DETECTING AND ADJUSTING FOR ATTRITION BIAS IN LONGITUDINAL SURVEY PANELS

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by

Veronica L. Roth

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The dissertation of Veronica Roth was reviewed and approved* by the following:

David Johnson
Professor of Sociology, Demography, and Human Development and Family Studies
Dissertation Advisor
Chair of Committee

Paul Amato
Arnold and Bette Hoffman Professor of Family Sociology and Demography

Kurt Johnson
Director of the Survey Research Center

Eric Plutzer
Academic Director, Survey Research Center
Professor of Political Science

Melissa Hardy
Distinguished Professor of Sociology, Demography, and Human Development and Family Studies
Sociology Graduate Officer

*Signatures are on file in the Graduate School
Abstract

The use of panel studies, in which the same people are interviewed at least twice in two different time periods, provides researchers with the ability to explore a multitude of issues. Researchers can explore change over time, better establish temporal order of events, and have the option to use a wide array of models that are only possible with longitudinal survey data (Johnson, 1988; Toon, 2000). With more waves of data, however, comes the potential for more problems in data collection and analysis. Researchers may feel pressured to choose between question consistency and updating surveys for contemporary language or issues (Olsen, 2005).

For my dissertation, I explore how the detection and correction of attrition may be performed after data is collected. Although the prevention of attrition in the collection phase may be ideal, the proliferation of large and widely available datasets from the government and academia means that a considerable amount of research is performed by those without any ability to impact data collection. Given the rise of computing power and the increasing knowledge of multiple imputation and complex statistical models, such as fixed and random effects, today’s researcher may have an increased ability to perform necessary adjustments for the problems that plague panel studies. The central research question for this dissertation is: Given the presence of attrition, and the implications of attrition for biased estimates, what procedures will aid researchers in estimating valid findings?
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Chapter 1

Introduction

The use of panel studies, in which the same people are interviewed at least twice in two different time periods, provides researchers with the ability to explore a multitude of issues. Researchers can explore change over time, better establish temporal order of events, and have the option to use a wide array of models that are only possible with longitudinal survey data (Johnson, 1988; Toon, 2000). With more waves of data, however, comes the potential for more problems in data collection and analysis. Researchers may feel pressured to choose between question consistency and updating surveys for contemporary language or issues (Olsen, 2005). Respondents may experience some form of panel conditioning which may make their responses differ from the population because of the researcher’s intervention (Lazarsfeld, 1940). Respondents also attrite from the survey, and if members with similar characteristics are more likely to attrite, this may introduce bias (Ahern and Le Brocque, 2005; Olson & Witt, 2011). Researchers who rely on longitudinal panel datasets must be able to understand these processes and, whenever possible, adjust for the bias.

In this study, I explore the problems of attrition and panel conditioning in panel datasets. I show how the detection of attrition and panel conditioning may be performed and how the use of refreshment samples may correct for attrition in secondary datasets. Although the prevention of attrition in the collection phase is ideal (Olsen, 2005; Schafer and Graham, 2002), the proliferation of large and widely available datasets from the government and academia means that a considerable amount of research is performed by those without any ability to impact data collection. Given the rise of computing power and the increasing knowledge of multiple imputation and complex statistical models, such as fixed and random effects, today’s researcher
may have an increased ability to better understand the biases in panel studies and to perform necessary adjustments for these problems.

Overview

Chapter 2 - The Problem of Attrition in Panel Studies:

In chapter 2, I explore the impact of attrition as the possible driver of the inconsistent results in trajectories of marital happiness. So long as the mechanisms underlying attrition are uncorrelated to the main research questions, the researcher should be able to use weights to correct for nonrepresentativeness. If the mechanisms of attrition are correlated to the main variables of interest, and certain measures could somehow capture this, weighting or the use of control variables will also be assumed to adjust for differences in the sample. However, it is difficult to be certain the appropriate measures have been included, and just as difficult to be certain that the respondents who leave a study do not differ in key ways from respondents who stay in a study. While nonresponse and attrition may sometimes be random (Olson & Witt, 2011; Singer, 2006), outside of descriptive measures that can be compared to Census estimates or large, nationally representative studies, more intensive analyses and certain assumptions must be made to discern the impact of attrition.

Marital quality is known to be related to attrition bias and may not be adjusted through the use of weights or controlling for demographic variables in a multivariate model (Hill, 1997). Furthermore, the trajectories of marital happiness have been the subject of a long debate in family research (James, 2015; VanLaningham et al, 2001). Using the Marital Instability over the Life Course (MILC) dataset, and the National Longitudinal Survey of Youth 1979 (NLSY) I assess the impact of attrition on estimates of marital happiness. The comparison of these datasets
is helpful given the higher attrition and focus on marital quality in the MILC should make this dataset more vulnerable to selective attrition on measures of marital quality. I then use the refreshment panel collected in the last wave to detect attrition bias. I find that both the MILC and NLSY have higher estimates of marital happiness when compared to respondents from a new cross-section. I also find that trajectories of marital happiness are not biased by attrition in the NLSY, but are biased in the MILC.

Chapter 3-Panel Conditioning

Chapter 3 focuses on detecting the impact of panel conditioning on measures of marital quality. Researchers have long been concerned with the idea that respondents react differently due to interviewer interventions. In 1924, researchers discovered that productivity of workers at the Hawthorne factory increased when participants knew they were being observed (Wickstrom & Bendix, 2000). Social scientists recognized that reactivity could bias experimental results, and this term became known as the Hawthorne effect. Survey studies may also be vulnerable to biases related to reactivity, commonly known as social desirability bias (Krosnick, 1991). Both social desirability bias and reactivity have important implications for the validity of results and are widely applicable to research on human subjects.

Panel conditioning is a related idea, but is more specific in that it relates to repeated observations of respondents in longitudinal surveys. This research is based heavily in psychological paradigms, beginning with Lazarsfield’s (1940) explanation of the mechanisms of time-in-sample bias. Respondents may reflect upon an attitude that was previously unexamined, and change an opinion in the next wave; conversely, they may feel more strongly about an attitude after a survey, leading to more extreme views (see also Fishkin 1997; Goodin &
Niemeyer, 2003). While panel conditioning is explicitly related to longitudinal research, the ways in which respondents react to repeated observations is heavily contextualized, and may be one reason why panel conditioning is more difficult to study when compared to related concepts, such as social desirability bias (Warren & Halpern-Manners, 2012).

For researchers who study marital quality, panel conditioning is an important phenomenon that seems to have received little study in the context of marital research, although there are a couple of notable exceptions. Bussell and colleagues (1995) found that having respondents verbalize their relationships and express feelings can lead to both positive and negative changes in reports about family processes, a bias that researchers may not plan for when conducting their study. Veroff and colleagues (1992) found that respondents who were asked fewer questions in a middle wave of a survey had smaller variances on a marital quality scale, although the differences in variances was alleviated in later waves of the scales, perhaps due to attrition or perhaps due to panel conditioning affecting all respondents as years in the panel accumulated.

Using the MILC, I analyze the reliability and variability of four measures of marital quality. I test for indicators of panel conditioning, including whether there is increasing opinionation in the survey and whether attitudes crystalize and the scales show less variation later in the survey. I also show the reliability of the scales. I find that variation decreases as respondents stay in the survey, controlling for changes in the individual’s means scores on the scales. I find some support for crystallization of attitudes, but no support for increasing opinionation in later waves of the survey.

Chapter 4-Refreshment Imputation
Chapter 4 demonstrates the use of a refreshment sample to adjust imputation estimates of longitudinal panel data subject to attrition. A few papers have found that refreshment panels may be useful, but these articles have tended to rely on short duration panels, which have a new survey every month or every few months (Bailar, 1975; Deng et al, 2013; Hirano et. al, 2001, Guisti & Little, 2011). Researchers have been reticent to use refreshment samples in the imputation as this may lead to a positive bias (Reiter, 2008; Rubin, 1987), although recent research shows that the bias is small, consistent with recent research by Deng and colleagues (2013) and this method of adjustment has many strengths, especially when compared to listwise and weighted models.

