagnosis in 2006 (*n* = 4,357). This conditional inference, only including respondents who did not report having cardiovascular disease in 2006, limits sample size.

[17] https://www.cdc.gov/obesity/adult/defining.html

In addition to the variables listed in Equation 4.1, an indicator variable representing a change in status between waves is included for each of the health conditions, health behaviors, and biomarkers. For example, indicators for development of diabetes from 2006 to 2014, and an increase or decrease in mildly vigorous exercise between 2006 and 2014 are included as predictors. Obesity, mildly vigorous activity, and smoking each have two change indicators (e.g., increase and decrease, start and stop) while the other change indicators only denote the development of that condition[18], or for the continuous biomarkers, the mathematical difference of 2014 from 2006. The final analytic model is:

$$logit\big(p(CVD_{2014}|CVD_{2006}=0)\big) = Age + Age^2 + Gender + Age \times Gender + Race/Ethnicity + Diabetes_{2006} + \Delta Diabetes + HBP_{2006} + \Delta HBP + Obesity_{2006} + \Delta^{-}Obesity + \Delta^{+}Obesity + Activity_{2006} + \Delta^{-}Activity + \Delta^{+}Activity + Smoking_{2006} + \Delta^{-}Smoking + \Delta^{+}Smoking + lnCRP_{2006} + \Delta lnCRP + CystatinC_{2006} + \Delta CystatinC \quad (4.2)$$

Here Δ is the change between 2006 and 2014, with Δ^{-} denoting a decreased change (e.g., lower BMI category, less physical activity, decreased smoking) and Δ^{+} denoting an increased change (e.g., higher BMI category, more physical activity, increased smoking).

Both sets of logistic regression models (Equations 4.1 and 4.2) were estimated using PROC SURVEYLOGISTIC in SAS 9.4. The corresponding 2014 weights were used to analyze the model.

The most relevant weights for this analysis are the *core respondent weight* (referring to the core HRS survey) and the *respondent biomeasure weight*. The respondent sample weight,

[18] It is assumed here that an individual cannot become "undiagnosed" with a health condition (e.g., hypertension, diabetes).

which will be referred to as the base weight in this paper, is the product of the inverse of the probabilities of selecting a household and the individual respondent within households. A poststratification adjustment is also incorporated, based on the American Community Survey (ACS), for differential nonresponse for the HRS survey based on age, gender, race/ethnicity, and geography (Ofstedal, Weir, Chen, & Wagner, 2011). The biomarker weight, also referred to here as the biomeasure weight, is the product of the base weight and a nonresponse adjustment based on a propensity model predicting the probability of completing the biomeasure portion of the interview, using as predictors age, sex, race/ethnicity, education, marital or partner status, and a number of health factors from the interview wave including self-rated health, number of physical limitations, hypertension, heart conditions, myocardial infarction, angina, congestive heart failure or stroke. Following the application of the nonresponse adjustment factor, the biomeasure weights were post-stratified to age, gender, and race distributions from the HRS sample (Crimmins et al., 2013).

The biomeasure weight is the recommended weight to use when analyzing HRS biomarkers. However, the imputation models proposed in this study do include a large share of the predictor variables included in the nonresponse propensity model for the biomeasure weights, and impute beyond those who consented at each E-FTF cycle. Imputing biomarkers for core HRS respondents who did not provide consent to collect biomeasures, but do have a non-zero base weight, would greatly increase the sample size available for analyses. This is potentially advantageous to researchers because it would include non-consenters and proxy respondents (specific to HRS) especially when observed biomarker values in other waves are available for these respondents given the longitudinal data used in this study. The base weight is based on MAR. No adjustments were made to the base weights to ensure there is no confounding between

the imputation method and additional post-survey adjustments. In order to understand the impact of imputing and analyzing beyond the consenting E-FTF sample, the effect of both the biomeasure weight and the base weight are also explored.

4.2.3 Imputation plan

As discussed above there are three imputation approaches to be considered in relation to SRMI. The SRMI algorithm is based on an approximation of a Gibbs sampling algorithm (Geman & Geman, 1984; Gelfand & Smith, 1990) and draws missing values from a predictive distribution corresponding to the conditional density:

$$g_j\left(Y_j \middle| Y_1^{(t)}, Y_2^{(t)}, \ldots, Y_{j-1}^{(t)}, Y_{j+1}^{(t-1)}, \ldots, Y_k^{(t-1)}, X, \theta_j\right) = g_j\left(Y_j \middle| X, \theta_j\right) \quad (4.3)$$

where X is an $n \times p$ matrix containing all variables with no missing values; $Y_1, Y_2, \ldots Y_k$ denote k variables with missing values, ordered by the amount of missing cases, from least to most; g_j is the conditional density specified by the regression defined by the variable type of Y_j; θ_j is a vector of unknown regression parameters (i.e., regression coefficients) with a non-informative prior; and t is the imputation iteration round. During the first imputation iteration, Y_1 (the variable with the smallest amount of missing data) is regressed on variables with complete data and values are drawn from the predictive distribution defined by the imputation model for that variable for all applicable cases. This process is followed by Y_2 (the variable with the second smallest amount of missing data) which is regressed on all the complete data variables as well as Y_1 and a similar draw from its predictive distribution, or mathematically, $g_2\left(Y_2 \middle| Y_1^{(1)}, X, \theta_2\right)$. The algorithm repeats this process through all k variables with missing data. During the remaining imputation rounds ($t > 1$), all missing values are re-imputed using the new imputed values from

the previous round using re-estimated regression models for each variable. After an initial "burn in" series of iterations, multiple final draws are made from the predictive posterior for each variable with item missing data. Typically, $M >= 10$ imputed values are generated (Rubin, 1987; Schafer, 1997) with more recent research supporting larger numbers of MI replicates for some missing data problems (see Bodner, 2008).

The SRMI approach was used in each of three imputation plans to consider alternative ways of handling the longitudinal features of the biomarker data considered in this investigation.

1) Cross-sectional approach – In general, the imputation model for each wave of data ($w = 1, 2,\ldots W$) only includes variables collected in that wave of data collection. Thus the p variables in X and k variables with missing values in Equation 4.3 are limited to wave w. Imputation models are independent of other waves. This approach ignores the longitudinal nature of the data collection.
2) Sequential approach – Here each wave of data is imputed using all of the waves preceding it. For wave $w = 1$, there are no previous waves used as part of the imputation model and thus looks like the cross-sectional approach for $w = 1$. This means that the sequential imputation model for wave 1 should resemble the cross-sectional imputation model for wave 1 given neither utilizes additional waves of data in the imputation models. For waves $w > 1$, fully observed and imputed variables from waves $1,\ldots,w-1$ are included in the imputation model as part of matrix X.
3) Wide approach – Wide refers to the imputation model in which missing data for all waves are imputed simultaneously. In this study, data from all W waves are included in a single imputation model. This means that in relation to Equation 4.3, the X matrix includes all complete variables across all W waves, and the k variables with missing data

Cross-sectional

		Years used in imputation model…		
		2006	2010	2014
…for *w* =	2006	X,Y		
	2010		X,Y	
	2014			X,Y

Sequential

		Years used in imputation model…		
		2006	2010	2014
…for *w* =	2006	X,Y		
	2010	X*	X,Y	
	2014	X*	X*	X,Y

Wide

		Years used in imputation model…		
		2006	2010	2014
…for *w* =	2006	X,Y	X,Y	X,Y
	2010	X,Y	X,Y	X,Y
	2014	X,Y	X,Y	X,Y

Figure 4-1. Cross-sectional, sequential, and wide imputation approaches by wave. Y denotes variables with missing data, X denotes variables fully observed, and X* denotes variables fully observed and variables "complete" due to imputation.

includes all variables across all *W* waves. This approach would result in similar imputation models for wave *W* variables compared to the sequential approach for wave *W* if the missingness pattern was monotonic (which it is not).

For this study, $W = 3$ with w corresponding to HRS 2006, 2010, and 2014. Each of the three approaches corresponding to the HRS waves used in this study are detailed visually in Figure 4-1. Like in Equation 4.3, Y denotes variables with missing values, X denotes fully observed variables, and X^* denotes fully observed variables as well as variables "complete" through imputation. Items in the diagonal represent variables in the imputation model from the current wave. Items in the lower off-diagonal represent variables included in the imputation model from before wave w while items in the upper off-diagonal represents variables in the model coming after wave w.

All of the potential variables included in the imputation models are detailed in Table 4-2. Distributions of the continuous variables are included in Table 4-3a while distributions of categorical variables are included in Table 4-3b. Because imputation models should be congenial with the analysis model (e.g., von Hippel, 2009, 2013; Heeringa et al., 2017), all of the demographic, health condition, and health behavior variables used in the cross-sectional multivariate analysis mentioned previously are included in the imputation model. In addition to these variables, a broader set of health related measures and conditions associated with the HRS biomeasure weighting and the remaining biomarkers are included in the model (e.g., Heeringa et al., 2017) including self-rated health, stroke, arthritis, lung disease, cancer, and chronic pain. Self-rated health is included in the model with four categories with "Fair" and "Poor" combined ("Fair/Poor") due to small sample sizes in the latter. The remaining health conditions are all dichotomous indicators, based on self-report of a doctor's diagnosis. Although the HRS cohort sample recruitment was based on a complex multistage probability sample design, the imputation models applied here do not explicitly include strata and cluster variables or the HRS weights as predictors in the imputation model (Heeringa et al., 2017). This omission could lead to bias if the design variables are informative to the multiple imputation estimates (Reiter, Raghunathan, & Kinney, 2006).

Table 4-3a. Unweighted distributions of observed unimputed continuous variables for imputation by year

Variable	Year	Sample size	Min	P5	Q1	Median	Mean	Q3	P95	Max	StdDev
Age in 2006 (centered at age 68.5)	2006	7,954	-18.50	-14.50	-8.50	-0.50	0.00	6.50	17.50	35.50	9.99
	2010	6,631	-18.50	-15.50	-9.50	-2.50	-1.75	4.50	14.50	35.50	9.49
	2014	5,406	-18.50	-15.50	-10.50	-3.50	-3.12	2.50	12.50	27.50	8.80
Functional limitations	2006	7,954	0.00	0.00	1.00	2.00	3.85	6.00	12.00	22.00	3.91
	2010	6,631	0.00	0.00	1.00	3.00	4.30	6.00	13.00	22.00	4.11
	2014	5,406	0.00	0.00	1.00	3.00	4.62	7.00	14.00	22.00	4.35
HbA1c	2006	6,159	4.07	4.88	5.34	5.69	5.87	6.15	7.53	15.14	1.00
	2010	5,130	3.78	5.02	5.40	5.68	5.89	6.06	7.67	15.17	0.95
	2014	4,361	3.60	4.96	5.42	5.72	6.02	6.32	7.99	15.85	1.02
HDL	2006	4,755	14.08	32.00	43.20	52.16	54.46	64.48	84.64	139.52	16.02
	2010	5,054	13.64	31.96	42.74	51.36	53.54	62.13	83.68	121.40	15.69
	2014	4,036	4.89	33.68	43.05	52.95	55.32	64.53	85.71	217.39	16.89
Total cholesterol	2006	5,853	89.10	140.08	169.22	196.27	201.16	227.48	281.59	405.41	42.18
	2010	5,052	91.32	123.77	158.82	188.67	190.96	218.52	267.84	376.87	43.39
	2014	4,310	104.87	128.26	161.56	189.20	192.13	218.96	265.74	365.66	42.30
Cystatin C	2006	5,778	0.28	0.65	0.84	1.04	1.12	1.24	1.82	10.17	0.53
	2010	5,062	0.07	0.66	0.87	1.06	1.17	1.33	2.01	9.09	0.51
	2014	4,342	0.31	0.69	0.91	1.10	1.23	1.39	2.07	9.33	0.55
CRP	2006	5,874	0.03	0.27	0.94	2.06	4.69	5.00	16.56	280.00	9.57
	2010	5,053	0.05	0.26	0.83	1.84	3.86	3.98	12.83	185.36	8.14
	2014	4,335	0.02	0.13	0.51	1.37	3.75	3.69	14.37	164.66	8.05
ln(CRP)	2006	5,874	-3.51	-1.31	-0.06	0.72	0.75	1.61	2.81	5.63	1.25
	2010	5,053	-3.00	-1.35	-0.19	0.61	0.60	1.38	2.55	5.22	1.19
	2014	4,335	-4.17	-2.06	-0.68	0.32	0.31	1.30	2.66	5.10	1.45

Note. Only includes HRS 2006 biomeasure eligible respondents.

Table 4-3b. Unweighted proportions of observed unimputed categorical variables for imputation by year

Variable		2006	2010	2014	Variable		2006	2010	2014
Gender	Male	42.3%	41.3%	39.9%	Hypertension	No	41.9%	35.9%	32.6%
	Female	57.7%	58.7%	60.1%		Yes	58.0%	63.9%	67.3%
Race/ethnicity	Non-Hispanic other	77.7%	77.7%	77.4%		Missing	0.1%	0.2%	0.1%
	Non-Hispanic black	14.2%	14.1%	14.1%	Diabetes	No	79.4%	75.4%	73.7%
	Hispanic	8.1%	8.2%	8.5%		Yes	20.5%	24.6%	26.3%
Education	Less than high school	25.4%	23.1%	21.5%		Missing	0.1%	<0.01%	<0.1%
	High school graduate	49.1%	49.6%	49.9%	Cancer	No	84. 9%	82.2%	80.3%
	Some college	4.4%	4.7%	4.7%		Yes	15.1%	17.7%	19.6%
	College graduate	21.1%	22.7%	23.9%		Missing	0.1%	0.1%	0.1%
Self-rated health	Excellent	11.1%	9.0%	7.2%	Lung disease	No	89. 7%	88.4%	88.0%
	Very good	29.8%	31.2%	29.5%		Yes	10.2%	11.5%	11.9%
	Good	30.7%	32.5%	34.6%		Missing	0.1%	0.1%	0.1%
	Fair/Poor	28.4%	27.2%	28.7%	Heart disease	No	74.7%	72.2%	69.3%
	Missing	0.1%	0.1%	0.1%		Yes	25.3%	27.7%	30.7%
Mildly vigorous activity	At least 1/week	83.5%	78.8%	77.3%		Missing	<0.1%	0.1%	0.1%
	1-3 times/month	6.4%	8.3%	8.6%	Stroke	No	93.2%	91.7%	90.6%
	Hardly ever/never	10.1%	12.8%	14.0%		Yes	6.3%	7.7%	8.6%
	Missing	0.0%	0.1%	0.2%		Missing	0.5%	0.6%	0.1%
Body mass index (BMI)	Underweight/Normal (<25)	30.3%	29.9%	30.0%	Arthritis	No	38. 7%	34.1%	31.3%
	Overweight (25-29.9)	37.6%	36.4%	36.1%		Yes	61.3%	65.7%	68.6%
	Obese (>30)	30.1%	31.9%	32.2%		Missing	<0.1%	0.2%	0.1%
	Missing	2.1%	1.8%	1.8%	Chronic pain	No	77.9%	76.2%	74.2%
Smoking status	Non-smoker	43.6%	44.6%	46.4%		Yes	22.0%	23.5%	25.2%
	Former smoker	43.1%	44.4%	44.3%		Missing	0.1%	0.2%	0.6%
	Current smoker	13.3%	10.9%	9.3%					
	Missing	0.0%	0.0%	<0.1%					

Note. Only includes HRS 2006 biomeasure eligible respondents. 2006 sample size = 7,954. 2010 sample size = 6,631. 2014 sample size = 5,406.

All SRMI imputations were conducted using IVEware (Raghunathan, Solenberger, Berglund, & van Hoewyk, 2016), an imputation package developed by the Survey Research Center at the Institute for Social Research at the University of Michigan to conduct SRMI imputations and analysis. In terms of building the SRMI imputation models (i.e., predictive distributions) for individual variables, a minimum R^2 (MINRSQD) for variable inclusion in the imputation model was set at 0.005 to eliminate non-informative variables in the imputation model[19]. An imputation bound was set for Cystatin C to prevent imputing negative values.

Multiple imputation was employed for each imputation approach (cross-sectional, sequential, and wide). Multiple imputation inference (Rubin, 1987) repeats the imputation process over a set of independent repetitions $l = 1,2,\ldots M$. Multiple imputation is a method that allows the uncertainty due to imputation to be reflected in the construction of standard errors and confidence intervals for estimated statistics. Ten independent imputations ($M = 10$)[20], or repetitions, were completed for each approach.

Because of the multi-step procedure of the sequential approach imputation, multiple imputation is not conducted at each wave. Rather, M imputations are performed at wave 1 and then a single imputation is done for subsequent waves using the imputation m from $w = 1$ as the base. The final result is M independent imputations at wave 1, and M "dependent" imputations (dependent on imputed values from wave 1 at a subsequent wave) for the second and third waves.

[19] Alternative fixed covariate imputation model including demographics, current wave binary health effects, and current wave biomeasures were also tested to confirm that the R^2 selection criterion was not adding unnecessary variability into the between imputation variance. There was no systematic evidence to support this assertion.

[20] Additional tests using m=100 repetitions were also run to verify the results of m=10 and resulted in very similar final estimates.

The multiple imputation estimates are generated using Rubin's combining rules (Rubin, 1987) programmed in PROC MIANALYZE in SAS 9.4 using the estimates for each repetition from SURVEYMEANS OR SURVEYLOGISTIC to incorporate the complex survey sample design. A population parameter (θ) is estimated as:

$$\bar{\theta} = \frac{1}{M}\sum_{l=1}^{M}\hat{\theta}_l$$

where $\hat{\theta}_l$ is the estimate θ from imputed data set $l = 1, \ldots, M$. The multiple imputation variance for $\bar{\theta}$ is estimated as:

$$var(\bar{\theta}) = \bar{U} + \left(\frac{M+1}{M}\right) \cdot B$$

where $\bar{U}$ is the within-imputation variance, or the average variance of $\hat{\theta}_l$ using the sample design (stratification, clustering, and weights), for each of the *M* imputed data sets computed:

$$\bar{U} = \frac{1}{M}\sum_{l=1}^{M} var(\hat{\theta}_l)$$

and B is the between-imputation variance, or the variance of the *M* sets of parameter estimates:

$$B = \frac{1}{M-1}\sum_{l=1}^{M}(\hat{\theta}_l - \bar{\theta})^2$$

A statistic used to evaluate the quality of the multiple imputation is the fraction of missing information (FMI) – a measure of uncertainty about the imputed values – calculated from the ratio of between-imputation variance to the total variance:

$$\hat{\gamma}_{mi} = \left[\frac{\left(\frac{M+1}{M}\right) \cdot B}{\left(\frac{M+1}{M}\right) \cdot B + \bar{U}}\right] = \left[\frac{\left(\frac{M+1}{M}\right) \cdot B}{T}\right]$$

FMI is commonly compared to the missing rate for a variable as a measure of the relative efficiency of recovering statistical information. FMI is multiplied by 100% in this paper to emphasize this comparison. Good predictors in an imputation model will decrease the between-imputation variance (*B*) and thus decrease the FMI below the missing rate. An FMI at or close to the missing rate suggests poor prediction from the imputation model. However, instability in the imputation can lead to instability in the FMI leading to values that can exceed the missing data rate (Bodner, 2008). In addition, FMI for estimates based on multiple variables (e.g., linear or logistic regression coefficients) are not as straightforward to interpret as for means or proportions for a single variable.

One final metric used is the coefficient of variation used with the means and proportions as a standardized measure of dispersion or a measure of estimate stability. The coefficient of variation (CV) is the ratio of the standard error of an estimate and the estimate itself:

$$CV = \frac{SE(\bar{\theta})}{\bar{\theta}}$$

4.2.4 Research questions

For each of the descriptive and multivariate models, the research questions are:

(1) How do point estimates (e.g., means, proportions, regression coefficients) differ under each longitudinal imputation approach?

(2) Is there a consistent reduction in the variances of the point estimates across the differing imputation approaches?

(3) For univariate measures, how much do the different imputation approaches reduce the fraction of missing information (FMI) compared to the item missing rate? Is the reduction pattern consistent across estimates within imputation approaches?

(4) What additional impact does switching to the base respondent weights from the biomeasure weights and increasing the analyzable sample have on the above issues?

4.3 Results

This section focuses on the results of the multiple univariate and multivariate analyses proposed in Section 4.2.2 using the various imputation approaches described in Section 4.2.3. Sections 4.3.1 and 4.3.2 examine the descriptive statistics (means, the proportion at risk, and percentiles) by E-FTF wave for both Cystatin C and CRP, respectively. Section 4.3.3 compares and summarizes the univariate results from the two previous sections. Section 4.3.4 examines the cross-sectional multivariate model looking at the logistic regression coefficients and associated standard errors across the imputation strategies. Similarly, Section 4.3.5 examines the longitudinal multivariate model and its logistic regression coefficients and standard errors by imputation approach. Each section looks first at the biomeasure weighted analyses and then the HRS base weighted analyses.

Interpretation of the observed cases and imputed estimates should be made with caution. Estimates based on observed cases are complete case analysis, and assume missing data to be MCAR. Biomarker weighted analysis of the observed data implies that item missing data among consenting respondents is MCAR and that item missing data among non-consenters is MAR based on the weighting model. Base weighted analysis of the observed data assumes that both the non-consent and item missing data are MCAR.

4.3.1 Cystatin C – univariate characteristics

The sample size, mean, standard error, CV, and FMI (missing rate for observed cases) for Cystatin C are provided in Table 4-4 by imputation approach nested within years (rows) and

weighting variable (columns). Biomeasure weighted estimates are displayed before base weighted estimates. Overall, there are 5,724 observed cases with Cystatin C measurement out of 6,203 possible cases with biomeasure weights for the 2006 data resulting in an item missing rate of 7.7%. The observed mean for Cystatin C is 1.081 mg/L with a standard error of 0.0075 mg/L. The imputed means shift the estimate of the mean less than a hundredth of a mg/L for each of three imputation approaches, and the standard errors of the imputation-based estimates of means are close to the observed standard error of the mean. The CVs are equivalent across imputation approaches. The FMI of the mean is smaller than the missing rate by anywhere from a quarter (sequential approach) to a half (wide approach). Overall, the wide approach sees a smaller change in the mean, but the largest decrease in FMI from the missing rate.

When applying the base weights, there is a slightly larger sample size for 2006 (n = 5,778), but a much larger missing rate (27.4%). The base weights result in a slightly lower complete case mean (1.074 mg/L) and standard error (0.0070) for Cystatin C compared to the biomeasure weighted mean. When using the multiply imputed values with a total sample size of 7,954, means increased sample size for each of the three approaches rising to 1.090 mg/L for the cross-sectional approach, 1.092 mg/L for the sequential approach, and 1.085 mg/L for the wide approach. Similar to the biomeasure weighted estimates, no meaningful difference is seen in the standard errors of the mean or CVs even though there was an increase of over 2,150 observations. While the sequential approach resulted in the least change in FMI under the biomeasure weights, it exhibits the largest change under the base weights with more than a three-fifths relative reduction to 10.2%. Both the cross-sectional and wide methods show a decrease in the FMI to 21.1% and 19.1% from the missing rate, respectively.

Similar but less prominent patterns appear for Cystatin C in 2010. With 5,062 observed cases and a 3.2% missing rate, the mean Cystatin C in 2010 is slightly larger than what was observed in 2006 with a mean of 1.133 mg/L, a relative increase of about 5%. This increase is expected given Cystatin C is associated with healthy aging (Sarnak et al., 2008). When examining the estimates for the imputed data, the means, standard errors, and CVs are virtually the same as the observed. However, the FMIs for the three approaches do see a significant drop, as with the 2006 estimates.

Estimates change more when applying the base weights to Cystatin C in 2010. Just as with the 2006 data, the base weighted complete case mean is slightly lower than the biomeasure weighted mean, down to 1.130 mg/L. The mean estimates rise to 1.137 mg/L for the cross-sectional, to 1.143 mg/L for the sequential, and 1.146 mg/L for the wide approach. The standard error remains relatively consistent, even with sample size increases. The pattern of the FMIs is not consistent with previous findings. There is an FMI (for the sequential approach) above the missing rate of 23.7%, with an FMI of 24.6%. The wide imputation only sees a small drop in FMI down to 22.8% while the cross-sectional sees a larger drop down to 15.2%.

The 2014 Cystatin C estimates are more reminiscent of the 2010 data than the 2006 data. With a missing rate of 1.6% and 4,342 observed cases, the means and standard errors do not shift at all across the different approaches from a mean of 1.189 mg/L (another small increase) and standard error of around 0.0103 when using the biomeasure weights. When using the imputed values, the sample size increases by less than 100 cases to 4,413. While the sequential and wide approaches see FMIs half of the missing rate, the cross-sectional FMI are unstable, exceeding the missing rate.

When applying the base weights, the observed mean only shifts about a thousandth of a mg/L. The inclusion of the nearly 1,100 additional sample cases (n = 5,406) does change the mean Cystatin C across the three imputation approaches (1.197, 1.203, and 1.206, respectively), but the FMIs for the cross-sectional and sequential mean estimates both exceed the base weight missing rate for Cystatin C of 19.7%, with the wide approach matching the missing rate of 19.5%.

The proportion at risk of chronic kidney disease refers to those with a value of Cystatin C greater than 1.55 mg/L. The 2006 observed data produces a biomeasure weighted estimate of 9.2% at risk of chronic kidney disease (see Table 4-5). Increases in the proportion at risk are seen across all three approaches corresponding with the rising means in the previous section. Consistent with the increase in means, the estimated proportion at risk for the cross-sectional and sequential approaches is 10.0%, while under the wide approach, the proportion did not rise as much. No substantive change is seen in the standard error of the proportions, but the CVs all see some decrease due to change in the estimate of the denominator. While the FMI of the means all shows a decrease for the 2006 biomeasure weighted Cystatin C, the decreases are not as substantial for proportion at risk. The cross-sectional and wide approaches FMIs drop by about a tenth of a percent from the missing rate of 7.7%, but the sequential FMI increases to exceed the missing rate.

The Cystatin C proportion at risk drops slightly to 8.6% for the observed cases when applying the base weight. The various imputation approaches have a large effect on the proportion at risk rising to 12.0% for the cross-sectional, 12.1% for the sequential, and 10.9% for the wide. While there is a substantial gain in the sample size, the standard errors actually increase across the different approaches from 0.0043 to 0.0054 for cross-sectional, 0.0050 for sequential,

and 0.0051 for wide. The CVs are lower and the confidence intervals for these proportions do not overlap with the complete case analysis unlike the biomeasure weighted confidence intervals (see Figure 4-2). Abnormal patterns in the FMIs are also observed with the cross-sectional FMI increasing to 34.2% (27.4% missing rate) and the wide increasing to 42.2%. The sequential approach FMI is lower at 17.0%.

The 2010 biomeasure weighted proportion at risk increases from the 2006 proportion to 12.6%, corresponding with the increase in mean Cystatin C. Small increases in the proportion at risk are observed across the different imputation approaches. CVs and FMIs all show reductions. When using the base weights, the estimated proportions increase by over two full percentage points which place the confidence intervals for each of the approaches nearly, if not completely, outside of the observed data confidence intervals (see Figure 4-2). Relatively unchanging standard errors result in lower CVs across the imputation approaches. The sequential FMI again sits above the missing rate while the others do exhibit some recovery of statistical information.

For the 2014 Cystatin C, the proportion at risk increases slightly to 14.5% consistent with the increase in the mean. Comparing the complete case proportions to the imputed proportions, the proportions at risk again change less than half a percentage point for the biomeasure weighted cases. While the FMIs for the sequential and wide approaches are nearly half the missing data rate, a doubling in FMI for the cross-sectional imputation is present, as with the means. The base weights do not change the complete case proportion at risk, but do result in shifts for the three imputation approaches, increasing each by at least 2.5 percentage points, up to as much as 17.4% for the wide imputation. This also results in lower CVs. Again, the confidence intervals for 2014 Cystatin C imputed proportions compared to the complete case proportions do not overlap (see Figure 4-2). The sequential approach FMI for the proportion at risk is seen to

increase above the missing rate here (21.9% compared to 19.7%), but decreases are observed for the other two imputation approaches.

Table 4-6 displays the estimated values for the 5th, 25th (Q1), 50th (median), 75th (Q3), and 95th percentiles across the columns with their associated standard errors underneath in parentheses. When considering the overall distribution for Cystatin C, there is little change in the lower half of the distribution in relation to the 5th, 25th, and 50th percentiles for the biomeasure weighted cases across the three imputation approaches with most cases changing less than three hundredths of a mg/L (see Table 4-6). The more notable changes are on the higher, more skewed end of the distribution (75th and 95th) where the change is closer to a tenth of a mg/L, though this effect is more pronounced in the 2006 data than 2014 data (see Figure 4-3). There are some large increases in the standard error estimates of these upper percentiles for some imputation approaches (e.g., 75th percentile of the 2006 biomeasure weighted Cystatin C using the cross-sectional approach). This inflation is primarily due to the increased variability across the 10 repetitions. When expanding to all HRS base weighted observations, even larger increases in the 75th and 95th percentiles can be observed while a decrease in the 5th percentile emerges suggesting the increase of sample using the base weights generally broadens the entire distribution and not just the top quartile.

Table 4-4. Observed and imputed means and standard errors of Cystatin C by year and imputation approach

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	5,724	1.081	0.0075	0.0070	7.7%	5,778	1.074	0.0070	0.0065	27.4%
Cross-sectional	6,203	1.085	0.0076	0.0070	4.7%	7,954	1.090	0.0073	0.0067	21.1%
Sequential	6,203	1.085	0.0076	0.0070	5.8%	7,954	1.092	0.0071	0.0065	10.2%
Wide	6,203	1.083	0.0075	0.0069	3.7%	7,954	1.085	0.0071	0.0066	19.1%
2010										
Observed	5,062	1.133	0.0090	0.0079	3.2%	5,062	1.130	0.0086	0.0076	23.7%
Cross-sectional	5,228	1.134	0.0090	0.0079	1.7%	6,631	1.137	0.0085	0.0075	15.2%
Sequential	5,228	1.134	0.0089	0.0078	0.9%	6,631	1.143	0.0090	0.0079	24.6%
Wide	5,228	1.133	0.0090	0.0079	1.8%	6,631	1.146	0.0086	0.0075	22.8%
2014										
Observed	4,342	1.189	0.0103	0.0087	1.6%	4,342	1.188	0.0101	0.0085	19.7%
Cross-sectional	4,413	1.189	0.0104	0.0087	3.2%	5,406	1.197	0.0104	0.0087	22.2%
Sequential	4,413	1.189	0.0103	0.0087	0.7%	5,406	1.203	0.0102	0.0085	20.8%
Wide	4,413	1.189	0.0103	0.0087	0.9%	5,406	1.206	0.0103	0.0086	19.5%

Note. FMI for observed is the missing rate.

Table 4-5. Observed and imputed proportion at risk for Cystatin C by year and imputation approach

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	5,724	0.092	0.0046	0.0504	7.7%	5,778	0.086	0.0043	0.0501	27.4%
Cross-sectional	6,203	0.100	0.0048	0.0481	6.9%	7,954	0.120	0.0054	0.0449	34.2%
Sequential	6,203	0.100	0.0048	0.0479	9.2%	7,954	0.121	0.0050	0.0417	17.0%
Wide	6,203	0.097	0.0046	0.0475	7.0%	7,954	0.109	0.0051	0.0469	42.2%
2010										
Observed	5,062	0.126	0.0063	0.0500	3.2%	5,062	0.124	0.0061	0.0492	23.7%
Cross-sectional	5,228	0.129	0.0063	0.0491	1.7%	6,631	0.147	0.0061	0.0414	20.4%
Sequential	5,228	0.129	0.0063	0.0489	1.8%	6,631	0.150	0.0066	0.0437	25.8%
Wide	5,228	0.127	0.0063	0.0493	2.8%	6,631	0.148	0.0062	0.0421	21.3%
2014										
Observed	4,342	0.145	0.0067	0.0461	1.6%	4,342	0.145	0.0068	0.0468	19.7%
Cross-sectional	4,413	0.148	0.0067	0.0457	3.1%	5,406	0.171	0.0068	0.0398	15.3%
Sequential	4,413	0.147	0.0067	0.0454	0.8%	5,406	0.173	0.0072	0.0417	21.9%
Wide	4,413	0.147	0.0067	0.0457	0.9%	5,406	0.174	0.0071	0.0407	18.0%

Note. FMI for observed is the missing rate.

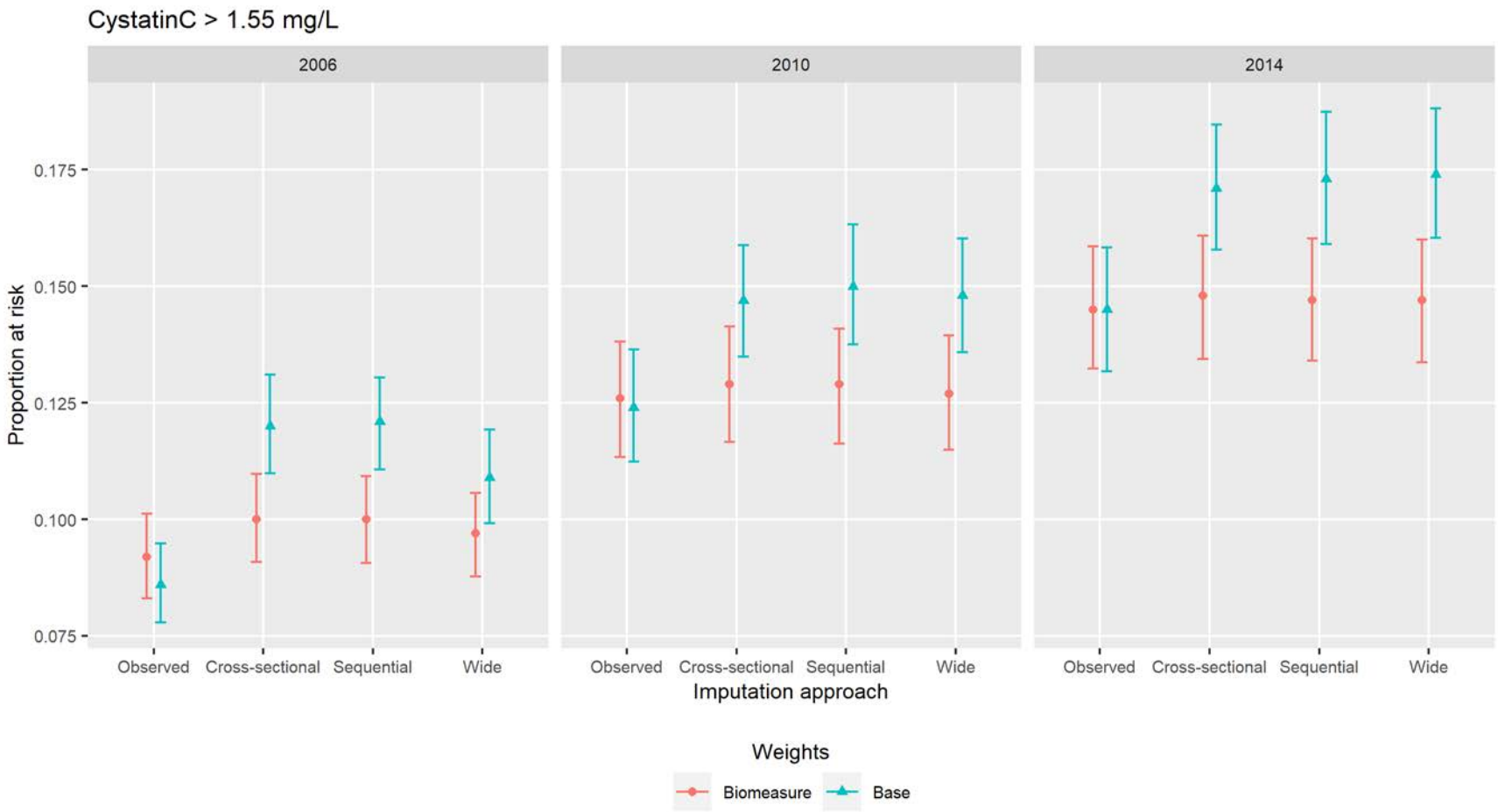

Figure 4-2. Proportion at risk for Cystatin C by year, analysis weight, and imputation approach. 95% confidence interval of the proportions included.

Table 4-6. Observed and imputed percentiles of Cystatin C by year and imputation approach

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.643	0.805	0.945	1.153	1.757	0.646	0.805	0.946	1.149	1.727
(SE)	(0.010)	(0.005)	(0.006)	(0.009)	(0.031)	(0.010)	(0.005)	(0.005)	(0.009)	(0.031)
Cross-sectional	0.647	0.838	0.969	1.212	1.817	0.577	0.840	0.978	1.240	1.877
(SE)	(0.016)	(0.015)	(0.014)	(0.034)	(0.016)	(0.013)	(0.014)	(0.023)	(0.017)	(0.025)
Sequential	0.649	0.837	0.969	1.205	1.815	0.579	0.840	0.988	1.240	1.879
(SE)	(0.018)	(0.015)	(0.015)	(0.030)	(0.017)	(0.013)	(0.015)	(0.022)	(0.016)	(0.029)
Wide	0.649	0.838	0.969	1.170	1.814	0.584	0.840	0.970	1.240	1.826
(SE)	(0.017)	(0.015)	(0.015)	(0.015)	(0.018)	(0.012)	(0.014)	(0.015)	(0.015)	(0.019)
2010										
Observed	0.650	0.849	1.025	1.269	1.943	0.647	0.848	1.025	1.266	1.924
(SE)	(0.009)	(0.006)	(0.007)	(0.012)	(0.035)	(0.010)	(0.006)	(0.007)	(0.012)	(0.034)
Cross-sectional	0.646	0.849	1.029	1.280	1.948	0.586	0.846	1.049	1.332	1.959
(SE)	(0.010)	(0.007)	(0.007)	(0.013)	(0.035)	(0.014)	(0.009)	(0.007)	(0.013)	(0.026)
Sequential	0.645	0.849	1.029	1.277	1.946	0.590	0.849	1.049	1.336	1.977
(SE)	(0.010)	(0.006)	(0.007)	(0.012)	(0.034)	(0.014)	(0.007)	(0.009)	(0.014)	(0.027)
Wide	0.646	0.849	1.029	1.277	1.944	0.605	0.851	1.050	1.334	1.982
(SE)	(0.010)	(0.006)	(0.007)	(0.012)	(0.035)	(0.014)	(0.008)	(0.007)	(0.012)	(0.028)
2014										
Observed	0.669	0.890	1.072	1.338	1.984	0.667	0.889	1.072	1.339	1.981
(SE)	(0.007)	(0.006)	(0.007)	(0.013)	(0.040)	(0.008)	(0.006)	(0.007)	(0.013)	(0.039)
Cross-sectional	0.668	0.892	1.074	1.347	1.988	0.619	0.892	1.092	1.397	2.043
(SE)	(0.008)	(0.006)	(0.007)	(0.014)	(0.038)	(0.016)	(0.006)	(0.010)	(0.013)	(0.035)
Sequential	0.666	0.891	1.075	1.344	1.987	0.625	0.894	1.095	1.400	2.062
(SE)	(0.008)	(0.006)	(0.006)	(0.013)	(0.039)	(0.016)	(0.005)	(0.010)	(0.013)	(0.035)
Wide	0.667	0.890	1.074	1.345	1.988	0.630	0.894	1.094	1.400	2.083
(SE)	(0.008)	(0.005)	(0.007)	(0.014)	(0.038)	(0.015)	(0.004)	(0.011)	(0.014)	(0.041)

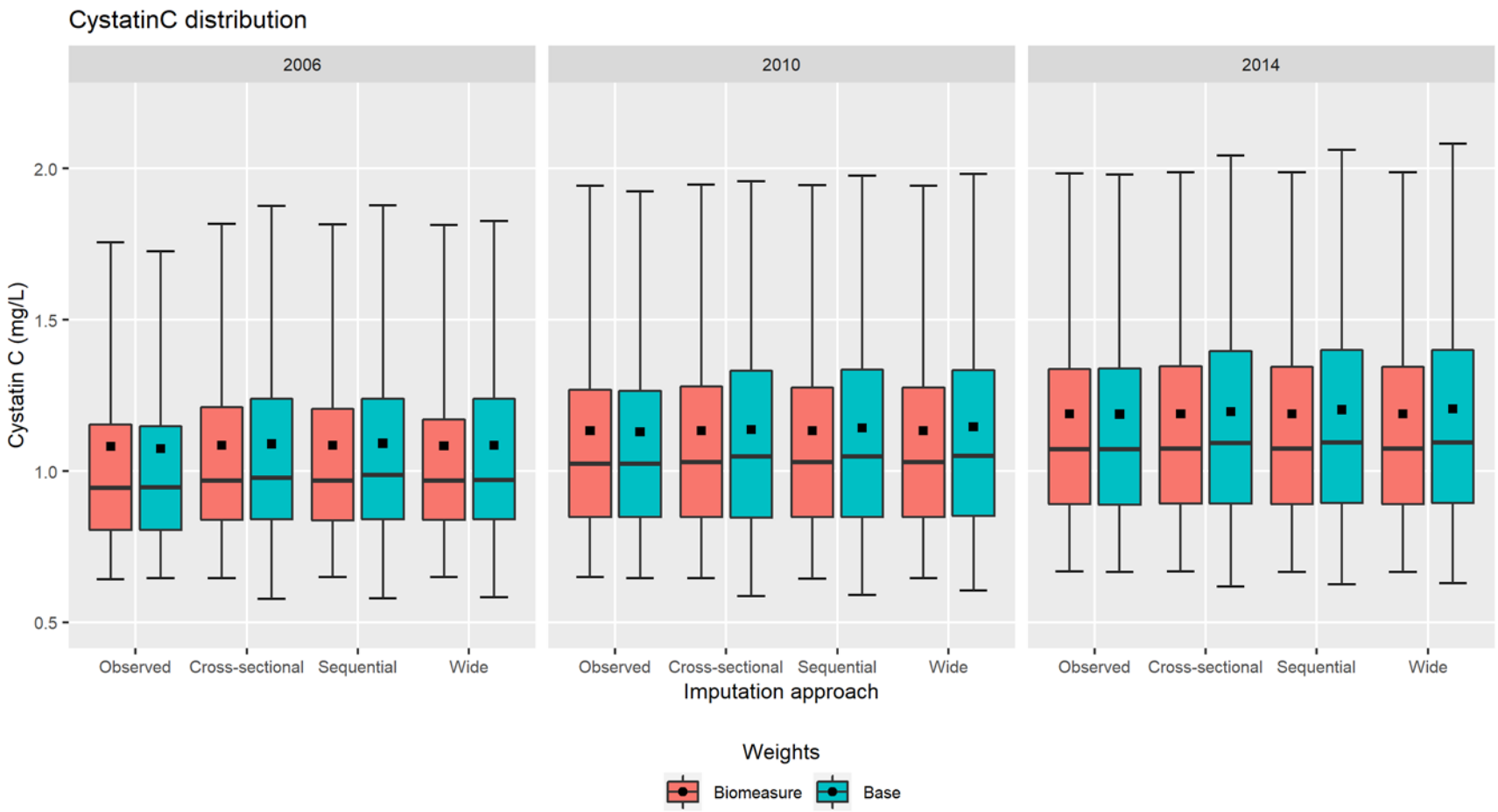

Figure 4-3. Distribution of Cystatin C by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table 4-6. Black squares represent means.

4.3.2 C-reactive protein – univariate characteristics

Table 4-7 displays the means and associated standard errors of the natural log transformed CRP, ln(CRP). The original scale CRP values are not displayed here but are included in Appendix E.

The observed mean of 2006 biomeasure weighted ln(CRP) is 0.718 (corresponding to 2.050 ug/mL on the original CRP scale) with a standard error of 0.0193 and an item missing rate of 6.2% (n = 5,817). Looking across the three imputation approaches, the mean ln(CRP) is virtually unchanged, but with minor drops in the standard errors resulting in slightly reduced CVs. The FMI of the means all decrease with the cross-sectional and sequential approach FMIs dropping to almost half of the missing rate (3.5% and 3.3%, respectively).

The 2006 base weighted ln(CRP) estimates show a similar pattern to Cystatin C of increasing means. The estimates of ln(CRP) means under the cross-sectional and sequential approaches both increase to 0.731 and 0.732, respectively, from the observed 0.721. Overall the observed standard error is larger than the standard errors of the imputed means corresponding with the sample size increase. The FMI for the cross-sectional and sequential imputations is reduced from the item missing rate of 26.2% to 16.5% and 14.3%, respectively. One deviation from this overall pattern is the wide approach where the mean and standard error do not change and the estimated FMI is slightly larger than the item missing rate.

The 2010 biomeasure weighted ln(CRP) mean is lower than the 2006 mean at 0.563, the reverse effect observed with Cystatin C. This suggests that the retained sample has lower inflammation levels, perhaps due to panel loss due to mortality. The imputed means are slightly lower than the observed mean at around 0.560 on average. The FMIs of the mean are all smaller

than the missing rate (3.3%) at 2.4% for cross-sectional, 1.5% for sequential, and 0.7% for wide approaches. When applying the base weights, the ln(CRP) mean drops slightly to 0.556 with an item missing rate of 23.8%. The mean ln(CRP) for the sequential approach is in the same general range as the biomeasure weighted estimates, but the cross-sectional and wide approaches result in slightly higher means (0.567 and 0.571, respectively). The 2010 base weighted estimates is also the first real variability in the standard errors seen here with the cross-sectional standard error dropping from the observed 0.0198 to 0.0185 and the wide standard error increasing to 0.0212. The FMI associated with the cross-sectional mean (17.3%) sees a significant drop from the missing rate (23.8%), while the sequential FMI (23.1%) is sits close to the missing rate and the wide is significantly larger than the missing rate.

Finally the 2014 biomeasure weighted ln(CRP) means decrease to 0.254, with a standard error increasing to 0.0236. Nearly two percent of cases had missing values. While the sample size increase using imputation is small given the biomeasure weights, there are no differences in the means, standard errors, or CVs for ln(CRP). The sequential approach FMI is much smaller than the missing rate at 0.3% while the wide approach FMI is slightly larger at 2.2%. The use of the base HRS weights slightly increases the observed mean (0.257) with the wide approach displaying largest shift in the estimated means (0.269). Some minor reductions in the standard errors and CVs are present, but the cross-sectional and wide approaches FMIs are higher than the missing rate (19.8%), where the sequential approach FMI drops to only 4.1%.

Examining the proportion at risk of high CRP (i.e., high levels of systemic inflammation), the estimated proportions (and their associated standard errors) remain virtually the same across imputation approaches when using the biomeasure weights for each of the three years (see Table 4-8 and Figure 4-4). Some 38.1% had high levels of systemic inflammation in

2006, 31.8% in 2010, and 28.4% in 2014. This drop is consistent with the decreasing means in ln(CRP) noted in the previous section. A consistent decrease in the associated FMI is observed across all imputation approaches and years, the one exception being the cross-sectional imputation for 2014). In general, the different imputation approaches do very little to change the estimated proportion at risk.

When applying the base weights, some movement in the estimates occurs compared to the biomeasure weights. The base weighted proportion at risk estimated from the observed data for 2006 remains the same as the biomeasure weighted proportion, but there is a very weak effect increasing the proportion at risk for the cross-sectional and sequential approaches. The proportion at risk using the wide approach is not different from the observed. The cross-sectional and wide approach standard errors and CVs are smaller. The FMIs of the proportion are all smaller than the missing rate (26.2%), with the base weights for 2006 having the smallest reduction for the wide approach at 19.1%, and the largest reduction for the cross-sectional approach at 12.7%.

The 2010 base weighted observed proportions at risk are slightly below the biomeasure weighted estimate of 31.8%. Minor increases occur in the estimated proportion at risk with the wide imputation approach having the largest increase to 32.2%. Minor increases in standard errors and CV are seen across all imputation approaches. However, the FMIs for the proportion at risk using the base weights in 2010 range from slightly reduced in the sequential approach at 22.2% to largely increased at 26.9% for the cross-sectional approach compared to the missing rate of 23.8%.

Finally, the 2014 estimates using the base weights are relatively unchanged compared to the biomeasure weights. The various imputations do little to change the proportion at risk. Again, variability is seen in the FMIs for the CRP proportion at risk. While the missing rate is 19.8%, the sequential approach results in a lower FMI of 8.7% while the cross-sectional approach FMI remains below the missing rate and the wide approach FMI is increases nearly 50 percent larger.

Consistent with the previous evaluation of the means and proportion at risk, there is no strong change in the selected percentiles nor in their associated standard errors for ln(CRP) regardless of the analysis weight used (see Table 4-9 and Figure 4-5). Table 4-9 shows some small differences across the percentiles in the hundredths place, but these changes are virtually indistinguishable in Figure 4-5. No reduction or major change in the standard errors is observed in Table 4-9. This effect seems consistent across years. Overall, the imputation of CRP appears to change any univariate descriptive measure compared to the observed cases.

Table 4-7. Observed and imputed means and standard errors of C-reactive protein (natural log transform) by year and imputation approach

	Biomeasure weighted					Base weighted				
ln(CRP)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	5,817	0.718	0.0193	0.0269	6.2%	5,874	0.721	0.0203	0.0281	26.2%
Cross-sectional	6,203	0.719	0.0185	0.0257	3.5%	7,954	0.731	0.0195	0.0267	16.5%
Sequential	6,203	0.720	0.0189	0.0262	3.3%	7,954	0.732	0.0198	0.0270	14.3%
Wide	6,203	0.717	0.0186	0.0260	5.8%	7,954	0.721	0.0195	0.0271	26.9%
2010										
Observed	5,053	0.563	0.0194	0.0345	3.3%	5,053	0.556	0.0198	0.0357	23.8%
Cross-sectional	5,228	0.560	0.0195	0.0347	2.4%	6,631	0.567	0.0185	0.0325	17.3%
Sequential	5,228	0.561	0.0195	0.0347	1.5%	6,631	0.562	0.0201	0.0357	23.1%
Wide	5,228	0.560	0.0194	0.0347	0.7%	6,631	0.571	0.0212	0.0371	28.7%
2014										
Observed	4,335	0.254	0.0236	0.0929	1.8%	4,335	0.257	0.0246	0.0955	19.8%
Cross-sectional	4,413	0.254	0.0241	0.0949	1.8%	5,406	0.258	0.0246	0.0952	21.4%
Sequential	4,413	0.254	0.0236	0.0929	0.3%	5,406	0.263	0.0225	0.0858	4.1%
Wide	4,413	0.254	0.0240	0.0943	2.2%	5,406	0.269	0.0241	0.0897	21.5%

Note. FMI for observed is the missing rate.

Table 4-8. Observed and imputed proportion at risk for C-reactive protein by year and imputation approach

	Biomeasure weighted					Base weighted				
Proportion at risk (>= 3.0 ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	5,817	0.381	0.0086	0.0225	6.2%	5,874	0.381	0.0088	0.0230	26.2%
Cross-sectional	6,203	0.381	0.0082	0.0215	3.7%	7,954	0.385	0.0079	0.0206	12.7%
Sequential	6,203	0.381	0.0083	0.0218	4.7%	7,954	0.384	0.0084	0.0218	16.6%
Wide	6,203	0.381	0.0082	0.0215	4.4%	7,954	0.381	0.0079	0.0207	19.1%
2010										
Observed	5,053	0.318	0.0067	0.0210	3.3%	5,053	0.315	0.0069	0.0218	23.8%
Cross-sectional	5,228	0.318	0.0067	0.0211	2.4%	6,631	0.320	0.0073	0.0230	26.9%
Sequential	5,228	0.318	0.0068	0.0212	1.9%	6,631	0.318	0.0071	0.0222	22.2%
Wide	5,228	0.318	0.0068	0.0212	2.2%	6,631	0.322	0.0071	0.0220	26.3%
2014										
Observed	4,335	0.284	0.0073	0.0258	1.8%	4,335	0.285	0.0075	0.0263	19.8%
Cross-sectional	4,413	0.284	0.0075	0.0262	2.6%	5,406	0.283	0.0074	0.0263	18.7%
Sequential	4,413	0.284	0.0074	0.0260	0.8%	5,406	0.284	0.0075	0.0263	8.7%
Wide	4,413	0.284	0.0074	0.0261	1.7%	5,406	0.287	0.0079	0.0276	27.9%

Note. FMI for observed is the missing rate.