Using the General Social Survey, I use two dependent variables, support for gay marriage and self-rated health. Support for gay marriage has been changing in the US in the past decade (Banuach, 2012), while self-rated health is a relatively stable measure at the population level. I perform simulations to assess the ability of the refreshment panel to adjust the imputation, and compare this method to the use of raked and IPW weights as well as a listwise model. All of these models are compared to a true score model to ascertain the bias introduced by attrition and alleviated by the competing methods of adjustment. I find that refreshment panels adjust imputations when analyzing a cross-sectional model from the final wave of a panel dataset, and this is due to improved estimates of standard errors leading to better efficiency, as the b-coefficients were still biased. While I do not find support for improved estimates of either the coefficients or standard errors when using fixed effects analysis, including the refreshment panel data in the imputation was not detrimental and therefore the datasets could be imputed together and used for different analyses, saving the researcher the hassle of imputing the datasets separately.
The goal of this study is to highlight the process of attrition and panel conditioning in the social sciences. I provide a framework for detection using methods that are available to researchers who use longitudinal datasets. I also show how multiple imputation, which is increasingly common in the social sciences (Johnson and Young, 2011) can be combined with new data to help alleviate attrition without any sophisticated knowledge of statistical programming (Deng et al, 2013).
Chapter 2

Assessing the Possibility and Impact of Selective Attrition on Estimates of Marital Happiness

Longitudinal panel datasets allow researchers to study change and life course events with a dataset that helps establish temporal ordering of variables and yields more valid inferences, yet this research also poses a unique set of challenges. One of the most common problems with panel data is the attrition of respondents from the sample. Estimates of change may be biased due to the loss of cases if those who attrite differ from those remaining in the sample. Attrition from the study over time is a common problem for all longitudinal panel studies, although less than a quarter of social science papers attempted any method to correct for attrition (Ahern and Le Brocque, 2005). Research studies that have examined the effect of panel attrition on substantive research findings, such as educational attainment or health, have generally found only modest effects as the characteristics of the respondents that usually lead to attrition are weakly related to the relationship between the substantive variables examined in the models (Falaris & Peters, 1998; Gray et al, 1996; Green et al, 1996). In some cases, however, there is an expectation that the important model variables may be related to the model variables. One such situation is related to research on marital quality. As marriages with lower marital quality are more likely to be disrupted and, perhaps, respondents are unwilling to discuss their marriage, the likelihood of leaving the sample is higher (Hill, 1997). This selective attrition can bias the estimates of how marital quality changes over the course of the marriage.

In this chapter I examine and estimate the impact of attrition on trajectories of marital happiness in two nationally representative multiple wave panel studies. One dataset, the Marital Instability over the Life Course study (MILC), a nationally representative RDD survey, was
developed to measure marital quality and other issues related to families. The other dataset, the National Longitudinal Study of Youth 1979 (NLSY), a nationally representative in-person interview, is primarily focused on labor market and educational issues, although it has a few measures related to marriage, including having the same question on marital happiness that was used in the MILC. Both of these datasets have been used to study marital happiness over the life course, a trajectory that has been the subject of a long debate in family research (VanLaningham et al, 2001). Many cross-sectional studies had concluded there was a U-shaped curve in happiness, yet VanLaningham and colleagues (2001) used 5 waves of the MILC to show a decline model with a fixed effects analysis. More recently, James (2015) found that there are varying trajectories of marital happiness, including a U-shaped curve, using the NLSY and a pattern mixture analysis.

Using both the NLSY and MILC in this study, I will investigate whether attrition bias led to a sample with marital happiness. I use two large, nationally representative datasets to assess the impact of attrition on estimates of marital happiness as well as a refreshment sample. One dataset, the Marital Instability over the Life Course study (MILC), was developed to measure marital quality and other issues related to families. The other dataset, the National Longitudinal Study of Youth 1979 (NLSY), is primarily focused on labor market and educational issues, although it has a few measures related to marriage, including having the same question on marital happiness that was used in the MILC. There are a number of benefits to comparing these datasets. The main benefit of the surveys is the difference in focus. Given prior research on selective attrition for those in lower quality marriages (Hill, 1997), the MILC should be more vulnerable to positive bias of marital happiness, given that there are several questions about marital quality and for respondents in unhappier marriages, it is plausible that the interview
would be unpleasant. For those in the NLSY, who get fewer than 10 questions on marital quality, in addition to marital history, there would be less of a negative reaction to the survey for respondents in poorer quality marriages. Another advantage of these datasets is that they span at least 20 years, which allows an analysis of the same individuals over two decades, which is imperative for a study on individual changes in marital happiness as well as allowing for attrition to make an impact on the results. Finally, the MILC also has a refreshment sample that will allow for comparisons of the two panel studies with a new sample of data for the year 2000, approximately 20 years after the two panels began.

Literature Review

Although attrition is a common occurrence in panel studies, the impact of attrition may not be thoroughly investigated or properly accounted for in research. In their comprehensive study of how social scientists deal with attrition, Ahern and Le Brocque (2005) found that less than a quarter of researchers using a panel acknowledged the possible consequences of attrition or attempted any kind of correction. When attrition is studied, analyses tend to focus on demographic characteristics, such as race, gender, and marital status; generally, attrition is higher among younger, unmarried, non-white, males than females, although there is evidence that these differences are lessening in recent years (Gray et al, 1996; Olson & Witt, 2011). Those who had lived in their residence for less than ten years or lived in urban areas are less likely to be contacted (Gray et al, 1996), and this may be due to residential mobility and youthfulness. Those with fewer years of education or had lower or missing values for income are more likely to refuse (ibid).
Household characteristics have also been linked to attrition. Respondents who have moved recently are at higher risk for attrition (Booth & Johnson, 1986). Separated or divorced individuals tend to be more likely to attrite as well (Lillard & Panis, 1998; Hill, 1997). Employment is also correlated with attrition, ostensibly because individuals who work more have less time to participate. While this had led to lower rates of attrition amongst women, the attrition gender gap has closed in recent years (Olson & Witt, 2011). Employment of women was related to attrition in the NLSY 79 cohort (Aughinbaugh, 2004).

Researchers focus on demographic factors is unsurprising, given the relative ease of identifying departures of the sample from population parameters or, in the specific case of the longitudinal panel, departures from the previous wave. Many demographic characteristics, such as race or gender do not change, while others, such as age, have specific patterns of change (Battaglia et al, 2009; Winship and Radbill, 1994). Even if the researcher cannot be certain of a change, such as with marital status, educational attainment in juvenile populations, or even the mortality of the respondent, there are several surveys as well as Census data that the researcher can use for comparison. For example, while I may not be able to state for certain whether or not someone who leaves a survey has stayed married or divorced, I can use a survey such as the American Community Survey to understand if my sample has a similar proportion of married respondents. Researchers may use this demographic information to create weights to adjust for these departures from the population or the initial sample. Raked weights are created by finding expected proportions for a few variables, such as race and gender, and then using an iterative method to create a weight that will analyze the sample as though there were enough individuals for each category (Battaglia, et al, 2009).
For longitudinal panel data, researchers may use an inverse propensity weight (IPW) which is created from a logistic regression that predicts attrition based on several characteristics, such as race, gender, education, income and household or geographical characteristics. One benefit of the IPW is that researchers can use more variables, as logistic will generate only one probability per case no matter how many variables are used in the equation, whereas raked weights generally benefit from have only a few important demographic variables as they may take more time to converge, although new software programs may make this less time consuming (Battaglia, 2009; Carlson and Williams, 2001).