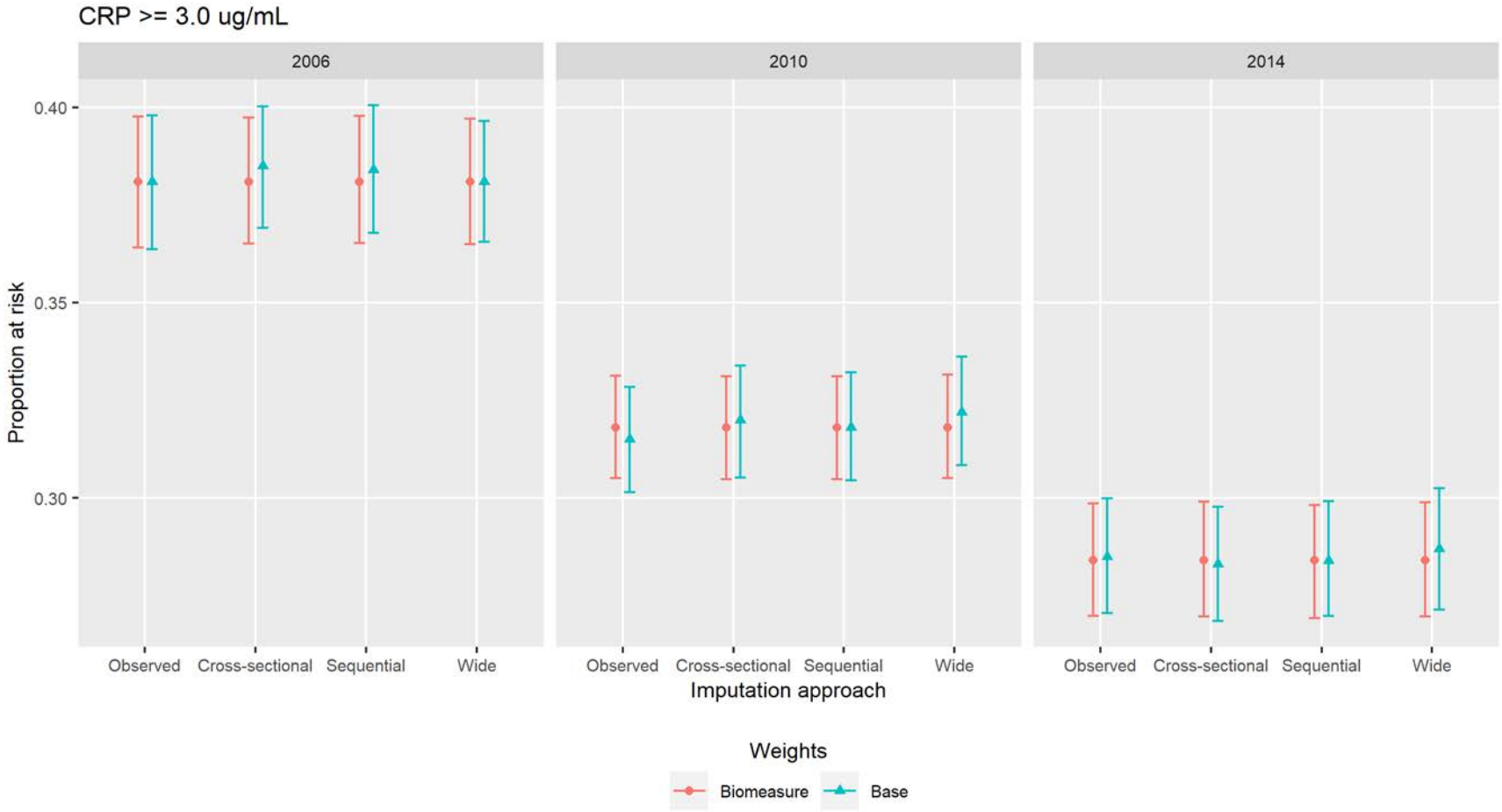

Figure 4-4. Proportion at risk for C-reactive protein by year, analysis weight, and imputation approach. 95% confidence interval of the proportions included.

Table 4-9. Observed and imputed percentiles of C-reactive protein (natural log transform) by year and imputation approach

	Biomeasure weighted					Base weighted				
ln(CRP)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	-1.381	-0.099	0.675	1.571	2.768	-1.367	-0.090	0.677	1.560	2.767
(SE)	(0.052)	(0.033)	(0.032)	(0.029)	(0.044)	(0.050)	(0.035)	(0.032)	(0.030)	(0.045)
Cross-sectional	-1.372	-0.100	0.677	1.578	2.773	-1.336	-0.086	0.717	1.579	2.789
(SE)	(0.051)	(0.034)	(0.033)	(0.029)	(0.043)	(0.043)	(0.030)	(0.033)	(0.029)	(0.041)
Sequential	-1.367	-0.101	0.676	1.576	2.775	-1.337	-0.089	0.717	1.579	2.792
(SE)	(0.051)	(0.034)	(0.033)	(0.029)	(0.043)	(0.045)	(0.036)	(0.033)	(0.029)	(0.042)
Wide	-1.374	-0.105	0.676	1.572	2.769	-1.343	-0.099	0.701	1.560	2.776
(SE)	(0.051)	(0.033)	(0.033)	(0.029)	(0.045)	(0.047)	(0.032)	(0.035)	(0.034)	(0.041)
2010										
Observed	-1.397	-0.233	0.557	1.331	2.521	-1.388	-0.236	0.545	1.326	2.516
(SE)	(0.038)	(0.028)	(0.027)	(0.025)	(0.028)	(0.039)	(0.028)	(0.028)	(0.025)	(0.033)
Cross-sectional	-1.395	-0.235	0.555	1.331	2.520	-1.362	-0.221	0.557	1.342	2.532
(SE)	(0.040)	(0.029)	(0.027)	(0.024)	(0.030)	(0.027)	(0.027)	(0.023)	(0.026)	(0.032)
Sequential	-1.397	-0.232	0.555	1.332	2.522	-1.378	-0.231	0.559	1.339	2.525
(SE)	(0.039)	(0.030)	(0.026)	(0.025)	(0.030)	(0.036)	(0.032)	(0.025)	(0.025)	(0.035)
Wide	-1.400	-0.236	0.555	1.333	2.522	-1.373	-0.218	0.564	1.349	2.528
(SE)	(0.039)	(0.028)	(0.025)	(0.025)	(0.029)	(0.032)	(0.031)	(0.025)	(0.026)	(0.030)
2014										
Observed	-2.198	-0.728	0.250	1.252	2.625	-2.186	-0.726	0.248	1.255	2.628
(SE)	(0.059)	(0.031)	(0.036)	(0.029)	(0.054)	(0.066)	(0.032)	(0.037)	(0.028)	(0.056)
Cross-sectional	-2.195	-0.727	0.250	1.253	2.623	-2.137	-0.719	0.248	1.252	2.625
(SE)	(0.060)	(0.032)	(0.036)	(0.029)	(0.053)	(0.070)	(0.030)	(0.036)	(0.031)	(0.056)
Sequential	-2.190	-0.726	0.250	1.251	2.623	-2.138	-0.715	0.253	1.254	2.643
(SE)	(0.060)	(0.031)	(0.037)	(0.029)	(0.052)	(0.066)	(0.032)	(0.035)	(0.030)	(0.052)
Wide	-2.202	-0.727	0.252	1.252	2.626	-2.150	-0.712	0.267	1.268	2.642
(SE)	(0.057)	(0.032)	(0.037)	(0.029)	(0.056)	(0.064)	(0.032)	(0.036)	(0.033)	(0.054)

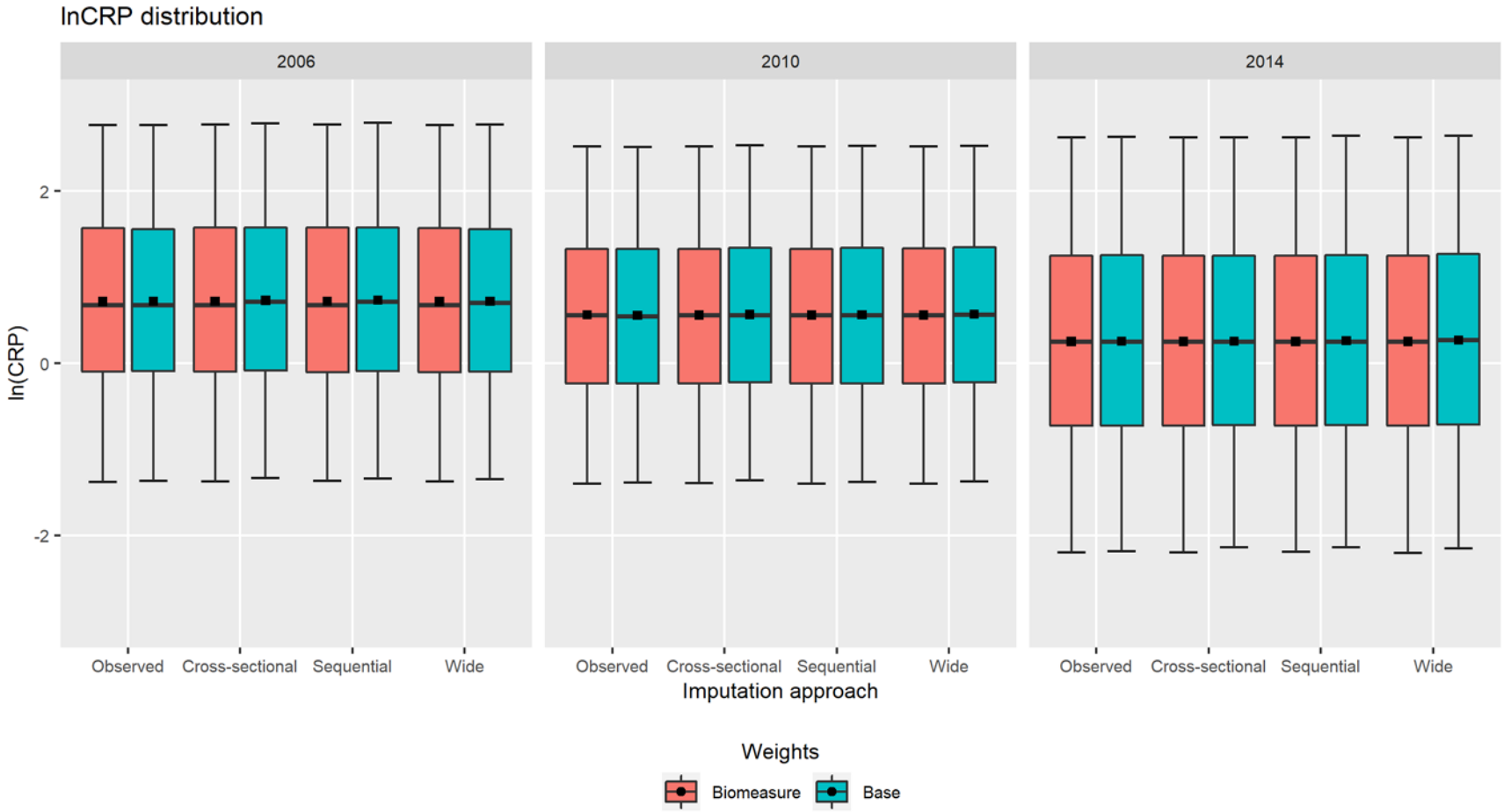

Figure 4-5. Distribution of C-reactive protein (natural log transform) by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table 4-9. Black squares represent means.

4.3.3 Summary of univariate findings

In order to better generalize over the multiple univariate estimates, the mean and median CV and FMI were calculated for each imputation approach and weight combination. Each mean and median is computed across both biomeasures, both parameters (mean and proportion), and all three waves[21]. Given variability in CVs across biomeasure, parameter, and wave, a mean and median relative difference was also calculated to better account for differences in scale[22]. The same calculation was done for FMI.

For the biomeasure weighted estimates, there are very little gains in the CV for the three imputation approaches which makes sense given the relatively small sample size increase (see Table 4-10). The sequential approach has the largest reduction in mean CV and mean relative difference in CV, though the latter is only about a 1% improvement. For the median CV, the cross-sectional approach narrowly comes out on top while the median relative difference again favors the sequential approach. Similarly, the average and median FMI are much lower than the missing data rate with the sequential approach showing the largest drop. The mean relative difference for the sequential approach is 55% (50% for the median) of the observed missing rate followed by the wide approach at 72% (68% for the median).

[21] For example, the mean CV would be calculated as follows:

$$\overline{CV}_{wt,imp} = \left(\sum_{i} \sum_{j} \sum_{w} CV_{i,j,w,wt,imp} \right) / IJW$$

where *i* is the parameter, *j* is the biomeasure, *w* is the wave, *wt* is the weighting variable, and *imp* is the imputation approach. *I*, *J*, and *W* would result in a value of 12 based on the two parameters for two biomeasures across three waves of data.

[22] For example, the CV relative difference would be calculated as follows: $\left(CV_{i,j,w,wt,imp} - CV_{i,j,w,wt,\text{Observed}}\right) / CV_{i,j,w,wt,\text{Observed}}$. If calculating the mean, this value is then substituted in the formula in footnote 21.

When considering the base weighted estimates, some larger gains are seen for the CV of the estimates. The sequential again has the lowest mean CV while the cross-sectional has the lowest median CV. Alternatively when considering the mean relative difference, the cross-sectional has the advantage with an improvement of nearly 4.8% compared to sequential at around 4.5%. This is echoed in the median values. The results for the FMI are consistent showing the sequential approach to have the largest gains in recovering statistical information. The wide imputation using the base weights shows a mean FMI, as well as a median and mean relative difference in FMI, exceeding the complete case analysis.

Table 4-10. Mean and median univariate CV and FMI across biomeasures, parameters, and years

	Mean CV	Mean FMI	Mean Relative Difference in CV	Mean Relative Difference in FMI
Biomeasure weighted				
Observed	0.0328	3.97%	-	-
Cross-sectional	0.0326	3.14%	99.21%	96.36%
Sequential	0.0324	2.64%	98.91%	55.12%
Wide	0.0325	2.83%	99.03%	71.93%
Base weighted				
Observed	0.0333	23.41%	-	-
Cross-sectional	0.0311	20.14%	95.17%	86.85%
Sequential	0.0307	17.44%	95.52%	75.20%
Wide	0.0314	24.44%	96.34%	104.76%
	Median CV	Median FMI	Median Relative Difference in CV	Median Relative Difference in FMI
Biomeasure weighted				
Observed	0.0263	3.26%	-	-
Cross-sectional	0.0260	2.86%	99.96%	71.59%
Sequential	0.0261	1.60%	99.28%	50.92%
Wide	0.0261	2.20%	99.59%	67.75%
Base weighted				
Observed	0.0272	23.73%	-	-
Cross-sectional	0.0265	19.50%	96.66%	81.94%
Sequential	0.0267	18.90%	98.00%	78.21%
Wide	0.0273	22.16%	97.52%	100.90%

Note. CV = coefficient of variation. FMI = fraction of missing information.

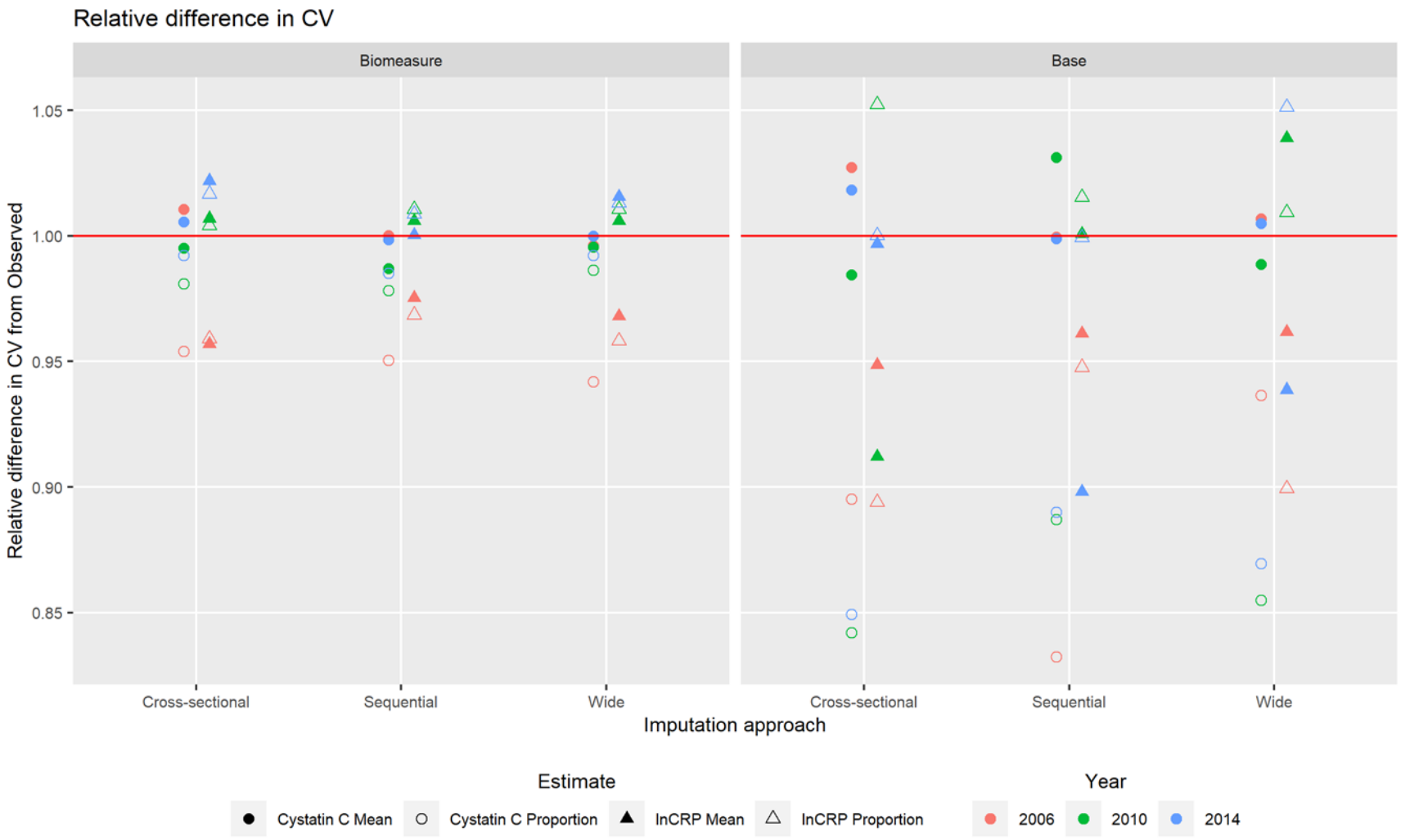

Figure 4-6. Relative difference in univariate CV from observed across biomeasures, parameters, and years.

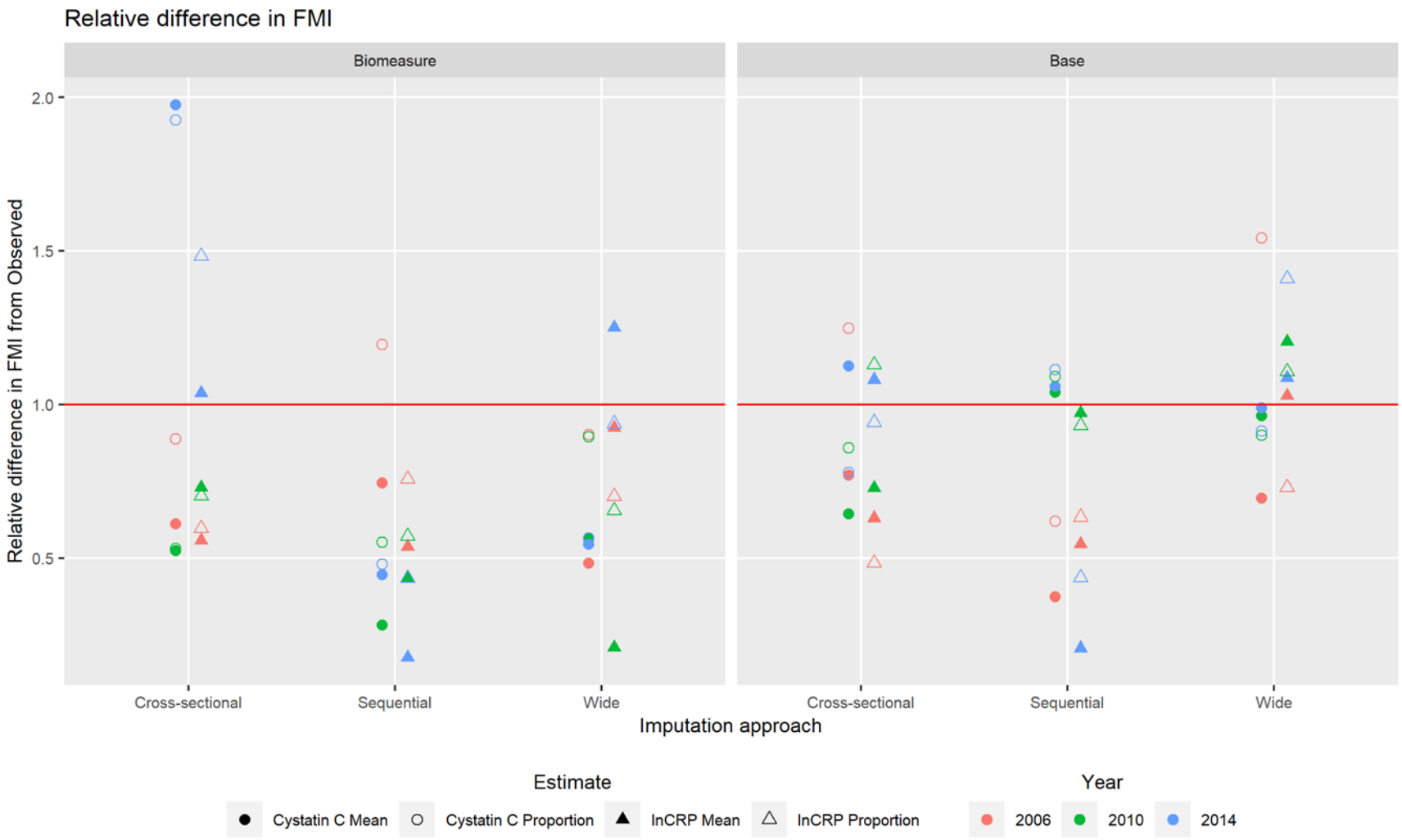

Figure 4-7. Relative difference in univariate FMI from observed across biomeasures, parameters, and years.

4.3.4 Cross-sectional multivariate model

Given similarities among the models results for the three years, only the 2006 model and its coefficient estimates are discussed in this section. The 2006 data have the largest change in sample size and should therefore reflect the largest changes in coefficients and standard errors. Model results for 2010 and 2014 are included Appendix F. Notable differences between years will be highlighted at the end of the section. Statistical significance in this section is defined at a critical value of 0.05.

The complete case analysis modeling cardiovascular disease in 2006 using the biomeasure weights has 5,614 cases. Beginning with the demographic controls (see Table 4-11), females and those of Hispanic ethnicity are both less likely to be diagnosed with cardiovascular disease over males and other non-Hispanic, respectively. Age increases the likelihood of receiving this diagnosis though the effect is somewhat reduced for females. Health conditions including hypertension and diabetes expectedly show up as significant predictors as they are common comorbidities with cardiovascular disease. Obesity (BMI > 30) counterintuitively estimates a negative effect on the likelihood of cardiovascular disease in this estimated model relative to those with a BMI under 25, though this may be a multivariable finding given other variables in the model. For health behaviors, respondents with hardly any or no mildly vigorous activity have a much larger chance of being diagnosed with cardiovascular disease over those who perform weekly activity as are current smokers compared to those who have never smoked. Of the two biomarkers included in the model, only Cystatin C had a significant observed effect on the likelihood of cardiovascular disease.

For each of the imputed models, regardless of approach, the overall analytic sample size increased by over 10 percent to a final sample size of 6,203. Starting with the cross-sectional imputation approach, reductions in multiple standard errors of the logistic regression coefficients are seen which are anticipated given the substantial sample size increase. Larger, more notable standard error reductions include overweight ($SE(\hat{\beta}_{Observed})$ = 0.115 down to $SE(\hat{\beta}_{Cross-sectional})$ = 0.097), non-Hispanic blacks (0.111 down to 0.099), hardly ever/never mildly vigorous activity (0.130 down to 0.120), and Cystatin C (0.081 down to 0.074). Few standard errors (namely obesity) increased from the observed model to the cross-sectional approach imputation. Many of the significant coefficients remain similar to the observed parameter estimates. Some of the larger coefficient changes include obesity ($\hat{\beta}_{cross-sectional}$ = -0.191 down from $\hat{\beta}_{observed}$ = -0.245), non-Hispanic black (-0.204 up to -0.178), and Cystatin C (0.401 down from 0.436).

The sequential approach results look very similar to the cross-sectional results in terms of coefficients and standard errors. The wide approach also exhibits a number of similarities across the other approaches. One notable deviation is the coefficient for Cystatin C which to is closer to zero for the wide approach while maintaining the standard error reduction seen with the cross-sectional and sequential approaches. However this attenuation is not significantly large enough to change the general interpretation of the effect (see Figure 4-8). While still a non-significant variable in the model, ln(CRP) also sees attenuation of the estimated coefficient, but no real change in the standard error.

When applying the base HRS weights to the analysis, the observed sample size increases by less than 100 cases from the biomeasure weighted analysis up to 5,667. Most of the same

patterns above hold with most logistic regression coefficients maintaining the relatively same estimate scale moving less than a few hundredths in either direction for the observed data (see Table 4-12). One exception is the coefficient for Hispanics increasing from $\hat{\beta}_{biomeasure}$ = -0.396 to $\hat{\beta}_{base}$ = -0.513 for the observed model.

When using all of the imputed values, the analytic sample size rises to 7,954 – nearly a forty percent increase in available sample. Most of the imputed estimates (regardless of imputation approach) also see minimal changes. Some larger changes are Hispanics ($\hat{\beta}_{base,observed}$ = -0.513 to $\hat{\beta}_{base,cross-sectional}$ = -0.609), non-Hispanic blacks (-0.213 to -0.261), former smokers (0.153 to 0.194), and Cystatin C (0.440 to 0.348), with the former three getting larger. Regarding the latter, the imputed base weighted Cystatin C coefficients see much more attenuation toward zero ($\hat{\beta}_{base,observed}$ = 0.440 to $\hat{\beta}_{base,wide}$ = 0.350) than with the biomeasure weighted coefficients ($\hat{\beta}_{biomeasure,observed}$ = 0.436 to $\hat{\beta}_{biomeasure,wide}$ = 0.389), but also see a large reduction in standard errors especially for the wide approach ($SE(\hat{\beta}_{base,observed})$ = 0.080 to $SE(\hat{\beta}_{base,wide})$ = 0.061 vs. $SE(\hat{\beta}_{biomeasure,observed})$ = 0.081 to $SE(\hat{\beta}_{biomeasure,wide})$ = 0.073) (see also Figure 4-8).

Given the increase in sample size, there are consistent reductions in standard errors within the imputation models, more so than with the biomeasure weighted model. This is seen particularly in the standard error of the coefficients for females (0.081 to 0.067 using the wide approach), Hispanics (0.136 to 0.122), overweight (0.099 to 0.073), obese (0.109 to 0.085), and current smoker (0.128 to 0.096). In particular Cystatin C sees one of the largest gains with the wide approach having an estimated coefficient standard error of 0.061 compared to the fully observed 0.080. Most standard errors remain fairly close to the biomeasure weighted model, but

some indicators do experience larger changes (e.g., Hispanic, from $\hat{\beta}$ = -0.434 to $\hat{\beta}$ = -0.609). Cystatin C sees greater attenuation in the regression coefficients with the base weights in contrast to reduced standard errors. In general however, the interpretation and conclusions of the model do not fundamentally change.

Figure 4-8 displays odds ratios and confidence intervals for both ln(CRP) and Cystatin C for the 2006 models using both the biomeasure and base weights. Given relative ranges and scales of both biomarkers (Cystatin C has a range of less than 7; ln(CRP) has a range of less than 5), it is less informative to use a one unit increase to examine these coefficient estimates. A one standard deviation change was used for each biomarker coefficient. Using the observed data, one standard deviation was calculated to be about 1.25 for ln(CRP) and about 0.50 for Cystatin C. Using these values, Figure 4-8 shows how the imputed values seem to attenuate the effect of each biomarker, though the confidence intervals – even for the significant predictor Cystatin C – do not fundamentally change.

When looking at the 2010 and 2014 data, there are some minor differences from the estimated models compared to 2006 (see Appendix F). The estimated effects for females ($\hat{\beta}_{2006}$ = -0.254 to $\hat{\beta}_{2014}$ = -0.373) and Hispanics ($\hat{\beta}_{2006}$ = -0.396 to $\hat{\beta}_{2014}$ = 0.482) do increase across the three waves likely due to the changing demographic profile from wave to wave given the restriction to include only those who were biomeasure eligible in 2006. The puzzling negative coefficient for those classified as obese goes away in both 2010 and 2014. While the 2006 model saw a significant increase in the odds of having cardiovascular disease in current smokers (holding all other factors constant), the 2010 and 2014 models saw former smoker status as the larger, significant predictor of cardiovascular disease ($\hat{\beta}_{2006}$ = 0.184 to $\hat{\beta}_{2014}$ = 0.260) with

current smoker showing no significant effect ($\hat{\beta}_{2006}$ = 0.286 to $\hat{\beta}_{2014}$ = 0.200). In 2010, the effects for non-Hispanic blacks increased ($\hat{\beta}_{2006}$ = -0.178 to $\hat{\beta}_{2010}$ = -0.306) while the effect for little to no activity ($\hat{\beta}_{2006}$ = 0.397 to $\hat{\beta}_{2010}$ = 0.230) goes away. These changes are not observed in the 2014 models. Regarding the included biomarkers, the effect for Cystatin C (and the non-significant ln(CRP)) remains fairly constant across the waves. In terms of the different approaches and weights, there are no patterns observed that differed from what was shared previously.

Table 4-11. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using biomeasure weights

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.047 (0.007)****	0.049 (0.006)****	0.049 (0.006)****	0.049 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.254 (0.086)**	-0.264 (0.081)**	-0.266 (0.081)**	-0.262 (0.081)**
Age x Female	-0.017 (0.007)*	-0.014 (0.007)*	-0.014 (0.007)*	-0.014 (0.007)*
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.396 (0.142)**	-0.434 (0.136)**	-0.433 (0.136)**	-0.431 (0.136)**
Non-Hispanic black	-0.178 (0.111)	-0.204 (0.099)*	-0.204 (0.099)*	-0.200 (0.098)*
Health conditions				
Hypertension	0.734 (0.082)****	0.734 (0.080)****	0.733 (0.080)****	0.734 (0.080)****
Diabetes	0.580 (0.063)****	0.596 (0.060)****	0.593 (0.061)****	0.590 (0.061)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.166 (0.115)	-0.178 (0.097)	-0.179 (0.096)	-0.178 (0.099)
Obese (BMI > 30)	-0.245 (0.104)*	-0.191 (0.110)	-0.189 (0.109)	-0.187 (0.109)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.115 (0.154)	0.087 (0.142)	0.089 (0.142)	0.091 (0.142)
Hardly ever/never	0.397 (0.130)**	0.399 (0.122)**	0.394 (0.121)**	0.400 (0.121)**
Smoking status (ref: never smoked)				
Current smoker	0.286 (0.134)*	0.294 (0.129)*	0.292 (0.129)*	0.295 (0.128)*
Former smoker	0.184 (0.104)	0.203 (0.105)	0.203 (0.104)	0.202 (0.104)
Biomeasures				
ln(CRP)	0.035 (0.032)	0.023 (0.031)	0.026 (0.031)	0.022 (0.031)
Cystatin C	0.436 (0.081)****	0.401 (0.074)****	0.399 (0.073)****	0.389 (0.073)****
Intercept	-2.092 (0.166)****	-2.078 (0.164)****	-2.075 (0.163)****	-2.065 (0.162)****

Note. Sample sizes: observed n = 5,614; imputed n = 6,203.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table 4-12. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using base weights

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.047 (0.007)****	0.053 (0.006)****	0.052 (0.006)****	0.053 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.249 (0.081)**	-0.283 (0.068)****	-0.286 (0.068)****	-0.275 (0.067)****
Age x Female	-0.018 (0.007)*	-0.013 (0.005)*	-0.013 (0.005)*	-0.013 (0.005)*
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.513 (0.149)**	-0.609 (0.122)****	-0.610 (0.122)****	-0.602 (0.122)****
Non-Hispanic black	-0.213 (0.112)	-0.261 (0.109)*	-0.260 (0.108)*	-0.251 (0.108)*
Health conditions				
Hypertension	0.730 (0.083)****	0.724 (0.069)****	0.723 (0.069)****	0.723 (0.069)****
Diabetes	0.552 (0.062)****	0.533 (0.064)****	0.531 (0.064)****	0.522 (0.064)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.159 (0.115)	-0.131 (0.073)	-0.136 (0.072)	-0.126 (0.073)
Obese (BMI > 30)	-0.225 (0.101)	-0.134 (0.088)	-0.139 (0.086)	-0.121 (0.085)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.075 (0.154)	0.068 (0.143)	0.069 (0.142)	0.074 (0.143)
Hardly ever/never	0.364 (0.135)**	0.340 (0.098)***	0.337 (0.099)***	0.353 (0.098)***
Smoking status (ref: never smoked)				
Current smoker	0.256 (0.133)	0.234 (0.097)*	0.232 (0.097)*	0.242 (0.096)*
Former smoker	0.153 (0.100)	0.194 (0.081)*	0.195 (0.081)*	0.196 (0.081)*
Biomeasures				
ln(CRP)	0.036 (0.032)	0.029 (0.031)	0.033 (0.028)	0.024 (0.028)
Cystatin C	0.440 (0.080)****	0.348 (0.077)****	0.358 (0.067)****	0.350 (0.061)****
Intercept	-2.084 (0.158)****	-1.965 (0.139)****	-1.974 (0.129)****	-1.974 (0.128)****

Note. Sample sizes: observed n = 5,667; imputed n = 7,954.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

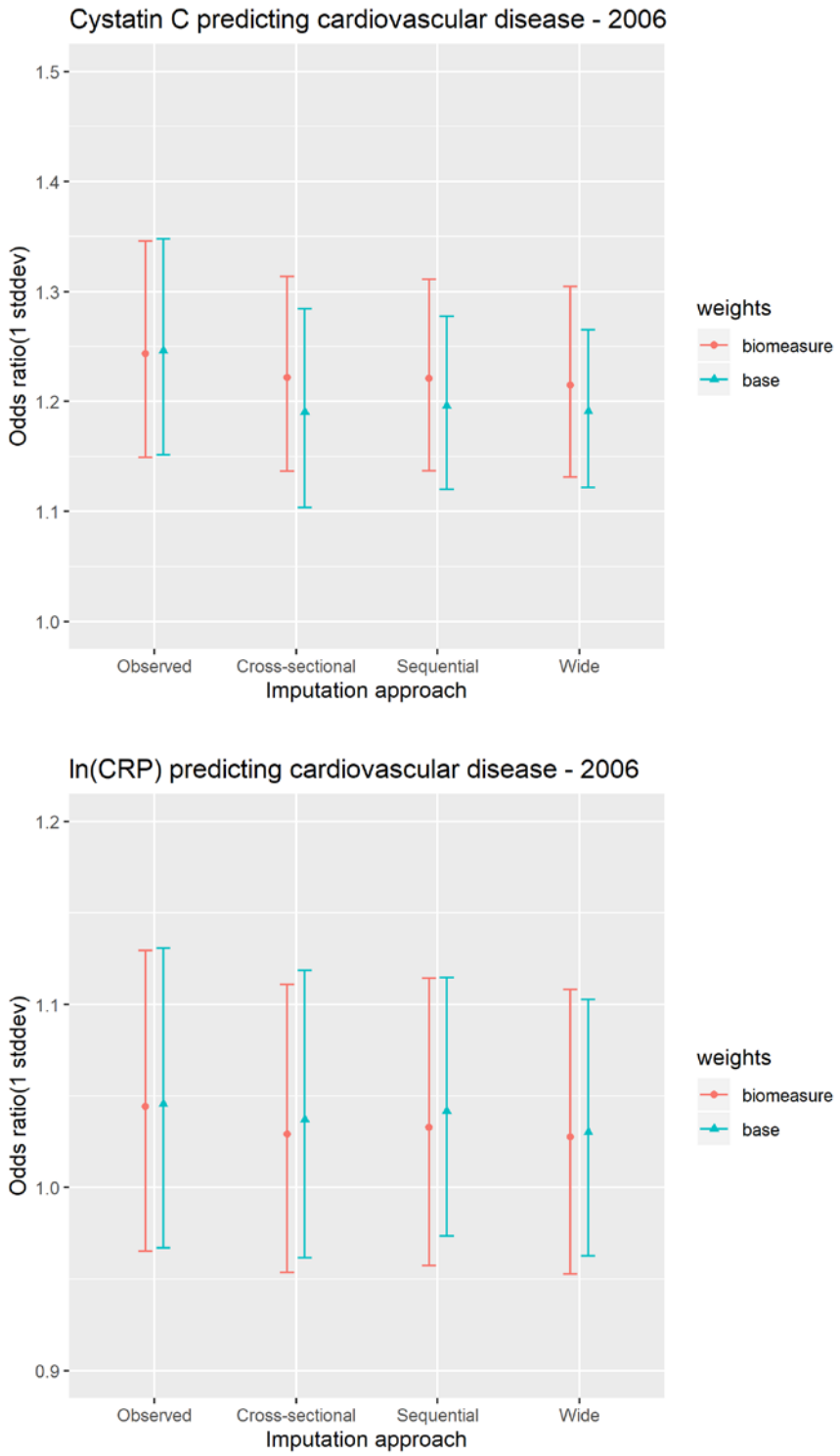

Figure 4-8. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2006 by imputation approach and analysis weight. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

4.3.5 Longitudinal multivariate model

Using the biomeasure weight, the observed sample size for the longitudinal multivariate model is 2,728 while the imputed sample size is 3,545, a 30% increase in analytic sample size, which primarily is due to the addition of over 600 cases that did not consent to biomeasure collection in 2006. Statistical significance in this section is defined at a critical value of 0.05.

In the observed model, age, gender, diabetes, and former smoker are all significant predictors of developing cardiovascular disease, similar to the cross-sectional model (see Table 4-13). These findings are also consistent with the literature as potential risk factors. However, race/ethnicity, hypertension, obesity, and mildly vigorous activity as well as the age by gender interaction are not found to be significant in these models like in the cross-sectional model though the coefficients for Hispanic and hypertension are relatively similar to the coefficients from the cross-sectional model. Cystatin C is also a significant predictor in this model ($\hat{\beta}$ = 0.694) along with the change variable for Cystatin C ($\hat{\beta}$ = 0.367). The initial wave of Cystatin C measurement appears to have a larger effect than more recent changes on the likelihood of developing cardiovascular disease than recent changes in one's kidney health. The transformed CRP has virtually no predictive power for predicting the development of cardiovascular disease ($\hat{\beta}$ = 0.000) with the inclusion of Cystatin C and other known risk factors.

Focusing first on the cross-sectional approach, large drops in the standard errors are fairly consistent across all of the predictors including for Hispanic ($SE\left(\hat{\beta}_{observed}\right)$ = 0.286 down to $SE\left(\hat{\beta}_{cross-sectional}\right)$ = 0.231), hypertension (0.229 down to 0.183), current smoker (0.231 down to 0.184), recently quit smoking (0.336 down to 0.258), and Cystatin C (0.217 down to 0.179). In conjunction with larger estimated coefficients, this led to large changes in statistical significance

for hypertension and recently quit smoking. However many coefficients attenuated toward zero including females and Cystatin C effecting the statistical significance of the former, but not the latter.

Similar to the cross-sectional analysis, a comparison of the three approaches does little to differentiate them from each other when looking at the coefficients and their associated standard errors. Much of the variability in the imputation approaches has to do with Cystatin C. All three approaches do see a large drop in the Cystatin C regression coefficients and the associated standard errors. The sequential approach is the closest to the observed estimates with the wide approach showing the largest drop for both the coefficient and standard error (see Figure 4-9). The variation in the Cystatin C change variable is not as drastic as the main Cystatin C though the wide approach does result in a larger drop in the coefficient, but not in the standard error. These result in very similar confidence intervals (see Figure 4-10).

When applying the base weights, the observed sample size remains the same, but the imputed sample size rises to 4,357 – a 60% increase in sample size. This increase includes the 600 that did not consent to biomeasure collection in 2006, nearly 500 that did not consent in 2014, about 325 who did consent in either 2006 or 2014, and the remainder some other form of missingness across the many analysis variables and biomarkers.

Reviewing the observed data model, the general findings discussed above do not really change with many of the coefficients and standard errors being relatively comparable (see Table 4-14). In terms of the model interpretation, the only difference is that the indicator for recently quit smoking is significant in the observed model with the coefficient rising from $\hat{\beta}_{biomeasure}$ = 0.658 up to $\hat{\beta}_{base}$ = 0.735 with only a moderate increase in the standard error.

The three imputation approaches do see more differences given the large sample increase. Under the cross-sectional approach with the base weights, the female coefficient remains a significant predictor seeing a large drop in the coefficient standard error. A previous diagnosis of hypertension (as of 2006) becomes significant in the cross-sectional imputation similar to when using the biomeasure weight, but a recent diagnosis of hypertension (between 2006 and 2014) is also found to be significant seeing a large jump with the coefficient ($\hat{\beta}_{observed}$ = 0.137 up to $\hat{\beta}_{cross-sectional}$ = 0.456) as well as a large drop in the standard error ($SE(\hat{\beta}_{observed})$ = 0.216 down to $SE(\hat{\beta}_{cross-sectional})$ = 0.154). The coefficient for recently quit smoking remains significant in the cross-sectional imputation, but also sees the current smoker as of 2006 indicator as significant thanks to an enlarged coefficient and reduced standard error. Cystatin C under the cross-sectional approach sees a similar attenuation of the coefficient and reduction in standard error as with the biomeasure weights.

The sequential and wide approaches offer few differences from the cross-sectional approach estimates. The wide approach does see recent weight gain (as measured by transitioning up a BMI category) as a significant predictor of developing cardiovascular disease. Most of the difference again focuses around Cystatin C. The 2006 Cystatin C concentration sees some variability with the sequential approach not enjoying as large of a standard error drop ($SE(\hat{\beta}_{observed})$ = 0.225 down to $SE(\hat{\beta}_{sequential})$ = 0.198) as compared to the cross-sectional or wide approaches ($SE(\hat{\beta}_{cross-sectional})$ = 0.168; $SE(\hat{\beta}_{wide})$ = 0.158), which is similar to the biomeasure weighted results. The wide approach also sees the largest attenuation of the logistic regression coefficient ($\hat{\beta}_{wide}$ = 0.432 down from $\hat{\beta}_{observed}$ = 0.685) compared to the other approaches ($\hat{\beta}_{cross-sectional}$ = 0.540; $\hat{\beta}_{sequential}$ = 0.500). However, these differences do not

substantially alter the overall interpretation and are generally consistent with the results when using the biomeasure weights for analysis (see Figure 4-9). A similar conclusion is reached for the Cystatin C change variable (see Figure 4-10).

Table 4-13. Logistic regression logit coefficients and standard errors of predicting development of cardiovascular disease by 2014 (biomeasure weight)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.052 (0.014)***	0.052 (0.010)****	0.051 (0.010)****	0.052 (0.010)****
Age (squared)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	-0.313 (0.140)*	-0.228 (0.122)	-0.233 (0.123)	-0.227 (0.122)
Age x Female	-0.012 (0.016)	-0.010 (0.013)	-0.009 (0.013)	-0.009 (0.013)
Race/ethnicity (ref: Non-Hispanic other)				
Hispanic	-0.527 (0.286)	-0.351 (0.231)	-0.346 (0.232)	-0.344 (0.231)
Non-Hispanic black	-0.071 (0.188)	-0.110 (0.160)	-0.114 (0.161)	-0.103 (0.161)
Health conditions				
Hypertension (2006)	0.417 (0.229)	0.480 (0.183)**	0.472 (0.183)**	0.471 (0.183)**
Recent HBP diagnosis	0.172 (0.214)	0.347 (0.188)	0.331 (0.190)	0.327 (0.188)
Diabetes (2006)	0.619 (0.159)***	0.567 (0.142)****	0.566 (0.143)****	0.559 (0.143)****
Recent diagnosis diabetes	0.153 (0.203)	0.250 (0.162)	0.251 (0.163)	0.251 (0.162)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.043 (0.190)	0.106 (0.142)	0.090 (0.142)	0.111 (0.144)
Obese (2006)	0.074 (0.157)	0.024 (0.166)	0.023 (0.168)	0.028 (0.169)
Decreased BMI category	-0.142 (0.214)	0.052 (0.187)	0.024 (0.188)	0.003 (0.190)
Increased BMI category	0.180 (0.162)	0.143 (0.143)	0.143 (0.139)	0.159 (0.140)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.142 (0.304)	-0.314 (0.249)	-0.317 (0.249)	-0.329 (0.247)
Hardly ever/never (2006)	-0.078 (0.347)	-0.190 (0.331)	-0.185 (0.333)	-0.196 (0.330)
Decreased daily activity	-0.154 (0.357)	-0.007 (0.247)	-0.017 (0.245)	0.007 (0.245)
Increased daily activity	-0.008 (0.188)	0.010 (0.185)	0.005 (0.185)	0.007 (0.185)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.193 (0.231)	0.268 (0.184)	0.283 (0.185)	0.273 (0.185)
Former smoker (2006)	0.304 (0.118)*	0.278 (0.113)*	0.279 (0.114)*	0.277 (0.112)*
Recently quit smoking	0.658 (0.336)	0.754 (0.258)**	0.722 (0.259)**	0.752 (0.261)**
Recently started smoking	-0.160 (0.751)	-0.491 (0.701)	-0.481 (0.700)	-0.477 (0.700)
Biomeasures				
ln(CRP) (2006)	0.000 (0.057)	0.022 (0.050)	0.025 (0.052)	0.033 (0.048)
ln(CRP) change	-0.072 (0.054)	-0.034 (0.042)	-0.034 (0.042)	-0.037 (0.046)
Cystatin C (2006)	0.694 (0.217)**	0.511 (0.179)**	0.553 (0.189)**	0.487 (0.172)**
Cystatin C change	0.367 (0.128)**	0.354 (0.093)***	0.355 (0.096)***	0.338 (0.110)**
Intercept	-2.778 (0.251)****	-2.734 (0.234)****	-2.761 (0.245)****	-2.703 (0.224)****

Note. Sample sizes: 2,728 for observed, 3,545 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table 4-14. Logistic regression logit coefficient and standard errors predicting development of cardiovascular disease by 2014 (base weight)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.051 (0.015)**	0.052 (0.011)****	0.052 (0.010)****	0.053 (0.010)****
Age (squared)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.294 (0.143)*	-0.273 (0.103)**	-0.275 (0.103)**	-0.266 (0.101)**
Age x Female	-0.011 (0.016)	-0.013 (0.012)	-0.013 (0.012)	-0.012 (0.012)
Race/ethnicity (ref: Non-Hispanic other)				
Hispanic	-0.510 (0.277)	-0.328 (0.168)	-0.318 (0.168)	-0.316 (0.169)
Non-Hispanic black	-0.079 (0.194)	-0.244 (0.154)	-0.239 (0.155)	-0.233 (0.155)
Health conditions				
Hypertension (2006)	0.409 (0.235)	0.514 (0.149)***	0.502 (0.149)***	0.504 (0.150)***
Recent HBP diagnosis	0.137 (0.216)	0.456 (0.154)**	0.427 (0.153)**	0.422 (0.152)**
Diabetes (2006)	0.612 (0.160)***	0.527 (0.127)****	0.524 (0.129)****	0.522 (0.127)****
Recent diagnosis diabetes	0.207 (0.206)	0.288 (0.157)	0.293 (0.158)	0.296 (0.158)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.064 (0.155)	-0.073 (0.144)	-0.065 (0.146)	-0.073 (0.143)
Obese (2006)	0.050 (0.192)	-0.016 (0.141)	-0.019 (0.139)	-0.008 (0.136)
Decreased BMI category	-0.163 (0.211)	0.039 (0.168)	0.023 (0.166)	0.012 (0.168)
Increased BMI category	0.174 (0.158)	0.285 (0.156)	0.294 (0.150)	0.303 (0.153)*
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.092 (0.307)	-0.403 (0.233)	-0.413 (0.237)	-0.425 (0.235)
Hardly ever/never (2006)	-0.069 (0.348)	-0.229 (0.279)	-0.224 (0.280)	-0.228 (0.277)
Decreased daily activity	-0.176 (0.356)	0.021 (0.223)	0.013 (0.222)	0.030 (0.225)
Increased daily activity	-0.013 (0.186)	0.145 (0.142)	0.151 (0.142)	0.150 (0.143)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.172 (0.233)	0.360 (0.165)*	0.369 (0.164)*	0.374 (0.163)*
Former smoker (2006)	0.307 (0.121)*	0.247 (0.108)*	0.249 (0.108)*	0.250 (0.107)*
Recently quit smoking	0.735 (0.350)*	0.600 (0.227)**	0.589 (0.227)**	0.605 (0.229)**
Recently started smoking	-0.114 (0.743)	-0.658 (0.688)	-0.654 (0.688)	-0.643 (0.687)
Biomeasures				
ln(CRP) (2006)	0.016 (0.057)	0.036 (0.058)	0.044 (0.053)	0.050 (0.045)
ln(CRP) change	-0.080 (0.056)	-0.025 (0.045)	-0.032 (0.046)	-0.040 (0.045)
Cystatin C (2006)	0.685 (0.225)**	0.540 (0.168)**	0.500 (0.198)*	0.432 (0.158)**
Cystatin C change	0.388 (0.131)**	0.306 (0.093)**	0.327 (0.101)**	0.305 (0.107)**
Intercept	-2.792 (0.253)****	-2.641 (0.214)****	-2.604 (0.244)****	-2.539 (0.207)****

Note. Sample sizes: 2,728 for observed, 4,357 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

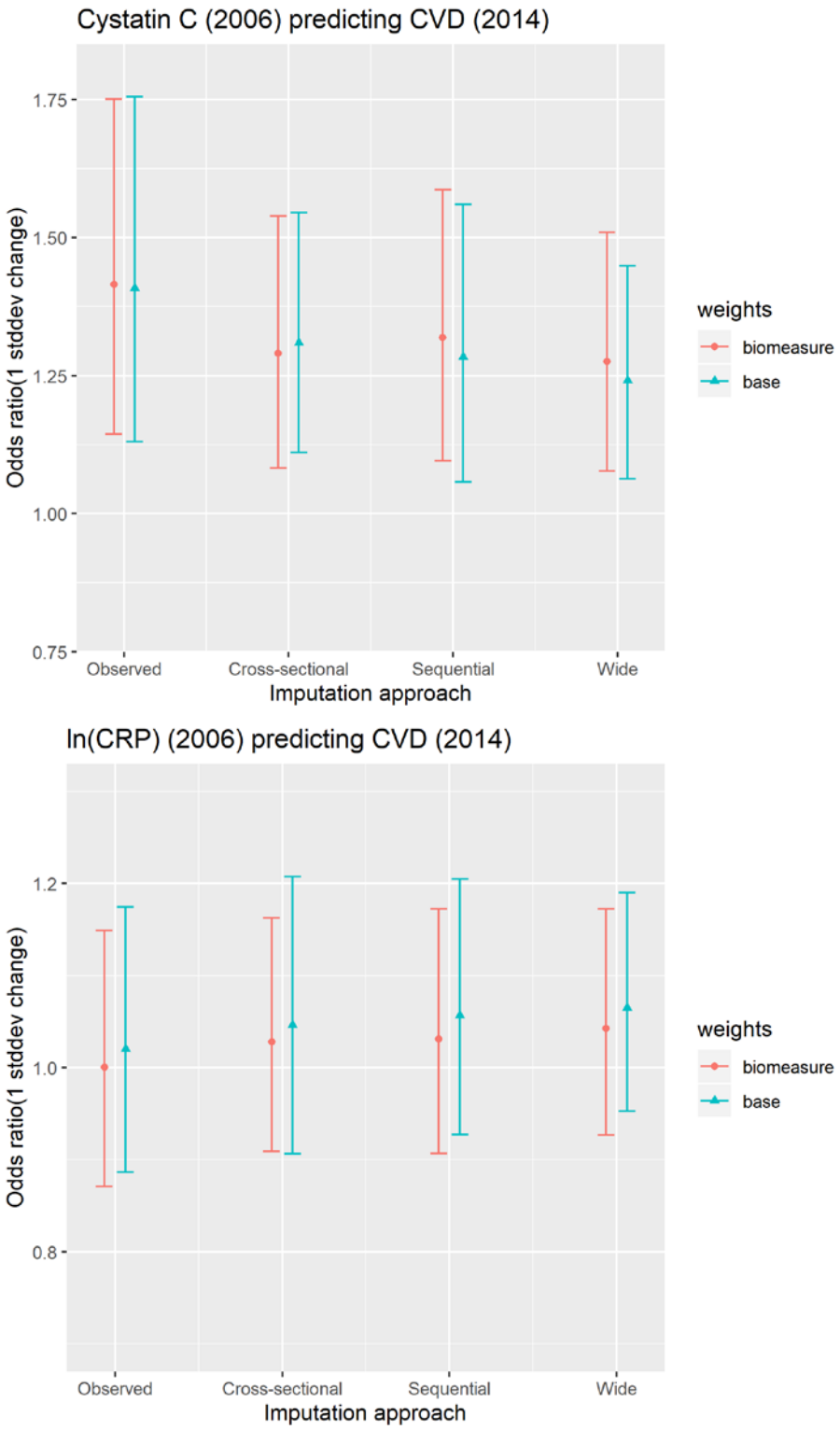

Figure 4-9. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting the development of cardiovascular disease by 2014 by imputation approach and analysis weight. Odds ratio is based on 1 standard deviation change in each biomarker: 0.50 for Cystatin C and 1.25 for ln(CRP). 95% confidence interval of the odds ratio included.