So long as the mechanisms underlying attrition are uncorrelated to the main research questions, the researcher should be able to use weights to correct for nonrepresentativeness. If the mechanisms of attrition are correlated to the main variables of interest, and certain measures could somehow capture this association, weighting or the use of control variables will also adjust for differences in the sample. However, it is difficult to be certain the appropriate measures have been included, and just as difficult to be certain that the respondents who leave a study do not differ in key ways from respondents who stay in a study. While nonresponse and attrition may sometimes be random (Olson & Witt, 2011; Singer, 2006), outside of descriptive measures that can be compared to Census estimates or large, nationally representative studies, more intensive analyses and certain assumptions must be made to discern the impact of attrition. Particularly problematic for social science researchers is the desire to study attitudes that change over time. While these time varying covariates are essential to a broad understanding of social phenomena, they are often related to several other characteristics and demographic variables may only capture part of this association. While researchers who study attrition have the benefit of prior information for respondents who attrite, they cannot be certain that changes between waves
contribute to attrition. Fixed-effects models can control for all stable traits, whether or not they are observed, thus alleviating some issues of intra-individual unobserved heterogeneity (Allison, 2009; Johnson 1995). When change occurs at different rates between individuals, and this process is not completely observed even for those who respond, the estimation of the impact of attrition may be more difficult to assess (Collins and Graham, 1991). This is due to differences in growth between individuals, which are not captured between waves and are increasingly difficult to adjust for as heterogeneity increases or the correlation of the proxy to the desired outcome decreases (Graham & Collins, 1991). For example, if we observe the link between education and income, but do not measure education or income for individuals in later waves, we will not fully know what this individual’s scores should be for either variable. If we do not even have education in the dataset, nor any other variables that correlate to changes in income, then it will be much more difficult to predict income and we will lose important information in income growth even for those who stay in the panel. While researchers may not be able to recover all information, it is important to assess the extent to which bias exists when using longitudinal panel datasets.

While attrition in general is cause for concern for any panel study, this paper focuses on marital happiness specifically for several reasons. Attrition is higher for those in lower quality marriages, and this has been shown to underestimate the prevalence of divorce (Hill, 1997). Divorce has been linked to lower mental and physical health outcomes for adults (Amato, 2010). Children of divorce have higher rates of anxiety and depression (ibid.) and lower socioeconomic attainment of offspring (Amato and Booth, 1997). Marital happiness is a key part of marital quality, and is crucial in building strong marriages and keeping families together (Johnson et al, 1986). Marital satisfaction is linked to better parenting outcomes as well as better physical and
mental health (Bradbury et al, 2000; Kiecolt-Glaser et al, 1987; Umberson et al, 2005). From a methodological standpoint, estimates of marital happiness have led to different trajectories depending on the type of data and the method of analysis. Marital happiness was generally believed to have a U-shaped curve with a decline in the beginning of the marriage and then increasing in later years, however, this finding was primarily ascertained by using cross-sectional data (VanLaningham et al, 2001). Using the first five waves of the Marital Instability over the Life Course study, however, a fixed-effects model showed an initial sharp decrease with a leveling out of marital happiness in middle years, with a final decline in later years. Furthermore, different cohorts evidenced different trends, with the 1961-1965 and 1971-1975 marital cohorts exhibiting a quadratic function and the other five cohorts exhibiting cubic curves, though these curves are not visually similar. A pattern mixture model analysis of marital happiness in the National Longitudinal Study of Youth 1979 cohort did not reveal an obvious upward trend in marital happiness for longer durations of marriage (James, 2015).

Family researchers have long debated the circumstances of these differing results. Some researchers have focused on life transitions, differing levels of initial happiness, or demographic factors (James, 2015; Umberson, 2005) while others have focused on the use of panel data or cohort explanations (Elder, 1994; VanLaningham et al, 2001). For this study, I test the impact of attrition on the trajectory of marital happiness, as well as the level of reported happiness for the year 2000, by formulating three hypotheses.

Another advantage of studying marital quality and attrition is the availability of rich information over several datasets that can be used to test different hypotheses related to attrition. The Marital Instability over the Life Course study (MILC) and the NLSY span at least 20 years, which allows an analysis of the same individuals over two decades. This is imperative for a study
on individual changes in marital happiness as well as allowing for attrition to make an impact on the results. The MILC is a dataset that contains several questions about marital quality, and should be more sensitive to the attrition of lower quality marriages as people would likely find spending half an hour or more in an interview about an unhappy marriage unpleasant. For the NLSY, the questions were primarily on work and education, therefore, the NLSY should not have the same sensitivity to attrition and marital quality. Finally, the MILC also has a refreshment sample that will allow for comparisons of the two panel studies with a new sample of data for the year 2000, approximately 20 years after the two panels began.

Hypotheses

In order to test the impact of attrition on marital happiness, I developed three hypotheses that focus on the marital happiness trajectories of the Marital Instability over the Life Course dataset. The National Longitudinal Survey of Youth (NLSY) is useful for comparing the trajectories of marital happiness, while the Work and Family Life Survey (WFLS) allows the comparison of a new sample who has not been through attrition to the MILC.

H1: Those in an unhappy marriage should be more likely to attrite from a survey about marriage, such as the MILC, when compared to a survey that has few questions about marriage, such as the NLSY. Therefore, the difference in happiness trajectories between the MILC stayers and the MILC full panel will be larger than the differences between the NLSY stayers and the NLSY full panel fixed effects models.

H2: The happier marriages of those who remain in panel surveys will cause an upturn in the trajectories of marital happiness.
H3: Due to selective attrition, the 2000 estimate of marital happiness will be higher for the MILC and NLSY panels than the WFLS cross-section, net of control variables.

Methods:

One dataset used for this paper is the Marital Instability over the Life Course study. This data set was originally collected in 1980, and had five follow-ups: 1983, 1988, 1992-1994, 1997, and 2000 (Booth, et.al, 2000). The sample is of persons married in 1980, and the first wave sample size is 2,033. The sample was a clustered, random digit dial, and all interviews were conducted over telephone. In addition to being currently married, the sample was also restricted to people who were under 55, and also had spouses under the age of 55. I will also use the companion sample, the Work and Family Life Survey (WFLS) which contains 670 women interviewed in 2000 who would have been eligible for the 1980 wave of the study. I will finally add the comparison sample of 794 women whom are representative of married women in 2000.

The second dataset for this chapter is the National Longitudinal Survey of Youth 1979 (NLSY79). This panel dataset surveyed 12,685 born between 1957-1964, starting in 1979 and ending in 2010 using personal interviews. These surveys ask a variety of questions of respondents, including some measures of marital happiness and conflict. While the NLSY79 has a complete marital history for all respondents until they attrite, marital quality measures were only asked of female respondents in 1988, 1992, and biennially from 2000 to 2010.

The decision to restrict the analysis to women was made out of necessity for the comparison of the two panels, as the NLSY only asked questions on marital quality of female respondents, restricting this analysis to women. There were 4,735 married women in the NLSY.
Since the NLSY began in 1979, but did not ask the first marital quality questions until 1988, the first estimates of marital happiness in the NLSY are subject to attrition.

Table 2-1 shows the number and percentage of women in the NLSY and MILC. Respondents of the NLSY and MILC differ due to the recruitment strategies of the studies, and this has implications for the analysis. As the MILC recruited married respondents, older respondents were either in a higher order marriage or had not experienced a divorce. The NLSY, recruiting only respondents between the ages of 16 and 23 in 1980 have information on the marital transitions of these younger women. Therefore, for respondents over the age of 23, there is a selection effect of marital quality. The NLSY retained 62% of female respondents who began the survey while the MILC retained 51%. The NLSY made attempts to survey respondents who had attrited, especially in the earlier years of the survey although eventually some of these attritors were no longer contacted (Center for Human Resource Research, n.d.), while the MILC study has only monotonic attrition. When considering the eligible participants, retention is still higher in the NLSY throughout the 1980s, however, retention in the MILC is the same or better in the 1990’s and in 2000. The NLSY has a slow drop in participation throughout the survey, while the MILC has a large drop in participation after the first wave, but the decrease slows for later waves.