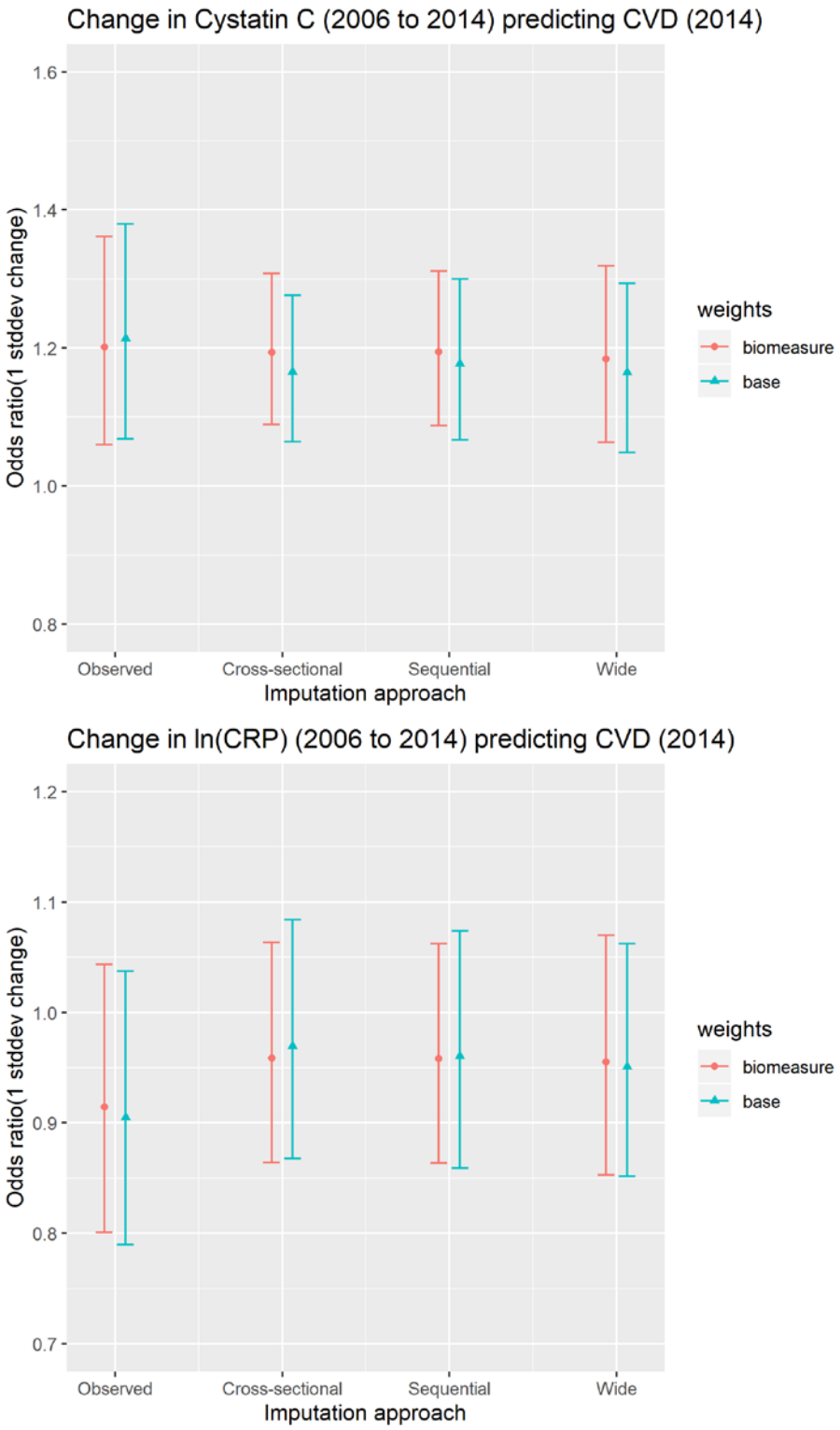

Figure 4-10. Odds ratios of change in Cystatin C and change in ln(CRP) in logistic regression model predicting the development of cardiovascular disease by 2014 by imputation approach and analysis weight. Odds ratio is based on 1 standard deviation change in each biomarker: 0.50 for Cystatin C and 1.25 for ln(CRP). 95% confidence interval of the odds ratio included.

4.3.6 Subgroup impact

In addition to primary analyses investigating the whole sample, it was important to verify that the findings from the previous sections would hold in subgroup analyses. In order to confirm this issue, all of the previous univariate and multivariate analyses were reexamined by two common subgroup variables: gender and race/ethnicity. Analyzing by these subgroups resulted in few differences in the missingness rate for Cystatin C and CRP.

The results show that the general patterns observed in the previous sections for both the univariate and multivariate analyses hold for both males and females (see Appendix G). In terms of distributional measures, the overall pattern between males and females is different with females having consistently higher levels of Cystatin C (see Tables G1-1 through G1-4 and Figure G1-1) and CRP (see Tables G1-7 through G1-10 and Figure G1-2) than males (and thus higher proportions of those at risk). The different imputation approaches positively also shift the female means or proportions more than the male's. Cases of FMIs for means and proportions exceeding the missing rate is increased when looking at these subgroups, with females more likely to have an FMI larger than the missing rate.

When looking at gender subgroups for the multivariate models, there are differences in the key substantive findings for the cross-sectional model. For example, significant negative coefficients for Hispanic and non-Hispanic black are only present for males but not females, and little to no mildly vigorous activity is only significant for females. However, the general patterns related to the weights and imputation approaches are consistent. First, the sample size increase greatly benefits the standard errors of all analysis variables, with the biomarkers (specifically Cystatin C) seeing particularly acute gains. Second, while there are small coefficient shifts across

all analysis variables, the heavily imputed biomarkers (Cystatin C in particular) see consistent attenuation in the coefficient. The longitudinal analysis models conclude similarly.

For the race/ethnicity subgroups (see Appendix H), non-Hispanic black respondents have consistently higher Cystatin C levels than non-Hispanic other respondents and Hispanic respondents, which are relatively similar (see Tables H1-1 through H1-6 and Figure H1-1). A similar pattern emerges for ln(CRP) with non-Hispanic black respondents having higher levels than Hispanic respondents which is higher than the levels for non-Hispanic other respondents, though this effect diminishes from 2006 to 2014 (see Tables H1-10 through H1-15 and Figure H1-3). The different imputation approaches positively shift the subgroup means and proportions for all race/ethnic subgroups. Like the gender subgroups, the number of FMIs for means and proportions exceeding the missing rate increased when looking at these subgroups with the Hispanic subgroup having a majority of FMIs larger than the missing rate.

When looking at race/ethnic subgroups for the multivariate models, there are differences in the key substantive findings for the cross-sectional model. Like the subgroup analysis by gender, the general patterns related to the weights and imputation approaches are consistent with the full sample with the sample size increase benefiting the standard errors of all analysis variables, with the biomarkers (specifically Cystatin C) seeing particularly acute gains. Second, while there are small coefficient shifts across all analysis variables, the heavily imputed biomarkers (Cystatin C in particular) see consistent reduction in the coefficient toward zero. The longitudinal analysis models conclude similarly. The observed longitudinal models for Hispanics suffer greatly from small samples size with repeated warnings of questionable model fit which can be observed with overly large coefficients (e.g., mildly vigorous activity 1-3 times/month,

smoking status). The imputed models mostly remove these large coefficients (the one exception being recently started smoking using when estimated with the biomeasure weights).

4.4 Discussion

In this study, three alternative imputation approaches – cross-sectional, sequential, and wide – for sequential regression multivariate imputation (SRMI) were examined for two recurrently collected biomarkers (one transformed and one not) from a three wave longitudinal study. In addition, two sets of analysis weights – one restricted to biomeasure eligible respondents and one encompassing all core respondents – were compared to evaluate how these imputation approaches impacted an expanded inference space while also increasing the analytic sample size. The impact of these imputation approaches and weighting decisions was measured on distributional characteristics including means, proportions, and percentiles as well as within two multivariate logistic regression models using cross-sectional and longitudinal variables.

For univariate measures, the various imputation approaches had the same means, proportions, and an overall response distribution when using biomeasure weights for either Cystatin C or ln(CRP). This is most likely because the sample size gain is relatively small (less than a 10% increase) given very few biomarkers were missing when the biomeasure was successfully collected. These results seem consistent with the assertion from Schafer (1999) that missingness below 5% is inconsequential and may suggest that imputing for only biomeasure consenters with a valid biomarker weight is not worth the estimation effort for negligible changes. However the FMI was consistently less than the missing data rate for all three approaches suggesting that the multiple imputation models benefited, at least somewhat, from utilizing the multivariate relationship between the biomarkers and other covariates.

When expanding the analysis to all cases with a valid base weight, significant shifts in the means, proportions, and distributional extremes (5^{th} and 95^{th} percentiles) were seen for Cystatin C, but not for ln(CRP). This suggests that the decision to exclude imputed cases with non-zero base respondent weights could lead to substantively underestimating the population prevalence of poor kidney function for those aged 50 or older by as much as 40%. Expanding the imputed sample led to large sample size gains and standard error reductions, but a corresponding proportional reduction in the standard errors was not consistently observed. In addition, a consistent reduction in the FMI from the missing rate like with the biomeasure weights was not seen with a higher rate of FMIs often exceeding the missing data rate. This may suggest that the imputations for this expanded respondent set may be less reliable given these cases are less likely to have concurrent, prior, or future biomarker values from which to base the imputation, being the most important predictors in the imputation models.

For multivariate analyses, the various imputation approaches resulted in some coefficient change across the predictor and control variables, but overall reduced the coefficient standard errors across the majority of included variables due to the sizable increases in analytic sample size. This helped solidify the statistical significance of many risk factors within the model associated with cardiovascular disease. Cystatin C saw consistent downward trend of the coefficient towards zero in these multivariate models, but also significant reductions in the standard errors. Simulation studies have shown this downward trend grows as the missing rate increases and as the number of auxiliary variables increases (Hardt, Herke, & Leonhart, 2012). The natural log transformed CRP saw minimal change due to its small coefficient size in all models after controlling for Cystatin C. The use of base weights amplified the above effects slightly.

In comparing imputation approaches, the imputed estimates (e.g., means, regression coefficients) when using the biomeasure weights were not statistically or substantively different from one another responding to the first research question on whether there are differences in point estimates between the three approaches. However these estimates were occasionally statistically different from the observed estimates especially when using the base weights. In addition, research question two was answered affirmatively as reductions in point estimate standard errors were generally observed, mostly attributable to the increase in sample size. While there was some variability across individual estimated parameters and years, the sequential approach resulted in the largest average reductions in CV and FMI for both the biomeasure and base weighted univariate estimates.

One finding that seemed relatively unexpected was that the wide imputation approach, using all waves available including future biomarker values, did not result in the largest reductions in FMI. For the univariate estimates, the wide imputation was typically second-best when using biomeasure weights, but equivalent to, if not worse than, the complete case analysis results when using the base weights. In the multivariate regression models, the wide approach often resulted in the largest attenuation of logistic regression coefficients as well as the largest reduction in standard errors, though this finding did not result in substantive changes. It is possible this is a result of model over-fitting and that the cross-wave correlations of the health measures and biomarker values may be adding unanticipated noise to the estimates, though this is generally associated with smaller sample sizes (e.g., clinical trials).

Related to this issue is the instability in the FMIs, which is a cause for concern for some of these conclusions as a number of the univariate estimates had FMIs exceeding the missing data rate. This seemed of particular concern for the 2014 values and when the base weights were

applied. Historically 10 repetitions has been recommended as sufficient for multiple imputation (Rubin, 1987; Schafer, 1997). Historical measures of imputation efficiency like Rubin's (1987) Method, $\left(1+\frac{\hat{\gamma}_{mi}}{m}\right)^{-1}$, suggest that even with the largest missingness observed in these analyses (i.e., 2006 base weighted Cystatin C at 27.4% missing) that those estimates would be 97.3% as efficient as having ∞ replicates. Follow-up analyses using 100 repetitions (see footnote 20) did not seemingly improve the FMI stability. However, more recent studies have found that these historical recommendations and measures may be insufficient given imputation variability (Bodner, 2008). For example, Madley-Dowd, Hughes, Tilling, and Heron (2019) showed that the FMI for a simulated bivariate regression could take nearly 1,000 repetitions before achieving FMI stability. Reproducing these analyses with 1,000 repetitions (or more) may resolve some concerns regarding the instability in the FMI and whether a particular imputation approach is truly better at recovering statistical information than another and allow the third research question to be more clearly answered.

The secondary component of this study is the imputation of all biomeasure eligible cases and including them in analyses by applying the base respondent weights. In general, the imputation and use of these additional cases has clear sample size advantages for the univariate and multivariate analyses which is primarily beneficial for decreasing standard errors. However, the significant shifts in high-levels of Cystatin C (i.e., proportion at risk) show that with higher levels of missingness (>20%), multiple imputation may be able to correct for potential biases in biomarkers due to non-consent. This affirmatively answers the fourth research question, but this should not be taken as a general rule. The results for ln(CRP) suggest that the weights made little difference in the point estimates and that benefits of expanding the analytic sample may be

biomarker dependent. One area of concern regarding use of the base weights is that no adjustment was made to account for the change in the estimable population.

Ultimately, the multiple imputation approach one chooses may be dependent on data availability and the specific needs of the study as opposed to the nature of the data collection itself. For studies considering multiple imputation for this type of biomeasure data, the sequential imputation approach might be recommended as it maximizes the amount of informative covariates to date, especially other biomarkers, which can be used in the imputation model. This imputation approach is straightforward to implement for existing studies and can be integrated into data processing without needing to wait for future waves of data collection like the wide approach.

As mentioned at the beginning of this chapter, there are a number of other imputation methods that could be considered for longitudinal biomeasure data. A direct comparison to predictive mean matching (PMM) could serve as a good contrast to SRMI in that it does not make use of the multivariate relationships of biomarkers with other demographic, health, and biomeasure variables. However there are other factors not covered previously that could extend and further inform this work.

The data used in this chapter only had three waves of data collection. But studies with a much large number of waves may need to restrict how many waves are included in a wide (or wide-like) approach. One example is two-fold fully conditional specification (FCS; Nevalainen et al., 2009) alternately known as the moving time window (MTW) approach (Kalaycioglu, Copas, King, & Omar, 2016). Two-fold FCS is a variant of standard FCS (another name for SRMI or MICE) which explicitly uses the temporal relationship between variables in

longitudinal data to impute like the wide approach, but only uses a particular time window. The core idea behind two-fold FCS is to take observations that are time adjacent (e.g., *w*-2, *w*-1, *w*+1, *w*+2) to impute wave *w.* Therefore this method is only optimal for studies with a large number of waves. Two-fold FCS is also doubly iterative as it imputes b_w within-time iterations (using previous and future values only as predictors) followed by b_a between-time iterations. When $b_a = 1$, then two-fold FCS is essentially traditional FCS.

Welch, Bartlett, & Petersen (2014) describe the Stata command *twofold* which completes two-fold FCS using the *mi impute chained* command, and is the only packaged implementation of this approach to date. This command limits the types of imputation that *mi impute chained* can perform to parametric imputation models including linear, logistic, and multinomial.

A fact observed in previous chapters was that multiple mechanisms might be at play for why biomeasures may be missing from a data set. For example, missingness due to non-consent may have a differential impact on biomeasures then missingness due to ineligibility. Unlike the concepts described previously in this chapter, this issue can often be at the biomeasure level (e.g., dried blood spot assay) rather than the biomarker level (e.g., Cystatin C). This may mean that the appropriate predictors for imputing one missing value may not be sufficient to impute another.

One proposed method to address multiple sources of missingness is called two-stage imputation. Two-stage multiple imputation (Harel, 2003, 2007) accounts for multiple missingness mechanisms in the model by specifying $Y = (Y_{obs}, Y_{mis})$ where $Y_{mis} = \left(Y_{mis}^{A}, Y_{mis}^{B}\right)$. Y_{mis}^{A} and Y_{mis}^{B} are imputed independently each with its unique set of *m* and *n* imputations, respectively, resulting in a total of $N = m \times n$ data sets. Two-stage multiple imputation utilizes

adapted combining rules from Rubin (1987) with extensions from Shen (2000). The approach described by Harel (2003, 2007) only focuses on two missing data mechanisms, but could be expanded if multiple missing data mechanisms could be reasonably measured and identified.

One critique to the two-stage imputation approach for this type of missing data is that one (or more) mechanisms may be directly related to the missingness itself (e.g., non-consent, biomeasure ineligibility) suggesting a not missing at random (NMAR) mechanism is at play. The exclusion of NMAR methods is a limitation of what is covered here in this paper. While there may be a fair amount of understanding regarding the general patterns of missingness for biomeasures, there are still factors and situations that may not be able to be properly accounted for using the observable variables. One of the most common NMAR imputation methods are pattern-mixture models (Little, 1993, 2009). Pattern-mixture models assume that the distributions of Y are a combination of responders and nonresponders using the missing data rate of Y as the mixing probabilities. A variety of assumptions can be set for the unobserved distribution $P(Y|R = 0)$, which makes these models good for sensitivity analyses.

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CHAPTER 5

Conclusion

5.1 Future research

While this research is some of the first to consider the implications of recurrent biomeasure collection, much has yet to be explored in relation to longitudinal collection of biomeasures. HRS, SHARE, and NSHAP (to name a few) all have opportunities to explore recurrent biomeasure consent and collection, and explore methodological and statistical issues beyond those discussed in this dissertation. Some opportunities for future research are described below:

Expand continuation ratio logit model covariates to include survey resistance measures. The expansion of indicators for the consent model in Chapter 3 provided valuable insights into biomeasure consent as a within survey request. Survey response and ineligibility due to mode are fundamentally tied to survey resistance as well. Including survey resistance measures in the continuation ratio models examined in Chapter 2 may add additional insights into these sources of non-observation.

Incorporate recent eligibility and new cohort recruitment into bias analyses. The bias analysis conducted in Chapter 2 strategically excluded respondents not biomeasure eligible in 2006 and new cohort respondents added in 2010. These exclusions, in order to focus on 2006 biomeasure eligible respondents, have their own implications on bias of estimates in 2010 and

the outcome distribution as a whole, potentially counteracting the large shifts in estimates due to mortality. Such assertions cannot be substantiated without such an investigation.

Interviewer continuity experiments. As interviewer continuity generally resulted in increased non-consent for both consenters and non-consenters, only an experiment randomly assigning returning interviewers to recontact and reinterview a subset of previous respondents can confirm how much of this effect is due directly to interviewer continuity as opposed to some other factor (e.g., time between biomeasure collections).

Additional analyses on the interplay of interviewer continuity with survey response and biomeasure consent. While interviewer continuity generally had a negative effect on biomeasure consent in these analyses, some theory suggests that interviewer continuity should benefit survey response generally. Additional analyses investigating the impact of interviewer continuity on HRS response relative to biomeasure consent may help to better understand potential tradeoffs.

Replication of longitudinal consent findings. Further investigations into changes in health, interviewer continuity, and reasons for non-consent should be replicated for other longitudinal surveys collecting biomeasures to confirm whether these findings hold. In particular, surveys with a shorter between-wave biomeasure collection window would be ideal to help disentangle factors that are associated with time given the four-year window between biomeasures requests in HRS. In addition, different biomeasure collection approaches outside of non-medically trained field interviewers, like the mail-back approach, would also benefit from this type of investigation.

Consent wording experiment to remind respondents of previous response. Respondent memory and cognition had a significant effect for previous consenters in consenting to a second

wave of biomeasures. Almost 8% of previous DBS consenters chose not to consent in the following E-FTF wave. Given the four-year gap between biomeasure requests in HRS, respondents with poor memory or memory loss may be more likely to forget the previous request and their associated response. Previous work in administrative data linkage consent has found that reminding a respondent of their previous consent behavior can increase the rate of consent (Sala, Knies, & Burton, 2014). A consent wording experiment that reminded a random subset of biomeasure eligible respondents of their previous consent could be conducted to see if the reminder elicits increased consent. This would be a beneficial experiment for HRS to conduct in the future.

Responsive design for biomeasure collection. Chapters 2 and 3 provided plenty of evidence regarding how previous patterns of behavior influenced future biomeasure eligibility and consent. Knowledge regarding previous eligibility or the type of refusal to biomeasure collection could be harnessed through responsive design to directly target particular respondent groups with appropriate interventions (e.g., reminder of previous consent) to improve consent in future waves.

Further exploration of mixed mode survey resistance measures. While not specific to biomeasure collection, the initial investigations into mode-specific survey resistance measures could potentially have implications for mixed mode panel studies more broadly. Further effort should be considered relating to alternative survey resistance measures and indices, differences in survey resistance measures and indices by mode, and sources of interviewer variance.

Confirm imputation approach conclusions with increased replications. The findings in Chapter 4 are somewhat uncertain due to the potentially unstable fractions of missing

information (FMI) which were a primary indicator of imputation quality in these analyses. Increasing the number of imputation replications to at least 1,000 will help to solidify whether the sequential approach is truly the superior of the three approaches considered. In addition, the examination of the remaining biomarker outcomes, especially HbA1c, could serve to confirm and expand the understanding of these imputation approaches and their relative benefits.

Consider additional imputation approaches for longitudinal biomarkers. Chapter 4 barely scratched the surface of the imputation approaches to consider for longitudinal biomarkers. Section 4.4.1 identified multiple approaches to consider in future investigations. Predictive mean matching is a common imputation technique known to do well with skewed data and would serve as a foil to SRMI that relies on a univariate distribution and not conditional distributions. Two-fold fully conditional specification would be a natural extension of the sequential and wide approaches considered here by using the data immediately preceding and following the given time point. Two-stage imputation would potentially allow separate models to be estimated, for example, for biomeasure consenting respondents and non-consenting respondents assuming the mechanisms are fundamentally different. Finally, pattern-mixture models could help to test the sensitivity of the missing at random and not missing at random assumptions for these biomeasures.

5.2 References

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APPENDIX A

Predictors of Nursing Home and Proxy States

In order to evaluate the appropriateness of combining nursing home and proxy respondent ineligibles as a single eligibility group, two logistic regression models were estimated predicting being a nursing home respondent and a proxy respondent, respectively. The covariates were the same used in the nested analytic model referenced in Equation 2.2 and estimated in Section 2.4.2 including respondent characteristics, household characteristics, cognition, and health measures. One final logistic regression model was estimated combining the two possible outcomes.

There are a number of similar significant covariates between the two separate models (see Table A-1). Age and both cognition measures were significant predictors of each ineligible state and had similar magnitudes of effect across the two models with older respondents having an increased odds of being in either eligibility group and higher cognition scores – denoting better cognitive functioning – decreasing the odds of group membership. Education also saw similar symmetry across the two models though the odds ratios for each education level were much higher in the nursing home model compared to the proxy model. Non-Hispanic blacks were significantly less likely to be a nursing home and proxy respondent compared to non-Hispanic other in both models. Those with less frequent physical activity (1-3 times a week for the proxy respondent model and hardly ever/never for the nursing home respondent model) are more likely to be categorized into these groups.

There are two significant covariates that are very different across the two prediction models. First, the effects for Hispanics were very different across the two eligibility models with Hispanics being significantly less likely to be in a nursing home than non-Hispanic other but no significant effect for the proxy model. Employment status also saw a large negative effect with those currently working having 0.17 times the odds of being a nursing home respondent. The proxy model does not see any uniquely significant variables.

When combining the nursing home and proxy states into a single outcome, many of the effects observed previously remain including age, education, cognition, and mildly vigorous activity. Combining the two eligibility outcomes does negate the effect for Hispanics and current employment and does result in a significant effect for fair/poor self-rated health. These commonalities serve as good evidence to combine these two eligibility outcomes.

Table A-1. Logistic regression models predicting proxy and nursing home state of 2010 HRS respondents ineligible for biomeasure collection

	Proxy respondent	Nursing home respondent	Proxy or nursing home respondent
Respondent characteristics			
Age (years)	1.08 (0.009)****	1.08 (0.012)****	1.08 (0.008)****
Female	0.86 (0.129)	1.32 (0.276)	0.90 (0.125)
Education (ref: less than HS)			
High school	1.47 (0.241)*	1.83 (0.414)**	1.51 (0.232)**
Some college	1.60 (0.647)	2.61 (1.362)	1.75 (0.640)
College graduate	1.57 (0.364)	2.15 (0.667)*	1.59 (0.345)*
Race/ethnicity (ref: Non-Hispanic other)			
Non-Hispanic black	0.50 (0.105)***	0.38 (0.108)***	0.51 (0.097)****
Hispanic	1.27 (0.282)	0.23 (0.104)***	1.05 (0.225)
Currently employed	1.17 (0.234)	0.16 (0.098)**	0.97 (0.186)
Attends religious services at least 1/wk	0.90 (0.123)	1.24 (0.227)	0.92 (0.116)
Household characteristics			
Impediments to entry	0.69 (0.157)	0.86 (0.231)	0.75 (0.150)
Own home	1.37 (0.254)	0.65 (0.144)	0.93 (0.149)
Rural	0.84 (0.125)	0.89 (0.175)	0.90 (0.124)
Another eligible HH member	1.18 (0.186)	0.91 (0.187)	1.06 (0.152)
Cognition and health			
Word recall score	0.83 (0.020)****	0.80 (0.027)****	0.83 (0.019)****
Mental status score	0.79 (0.019)****	0.88 (0.030)****	0.82 (0.019)****
Self-rated health (ref: Excellent)			
Very good	1.24 (0.352)	2.10 (1.050)	1.22 (0.335)
Good	1.24 (0.356)	1.45 (0.736)	1.20 (0.328)
Fair/Poor	1.75 (0.522)	2.29 (1.184)	1.75 (0.497)*
Mildly vigorous activity (ref: At least 1/wk)			
1-3 times/month	1.73 (0.380)*	1.50 (0.473)	1.93 (0.387)***
Hardly ever/never	1.43 (0.279)	2.00 (0.480)**	1.51 (0.271)*
No. of functional limitations	0.99 (0.020)	1.03 (0.025)	1.01 (0.018)
No. of chronic conditions	1.02 (0.057)	1.11 (0.080)	1.03 (0.053)

Note. Models conditional on HRS 2006 biomeasure eligible respondents. Sample size = 699. Odds ratios and standard errors presented.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

APPENDIX B

Reason for Previous Non-consent as a Predictor of Eligibility State

The respondent's logic for refusing to consent to biomeasure collection could be reflective of concerns related to their health or current situation as opposed to a general resistance toward the survey or the nature of the biomeasure request itself. Someone willing to participate but concerned about compromising their health further may be differentially willing to participate at a future time. HRS paradata allows for disentangling those reasons.

When a respondent refused to consent, interviewers immediately recorded the reason(s) for the refusal (survey item KI953 for HRS 2006) including the respondent (or the interviewer) did not feel it safe to complete the collection, the respondent did not understand the instructions, the respondent had hemophilia or was taking a blood thinning medication (anticoagulant), there was no suitable location for the collection, and the respondent refused or was not willing to complete the measurement. The final reason is the only one that does not have an explicit situational or health related factor as a reason for non-consent. These cases can be classified as straight refusals while the other reasons could be categorized as health-related refusals.

Looking at the two-wave model, the single indicator of DBS non-consent in Table 2-7b can be replaced with the dual indicators divided by health and non-health related reasons. Changing to two indicators adds nothing significant to the mortality model and do not result in substantive changes in the previous interpretation (Table B-2). In the nonresponse model, those

who provided a straight refusal to DBS collection in the previous wave had only 0.36 times the odds of responding in the current wave compared to those who consented previously suggesting a useful indicator of future nonresponse in the reason for DBS refusal. The health-related refusal to consent had no significant effect in predicting future response (OR = 1.14). The addition of these indicators made little substantive change in the odds ratios for this model.

Health-related refusals had nearly 0.6 times the odds of non-nursing home, self-response over those who consented previously. The straight refusal did not show a significant difference from previous consenters. The addition of previous DBS non-consent does remove the significant effect of "fair/poor" self-rated health.

For the biomeasure eligibility model, straight refusal results in 0.35 times the odds of being a biomeasure eligible respondent in the subsequent E-FTF wave compared to consenters with no significant effect observed for health-related refusals. As this transition is related to completing a telephone interview, this suggests that straight refusal to previous DBS collection serves as a general indicator of survey resistance. The only notable change of the remaining odds ratios is non-Hispanic black whose effect is strengthened from 1.65 times the odds compared to non-Hispanic other to 1.82 times the odds when holding previous DBS consent constant.

Both health-related and straight refusal to previous DBS consent are significant in predicting future consent but at differential rates. A straight refusal results in a tenth of the odds of future consent while health-related refusal is a quarter of the odds of consent compared to previous consenters. There are many more demographic and health variable coefficients that change with the inclusion of reason for previous non-consent given the correlated nature of the new variables and the outcome. The significant effect of non-Hispanic blacks is no longer

present. The number of chronic conditions also becomes insignificant. The significance levels for church attendance, mental status score, and little/no mildly vigorous activity diminish due to increased standard errors and odds ratios getting closer to one.

The reason for previous consent refusal is informative about future nonresponse and eligibility related to mode. These results strengthen the idea that biomeasure consent can serve as a good indicator of survey resistance when considering future waves of data collection. The significant effect of health-related consent refusal with proxy and nursing home respondents suggests that their compromised health status when asked to provide biomeasures may be indicative of an increased need for help and support in the future.

Table B-1. Continuation ratio logit model odds ratios predicting sequential 2010 eligibility states based on 2006 respondent and household characteristics and reason for dried blood spot consent refusal

	Alive vs. Deceased	Respondent vs. Non-respondent	Self- vs. Nursing home/Proxy-respondent	Biomeasure eligible vs. Ineligible respondent	Consenter vs. Non-consenter	Parallel slopes test
Respondent characteristics						
Age (years)	0.95 (0.004)****	1.00 (0.007)	0.93 (0.007)****	1.00 (0.008)	0.99 (0.006)	****
Female	1.58 (0.137)****	0.94 (0.113)	1.10 (0.153)	0.84 (0.103)	0.92 (0.086)	****
Education (ref: less than HS)						
High school	0.96 (0.091)	1.03 (0.154)	0.66 (0.101)**	1.16 (0.177)	0.98 (0.114)	
Some college	1.14 (0.284)	0.72 (0.192)	0.57 (0.207)	1.22 (0.370)	1.42 (0.346)	
College graduate	1.03 (0.137)	0.85 (0.157)	0.63 (0.136)*	0.94 (0.177)	0.89 (0.130)	
Race/ethnicity (ref: Non-Hispanic other)						
Non-Hispanic black	1.44 (0.172)**	1.40 (0.249)	2.00 (0.385)****	1.82 (0.368)**	0.89 (0.112)	**
Hispanic	1.47 (0.223)*	0.99 (0.200)	0.97 (0.209)	0.74 (0.146)	0.92 (0.156)	
Currently employed	1.55 (0.205)***	1.11 (0.155)	1.03 (0.198)	0.79 (0.107)	1.09 (0.116)	*
Attends church at least 1/wk	1.39 (0.114)****	0.98 (0.112)	1.08 (0.137)	1.42 (0.170)**	1.23 (0.109)*	
Household characteristics						
Impediments to entry	1.14 (0.139)	1.40 (0.285)	1.38 (0.279)	0.95 (0.171)	1.00 (0.140)	
Own home	1.20 (0.118)	0.90 (0.145)	1.07 (0.174)	1.33 (0.202)	1.00 (0.122)	
Rural	1.16 (0.102)	1.33 (0.171)*	1.11 (0.153)	0.96 (0.120)	0.91 (0.087)	
Another eligible HH member	1.25 (0.113)*	1.04 (0.134)	0.95 (0.137)	0.96 (0.127)	1.07 (0.107)	
Cognition and health						
Word recall score	1.08 (0.015)****	1.05 (0.021)*	1.20 (0.027)****	1.01 (0.021)	0.98 (0.015)	****
Mental status score	1.05 (0.016)**	1.08 (0.024)***	1.22 (0.029)****	1.04 (0.026)	1.05 (0.020)*	****
Self-rated health (ref: Excellent)						
Very good	0.79 (0.172)	0.92 (0.168)	0.82 (0.224)	0.73 (0.147)	1.00 (0.147)	
Good	0.50 (0.106)***	1.00 (0.193)	0.84 (0.230)	0.62 (0.127)*	0.96 (0.147)	
Fair/Poor	0.36 (0.078)****	0.82 (0.181)	0.58 (0.166)	0.82 (0.200)	1.05 (0.187)	**
Mildly vigorous activity (ref: At least 1/wk)						
1-3 times/month	1.15 (0.175)	0.96 (0.211)	0.52 (0.105)***	1.24 (0.315)	0.83 (0.137)	*
Hardly ever/never	0.56 (0.058)****	1.01 (0.223)	0.67 (0.122)*	0.97 (0.222)	0.72 (0.116)*	*
No. of functional limitations	0.96 (0.010)****	1.03 (0.021)	1.00 (0.018)	0.99 (0.020)	0.98 (0.014)	*
No. of chronic conditions	0.87 (0.028)****	1.17 (0.060)**	0.96 (0.050)	1.08 (0.056)	1.07 (0.042)	****
Previous non-observation source						
Health-related DBS consent refusal	0.80 (0.127)	1.14 (0.399)	0.59 (0.146)*	1.20 (0.475)	0.27 (0.049)****	****
Straight refusal to DBS consent	0.88 (0.097)	0.36 (0.045)****	0.73 (0.125)	0.35 (0.045)****	0.10 (0.009)****	****

Note. The parallel slopes test is a Wald chi-square test with 4 degrees of freedom. HS = high school. DBS = dried blood spot.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

APPENDIX C

Survey Resistance Measure Multicollinearity

C.1 Accounting for multicollinearity between survey resistance variables

There are many dimensions of survey resistance (Sakshaug, Couper, & Ofstedal, 2010; Sakshaug, Couper, Ofstedal, & Weir, 2012). Some measures of resistance in an interviewer administered survey come in the form of post-survey interviewer observations. These interviewer observations include behavioral observations of the respondent (e.g., "Did the respondent ask about the length of interview?") and subjective assessments of the respondent during the survey interview (e.g., "How attentive was the respondent?"). Attempting to use a large number of these observations in a single analysis quickly uses up degrees of freedom and raises the potential issue of collinearity between items, both of which may have unknown or undesirable consequences on an analysis. This problem intensifies if one wishes to use variables from multiple waves of collection.

Sakshaug et al. (2012) created two indices from seven post-survey observations collected in the Health and Retirement Study (HRS) from the previous wave of data collection to summarize two aspects of survey resistance: uncooperativeness and confidentiality concerns. The confidentiality concern index includes:

- "During the interview, how often did the respondent express concern about whether his/her answers would be kept confidential?" (never, **seldom**, **often**)

- "During the interview, how often did the respondent ask you why you needed to know the answer to some questions" (never, **seldom**, **often**)
- "How truthful do you believe the respondent was regarding his/her answers on financial questions?" (completely truthful, mainly truthful, **about half and half**, **mainly untruthful**)

The uncooperativeness index includes:

- "How was the respondent's cooperation during the interview?" (excellent, **good**, **fair**, **poor)**
- "During the interview, how often did the respondent ask how much longer the interview would last?" (never, **seldom**, **often**)
- "How much did the respondent seem to enjoy the interview?" (a great deal, quite a bit, **some**, **a little**, **not at all**)
- "How would you describe the level of resistance from the respondent?" (low/passive, **moderate**, **high**)

For both indices, a value of 1 was assigned if the interviewer recorded a negative response (e.g., expressing concern about confidentiality or displaying uncooperative behavior) which are denoted by the bold underlined responses above. This results in a confidentiality index range of 0 to 3 and an uncooperativeness index range of 0 to 4.

These indices are reasonable, but little detail is provided in Sakshaug et al. (2012) as to how these indices were formulated beyond the theoretical explanation provided. The use of these indices is a potential solution to correct for problems with multicollinearity in analytic models.

However, the final indicator of the uncooperative index – level of resistance – was only collected in HRS 2006 and is therefore not applicable for any other years which impacts the analyses conducted in Chapter 3. Another post-survey interviewer observation is a potential replacement in the uncooperative index: respondent attentiveness. Sakshaug et al. (2012) did test attentiveness independently in their analysis as a measure of acquiescence, though this proved to be an insignificant factor in their final model. As attentiveness encompasses the focus and relative interest a respondent may have during the survey interview, its inclusion in the uncooperativeness index seems consistent with the other indicators like enjoyment and asking how much longer the interview would last. Attentiveness is included in the uncooperativeness index as follows:

- "How attentive was the respondent to the questions during the interview?" (**not at all attentive**, **somewhat attentive**, very attentive)

In order to explore the creation and use of these indices, a number of different approaches on how to account for or summarize these measures are considered: (1) tetrachoric correlations, (2) exploratory factor analysis, and (3) latent class analysis. Response options for all seven potential resistance variables were collapsed to match the indices in Sakshaug et al. (2012).

C.1.1 Tetrachoric correlations

Tetrachoric correlations were used as opposed to the more common Pearson correlations because the indicators are dichotomous and not continuous. The tetrachoric correlations between the seven variables are examined independently for both wave 1 (W1; E-FTF) and wave 2 (W2; CATI) consistent with the definitions provided in Chapter 3.

The tetrachoric correlations within each wave suggest anywhere from a weak (minimum: 0.18) to moderately strong (maximum: 0.68) correlation between within wave indicators (Table C-1). The pattern in the correlations is very consistent for both W1 and W2. The cooperation indicator has the most moderately strong correlations (between 0.50 and 0.70) with respondent attentiveness, enjoyment, being rated as truthful on financial questions, and never asking why this information was needed. Ever asking why this information was needed is also moderately correlated with asking how long the interview would take and if they expressed concern with confidentiality. Attentiveness is moderately correlated with respondent enjoyment and truthfulness on financial questions.

These findings indicate that there is a potential concern regarding multicollinearity of these resistance variables. Practically this could mean that if any one of these variables was found to be significant in the consent model that it could be containing information related to any of its moderately associated variables. These correlations are further explored through factor analysis.

Table C-1. Tetrachoric correlations between wave 1 (W1) and wave 2 (W2) survey resistance indicators

	How long W1	Confidentiality W1	Cooperative W1	Enjoy W1	Why need W1	Truth financial W1	Inattentive W1	How long W2	Confidentiality W2	Cooperative W2	Enjoy W2	Why need W2	Truth financial W2	Inattentive W2
How long W1	1													
Confidentiality W1	0.38	1												
Cooperative W1	0.38	0.42	1											
Enjoy W1	0.40	0.27	0.61	1										
Why need W1	0.58	0.65	0.52	0.40	1									
Truth financial W1	0.32	0.34	0.60	0.43	0.40	1								
Inattentive W1	0.35	0.21	0.68	0.54	0.33	0.53	1							
How long W2	0.36	0.16	0.20	0.18	0.24	0.17	0.20	1						
Confidentiality W2	0.16	0.31	0.19	0.10	0.26	0.14	0.12	0.38	1					
Cooperative W2	0.18	0.13	0.31	0.25	0.21	0.26	0.27	0.44	0.39	1				
Enjoy W2	0.18	0.10	0.24	0.33	0.15	0.19	0.24	0.39	0.19	0.62	1			
Why need W2	0.20	0.27	0.22	0.13	0.35	0.13	0.17	0.60	0.63	0.54	0.33	1		
Truth financial W2	0.12	0.13	0.23	0.21	0.19	0.31	0.24	0.34	0.35	0.66	0.43	0.42	1	
Inattentive W2	0.15	0.06	0.23	0.20	0.12	0.21	0.29	0.43	0.25	0.68	0.51	0.40	0.59	1

Note. Orange background encompasses all W1 variables; blue background encompasses all W2 variables. Red diagonal are between-wave correlations between the W1 and W2 variables. W1 = Wave 1 (2006/2008). W2 = Wave 2 (2008/2010).

C.1.2 Exploratory factor analysis

The tetrachoric correlation matrix was used as the base for an exploratory factor analysis followed by a Varimax rotation on the factor loadings. Random interviewer effects are not accounted for in these exploratory models. Again, the results for W1 and W2 are quite similar (see Table C-2). The exploratory factor analysis produced a three-factor model. However, the variance accounted for by the third factor was far below the first two factors even though the factor eigenvalues are positive, and all of the factor loadings were below 0.50. Therefore only the first two factors are presented and discussed here.

The first factor contains large factor loadings (based on a cutoff of 0.50) for cooperativeness, enjoyment, attentiveness, and truth on financial questions. This set of variables is very similar to the components of the uncooperativeness index established by Sakshaug et al. (2012) replacing how the long the interviewer would take with the truthfulness on financial questions. The second factor has a similar structure to the earlier confidentiality index with indicators for expressing concerns about confidentiality, asking why this information was necessary, and how long the interview would take. The latter indicator replaces the truthfulness on financial questions from the original index.

Upon further consideration, the first factor produced by the factor analysis contains all relative interviewer ratings of a respondent (e.g., “How cooperative was the respondent?” “How much did the respondent enjoy the interview?”) while the second factor contains more factual indicators (e.g., “How often did…?”). This may suggest that the factor analysis is detecting similarities due to the nature of the measure beyond being similar conceptual factors. Further investigation is needed to verify this assumption.

Table C-2. Varimax rotated factor loadings for exploratory factor analysis of survey resistance indicators

	Wave 1			Wave 2		
	Factor 1	**Factor 2**	**Uniqueness**	**Factor 1**	**Factor 2**	**Uniqueness**
How long	0.320	**0.540**	0.605	0.376	**0.542**	0.565
Confidentiality	0.184	**0.682**	0.500	0.176	**0.661**	0.532
Cooperative	**0.772**	0.355	0.279	**0.794**	0.346	0.250
Enjoy	**0.634**	0.268	0.527	**0.644**	0.172	0.555
Why need	0.302	**0.774**	0.310	0.320	**0.770**	0.305
Truth financial	**0.606**	0.287	0.550	**0.658**	0.281	0.488
Inattentive	**0.767**	0.152	0.389	**0.741**	0.218	0.403

Note. Factor loadings in bold black text are above a threshold of 0.50.

C.1.3 Latent class analysis

Given these resistance indicators are dichotomous, a latent class model is also considered to potentially reduce the number of dimensions for this problem. Only a simple latent class model with two and three latent classes is investigated here (see Table C-3). Random interviewer effects are not accounted for in these exploratory models.

Looking first at the W1 resistance indicators, the two class model reveals a “great” respondent class and a “poor” respondent class. The first latent class encompasses over three-fourths of the sample and is most likely to receive a positive response on all seven indicators. The lowest conditional probability is on high enjoyment (0.864). The second latent class sees more instances of negative ratings on cooperation, enjoyment, and truth on financial questions each with conditional probabilities less than 0.50 (0.294, 0.350, and 0.442, respectively). The remaining indicators have a conditional probability between 0.50 and 0.67 favoring a positive response. This “poor” respondent class has some similarities to the uncooperativeness index.

The first latent class in the 3-class model matches the 2-class model – the "great" respondent class – both in terms of conditional probabilities and the class probability. The second largest latent class (13.8% of the sample) is a slightly more extreme version of the "poor" respondent class with lower conditional probabilities of excellent cooperation (0.123), high enjoyment (0.221), and truthful on financial questions (0.340). Attentiveness is a nearly even split while the remaining three variables (asking how long, asking why needed, and expressing concerns about confidentiality) are all near or above a conditional probability of 0.70. The final class boasts very high attentiveness (0.934), but very middle of road probabilities for everything else.

Examining the W2 models, a similar patterns for the 2-class model is observed. A "great" respondent class includes the majority of cases (76.4%) though the conditional probability for enjoyment is not as high (0.755) as the W1 model. The second class has low conditional probabilities for enjoyment (0.245) and truthful on financial questions (0.378), but a much higher conditional probability for excellent cooperation (0.636).

The W2 3-class model again repeats the "great" respondent class and the "poor" respondent classes from the 2-class model. The third class is quite different with low conditional probabilities for never asking how long (0.352), never asking why this was needed (0.189), high enjoyment (0.303), and truthfulness on financial questions (0.385).

In general, these classifications are somewhat informative but the overall model does not quite provide the level of gradation and clear direction as the factor analysis and originally proposed resistance indices.

Table C-3. Latent class models on survey resistance indicators by wave

	2-class model		3-class model		
Wave 1	**Class 1**	**Class 2**	**Class 1**	**Class 2**	**Class 3**
How long (Never asked)	0.906	0.578	0.913	0.627	0.454
Why need (Never asked)	0.974	0.663	0.987	0.758	0.411
Confidentiality (Never)	0.941	0.667	0.952	0.767	0.429
Very attentive	0.982	0.659	0.976	0.509	0.934
Excellent cooperation	0.944	0.294	0.936	0.123	0.622
Enjoy (Very much/Quite a bit)	0.864	0.350	0.856	0.221	0.612
Truth financial (Completely/Mainly)	0.902	0.442	0.894	0.340	0.664
Estimated class size	**0.771**	**0.229**	**0.770**	**0.138**	**0.092**

	2-class model		3-class model		
Wave 2	**Class 1**	**Class 2**	**Class 1**	**Class 2**	**Class 3**
How long (Never asked)	0.932	0.566	0.931	0.721	0.352
Why need (Never asked)	0.986	0.735	0.982	1.000	0.189
Confidentiality (Never)	0.976	0.820	0.973	0.941	0.614
Very attentive	0.973	0.583	0.983	0.611	0.613
Excellent cooperation	0.846	0.636	0.851	0.659	0.626
Enjoy (Very much/Quite a bit)	0.755	0.245	0.779	0.232	0.303
Truth financial (Completely/Mainly)	0.888	0.378	0.904	0.415	0.385
Estimated class size	**0.764**	**0.236**	**0.726**	**0.199**	**0.075**

C.1.4 Comparison of consent models with all resistance variables versus resistance indices

There is evidence of multicollinearity between the seven survey resistance variables examined. The preliminary factor analysis and latent class analysis offer differing degrees of support for the indices used by Sakshaug et al. (2012). Given the previous establishment of these two indices from Sakshaug et al. (2012) and the similar pattern seen in the factor analysis, a final comparison of the consent model by using the adapted indices mentioned at the beginning of this appendix is considered.

By using an index instead of individual indicators, this reduces the number of estimated survey resistance coefficients in the consent models considered in Chapter 3 from 10 to 3 (call attempts, uncooperative index, and confidentiality index) for W1 and W2 for a total of 14 less

coefficients estimated. The models presented here were preliminary models to those presented in Chapter 3. The models presented here were part of the early model building process and include both consenters and non-consenters in a single model. Model 1 includes measures only from the previous telephone wave (W2) while Model 2 includes measures from the previous E-FTF wave (W1). Only the relevant survey resistance indicators for W1 and W2 are presented in the corresponding tables.

Predicting consent to physical measurements (PM) in Model 1, only one W2 indicator is significant: asked about why information was needed. When replacing the individual W2 factors with the two resistance indices, both indices are significant with each value increase on the confidentiality index having 0.767 times the odds of PM consent (which includes the significant indicator from the original model) and each increase on the uncooperative index having 0.911 times the odds of PM consent. Introducing the W1 indicators in Model 2, the one significant effect for W2 is weakened but four W1 indicators appear as significant: asked why information was needed, untruthful on financial questions, poor cooperation, and did not enjoy – the first two corresponding to the confidentiality index and the latter to the uncooperative index. Replacing the individual indicators in Model 2, the W2 confidentiality index is still significant, but the odds ratio is not as large. Both W1 indices are significant each with odds ratios around 0.74.

For the dried blood spot (DBS) consent model, similar patterns are observed, but more individual indicators appear as significant predictors. In Model 1, asking about confidentiality is significant (corresponding to the W2 confidentiality index) while being rated as uncooperative, asking how long, and inattentiveness are significant indicators (corresponding to the W2 uncooperative index). However, being rated as inattentive actually results in an odds ratio greater than one meaning less attentive respondents are more likely to consent to DBS collection.

Transitioning to Model 1 with the indices, both W2 survey resistance indices are significant. The inclusion of W1 resistance indicators in Model 2 maintained by lessened the effects seen in the W2 indicators in Model 1. Five indicators from W1 were significant. Model 2 with the indices sees both W1 indices as significant predictors, but only the W2 confidentiality index remains significant though greatly reduced.

Further investigation discovered that the inattentive measure for W2 when not included with the other survey resistance indicators resulted in an odds ratio less than one for both the PM and DBS consent models, though not always as a statistically significant predictor. This is a key example of how multicollinearity can impact the interpretation of such models.

C.1.5 Discussion

Overall, the statistical evidence supports the hypothesis that these post-survey interviewer observations are in fact correlated and can be summarized into two factors (or indices). The use of these two indices over the use of seven individual indicators did not substantively change the conclusions of the analysis while simultaneously freeing up 14 degrees of freedom for analysis. While interpretation of individual indicators is no longer possible, any interpretation may be subject to scrutiny given the moderate correlations between indicators as evidenced by the inattentiveness indicator. Given the benefits of summarizing survey resistance this way, the pair of survey resistance indices for uncooperativeness and confidentiality were used in the final models in Chapter 3.

Table C-4. Comparison of individual survey resistance indicators and survey resistance indices in the physical measurement consent model

	Model 1		Model 2	
	Indicators	Indices	Indicators	Indices
	Odds Ratio (SE)	Odds Ratio (SE)	Odds Ratio (SE)	Odds Ratio (SE)
Survey resistance (W2)				
Nonrespondent in W2	0.612 (0.436)	0.592 (0.419)	0.473 (0.352)	0.450 (0.334)
No. of contact attempts	0.994 (0.006)	0.994 (0.006)	0.998 (0.006)	0.999 (0.006)
Asked about confidentiality	0.849 (0.145)		0.948 (0.169)	
Asked why information was needed	0.637 (0.102)**		0.668 (0.110)*	
Untruthful on financial questions	0.845 (0.095)		0.974 (0.113)	
Confidentiality Index		0.767 (0.053)****		0.850 (0.062)*
Rated uncooperative	0.794 (0.095)		0.870 (0.107)	
Asked how long interview would last	0.813 (0.100)		0.861 (0.110)	
Rated as not enjoying interview	0.967 (0.100)		1.078 (0.114)	
Rated as inattentive	1.129 (0.158)		1.192 (0.172)	
Uncooperative Index		0.911 (0.040)*		0.988 (0.045)
Survey resistance (W1)				
No. of contact attempts			1.008 (0.010)	1.008 (0.010)
Asked about confidentiality			0.872 (0.119)	
Asked why information was needed			0.725 (0.104)*	
Untruthful on financial questions			0.636 (0.070)****	
Confidentiality Index				0.729 (0.045)****
Rated cooperation (ref: Excellent)			0.562 (0.066)****	
Asked how long interview would last			1.062 (0.129)	
Rated as not enjoying interview			0.588 (0.065)****	
Rated as inattentive			1.215 (0.178)	
Uncooperative Index				0.749 (0.033)****

Note. W1 = Wave 1, or HRS 2006 and HRS 2008 enhanced face-to-face (E-FTF) interviews. W2 = Wave 2, or HRS 2008 and HRS 2010 computer-assisted telephone interviews (CATI).

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

Table C-5. Comparison of individual survey resistance indicators and survey resistance indices in the dried blood spot consent model

	Model 1		Model 2	
	Indicators	Indices	Indicators	Indices
	Odds Ratio (SE)	Odds Ratio (SE)	Odds Ratio (SE)	Odds Ratio (SE)
Survey resistance (W2)				
Nonrespondent in W2	0.497 (0.264)	0.471 (0.249)	0.424 (0.232)	0.401 (0.220)
No. of contact attempts	0.998 (0.004)	0.998 (0.004)	1.002 (0.005)	1.002 (0.005)
Asked about confidentiality	0.676 (0.081)***		0.752 (0.092)*	
Asked why information was needed	0.817 (0.097)		0.872 (0.106)	
Untruthful on financial questions	0.863 (0.070)		0.936 (0.078)	
Confidentiality Index		0.776 (0.039)****		0.841 (0.044)***
Rated uncooperative	0.694 (0.059)****		0.762 (0.066)**	
Asked how long interview would last	0.749 (0.065)***		0.800 (0.071)*	
Rated as not enjoying interview	0.927 (0.067)		1.006 (0.075)	
Rated as inattentive	1.246 (0.129)*		1.275 (0.135)*	
Uncooperative Index		0.874 (0.027)****		0.941 (0.030)
Survey resistance (W1)				
No. of contact attempts			1.006 (0.007)	1.006 (0.007)
Asked about confidentiality			0.670 (0.062)****	
Asked why information was needed			0.744 (0.077)**	
Untruthful on financial questions			0.847 (0.070)*	
Confidentiality Index				0.734 (0.033)****
Rated cooperation (ref: Excellent)			0.537 (0.046)****	
Asked how long interview would last			1.011 (0.087)	
Rated as not enjoying interview			0.764 (0.060)***	
Rated as inattentive			1.001 (0.107)	
Uncooperative Index				0.779 (0.025)****

Note. W1 = Wave 1, or HRS 2006 and HRS 2008 enhanced face-to-face (E-FTF) interviews. W2 = Wave 2, or HRS 2008 and HRS 2010 computer-assisted telephone interviews (CATI).

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

C.2 Systematic differences in post-survey observations across survey modes

One study assumption in Chapter 3 is that interviewer observations related to survey resistance differ depending on the survey mode, because of the inherent differences of each mode and the timing of a particular wave (e.g., last E-FTF wave) relative to the wave of interest. Unfortunately, there seems to be no literature related to this phenomenon and if it should be accounted for. In order to further explore and justify this assumption, two investigations were completed: (1) examine distributions of survey resistance variables across the two interview modes and (2) compare tetrachoric correlations of the resistance indicators between W1 and W2 for the analytic sample.

C.2.1 Survey resistance distributions by survey mode

Table C-6 summarizes the weighted distributions for each of the seven previously discussed survey resistance variables for the entire HRS sample from 2006 through 2012. The Rao-Scott Chi-Square statistic for each comparison is reported to best account for the sample design and weighting (Heeringa, West, & Berglund, 2010). Two indicators (truth on financial questions and if the respondent ever asked why this information was needed) are excluded from HRS 2012 as they were removed from the post-survey assessment.

Focusing on the differences across modes, the only variables that consistently exhibit a difference by mode are if the respondent asked why this information was needed, if the respondent expressed concern over confidentiality, and interviewer-rated respondent enjoyment. Questions why this information is needed is more likely to occur in the E-FTF interview primarily due to an increase in the “seldom” category. Expressing concerns about keeping responses confidential is also more likely to occur in the E-FTF interview with increases in both

Table C-6. Differences in survey resistance variables by mode for four waves of the Health and Retirement Study

		2006		2008		2010		2012	
Survey resistance variable		**E-FTF**	**CATI**	**E-FTF**	**CATI**	**E-FTF**	**CATI**	**E-FTF**	**CATI**
How Long	Never	84.5	82.2	82.8	83.5	78.1	79.6	80.6	80.3
	Seldom	12.5	14.5	13.6	13.2	18.4	17.2	16.5	16.1
	Often	3.0	3.3	3.6	3.3	3.5	3.2	2.9	3.6
	Rao-Scott Chi-square	***8.21***	*****	***0.90***	***n.s.***	***3.60***	***n.s.***	***4.34***	***n.s.***
Why Need	Never	91.0	93.6	89.4	93.5	87.6	90.8	-	-
	Seldom	7.8	5.5	9.3	5.5	11.2	8.1	-	-
	Often	1.2	0.9	1.2	1.0	1.2	1.1	-	-
	Rao-Scott Chi-square	***21.34***	*****	***56.38***	*****	***24.91***	*****	**-**	**-**
Confidentiality	Never	88.6	92.9	87.2	93.1	82.8	92.6	89.0	93.3
	Seldom	10.1	6.3	11.3	6.2	15.7	6.7	9.9	6.0
	Often	1.2	0.8	1.5	0.7	1.5	0.7	1.1	0.7
	Rao-Scott Chi-square	***52.71***	*****	***83.89***	*****	***196.08***	*****	***58.50***	*****
Attentiveness	Not at all	0.6	0.5	0.6	0.4	0.6	0.5	0.7	0.7
	Somewhat	9.7	8.8	10.3	9.7	13.4	13.1	13.5	14.7
	Very	89.7	90.8	89.1	89.9	86.0	86.4	85.8	84.5
	Rao-Scott Chi-square	***3.67***	***n.s.***	***2.61***	***n.s.***	***0.29***	***n.s.***	***2.16***	***n.s.***
Cooperation	Excellent	77.8	76.6	77.2	76.8	73.8	71.8	71.0	71.1
	Good	19.2	21.0	20.0	20.7	22.5	24.0	25.2	24.8
	Fair	2.8	2.1	2.5	2.3	3.2	3.8	3.5	3.3
	Poor	0.2	0.3	0.4	0.2	0.4	0.5	0.4	0.8
	Rao-Scott Chi-square	***11.17***	*****	***2.64***	***n.s.***	***4.55***	***n.s.***	***5.86***	***n.s.***
Enjoy	Great deal	37.9	28.1	38.9	33.6	26.7	22.3	23.0	15.4
	Quite a bit	34.1	33.1	34.1	32.0	35.8	32.0	37.8	30.9
	Some	20.6	28.0	21.5	27.3	28.5	32.1	30.1	37.1
	A little	5.9	8.2	4.0	5.4	7.0	9.9	7.1	13.1
	Not at all	1.5	2.5	1.5	1.8	2.0	3.7	2.0	3.5
	Rao-Scott Chi-square	***106.91***	*****	***38.85***	*****	***64.57***	*****	***167.94***	*****
Truth financial	Completely	79.1	79.2	77.9	80.0	72.6	72.8	-	-
	Mainly truthful	18.1	17.9	18.7	16.8	24.0	23.0	-	-
	Half and half	2.3	2.5	3.0	2.6	2.9	3.6	-	-
	Mainly untruthful	0.5	0.4	0.4	0.6	0.5	0.6	-	-
	Rao-Scott Chi-square	***1.01***	***n.s.***	***7.82***	*****	***4.61***	***n.s.***	**-**	**-**

Note. Percentages are weighted. Rao-Scott Chi-square statistics adjust for survey design (Heeringa, West, & Berglund, 2010). Base sample: 2006 - 17,106; 2008 - 15,840; 2010 - 20,337; 2012 - 18,851.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

the "seldom" and "often" categories. Enjoyment is also more likely to be rated higher in the E-FTF interview. The E-FTF assessment of enjoyment can be anywhere from 8 to 14 percentage point higher for the combined "great deal" and "quite a bit" categories.

While it is not the focus of this analysis, it is interesting to note the change in these distributions over time from wave to wave. Many of the "best" or "positive" categories for each resistance indicator greatly reduce from 2006 to 2012. It is unclear if this is due to the growing trend of resistance to surveys generally, if this is evidence of panel fatigue, or a change in interviewer training regarding post-survey observations.

C.2.2 Between wave correlations of survey resistance indicators and indices

The second analysis revisits the tetrachoric correlations between the seven dichotomous survey resistance indicators from W1 with those from W2. Table C-1 already displayed the tetrachoric correlation values both within and between each wave. Figure C-1 reproduces this data visually showing the corresponding correlations highlighting the differences between the W1 and W2 correlations. Variables from the same wave have a higher correlation (on average) than with any variable from the alternative wave. The only real exception is the same variable from the other wave where its correlation is (on average) in the same range as the lowest of the variables from the current wave.

To verify these findings also applied to the proposed resistance indices, a standard Pearson correlation and a polychoric correlation on the two indices within and between waves was conducted. Similar to the individual indicators, within wave correlations are much higher than between wave correlations even for the same index. For W1, the two indices have a moderate correlation with each other ($p_{Pearson} = 0.47; p_{polychoric} = 0.58$). This correlation is not as strong in W2 ($p_{Pearson} = 0.35; p_{polychoric} = 0.46$). The between wave Pearson correlations have a range of 0.18 and 0.25 while the polychoric correlations have a range of 0.24

to 0.31. The uncooperativeness index between W1 and W2 is the strongest of the between wave correlations ($p_{Pearson} = 0.25; p_{polychoric} = 0.31$).

C.2.3 Discussion

Overall these results suggest that within wave resistance variables have a stronger association with each other than with between wave resistance variables most likely due to interviewer continuity. While this does support the hypothesis that there are potential mode differences in resistance variables, these could also be differences related to at least two other

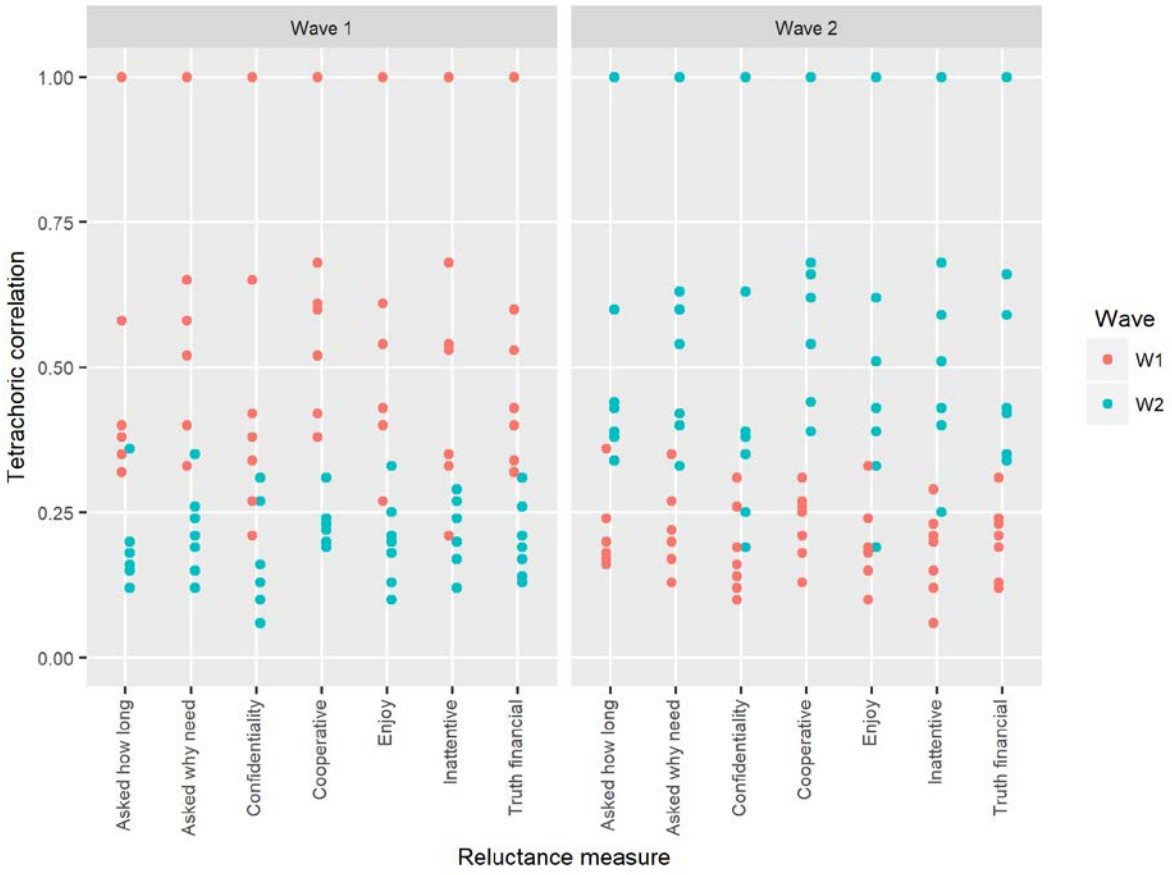

Figure C-1. Tetrachoric correlations between wave 1 (W1) and wave 2 (W2) survey resistance indicators.

phenomenon. First, there is only a small proportion of panelists that have the same interviewer from W1 to W2 suggesting that some of the observation changes may related to the perception of a new interviewer. Second, the passage of time can lead to changes in attitude. This could include an increasing resistance to participate as part of the panel as well as temporary changes in interest or cooperativeness.

APPENDIX D

Model 4 Results from Multilevel Logistic Regressions on Wave 1 Non-consenters

Below are the full two-level random effects logistic regression model results for physical measurement and dried blood spot non-consenters including the interaction term of interviewer continuity and reason for wave 1 consent refusal (Model 4).

Table D-1. Predictors of wave 3 biomeasure consent for wave 1 non-consenters (physical measurements and dried blood spot) including the interaction term of interviewer continuity and reason for wave 1 consent refusal (Model 4)

	Physical measurements	Dried blood spot
	Odds Ratio	Odds Ratio
Respondent Characteristics		
Age (years)	0.98 (0.94, 1.01)	1.01 (0.99, 1.02)
Female	1.29 (0.84, 1.97)	0.92 (0.72, 1.18)
Education (ref: less than HS)		
High school	1.17 (0.61, 2.25)	1.19 (0.83, 1.72)
Some college	1.61 (0.70, 3.73)	0.90 (0.60, 1.35)
College graduate	1.09 (0.45, 2.68)	0.90 (0.57, 1.42)
Race/ethnicity (ref: Non-Hispanic other)		
Non-Hispanic black	0.78 (0.40, 1.49)	1.03 (0.70, 1.53)
Hispanic (English interview)	1.29 (0.37, 4.57)	1.30 (0.69, 2.48)
Hispanic (Spanish interview)	10.05 (0.84, 120.37)	2.70 (1.10, 6.60)*
Attends religious services at least 1/wk	1.35 (0.82, 2.22)	1.01 (0.78, 1.32)
Another eligible HH member	0.73 (0.46, 1.17)	1.06 (0.83, 1.36)
Health status indicators (W1)		
Self-rated health (ref: Excellent)		
Very good	1.02 (0.35, 2.95)	1.04 (0.65, 1.64)
Good	1.21 (0.42, 3.51)	1.12 (0.69, 1.80)
Fair/Poor	1.14 (0.36, 3.65)	1.07 (0.62, 1.86)
BMI (ref: Underweight/Normal)		
Overweight	0.80 (0.38, 1.67)	1.11 (0.81, 1.51)
Obese	0.73 (0.37, 1.46)	1.34 (1.03, 1.73)*
Did not report	0.59 (0.13, 2.64)	1.56 (0.75, 3.22)
Diabetes	0.89 (0.44, 1.82)	1.19 (0.95, 1.49)
Mildly vigorous activity (ref: At least 1/wk)		
1-3 times/month	0.58 (0.23, 1.47)	0.74 (0.49, 1.12)
Hardly ever/never	0.84 (0.28, 2.54)	1.11 (0.65, 1.90)
No. of functional limitations	0.91 (0.84, 0.99)*	0.97 (0.93, 1.01)
Ever visited doctor in last 2 years (W1)	1.52 (0.59, 3.92)	0.95 (0.57, 1.59)
Change in health status		
Self-rated health (ref: No change)		
Declined	1.05 (0.59, 1.88)	0.86 (0.64, 1.15)
Improved	1.54 (0.62, 3.84)	1.12 (0.78, 1.60)
BMI (ref: No change)		
Declined	1.55 (0.53, 4.53)	1.38 (0.92, 2.08)
Improved	2.52 (1.19, 5.33)*	0.78 (0.57, 1.08)
Developed diabetes	1.86 (0.67, 5.18)	1.19 (0.72, 1.97)
Mildly vigorous activity (ref: No change)		
Declined	0.82 (0.48, 1.40)	1.18 (0.87, 1.59)
Improved	0.79 (0.26, 2.36)	0.90 (0.54, 1.52)
Change in no. functional limitations	0.95 (0.88, 1.04)	1.00 (0.96, 1.04)
Ever visited doctor in last 2 years (W3)	1.70 (0.68, 4.30)	1.08 (0.74, 1.58)

(continued)

Table D-1. Predictors of wave 3 biomeasure consent for wave 1 non-consenters (physical measurements and dried blood spot) including the interaction term of interviewer continuity and reason for wave 1 consent refusal (Model 4) (continued)

	Physical measurements	Dried blood spot
	Odds Ratio	Odds Ratio
Cognition indices		
Word recall score (W1)	0.90 (0.81, 0.99)*	0.96 (0.92, 1.00)
Mental status score (W1)	1.10 (0.97, 1.24)	0.98 (0.92, 1.05)
Change in word recall score	0.99 (0.88, 1.12)	1.00 (0.96, 1.04)
Change in mental status score	1.08 (0.93, 1.25)	0.99 (0.90, 1.08)
Survey resistance (W1)		
No. of contact attempts	1.02 (0.98, 1.06)	1.01 (0.99, 1.03)
Uncooperative Index	0.96 (0.80, 1.15)	1.01 (0.91, 1.13)
Confidentiality Index	0.66 (0.52, 0.84)***	0.80 (0.70, 0.91)**
Survey resistance (W2)		
Nonrespondent in W2	0.22 (0.01, 5.13)	0.65 (0.14, 3.08)
No. of contact attempts	1.01 (0.98, 1.04)	1.00 (0.99, 1.01)
Uncooperative Index	1.13 (0.92, 1.39)	0.98 (0.89, 1.08)
Confidentiality Index	0.73 (0.54, 1.00)*	0.81 (0.68, 0.98)*
Survey resistance (W3)		
No. of contact attempts	0.99 (0.95, 1.02)	0.99 (0.97, 1.01)
Panel status		
Ever a nonrespondent before W1	0.66 (0.33, 1.32)	0.84 (0.59, 1.20)
Interviewer continuity		
E-FTF interviewer continuity	1.01 (0.14, 7.08)	1.39 (0.49, 3.93)
Previous biomeasure consent		
Straight refusal to PM sample (W1)	0.69 (0.36, 1.30)	
Straight refusal to DBS sample (W1)		0.56 (0.40, 0.80)**
Continuity and consent interactions		
Interviewer continuity * PM refusal	0.53 (0.07, 4.09)	
Interviewer continuity * DBS refusal		0.45 (0.16, 1.26)
Interviewer attributes		
Age (years)	0.99 (0.97, 1.02)	0.98 (0.97, 1.00)**
Female	0.53 (0.28, 1.01)	1.29 (0.93, 1.79)
Race (ref: Non-Hispanic other)		
Non-Hispanic black	0.46 (0.22, 0.96)*	0.72 (0.54, 0.96)*
Hispanic	0.26 (0.08, 0.87)*	0.95 (0.62, 1.46)
Education (ref: HS graduate)		
Some college	0.87 (0.39, 1.96)	0.79 (0.52, 1.22)
College graduate	0.83 (0.37, 1.83)	0.91 (0.60, 1.36)
Advanced degree	0.63 (0.29, 1.35)	0.83 (0.53, 1.29)
New hire	1.21 (0.66, 2.19)	0.68 (0.53, 0.89)**
Interviewer variance	1.81 (0.38, 8.47)	1.16 (0.87, 1.56)

Note. Odd ratios 95% confidence intervals are based on jackknife standard errors from a two-level random effects logistic regression model. CI = confidence interval. PM = physical measurements. DBS = dried blood spot. W1 = Wave 1. W2 = Wave 2. W3 = Wave 3. HS = high school.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$. Recommended Bonferroni correction is $\alpha = 0.0008$.

APPENDIX E

Original Scale CRP Descriptive Results

Table E-1. Observed and imputed means and standard errors of C-reactive protein (back-transformed from natural log transform) by year and imputation approach

	Biomeasure weighted					Base weighted				
CRP (ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	5,817	4.473	0.1141	0.0255	6.2%	5,874	4.448	0.1155	0.0260	26.2%
Cross-sectional	6,203	4.483	0.1157	0.0258	8.5%	7,954	4.523	0.1210	0.0268	18.9%
Sequential	6,203	4.494	0.1145	0.0255	6.8%	7,954	4.539	0.1126	0.0248	13.2%
Wide	6,203	4.476	0.1155	0.0258	6.5%	7,954	4.457	0.1185	0.0266	31.6%
2010										
Observed	5,053	3.761	0.1363	0.0362	3.3%	5,053	3.717	0.1306	0.0351	23.8%
Cross-sectional	5,228	3.747	0.1336	0.0357	0.8%	6,631	3.724	0.1138	0.0305	12.3%
Sequential	5,228	3.754	0.1344	0.0358	1.5%	6,631	3.711	0.1251	0.0337	20.3%
Wide	5,228	3.746	0.1346	0.0359	0.5%	6,631	3.722	0.1223	0.0329	12.0%
2014										
Observed	4,335	3.641	0.1486	0.0408	1.8%	4,335	3.679	0.1667	0.0453	19.8%
Cross-sectional	4,413	3.649	0.1495	0.0410	2.7%	5,406	3.683	0.1727	0.0469	27.1%
Sequential	4,413	3.633	0.1466	0.0404	0.5%	5,406	3.676	0.1533	0.0417	10.4%
Wide	4,413	3.653	0.1547	0.0423	2.9%	5,406	3.699	0.1533	0.0414	9.9%

Note. FMI for observed is the missing rate.

Table E-2. Observed and imputed percentiles of CRP (back-transformed from natural log transform) by year and imputation approach

	Biomeasure weighted					Base weighted				
CRP (ug/mL)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.251	0.905	1.964	4.813	15.922	0.255	0.914	1.968	4.757	15.908
(SE)	(0.013)	(0.030)	(0.061)	(0.138)	(0.705)	(0.013)	(0.032)	(0.061)	(0.141)	(0.723)
Cross-sectional	0.254	0.905	1.967	4.844	16.002	0.263	0.918	2.048	4.850	16.262
(SE)	(0.013)	(0.030)	(0.063)	(0.138)	(0.682)	(0.011)	(0.027)	(0.066)	(0.138)	(0.673)
Sequential	0.255	0.904	1.967	4.836	16.038	0.263	0.915	2.048	4.852	16.313
(SE)	(0.013)	(0.030)	(0.063)	(0.140)	(0.692)	(0.012)	(0.033)	(0.066)	(0.142)	(0.685)
Wide	0.253	0.901	1.966	4.818	15.950	0.261	0.906	2.016	4.760	16.053
(SE)	(0.013)	(0.029)	(0.064)	(0.141)	(0.724)	(0.012)	(0.029)	(0.070)	(0.163)	(0.664)
2010										
Observed	0.247	0.792	1.745	3.786	12.443	0.249	0.790	1.725	3.765	12.378
(SE)	(0.009)	(0.022)	(0.046)	(0.094)	(0.349)	(0.009)	(0.022)	(0.048)	(0.096)	(0.401)
Cross-sectional	0.248	0.790	1.742	3.786	12.431	0.256	0.801	1.745	3.826	12.577
(SE)	(0.009)	(0.022)	(0.046)	(0.093)	(0.366)	(0.007)	(0.022)	(0.041)	(0.101)	(0.399)
Sequential	0.247	0.793	1.742	3.789	12.456	0.252	0.794	1.749	3.814	12.497
(SE)	(0.009)	(0.023)	(0.046)	(0.094)	(0.369)	(0.009)	(0.025)	(0.043)	(0.097)	(0.430)
Wide	0.247	0.790	1.742	3.791	12.458	0.253	0.804	1.758	3.855	12.533
(SE)	(0.009)	(0.022)	(0.044)	(0.095)	(0.364)	(0.008)	(0.025)	(0.043)	(0.101)	(0.376)
2014										
Observed	0.111	0.483	1.284	3.496	13.800	0.112	0.484	1.281	3.507	13.845
(SE)	(0.006)	(0.149)	(0.046)	(0.103)	(0.735)	(0.008)	(0.015)	(0.047)	(0.100)	(0.782)
Cross-sectional	0.111	0.483	1.284	3.499	13.784	0.118	0.487	1.281	3.469	13.809
(SE)	(0.007)	(0.015)	(0.046)	(0.101)	(0.719)	(0.008)	(0.014)	(0.047)	(0.110)	(0.767)
Sequential	0.112	0.484	1.284	3.495	13.781	0.118	0.489	1.288	3.506	14.051
(SE)	(0.007)	(0.015)	(0.047)	(0.103)	(0.713)	(0.008)	(0.016)	(0.045)	(0.107)	(0.736)
Wide	0.111	0.483	1.286	3.497	13.813	0.117	0.491	1.306	3.555	14.042
(SE)	(0.006)	(0.015)	(0.047)	(0.101)	(0.772)	(0.007)	(0.016)	(0.047)	(0.116)	(0.755)

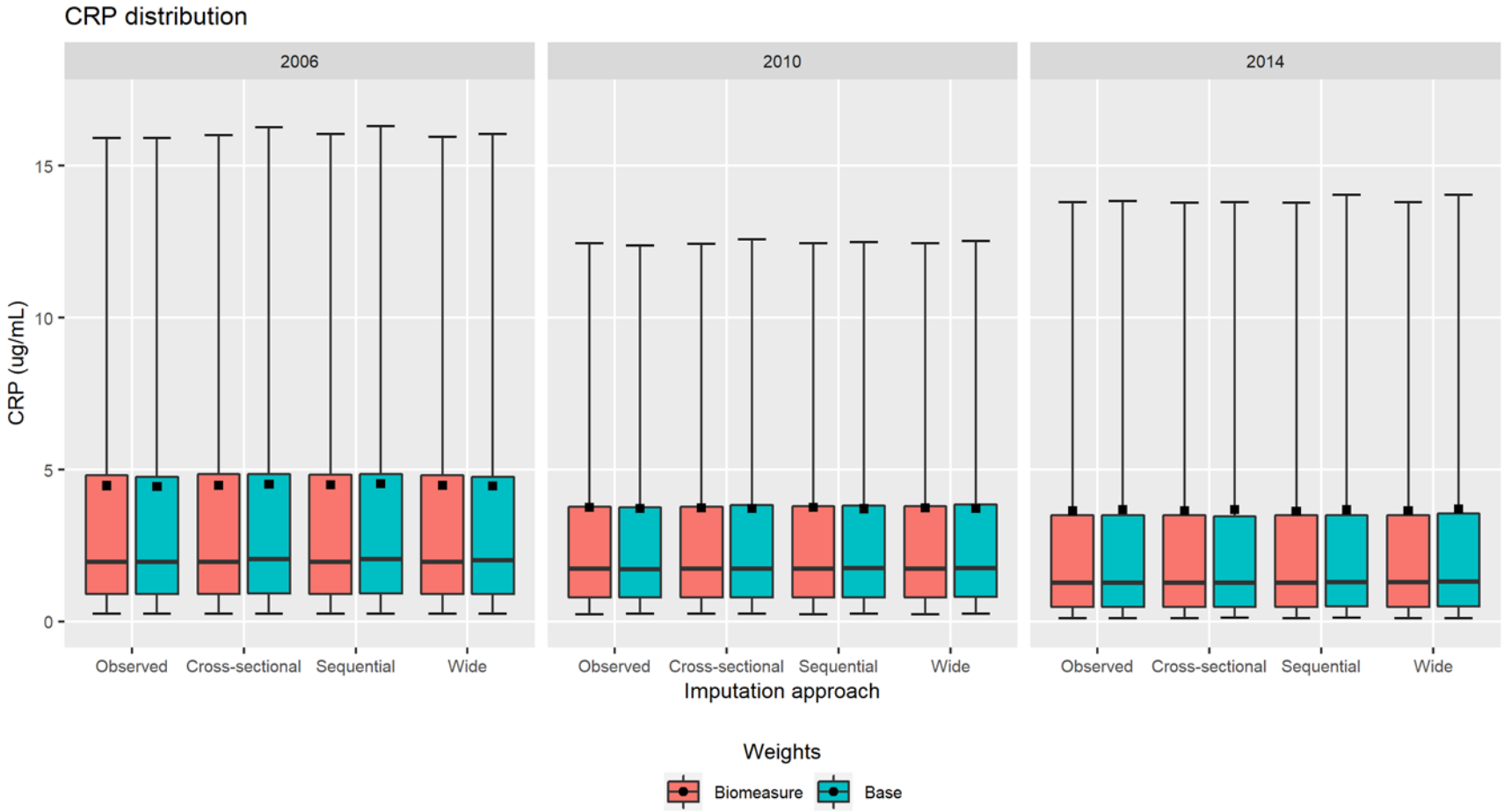

Figure E-1. Distribution of CRP (back-transformed from natural log transform) by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table E-2. Black squares represent means.

APPENDIX F

Cross-sectional Multivariate Models for 2010 and 2014

Table F-1. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using biomeasure weights

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.050 (0.006)****	0.049 (0.006)****	0.049 (0.006)****	0.049 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.312 (0.088)***	-0.310 (0.086)***	-0.314 (0.086)***	-0.315 (0.086)***
Age x Female	-0.019 (0.007)**	-0.018 (0.006)**	-0.018 (0.006)**	-0.018 (0.006)**
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.517 (0.156)**	-0.530 (0.167)**	-0.528 (0.167)**	-0.529 (0.167)**
Non-Hispanic black	-0.306 (0.124)*	-0.305 (0.116)**	-0.301 (0.116)**	-0.304 (0.115)**
Health conditions				
Hypertension	0.681 (0.094)****	0.694 (0.091)****	0.693 (0.091)****	0.693 (0.092)****
Diabetes	0.605 (0.094)****	0.602 (0.087)****	0.601 (0.087)****	0.597 (0.087)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.079 (0.117)	-0.093 (0.088)	-0.096 (0.086)	-0.084 (0.084)
Obese (BMI > 30)	-0.041 (0.089)	-0.046 (0.112)	-0.049 (0.112)	-0.042 (0.112)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.029 (0.165)	0.036 (0.167)	0.038 (0.166)	0.033 (0.167)
Hardly ever/never	0.230 (0.123)	0.270 (0.113)*	0.271 (0.113)*	0.265 (0.113)*
Smoking status (ref: never smoked)				
Current smoker	0.203 (0.147)	0.223 (0.147)	0.222 (0.146)	0.218 (0.147)
Former smoker	0.297 (0.092)**	0.317 (0.089)***	0.318 (0.089)***	0.315 (0.088)***
Biomeasures				
ln(CRP)	0.037 (0.032)	0.031 (0.031)	0.033 (0.032)	0.038 (0.032)
Cystatin C	0.441 (0.098)****	0.426 (0.094)****	0.421 (0.092)****	0.426 (0.094)****
Intercept	-2.013 (0.158)****	-2.001 (0.148)****	-1.992 (0.147)****	-2.001 (0.148)****

Note. Sample sizes: observed n = 4,958; imputed n = 5,228.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table F-2. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using base weights

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.051 (0.006)****	0.051 (0.006)****	0.052 (0.006)****	0.053 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.321 (0.091)***	-0.305 (0.075)****	-0.310 (0.075)****	-0.310 (0.075)****
Age x Female	-0.018 (0.007)**	-0.017 (0.006)**	-0.017 (0.006)**	-0.017 (0.006)**
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.483 (0.154)**	-0.521 (0.149)***	-0.526 (0.148)***	-0.526 (0.149)***
Non-Hispanic black	-0.317 (0.125)*	-0.358 (0.106)***	-0.358 (0.106)***	-0.358 (0.105)***
Health conditions				
Hypertension	0.658 (0.093)****	0.660 (0.081)****	0.655 (0.082)****	0.656 (0.082)****
Diabetes	0.611 (0.092)****	0.571 (0.078)****	0.566 (0.078)****	0.562 (0.078)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.102 (0.119)	-0.083 (0.078)	-0.088 (0.076)	-0.081 (0.075)
Obese (BMI > 30)	-0.057 (0.092)	-0.055 (0.105)	-0.053 (0.103)	-0.053 (0.103)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.003 (0.166)	0.077 (0.130)	0.078 (0.129)	0.072 (0.130)
Hardly ever/never	0.201 (0.126)	0.257 (0.111)*	0.256 (0.112)*	0.253 (0.112)*
Smoking status (ref: never smoked)				
Current smoker	0.218 (0.145)	0.233 (0.126)	0.231 (0.127)	0.223 (0.128)
Former smoker	0.324 (0.090)***	0.298 (0.079)***	0.297 (0.079)***	0.294 (0.079)***
Biomeasures				
ln(CRP)	0.041 (0.033)	0.036 (0.032)	0.043 (0.034)	0.054 (0.032)
Cystatin C	0.457 (0.096)****	0.364 (0.075)****	0.344 (0.073)****	0.338 (0.066)****
Intercept	-1.987 (0.154)****	-1.902 (0.142)****	-1.873 (0.141)****	-1.873 (0.139)****

Note. Sample sizes: observed n = 4,958; imputed n = 6,631.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

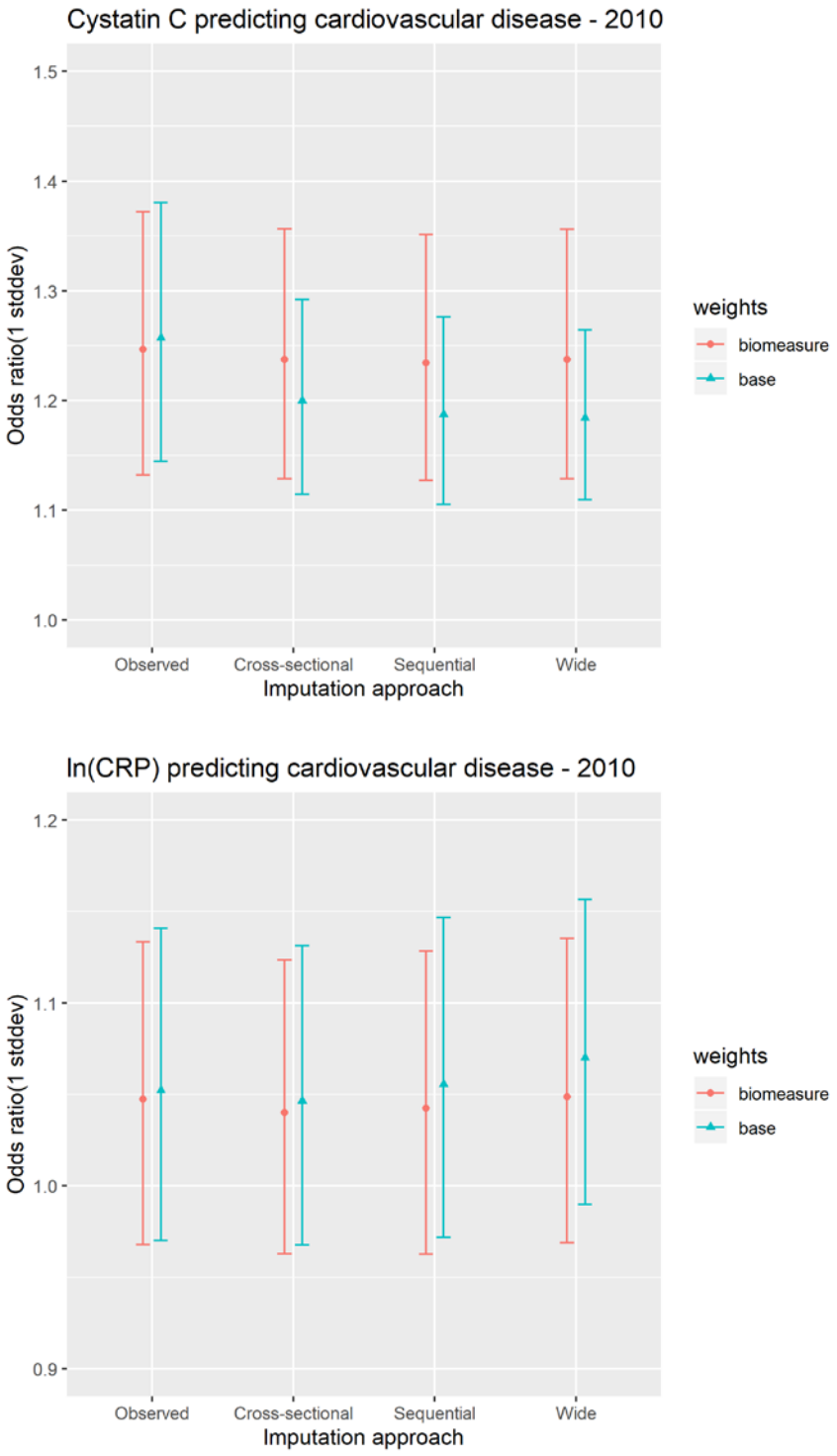

Figure F-1. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2010 by imputation approach and analysis weight. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

Table F-3. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using biomeasure weights

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.051 (0.008)****	0.050 (0.008)****	0.050 (0.008)****	0.050 (0.008)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.373 (0.078)****	-0.342 (0.075)****	-0.345 (0.075)****	-0.344 (0.075)****
Age x Female	-0.022 (0.010)*	-0.018 (0.010)	-0.018 (0.010)	-0.017 (0.010)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.482 (0.181)*	-0.500 (0.180)**	-0.502 (0.180)**	-0.500 (0.180)**
Non-Hispanic black	-0.134 (0.102)	-0.164 (0.119)	-0.166 (0.119)	-0.164 (0.119)
Health conditions				
Hypertension	0.579 (0.116)****	0.592 (0.108)****	0.587 (0.108)****	0.587 (0.108)****
Diabetes	0.496 (0.101)****	0.503 (0.101)****	0.504 (0.101)****	0.504 (0.101)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.089 (0.111)	-0.106 (0.109)	-0.111 (0.108)	-0.111 (0.109)
Obese (BMI > 30)	-0.094 (0.112)	-0.094 (0.106)	-0.096 (0.105)	-0.097 (0.106)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.189 (0.138)	0.182 (0.133)	0.181 (0.133)	0.185 (0.133)
Hardly ever/never	0.334 (0.124)**	0.331 (0.119)**	0.330 (0.120)**	0.329 (0.119)**
Smoking status (ref: never smoked)				
Current smoker	0.200 (0.129)	0.207 (0.124)	0.211 (0.124)	0.206 (0.123)
Former smoker	0.260 (0.078)**	0.270 (0.076)***	0.270 (0.076)***	0.269 (0.076)***
Biomeasures				
ln(CRP)	0.012 (0.032)	0.011 (0.032)	0.010 (0.031)	0.014 (0.031)
Cystatin C	0.483 (0.093)****	0.447 (0.081)****	0.453 (0.081)****	0.447 (0.081)****
Intercept	-1.797 (0.163)****	-1.763 (0.159)****	-1.763 (0.158)****	-1.757 (0.159)****

Note. Sample sizes: observed n = 4,256; imputed n = 4,413.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table F-4. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using base weights

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.052 (0.008)****	0.053 (0.008)****	0.053 (0.008)****	0.054 (0.008)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.358 (0.079)****	-0.357 (0.062)****	-0.356 (0.061)****	-0.352 (0.061)****
Age x Female	-0.022 (0.010)*	-0.022 (0.009)*	-0.021 (0.009)*	-0.021 (0.009)*
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.466 (0.181)*	-0.528 (0.146)***	-0.522 (0.145)***	-0.518 (0.145)***
Non-Hispanic black	-0.115 (0.103)	-0.272 (0.100)**	-0.268 (0.101)**	-0.269 (0.101)**
Health conditions				
Hypertension	0.551 (0.117)****	0.585 (0.096)****	0.569 (0.097)****	0.569 (0.097)****
Diabetes	0.526 (0.101)****	0.511 (0.082)****	0.516 (0.081)****	0.517 (0.080)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.104 (0.108)	-0.156 (0.092)	-0.164 (0.091)	-0.161 (0.090)
Obese (BMI > 30)	-0.120 (0.112)	-0.097 (0.092)	-0.102 (0.089)	-0.098 (0.089)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.175 (0.135)	0.277 (0.116)*	0.277 (0.116)*	0.281 (0.116)*
Hardly ever/never	0.318 (0.131)*	0.280 (0.107)**	0.290 (0.107)**	0.287 (0.108)**
Smoking status (ref: never smoked)				
Current smoker	0.175 (0.131)	0.280 (0.120)*	0.280 (0.120)*	0.283 (0.120)*
Former smoker	0.279 (0.079)***	0.275 (0.072)***	0.277 (0.073)***	0.279 (0.073)***
Biomeasures				
ln(CRP)	0.017 (0.034)	0.013 (0.031)	0.016 (0.033)	0.013 (0.030)
Cystatin C	0.488 (0.095)****	0.389 (0.071)****	0.397 (0.076)****	0.399 (0.072)****
Intercept	-1.793 (0.166)****	-1.633 (0.150)****	-1.634 (0.152)****	-1.642 (0.151)****

Note. Sample sizes: observed n = 4,256; imputed n = 5,406.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

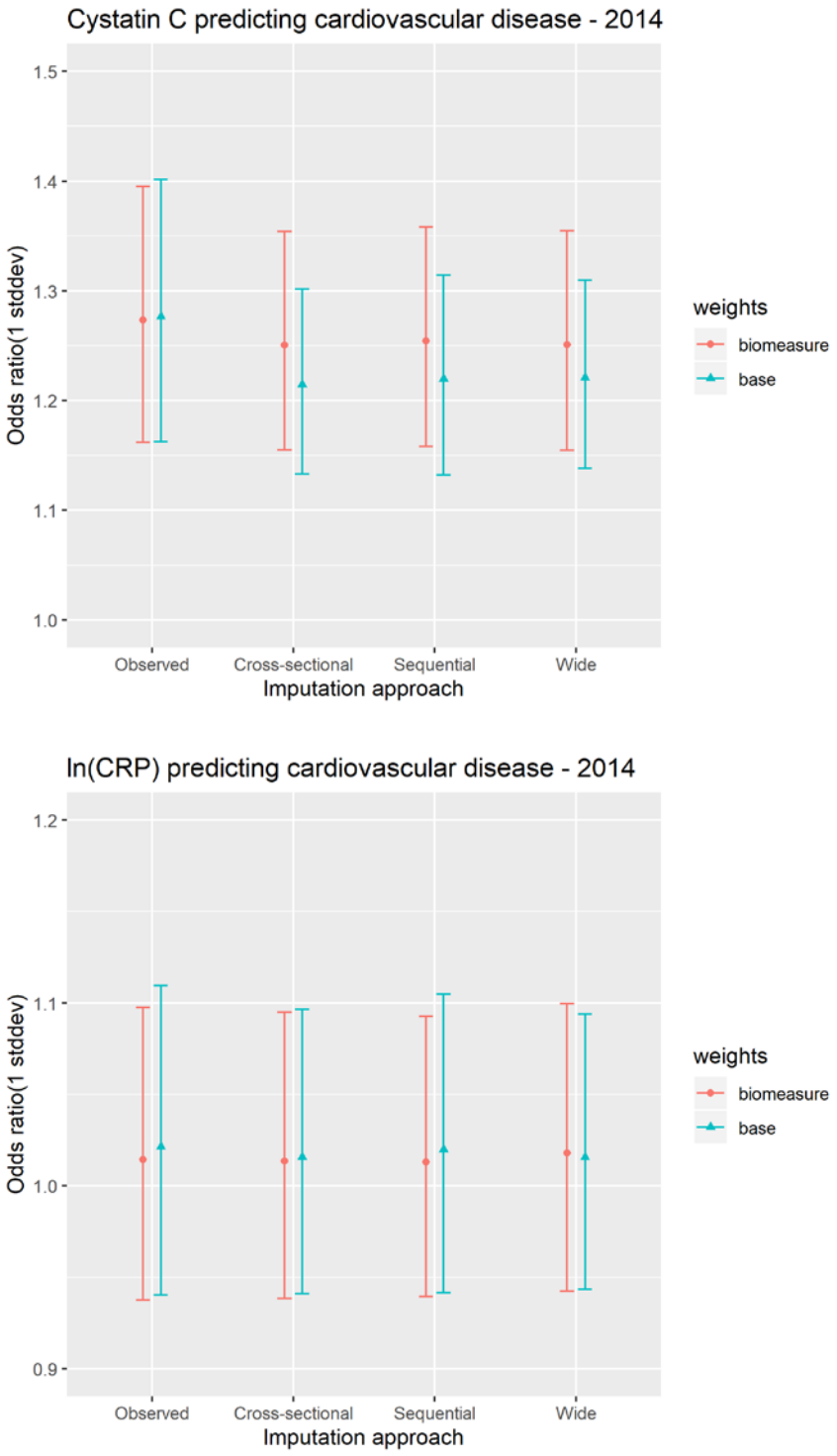

Figure F-2. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2014 by imputation approach and analysis weight. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

APPENDIX G

Gender Subgroup Analyses

The following sections include tables and figures to show the results of the subgroup analyses by gender in conjunction with Section 4.3.6. Section G.1 reviews the univariate characteristics for males and females like Sections 4.3.1 and 4.3.2. Section G.2 includes the cross-sectional multivariate models covering Section 4.3.4 and Appendix F. Section G.3 covers the longitudinal multivariate models like Section 4.3.5.

G.1 Univariate characteristics by gender

Table G1-1. Observed and imputed means and standard errors of Cystatin C by year and imputation approach (males)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	2,399	1.064	0.0083	0.0078	7.8%	2,422	1.061	0.0078	0.0074	28.0%
Cross-sectional	2,601	1.068	0.0090	0.0085	12.7%	3,365	1.069	0.0097	0.0091	27.6%
Sequential	2,601	1.067	0.0086	0.0080	6.5%	3,365	1.070	0.0092	0.0086	14.6%
Wide	2,601	1.068	0.0087	0.0082	10.2%	3,365	1.073	0.0086	0.0081	14.1%
2010										
Observed	2,070	1.125	0.0100	0.0089	4.1%	2,070	1.122	0.0103	0.0091	24.4%
Cross-sectional	2,159	1.126	0.0102	0.0091	1.2%	2,737	1.125	0.0118	0.0105	24.8%
Sequential	2,159	1.126	0.0104	0.0093	6.2%	2,737	1.131	0.0123	0.0109	32.9%
Wide	2,159	1.125	0.0105	0.0093	4.1%	2,737	1.137	0.0109	0.0096	18.5%
2014										
Observed	1,745	1.168	0.0148	0.0127	1.6%	1,745	1.167	0.0150	0.0128	19.1%
Cross-sectional	1,774	1.169	0.0147	0.0126	0.9%	2,158	1.177	0.0143	0.0122	19.5%
Sequential	1,774	1.168	0.0148	0.0127	1.0%	2,158	1.184	0.0163	0.0138	26.2%
Wide	1,774	1.168	0.0147	0.0126	0.6%	2,158	1.190	0.0149	0.0125	10.0%

Note. FMI for observed is the missing rate.

Table G1-2. Observed and imputed means and standard errors of Cystatin C by year and imputation approach (females)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	3,325	1.095	0.0097	0.0089	7.7%	3,356	1.084	0.0088	0.0081	26.9%
Cross-sectional	3,602	1.100	0.0986	0.0896	4.9%	4,589	1.108	0.0088	0.0079	17.9%
Sequential	3,602	1.101	0.0101	0.0091	7.8%	4,589	1.111	0.0088	0.0079	6.5%
Wide	3,602	1.097	0.0099	0.0090	4.4%	4,589	1.095	0.0093	0.0085	23.9%
2010										
Observed	2,992	1.140	0.0132	0.0116	2.5%	2,992	1.136	0.0124	0.0109	23.2%
Cross-sectional	3,069	1.141	0.0131	0.0115	1.4%	3,894	1.147	0.0114	0.0100	13.6%
Sequential	3,069	1.141	0.0130	0.0114	0.8%	3,894	1.151	0.0124	0.0108	27.6%
Wide	3,069	1.140	0.0132	0.0116	1.0%	3,894	1.152	0.0122	0.0106	26.0%
2014										
Observed	2,597	1.205	0.0130	0.0108	1.6%	2,597	1.204	0.0127	0.0105	20.0%
Cross-sectional	2,639	1.205	0.0131	0.0109	3.6%	3,248	1.213	0.0127	0.0105	17.0%
Sequential	2,639	1.205	0.0131	0.0108	0.7%	3,248	1.218	0.0118	0.0097	5.6%
Wide	2,639	1.205	0.0131	0.0108	1.3%	3,248	1.218	0.0137	0.0112	26.3%

Note. FMI for observed is the missing rate.

Table G1-3. Observed and imputed at proportion at risk for Cystatin C by year and imputation approach (males)

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Prop.	SE	CV	FMI	n	Prop.	SE	CV	FMI
2006										
Observed	2,399	0.078	0.0061	0.0781	7.8%	2,422	0.075	0.0057	0.0759	28.0%
Cross-sectional	2,601	0.087	0.0069	0.0784	18.6%	3,365	0.106	0.0071	0.0674	30.0%
Sequential	2,601	0.086	0.0063	0.0728	7.6%	3,365	0.105	0.0067	0.0637	18.5%
Wide	2,601	0.085	0.0060	0.0711	6.7%	3,365	0.099	0.0066	0.0666	34.8%
2010										
Observed	2,070	0.112	0.0082	0.0731	4.1%	2,070	0.110	0.0082	0.0745	24.4%
Cross-sectional	2,159	0.117	0.0085	0.0725	2.3%	2,737	0.134	0.0096	0.0718	31.2%
Sequential	2,159	0.116	0.0084	0.0727	3.7%	2,737	0.138	0.0096	0.0695	27.6%
Wide	2,159	0.115	0.0085	0.0743	3.5%	2,737	0.136	0.0087	0.0643	16.0%
2014										
Observed	1,745	0.143	0.0105	0.0732	1.6%	1,745	0.143	0.0107	0.0746	19.1%
Cross-sectional	1,774	0.146	0.0105	0.0720	1.8%	2,158	0.167	0.0102	0.0614	12.2%
Sequential	1,774	0.145	0.0104	0.0716	1.3%	2,158	0.170	0.0116	0.0679	29.5%
Wide	1,774	0.145	0.0103	0.0708	0.7%	2,158	0.174	0.0109	0.0628	15.6%

Note. FMI for observed is the missing rate.

Table G1-4. Observed and imputed at proportion at risk for Cystatin C by year and imputation approach (females)

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Prop.	SE	CV	FMI	n	Prop.	SE	CV	FMI
2006										
Observed	3,325	0.102	0.0050	0.0486	7.7%	3,356	0.096	0.0047	0.0493	26.9%
Cross-sectional	3,602	0.111	0.0054	0.0482	9.5%	4,589	0.133	0.0061	0.0455	32.1%
Sequential	3,602	0.112	0.0057	0.0507	19.6%	4,589	0.134	0.0061	0.0452	20.8%
Wide	3,602	0.107	0.0052	0.0492	10.0%	4,589	0.118	0.0072	0.0609	54.6%
2010										
Observed	2,992	0.136	0.0089	0.0652	2.5%	2,992	0.135	0.0087	0.0645	23.2%
Cross-sectional	3,069	0.138	0.0088	0.0636	1.2%	3,894	0.157	0.0088	0.0558	25.9%
Sequential	3,069	0.139	0.0087	0.0630	0.6%	3,894	0.160	0.0083	0.0514	19.5%
Wide	3,069	0.137	0.0088	0.0645	1.7%	3,894	0.157	0.0086	0.0549	25.9%
2014										
Observed	2,597	0.147	0.0075	0.0511	1.6%	2,597	0.146	0.0075	0.0515	20.0%
Cross-sectional	2,639	0.149	0.0077	0.0517	4.7%	3,248	0.175	0.0083	0.0475	17.9%
Sequential	2,639	0.149	0.0076	0.0511	1.1%	3,248	0.175	0.0083	0.0470	10.3%
Wide	2,639	0.148	0.0076	0.0515	1.4%	3,248	0.175	0.0082	0.0470	13.7%

Note. FMI for observed is the missing rate.

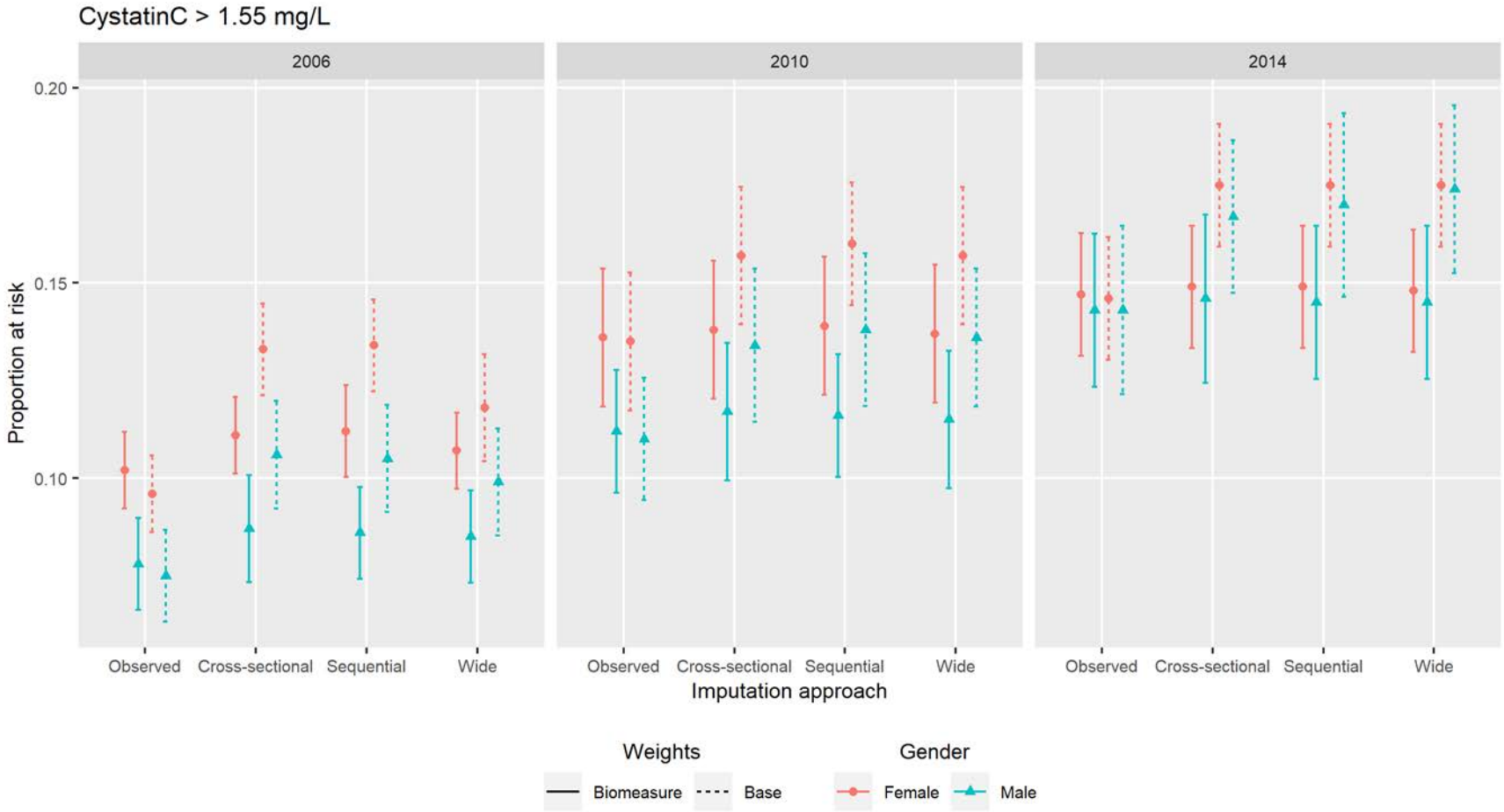

Figure G1-1. Proportion at risk for Cystatin C by year, gender, analysis weight, and imputation approach. 95% confidence interval of the proportion included.