The MILC only had six waves of interviews, therefore there are two fewer years of observations of marital happiness than found in the NLSY. The MILC only included respondents under 55 years old, resulting in censoring of longer duration marriages. Furthermore, first and second marriages may be left censored in this dataset, as respondents entered the study only after marriage, not before marriage as was the case in the NLSY.
Table 2-1. Sample Sizes of Female Respondents from the National Longitudinal Survey 1979 Cohort (NLSY) Marital Instability over the Life Course (MILC), Work and Family Life Survey Refresher (WFLS-R) and Work and Family Life Survey Cross-section (WFLS-X)

<table>
<thead>
<tr>
<th>Year</th>
<th>NLSY</th>
<th>MILC</th>
<th>WFLS-R</th>
<th>WFLS-X</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>% of Stayers</td>
<td>From Remaining N</td>
<td>From Total N</td>
</tr>
<tr>
<td>1979</td>
<td>6283</td>
<td>100%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>1980</td>
<td>6049</td>
<td>96%</td>
<td>96%</td>
<td>1212</td>
</tr>
<tr>
<td>1981</td>
<td>6064</td>
<td>97%</td>
<td>97%</td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>6035</td>
<td>97%</td>
<td>96%</td>
<td></td>
</tr>
<tr>
<td>1983</td>
<td>6073</td>
<td>97%</td>
<td>97%</td>
<td>957</td>
</tr>
<tr>
<td>1984</td>
<td>6014</td>
<td>96%</td>
<td>96%</td>
<td></td>
</tr>
<tr>
<td>1985</td>
<td>5523</td>
<td>96%</td>
<td>88%</td>
<td></td>
</tr>
<tr>
<td>1986</td>
<td>5418</td>
<td>94%</td>
<td>86%</td>
<td></td>
</tr>
<tr>
<td>1987</td>
<td>5369</td>
<td>93%</td>
<td>85%</td>
<td></td>
</tr>
<tr>
<td>1988</td>
<td>5312</td>
<td>92%</td>
<td>85%</td>
<td>823</td>
</tr>
<tr>
<td>1989</td>
<td>5409</td>
<td>94%</td>
<td>86%</td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>5324</td>
<td>92%</td>
<td>85%</td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>4547</td>
<td>93%</td>
<td>72%</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>4535</td>
<td>92%</td>
<td>72%</td>
<td>753</td>
</tr>
<tr>
<td>1993</td>
<td>4547</td>
<td>93%</td>
<td>72%</td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td>4480</td>
<td>91%</td>
<td>71%</td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>4361</td>
<td>89%</td>
<td>69%</td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td></td>
<td></td>
<td></td>
<td>676</td>
</tr>
<tr>
<td>1998</td>
<td>4299</td>
<td>88%</td>
<td>68%</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>4113</td>
<td>84%</td>
<td>65%</td>
<td>620</td>
</tr>
<tr>
<td>2002</td>
<td>3955</td>
<td>82%</td>
<td>63%</td>
<td></td>
</tr>
<tr>
<td>2004</td>
<td>3984</td>
<td>81%</td>
<td>63%</td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>3916</td>
<td>80%</td>
<td>62%</td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>3975</td>
<td>81%</td>
<td>63%</td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>3896</td>
<td>80%</td>
<td>62%</td>
<td></td>
</tr>
</tbody>
</table>

Note: "a" denotes years in which NLSY respondents received marital happiness questions.

Respondents who had did not answer the marital happiness question even though they had not attrited from the sample and were still married were excluded from the analysis for that wave. This represented approximately 1.9% of the observations in the MILC and 2.2% of the observations in the NLSY, or 2.2% of total observations in this study. The exclusion of such a small percent of the married respondents is not likely to have much impact on the findings (Allison, 2002). Furthermore, excluding imputed cases when the dependent variable is missing
may be a preferable procedure, as simulation studies have found that the inclusion of cases imputed on the dependent variable does not alleviate problems of missingness (VonHipple, 2007).

**Variables:** The dependent variable in this analysis is marital happiness. In MILC, the question was worded “Taking all things together, how would you describe your marriage? Would you say that your marriage is very happy, pretty happy, or not too happy?” In the NLSY, the wording was “Would you say that your marriage is very happy, pretty happy, or not too happy?” In the MILC survey instrument, there were seven questions that measured the level of happiness with certain aspects of the marriage, such as sexual satisfaction or time spent together. To keep the comparison of the surveys as consistent as possible, I only analyzed the single overlapping question that the MILC and NLSY share measuring marital happiness. For this study, marital happiness is coded so that $1=\text{Not too happy}$ $2=\text{Pretty happy}$, $3=\text{Very happy}$.

The main independent variable of interest is the duration of the marriage, which is specified in terms of years. Marital cohort and the period of the interview are also in the model. For the NLSY, the month and year of marriage and interview were available and were coded as century months. For the MILC, the year of marriage was available in the first wave, and when calculating the duration of the marriage, six months were added to the century month variables to estimate the average duration more closely and increase consistency with the NLSY data. In the second through sixth waves, the MILC had both the month and year available, and both were used in calculating marital duration.

In the NLSY, age was asked in the initial wave, and was also calculated into century months for this analysis. For the MILC, age was asked in every wave. As respondents are prone
to rounding or falsifying information on age, this value fluctuated more than expected for some respondents. For this reason, age was averaged over all the waves the respondent participated in, and then recalculated for each wave so the time between waves was consistent with change in age. Family income was first recoded into similar categories (1 = less than $5000, 2 = $5,001 to $9999, 3 = $10,000 to $14,999, 4 = $15,000 to $19,999, 5 = $20,000 to $24,999, 6 = $25,000 to $29,999, 7 = $30,000 to $39,999, 8 = $40,000 to $49,999, 9 = $50,000 to $59,999, 10 = $60,000 or more) and then recoded again into the midpoint value for each category and adjusted for inflation using the Consumer Price Index (Bureau of Labor Statistics, 2015), with a base year of 2000. Finally, for this analysis, the variable was transformed with a logarithmic function. Other demographic variables include education, number of kids and whether or not the respondent was white.

Three analyses are used to describe and assess the impact of attrition. OLS regressions predicting marital happiness are used to compare the MILC and WFLS-R while another regression compares the NLSY and WFLS-X. A logistic regression compares the MILC and NLSY in terms of correlates of attrition in the two samples. Finally, a fixed effects model predicts the changes in marital happiness in the NLSY and MILC for both the available samples and for a sample restricted to those who did not attrite.

For the OLS regressions, the data were multiply imputed using the MI procedure in Stata 13. I used the chained equations specification while imputing, and analyzed the data with the prefix “mi est:” to ensure that Rubin’s rules for standard errors were utilized during the estimation of the models (Rubin, 1996; StataCorp LP, 2009). I imputed 25 datasets and then restricted the analysis of the data to those who had an observed score on the dependent variable, marital happiness. Deleting the cases without observed information for marital happiness should lower the estimates of random error in the model, as these cases cannot add any information
(Von Hippel, 2007). Because the selection of the MILC and the refreshment sample, WFLS-R, are the same, weights were not used in the analysis as the weights would have corrected for attrition and this model is not meant to be generalized, but is a descriptive comparison of the datasets. Due to the different sampling methods of the NLSY and WFLS-X, weights were used in the analysis.