Table G1-5. Observed and imputed percentiles of Cystatin C by year and imputation approach (males)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.659	0.814	0.946	1.137	1.663	0.660	0.815	0.949	1.137	1.641
(SE)	(0.010)	(0.006)	(0.007)	(0.011)	(0.035)	(0.009)	(0.006)	(0.007)	(0.011)	(0.034)
Cross-sectional	0.649	0.835	0.967	1.168	1.744	0.557	0.839	0.974	1.239	1.813
(SE)	(0.019)	(0.014)	(0.014)	(0.015)	(0.051)	(0.033)	(0.015)	(0.020)	(0.017)	(0.031)
Sequential	0.649	0.837	0.967	1.168	1.736	0.562	0.839	0.976	1.239	1.808
(SE)	(0.019)	(0.014)	(0.015)	(0.014)	(0.044)	(0.030)	(0.015)	(0.018)	(0.017)	(0.036)
Wide	0.669	0.837	0.967	1.168	1.739	0.601	0.839	0.981	1.238	1.782
(SE)	(0.028)	(0.014)	(0.015)	(0.015)	(0.045)	(0.030)	(0.015)	(0.021)	(0.017)	(0.038)
2010										
Observed	0.656	0.853	1.028	1.257	1.888	0.655	0.852	1.029	1.256	1.881
(SE)	(0.012)	(0.008)	(0.009)	(0.016)	(0.042)	(0.014)	(0.009)	(0.009)	(0.016)	(0.041)
Cross-sectional	0.655	0.853	1.033	1.267	1.900	0.582	0.844	1.047	1.319	1.916
(SE)	(0.013)	(0.009)	(0.009)	(0.018)	(0.043)	(0.025)	(0.011)	(0.009)	(0.021)	(0.038)
Sequential	0.654	0.852	1.032	1.267	1.891	0.590	0.847	1.049	1.323	1.934
(SE)	(0.013)	(0.009)	(0.009)	(0.017)	(0.043)	(0.024)	(0.010)	(0.010)	(0.021)	(0.039)
Wide	0.653	0.853	1.031	1.265	1.893	0.607	0.854	1.050	1.326	1.940
(SE)	(0.014)	(0.009)	(0.009)	(0.018)	(0.042)	(0.020)	(0.010)	(0.009)	(0.018)	(0.040)
2014										
Observed	0.663	0.880	1.061	1.313	1.959	0.661	0.879	1.061	1.314	1.951
(SE)	(0.015)	(0.011)	(0.014)	(0.017)	(0.052)	(0.016)	(0.012)	(0.014)	(0.018)	(0.051)
Cross-sectional	0.660	0.881	1.063	1.319	1.964	0.609	0.877	1.086	1.376	2.002
(SE)	(0.017)	(0.011)	(0.014)	(0.017)	(0.052)	(0.026)	(0.012)	(0.012)	(0.024)	(0.043)
Sequential	0.660	0.881	1.063	1.316	1.961	0.613	0.881	1.086	1.383	2.026
(SE)	(0.017)	(0.012)	(0.014)	(0.017)	(0.053)	(0.025)	(0.012)	(0.012)	(0.029)	(0.049)
Wide	0.662	0.881	1.063	1.317	1.962	0.626	0.882	1.088	1.386	2.046
(SE)	(0.016)	(0.011)	(0.014)	(0.017)	(0.052)	(0.023)	(0.011)	(0.011)	(0.024)	(0.049)

Table G1-6. Observed and imputed percentiles of Cystatin C by year and imputation approach (females)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.625	0.797	0.946	1.169	1.809	0.629	0.797	0.944	1.161	1.780
(SE)	(0.010)	(0.005)	(0.007)	(0.011)	(0.031)	(0.010)	(0.005)	(0.007)	(0.012)	(0.030)
Cross-sectional	0.641	0.838	0.969	1.237	1.867	0.580	0.839	0.987	1.277	1.916
(SE)	(0.016)	(0.015)	(0.014)	(0.017)	(0.039)	(0.014)	(0.015)	(0.025)	(0.025)	(0.030)
Sequential	0.648	0.834	0.969	1.238	1.875	0.582	0.839	1.007	1.289	1.924
(SE)	(0.018)	(0.015)	(0.014)	(0.017)	(0.039)	(0.016)	(0.015)	(0.023)	(0.022)	(0.032)
Wide	0.647	0.836	0.969	1.235	1.853	0.583	0.839	0.970	1.240	1.874
(SE)	(0.017)	(0.015)	(0.014)	(0.017)	(0.038)	(0.017)	(0.015)	(0.015)	(0.017)	(0.035)
2010										
Observed	0.642	0.847	1.024	1.280	1.978	0.640	0.846	1.022	1.276	1.967
(SE)	(0.009)	(0.006)	(0.007)	(0.012)	(0.035)	(0.010)	(0.007)	(0.009)	(0.015)	(0.053)
Cross-sectional	0.640	0.848	1.027	1.289	1.978	0.583	0.848	1.048	1.344	1.987
(SE)	(0.010)	(0.007)	(0.009)	(0.015)	(0.051)	(0.017)	(0.008)	(0.008)	(0.016)	(0.038)
Sequential	0.640	0.847	1.026	1.288	1.979	0.589	0.849	1.049	1.348	2.004
(SE)	(0.010)	(0.007)	(0.009)	(0.015)	(0.050)	(0.021)	(0.009)	(0.010)	(0.018)	(0.039)
Wide	0.640	0.847	1.027	1.288	1.977	0.601	0.849	1.048	1.341	2.008
(SE)	(0.011)	(0.007)	(0.009)	(0.015)	(0.052)	(0.018)	(0.008)	(0.009)	(0.019)	(0.039)
2014										
Observed	0.673	0.897	1.079	1.355	2.012	0.672	0.896	1.079	1.355	2.012
(SE)	(0.010)	(0.006)	(0.008)	(0.016)	(0.063)	(0.011)	(0.006)	(0.008)	(0.015)	(0.061)
Cross-sectional	0.669	0.898	1.084	1.359	2.013	0.627	0.896	1.102	1.409	2.085
(SE)	(0.010)	(0.007)	(0.010)	(0.016)	(0.061)	(0.021)	(0.006)	(0.010)	(0.016)	(0.047)
Sequential	0.670	0.898	1.081	1.359	2.015	0.633	0.903	1.104	1.414	2.088
(SE)	(0.011)	(0.006)	(0.009)	(0.015)	(0.061)	(0.019)	(0.007)	(0.009)	(0.017)	(0.049)
Wide	0.668	0.899	1.081	1.360	2.013	0.631	0.899	1.104	1.409	2.115
(SE)	(0.011)	(0.007)	(0.009)	(0.016)	(0.061)	(0.020)	(0.009)	(0.011)	(0.017)	(0.063)

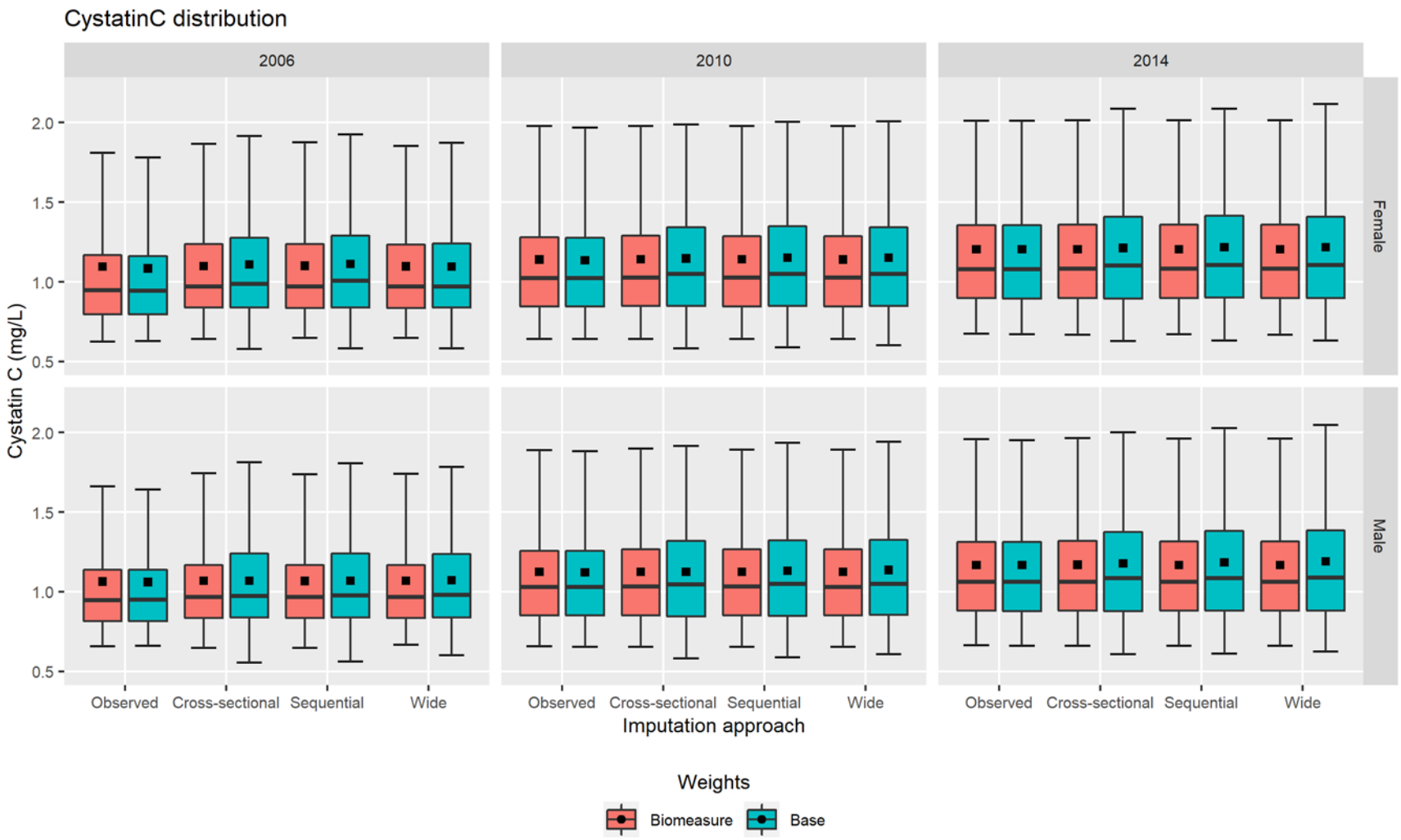

Figure G1-2. Distribution of Cystatin C comparing gender by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table G1-5 and G1-6. Black squares represent means.

Table G1-7. Observed and imputed means and standard errors of C-reactive protein (natural log transform) by year and imputation approach (males)

	Biomeasure weighted					Base weighted				
ln(CRP)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	2,436	0.559	0.0303	0.0542	6.3%	2,460	0.567	0.0309	0.0546	26.9%
Cross-sectional	2,601	0.559	0.0290	0.0519	3.9%	3,365	0.579	0.0316	0.0546	26.5%
Sequential	2,601	0.562	0.0287	0.0510	6.0%	3,365	0.582	0.0305	0.0525	23.7%
Wide	2,601	0.567	0.0292	0.0515	3.5%	3,365	0.602	0.0300	0.0498	25.0%
2010										
Observed	2,066	0.496	0.0351	0.0708	4.3%	2,066	0.490	0.0365	0.0746	24.5%
Cross-sectional	2,159	0.496	0.0347	0.0699	4.6%	2,737	0.514	0.0323	0.0629	14.2%
Sequential	2,159	0.495	0.0337	0.0681	1.6%	2,737	0.502	0.0335	0.0668	16.5%
Wide	2,159	0.490	0.0341	0.0695	1.1%	2,737	0.508	0.0355	0.0699	15.6%
2014										
Observed	1,743	0.134	0.0399	0.2971	1.7%	1,743	0.137	0.0412	0.3019	19.2%
Cross-sectional	1,774	0.141	0.0398	0.2832	0.8%	2,158	0.168	0.0405	0.2402	22.3%
Sequential	1,774	0.133	0.0397	0.2973	0.4%	2,158	0.164	0.0418	0.2558	16.7%
Wide	1,774	0.136	0.0396	0.2923	1.1%	2,158	0.174	0.0397	0.2281	12.0%

Note. FMI for observed is the missing rate.

Table G1-8. Observed and imputed means and standard errors of C-reactive protein (natural log transform) by year and imputation approach (females)

	Biomeasure weighted					Base weighted				
ln(CRP)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	3,381	0.852	0.0242	0.0284	6.1%	3,414	0.848	0.0247	0.0291	25.6%
Cross-sectional	3,602	0.854	0.0232	0.0272	4.9%	4,589	0.860	0.0216	0.0252	7.6%
Sequential	3,602	0.854	0.0235	0.0276	1.7%	4,589	0.858	0.0243	0.0283	19.2%
Wide	3,602	0.844	0.0229	0.0272	3.8%	4,589	0.823	0.0215	0.0262	11.8%
2010										
Observed	2,987	0.614	0.0226	0.0368	2.7%	2,987	0.607	0.0224	0.0369	23.3%
Cross-sectional	3,069	0.611	0.0226	0.0370	0.9%	3,894	0.609	0.0221	0.0363	17.6%
Sequential	3,069	0.613	0.0228	0.0372	1.4%	3,894	0.610	0.0228	0.0373	24.6%
Wide	3,069	0.615	0.0226	0.0368	0.8%	3,894	0.621	0.0238	0.0383	39.7%
2014										
Observed	2,592	0.346	0.0328	0.0949	1.8%	2,592	0.350	0.0342	0.0978	20.2%
Cross-sectional	2,639	0.341	0.0331	0.0970	1.2%	3,248	0.326	0.0351	0.1075	27.7%
Sequential	2,639	0.345	0.0330	0.0956	0.6%	3,248	0.338	0.0324	0.0961	13.1%
Wide	2,639	0.345	0.0335	0.0973	2.4%	3,248	0.341	0.0333	0.0976	17.6%

Note. FMI for observed is the missing rate.

Table G1-9. Observed and imputed proportion at risk for C-reactive protein by year and imputation approach (males)

	Biomeasure weighted					Base weighted				
Proportion at risk (>= 3.0 ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	2,436	0.314	0.0127	0.0403	6.3%	2,460	0.314	0.0129	0.0411	26.9%
Cross-sectional	2,601	0.315	0.0122	0.0385	2.7%	3,365	0.324	0.0124	0.0382	23.8%
Sequential	2,601	0.316	0.0125	0.0395	12.8%	3,365	0.323	0.0126	0.0390	26.0%
Wide	2,601	0.318	0.0122	0.0384	4.8%	3,365	0.329	0.0120	0.0365	23.1%
2010										
Observed	2,066	0.280	0.0109	0.0390	4.3%	2,066	0.276	0.0112	0.0406	24.5%
Cross-sectional	2,159	0.282	0.0107	0.0382	4.0%	2,737	0.290	0.0103	0.0355	8.5%
Sequential	2,159	0.281	0.0107	0.0380	1.7%	2,737	0.286	0.0110	0.0386	24.2%
Wide	2,159	0.280	0.0107	0.0381	2.0%	2,737	0.288	0.0118	0.0410	26.9%
2014										
Observed	1,743	0.257	0.0131	0.0509	1.7%	1,743	0.257	0.0134	0.0520	19.2%
Cross-sectional	1,774	0.258	0.0132	0.0510	2.8%	2,158	0.262	0.0133	0.0507	24.1%
Sequential	1,774	0.256	0.0130	0.0509	0.2%	2,158	0.261	0.0131	0.0503	13.3%
Wide	1,774	0.257	0.0129	0.0502	0.6%	2,158	0.264	0.0134	0.0505	17.7%

Note. FMI for observed is just missing rate.

Table G1-10. Observed and imputed proportion at risk for C-reactive protein by year and imputation approach (females)

	Biomeasure weighted					Base weighted				
Proportion at risk (>= 3.0 ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	3,381	0.437	0.0105	0.0241	6.1%	3,414	0.436	0.0108	0.0248	25.6%
Cross-sectional	3,602	0.437	0.0101	0.0231	4.9%	4,589	0.436	0.0094	0.0215	7.4%
Sequential	3,602	0.437	0.0100	0.0230	1.6%	4,589	0.436	0.0106	0.0242	21.5%
Wide	3,602	0.434	0.0100	0.0231	3.1%	4,589	0.425	0.0093	0.0220	9.0%
2010										
Observed	2,987	0.348	0.0086	0.0247	2.7%	2,987	0.345	0.0088	0.0255	23.3%
Cross-sectional	3,069	0.346	0.0086	0.0248	1.8%	3,894	0.342	0.0098	0.0286	32.4%
Sequential	3,069	0.347	0.0085	0.0246	1.5%	3,894	0.343	0.0089	0.0258	23.7%
Wide	3,069	0.348	0.0086	0.0248	2.3%	3,894	0.349	0.0091	0.0260	32.0%
2014										
Observed	2,592	0.305	0.0097	0.0319	1.8%	2,592	0.307	0.0100	0.0326	20.2%
Cross-sectional	2,639	0.304	0.0098	0.0323	2.0%	3,248	0.299	0.0107	0.0358	30.4%
Sequential	2,639	0.305	0.0098	0.0322	1.4%	3,248	0.302	0.0097	0.0323	13.7%
Wide	2,639	0.305	0.0099	0.0324	2.1%	3,248	0.304	0.0104	0.0342	24.6%

Note. FMI for observed is just missing rate.

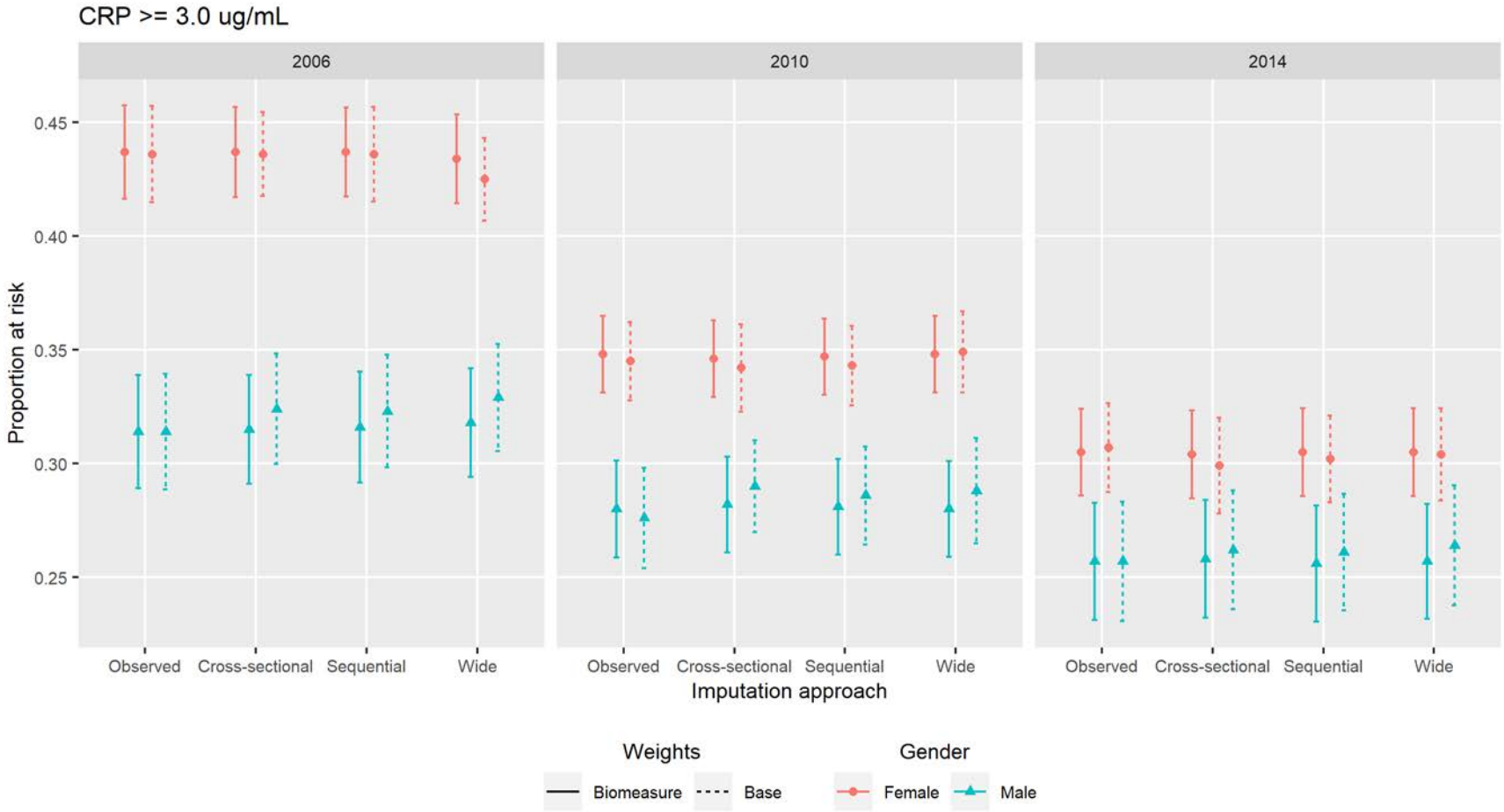

Figure G1-3. Proportion at risk for C-reactive protein by year, gender, analysis weight, and imputation approach. 95% confidence interval of the proportion included.

Table G1-11. Observed and imputed percentiles of CRP (natural log transform) by year and imputation approach (males)

	Biomeasure weighted					Base weighted				
ln(CRP)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	-1.444	-0.227	0.478	1.338	2.612	-1.418	-0.221	0.483	1.327	2.615
(SE)	(0.057)	(0.034)	(0.039)	(0.061)	(0.075)	(0.049)	(0.032)	(0.039)	(0.058)	(0.072)
Cross-sectional	-1.449	-0.228	0.479	1.344	2.615	-1.411	-0.218	0.528	1.371	2.642
(SE)	(0.057)	(0.034)	(0.041)	(0.058)	(0.070)	(0.056)	(0.036)	(0.041)	(0.053)	(0.075)
Sequential	-1.437	-0.228	0.480	1.343	2.617	-1.400	-0.217	0.530	1.368	2.628
(SE)	(0.057)	(0.034)	(0.040)	(0.057)	(0.070)	(0.053)	(0.038)	(0.040)	(0.049)	(0.064)
Wide	-1.436	-0.223	0.483	1.356	2.618	-1.389	-0.193	0.544	1.393	2.661
(SE)	(0.053)	(0.031)	(0.039)	(0.058)	(0.069)	(0.052)	(0.034)	(0.044)	(0.050)	(0.063)
2010										
Observed	-1.358	-0.320	0.431	1.217	2.564	-1.354	-0.312	0.421	1.194	2.564
(SE)	(0.033)	(0.047)	(0.044)	(0.043)	(0.064)	(0.031)	(0.046)	(0.042)	(0.045)	(0.065)
Cross-sectional	-1.359	-0.318	0.434	1.220	2.564	-1.348	-0.289	0.449	1.253	2.573
(SE)	(0.033)	(0.048)	(0.041)	(0.041)	(0.063)	(0.040)	(0.044)	(0.038)	(0.040)	(0.068)
Sequential	-1.361	-0.318	0.433	1.218	2.562	-1.357	-0.301	0.449	1.234	2.555
(SE)	(0.035)	(0.047)	(0.041)	(0.041)	(0.063)	(0.043)	(0.047)	(0.040)	(0.041)	(0.063)
Wide	-1.366	-0.328	0.429	1.216	2.562	-1.351	-0.286	0.447	1.244	2.562
(SE)	(0.033)	(0.047)	(0.042)	(0.042)	(0.064)	(0.040)	(0.046)	(0.041)	(0.046)	(0.063)
2014										
Observed	-2.287	-0.886	0.096	1.134	2.584	-1.354	-0.312	0.421	1.194	2.564
(SE)	(0.132)	(0.060)	(0.046)	(0.066)	(0.098)	(0.031)	(0.046)	(0.042)	(0.045)	(0.065)
Cross-sectional	-2.284	-0.880	0.100	1.148	2.588	-1.348	-0.289	0.449	1.253	2.573
(SE)	(0.132)	(0.059)	(0.046)	(0.066)	(0.093)	(0.040)	(0.044)	(0.038)	(0.040)	(0.068)
Sequential	-2.283	-0.884	0.094	1.133	2.584	-1.357	-0.301	0.449	1.234	2.555
(SE)	(0.130)	(0.059)	(0.045)	(0.065)	(0.090)	(0.043)	(0.047)	(0.040)	(0.041)	(0.063)
Wide	-2.287	-0.885	0.098	1.137	2.586	-1.351	-0.286	0.447	1.244	2.562
(SE)	(0.130)	(0.060)	(0.046)	(0.066)	(0.092)	(0.040)	(0.046)	(0.041)	(0.046)	(0.063)

Table G1-12. Observed and imputed percentiles of CRP (natural log transform) by year and imputation approach (females)

	Biomeasure weighted					Base weighted				
ln(CRP)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	-1.268	0.051	0.869	1.741	2.876	-1.267	0.050	0.869	1.722	2.869
(SE)	(0.067)	(0.039)	(0.034)	(0.029)	(0.035)	(0.067)	(0.039)	(0.034)	(0.034)	(0.041)
Cross-sectional	-1.257	0.051	0.868	1.738	2.878	-1.234	0.052	0.876	1.728	2.887
(SE)	(0.063)	(0.039)	(0.037)	(0.031)	(0.033)	(0.054)	(0.039)	(0.035)	(0.028)	(0.037)
Sequential	-1.258	0.050	0.867	1.734	2.879	-1.240	0.044	0.870	1.729	2.888
(SE)	(0.065)	(0.040)	(0.036)	(0.030)	(0.032)	(0.060)	(0.042)	(0.040)	(0.032)	(0.039)
Wide	-1.276	0.042	0.846	1.729	2.877	-1.283	0.005	0.835	1.703	2.859
(SE)	(0.067)	(0.040)	(0.038)	(0.034)	(0.036)	(0.068)	(0.037)	(0.031)	(0.032)	(0.039)
2010										
Observed	-1.460	-0.158	0.655	1.408	2.489	-1.462	-0.160	0.650	1.398	2.476
(SE)	(0.050)	(0.036)	(0.027)	(0.034)	(0.040)	(0.049)	(0.036)	(0.025)	(0.034)	(0.040)
Cross-sectional	-1.458	-0.160	0.653	1.405	2.484	-1.412	-0.166	0.645	1.403	2.493
(SE)	(0.053)	(0.035)	(0.027)	(0.034)	(0.037)	(0.057)	(0.037)	(0.026)	(0.035)	(0.040)
Sequential	-1.456	-0.160	0.655	1.407	2.489	-1.428	-0.174	0.646	1.409	2.500
(SE)	(0.051)	(0.036)	(0.027)	(0.034)	(0.039)	(0.052)	(0.036)	(0.026)	(0.033)	(0.042)
Wide	-1.458	-0.156	0.655	1.411	2.490	-1.415	-0.158	0.653	1.422	2.495
(SE)	(0.050)	(0.036)	(0.027)	(0.034)	(0.040)	(0.049)	(0.039)	(0.025)	(0.034)	(0.045)
2014										
Observed	-2.137	-0.590	0.389	1.327	2.649	-2.134	-0.586	0.388	1.333	2.658
(SE)	(0.069)	(0.049)	(0.041)	(0.040)	(0.071)	(0.074)	(0.050)	(0.043)	(0.040)	(0.058)
Cross-sectional	-2.135	-0.596	0.380	1.323	2.643	-2.113	-0.609	0.352	1.309	2.637
(SE)	(0.068)	(0.050)	(0.043)	(0.038)	(0.069)	(0.070)	(0.049)	(0.047)	(0.042)	(0.066)
Sequential	-2.132	-0.591	0.385	1.326	2.647	-2.093	-0.604	0.361	1.320	2.661
(SE)	(0.069)	(0.050)	(0.041)	(0.039)	(0.067)	(0.072)	(0.048)	(0.044)	(0.038)	(0.069)
Wide	-2.140	-0.593	0.386	1.326	2.652	-2.117	-0.597	0.372	1.329	2.658
(SE)	(0.067)	(0.050)	(0.041)	(0.039)	(0.067)	(0.071)	(0.051)	(0.042)	(0.038)	(0.063)

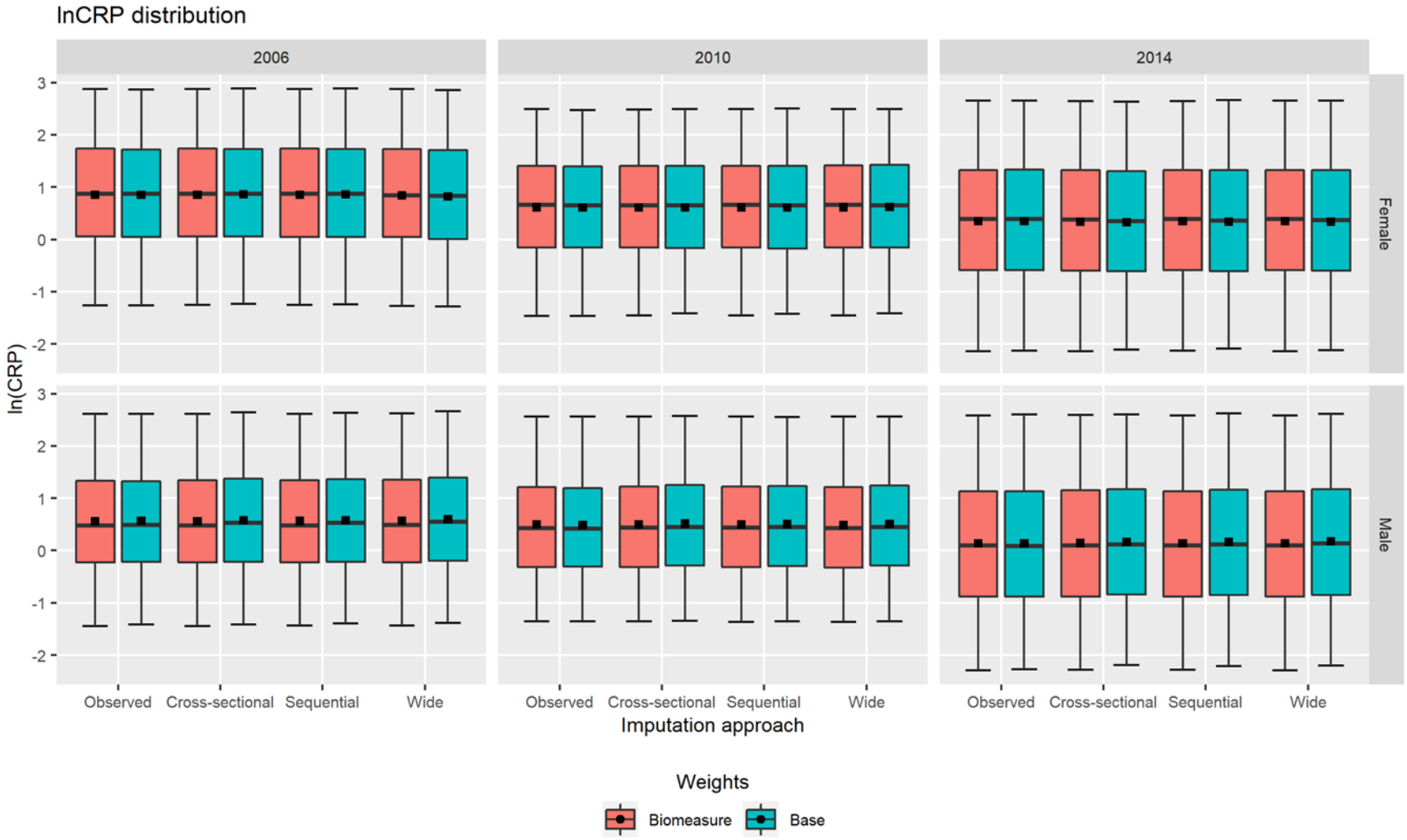

Figure G1-4. Distribution of C-reactive protein (natural log transform) comparing gender by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table G1-11 and G1-12. Black squares represent means.

G.2 Cross-sectional multivariate model by gender

Table G2-1. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using biomeasure weights (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.051 (0.008)****	0.053 (0.007)****	0.053 (0.007)****	0.053 (0.007)****
Age (squared)	-0.001 (0.001)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.614 (0.229)**	-0.649 (0.223)**	-0.649 (0.223)**	-0.646 (0.223)**
Non-Hispanic black	-0.351 (0.192)	-0.386 (0.177)*	-0.386 (0.176)*	-0.380 (0.176)*
Health conditions				
Hypertension	0.666 (0.116)****	0.661 (0.107)****	0.662 (0.107)****	0.660 (0.108)****
Diabetes	0.581 (0.140)***	0.572 (0.130)****	0.570 (0.131)****	0.565 (0.130)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.113 (0.152)	-0.125 (0.143)	-0.127 (0.142)	-0.128 (0.143)
Obese (BMI > 30)	-0.183 (0.170)	-0.079 (0.166)	-0.081 (0.164)	-0.082 (0.165)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.070 (0.238)	0.030 (0.225)	0.032 (0.225)	0.029 (0.226)
Hardly ever/never	0.244 (0.178)	0.247 (0.166)	0.242 (0.166)	0.248 (0.168)
Smoking status (ref: never smoked)				
Current smoker	0.298 (0.212)	0.287 (0.202)	0.287 (0.202)	0.283 (0.201)
Former smoker	0.140 (0.151)	0.145 (0.147)	0.146 (0.147)	0.146 (0.147)
Biomeasures				
ln(CRP)	0.036 (0.041)	0.024 (0.041)	0.025 (0.041)	0.024 (0.044)
Cystatin C	0.482 (0.148)**	0.442 (0.138)**	0.441 (0.140)**	0.463 (0.145)**
Intercept	-2.013 (0.290)****	-1.989 (0.273)****	-1.986 (0.274)****	-2.009 (0.280)****

Note. Sample sizes: observed n = 2,384; imputed n = 2,601.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table G2-2. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using biomeasure weights (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.028 (0.006)****	0.031 (0.005)****	0.031 (0.005)****	0.031 (0.005)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.213 (0.195)	-0.262 (0.187)	-0.262 (0.187)	-0.260 (0.187)
Non-Hispanic black	-0.048 (0.147)	-0.061 (0.130)	-0.062 (0.129)	-0.058 (0.129)
Health conditions				
Hypertension	0.794 (0.119)****	0.800 (0.111)****	0.798 (0.111)****	0.802 (0.111)****
Diabetes	0.585 (0.123)****	0.627 (0.108)****	0.624 (0.109)****	0.623 (0.110)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.223 (0.115)	-0.230 (0.106)*	-0.230 (0.104)*	-0.227 (0.107)*
Obese (BMI > 30)	-0.304 (0.153)	-0.298 (0.145)*	-0.293 (0.144)*	-0.286 (0.142)*
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.203 (0.254)	0.188 (0.219)	0.188 (0.219)	0.197 (0.220)
Hardly ever/never	0.552 (0.186)**	0.556 (0.161)***	0.551 (0.161)***	0.556 (0.161)***
Smoking status (ref: never smoked)				
Current smoker	0.292 (0.177)	0.317 (0.167)	0.314 (0.166)	0.321 (0.166)
Former smoker	0.230 (0.119)	0.259 (0.121)*	0.258 (0.121)*	0.259 (0.121)*
Biomeasures				
ln(CRP)	0.031 (0.042)	0.019 (0.038)	0.024 (0.039)	0.016 (0.037)
Cystatin C	0.404 (0.110)***	0.372 (0.103)***	0.370 (0.100)***	0.342 (0.103)***
Intercept	-2.439 (0.149)****	-2.440 (0.141)****	-2.439 (0.139)****	-2.408 (0.143)****

Note. Sample sizes: observed n = 3,230; imputed n = 3,602.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-3. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using base weights (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.050 (0.008)****	0.056 (0.006)****	0.056 (0.006)****	0.057 (0.006)****
Age (squared)	-0.001 (0.001)	-0.001 (0.000)*	-0.001 (0.000)*	-0.001 (0.000)*
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.804 (0.210)***	-0.820 (0.193)****	-0.825 (0.193)****	-0.814 (0.192)****
Non-Hispanic black	-0.440 (0.193)*	-0.417 (0.170)*	-0.411 (0.168)*	-0.398 (0.169)*
Health conditions				
Hypertension	0.681 (0.120)****	0.659 (0.093)****	0.657 (0.093)****	0.658 (0.093)****
Diabetes	0.578 (0.137)****	0.505 (0.123)****	0.503 (0.123)****	0.495 (0.122)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.150 (0.152)	-0.166 (0.104)	-0.172 (0.105)	-0.156 (0.102)
Obese (BMI > 30)	-0.190 (0.171)	-0.144 (0.132)	-0.148 (0.129)	-0.125 (0.127)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.050 (0.237)	0.022 (0.212)	0.020 (0.210)	0.021 (0.212)
Hardly ever/never	0.172 (0.188)	0.202 (0.141)	0.196 (0.143)	0.214 (0.142)
Smoking status (ref: never smoked)				
Current smoker	0.243 (0.211)	0.167 (0.165)	0.172 (0.165)	0.182 (0.164)
Former smoker	0.079 (0.142)	0.161 (0.106)	0.167 (0.106)	0.165 (0.106)
Biomeasures				
ln(CRP)	0.044 (0.046)	0.042 (0.048)	0.033 (0.040)	0.026 (0.042)
Cystatin C	0.552 (0.159)**	0.386 (0.132)**	0.442 (0.139)**	0.421 (0.129)**
Intercept	-2.054 (0.282)****	-1.803 (0.221)****	-1.857 (0.224)****	-1.848 (0.216)****

Note. Sample sizes: observed n = 2,406; imputed n = 3,365.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-4. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using base weights (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.027 (0.006)****	0.036 (0.006)****	0.036 (0.006)****	0.037 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.274 (0.196)	-0.436 (0.156)**	-0.436 (0.155)**	-0.429 (0.156)**
Non-Hispanic black	-0.044 (0.147)	-0.155 (0.130)	-0.155 (0.130)	-0.149 (0.130)
Health conditions				
Hypertension	0.766 (0.120)****	0.785 (0.092)****	0.784 (0.092)****	0.784 (0.092)****
Diabetes	0.529 (0.123)****	0.567 (0.096)****	0.565 (0.097)****	0.556 (0.096)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.168 (0.112)	-0.112 (0.083)	-0.115 (0.082)	-0.111 (0.084)
Obese (BMI > 30)	-0.259 (0.155)	-0.147 (0.116)	-0.150 (0.115)	-0.137 (0.115)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.123 (0.261)	0.139 (0.180)	0.140 (0.179)	0.154 (0.181)
Hardly ever/never	0.575 (0.176)**	0.487 (0.151)**	0.486 (0.151)**	0.500 (0.151)***
Smoking status (ref: never smoked)				
Current smoker	0.279 (0.175)	0.310 (0.118)**	0.307 (0.117)**	0.315 (0.117)**
Former smoker	0.224 (0.118)	0.224 (0.099)*	0.223 (0.098)*	0.223 (0.099)*
Biomeasures				
ln(CRP)	0.024 (0.041)	0.016 (0.038)	0.029 (0.036)	0.019 (0.033)
Cystatin C	0.373 (0.104)***	0.319 (0.095)**	0.303 (0.079)***	0.304 (0.082)***
Intercept	-2.395 (0.144)****	-2.386 (0.134)****	-2.377 (0.123)****	-2.371 (0.125)****

Note. Sample sizes: observed n = 3,261; imputed n = 4,589.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

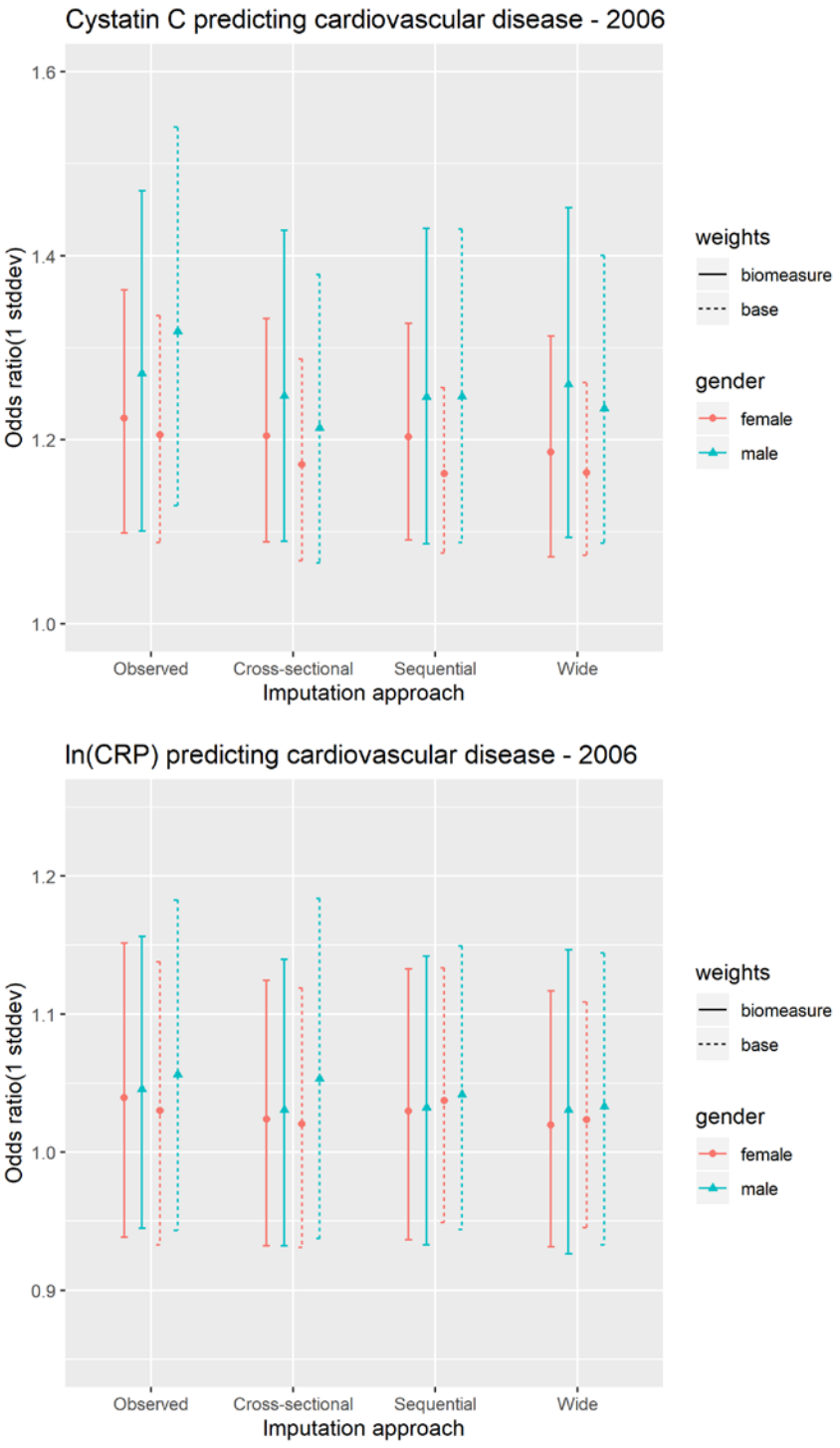

Figure G2-1. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2006 by imputation approach, analysis weight, and gender. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

Table G2-5. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using biomeasure weights (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.054 (0.007)****	0.052 (0.007)****	0.053 (0.007)****	0.052 (0.007)****
Age (squared)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.785 (0.284)**	-0.885 (0.293)**	-0.883 (0.292)**	-0.884 (0.292)**
Non-Hispanic black	-0.788 (0.191)***	-0.760 (0.182)****	-0.746 (0.182)****	-0.749 (0.182)****
Health conditions				
Hypertension	0.502 (0.123)***	0.506 (0.122)****	0.504 (0.122)****	0.508 (0.122)****
Diabetes	0.655 (0.130)****	0.648 (0.126)****	0.650 (0.125)****	0.647 (0.126)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.037 (0.158)	-0.061 (0.151)	-0.057 (0.151)	-0.060 (0.150)
Obese (BMI > 30)	0.049 (0.171)	0.039 (0.166)	0.036 (0.165)	0.031 (0.166)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.100 (0.173)	-0.054 (0.180)	-0.055 (0.179)	-0.057 (0.180)
Hardly ever/never	0.120 (0.193)	0.186 (0.187)	0.195 (0.186)	0.191 (0.186)
Smoking status (ref: never smoked)				
Current smoker	0.147 (0.243)	0.099 (0.240)	0.098 (0.239)	0.090 (0.239)
Former smoker	0.251 (0.123)*	0.251 (0.118)*	0.252 (0.117)*	0.249 (0.117)*
Biomeasures				
ln(CRP)	0.026 (0.052)	0.021 (0.053)	0.024 (0.053)	0.030 (0.054)
Cystatin C	0.428 (0.164)*	0.413 (0.159)**	0.406 (0.159)*	0.409 (0.161)*
Intercept	-1.769 (0.265)****	-1.744 (0.257)****	-1.738 (0.258)****	-1.738 (0.261)****

Note. Sample sizes: observed n = 2,049; imputed n = 2,159.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-6. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using biomeasure weights (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.026 (0.006)****	0.028 (0.006)****	0.028 (0.006)****	0.028 (0.006)****
Age (squared)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.273 (0.222)	-0.239 (0.180)	-0.241 (0.179)	-0.241 (0.179)
Non-Hispanic black	-0.037 (0.138)	-0.037 (0.139)	-0.038 (0.138)	-0.042 (0.137)
Health conditions				
Hypertension	0.865 (0.153)****	0.886 (0.149)****	0.884 (0.149)****	0.881 (0.149)****
Diabetes	0.565 (0.118)****	0.569 (0.113)****	0.567 (0.113)****	0.562 (0.112)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.129 (0.112)	-0.130 (0.113)	-0.139 (0.115)	-0.114 (0.109)
Obese (BMI > 30)	-0.159 (0.153)	-0.159 (0.153)	-0.158 (0.151)	-0.141 (0.151)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.235 (0.286)	0.172 (0.280)	0.180 (0.278)	0.170 (0.279)
Hardly ever/never	0.380 (0.156)*	0.391 (0.149)**	0.383 (0.151)*	0.373 (0.150)*
Smoking status (ref: never smoked)				
Current smoker	0.270 (0.206)	0.350 (0.202)	0.348 (0.202)	0.347 (0.202)
Former smoker	0.345 (0.127)**	0.379 (0.124)**	0.381 (0.123)**	0.377 (0.123)**
Biomeasures				
ln(CRP)	0.054 (0.041)	0.047 (0.039)	0.047 (0.040)	0.049 (0.040)
Cystatin C	0.444 (0.129)**	0.429 (0.123)***	0.424 (0.122)***	0.431 (0.123)***
Intercept	-2.567 (0.225)****	-2.561 (0.214)****	-2.553 (0.213)****	-2.568 (0.214)****

Note. Sample sizes: observed n = 2,909; imputed n = 3,069.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-7. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using base weights (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.055 (0.007)****	0.055 (0.007)****	0.057 (0.007)****	0.057 (0.006)****
Age (squared)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.738 (0.300)*	-0.763 (0.249)**	-0.766 (0.250)**	-0.763 (0.250)**
Non-Hispanic black	-0.810 (0.191)****	-0.739 (0.173)****	-0.731 (0.173)****	-0.726 (0.173)****
Health conditions				
Hypertension	0.518 (0.123)****	0.448 (0.116)***	0.447 (0.116)***	0.450 (0.117)***
Diabetes	0.662 (0.129)****	0.653 (0.116)****	0.652 (0.116)****	0.649 (0.117)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.084 (0.161)	-0.063 (0.138)	-0.063 (0.137)	-0.061 (0.136)
Obese (BMI > 30)	0.002 (0.176)	0.004 (0.169)	-0.001 (0.169)	-0.003 (0.168)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.134 (0.172)	-0.015 (0.157)	-0.013 (0.156)	-0.016 (0.156)
Hardly ever/never	0.096 (0.195)	0.150 (0.174)	0.155 (0.175)	0.153 (0.174)
Smoking status (ref: never smoked)				
Current smoker	0.182 (0.242)	0.149 (0.223)	0.144 (0.224)	0.141 (0.227)
Former smoker	0.283 (0.123)*	0.270 (0.127)*	0.266 (0.127)*	0.267 (0.127)*
Biomeasures				
ln(CRP)	0.025 (0.055)	0.026 (0.050)	0.041 (0.050)	0.040 (0.050)
Cystatin C	0.422 (0.167)*	0.342 (0.133)*	0.279 (0.133)*	0.279 (0.127)*
Intercept	-1.722 (0.270)****	-1.632 (0.242)****	-1.560 (0.238)****	-1.561 (0.236)****

Note. Sample sizes: observed n = 2,049; imputed n = 2,737.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-8. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using base weights (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.029 (0.006)****	0.030 (0.006)****	0.031 (0.005)****	0.031 (0.005)****
Age (squared)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.254 (0.229)	-0.309 (0.159)	-0.317 (0.159)*	-0.322 (0.158)*
Non-Hispanic black	-0.056 (0.140)	-0.131 (0.126)	-0.136 (0.125)	-0.144 (0.124)
Health conditions				
Hypertension	0.800 (0.152)****	0.867 (0.121)****	0.857 (0.121)****	0.858 (0.121)****
Diabetes	0.571 (0.117)****	0.503 (0.104)****	0.495 (0.104)****	0.490 (0.103)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.138 (0.111)	-0.117 (0.093)	-0.123 (0.096)	-0.117 (0.091)
Obese (BMI > 30)	-0.147 (0.151)	-0.141 (0.129)	-0.128 (0.126)	-0.131 (0.122)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.207 (0.290)	0.192 (0.210)	0.195 (0.209)	0.184 (0.211)
Hardly ever/never	0.341 (0.155)*	0.384 (0.126)**	0.375 (0.128)**	0.375 (0.129)**
Smoking status (ref: never smoked)				
Current smoker	0.266 (0.206)	0.349 (0.169)*	0.349 (0.169)*	0.340 (0.168)*
Former smoker	0.366 (0.123)**	0.330 (0.098)***	0.330 (0.097)***	0.325 (0.097)***
Biomeasures				
ln(CRP)	0.060 (0.042)	0.050 (0.044)	0.047 (0.046)	0.069 (0.042)
Cystatin C	0.475 (0.124)***	0.376 (0.103)***	0.387 (0.104)***	0.377 (0.097)***
Intercept	-2.547 (0.215)****	-2.461 (0.170)****	-2.469 (0.170)****	-2.467 (0.163)****

Note. Sample sizes: observed n = 2,909; imputed n = 3,894.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

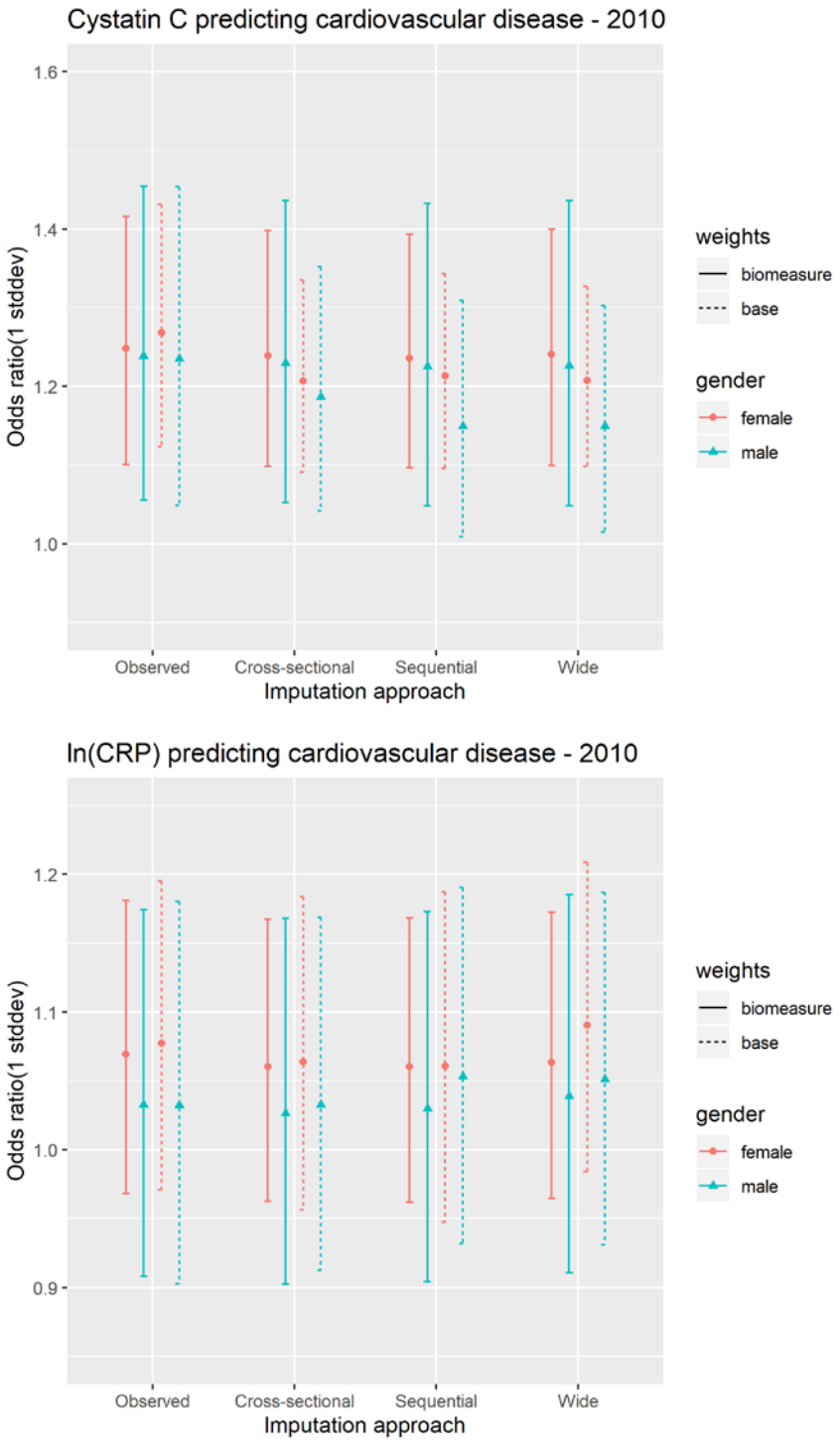

Figure G2-2. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2010 by imputation approach, analysis weight, and gender. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

Table G2-9. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using biomeasure weights (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.053 (0.009)****	0.051 (0.009)****	0.051 (0.009)****	0.051 (0.009)****
Age (squared)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.959 (0.270)***	-0.952 (0.263)***	-0.955 (0.263)***	-0.951 (0.263)***
Non-Hispanic black	-0.495 (0.200)*	-0.558 (0.206)**	-0.559 (0.206)**	-0.560 (0.206)**
Health conditions				
Hypertension	0.431 (0.153)**	0.432 (0.151)**	0.435 (0.151)**	0.434 (0.151)**
Diabetes	0.458 (0.170)**	0.478 (0.167)**	0.479 (0.167)**	0.480 (0.167)**
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.262 (0.155)	-0.263 (0.151)	-0.272 (0.151)	-0.270 (0.151)
Obese (BMI > 30)	-0.139 (0.188)	-0.134 (0.189)	-0.140 (0.188)	-0.142 (0.189)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.035 (0.194)	-0.046 (0.190)	-0.045 (0.190)	-0.044 (0.190)
Hardly ever/never	0.281 (0.181)	0.281 (0.179)	0.284 (0.179)	0.281 (0.179)
Smoking status (ref: never smoked)				
Current smoker	-0.027 (0.230)	-0.022 (0.231)	-0.023 (0.230)	-0.026 (0.231)
Former smoker	0.155 (0.132)	0.151 (0.130)	0.154 (0.130)	0.151 (0.130)
Biomeasures				
ln(CRP)	0.010 (0.050)	0.011 (0.050)	0.009 (0.050)	0.015 (0.050)
Cystatin C	0.345 (0.185)	0.362 (0.187)	0.362 (0.187)	0.357 (0.185)
Intercept	-1.184 (0.239)****	-1.203 (0.242)****	-1.199 (0.241)****	-1.193 (0.240)****

Note. Sample sizes: observed n = 1,726; imputed n = 1,774.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-10. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using biomeasure weights (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.026 (0.007)***	0.030 (0.006)****	0.030 (0.006)****	0.030 (0.006)****
Age (squared)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.094 (0.241)	-0.133 (0.240)	-0.134 (0.240)	-0.134 (0.240)
Non-Hispanic black	0.064 (0.123)	0.054 (0.149)	0.052 (0.150)	0.055 (0.150)
Health conditions				
Hypertension	0.759 (0.143)****	0.768 (0.136)****	0.758 (0.134)****	0.758 (0.134)****
Diabetes	0.529 (0.113)****	0.528 (0.110)****	0.527 (0.109)****	0.527 (0.109)****
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.117 (0.137)	0.019 (0.135)	0.014 (0.137)	0.013 (0.138)
Obese (BMI > 30)	0.046 (0.137)	-0.116 (0.136)	-0.114 (0.133)	-0.114 (0.135)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.640 (0.184)**	0.606 (0.164)***	0.603 (0.165)***	0.612 (0.163)***
Hardly ever/never	0.399 (0.217)	0.388 (0.206)	0.385 (0.206)	0.384 (0.206)
Smoking status (ref: never smoked)				
Current smoker	0.431 (0.228)	0.428 (0.221)	0.435 (0.220)*	0.427 (0.219)
Former smoker	0.368 (0.115)**	0.386 (0.110)***	0.382 (0.110)***	0.382 (0.109)***
Biomeasures				
ln(CRP)	0.021 (0.046)	0.018 (0.045)	0.018 (0.044)	0.020 (0.045)
Cystatin C	0.566 (0.113)****	0.498 (0.097)****	0.506 (0.099)****	0.501 (0.099)****
Intercept	-2.701 (0.178)****	-2.581 (0.170)****	-2.583 (0.167)****	-2.575 (0.167)****

Note. Sample sizes: observed n = 2,530; imputed n = 2,639.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-11. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using base weights (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.053 (0.009)****	0.054 (0.008)****	0.053 (0.008)****	0.054 (0.008)****
Age (squared)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.925 (0.256)***	-0.851 (0.205)****	-0.839 (0.205)****	-0.835 (0.206)****
Non-Hispanic black	-0.505 (0.205)*	-0.573 (0.172)***	-0.571 (0.172)***	-0.573 (0.173)***
Health conditions				
Hypertension	0.406 (0.154)*	0.367 (0.134)**	0.357 (0.135)**	0.355 (0.134)**
Diabetes	0.489 (0.171)**	0.497 (0.142)***	0.501 (0.143)***	0.499 (0.142)***
BMI (ref: under/normal weight)				
Overweight ($25 \leq$ BMI < 30)	-0.272 (0.154)	-0.271 (0.120)*	-0.286 (0.122)*	-0.280 (0.121)*
Obese (BMI > 30)	-0.164 (0.189)	-0.160 (0.167)	-0.186 (0.168)	-0.168 (0.167)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.047 (0.189)	0.060 (0.166)	0.064 (0.165)	0.067 (0.165)
Hardly ever/never	0.252 (0.187)	0.279 (0.152)	0.279 (0.151)	0.277 (0.152)
Smoking status (ref: never smoked)				
Current smoker	-0.040 (0.227)	0.251 (0.235)	0.242 (0.233)	0.256 (0.233)
Former smoker	0.192 (0.137)	0.279 (0.128)*	0.282 (0.127)*	0.286 (0.127)*
Biomeasures				
ln(CRP)	0.010 (0.052)	0.002 (0.049)	0.018 (0.049)	0.007 (0.050)
Cystatin C	0.357 (0.188)	0.319 (0.163)	0.318 (0.160)*	0.329 (0.152)*
Intercept	-1.192 (0.237)****	-1.179 (0.240)****	-1.161 (0.235)****	-1.185 (0.232)****

Note. Sample sizes: observed n = 1,726; imputed n = 2,158.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G2-12. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using base weights (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.028 (0.006)****	0.029 (0.006)****	0.029 (0.006)****	0.029 (0.006)****
Age (squared)	0.001 (0.001)*	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
Race/ethnicity (ref: non-Hispanic other)				
Hispanic	-0.094 (0.239)	-0.263 (0.207)	-0.266 (0.206)	-0.262 (0.206)
Non-Hispanic black	0.095 (0.123)	-0.117 (0.126)	-0.113 (0.127)	-0.114 (0.127)
Health conditions				
Hypertension	0.722 (0.147)****	0.791 (0.116)****	0.769 (0.117)****	0.772 (0.117)****
Diabetes	0.555 (0.117)****	0.518 (0.091)****	0.529 (0.091)****	0.532 (0.090)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	0.024 (0.138)	-0.081 (0.119)	-0.082 (0.118)	-0.084 (0.118)
Obese (BMI > 30)	-0.142 (0.134)	-0.101 (0.116)	-0.089 (0.114)	-0.101 (0.113)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.617 (0.184)**	0.667 (0.171)****	0.661 (0.173)***	0.668 (0.171)****
Hardly ever/never	0.415 (0.218)	0.276 (0.181)	0.296 (0.180)	0.295 (0.180)
Smoking status (ref: never smoked)				
Current smoker	0.402 (0.226)	0.339 (0.174)	0.343 (0.172)*	0.337 (0.174)
Former smoker	0.369 (0.117)**	0.300 (0.092)**	0.299 (0.092)**	0.299 (0.092)**
Biomeasures				
ln(CRP)	0.029 (0.049)	0.024 (0.046)	0.013 (0.046)	0.018 (0.042)
Cystatin C	0.571 (0.119)****	0.437 (0.093)****	0.450 (0.095)****	0.448 (0.095)****
Intercept	-2.669 (0.186)****	-2.393 (0.167)****	-2.398 (0.163)****	-2.394 (0.163)****

Note. Sample sizes: observed n = 2,530; imputed n = 3,248.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

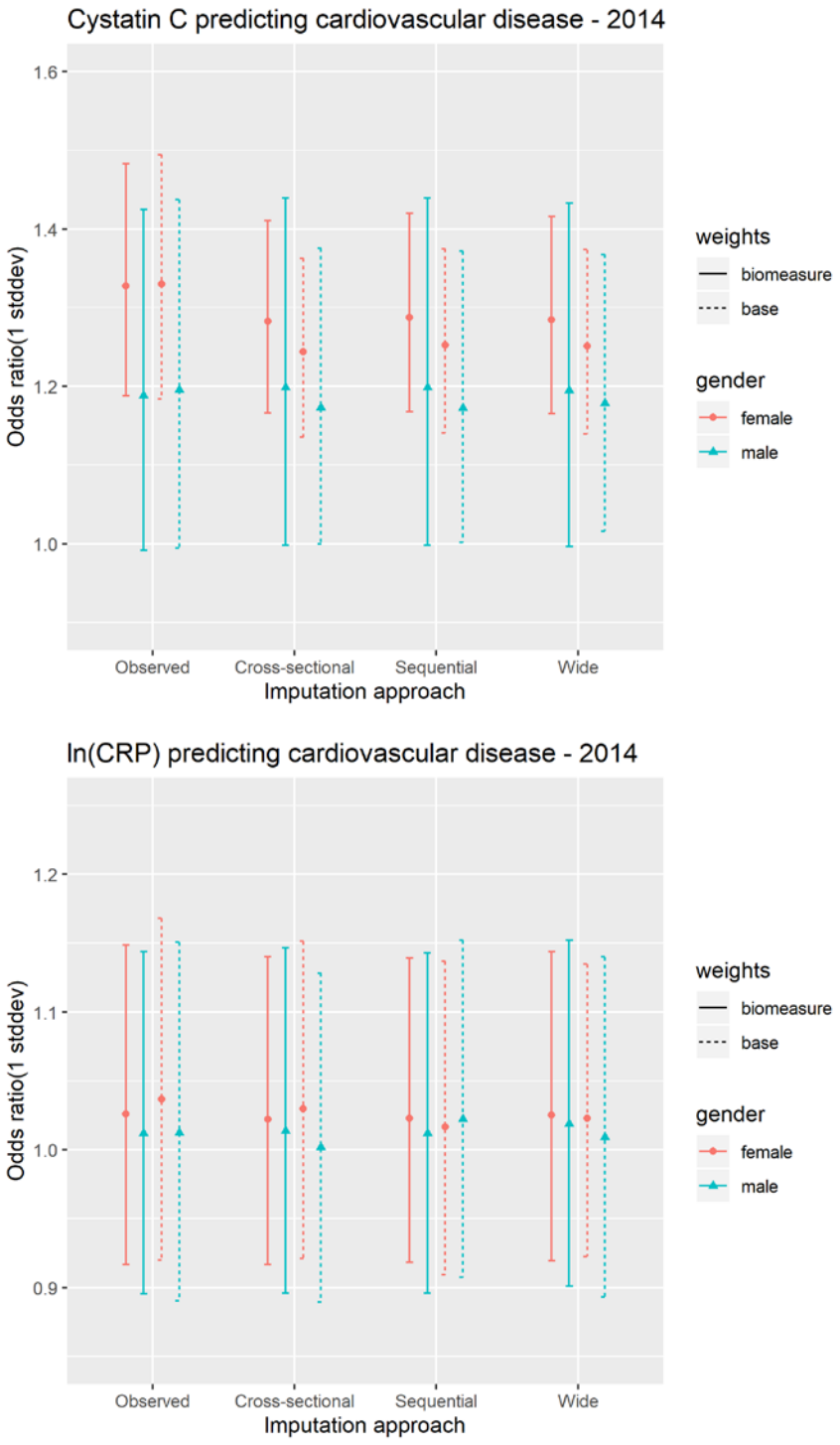

Figure G2-3. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2014 by imputation approach, analysis weight, and gender. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

G.3 Longitudinal multivariate model by gender

Table G3-1. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (biomeasure weight) (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.057 (0.017)**	0.058 (0.013)****	0.058 (0.013)****	0.058 (0.013)****
Age (squared)	-0.002 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Race/ethnicity (ref: Non-Hispanic other)				
Hispanic	-0.852 (0.520)	-0.716 (0.405)	-0.713 (0.402)	-0.711 (0.405)
Non-Hispanic black	-0.691 (0.424)	-0.410 (0.329)	-0.409 (0.327)	-0.404 (0.330)
Health conditions				
High blood pressure (2006)	0.167 (0.242)	0.185 (0.226)	0.187 (0.224)	0.185 (0.228)
Recent HBP diagnosis	-0.117 (0.253)	0.022 (0.237)	0.022 (0.236)	0.015 (0.236)
Diabetes (2006)	0.735 (0.266)**	0.777 (0.228)***	0.775 (0.228)***	0.778 (0.227)***
Recent diagnosis diabetes	0.028 (0.298)	0.149 (0.262)	0.150 (0.262)	0.148 (0.263)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.043 (0.308)	0.125 (0.232)	0.125 (0.232)	0.117 (0.231)
Obese (2006)	0.101 (0.269)	0.168 (0.265)	0.158 (0.265)	0.142 (0.265)
Decreased BMI category	-0.193 (0.349)	0.070 (0.286)	0.056 (0.286)	0.049 (0.290)
Increased BMI category	0.387 (0.266)	0.354 (0.274)	0.364 (0.273)	0.352 (0.275)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.336 (0.372)	-0.649 (0.350)	-0.649 (0.352)	-0.646 (0.351)
Hardly ever/never (2006)	-0.219 (0.518)	-0.547 (0.564)	-0.545 (0.565)	-0.555 (0.560)
Decreased daily activity	0.265 (0.470)	0.475 (0.384)	0.472 (0.384)	0.483 (0.380)
Increased daily activity	-0.086 (0.238)	-0.236 (0.216)	-0.239 (0.215)	-0.241 (0.213)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.127 (0.347)	0.256 (0.315)	0.252 (0.317)	0.240 (0.314)
Former smoker (2006)	0.376 (0.198)	0.270 (0.190)	0.274 (0.190)	0.272 (0.190)
Recently quit smoking	0.929 (0.476)	0.849 (0.387)*	0.851 (0.387)*	0.863 (0.390)*
Recently started smoking	0.057 (1.016)	-0.249 (1.038)	-0.241 (1.034)	-0.231 (1.032)
Biomeasures				
ln(CRP) (2006)	0.041 (0.109)	0.053 (0.099)	0.057 (0.101)	0.083 (0.098)
ln(CRP) change	-0.094 (0.082)	-0.051 (0.076)	-0.053 (0.074)	-0.068 (0.078)
Cystatin C (2006)	0.511 (0.447)	0.401 (0.376)	0.441 (0.388)	0.394 (0.382)
Cystatin C change	0.241 (0.246)	0.327 (0.224)	0.312 (0.220)	0.305 (0.241)
Intercept	-2.391 (0.502)****	-2.468 (0.445)****	-2.503 (0.457)****	-2.464 (0.426)****

Note. Sample sizes: 1,062 for observed, 1,355 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G3-2. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (biomeasure weight) (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.035 (0.012)**	0.036 (0.009)****	0.036 (0.009)****	0.037 (0.009)****
Age (squared)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Race/ethnicity (ref: Non-Hispanic other)				
Hispanic	-0.219 (0.304)	-0.085 (0.272)	-0.077 (0.272)	-0.081 (0.274)
Non-Hispanic black	0.302 (0.217)	0.050 (0.229)	0.047 (0.229)	0.055 (0.229)
Health conditions				
High blood pressure (2006)	0.696 (0.300)*	0.744 (0.220)***	0.726 (0.219)***	0.726 (0.214)***
Recent HBP diagnosis	0.521 (0.310)	0.649 (0.255)*	0.621 (0.258)*	0.621 (0.256)*
Diabetes (2006)	0.605 (0.238)*	0.444 (0.194)*	0.445 (0.196)*	0.433 (0.195)*
Recent diagnosis diabetes	0.377 (0.284)	0.405 (0.217)	0.407 (0.218)	0.408 (0.215)
BMI (ref: Under/normal weight)				
Overweight (2006)	-0.027 (0.226)	-0.075 (0.187)	-0.076 (0.188)	-0.062 (0.192)
Obese (2006)	-0.114 (0.213)	0.017 (0.213)	-0.006 (0.216)	0.044 (0.223)
Decreased BMI category	-0.125 (0.304)	0.014 (0.252)	-0.031 (0.257)	-0.059 (0.271)
Increased BMI category	0.017 (0.226)	-0.027 (0.191)	-0.043 (0.189)	-0.001 (0.189)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	0.589 (0.558)	0.438 (0.509)	0.437 (0.502)	0.395 (0.501)
Hardly ever/never (2006)	0.525 (0.572)	0.270 (0.454)	0.286 (0.457)	0.264 (0.458)
Decreased daily activity	-1.503 (0.644)*	-0.949 (0.525)	-0.978 (0.520)	-0.918 (0.521)
Increased daily activity	0.098 (0.285)	0.259 (0.275)	0.264 (0.276)	0.260 (0.277)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.319 (0.363)	0.349 (0.287)	0.373 (0.283)	0.358 (0.284)
Former smoker (2006)	0.270 (0.161)	0.305 (0.132)*	0.302 (0.133)*	0.302 (0.131)*
Recently quit smoking	0.436 (0.431)	0.557 (0.310)	0.512 (0.321)	0.547 (0.318)
Recently started smoking	-0.485 (0.876)	-0.875 (0.797)	-0.866 (0.800)	-0.855 (0.796)
Biomeasures				
log(CRP) (2006)	-0.009 (0.085)	0.017 (0.071)	0.018 (0.080)	0.015 (0.069)
log(CRP) change	-0.035 (0.073)	-0.013 (0.053)	-0.010 (0.055)	0.000 (0.056)
Cystatin C (2006)	0.834 (0.246)**	0.576 (0.213)**	0.627 (0.202)**	0.548 (0.184)**
Cystatin C change	0.467 (0.170)**	0.380 (0.116)**	0.390 (0.118)**	0.365 (0.132)**
Intercept	-3.626 (0.329)****	-3.331 (0.269)****	-3.359 (0.258)****	-3.282 (0.231)****

Note. Sample sizes: 1,666 for observed, 2,190 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G3-3. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (base weight) (males)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.055 (0.018)**	0.055 (0.012)****	0.056 (0.012)****	0.056 (0.012)****
Age (squared)	-0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Race/ethnicity (ref: Non-Hispanic other)				
Hispanic	-0.811 (0.504)	-0.431 (0.308)	-0.425 (0.307)	-0.424 (0.312)
Non-Hispanic black	-0.670 (0.439)	-0.397 (0.277)	-0.400 (0.277)	-0.397 (0.279)
Health conditions				
High blood pressure (2006)	0.159 (0.248)	0.186 (0.210)	0.185 (0.206)	0.186 (0.207)
Recent HBP diagnosis	-0.146 (0.260)	0.016 (0.189)	-0.007 (0.187)	-0.015 (0.187)
Diabetes (2006)	0.727 (0.270)**	0.687 (0.215)**	0.692 (0.214)**	0.688 (0.214)**
Recent diagnosis diabetes	0.021 (0.293)	0.107 (0.258)	0.113 (0.258)	0.107 (0.260)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.021 (0.300)	0.036 (0.223)	0.025 (0.226)	0.025 (0.224)
Obese (2006)	0.106 (0.261)	-0.017 (0.242)	-0.047 (0.241)	-0.038 (0.238)
Decreased BMI category	-0.222 (0.349)	0.076 (0.289)	0.073 (0.287)	0.079 (0.289)
Increased BMI category	0.380 (0.258)	0.506 (0.256)*	0.544 (0.254)*	0.521 (0.255)*
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.275 (0.379)	-0.577 (0.306)	-0.575 (0.310)	-0.577 (0.310)
Hardly ever/never (2006)	-0.204 (0.528)	-0.509 (0.472)	-0.502 (0.472)	-0.513 (0.472)
Decreased daily activity	0.257 (0.474)	0.429 (0.322)	0.414 (0.320)	0.426 (0.320)
Increased daily activity	-0.120 (0.240)	-0.032 (0.199)	-0.026 (0.198)	-0.029 (0.198)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.114 (0.351)	0.551 (0.339)	0.545 (0.337)	0.555 (0.338)
Former smoker (2006)	0.395 (0.204)	0.359 (0.184)	0.362 (0.184)*	0.365 (0.183)*
Recently quit smoking	0.909 (0.474)	0.576 (0.365)	0.579 (0.363)	0.587 (0.367)
Recently started smoking	0.074 (1.011)	-0.643 (1.035)	-0.653 (1.040)	-0.626 (1.033)
Biomeasures				
ln(CRP) (2006)	0.050 (0.109)	0.020 (0.108)	0.054 (0.095)	0.056 (0.093)
ln(CRP) change	-0.113 (0.085)	-0.042 (0.077)	-0.033 (0.076)	-0.058 (0.078)
Cystatin C (2006)	0.471 (0.456)	0.489 (0.333)	0.383 (0.358)	0.337 (0.313)
Cystatin C change	0.271 (0.252)	0.275 (0.199)	0.262 (0.199)	0.289 (0.228)
Intercept	-2.371 (0.501)****	-2.470 (0.401)****	-2.359 (0.421)****	-2.333 (0.359)****

Note. Sample sizes: 1,062 for observed, 1,656 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table G3-4. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (base weight) (females)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.036 (0.011)**	0.033 (0.007)****	0.034 (0.007)****	0.035 (0.007)****
Age (squared)	0.002 (0.001)*	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Race/ethnicity (ref: Non-Hispanic other)				
Hispanic	-0.223 (0.310)	-0.252 (0.235)	-0.244 (0.236)	-0.245 (0.237)
Non-Hispanic black	0.272 (0.221)	-0.193 (0.209)	-0.185 (0.209)	-0.185 (0.208)
Health conditions				
High blood pressure (2006)	0.680 (0.308)*	0.809 (0.182)****	0.790 (0.182)****	0.794 (0.181)****
Recent HBP diagnosis	0.469 (0.308)	0.868 (0.224)***	0.832 (0.228)***	0.836 (0.227)***
Diabetes (2006)	0.595 (0.242)*	0.410 (0.181)*	0.411 (0.184)*	0.409 (0.182)*
Recent diagnosis diabetes	0.451 (0.298)	0.472 (0.195)*	0.482 (0.194)*	0.486 (0.189)*
BMI (ref: Under/normal weight)				
Overweight (2006)	-0.028 (0.225)	-0.199 (0.155)	-0.167 (0.155)	-0.192 (0.155)
Obese (2006)	-0.105 (0.212)	-0.081 (0.191)	-0.063 (0.195)	-0.052 (0.195)
Decreased BMI category	-0.155 (0.298)	-0.022 (0.220)	-0.049 (0.222)	-0.067 (0.233)
Increased BMI category	0.008 (0.223)	0.149 (0.184)	0.131 (0.177)	0.170 (0.179)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	0.633 (0.579)	0.042 (0.447)	0.022 (0.443)	-0.008 (0.437)
Hardly ever/never (2006)	0.544 (0.583)	0.126 (0.420)	0.134 (0.427)	0.143 (0.422)
Decreased daily activity	-1.589 (0.665)*	-0.870 (0.493)	-0.877 (0.495)	-0.837 (0.488)
Increased daily activity	0.126 (0.289)	0.326 (0.222)	0.337 (0.219)	0.333 (0.222)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.306 (0.352)	0.250 (0.191)	0.270 (0.189)	0.269 (0.189)
Former smoker (2006)	0.260 (0.160)	0.184 (0.125)	0.183 (0.125)	0.185 (0.124)
Recently quit smoking	0.585 (0.455)	0.610 (0.269)*	0.596 (0.276)*	0.613 (0.270)*
Recently started smoking	-0.377 (0.880)	-0.774 (0.782)	-0.746 (0.783)	-0.744 (0.778)
Biomeasures				
log(CRP) (2006)	0.014 (0.087)	0.058 (0.077)	0.044 (0.079)	0.056 (0.067)
log(CRP) change	-0.035 (0.074)	-0.008 (0.062)	-0.028 (0.060)	-0.019 (0.060)
Cystatin C (2006)	0.832 (0.247)**	0.583 (0.201)**	0.571 (0.204)**	0.495 (0.158)**
Cystatin C change	0.479 (0.174)**	0.343 (0.130)**	0.384 (0.135)**	0.335 (0.139)*
Intercept	-3.615 (0.336)****	-3.252 (0.265)****	-3.248 (0.266)****	-3.155 (0.221)****

Note. Sample sizes: 1,666 for observed, 2,701 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

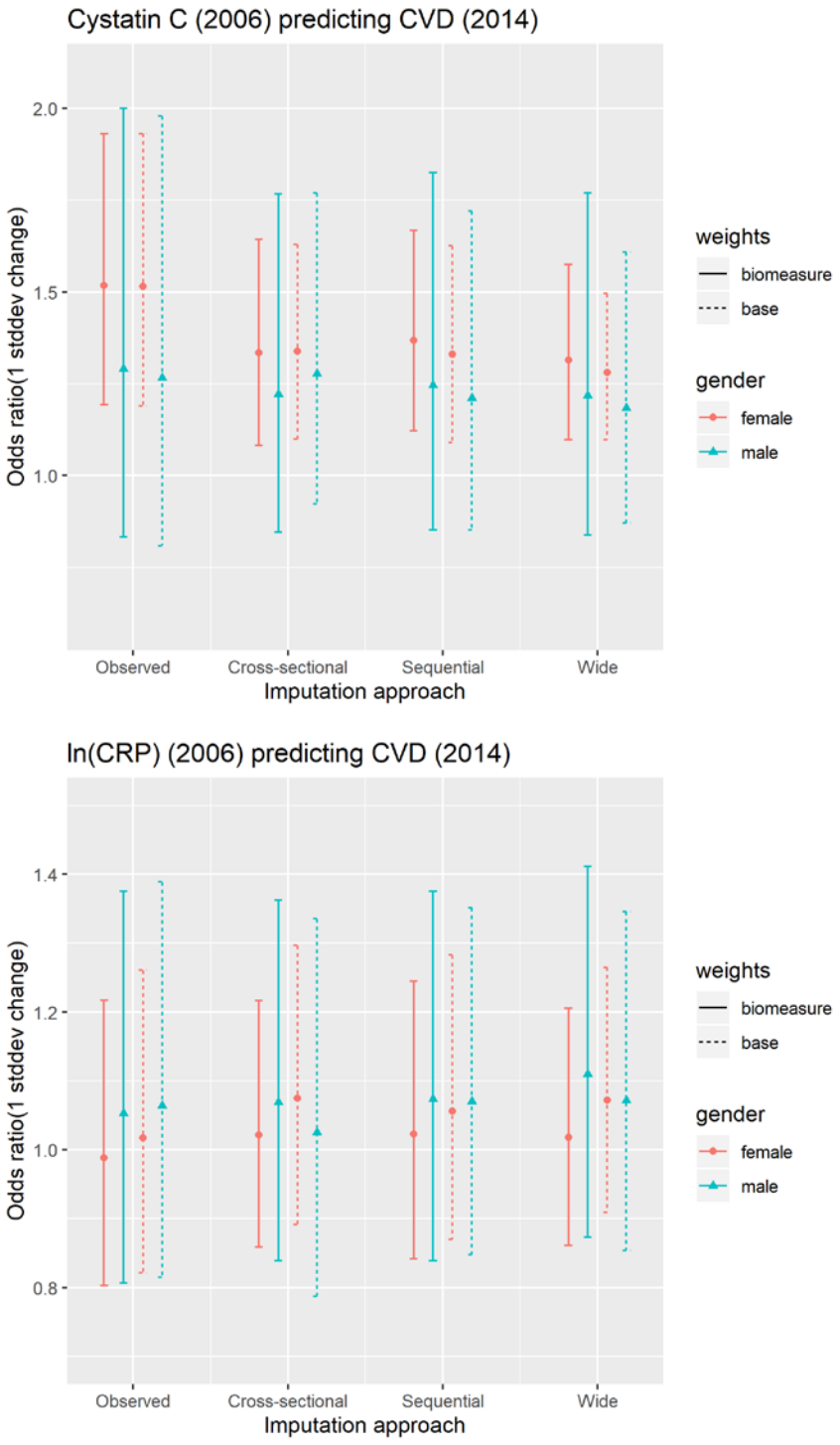

Figure G3-1. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting the development of cardiovascular disease by 2014 by imputation approach, analysis weight, and gender. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

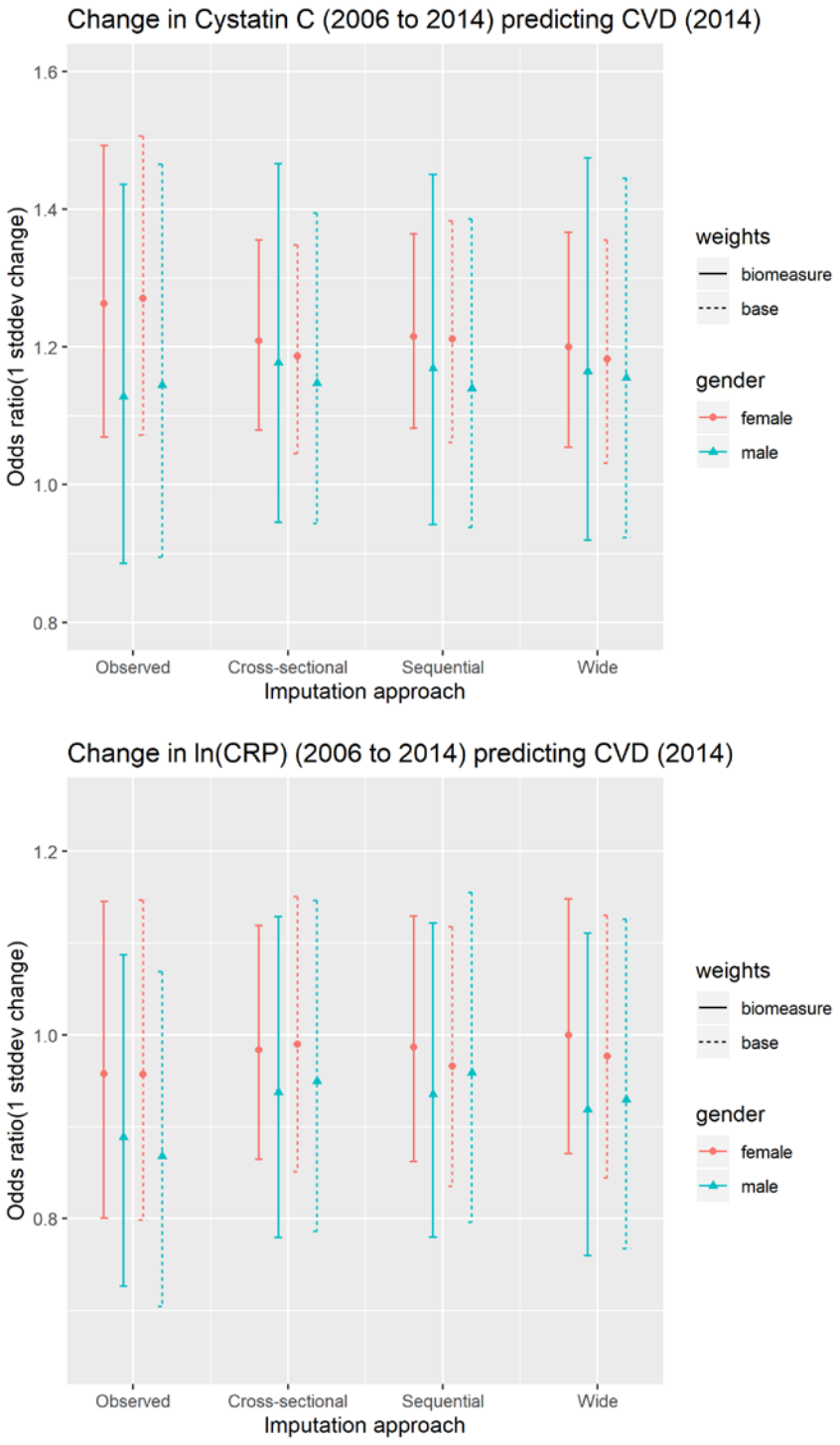

Figure G3-2. Odds ratios of change in Cystatin C and change in ln(CRP) in logistic regression model predicting the development of cardiovascular disease by 2014 by imputation approach, analysis weight, and gender. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

APPENDIX H

Race/ethnicity Subgroup Analyses

The following sections include tables and figures to show the results of the subgroup analyses by race/ethnicity in conjunction with Section 4.3.6. Section H.1 reviews the univariate characteristics for Hispanics, non-Hispanic blacks, and non-Hispanic others like Sections 4.3.1 and 4.3.2. Section H.2 includes the cross-sectional multivariate models covering Section 4.3.4 and Appendix F. Section H.3 covers the longitudinal multivariate models like Section 4.3.5.

H.1 Univariate characteristics by race/ethnicity

Table H1-1. Observed and imputed means and standard errors of Cystatin C by year and imputation approach (non-Hispanic other)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	4,556	1.073	0.0079	0.0074	7.5%	4,603	1.068	0.0074	0.0070	25.5%
Cross-sectional	4,926	1.078	0.0083	0.0077	4.5%	6,180	1.085	0.0079	0.0073	23.9%
Sequential	4,926	1.078	0.0080	0.0074	3.7%	6,180	1.087	0.0078	0.0072	17.1%
Wide	4,926	1.077	0.0081	0.0075	2.7%	6,180	1.082	0.0080	0.0073	20.4%
2010										
Observed	4,011	1.126	0.0099	0.0088	2.8%	4,011	1.123	0.0094	0.0084	22.1%
Cross-sectional	4,126	1.127	0.0098	0.0087	1.4%	5,152	1.131	0.0094	0.0083	16.7%
Sequential	4,126	1.127	0.0098	0.0087	1.5%	5,152	1.135	0.0096	0.0085	17.9%
Wide	4,126	1.126	0.0097	0.0087	1.8%	5,152	1.139	0.0095	0.0083	23.3%
2014										
Observed	3,387	1.178	0.0107	0.0091	1.7%	3,387	1.177	0.0108	0.0091	19.1%
Cross-sectional	3,446	1.179	0.0109	0.0092	3.9%	4,185	1.186	0.0113	0.0095	25.5%
Sequential	3,446	1.178	0.0107	0.0091	0.9%	4,185	1.194	0.0109	0.0091	19.4%
Wide	3,446	1.179	0.0107	0.0091	1.2%	4,185	1.197	0.0110	0.0092	18.6%

Note. FMI for observed is the missing rate.

Table H1-2. Observed and imputed means and standard errors of Cystatin C by year and imputation approach (non-Hispanic black)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	688	1.178	0.0298	0.0253	11.8%	692	1.155	0.0291	0.0252	38.9%
Cross-sectional	780	1.172	0.0277	0.0236	5.4%	1,133	1.150	0.0255	0.0222	21.9%
Sequential	780	1.170	0.0283	0.0242	10.7%	1,133	1.147	0.0249	0.0217	21.1%
Wide	780	1.162	0.0268	0.0231	3.1%	1,133	1.125	0.0217	0.0193	13.6%
2010										
Observed	668	1.229	0.0339	0.0276	5.4%	668	1.228	0.0351	0.0286	28.7%
Cross-sectional	706	1.224	0.0337	0.0275	3.3%	937	1.216	0.0299	0.0246	9.7%
Sequential	706	1.232	0.0333	0.0270	5.0%	937	1.229	0.0318	0.0259	25.7%
Wide	706	1.231	0.0332	0.0270	3.4%	937	1.227	0.0313	0.0255	12.1%
2014										
Observed	582	1.255	0.0356	0.0284	1.5%	582	1.260	0.0353	0.0280	23.8%
Cross-sectional	591	1.254	0.0357	0.0285	2.4%	764	1.272	0.0324	0.0255	17.5%
Sequential	591	1.257	0.0356	0.0283	1.5%	764	1.265	0.0331	0.0261	17.9%
Wide	591	1.254	0.0355	0.0284	1.1%	764	1.269	0.0324	0.0255	6.2%

Note. FMI for observed is the missing rate.

Table H1-3. Observed and imputed means and standard errors of Cystatin C by year and imputation approach (Hispanic)

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Prop.	SE	CV	FMI	n	Prop.	SE	CV	FMI
2006										
Observed	480	1.058	0.0221	0.0209	3.4%	483	1.049	0.0181	0.0172	24.6%
Cross-sectional	497	1.060	0.0229	0.0216	5.6%	641	1.071	0.0215	0.0200	19.2%
Sequential	497	1.060	0.0228	0.0215	4.9%	641	1.080	0.0242	0.0224	36.3%
Wide	497	1.056	0.0215	0.0203	3.6%	641	1.058	0.0214	0.0202	15.9%
2010										
Observed	383	1.120	0.0311	0.0278	3.3%	383	1.111	0.0314	0.0282	29.3%
Cross-sectional	396	1.121	0.0324	0.0289	8.4%	542	1.125	0.0323	0.0287	29.6%
Sequential	396	1.119	0.0312	0.0279	5.8%	542	1.137	0.0316	0.0278	24.4%
Wide	396	1.119	0.0304	0.0271	2.4%	542	1.135	0.0306	0.0269	21.5%
2014										
Observed	373	1.268	0.0471	0.0372	0.8%	373	1.264	0.0442	0.0350	18.4%
Cross-sectional	376	1.268	0.0468	0.0369	0.2%	457	1.270	0.0405	0.0319	9.2%
Sequential	376	1.268	0.0468	0.0369	0.2%	457	1.263	0.0400	0.0316	7.5%
Wide	376	1.266	0.0468	0.0370	0.1%	457	1.254	0.0387	0.0309	6.0%

Note. FMI for observed is the missing rate.

Table H1-4. Observed and imputed at proportion at risk for Cystatin C by year and imputation approach (non-Hispanic other)

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Prop.	SE	CV	FMI	n	Prop.	SE	CV	FMI
2006										
Observed	4,556	0.088	0.0047	0.0541	7.5%	4,603	0.084	0.0046	0.0550	25.5%
Cross-sectional	4,926	0.097	0.0051	0.0525	9.0%	6,180	0.117	0.0058	0.0494	37.8%
Sequential	4,926	0.097	0.0050	0.0519	11.5%	6,180	0.117	0.0055	0.0466	20.0%
Wide	4,926	0.094	0.0047	0.0499	4.7%	6,180	0.107	0.0054	0.0502	36.4%
2010										
Observed	4,011	0.122	0.0065	0.0535	2.8%	4,011	0.120	0.0063	0.0524	22.1%
Cross-sectional	4,126	0.125	0.0066	0.0527	2.6%	5,152	0.143	0.0065	0.0457	23.5%
Sequential	4,126	0.124	0.0065	0.0526	1.7%	5,152	0.145	0.0070	0.0481	25.4%
Wide	4,126	0.122	0.0065	0.0529	2.7%	5,152	0.144	0.0066	0.0457	21.0%
2014										
Observed	3,387	0.140	0.0072	0.0518	1.7%	3,387	0.139	0.0074	0.0529	19.1%
Cross-sectional	3,446	0.142	0.0073	0.0514	3.7%	4,185	0.164	0.0073	0.0445	12.6%
Sequential	3,446	0.141	0.0072	0.0511	1.2%	4,185	0.168	0.0075	0.0447	14.8%
Wide	3,446	0.141	0.0072	0.0513	0.9%	4,185	0.169	0.0075	0.0445	15.4%

Note. FMI for observed is the missing rate.

Table H1-5. Observed and imputed at proportion at risk for Cystatin C by year and imputation approach (non-Hispanic black)

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Prop.	SE	CV	FMI	n	Prop.	SE	CV	FMI
2006										
Observed	688	0.138	0.0175	0.1269	11.8%	692	0.126	0.0152	0.1208	38.9%
Cross-sectional	780	0.147	0.0174	0.1180	10.5%	1,133	0.162	0.0166	0.1024	27.5%
Sequential	780	0.142	0.0165	0.1158	6.6%	1,133	0.157	0.0158	0.1005	30.8%
Wide	780	0.138	0.0170	0.1238	13.1%	1,133	0.138	0.0150	0.1082	38.8%
2010										
Observed	668	0.186	0.0199	0.1068	5.4%	668	0.186	0.0214	0.1148	28.7%
Cross-sectional	706	0.188	0.0207	0.1103	7.9%	937	0.201	0.0202	0.1005	19.3%
Sequential	706	0.193	0.0203	0.1050	13.3%	937	0.211	0.0227	0.1075	40.2%
Wide	706	0.193	0.0203	0.1050	8.5%	937	0.204	0.0204	0.0997	18.6%
2014										
Observed	582	0.193	0.0197	0.1020	1.5%	582	0.197	0.0205	0.1043	23.8%
Cross-sectional	591	0.193	0.0197	0.1021	1.8%	764	0.230	0.0194	0.0844	12.6%
Sequential	591	0.196	0.0204	0.1042	5.9%	764	0.224	0.0213	0.0952	19.7%
Wide	591	0.194	0.0201	0.1040	4.5%	764	0.227	0.0239	0.1053	27.6%

Note. FMI for observed is the missing rate.

Table H1-6. Observed and imputed at proportion at risk for Cystatin C by year and imputation approach (Hispanic)

	Biomeasure weighted					Base weighted				
Proportion at risk (> 1.55 mg/L)	n	Prop.	SE	CV	FMI	n	Prop.	SE	CV	FMI
2006										
Observed	480	0.077	0.0125	0.1615	3.4%	483	0.075	0.0101	0.1350	24.6%
Cross-sectional	497	0.082	0.0140	0.1708	15.9%	641	0.109	0.0139	0.1271	38.4%
Sequential	497	0.081	0.0134	0.1654	8.8%	641	0.112	0.0129	0.1154	35.7%
Wide	497	0.078	0.0125	0.1604	6.1%	641	0.093	0.0126	0.1358	13.5%
2010										
Observed	383	0.111	0.0188	0.1695	3.3%	383	0.107	0.0198	0.1844	29.3%
Cross-sectional	396	0.117	0.0201	0.1720	11.2%	542	0.142	0.0217	0.1530	45.5%
Sequential	396	0.114	0.0196	0.1721	13.4%	542	0.149	0.0237	0.1584	30.6%
Wide	396	0.111	0.0186	0.1677	4.2%	542	0.138	0.0216	0.1567	25.9%
2014										
Observed	373	0.174	0.0189	0.1085	0.8%	373	0.170	0.0178	0.1043	18.4%
Cross-sectional	376	0.175	0.0189	0.1078	1.1%	457	0.200	0.0218	0.1094	26.6%
Sequential	376	0.174	0.0189	0.1085	1.1%	457	0.186	0.0207	0.1110	29.0%
Wide	376	0.174	0.0189	0.1088	0.6%	457	0.185	0.0186	0.1003	17.2%

Note. FMI for observed is the missing rate.

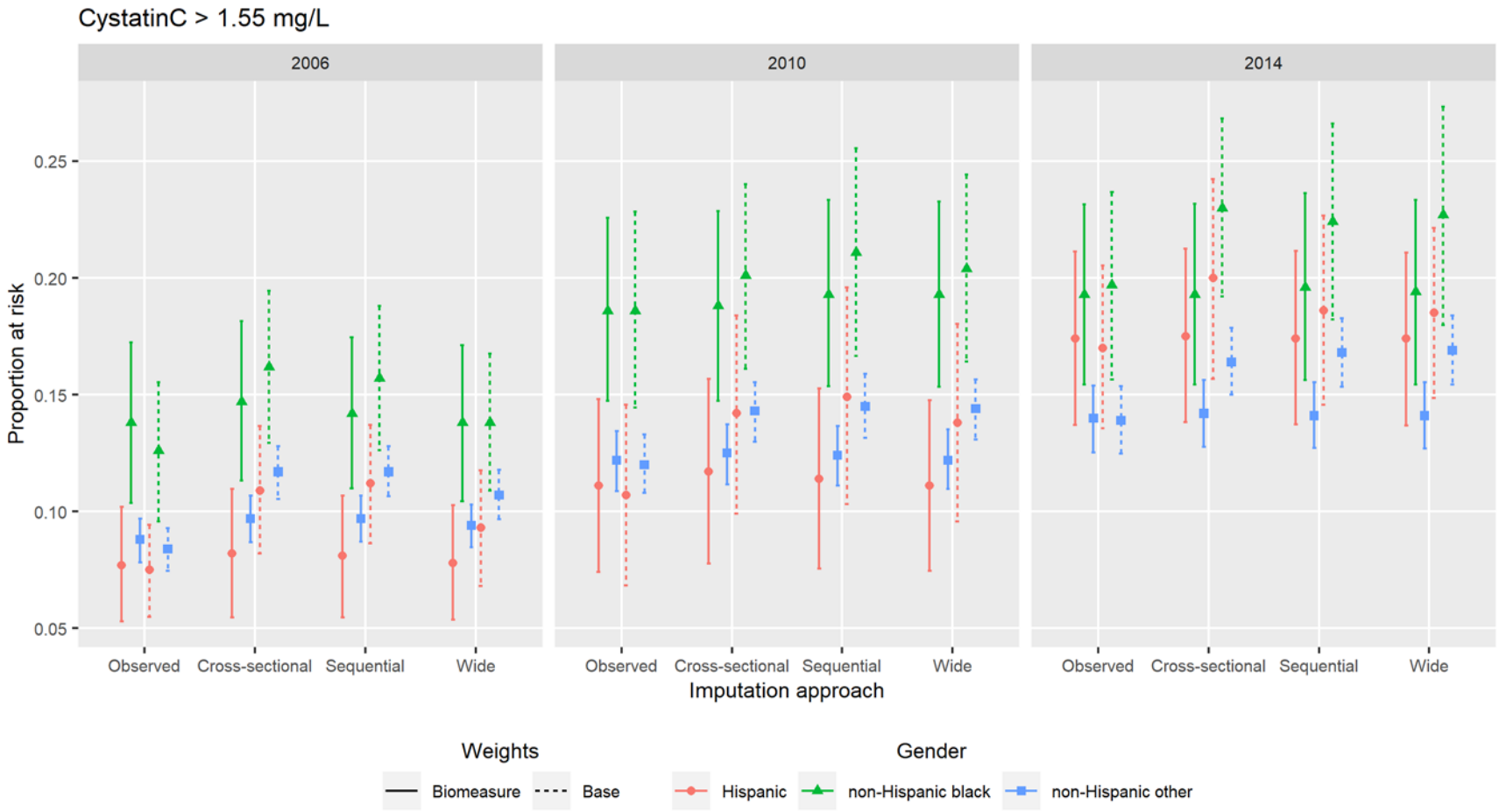

Figure H1-1. Proportion at risk for Cystatin C by year, race/ethnicity, analysis weight, and imputation approach. 95% confidence interval of the proportion included.