For the logistic regression and the fixed effects model, the data were organized so that each marriage became a case. A person who was only married once during the interview contributed one marriage. A person who had been married twice during the fielding, however, contributed two observations. After the data were stacked by marriages, instead of respondents, the data were reshaped into marriage-years, so that each observation contains one marital year. For respondents who had one or more waves without being married, the intervening waves are dropped from the analysis as the person would not be asked about marital happiness. The logistic regression uses attrition in the next wave as the dependent variable and several demographics and wave of the survey as independent variables and is similar to Lilard and Panis’ approach (pp. 441-443, 1998).

Changes in marital happiness were estimated with fixed effects models. Because the research question concerns panel conditioning, the models were restricted so that those who had not answered the marital happiness question were dropped from the analysis. Although multiple imputation is generally recommended to deal with missing data (Allison, 2001; Johnson & Young, 2011; Schafer & Graham 2006), fixed effects models yield more reliable estimates in the presence of missing data (Allison, 2009).

Results
Descriptive and OLS Regression Analyses for Year 2000 Data

Table 2-2 shows the descriptive analyses of the Marital Instability over the Life Course (MILC) and the Work and Family Life Survey Refresher (WFLS-R) datasets. The WFLS-R was composed of a nationally representative sample of respondents interviewed for the first time in 2000. These respondents would have been eligible for the MILC in 1980 because they reported they were married at that time and were age 18 – 55 in 1980, but were not participants in the original panel. If panel conditioning and attrition do not impact the MILC, then the two datasets should be equivalent. The MILC panel has significantly more white respondents, as 89% of WFLS-R are white, compared to 95% of the MILC respondents. The MILC respondents are significantly older and have been married longer. The MILC had significantly fewer remarried individuals, though the difference was small with 2.6 marriages from the WFLS-R and 2.5 from the MILC panel. Marital happiness, the dependent variable of interest, is also slightly and significantly higher for the MILC, with a mean of 2.6 for the MILC and 2.5 for the WFLS-R.

Table 2-2. Descriptive Statistics for MILC and WFLS- R (2000 Data Only)

<table>
<thead>
<tr>
<th></th>
<th>MILC n=459</th>
<th>WFLS-R n=670</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean/SE</td>
<td>Mean/%SE</td>
</tr>
<tr>
<td>Income (log)</td>
<td>10.8/0.02</td>
<td>10.7/0.02</td>
</tr>
<tr>
<td>Education</td>
<td>14.2/0.11</td>
<td>13.7/0.09</td>
</tr>
<tr>
<td>White</td>
<td>95%/**</td>
<td>89%/**</td>
</tr>
<tr>
<td>Marital Duration (years)</td>
<td>31.7/0.46</td>
<td>29.7/0.52</td>
</tr>
<tr>
<td>Age (years)</td>
<td>54.7/0.39</td>
<td>54.6/0.37</td>
</tr>
<tr>
<td># of kids</td>
<td>2.6/0.05</td>
<td>2.5/0.04</td>
</tr>
<tr>
<td>Marital Happiness</td>
<td>2.6/0.03</td>
<td>2.5/0.02</td>
</tr>
<tr>
<td># of marriages</td>
<td>1.2/0.02</td>
<td>1.3/0.02</td>
</tr>
</tbody>
</table>

*p<.06 **p<.05 ***p<.01 ****p<.001
Note: Significance ascertained by logistic or bivariate regression models
Table 2-3, on the next page, shows OLS regression results for marital happiness. Model 1 shows the significant difference in marital happiness between these two datasets, with the MILC panel respondents reporting about 0.095 (p<0.01) points higher happiness. The effect persists in Model 2, although it drops slightly to 0.09 (p<0.01), when controlling for race, education, income, and other demographics in model 2. This persistence in the significantly greater happiness of the MILC panel respondents offers evidence against the third hypothesis, that the MILC and the WFLS would be comparable. Duration is specified as a quadratic relationship, a common finding in cross-sectional models (Spanier and Lewis, 1980). While the linear term is not significant, there is a significant increase in marital happiness for higher duration marriages (b=0.0002, p<0.05).

Table 2-3. OLS Regression of Martial Happiness: Comparison of MILC to WFLS Refresher (2000 Data Only)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(0.033)</td>
<td></td>
<td>(0.034)</td>
</tr>
<tr>
<td>MILC</td>
<td>0.095</td>
<td>**</td>
<td>0.090</td>
<td>**</td>
</tr>
<tr>
<td>White</td>
<td>0.172</td>
<td></td>
<td>0.098</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.058)</td>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Education</td>
<td>0.008</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (log)</td>
<td>0.059</td>
<td></td>
<td>0.038</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td># of kids</td>
<td>-0.009</td>
<td></td>
<td>-0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td># of marriages</td>
<td>0.038</td>
<td></td>
<td>0.038</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marital Duration (years)</td>
<td>-0.008</td>
<td></td>
<td>-0.008</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marital Duration (sq.)</td>
<td>0.0002</td>
<td>*</td>
<td>0.0002</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.530</td>
<td>***</td>
<td>1.624</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.021)</td>
<td></td>
<td>(0.434)</td>
</tr>
</tbody>
</table>

*p<.05 **p<.01 ***p<.001

Note: Data were imputed using Stata mi (m=25). Standard errors in parentheses
Next I compare the National Longitudinal Study of Youth-1979 (NLSY) and the Work and Family Life Study cross-section (WFLS-X). The WFLS-X has a sample of married people aged 18-55, and after restricting on age and gender, the sample should approximate the NLSY. While the NLSY is impacted by attrition and panel conditioning, like the MILC, this analysis does not provide a comparison on the types of questions asked, as the WFLS-X has the same question structure as the MILC and not the NLSY.

As shown in Table 2-4, there are several significant differences between the NLSY and WFLS-X. The WFLS-X respondents report, on average, 14.2 years of schooling compared to 13.7 in the NLSY (p<0.001). The NLSY also has significantly lower income, which may be due to larger size of the NLSY and great efforts in sample retention that may have helped keep poorer and less educated individuals in the sample. Respondents in the NLSY are significantly older have been married, on average, three years longer, and have more children, which is to be expected given the known associations of these variables to attrition (Olson and Witt, 2011; Booth & Johnson, 1985). Unlike the MILC, the NLSY does not have significantly fewer
marriages when compared to the WFLS-X. Finally, marital happiness reports are significantly though slightly higher for the NLSY, with an average rate of nearly 2.7 for the NLSY and nearly 2.5 for the WFLS-X.

Table 2-5. OLS Regression of Martial Happiness: Comparison of NLSY to WFLS Cross-section for NLSY R's Reporting First Marital Happiness (2000 Data Only) n=2825

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>NLSY</td>
<td>0.154 ***</td>
<td>0.164 ***</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>White</td>
<td>0.085 **</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Income (log)</td>
<td>0.067 **</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td></td>
</tr>
<tr>
<td># of marriages</td>
<td>0.057</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td># of kids</td>
<td>-0.008</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Marital Duration (years)</td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.497 ***</td>
<td>1.570 ***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.243)</td>
</tr>
</tbody>
</table>

*p < .01  **p < .05  ***p < .001
Note: Data were imputed using Stata mi (m=25). Standard errors in parentheses.

Table 2-5, on the next page, shows the OLS regression models for the NLSY and WFLS-X. The difference in marital happiness is unchanged after adding the demographic variables in Model 2. White respondents report their happiness as nearly a hundredth point higher than others, and while slight, this is a significant effect. Income is also positive and significant, with every increase in logged units corresponding to a nearly 0.07 point difference in marital happiness (p < .01). The relationship of happiness to duration is not significantly curvilinear, and this is contrary to several previous studies that use cross-sectional data (Rollins & Feldman,
1970; Spanier and Lewis, 1980). This is likely due to the small variation in marital duration, given the use of the 8 year birth cohort in the NLSY.