Table H1-7. Observed and imputed percentiles of Cystatin C by year and imputation approach (non-Hispanic other)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.650	0.810	0.949	1.154	1.723	0.651	0.810	0.949	1.151	1.700
(SE)	(0.008)	(0.005)	(0.006)	(0.009)	(0.033)	(0.008)	(0.005)	(0.006)	(0.009)	(0.033)
Cross-sectional	0.647	0.837	0.969	1.221	1.794	0.579	0.839	0.982	1.240	1.853
(SE)	(0.016)	(0.014)	(0.014)	(0.026)	(0.037)	(0.015)	(0.015)	(0.027)	(0.017)	(0.032)
Sequential	0.649	0.837	0.969	1.223	1.794	0.580	0.840	0.996	1.240	1.855
(SE)	(0.018)	(0.014)	(0.014)	(0.026)	(0.038)	(0.015)	(0.015)	(0.026)	(0.017)	(0.034)
Wide	0.649	0.838	0.969	1.178	1.770	0.599	0.840	0.974	1.240	1.820
(SE)	(0.017)	(0.015)	(0.014)	(0.021)	(0.039)	(0.023)	(0.015)	(0.017)	(0.016)	(0.022)
2010										
Observed	0.651	0.851	1.023	1.262	1.924	0.648	0.850	1.023	1.260	1.906
(SE)	(0.009)	(0.006)	(0.007)	(0.013)	(0.038)	(0.012)	(0.007)	(0.007)	(0.011)	(0.038)
Cross-sectional	0.647	0.853	1.027	1.270	1.931	0.588	0.848	1.044	1.324	1.945
(SE)	(0.011)	(0.007)	(0.008)	(0.013)	(0.038)	(0.017)	(0.008)	(0.009)	(0.015)	(0.029)
Sequential	0.647	0.851	1.026	1.269	1.925	0.593	0.850	1.047	1.325	1.960
(SE)	(0.011)	(0.007)	(0.008)	(0.013)	(0.037)	(0.016)	(0.008)	(0.008)	(0.016)	(0.031)
Wide	0.647	0.853	1.027	1.267	1.921	0.609	0.852	1.048	1.324	1.966
(SE)	(0.011)	(0.008)	(0.008)	(0.013)	(0.038)	(0.017)	(0.008)	(0.008)	(0.013)	(0.031)
2014										
Observed	0.673	0.890	1.070	1.330	1.928	0.671	0.889	1.069	1.331	1.924
(SE)	(0.009)	(0.007)	(0.008)	(0.014)	(0.039)	(0.009)	(0.007)	(0.008)	(0.014)	(0.038)
Cross-sectional	0.670	0.891	1.073	1.337	1.935	0.623	0.890	1.090	1.384	2.004
(SE)	(0.009)	(0.007)	(0.009)	(0.014)	(0.039)	(0.021)	(0.010)	(0.010)	(0.015)	(0.040)
Sequential	0.670	0.891	1.073	1.334	1.932	0.631	0.894	1.091	1.390	2.024
(SE)	(0.009)	(0.007)	(0.009)	(0.014)	(0.039)	(0.017)	(0.009)	(0.010)	(0.014)	(0.039)
Wide	0.670	0.891	1.073	1.336	1.934	0.633	0.894	1.093	1.390	2.050
(SE)	(0.009)	(0.007)	(0.009)	(0.014)	(0.039)	(0.017)	(0.009)	(0.011)	(0.015)	(0.046)

Table H1-8. Observed and imputed percentiles of Cystatin C by year and imputation approach (non-Hispanic black)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.609	0.789	0.965	1.213	1.988	0.613	0.792	0.962	1.203	1.907
(SE)	(0.023)	(0.011)	(0.016)	(0.027)	(0.183)	(0.019)	(0.011)	(0.014)	(0.025)	(0.129)
Cross-sectional	0.596	0.814	0.988	1.248	1.998	0.515	0.812	1.036	1.328	1.970
(SE)	(0.039)	(0.026)	(0.029)	(0.030)	(0.125)	(0.048)	(0.031)	(0.019)	(0.046)	(0.063)
Sequential	0.623	0.811	1.010	1.238	1.980	0.507	0.815	1.038	1.318	1.965
(SE)	(0.035)	(0.020)	(0.032)	(0.021)	(0.126)	(0.059)	(0.028)	(0.017)	(0.041)	(0.057)
Wide	0.607	0.793	0.970	1.235	1.955	0.515	0.789	1.028	1.281	1.909
(SE)	(0.044)	(0.027)	(0.016)	(0.020)	(0.120)	(0.056)	(0.023)	(0.020)	(0.034)	(0.061)
2010										
Observed	0.646	0.840	1.067	1.414	2.148	0.649	0.840	1.066	1.415	2.146
(SE)	(0.024)	(0.018)	(0.024)	(0.046)	(0.170)	(0.024)	(0.018)	(0.025)	(0.048)	(0.189)
Cross-sectional	0.629	0.840	1.071	1.415	2.145	0.566	0.840	1.089	1.451	2.113
(SE)	(0.031)	(0.018)	(0.025)	(0.046)	(0.162)	(0.039)	(0.020)	(0.023)	(0.043)	(0.093)
Sequential	0.633	0.842	1.073	1.429	2.153	0.576	0.844	1.101	1.484	2.155
(SE)	(0.029)	(0.017)	(0.024)	(0.045)	(0.135)	(0.042)	(0.021)	(0.025)	(0.050)	(0.092)
Wide	0.629	0.841	1.071	1.423	2.160	0.574	0.841	1.090	1.469	2.158
(SE)	(0.028)	(0.017)	(0.025)	(0.044)	(0.133)	(0.045)	(0.022)	(0.025)	(0.040)	(0.098)
2014										
Observed	0.618	0.861	1.075	1.409	2.256	0.619	0.860	1.079	1.415	2.268
(SE)	(0.027)	(0.014)	(0.020)	(0.035)	(0.147)	(0.027)	(0.014)	(0.025)	(0.036)	(0.149)
Cross-sectional	0.615	0.862	1.079	1.413	2.253	0.579	0.872	1.129	1.498	2.265
(SE)	(0.028)	(0.017)	(0.024)	(0.036)	(0.110)	(0.043)	(0.019)	(0.032)	(0.052)	(0.085)
Sequential	0.617	0.864	1.078	1.419	2.257	0.579	0.867	1.124	1.490	2.262
(SE)	(0.027)	(0.015)	(0.022)	(0.041)	(0.122)	(0.030)	(0.020)	(0.035)	(0.051)	(0.093)
Wide	0.616	0.862	1.077	1.411	2.253	0.578	0.864	1.124	1.492	2.287
(SE)	(0.027)	(0.015)	(0.023)	(0.036)	(0.106)	(0.036)	(0.019)	(0.030)	(0.058)	(0.110)

Table H1-9. Observed and imputed percentiles of Cystatin C by year and imputation approach (Hispanic)

	Biomeasure weighted					Base weighted				
Cystatin C (mg/L)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	0.621	0.770	0.895	1.060	1.804	0.625	0.769	0.897	1.058	1.730
(SE)	(0.021)	(0.012)	(0.011)	(0.018)	(0.126)	(0.020)	(0.011)	(0.011)	(0.016)	(0.104)
Cross-sectional	0.624	0.771	0.902	1.085	1.837	0.590	0.778	0.945	1.167	1.916
(SE)	(0.025)	(0.013)	(0.014)	(0.027)	(0.124)	(0.048)	(0.017)	(0.027)	(0.015)	(0.108)
Sequential	0.621	0.772	0.899	1.085	1.821	0.616	0.788	0.962	1.167	1.947
(SE)	(0.024)	(0.015)	(0.011)	(0.023)	(0.126)	(0.052)	(0.025)	(0.016)	(0.016)	(0.118)
Wide	0.624	0.773	0.901	1.083	1.789	0.611	0.780	0.946	1.144	1.822
(SE)	(0.022)	(0.015)	(0.014)	(0.027)	(0.121)	(0.050)	(0.016)	(0.028)	(0.031)	(0.108)
2010										
Observed	0.612	0.837	1.024	1.241	1.786	0.609	0.835	1.019	1.227	1.769
(SE)	(0.020)	(0.017)	(0.025)	(0.033)	(0.139)	(0.018)	(0.018)	(0.026)	(0.031)	(0.077)
Cross-sectional	0.603	0.836	1.025	1.250	1.817	0.541	0.831	1.044	1.316	1.887
(SE)	(0.027)	(0.018)	(0.027)	(0.038)	(0.130)	(0.062)	(0.026)	(0.032)	(0.046)	(0.081)
Sequential	0.603	0.835	1.024	1.249	1.797	0.558	0.833	1.044	1.317	1.948
(SE)	(0.029)	(0.017)	(0.026)	(0.036)	(0.132)	(0.040)	(0.022)	(0.029)	(0.044)	(0.130)
Wide	0.610	0.836	1.026	1.249	1.787	0.575	0.838	1.041	1.308	1.919
(SE)	(0.021)	(0.016)	(0.025)	(0.034)	(0.126)	(0.025)	(0.021)	(0.028)	(0.047)	(0.140)
2014										
Observed	0.688	0.929	1.092	1.399	2.147	0.689	0.932	1.097	1.392	2.148
(SE)	(0.025)	(0.021)	(0.017)	(0.032)	(0.459)	(0.026)	(0.021)	(0.018)	(0.031)	(0.269)
Cross-sectional	0.686	0.929	1.094	1.401	2.145	0.650	0.930	1.123	1.440	2.206
(SE)	(0.024)	(0.022)	(0.019)	(0.033)	(0.451)	(0.035)	(0.023)	(0.024)	(0.041)	(0.170)
Sequential	0.686	0.929	1.096	1.403	2.145	0.647	0.928	1.114	1.429	2.221
(SE)	(0.025)	(0.021)	(0.019)	(0.034)	(0.452)	(0.037)	(0.023)	(0.021)	(0.033)	(0.204)
Wide	0.683	0.928	1.093	1.399	2.145	0.631	0.923	1.112	1.420	2.181
(SE)	(0.024)	(0.021)	(0.019)	(0.034)	(0.452)	(0.043)	(0.023)	(0.022)	(0.039)	(0.217)

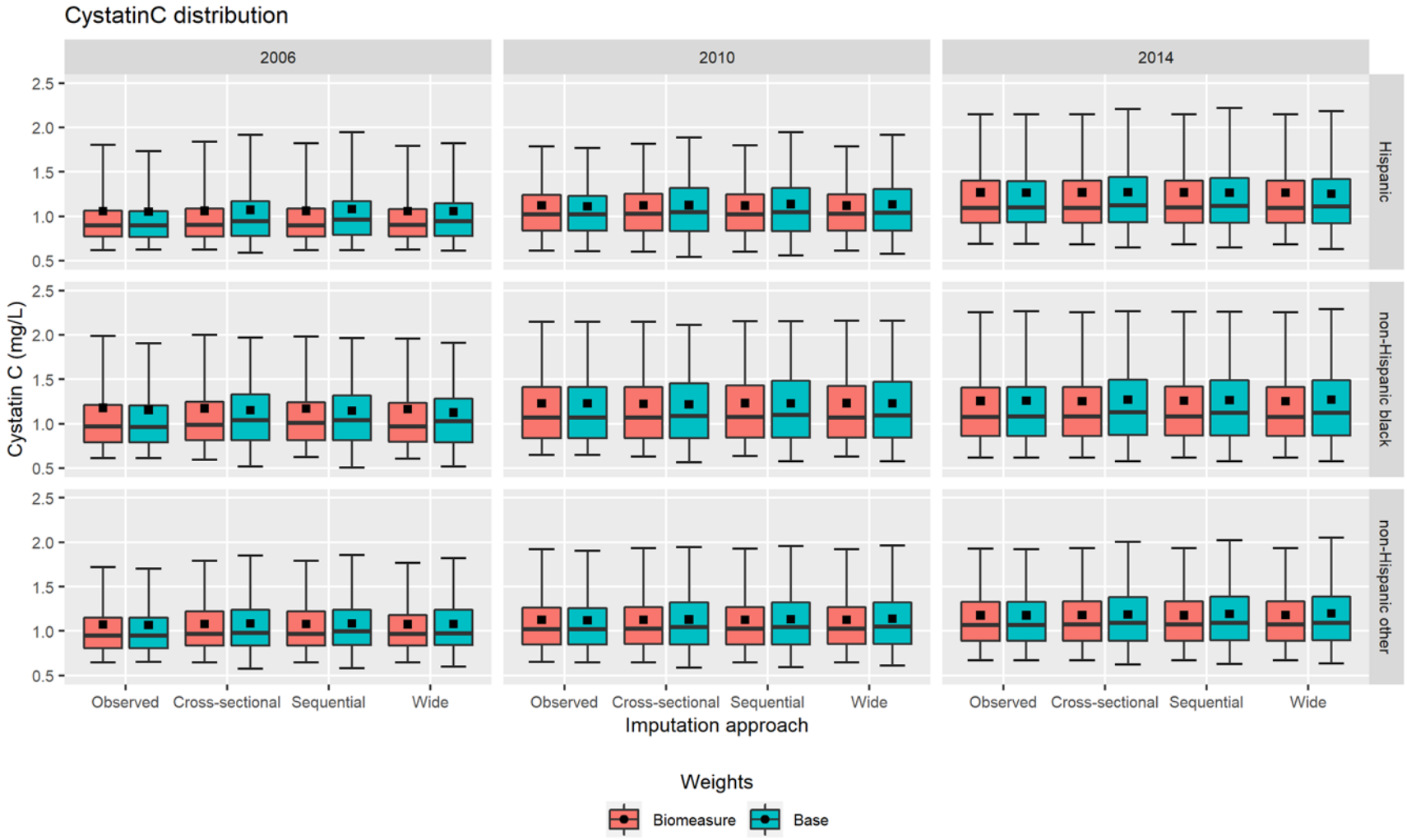

Figure H1-2. Distribution of Cystatin C comparing race/ethnicity by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table H1-7, H1-8, and H1-9. Black squares represent means.

Table H1-10. Observed and imputed means and standard errors of C-reactive protein (natural log transform) by year and imputation approach (non-Hispanic other)

	Biomeasure weighted					Base weighted				
ln(CRP)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	4,633	0.667	0.0204	0.0306	5.9%	4,682	0.675	0.0216	0.0319	24.2%
Cross-sectional	4,926	0.670	0.0197	0.0294	4.1%	6,180	0.691	0.0202	0.0293	11.7%
Sequential	4,926	0.671	0.0199	0.0297	2.1%	6,180	0.690	0.0213	0.0309	16.5%
Wide	4,926	0.667	0.0200	0.0300	6.8%	6,180	0.678	0.0219	0.0323	35.9%
2010										
Observed	4,005	0.527	0.0221	0.0418	2.9%	4,005	0.523	0.0226	0.0432	22.3%
Cross-sectional	4,126	0.525	0.0221	0.0421	1.8%	5,152	0.537	0.0214	0.0398	20.9%
Sequential	4,126	0.526	0.0219	0.0415	1.9%	5,152	0.530	0.0239	0.0451	32.3%
Wide	4,126	0.525	0.0218	0.0415	0.4%	5,152	0.538	0.0234	0.0434	22.9%
2014										
Observed	3,382	0.211	0.0257	0.1215	1.9%	3,382	0.217	0.0273	0.1259	19.2%
Cross-sectional	3,446	0.212	0.0263	0.1239	1.9%	4,185	0.224	0.0271	0.1213	20.8%
Sequential	3,446	0.212	0.0257	0.1214	0.7%	4,185	0.225	0.0249	0.1106	3.1%
Wide	3,446	0.212	0.0260	0.1226	2.4%	4,185	0.232	0.0268	0.1155	20.3%

Note. FMI for observed is the missing rate.

Table H1-11. Observed and imputed means and standard errors of C-reactive protein (natural log transform) by year and imputation approach (non-Hispanic black)

	Biomeasure weighted					Base weighted				
ln(CRP)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	699	1.096	0.0696	0.0635	10.4%	704	1.084	0.0649	0.0599	37.9%
Cross-sectional	780	1.063	0.0634	0.0597	2.0%	1,133	1.008	0.0577	0.0573	24.2%
Sequential	780	1.075	0.0676	0.0629	8.1%	1,133	1.012	0.0593	0.0586	34.8%
Wide	780	1.073	0.0643	0.0599	8.7%	1,133	1.007	0.0525	0.0521	21.0%
2010										
Observed	665	0.874	0.0533	0.0610	5.8%	665	0.869	0.0519	0.0597	29.0%
Cross-sectional	706	0.859	0.0541	0.0630	6.8%	937	0.818	0.0500	0.0611	19.7%
Sequential	706	0.856	0.0539	0.0629	7.6%	937	0.827	0.0502	0.0608	22.1%
Wide	706	0.860	0.0536	0.0624	4.5%	937	0.844	0.0545	0.0646	26.7%
2014										
Observed	580	0.639	0.0742	0.1161	1.9%	580	0.634	0.0746	0.1177	24.1%
Cross-sectional	591	0.628	0.0734	0.1168	2.3%	764	0.569	0.0742	0.1304	19.9%
Sequential	591	0.626	0.0720	0.1151	1.8%	764	0.602	0.0684	0.1136	12.9%
Wide	591	0.627	0.0739	0.1179	4.3%	764	0.613	0.0720	0.1173	11.9%

Note. FMI for observed is the missing rate.

Table H1-12. Observed and imputed means and standard errors of C-reactive protein (natural log transform) by year and imputation approach (Hispanic)

	Biomeasure weighted					Base weighted				
ln(CRP)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	485	0.870	0.0372	0.0428	2.4%	488	0.880	0.0406	0.0461	23.9%
Cross-sectional	497	0.867	0.0385	0.0444	7.0%	641	0.851	0.0453	0.0532	31.0%
Sequential	497	0.861	0.0373	0.0433	3.9%	641	0.857	0.0484	0.0564	26.2%
Wide	497	0.868	0.0372	0.0428	3.8%	641	0.866	0.0440	0.0508	18.2%
2010										
Observed	383	0.713	0.0438	0.0614	3.3%	383	0.702	0.0486	0.0692	29.3%
Cross-sectional	396	0.716	0.0535	0.0747	15.4%	542	0.694	0.0661	0.0952	39.0%
Sequential	396	0.709	0.0490	0.0692	8.4%	542	0.706	0.0628	0.0889	50.0%
Wide	396	0.706	0.0506	0.0717	7.4%	542	0.723	0.0582	0.0805	36.0%
2014										
Observed	373	0.416	0.0757	0.1819	0.8%	373	0.406	0.0768	0.1892	18.4%
Cross-sectional	376	0.419	0.0756	0.1806	0.5%	457	0.388	0.0764	0.1971	20.4%
Sequential	376	0.420	0.0757	0.1801	0.6%	457	0.399	0.0726	0.1819	17.7%
Wide	376	0.420	0.0756	0.1802	0.5%	457	0.394	0.0728	0.1850	22.0%

Note. FMI for observed is the missing rate.

Table H1-13. Observed and imputed proportion at risk for C-reactive protein by year and imputation approach (non-Hispanic other)

	Biomeasure weighted					Base weighted				
Proportion at risk (>= 3.0 ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	4,633	0.363	0.0095	0.0261	5.9%	4,682	0.366	0.0098	0.0268	24.2%
Cross-sectional	4,926	0.364	0.0091	0.0250	3.3%	6,180	0.372	0.0087	0.0235	11.5%
Sequential	4,926	0.365	0.0093	0.0254	5.2%	6,180	0.371	0.0094	0.0253	16.6%
Wide	4,926	0.364	0.0092	0.0252	4.4%	6,180	0.366	0.0086	0.0234	17.6%
2010										
Observed	4,005	0.304	0.0073	0.0240	2.9%	4,005	0.302	0.0076	0.0252	22.3%
Cross-sectional	4,126	0.303	0.0073	0.0241	2.1%	5,152	0.308	0.0083	0.0270	33.4%
Sequential	4,126	0.304	0.0073	0.0242	3.5%	5,152	0.306	0.0081	0.0263	29.0%
Wide	4,126	0.304	0.0073	0.0240	1.6%	5,152	0.309	0.0082	0.0264	30.2%
2014										
Observed	3,382	0.274	0.0082	0.0299	1.9%	3,382	0.276	0.0085	0.0309	19.2%
Cross-sectional	3,446	0.275	0.0083	0.0303	2.6%	4,185	0.275	0.0084	0.0304	19.2%
Sequential	3,446	0.274	0.0083	0.0303	1.1%	4,185	0.275	0.0084	0.0303	9.0%
Wide	3,446	0.274	0.0083	0.0301	1.8%	4,185	0.278	0.0088	0.0318	27.5%

Note. FMI for observed is just missing rate.

Table H1-14. Observed and imputed proportion at risk for C-reactive protein by year and imputation approach (non-Hispanic black)

	Biomeasure weighted					Base weighted				
Proportion at risk (>= 3.0 ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	699	0.520	0.0235	0.0451	10.4%	704	0.515	0.0210	0.0408	37.9%
Cross-sectional	780	0.510	0.0212	0.0416	3.3%	1,133	0.480	0.0182	0.0379	15.9%
Sequential	780	0.512	0.0228	0.0445	11.0%	1,133	0.486	0.0232	0.0477	48.0%
Wide	780	0.512	0.0229	0.0448	16.7%	1,133	0.488	0.0184	0.0377	18.0%
2010										
Observed	665	0.467	0.0188	0.0403	5.8%	665	0.462	0.0188	0.0406	29.0%
Cross-sectional	706	0.461	0.0189	0.0410	6.2%	937	0.432	0.0180	0.0416	12.9%
Sequential	706	0.460	0.0194	0.0423	8.6%	937	0.437	0.0181	0.0413	10.9%
Wide	706	0.459	0.0188	0.0409	4.6%	937	0.445	0.0217	0.0488	41.7%
2014										
Observed	580	0.391	0.0227	0.0581	1.9%	580	0.391	0.0228	0.0585	24.1%
Cross-sectional	591	0.388	0.0228	0.0587	2.6%	764	0.368	0.0217	0.0591	11.0%
Sequential	591	0.388	0.0223	0.0576	2.4%	764	0.379	0.0219	0.0579	15.2%
Wide	591	0.388	0.0226	0.0582	2.8%	764	0.381	0.0226	0.0594	17.3%

Note. FMI for observed is just missing rate.

Table H1-15. Observed and imputed proportion at risk for C-reactive protein by year and imputation approach (Hispanic)

	Biomeasure weighted					Base weighted				
Proportion at risk (>= 3.0 ug/mL)	n	Mean	SE	CV	FMI	n	Mean	SE	CV	FMI
2006										
Observed	485	0.419	0.0166	0.0396	2.4%	488	0.416	0.0163	0.0391	23.9%
Cross-sectional	497	0.419	0.0171	0.0409	4.3%	641	0.409	0.0190	0.0463	27.7%
Sequential	497	0.417	0.0162	0.0389	2.4%	641	0.411	0.0201	0.0490	40.7%
Wide	497	0.418	0.0168	0.0401	3.2%	641	0.417	0.0212	0.0507	25.3%
2010										
Observed	383	0.349	0.0204	0.0584	3.3%	383	0.344	0.0200	0.0581	29.3%
Cross-sectional	396	0.351	0.0229	0.0653	13.1%	542	0.347	0.0250	0.0721	37.9%
Sequential	396	0.348	0.0213	0.0613	6.8%	542	0.352	0.0250	0.0710	41.7%
Wide	396	0.350	0.0224	0.0638	7.8%	542	0.361	0.0232	0.0644	24.0%
2014										
Observed	373	0.301	0.0304	0.1013	0.8%	373	0.301	0.0305	0.1012	18.4%
Cross-sectional	376	0.302	0.0304	0.1007	0.3%	457	0.299	0.0287	0.0960	9.8%
Sequential	376	0.301	0.0305	0.1010	0.8%	457	0.300	0.0281	0.0936	13.4%
Wide	376	0.303	0.0305	0.1007	0.5%	457	0.302	0.0281	0.0930	17.3%

Note. FMI for observed is just missing rate.

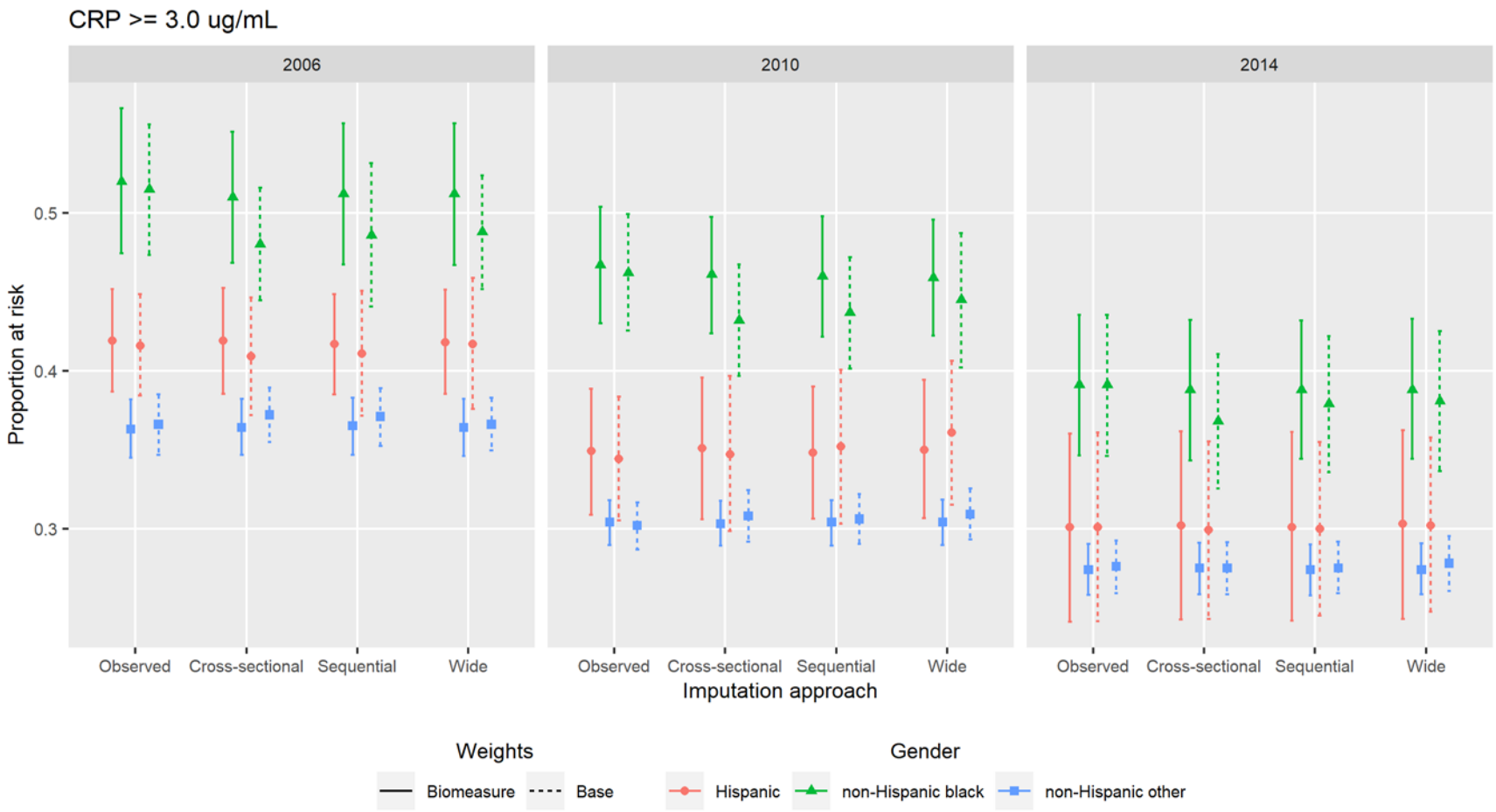

Figure H1-3. Proportion at risk for C-reactive protein by year, race/ethnicity, analysis weight, and imputation approach. 95% confidence interval of the proportion included.

Table H1-16. Observed and imputed percentiles of CRP (natural log transform) by year and imputation approach (non-Hispanic other)

	Biomeasure weighted					Base weighted				
ln(CRP)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	-1.401	-0.169	0.623	1.489	2.700	-1.388	-0.157	0.630	1.488	2.707
(SE)	(0.047)	(0.029)	(0.033)	(0.030)	(0.051)	(0.046)	(0.032)	(0.033)	(0.029)	(0.051)
Cross-sectional	-1.397	-0.162	0.630	1.499	2.719	-1.365	-0.142	0.673	1.525	2.748
(SE)	(0.046)	(0.028)	(0.030)	(0.031)	(0.052)	(0.042)	(0.029)	(0.029)	(0.030)	(0.049)
Sequential	-1.389	-0.163	0.632	1.498	2.721	-1.361	-0.146	0.667	1.523	2.749
(SE)	(0.050)	(0.028)	(0.029)	(0.032)	(0.054)	(0.045)	(0.035)	(0.034)	(0.032)	(0.051)
Wide	-1.401	-0.170	0.626	1.495	2.713	-1.370	-0.154	0.649	1.501	2.731
(SE)	(0.048)	(0.025)	(0.030)	(0.031)	(0.053)	(0.048)	(0.028)	(0.032)	(0.031)	(0.053)
2010										
Observed	-1.426	-0.272	0.513	1.285	2.490	-1.412	-0.268	0.502	1.278	2.480
(SE)	(0.040)	(0.031)	(0.030)	(0.028)	(0.042)	(0.041)	(0.031)	(0.030)	(0.027)	(0.043)
Cross-sectional	-1.426	-0.274	0.510	1.282	2.486	-1.385	-0.254	0.524	1.298	2.492
(SE)	(0.041)	(0.031)	(0.031)	(0.027)	(0.043)	(0.042)	(0.029)	(0.030)	(0.030)	(0.040)
Sequential	-1.425	-0.271	0.513	1.284	2.488	-1.406	-0.259	0.522	1.292	2.483
(SE)	(0.042)	(0.031)	(0.030)	(0.028)	(0.042)	(0.045)	(0.034)	(0.032)	(0.029)	(0.047)
Wide	-1.430	-0.276	0.512	1.285	2.486	-1.396	-0.246	0.527	1.303	2.491
(SE)	(0.039)	(0.031)	(0.030)	(0.028)	(0.042)	(0.043)	(0.037)	(0.033)	(0.029)	(0.040)
2014										
Observed	-2.243	-0.753	0.195	1.220	2.567	-2.229	-0.745	0.195	1.227	2.587
(SE)	(0.064)	(0.036)	(0.040)	(0.036)	(0.066)	(0.068)	(0.037)	(0.041)	(0.039)	(0.070)
Cross-sectional	-2.241	-0.752	0.198	1.221	2.565	-2.172	-0.736	0.205	1.220	2.577
(SE)	(0.062)	(0.036)	(0.040)	(0.037)	(0.065)	(0.070)	(0.033)	(0.039)	(0.035)	(0.072)
Sequential	-2.237	-0.751	0.197	1.218	2.568	-2.178	-0.741	0.206	1.225	2.597
(SE)	(0.063)	(0.036)	(0.041)	(0.035)	(0.065)	(0.069)	(0.037)	(0.038)	(0.038)	(0.066)
Wide	-2.240	-0.751	0.200	1.220	2.568	-2.189	-0.735	0.220	1.231	2.596
(SE)	(0.061)	(0.036)	(0.041)	(0.036)	(0.068)	(0.066)	(0.036)	(0.038)	(0.037)	(0.066)

Table H1-17. Observed and imputed percentiles of CRP (natural log transform) by year and imputation approach (non-Hispanic black)

	Biomeasure weighted					Base weighted				
ln(CRP)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	-1.389	0.256	1.182	2.009	3.231	-1.386	0.256	1.167	1.997	3.154
(SE)	(0.222)	(0.049)	(0.095)	(0.059)	(0.093)	(0.191)	(0.044)	(0.085)	(0.056)	(0.096)
Cross-sectional	-1.386	0.240	1.147	1.983	3.185	-1.260	0.182	1.015	1.922	3.132
(SE)	(0.206)	(0.050)	(0.082)	(0.056)	(0.103)	(0.160)	(0.059)	(0.071)	(0.055)	(0.093)
Sequential	-1.379	0.244	1.155	1.987	3.182	-1.269	0.187	1.038	1.924	3.123
(SE)	(0.212)	(0.054)	(0.092)	(0.059)	(0.115)	(0.149)	(0.052)	(0.085)	(0.052)	(0.090)
Wide	-1.339	0.245	1.148	1.987	3.163	-1.289	0.185	1.043	1.926	3.119
(SE)	(0.199)	(0.048)	(0.094)	(0.058)	(0.099)	(0.148)	(0.053)	(0.069)	(0.054)	(0.081)
2010										
Observed	-1.392	-0.101	0.982	1.754	2.842	-1.392	-0.107	0.970	1.757	2.842
(SE)	(0.157)	(0.076)	(0.069)	(0.052)	(0.084)	(0.157)	(0.078)	(0.070)	(0.053)	(0.085)
Cross-sectional	-1.367	-0.097	0.961	1.737	2.812	-1.298	-0.088	0.886	1.702	2.782
(SE)	(0.166)	(0.080)	(0.070)	(0.057)	(0.094)	(0.168)	(0.072)	(0.071)	(0.065)	(0.099)
Sequential	-1.390	-0.101	0.958	1.745	2.814	-1.352	-0.111	0.901	1.718	2.826
(SE)	(0.167)	(0.075)	(0.072)	(0.060)	(0.095)	(0.157)	(0.077)	(0.069)	(0.059)	(0.096)
Wide	-1.379	-0.101	0.959	1.740	2.814	-1.300	-0.086	0.923	1.723	2.831
(SE)	(0.158)	(0.081)	(0.069)	(0.056)	(0.096)	(0.132)	(0.077)	(0.073)	(0.063)	(0.128)
2014										
Observed	-1.917	-0.398	0.653	1.700	3.224	-1.929	-0.400	0.650	1.699	3.226
(SE)	(0.181)	(0.085)	(0.108)	(0.107)	(0.131)	(0.197)	(0.093)	(0.107)	(0.112)	(0.120)
Cross-sectional	-1.912	-0.391	0.647	1.698	3.216	-1.944	-0.439	0.583	1.592	3.122
(SE)	(0.173)	(0.086)	(0.108)	(0.108)	(0.133)	(0.185)	(0.094)	(0.098)	(0.109)	(0.123)
Sequential	-1.936	-0.402	0.644	1.699	3.215	-1.916	-0.407	0.621	1.651	3.133
(SE)	(0.176)	(0.088)	(0.106)	(0.109)	(0.132)	(0.208)	(0.086)	(0.100)	(0.105)	(0.124)
Wide	-1.946	-0.400	0.645	1.700	3.219	-1.897	-0.395	0.634	1.655	3.146
(SE)	(0.186)	(0.091)	(0.107)	(0.113)	(0.131)	(0.182)	(0.087)	(0.106)	(0.107)	(0.123)

Table H1-18. Observed and imputed percentiles of CRP (natural log transform) by year and imputation approach (Hispanic)

	Biomeasure weighted					Base weighted				
ln(CRP)	5th	25th (Q1)	Median	75th (Q3)	95th	5th	25th (Q1)	Median	75th (Q3)	95th
2006										
Observed	-1.017	0.130	0.777	1.639	2.717	-0.955	0.141	0.774	1.632	2.709
(SE)	(0.072)	(0.060)	(0.067)	(0.048)	(0.121)	(0.087)	(0.061)	(0.063)	(0.060)	(0.117)
Cross-sectional	-1.027	0.131	0.776	1.636	2.724	-1.019	0.110	0.783	1.618	2.748
(SE)	(0.090)	(0.064)	(0.070)	(0.049)	(0.127)	(0.119)	(0.059)	(0.067)	(0.060)	(0.118)
Sequential	-1.039	0.122	0.767	1.636	2.734	-1.056	0.124	0.787	1.623	2.756
(SE)	(0.083)	(0.065)	(0.068)	(0.048)	(0.131)	(0.112)	(0.073)	(0.069)	(0.062)	(0.121)
Wide	-1.017	0.132	0.776	1.636	2.721	-1.022	0.132	0.803	1.627	2.719
(SE)	(0.074)	(0.061)	(0.068)	(0.049)	(0.127)	(0.085)	(0.063)	(0.068)	(0.073)	(0.104)
2010										
Observed	-0.987	-0.058	0.681	1.423	2.508	-1.046	-0.058	0.646	1.420	2.508
(SE)	(0.161)	(0.082)	(0.063)	(0.057)	(0.136)	(0.398)	(0.099)	(0.065)	(0.058)	(0.138)
Cross-sectional	-0.997	-0.053	0.689	1.425	2.526	-1.129	-0.060	0.662	1.415	2.604
(SE)	(0.252)	(0.083)	(0.073)	(0.064)	(0.128)	(0.220)	(0.092)	(0.076)	(0.070)	(0.172)
Sequential	-0.995	-0.062	0.672	1.416	2.537	-1.130	-0.066	0.682	1.433	2.593
(SE)	(0.196)	(0.077)	(0.070)	(0.063)	(0.158)	(0.192)	(0.085)	(0.079)	(0.086)	(0.156)
Wide	-1.020	-0.060	0.674	1.415	2.522	-1.077	-0.048	0.685	1.445	2.582
(SE)	(0.333)	(0.086)	(0.071)	(0.068)	(0.148)	(0.196)	(0.095)	(0.069)	(0.078)	(0.156)
2014										
Observed	-1.720	-0.594	0.515	1.333	2.548	-1.732	-0.596	0.507	1.332	2.550
(SE)	(0.079)	(0.099)	(0.146)	(0.134)	(0.231)	(0.089)	(0.098)	(0.153)	(0.135)	(0.187)
Cross-sectional	-1.718	-0.593	0.517	1.336	2.547	-1.785	-0.598	0.469	1.328	2.574
(SE)	(0.079)	(0.099)	(0.144)	(0.131)	(0.230)	(0.143)	(0.092)	(0.137)	(0.124)	(0.186)
Sequential	-1.722	-0.593	0.520	1.337	2.549	-1.800	-0.599	0.504	1.325	2.559
(SE)	(0.080)	(0.098)	(0.144)	(0.133)	(0.206)	(0.127)	(0.093)	(0.123)	(0.126)	(0.179)
Wide	-1.722	-0.593	0.520	1.338	2.548	-1.820	-0.602	0.502	1.339	2.553
(SE)	(0.080)	(0.098)	(0.144)	(0.132)	(0.224)	(0.115)	(0.092)	(0.128)	(0.122)	(0.161)

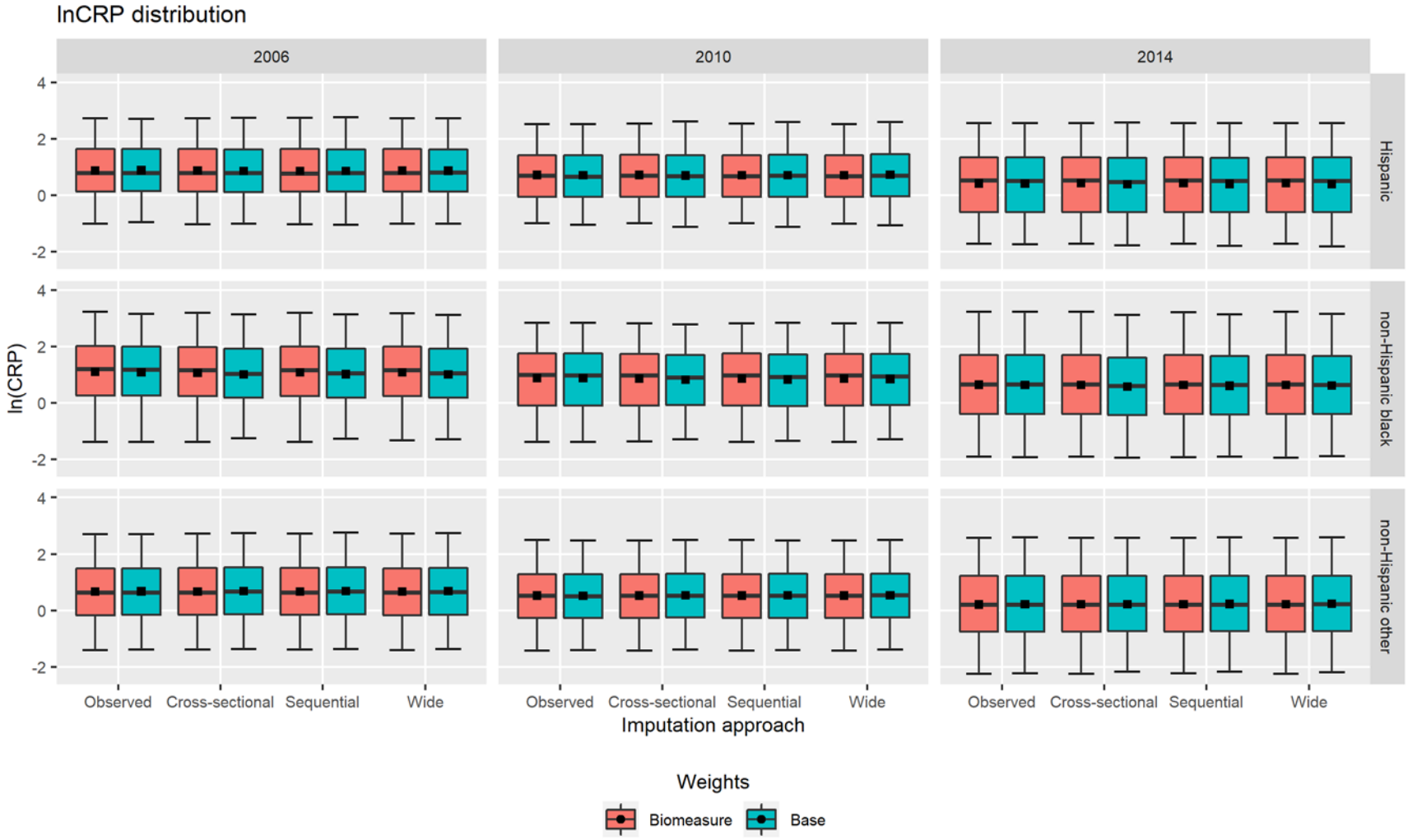

Figure H1-4. Distribution of C-reactive protein (natural log transform) comparing race/ethnicity by year, analysis weight, and imputation approach. Ends of whisker plot represent 5th and 95th percentiles corresponding with values in Table H1-16, H1-17, and H1-18. Black squares represent means.

H.2 Cross-sectional multivariate model by race/ethnicity

Table H2-1. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using biomeasure weights (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.043 (0.006)****	0.046 (0.006)****	0.046 (0.006)****	0.046 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.338 (0.091)***	-0.352 (0.083)****	-0.355 (0.083)****	-0.350 (0.083)****
Health conditions				
Hypertension	0.609 (0.082)****	0.617 (0.080)****	0.617 (0.080)****	0.618 (0.081)****
Diabetes	0.615 (0.084)****	0.627 (0.080)****	0.625 (0.081)****	0.620 (0.081)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.215 (0.127)	-0.152 (0.109)	-0.155 (0.108)	-0.157 (0.111)
Obese (BMI > 30)	-0.146 (0.115)	-0.155 (0.121)	-0.154 (0.120)	-0.154 (0.121)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.005 (0.164)	-0.021 (0.150)	-0.019 (0.150)	-0.017 (0.151)
Hardly ever/never	0.426 (0.142)**	0.417 (0.127)**	0.412 (0.126)**	0.420 (0.126)***
Smoking status (ref: never smoked)				
Current smoker	0.351 (0.149)*	0.353 (0.142)*	0.352 (0.142)*	0.353 (0.140)*
Former smoker	0.134 (0.113)	0.149 (0.114)	0.149 (0.114)	0.148 (0.114)
Biomeasures				
ln(CRP)	0.042 (0.035)	0.031 (0.034)	0.034 (0.035)	0.030 (0.034)
Cystatin C	0.449 (0.111)***	0.414 (0.101)****	0.410 (0.098)****	0.398 (0.102)****
Intercept	-2.000 (0.196)****	-1.994 (0.192)****	-1.988 (0.190)****	-1.974 (0.190)****

Note. Sample sizes: observed n = 4,489; imputed n = 4,926.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-2. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using biomeasure weights (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.012 (0.013)	0.018 (0.012)	0.018 (0.012)	0.018 (0.012)
Age (squared)	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Female	0.085 (0.240)	0.103 (0.225)	0.103 (0.224)	0.102 (0.222)
Health conditions				
Hypertension	1.449 (0.273)****	1.374 (0.264)****	1.373 (0.263)****	1.373 (0.262)****
Diabetes	0.433 (0.217)	0.452 (0.193)*	0.445 (0.193)*	0.459 (0.192)*
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.605 (0.278)*	-0.462 (0.267)	-0.443 (0.267)	-0.425 (0.269)
Obese (BMI > 30)	-0.451 (0.326)	-0.460 (0.259)	-0.446 (0.252)	-0.436 (0.247)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.076 (0.521)	0.110 (0.481)	0.112 (0.480)	0.120 (0.481)
Hardly ever/never	0.847 (0.293)**	0.787 (0.252)**	0.786 (0.254)**	0.779 (0.255)**
Smoking status (ref: never smoked)				
Current smoker	-0.174 (0.360)	-0.032 (0.325)	-0.030 (0.323)	-0.020 (0.324)
Former smoker	0.405 (0.216)	0.452 (0.214)*	0.453 (0.214)*	0.455 (0.213)*
Biomeasures				
ln(CRP)	0.045 (0.082)	0.037 (0.077)	0.034 (0.080)	0.029 (0.075)
Cystatin C	0.224 (0.127)	0.211 (0.116)	0.211 (0.119)	0.207 (0.114)
Intercept	-2.615 (0.527)****	-2.651 (0.482)****	-2.657 (0.485)****	-2.664 (0.483)****

Note. Sample sizes: observed n = 671; imputed n = 780.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-3. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using biomeasure weights (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.023 (0.015)	0.017 (0.012)	0.017 (0.012)	0.017 (0.012)
Age (squared)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	0.330 (0.344)	0.262 (0.331)	0.264 (0.331)	0.271 (0.332)
Health conditions				
Hypertension	1.970 (0.422)****	1.925 (0.390)****	1.926 (0.392)****	1.920 (0.393)****
Diabetes	0.293 (0.238)	0.292 (0.224)	0.285 (0.224)	0.273 (0.224)
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.224 (0.362)	-0.118 (0.323)	-0.100 (0.318)	-0.046 (0.336)
Obese (BMI > 30)	0.074 (0.347)	-0.448 (0.324)	-0.428 (0.327)	-0.379 (0.337)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	1.086 (0.487)*	0.867 (0.408)*	0.867 (0.408)*	0.883 (0.413)*
Hardly ever/never	-0.294 (0.373)	-0.154 (0.335)	-0.155 (0.333)	-0.161 (0.334)
Smoking status (ref: never smoked)				
Current smoker	0.452 (0.573)	0.357 (0.549)	0.358 (0.548)	0.360 (0.550)
Former smoker	0.788 (0.380)*	0.816 (0.354)*	0.816 (0.352)*	0.818 (0.354)*
Biomeasures				
ln(CRP)	-0.043 (0.132)	-0.052 (0.119)	-0.051 (0.120)	-0.045 (0.121)
Cystatin C	0.810 (0.343)*	0.670 (0.266)*	0.675 (0.269)*	0.685 (0.270)*
Intercept	-4.554 (0.691)****	-4.185 (0.608)****	-4.204 (0.609)****	-4.259 (0.612)****

Note. Sample sizes: observed n = 454; imputed n = 497.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-4. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using base weights (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.041 (0.006)****	0.051 (0.005)****	0.051 (0.005)****	0.051 (0.005)****
Age (squared)	0.000 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Female	-0.335 (0.087)***	-0.370 (0.067)****	-0.372 (0.067)****	-0.360 (0.066)****
Health conditions				
Hypertension	0.617 (0.086)****	0.654 (0.071)****	0.653 (0.070)****	0.653 (0.071)****
Diabetes	0.602 (0.084)****	0.564 (0.078)****	0.562 (0.078)****	0.548 (0.078)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.202 (0.128)	-0.113 (0.083)	-0.118 (0.082)	-0.106 (0.083)
Obese (BMI > 30)	-0.146 (0.113)	-0.126 (0.098)	-0.129 (0.096)	-0.107 (0.095)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.049 (0.171)	0.008 (0.157)	0.008 (0.156)	0.011 (0.157)
Hardly ever/never	0.383 (0.149)*	0.340 (0.107)**	0.338 (0.109)**	0.355 (0.107)***
Smoking status (ref: never smoked)				
Current smoker	0.318 (0.146)*	0.278 (0.106)**	0.276 (0.106)**	0.289 (0.104)**
Former smoker	0.107 (0.109)	0.131 (0.085)	0.133 (0.085)	0.133 (0.085)
Biomeasures				
ln(CRP)	0.046 (0.035)	0.038 (0.034)	0.037 (0.031)	0.027 (0.030)
Cystatin C	0.448 (0.110)***	0.334 (0.102)**	0.350 (0.084)****	0.348 (0.081)****
Intercept	-1.996 (0.191)****	-1.857 (0.161)****	-1.871 (0.147)****	-1.878 (0.147)****

Note. Sample sizes: observed n = 4,535; imputed n = 6,180.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-5. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using base weights (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.015 (0.012)	0.022 (0.009)*	0.022 (0.009)*	0.022 (0.009)*
Age (squared)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	0.178 (0.242)	0.059 (0.197)	0.045 (0.198)	0.049 (0.196)
Health conditions				
Hypertension	1.436 (0.254)****	1.001 (0.205)****	1.003 (0.206)****	1.013 (0.207)****
Diabetes	0.353 (0.205)	0.417 (0.157)**	0.418 (0.158)**	0.433 (0.157)**
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.511 (0.279)	-0.336 (0.179)	-0.315 (0.181)	-0.335 (0.178)
Obese (BMI > 30)	-0.367 (0.309)	-0.108 (0.222)	-0.107 (0.222)	-0.148 (0.218)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.161 (0.494)	-0.030 (0.322)	-0.030 (0.324)	-0.014 (0.323)
Hardly ever/never	0.839 (0.315)**	0.598 (0.162)***	0.589 (0.159)***	0.595 (0.158)***
Smoking status (ref: never smoked)				
Current smoker	-0.183 (0.357)	0.223 (0.243)	0.218 (0.241)	0.213 (0.240)
Former smoker	0.428 (0.229)	0.634 (0.167)***	0.627 (0.166)***	0.626 (0.166)***
Biomeasures				
ln(CRP)	-0.001 (0.084)	0.002 (0.083)	0.028 (0.079)	0.041 (0.075)
Cystatin C	0.231 (0.137)	0.259 (0.134)	0.245 (0.131)	0.225 (0.118)
Intercept	-2.758 (0.493)****	-2.733 (0.374)****	-2.738 (0.375)****	-2.711 (0.370)****

Note. Sample sizes: observed n = 675; imputed n = 1,133.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-6. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2006 using base weights (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.023 (0.016)	0.015 (0.014)	0.015 (0.014)	0.017 (0.014)
Age (squared)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	0.431 (0.311)	0.261 (0.253)	0.249 (0.257)	0.274 (0.258)
Health conditions				
Hypertension	1.885 (0.432)****	1.588 (0.310)****	1.587 (0.311)****	1.576 (0.311)****
Diabetes	0.131 (0.245)	0.079 (0.225)	0.074 (0.227)	0.064 (0.224)
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.241 (0.369)	-0.014 (0.293)	-0.047 (0.286)	0.007 (0.306)
Obese (BMI > 30)	0.062 (0.338)	-0.390 (0.288)	-0.420 (0.290)	-0.341 (0.299)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	1.041 (0.431)*	0.776 (0.397)	0.784 (0.397)*	0.780 (0.397)*
Hardly ever/never	-0.222 (0.343)	0.368 (0.369)	0.351 (0.364)	0.361 (0.371)
Smoking status (ref: never smoked)				
Current smoker	0.194 (0.496)	-0.345 (0.462)	-0.345 (0.451)	-0.387 (0.490)
Former smoker	0.758 (0.404)	0.805 (0.316)*	0.812 (0.312)**	0.802 (0.320)*
Biomeasures				
ln(CRP)	-0.011 (0.129)	-0.008 (0.107)	0.018 (0.113)	-0.013 (0.124)
Cystatin C	0.854 (0.335)*	0.601 (0.205)**	0.610 (0.225)**	0.597 (0.224)**
Intercept	-4.633 (0.698)****	-3.935 (0.530)****	-3.947 (0.545)****	-3.941 (0.540)****

Note. Sample sizes: observed n = 457; imputed n = 641.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

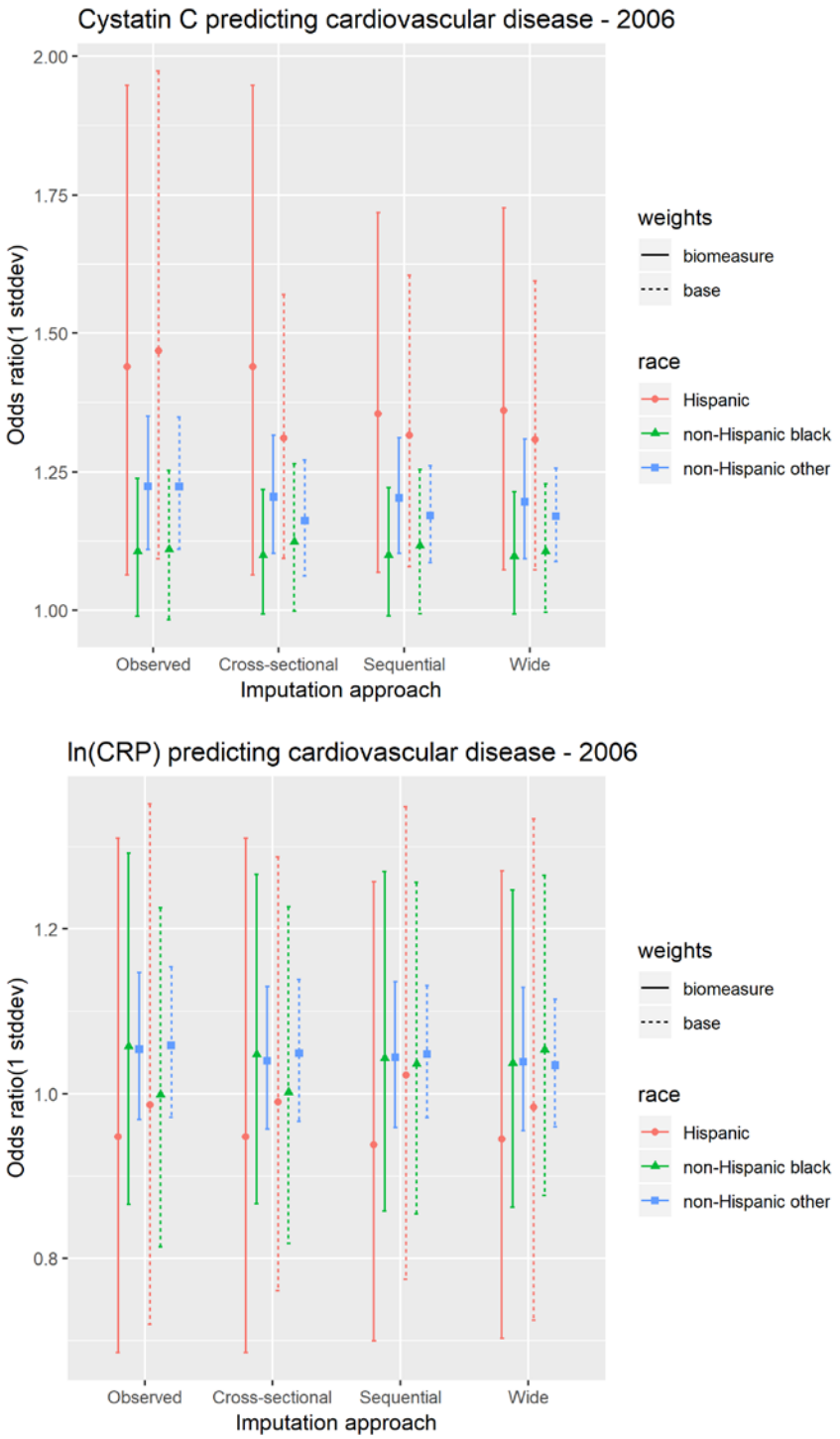

Figure H2-1. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2006 by imputation approach, analysis weight, and race/ethnicity. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

Table H2-7. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using biomeasure weights (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.041 (0.006)****	0.041 (0.006)****	0.042 (0.006)****	0.042 (0.006)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.399 (0.096)***	-0.408 (0.095)****	-0.411 (0.095)****	-0.411 (0.095)****
Health conditions				
Hypertension	0.639 (0.096)****	0.632 (0.092)****	0.629 (0.092)****	0.630 (0.092)****
Diabetes	0.612 (0.100)****	0.631 (0.095)****	0.628 (0.095)****	0.624 (0.095)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.063 (0.133)	-0.139 (0.095)	-0.139 (0.095)	-0.134 (0.093)
Obese (BMI > 30)	-0.123 (0.096)	-0.082 (0.127)	-0.076 (0.126)	-0.070 (0.127)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.007 (0.178)	0.019 (0.179)	0.021 (0.177)	0.015 (0.178)
Hardly ever/never	0.223 (0.138)	0.258 (0.131)*	0.255 (0.131)	0.250 (0.131)
Smoking status (ref: never smoked)				
Current smoker	0.171 (0.157)	0.169 (0.156)	0.172 (0.156)	0.167 (0.156)
Former smoker	0.256 (0.091)**	0.277 (0.087)**	0.277 (0.087)**	0.274 (0.086)**
Biomeasures				
ln(CRP)	0.038 (0.037)	0.034 (0.036)	0.036 (0.037)	0.041 (0.037)
Cystatin C	0.503 (0.118)****	0.487 (0.114)****	0.476 (0.112)****	0.476 (0.112)****
Intercept	-1.977 (0.184)****	-1.939 (0.172)****	-1.927 (0.170)****	-1.927 (0.171)****

Note. Sample sizes: observed n = 3,946; imputed n = 4,126.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-8. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using biomeasure weights (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.024 (0.013)	0.025 (0.011)*	0.023 (0.012)*	0.023 (0.011)*
Age (squared)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Female	0.487 (0.221)*	0.449 (0.224)*	0.447 (0.222)*	0.439 (0.222)*
Health conditions				
Hypertension	1.113 (0.293)***	1.215 (0.257)****	1.227 (0.258)****	1.219 (0.259)****
Diabetes	0.653 (0.188)**	0.599 (0.183)**	0.600 (0.182)**	0.591 (0.185)**
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	0.166 (0.351)	-0.178 (0.257)	-0.169 (0.259)	-0.174 (0.256)
Obese (BMI > 30)	-0.124 (0.262)	0.213 (0.317)	0.204 (0.312)	0.198 (0.310)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.039 (0.450)	-0.089 (0.450)	-0.089 (0.448)	-0.091 (0.447)
Hardly ever/never	0.401 (0.242)	0.518 (0.224)*	0.558 (0.223)*	0.544 (0.222)*
Smoking status (ref: never smoked)				
Current smoker	0.398 (0.314)	0.467 (0.300)	0.456 (0.298)	0.446 (0.295)
Former smoker	0.743 (0.246)**	0.800 (0.247)**	0.805 (0.249)**	0.802 (0.247)**
Biomeasures				
ln(CRP)	0.061 (0.099)	0.048 (0.092)	0.025 (0.093)	0.037 (0.092)
Cystatin C	0.167 (0.135)	0.174 (0.127)	0.184 (0.127)	0.211 (0.129)
Intercept	-3.413 (0.356)****	-3.502 (0.316)****	-3.504 (0.309)****	-3.523 (0.306)****

Note. Sample sizes: observed n = 655; imputed n = 706.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-9. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using biomeasure weights (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	-0.007 (0.025)	-0.002 (0.020)	-0.002 (0.020)	-0.002 (0.020)
Age (squared)	-0.004 (0.002)*	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Female	0.583 (0.364)	0.717 (0.258)**	0.701 (0.261)**	0.725 (0.260)**
Health conditions				
Hypertension	0.907 (0.434)*	1.231 (0.342)***	1.230 (0.347)***	1.227 (0.344)***
Diabetes	0.425 (0.454)	0.289 (0.382)	0.303 (0.390)	0.292 (0.391)
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.347 (0.395)	0.807 (0.439)	0.681 (0.394)	0.855 (0.400)*
Obese (BMI > 30)	0.691 (0.524)	-0.143 (0.428)	-0.338 (0.359)	-0.235 (0.342)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.896 (0.383)*	0.899 (0.300)**	0.892 (0.301)**	0.895 (0.299)**
Hardly ever/never	0.472 (0.361)	0.530 (0.341)	0.533 (0.345)	0.537 (0.343)
Smoking status (ref: never smoked)				
Current smoker	0.660 (0.619)	0.916 (0.670)	0.911 (0.660)	0.862 (0.640)
Former smoker	0.798 (0.409)	0.720 (0.333)*	0.726 (0.335)*	0.724 (0.337)*
Biomeasures				
ln(CRP)	0.066 (0.154)	0.030 (0.122)	0.058 (0.128)	0.068 (0.132)
Cystatin C	0.518 (0.307)	0.423 (0.256)	0.422 (0.259)	0.444 (0.251)
Intercept	-3.800 (0.859)****	-4.179 (0.669)****	-4.060 (0.676)****	-4.217 (0.673)****

Note. Sample sizes: observed n = 357; imputed n = 396.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-10. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using base weights (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.043 (0.006)****	0.045 (0.005)****	0.046 (0.005)****	0.046 (0.005)****
Age (squared)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.402 (0.099)***	-0.382 (0.083)****	-0.385 (0.083)****	-0.385 (0.083)****
Health conditions				
Hypertension	0.616 (0.096)****	0.616 (0.085)****	0.609 (0.085)****	0.611 (0.086)****
Diabetes	0.614 (0.097)****	0.583 (0.088)****	0.577 (0.087)****	0.573 (0.087)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.077 (0.134)	-0.130 (0.084)	-0.128 (0.084)	-0.126 (0.082)
Obese (BMI > 30)	-0.148 (0.099)	-0.069 (0.119)	-0.055 (0.118)	-0.058 (0.118)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.028 (0.177)	0.085 (0.139)	0.087 (0.138)	0.080 (0.139)
Hardly ever/never	0.188 (0.142)	0.285 (0.132)*	0.283 (0.133)*	0.281 (0.132)*
Smoking status (ref: never smoked)				
Current smoker	0.187 (0.156)	0.232 (0.133)	0.233 (0.134)	0.223 (0.135)
Former smoker	0.287 (0.090)**	0.268 (0.082)**	0.267 (0.082)**	0.264 (0.082)**
Biomeasures				
ln(CRP)	0.042 (0.037)	0.038 (0.036)	0.045 (0.037)	0.058 (0.035)
Cystatin C	0.522 (0.111)****	0.398 (0.087)****	0.366 (0.082)****	0.359 (0.072)****
Intercept	-1.957 (0.174)****	-1.856 (0.157)****	-1.820 (0.156)****	-1.815 (0.151)****

Note. Sample sizes: observed n = 3,946; imputed n = 5,152.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-11. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using base weights (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.026 (0.013)	0.028 (0.012)*	0.027 (0.012)*	0.027 (0.012)*
Age (squared)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	0.470 (0.218)*	0.277 (0.216)	0.261 (0.216)	0.259 (0.218)
Health conditions				
Hypertension	1.131 (0.293)***	1.073 (0.278)***	1.076 (0.279)***	1.069 (0.279)***
Diabetes	0.659 (0.192)**	0.560 (0.199)**	0.552 (0.199)**	0.558 (0.200)**
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	0.168 (0.358)	-0.186 (0.238)	-0.202 (0.242)	-0.199 (0.238)
Obese (BMI > 30)	-0.114 (0.268)	0.116 (0.297)	0.074 (0.289)	0.087 (0.291)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-0.025 (0.442)	-0.166 (0.349)	-0.181 (0.349)	-0.177 (0.346)
Hardly ever/never	0.399 (0.248)	0.225 (0.199)	0.242 (0.198)	0.238 (0.199)
Smoking status (ref: never smoked)				
Current smoker	0.345 (0.300)	0.281 (0.325)	0.257 (0.323)	0.251 (0.319)
Former smoker	0.712 (0.244)**	0.565 (0.221)*	0.566 (0.221)*	0.565 (0.218)**
Biomeasures				
ln(CRP)	0.058 (0.101)	0.082 (0.089)	0.079 (0.091)	0.072 (0.094)
Cystatin C	0.172 (0.137)	0.164 (0.128)	0.211 (0.138)	0.218 (0.128)
Intercept	-3.406 (0.359)****	-2.972 (0.418)****	-2.995 (0.419)****	-2.995 (0.408)****

Note. Sample sizes: observed n = 655; imputed n = 937.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-12. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2010 using base weights (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	-0.011 (0.025)	-0.007 (0.017)	-0.005 (0.016)	-0.005 (0.016)
Age (squared)	-0.004 (0.002)*	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Female	0.549 (0.380)	0.481 (0.235)*	0.449 (0.240)	0.454 (0.235)
Health conditions				
Hypertension	0.906 (0.467)	1.118 (0.351)**	1.115 (0.366)**	1.109 (0.365)**
Diabetes	0.482 (0.467)	0.257 (0.302)	0.254 (0.306)	0.230 (0.312)
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.349 (0.424)	0.840 (0.371)*	0.707 (0.307)*	0.813 (0.337)*
Obese (BMI > 30)	0.675 (0.540)	-0.383 (0.446)	-0.547 (0.389)	-0.493 (0.383)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.907 (0.397)*	0.456 (0.299)	0.454 (0.297)	0.471 (0.294)
Hardly ever/never	0.476 (0.354)	0.276 (0.336)	0.263 (0.339)	0.254 (0.343)
Smoking status (ref: never smoked)				
Current smoker	0.777 (0.655)	0.623 (0.607)	0.590 (0.595)	0.566 (0.578)
Former smoker	0.879 (0.424)*	0.839 (0.289)**	0.844 (0.287)**	0.838 (0.289)**
Biomeasures				
ln(CRP)	0.075 (0.164)	-0.001 (0.135)	0.032 (0.140)	0.048 (0.147)
Cystatin C	0.515 (0.302)	0.493 (0.252)	0.407 (0.256)	0.435 (0.265)
Intercept	-3.824 (0.864)****	-3.942 (0.572)****	-3.708 (0.498)****	-3.812 (0.538)****

Note. Sample sizes: observed n = 357; imputed n = 542.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

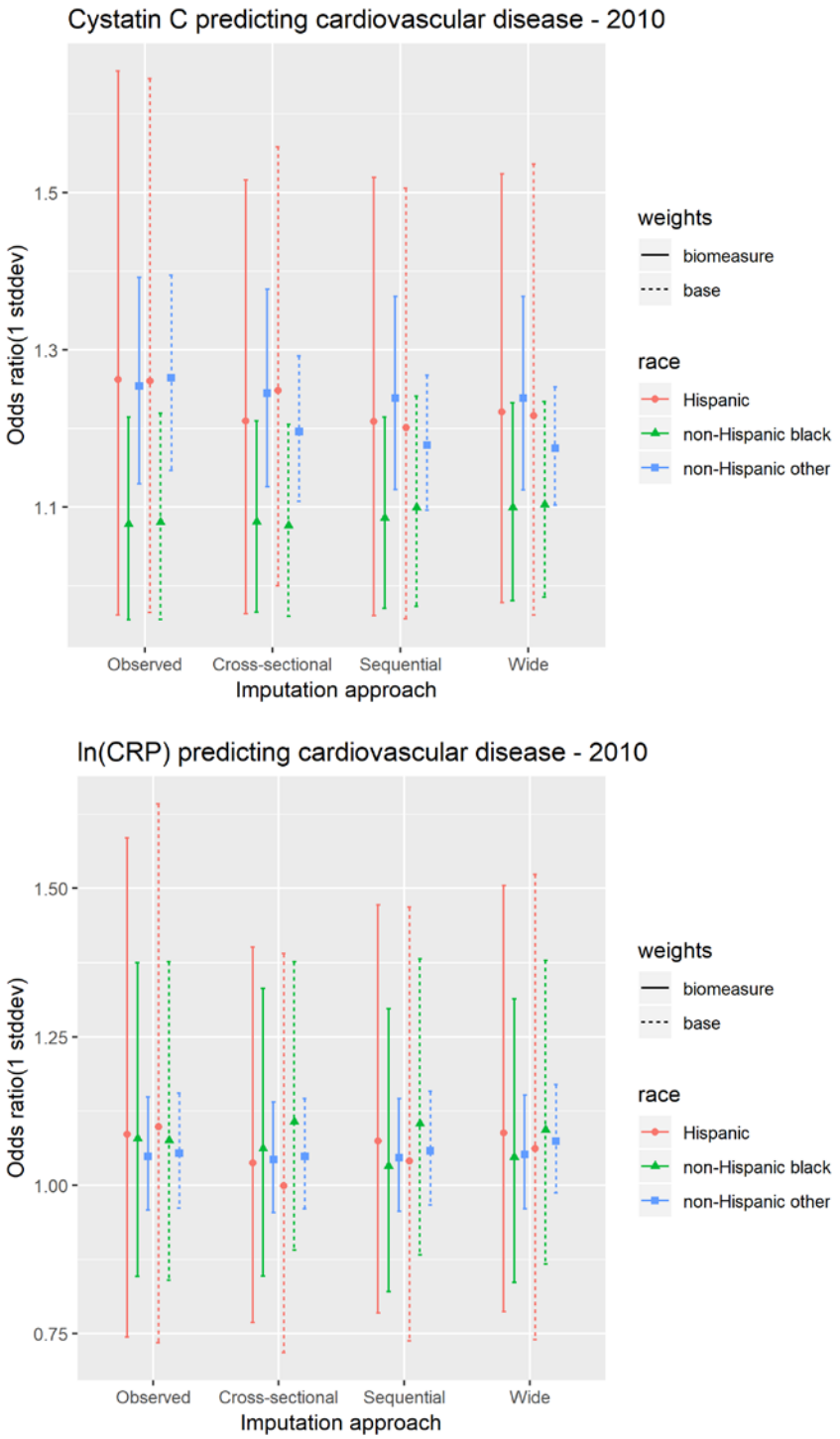

Figure H2-2. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2010 by imputation approach, analysis weight, and race/ethnicity. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

Table H2-13. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using biomeasure weights (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.042 (0.005)****	0.044 (0.005)****	0.044 (0.005)****	0.044 (0.005)****
Age (squared)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.419 (0.088)****	-0.400 (0.086)****	-0.402 (0.086)****	-0.402 (0.086)****
Health conditions				
Hypertension	0.577 (0.124)****	0.571 (0.120)****	0.567 (0.120)****	0.567 (0.120)****
Diabetes	0.526 (0.110)****	0.539 (0.109)****	0.538 (0.108)****	0.539 (0.108)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.102 (0.121)	-0.142 (0.115)	-0.138 (0.115)	-0.142 (0.116)
Obese (BMI > 30)	-0.136 (0.118)	-0.089 (0.116)	-0.083 (0.116)	-0.088 (0.116)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.253 (0.152)	0.240 (0.147)	0.239 (0.146)	0.243 (0.146)
Hardly ever/never	0.346 (0.134)*	0.354 (0.131)**	0.351 (0.132)**	0.349 (0.131)**
Smoking status (ref: never smoked)				
Current smoker	0.198 (0.144)	0.215 (0.135)	0.221 (0.135)	0.215 (0.135)
Former smoker	0.243 (0.086)**	0.261 (0.082)**	0.261 (0.082)**	0.259 (0.082)**
Biomeasures				
ln(CRP)	-0.001 (0.036)	0.000 (0.036)	0.000 (0.035)	0.005 (0.036)
Cystatin C	0.474 (0.111)****	0.465 (0.107)****	0.474 (0.107)****	0.466 (0.107)****
Intercept	-1.768 (0.182)****	-1.759 (0.182)****	-1.768 (0.180)****	-1.758 (0.181)****

Note. Sample sizes: observed n = 3,336; imputed n = 3,446.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-14. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using biomeasure weights (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.027 (0.018)	0.027 (0.016)	0.027 (0.016)	0.026 (0.016)
Age (squared)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)
Female	0.187 (0.299)	0.242 (0.304)	0.243 (0.303)	0.248 (0.304)
Health conditions				
Hypertension	0.923 (0.387)*	1.204 (0.384)**	1.209 (0.386)**	1.212 (0.386)**
Diabetes	0.561 (0.247)*	0.530 (0.245)*	0.535 (0.243)*	0.531 (0.243)*
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	0.059 (0.316)	-0.134 (0.324)	-0.294 (0.310)	-0.242 (0.323)
Obese (BMI > 30)	0.009 (0.312)	-0.084 (0.345)	-0.178 (0.334)	-0.146 (0.333)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.148 (0.361)	0.109 (0.339)	0.118 (0.343)	0.119 (0.340)
Hardly ever/never	0.459 (0.455)	0.415 (0.435)	0.439 (0.433)	0.440 (0.433)
Smoking status (ref: never smoked)				
Current smoker	0.226 (0.267)	0.188 (0.277)	0.160 (0.283)	0.169 (0.281)
Former smoker	0.330 (0.248)	0.279 (0.228)	0.270 (0.229)	0.273 (0.229)
Biomeasures				
ln(CRP)	0.133 (0.076)	0.116 (0.081)	0.110 (0.077)	0.105 (0.077)
Cystatin C	0.663 (0.217)**	0.396 (0.160)*	0.387 (0.153)*	0.386 (0.153)*
Intercept	-3.159 (0.561)****	-2.899 (0.529)****	-2.793 (0.541)****	-2.827 (0.533)****

Note. Sample sizes: observed n = 569; imputed n = 591.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-15. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using biomeasure weights (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	-0.044 (0.025)	-0.035 (0.025)	-0.035 (0.025)	-0.035 (0.025)
Age (squared)	-0.005 (0.002)*	-0.005 (0.002)*	-0.005 (0.002)*	-0.005 (0.002)*
Female	0.366 (0.356)	0.347 (0.275)	0.347 (0.276)	0.341 (0.277)
Health conditions				
Hypertension	0.467 (0.470)	0.504 (0.424)	0.502 (0.426)	0.500 (0.426)
Diabetes	0.057 (0.370)	0.000 (0.299)	0.001 (0.299)	-0.001 (0.300)
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.593 (0.497)	0.053 (0.393)	0.063 (0.389)	0.058 (0.389)
Obese (BMI > 30)	0.064 (0.465)	-0.605 (0.440)	-0.619 (0.433)	-0.615 (0.431)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-1.313 (0.724)	-1.268 (0.694)	-1.266 (0.695)	-1.270 (0.696)
Hardly ever/never	0.195 (0.358)	0.163 (0.246)	0.163 (0.247)	0.158 (0.247)
Smoking status (ref: never smoked)				
Current smoker	0.558 (0.622)	0.493 (0.568)	0.477 (0.572)	0.475 (0.571)
Former smoker	0.885 (0.387)*	0.792 (0.332)*	0.790 (0.330)*	0.788 (0.330)*
Biomeasures				
ln(CRP)	0.046 (0.106)	0.023 (0.095)	0.020 (0.095)	0.021 (0.095)
Cystatin C	0.506 (0.220)*	0.496 (0.198)*	0.502 (0.199)*	0.506 (0.199)*
Intercept	-2.594 (0.679)****	-2.505 (0.539)****	-2.511 (0.542)****	-2.507 (0.540)****

Note. Sample sizes: observed n = 351; imputed n = 376.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-16. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using base weights (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.043 (0.005)****	0.044 (0.005)****	0.044 (0.005)****	0.044 (0.005)****
Age (squared)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.401 (0.089)****	-0.378 (0.075)****	-0.379 (0.075)****	-0.375 (0.074)****
Health conditions				
Hypertension	0.553 (0.127)****	0.574 (0.106)****	0.560 (0.107)****	0.561 (0.107)****
Diabetes	0.550 (0.110)****	0.516 (0.092)****	0.518 (0.091)****	0.521 (0.091)****
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.129 (0.116)	-0.190 (0.098)	-0.193 (0.097)*	-0.193 (0.097)*
Obese (BMI > 30)	-0.146 (0.118)	-0.097 (0.102)	-0.098 (0.101)	-0.094 (0.100)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.244 (0.148)	0.350 (0.130)**	0.350 (0.130)**	0.355 (0.130)**
Hardly ever/never	0.319 (0.137)*	0.270 (0.123)*	0.274 (0.124)*	0.272 (0.124)*
Smoking status (ref: never smoked)				
Current smoker	0.170 (0.145)	0.282 (0.125)*	0.283 (0.125)*	0.287 (0.125)*
Former smoker	0.260 (0.086)**	0.260 (0.079)**	0.261 (0.080)**	0.263 (0.079)***
Biomeasures				
ln(CRP)	0.003 (0.038)	0.002 (0.035)	0.009 (0.037)	0.005 (0.034)
Cystatin C	0.487 (0.112)****	0.398 (0.091)****	0.412 (0.093)****	0.410 (0.086)****
Intercept	-1.771 (0.184)****	-1.627 (0.170)****	-1.637 (0.168)****	-1.641 (0.166)****

Note. Sample sizes: observed n = 3,336; imputed n = 4,185.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-17. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using base weights (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.032 (0.019)	0.030 (0.014)*	0.029 (0.014)*	0.029 (0.014)*
Age (squared)	0.000 (0.002)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	0.221 (0.299)	0.075 (0.249)	0.085 (0.250)	0.091 (0.249)
Health conditions				
Hypertension	0.812 (0.386)*	0.982 (0.380)**	0.990 (0.381)**	0.990 (0.382)**
Diabetes	0.591 (0.249)*	0.643 (0.211)**	0.661 (0.210)**	0.653 (0.211)**
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	0.079 (0.329)	-0.127 (0.323)	-0.262 (0.315)	-0.217 (0.319)
Obese (BMI > 30)	-0.020 (0.305)	0.072 (0.370)	-0.028 (0.368)	-0.001 (0.368)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	0.145 (0.357)	0.130 (0.246)	0.139 (0.252)	0.137 (0.249)
Hardly ever/never	0.467 (0.448)	0.381 (0.353)	0.410 (0.351)	0.400 (0.357)
Smoking status (ref: never smoked)				
Current smoker	0.248 (0.274)	0.407 (0.278)	0.375 (0.276)	0.398 (0.276)
Former smoker	0.296 (0.246)	0.272 (0.225)	0.277 (0.226)	0.271 (0.227)
Biomeasures				
ln(CRP)	0.159 (0.076)*	0.121 (0.079)	0.106 (0.072)	0.110 (0.073)
Cystatin C	0.632 (0.215)**	0.364 (0.151)*	0.359 (0.149)*	0.376 (0.152)*
Intercept	-3.048 (0.559)****	-2.786 (0.527)****	-2.707 (0.537)****	-2.758 (0.520)****

Note. Sample sizes: observed n = 569; imputed n = 764.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

Table H2-18. Logistic regression logit coefficients and standard errors for predicting cardiovascular disease in HRS 2014 using base weights (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	-0.036 (0.024)	-0.016 (0.019)	-0.015 (0.019)	-0.015 (0.019)
Age (squared)	-0.004 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Female	0.402 (0.360)	0.253 (0.272)	0.264 (0.263)	0.261 (0.264)
Health conditions				
Hypertension	0.441 (0.487)	0.540 (0.419)	0.466 (0.431)	0.456 (0.433)
Diabetes	0.115 (0.372)	0.095 (0.267)	0.135 (0.264)	0.136 (0.264)
BMI (ref: under/normal weight)				
Overweight (25 ≤ BMI < 30)	-0.601 (0.504)	-0.007 (0.316)	0.031 (0.307)	0.029 (0.308)
Obese (BMI > 30)	0.097 (0.460)	-0.780 (0.402)	-0.750 (0.384)	-0.775 (0.381)*
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3/month	-1.317 (0.714)	-1.428 (0.661)*	-1.383 (0.644)*	-1.391 (0.639)*
Hardly ever/never	0.181 (0.387)	0.354 (0.259)	0.396 (0.253)	0.388 (0.251)
Smoking status (ref: never smoked)				
Current smoker	0.563 (0.625)	0.482 (0.486)	0.490 (0.491)	0.452 (0.487)
Former smoker	0.985 (0.392)*	0.924 (0.303)**	0.930 (0.297)**	0.910 (0.294)**
Biomeasures				
ln(CRP)	0.029 (0.108)	0.048 (0.109)	0.005 (0.092)	0.010 (0.094)
Cystatin C	0.501 (0.225)*	0.468 (0.216)*	0.447 (0.183)*	0.472 (0.167)**
Intercept	-2.695 (0.703)****	-2.585 (0.539)****	-2.537 (0.539)****	-2.535 (0.542)****

Note. Sample sizes: observed n = 351; imputed n = 457.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001; **** = p < 0.0001.

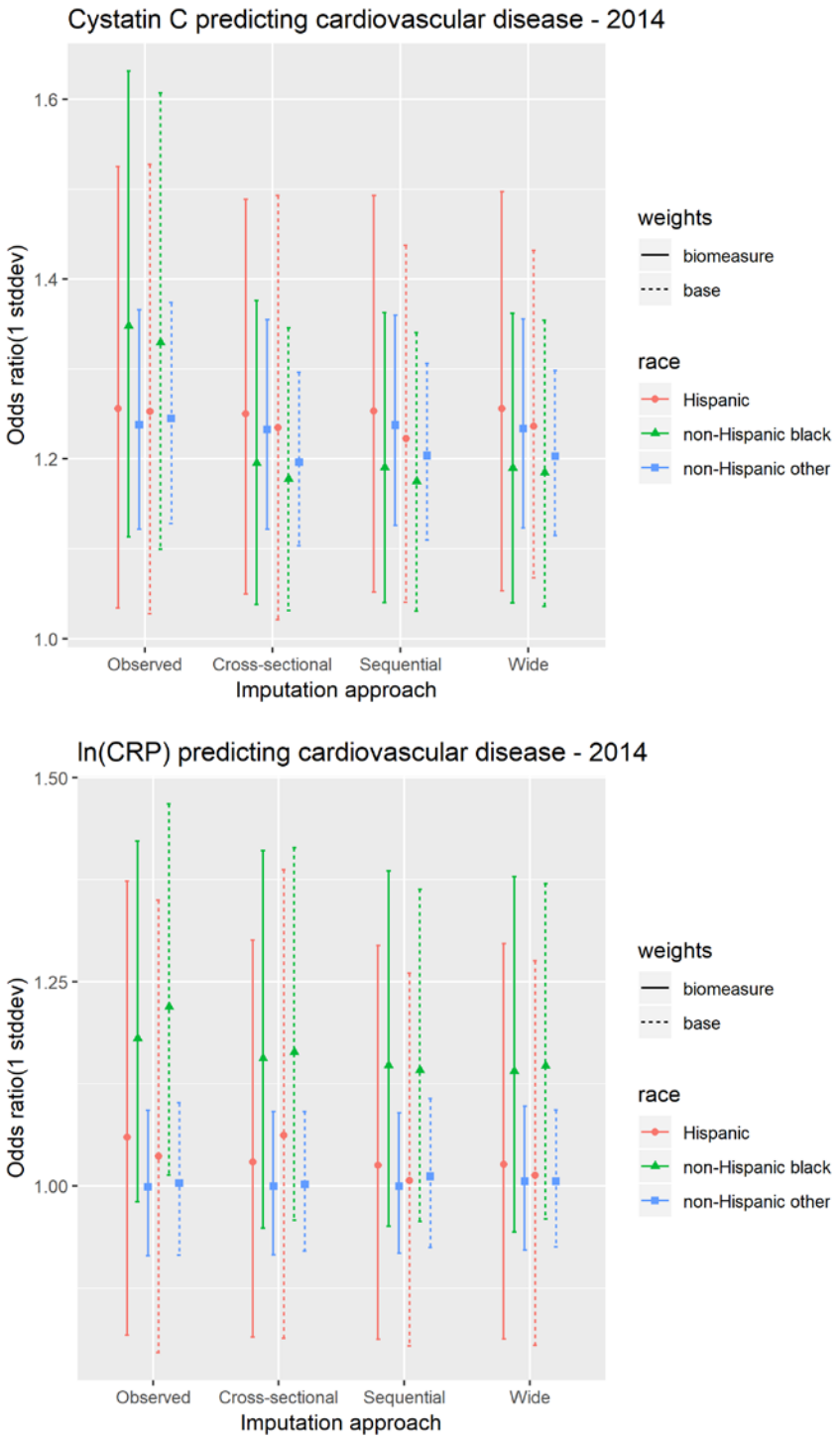

Figure H2-3. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting prevalence of cardiovascular disease in HRS 2014 by imputation approach, analysis weight, and race/ethnicity. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

H.3 Longitudinal multivariate model by race/ethnicity

Table H3-1. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (biomeasure weight) (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.049 (0.010)****	0.052 (0.007)****	0.051 (0.007)****	0.053 (0.007)****
Age (squared)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Female	-0.403 (0.149)**	-0.298 (0.130)*	-0.305 (0.132)*	-0.300 (0.130)*
Health conditions				
High blood pressure (2006)	0.429 (0.256)	0.490 (0.207)*	0.478 (0.206)*	0.480 (0.206)*
Recent HBP diagnosis	0.248 (0.235)	0.373 (0.211)	0.353 (0.212)	0.348 (0.211)
Diabetes (2006)	0.675 (0.171)***	0.635 (0.149)****	0.633 (0.150)****	0.628 (0.150)****
Recent diagnosis diabetes	0.194 (0.199)	0.271 (0.168)	0.269 (0.170)	0.269 (0.170)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.041 (0.184)	0.014 (0.187)	0.009 (0.187)	0.008 (0.189)
Obese (2006)	-0.026 (0.210)	0.114 (0.169)	0.106 (0.164)	0.113 (0.168)
Decreased BMI category	-0.096 (0.222)	0.045 (0.193)	0.059 (0.191)	0.041 (0.194)
Increased BMI category	0.199 (0.175)	0.149 (0.160)	0.153 (0.155)	0.163 (0.154)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.049 (0.345)	-0.239 (0.268)	-0.251 (0.269)	-0.250 (0.267)
Hardly ever/never (2006)	-0.090 (0.392)	-0.164 (0.392)	-0.172 (0.391)	-0.172 (0.390)
Decreased daily activity	-0.208 (0.396)	0.008 (0.276)	0.013 (0.275)	0.017 (0.276)
Increased daily activity	-0.069 (0.190)	-0.042 (0.194)	-0.048 (0.194)	-0.045 (0.194)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.289 (0.252)	0.349 (0.203)	0.365 (0.204)	0.358 (0.203)
Former smoker (2006)	0.314 (0.131)*	0.301 (0.123)*	0.302 (0.124)*	0.300 (0.121)*
Recently quit smoking	0.571 (0.391)	0.654 (0.324)*	0.609 (0.324)	0.642 (0.326)*
Recently started smoking	-0.249 (0.843)	-0.530 (0.794)	-0.520 (0.796)	-0.518 (0.795)
Biomeasures				
ln(CRP) (2006)	0.012 (0.065)	0.026 (0.059)	0.029 (0.060)	0.047 (0.055)
ln(CRP) change	-0.105 (0.060)	-0.058 (0.048)	-0.060 (0.047)	-0.067 (0.051)
Cystatin C (2006)	0.663 (0.241)**	0.552 (0.220)*	0.598 (0.231)*	0.513 (0.187)**
Cystatin C change	0.405 (0.149)**	0.372 (0.108)***	0.377 (0.110)***	0.356 (0.124)**
Intercept	-2.731 (0.273)****	-2.795 (0.270)****	-2.828 (0.284)****	-2.751 (0.244)****

Note. Sample sizes: 2,194 for observed, 3,337 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table H3-2. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (biomeasure weight) (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.024 (0.020)	0.035 (0.017)*	0.032 (0.016)*	0.034 (0.016)*
Age (squared)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Female	0.673 (0.533)	0.283 (0.469)	0.314 (0.477)	0.315 (0.460)
Health conditions				
High blood pressure (2006)	0.391 (0.661)	0.690 (0.486)	0.675 (0.491)	0.692 (0.486)
Recent HBP diagnosis	0.094 (0.830)	0.915 (0.584)	0.895 (0.610)	0.947 (0.619)
Diabetes (2006)	0.555 (0.404)	0.596 (0.286)*	0.638 (0.286)*	0.605 (0.281)*
Recent diagnosis diabetes	0.465 (0.616)	0.645 (0.506)	0.656 (0.500)	0.665 (0.504)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.054 (0.487)	-0.126 (0.420)	-0.135 (0.476)	-0.162 (0.491)
Obese (2006)	0.165 (0.472)	-0.116 (0.436)	-0.238 (0.498)	-0.207 (0.519)
Decreased BMI category	-0.163 (0.593)	0.284 (0.563)	-0.129 (0.678)	-0.297 (0.743)
Increased BMI category	-0.650 (0.536)	-0.508 (0.316)	-0.599 (0.329)	-0.563 (0.321)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.073 (0.902)	-0.656 (0.888)	-0.662 (0.890)	-0.769 (0.889)
Hardly ever/never (2006)	1.839 (0.741)*	-0.327 (0.866)	-0.284 (0.852)	-0.279 (0.811)
Decreased daily activity	-0.717 (0.882)	0.685 (0.659)	0.625 (0.629)	0.732 (0.645)
Increased daily activity	0.631 (0.532)	0.601 (0.481)	0.621 (0.485)	0.623 (0.483)
Smoking status (ref: never smoked)				
Current smoker (2006)	-0.596 (0.706)	0.068 (0.459)	0.051 (0.465)	0.072 (0.464)
Former smoker (2006)	-0.152 (0.343)	-0.112 (0.263)	-0.129 (0.259)	-0.132 (0.247)
Recently quit smoking	1.181 (0.789)	0.550 (0.606)	0.643 (0.609)	0.619 (0.621)
Recently started smoking	-14.22 (0.716)****	-13.35 (0.847)****	-13.42 (0.807)****	-13.62 (0.689)
Biomeasures				
log(CRP) (2006)	-0.073 (0.169)	0.032 (0.169)	0.053 (0.165)	0.012 (0.149)
log(CRP) change	0.008 (0.135)	0.037 (0.106)	0.037 (0.110)	0.076 (0.118)
Cystatin C (2006)	1.464 (0.468)**	0.223 (0.316)	0.212 (0.298)	0.078 (0.278)
Cystatin C change	0.560 (0.312)	0.180 (0.286)	0.183 (0.288)	0.305 (0.321)
Intercept	-4.243 (1.096)***	-2.980 (0.877)***	-2.896 (0.878)**	-2.739 (0.865)**

Note. Sample sizes: 297 for observed, 623 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table H3-3. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (biomeasure weight) (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	-0.039 (0.036)	0.035 (0.017)*	0.032 (0.016)*	0.034 (0.016)*
Age (squared)	-0.002 (0.003)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Female	0.156 (0.613)	0.283 (0.469)	0.314 (0.477)	0.315 (0.460)
Health conditions				
High blood pressure (2006)	0.407 (0.646)	0.690 (0.486)	0.675 (0.491)	0.692 (0.486)
Recent HBP diagnosis	-0.945 (0.977)	0.915 (0.584)	0.895 (0.610)	0.947 (0.619)
Diabetes (2006)	0.580 (0.546)	0.596 (0.286)*	0.638 (0.286)*	0.605 (0.281)*
Recent diagnosis diabetes	-0.340 (0.802)	0.645 (0.506)	0.656 (0.500)	0.665 (0.504)
BMI (ref: Under/normal weight)				
Overweight (2006)	-0.751 (0.653)	-0.126 (0.420)	-0.135 (0.476)	-0.162 (0.491)
Obese (2006)	0.288 (0.680)	-0.116 (0.436)	-0.238 (0.498)	-0.207 (0.519)
Decreased BMI category	-0.720 (0.887)	0.284 (0.563)	-0.129 (0.678)	-0.297 (0.743)
Increased BMI category	0.754 (0.521)	-0.508 (0.316)	-0.599 (0.329)	-0.563 (0.321)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-11.41 (1.282)****	-0.656 (0.888)	-0.662 (0.890)	-0.769 (0.889)
Hardly ever/never (2006)	0.381 (0.740)	-0.327 (0.866)	-0.284 (0.852)	-0.279 (0.811)
Decreased daily activity	-1.123 (1.216)	0.685 (0.659)	0.625 (0.629)	0.732 (0.645)
Increased daily activity	-0.671 (0.866)	0.601 (0.481)	0.621 (0.485)	0.623 (0.483)
Smoking status (ref: never smoked)				
Current smoker (2006)	-10.29 (0.693)****	0.068 (0.459)	0.051 (0.465)	0.072 (0.464)
Former smoker (2006)	1.058 (0.580)	-0.112 (0.263)	-0.129 (0.259)	-0.132 (0.247)
Recently quit smoking	12.60 (0.870)****	0.550 (0.606)	0.643 (0.609)	0.619 (0.621)
Recently started smoking	19.76 (1.281)****	-13.35 (0.847)****	-13.42 (0.807)****	-13.62 (0.689)****
Biomeasures				
log(CRP) (2006)	-0.343 (0.224)	0.032 (0.169)	0.053 (0.165)	0.012 (0.149)
log(CRP) change	0.401 (0.233)	0.037 (0.106)	0.037 (0.110)	0.076 (0.118)
Cystatin C (2006)	1.227 (1.035)	0.223 (0.316)	0.212 (0.298)	0.078 (0.278)
Cystatin C change	-0.045 (0.495)	0.180 (0.286)	0.183 (0.288)	0.305 (0.321)
Intercept	-3.875 (1.272)**	-2.980 (0.877)***	-2.896 (0.878)**	-2.739 (0.865)**

Note. Sample sizes: 237 for observed, 397 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table H3-4. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (base weight) (non-Hispanic other)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.049 (0.010)****	0.048 (0.007)****	0.049 (0.007)****	0.051 (0.007)****
Age (squared)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	-0.376 (0.152)*	-0.299 (0.117)*	-0.307 (0.118)**	-0.298 (0.116)*
Health conditions				
High blood pressure (2006)	0.429 (0.263)	0.554 (0.167)***	0.546 (0.166)**	0.550 (0.167)**
Recent HBP diagnosis	0.212 (0.236)	0.455 (0.180)*	0.432 (0.180)*	0.427 (0.181)*
Diabetes (2006)	0.667 (0.171)***	0.545 (0.134)****	0.541 (0.136)****	0.541 (0.135)****
Recent diagnosis diabetes	0.235 (0.206)	0.270 (0.175)	0.270 (0.176)	0.276 (0.176)
BMI (ref: Under/normal weight)				
Overweight (2006)	0.033 (0.180)	-0.100 (0.160)	-0.099 (0.161)	-0.114 (0.158)
Obese (2006)	-0.010 (0.213)	-0.032 (0.164)	-0.036 (0.161)	-0.036 (0.157)
Decreased BMI category	-0.123 (0.219)	0.031 (0.172)	0.045 (0.169)	0.033 (0.171)
Increased BMI category	0.181 (0.173)	0.285 (0.182)	0.292 (0.177)	0.297 (0.179)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	0.010 (0.344)	-0.341 (0.255)	-0.360 (0.260)	-0.365 (0.257)
Hardly ever/never (2006)	-0.056 (0.395)	-0.223 (0.341)	-0.227 (0.341)	-0.224 (0.336)
Decreased daily activity	-0.236 (0.392)	-0.038 (0.269)	-0.045 (0.268)	-0.036 (0.267)
Increased daily activity	-0.084 (0.188)	0.101 (0.163)	0.103 (0.163)	0.103 (0.164)
Smoking status (ref: never smoked)				
Current smoker (2006)	0.262 (0.256)	0.394 (0.175)*	0.404 (0.174)*	0.411 (0.172)*
Former smoker (2006)	0.310 (0.134)*	0.257 (0.120)*	0.258 (0.120)*	0.260 (0.119)*
Recently quit smoking	0.673 (0.404)	0.501 (0.277)	0.478 (0.277)	0.500 (0.277)
Recently started smoking	-0.201 (0.830)	-0.733 (0.796)	-0.730 (0.796)	-0.723 (0.795)
Biomeasures				
ln(CRP) (2006)	0.026 (0.066)	0.036 (0.068)	0.050 (0.063)	0.064 (0.055)
ln(CRP) change	-0.111 (0.062)	-0.045 (0.051)	-0.048 (0.051)	-0.062 (0.050)
Cystatin C (2006)	0.654 (0.246)*	0.580 (0.211)**	0.536 (0.242)*	0.452 (0.177)*
Cystatin C change	0.427 (0.150)**	0.317 (0.106)**	0.349 (0.114)**	0.325 (0.116)**
Intercept	-2.749 (0.275)****	-2.690 (0.263)****	-2.651 (0.291)****	-2.569 (0.235)****

Note. Sample sizes: 2,194 for observed, 2,740 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table H3-5. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (base weight) (non-Hispanic black)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	0.027 (0.021)	0.025 (0.016)	0.023 (0.016)	0.026 (0.016)
Age (squared)	0.000 (0.003)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	0.653 (0.557)	0.014 (0.392)	0.034 (0.395)	0.058 (0.384)
Health conditions				
High blood pressure (2006)	0.187 (0.628)	0.324 (0.448)	0.342 (0.445)	0.297 (0.448)
Recent HBP diagnosis	0.020 (0.796)	0.638 (0.560)	0.641 (0.583)	0.639 (0.587)
Diabetes (2006)	0.496 (0.394)	0.610 (0.263)*	0.628 (0.262)*	0.622 (0.260)*
Recent diagnosis diabetes	0.522 (0.590)	0.697 (0.371)	0.703 (0.370)	0.725 (0.366)*
BMI (ref: Under/normal weight)				
Overweight (2006)	0.087 (0.468)	0.094 (0.438)	0.109 (0.488)	0.108 (0.498)
Obese (2006)	0.052 (0.470)	0.309 (0.447)	0.233 (0.509)	0.288 (0.530)
Decreased BMI category	-0.484 (0.611)	0.293 (0.538)	-0.083 (0.658)	-0.217 (0.694)
Increased BMI category	-0.552 (0.519)	-0.086 (0.333)	-0.090 (0.335)	-0.062 (0.322)
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-0.250 (0.880)	-0.804 (0.630)	-0.857 (0.638)	-0.945 (0.661)
Hardly ever/never (2006)	1.513 (0.758)	0.052 (0.695)	0.088 (0.685)	0.102 (0.673)
Decreased daily activity	-0.347 (0.853)	0.607 (0.642)	0.592 (0.620)	0.695 (0.667)
Increased daily activity	0.715 (0.527)	0.681 (0.394)	0.697 (0.395)	0.711 (0.396)
Smoking status (ref: never smoked)				
Current smoker (2006)	-0.468 (0.718)	0.477 (0.448)	0.482 (0.448)	0.497 (0.447)
Former smoker (2006)	-0.136 (0.339)	-0.115 (0.240)	-0.107 (0.237)	-0.123 (0.232)
Recently quit smoking	0.891 (0.841)	0.296 (0.624)	0.330 (0.635)	0.312 (0.636)
Recently started smoking	-14.22 (0.717)****	-12.68 (0.606)****	-12.66 (0.616)****	-12.70 (0.608)****
Biomeasures				
log(CRP) (2006)	-0.031 (0.165)	0.083 (0.160)	0.092 (0.148)	0.033 (0.137)
log(CRP) change	-0.003 (0.131)	0.040 (0.100)	0.012 (0.104)	0.010 (0.110)
Cystatin C (2006)	1.449 (0.450)**	0.264 (0.328)	0.237 (0.336)	0.080 (0.292)
Cystatin C change	0.563 (0.329)	0.141 (0.259)	0.136 (0.298)	0.299 (0.322)
Intercept	-4.013 (1.073)***	-3.074 (0.767)****	-3.048 (0.778)****	-2.850 (0.781)***

Note. Sample sizes: 297 for observed, 480 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

Table H3-6. Logistic regression logit coefficients and standard errors predicting development of cardiovascular disease by 2014 (base weight) (Hispanic)

		Imputation approach		
	Observed	Cross-sectional	Sequential	Wide
Demographics				
Age (centered)	-0.034 (0.035)	-0.014 (0.021)	-0.014 (0.019)	-0.013 (0.018)
Age (squared)	-0.001 (0.003)	-0.003 (0.001)*	-0.003 (0.001)*	-0.003 (0.001)*
Female	0.138 (0.614)	-0.076 (0.308)	-0.026 (0.287)	-0.008 (0.295)
Health conditions				
High blood pressure (2006)	0.400 (0.649)	0.108 (0.477)	0.105 (0.474)	0.071 (0.466)
Recent HBP diagnosis	-0.908 (0.980)	0.363 (0.431)	0.237 (0.425)	0.277 (0.429)
Diabetes (2006)	0.588 (0.540)	0.175 (0.339)	0.169 (0.332)	0.207 (0.332)
Recent diagnosis diabetes	-0.303 (0.794)	-0.110 (0.442)	-0.044 (0.460)	0.044 (0.457)
BMI (ref: Under/normal weight)				
Overweight (2006)	-0.847 (0.638)	0.022 (0.417)	0.039 (0.425)	0.035 (0.373)
Obese (2006)	0.276 (0.657)	-0.348 (0.598)	-0.348 (0.581)	-0.401 (0.532)
Decreased BMI category	-0.702 (0.886)	-0.043 (0.573)	-0.221 (0.583)	-0.228 (0.585)
Increased BMI category	0.832 (0.525)	0.821 (0.366)*	0.789 (0.331)*	0.794 (0.330)*
Health behaviors				
Mildly vigorous activity (ref: weekly)				
1-3 times/month (2006)	-11.57 (1.314)****	-0.747 (0.911)	-0.574 (0.919)	-0.604 (0.938)
Hardly ever/never (2006)	0.354 (0.764)	-0.248 (0.720)	-0.127 (0.672)	-0.212 (0.647)
Decreased daily activity	-1.006 (1.189)	0.130 (0.790)	0.133 (0.796)	0.206 (0.794)
Increased daily activity	-0.704 (0.863)	-0.395 (0.318)	-0.315 (0.322)	-0.300 (0.324)
Smoking status (ref: never smoked)				
Current smoker (2006)	-10.34 (0.706)****	-0.601 (0.733)	-0.590 (0.735)	-0.620 (0.723)
Former smoker (2006)	1.094 (0.582)	0.716 (0.335)*	0.707 (0.313)*	0.645 (0.321)*
Recently quit smoking	12.64 (0.890)****	2.556 (1.088)*	2.794 (1.120)*	2.666 (1.091)*
Recently started smoking	19.79 (1.260)****	-0.013 (1.614)	0.055 (1.610)	0.168 (1.616)
Biomeasures				
log(CRP) (2006)	-0.361 (0.229)	-0.064 (0.159)	-0.145 (0.137)	-0.158 (0.142)
log(CRP) change	0.373 (0.237)	0.177 (0.161)	0.117 (0.128)	0.210 (0.145)
Cystatin C (2006)	1.230 (1.062)	0.457 (0.882)	0.604 (0.721)	0.747 (0.657)
Cystatin C change	0.044 (0.498)	0.584 (0.318)	0.425 (0.349)	0.293 (0.460)
Intercept	-3.918 (1.267)**	-2.753 (1.028)**	-2.841 (0.909)**	-2.844 (0.770)***

Note. Sample sizes: 237 for observed, 325 for imputed. Only includes 2006 respondents who had not been diagnosed with cardiovascular disease.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$; **** = $p < 0.0001$.

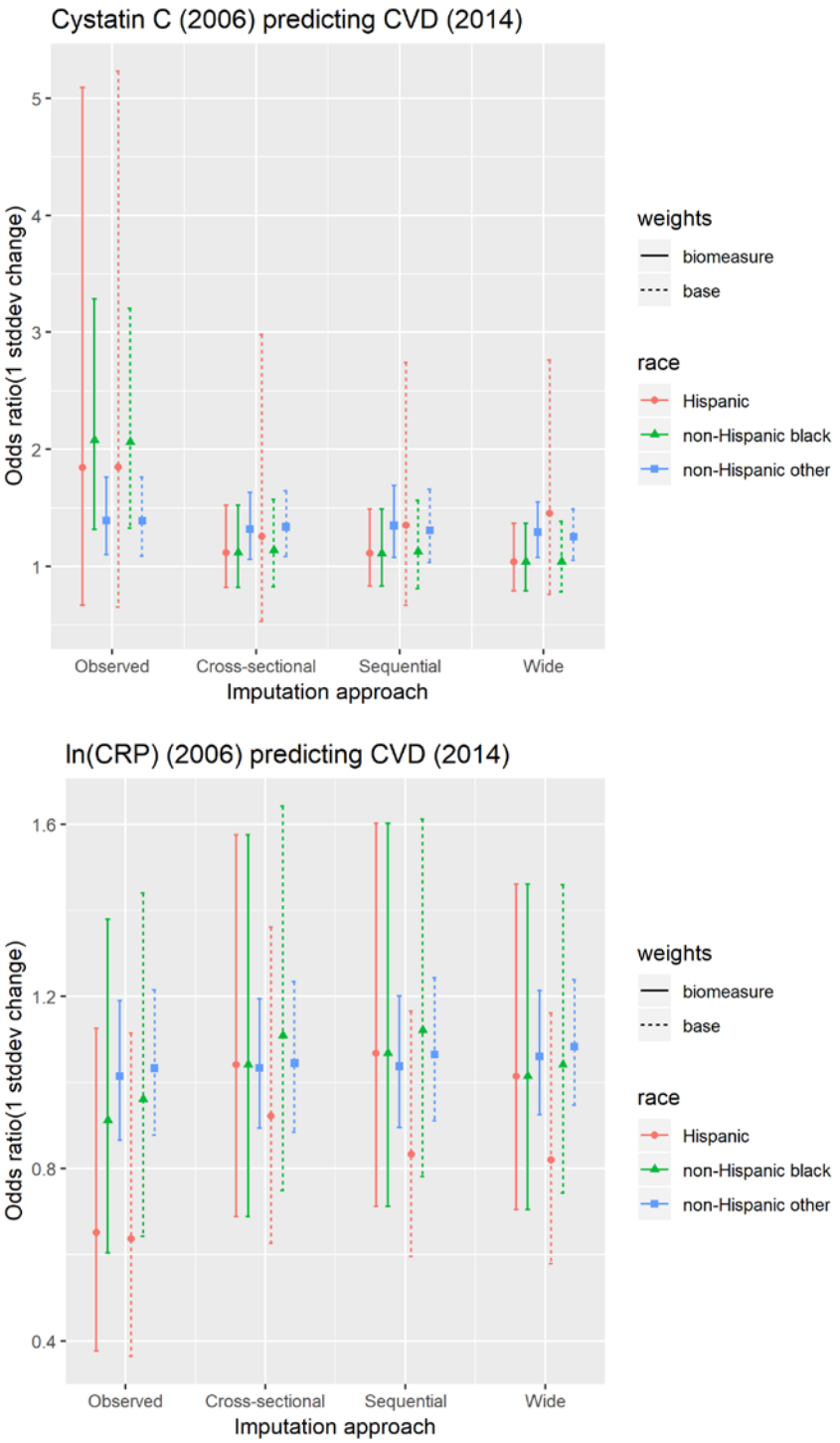

Figure H3-1. Odds ratios of Cystatin C and ln(CRP) in logistic regression model predicting the development of cardiovascular disease by 2014 by imputation approach, analysis weight, and race/ethnicity. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.

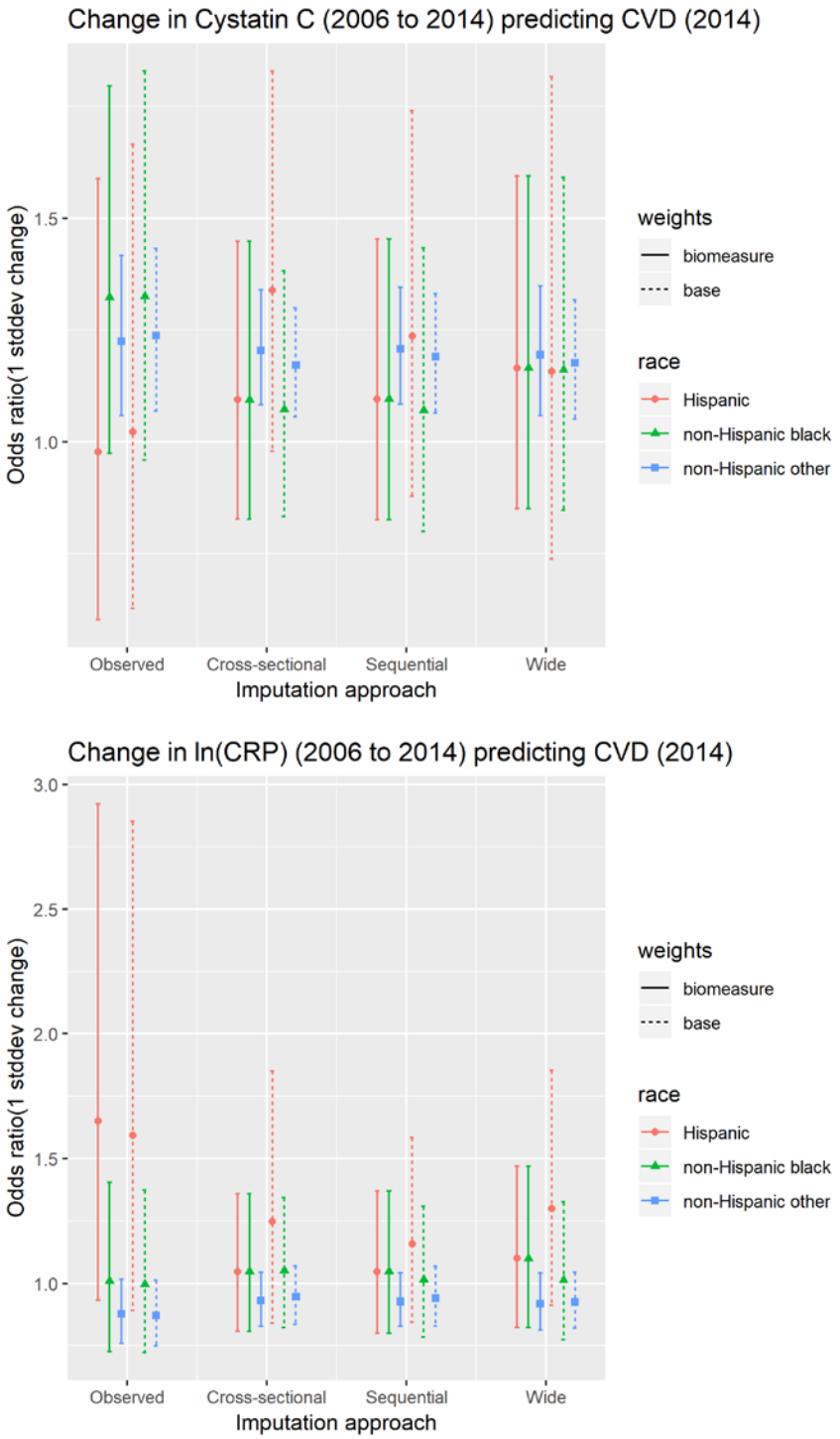

Figure H3-2. Odds ratios of change in Cystatin C and change in ln(CRP) in logistic regression model predicting the development of cardiovascular disease by 2014 by imputation approach, analysis weight, and race/ethnicity. Odds ratio is based on 1 standard deviation change in each biomarker: 1.25 for ln(CRP) and 0.50 for Cystatin C. 95% confidence interval of the odds ratio included.