The inability of the control variables to attenuate the difference of marital happiness between the two datasets may also be evidence for hypothesis three. The differences in the selection process should be dealt with through the use of the weights. The differences in the questionnaires, however, may also contribute to the differences in the estimates of marital happiness.

Attrition Model of the NLSY and MILC

In order to understand the correlates of attrition, below is a logistic model of the pooled MILC and NLSY datasets. Similar to Lilard and Panis’ approach (pp. 441-443, 1998), each case represents a single wave for each individual. The logistic regression uses attrition in the next wave as the dependent variable and several demographics and wave of the survey as independent variables. Interaction terms for the dataset show whether the NLSY and MILC differ, and in Table 2-6, below, the MILC is the dummy variable used, therefore the NLSY respondents are the reference group.
Table 2-6. Logistic Regression of Attrition  
(N=20,009)

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>MILC</td>
<td>3.13</td>
<td>*** 22.83</td>
</tr>
<tr>
<td>Marital happiness</td>
<td>0.16</td>
<td>* 1.17</td>
</tr>
<tr>
<td>MILC X Marital happiness</td>
<td>-0.26</td>
<td>* 0.77</td>
</tr>
<tr>
<td># of marriages</td>
<td>-0.06</td>
<td>0.94</td>
</tr>
<tr>
<td>R is white</td>
<td>0.39</td>
<td>** 1.47</td>
</tr>
<tr>
<td>MILC X white</td>
<td>-1.49</td>
<td>*** 0.23</td>
</tr>
<tr>
<td># of kids</td>
<td>0.41</td>
<td>*** 1.51</td>
</tr>
<tr>
<td># of kids squared</td>
<td>-0.10</td>
<td>** 0.91</td>
</tr>
<tr>
<td>MILC X # of kids</td>
<td>-0.58</td>
<td>** 0.56</td>
</tr>
<tr>
<td>MILC X # of kids squared</td>
<td>0.14</td>
<td>** 1.15</td>
</tr>
<tr>
<td># of waves</td>
<td>-1.82</td>
<td>*** 0.16</td>
</tr>
<tr>
<td># of waves squared</td>
<td>0.43</td>
<td>*** 1.54</td>
</tr>
<tr>
<td># of waves cubed</td>
<td>-0.04</td>
<td>*** 0.96</td>
</tr>
<tr>
<td>MILC X # of waves</td>
<td>0.06</td>
<td>1.06</td>
</tr>
<tr>
<td>MILC X # of waves squared</td>
<td>0.11</td>
<td>1.11</td>
</tr>
<tr>
<td>MILC X # of waves cubed</td>
<td>-0.03</td>
<td>** 0.97</td>
</tr>
</tbody>
</table>
| Constant                       | -57.29| 0.00 (68.37)

*tp<.06 *p<.05 **p<.01 ***p<.001

Note: Standard errors in parentheses; controlling for education, income, and percentage of answered questions
There are several important differences in the attrition of MILC and NLSY respondents. Figure 2-1 shows the differences in marital happiness rates. There is a significant decline in the probability to attrite for those who are happier in the MILC. The probability of attrition for the least happy MILC respondents is 0.24, and this drops slightly to 0.22. The probability of attrition is lower for the NLSY than the MILC in relation to marital happiness, which is consistent with the first hypothesis. The inverse relationship of attrition and happiness, which is significant, is difficult to explain. The probability of attrition increases from 0.09 for NLSY respondents in happy marriages to 0.12 for those in the happiest marriages.
Figure 2-2 shows the probability of attrition by race, which is coded as a dummy variable for whether or not the respondent is white. In the MILC, nearly 88% of the sample is white, and probability of attrition amongst the few non-white respondents is approximately 0.36, while it is 0.19 for white MILC respondents. In the NLSY there is once again a reversal of trends, with non-white respondents having a slightly lower probability of attrition. This may be because the NLSY dropped an oversample of poor white respondents from the NLSY in 1991 (Center for Human Resource Research, n.d.).
Figure 2-3 shows two U-shaped curves for the number of children and the probability of attrition. For the MILC, the probability of attrition actually decreases from 0 to 2 kids, but then begins to increase. For the NLSY, those with no or more than 4 kids have the least probability of attrition, and those with 2 kids have a higher probability.

![Figure 2-3. Probability of Attrition and Number of Kids by Dataset](image)

Figure 2-4, on the next page, shows the probability of attrition over time. Similar to Table 1, the MILC sees a steep drop in the probability of attrition until the fifth wave, when the MILC matches the NLSY. For the NLSY, only waves in which respondents had been asked a marital happiness question are included in this analysis. Attrition is lower than the MILC, yet still higher in the earlier waves than in the later waves for the NLSY.
In order to assess the impact of attrition and panel conditioning on changes in marital happiness, I estimated fixed effects models for the MILC and NLSY respondents. I also estimated a separate set of models that assess those who never attrited or the stayers. Table 8 shows the results of the fixed effects regressions for all respondents. Marital duration is significantly and negatively related to marital happiness, and the relationship is highly complex as it requires polynomial terms up to a quartic (4th) power. The relationship of duration and happiness is unchanged by the panel conditioning variables. There is also a significant interaction effect with the datasets. As illustrated in Figure 4, after approximately 18 years of marriage, the NLSY respondents experience a secondary sharp decline in marital happiness. The percentage of refusals are not significantly related to marital happiness. The percentage of DK
responses are only significant when interacted with the dataset term (MILC). Figure 5 shows that as the percentage of DK responses increases, marital happiness is predicted to increase in the NLSY while it decreases in the MILC.

On the next page, Table 2-7 shows the fixed effects models for those who completed the surveys. Duration is once again highly complex and significantly quartic. Figure 6 compares the MILC and NLSY stayers. The NLSY stayers have a nearly identical relationship to the total NLSY sample. Education and income are both significantly related to changes in marital happiness for the total sample. Education is not significant for stayers, although the slight increases in the standard error and decrease in the coefficient may be due to sample size. For each increase in logged income, there is approximately a 0.03 increase in changes in marital happiness, which is about 1% of the total possible scale in each wave.
Table 2-7. Fixed Effects Regression of Marital Happiness

<table>
<thead>
<tr>
<th></th>
<th>All Cases (N=5,471; 20,014 Obs.)</th>
<th></th>
<th>Stayers (N=4,009; 17,197 Obs.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td># of kids</td>
<td>-0.01 (0.01)</td>
<td>-0.01 (0.01)</td>
<td>0.00 (0.01)</td>
</tr>
<tr>
<td>Education</td>
<td>0.02 * (0.01)</td>
<td>0.02 (0.01)</td>
<td>0.02 (0.01)</td>
</tr>
<tr>
<td>Income (logged)</td>
<td>0.03 ** (0.01)</td>
<td>0.03 ** (0.01)</td>
<td>0.03 ** (0.01)</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.05 *** (0.01)</td>
<td>-0.07 *** (0.01)</td>
<td>-0.05 *** (0.01)</td>
</tr>
<tr>
<td>Duration squared</td>
<td>0.003 *** (0.001)</td>
<td>0.006 *** (0.001)</td>
<td>0.003 *** (0.001)</td>
</tr>
<tr>
<td>Duration cubed</td>
<td>-0.00009 *** (0.00002)</td>
<td>-0.00023 *** (0.00005)</td>
<td>-0.00009 *** (0.00002)</td>
</tr>
<tr>
<td>Duration quartic</td>
<td>0.000001 *** (0.000002)</td>
<td>0.000003 *** (0.000008)</td>
<td>0.000001 *** (0.000002)</td>
</tr>
<tr>
<td>MILC X Duration</td>
<td>0.02 (0.02)</td>
<td>0.03 (0.02)</td>
<td>0.02 (0.02)</td>
</tr>
<tr>
<td>MILC X Duration squared</td>
<td>-0.003 (0.002)</td>
<td>-0.003 * (0.002)</td>
<td>0.0001 * (0.0006)</td>
</tr>
<tr>
<td>MILC X Duration cubed</td>
<td>0.0001 * (0.00006)</td>
<td>0.0001 * (0.00006)</td>
<td>-0.000002 * (0.000002)</td>
</tr>
<tr>
<td>MILC X Duration quartic</td>
<td>-0.000002 * (0.0000009)</td>
<td>-0.000002 * (0.0000009)</td>
<td>-0.000002 * (0.0000009)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.38 *** (0.18)</td>
<td>2.43 *** (0.18)</td>
<td>2.38 *** (0.19)</td>
</tr>
</tbody>
</table>

*p<.06 *p<.05 **p<.01 ***p<.001

Note: Standard errors in parentheses
Figure 2-5 shows the trajectory of marital happiness over the duration of the marriage. As with past longitudinal studies, there is a sharper drop in happiness in the early years of the marriage, with the decline slowing between 7 to 9 years. There is another slight uptick in the decline around 20 years of marriage. Most notable, however, is the increase in marital happiness. In the NLSY this increase occurs at approximately 28 years of marriage, and there is very little difference between the total sample and the stayers only analysis. For the MILC, the uptick for the stayers begins a decade later, at 38 years of marriage. The uptick for the total sample is very slight, and occurs around year 41.

In Table 2-7, the final quartic term is positive for models 1 and 3. When the interaction is considered, the quartic X MILC term is actually negative, but this is because relative to the
NLSY, the increase occurs later. There is a significant upward curve in marital happiness. For the MILC, those who stay in all waves of the survey do have a higher level of happiness, and the upturn in happiness in the later years of a marriage is more noticeable. The general slope of the decline is generally unchanged when the analysis is restricted to the stayers.

Discussion & Conclusion

In this study, I used several analyses to explore the existence and impact of attrition on marital happiness in the Marital Instability over the Life Course study (MILC). The comparison to the National Longitudinal Survey of Youth shows the trajectories of marital happiness over several decades of marriage. Hypothesis 1 stated that the MILC should have a greater difference between the full sample and the stayers models when compared to the NLSY, and as shown in Figure 2-5, there is evidence for this hypothesis. The use of the fixed effects models allows for a fairly straightforward way to test differences due to attrition (Lilard and Panis, pp. 441-443, 1998) and the use of the NLSY, which has a questionnaire focused on education and occupation, highlights the possibility that the attrition effect may be due to a selection process. Those who stay in the MILC had happier marriages, but those who were in all waves of the NLSY had the same predicted happiness as the full sample.

There was also some support for hypothesis 3, which states that selective attrition would be more likely to yield estimates of higher marital happiness was upheld for the MILC panel when compared to the Work and Family Life Study (WFLS). The WFLS and the MILC have the same questions and are both RDD telephone surveys, and therefore should have similar estimates of marital happiness unless there is some sort of panel effect for the MILC. The increase in happiness for the NLSY is more difficult to explain, and this points out a limitation in the study.
One problem with comparing the NLSY and WFLS is that they have different questions. While having survey questionnaires with different themes is a benefit for comparing the MILC and NLSY, it is a detriment when using the WFLS and NLSY. The WFLS and MILC are also phone interviews, while the NLSY is a personal interview survey, and the differences in modes may have an impact on estimates. Although all surveys feature an interviewer, as opposed to a self-administered survey, phone interviews do yield different results from in-person interviews, with in-person interviews leading to better quality data (Holbrook, et al, 2003). Ideally, a refreshment sample for the NLSY would be used, and that would give a much clearer estimation of panel effects in the NLSY.

Although the MILC had a bias in the level of happiness, the trajectories for the MILC were similar. Hypothesis 2 stated that attrition in the MILC would account for the upward turn in happiness at later durations, but the upward curve is present in both the MILC and MILC stayer analyses, as shown in Figure 2-5. Although the curve for the MILC stayers looks more pronounced, there is a similar curve in the NLSY and NLSY stayers, although the upward curve happens at around 28 years of marriage in the NLSY instead of 38 years in the MILC. Attrition does not appear to impact the trajectory of marital happiness, and so the evidence does not support the second hypothesis.

Marital happiness is an important part of a healthy marriage and something family researchers have spent a great deal of time and effort to better understand (Bradbury et al, 2000). The upturn in marital happiness may not be due to attrition, which is good news for those who have been married for several decades. More research is necessary to show what precipitates this increase in happiness, although a study by James (2015) shows the implications of socio-economic status and cohabitation, amongst other predictors, can distinguish differing patterns of
marital happiness trajectories. Another interesting question raised is why the NLSY respondents experience this increase a decade sooner than MILC respondents. One possible explanation is the cohort differences between the surveys. While the MILC recruited respondents between the ages of 18 and 55 in the 1980, the NLSY recruited people between the ages of 15 and 22 in 1979. I attempted to test similar birth cohorts using the MILC and NLSY, but there are only 115 respondents in the MILC in the same age range as the NLSY, and has led to problems properly estimating models. Another important issue is the problem of error. Analyses not shown in this paper find that the confidence intervals for the predicted values of happiness tend to increase at later durations, and future work should consider whether changes in error, likely due to having fewer cases for higher duration marriages, are problematic, even if attrition is not the culprit.

While this study features a model of marital happiness, given the prior research of selective attrition in this area (Hill, 1997), many of these lessons can and should be applied to other questions. Simply analyzing a full sample model and repeating the analysis with only those who complete the survey is a straightforward way to alert the research to the possibility of bias (Lilar and Panis, 1998). Different variables have different relationships to attrition, and it is incumbent on researchers who use panel datasets to explore the issue in each study. Using different datasets may also shed more light on the impact of the survey itself on respondents, and may give those designing surveys more information on problems that the users of survey data face.
Chapter 3
The Impact of Panel Conditioning on Marital Quality

Longitudinal panel data sets have well established benefits. These studies allow researchers to estimate change over time and help establish temporal order (Johnson, 1988; Toon, 2000). Panel datasets, however, may also introduce bias due to repeated measures. This type of bias is known as panel conditioning, time in sample bias or reactivity, and may introduce bias if respondents recall previous responses that are not reflective of current attitudes or circumstances or, perhaps more likely in attitudinal research, if participating in a study causes deeper reflection of opinions that are no longer representative of the population. While researchers may perceive conditioning to be of concern when remembering information may be more likely, such as in surveys fielded weekly or monthly, panels which are fielded every few years may still be at risk for other types of panel conditioning, such as social desirability bias, opinionation, or deeper reflection on issues. Any of these problems may compromise the generalizability of the results of studies based on panels to the target population.

For researchers who study marital quality, panel conditioning is an important phenomenon that seems to have received little study in the context of marital research (see Veroff et al 1992 or Bussell et al 1995 for exceptions). Marital quality is an important construct in family research, and it has been linked to positive outcomes for children (Amato, 2010), commitment and stability in marriage (Schoebi et al, 2012), long-term recovery for offspring after divorce (Amato et al, 1995), and good communication skills of offspring (Bradbury et al, 2000). A healthy marriage matters not only to the individuals within the family, but is also an institution whose health is important to society (Acs, 2007; Nathan, 2007). While it is important to study the individual changes in marital quality, repeated observations may bias respondents in
ways that impact researcher results. For example, respondents may be less willing to admit to marital problems if they feel they need to impress an interviewer whom they will later speak with, and this may lead to underestimation of marital problems in the population or make it more difficult to understand how marital problems may or may not contribute to marital dissolution or how respondents work through marital problems to keep their marriages intact.

**Literature Review**

Although there are several studies of the effects of panel conditioning on voting behaviors, marketing research and public health issues, there is relatively little research on possible effects in many broader social science fields (Warren & Halpern-Manners, 2012). A great deal of work has been done on the types of questions and the reliability of scales that measure marital quality (Johnson et al, 1986; Karney & Bradbury, 1995). More research is needed to ascertain the validity changes over time of these measures as respondents remain in panel surveys to identify any conditioning biases, although there are two notable exceptions. Bussell and colleagues (1995) found that having respondents verbalize their relationships and express feelings can lead to both positive and negative changes in reports about family processes, a bias that researchers may not plan for when conducting their study. Veroff and colleagues (1992) found that respondents who were asked fewer questions in a middle wave of a survey had smaller variances on a marital quality scale, although the differences in variances was alleviated in later waves of the scales, perhaps due to attrition or perhaps due to panel conditioning affecting all respondents as years in the panel accumulated.

Researchers have long been concerned with the idea that respondents react differently due to interviewer interventions. In 1924, researchers discovered that productivity of workers at the Hawthorne factory increased when participants knew they were being observed (Wickstrom
Social scientists recognized that reactivity could bias experimental results, and this term became known as the Hawthorne effect. Survey studies may also be vulnerable to biases related to reactivity, commonly known as social desirability bias (Krosnick, 1991). Both social desirability bias and reactivity have important implications for the validity of results and are widely applicable to research on human subjects.

Panel conditioning is a related idea, but is more specific in that it relates to repeated observations of respondents in longitudinal surveys. This research is based heavily in psychological paradigms, beginning with Lazarsfield’s (1940) explanation of the mechanisms of time-in-sample bias. Respondents may reflect upon an attitude that was previously unexamined, and change an opinion in the next wave; conversely, they may feel more strongly about an attitude after a survey, leading to more extreme views (see also Fishkin 1997; Goodin & Niemeyer, 2003). While panel conditioning is explicitly related to longitudinal research, the ways in which respondents react to repeated observations is heavily contextualized, and may be one reason why panel conditioning is more difficult to study when compared to related concepts, such as social desirability bias (Warren & Halpern-Manners, 2012).

The type of question is likely to impact its susceptibility to panel conditioning. More difficult factual questions are more sensitive to panel conditioning than simpler questions (Toepoel et al, 2009; Dennis, 2001). Questions that are more likely to evoke social desirability bias may also be prone to conditioning effects. Uhrig (2011) used an experimental design that found women who had previously answered questions on body weight were more likely to report being heavier than women who had not been asked these questions, and men were more likely to admit to having a smaller physique if they had already received questions on their height and weight. In this case, repeated interviews seem to evoke more trust between respondents and
interviewers. Panel conditioning may also elicit the opposite effect, as respondents may also perceive a rapport with an interviewer as reason to give more socially desirable answers, such as higher levels of mental health or a happier marriage (Wooden & Li, 2013). Intelligence is also associated with higher social desirability bias (Cacioppo et al, 1996) and lengthy thought processes may decrease the tendency to make judgments (Jarvis and Petty, 1996; Petty & Cacioppo 1986).

Another possible concern is satisficing, in which respondents give approximate answers instead of making more of an effort to give an optimal answer. While the process of answering a survey question may not seem difficult to a lay person, social psychologists and survey methodologists have considered many steps in this communication and how problems might arise. Tourangeau (1984) outlined four steps that respondents go through to accurately respond to a question. The respondent must interpret the meaning of the question, search their memories for the correct response, integrate that information into a single response and then convey that response in a way that clearly communicates their meaning. By performing each of these steps thoroughly, a respondent has optimized his or her answers. (Krosnick, 1996). Satisficing is a failure to give an optimal response, and generally occurs in two ways, which Krosnick (1996) called weak and strong satisficing. Weak satisficing occurs when the respondent may choose to perform each of the four steps of response, but minimize the amount of effort expended. For example, a respondent may only make the effort to remember the last month or week an activity was performed, but not think of the exact day. Stronger forms of satisficing include failing to give a response or failing to even interpret the question and only giving an answer that may make sense even if it is not accurate.
Satisficing is often associated with the concept of cognitive burden (Krosnick, 1996; Krosnick & Alwin, 1987). Cognitive burden occurs when respondents search for information that the interviewer asked for, and then integrate the information available to them, integrating their knowledge or opinion given their interpretation of a question and the response options (Simon & Stedry 1968). Respondents may give less than optimal answers in order to reduce the amount of cognitive processing if the burden imposed is deemed too great, thereby basing answers on a limited subset of information that is easier for the respondent to access or integrate (Krosnick, 1991).

Satisficing deals more explicitly with cognitive burden, but there has been some research that links panel conditioning and cognitive burden. One aspect of panel conditioning is the problem of respondent memory. This is typically worrisome when respondents are asked the same question over a short period of time, and therefore intervals of longer than a year may help decrease a conditioning effect (Zwane et al, 2011; Veroff et al, 1992). Most studies of panel conditioning rely heavily on surveys fielded monthly or annually (Sturgis, 2009; Warren & Halpern-Manners, 2012), so it is plausible that respondents do remember answers and simply re-use the same answers to decrease their cognitive burden.

Both the crystallization of attitudes and satisficing would have similar evidence, i.e., the respondent’s attitude becomes more similar over time and therefore has a higher test-retest reliability. While satisficing would be derived from a respondent exerting less effort during the survey, crystallization would come about from a respondent becoming more committed to her opinion because she was surveyed in the first place.
Panel conditioning is not only highly contextual, with the manifestation of conditioning highly dependent on the types of questions, but the presence or absence of evidence is also influenced by the ability of researchers to use existing datasets to detect conditioning. Several studies have found that people interviewed about voting intentions are more likely to vote in an upcoming election (Clausen, 1969; Kraut & McConahay, 1973; Traugott & Katosh, 1979; Yalch, 1976), although Mann (2005) found no evidence of panel conditioning on voter behavior using an experimental design with a larger sample. Yan and Copeland (2010) did not find an effect of panel conditioning using the Consumer Expenditure Quarterly Interview Survey, although the researchers were unable to compare the second through fifth waves with the first wave. These inconsistencies in the methods and results of conditioning studies has led researchers to advocate the use of experimental designs in longitudinal surveys (Mann, 2005; Warren & Halpern-Manners, 2012) as well as more theoretically motivated studies of conditioning (Sturgis et al, 2009; Warren & Halpern-Manners, 2012).

For attitudinal researchers, the presence of panel conditioning may be ascertained by looking at whether opinionation increases. Researchers generally look for decreasing rates of don’t know or refusal responses compared to either a new sample in the panel, known as a refresher sample, or perhaps integrating an experimental design which skips respondents in and out of certain questions in different waves. For example, Binswanger and colleagues (2013) used the rate of “don’t know” responses and changes in response ordering to ascertain that those with only a high school education were more sensitive to panel conditioning on certain questions about government spending on the elderly, although this was not true for all questions. Another strategy is to use scale reliability and stability to look for evidence of crystallization of attitudes (Sturgis et al, 2009).
Using “don’t know” responses in conjunction with demographics such as age and education has also been useful in exploring issues of cognitive burden. Using a satisficing framework, “don’t know” responses can be indicative of cognitive burden. Several studies have shown that there is a relationship between cognitive ability and satisficing is the greater propensity for respondents with lower cognitive ability to answer “no opinion” in surveys (see also Bradburn and Sudman 1988; Krosnick et al, 2002; Fowler and Cannell 1996). Not only may respondents be attracted to refusing to answer survey questions, they may also be less likely to participate in the survey itself. Recently, Kaminska and colleagues (2010) demonstrated that the relationship between reluctance to participate and satisficing completely mediated by cognitive ability, which they measured with education, age, interviewer assessment and the number of requests the respondent made for more information about items.

Other studies, however, provide evidence for a more complicated relationship between educational attainment and satisficing. Positively worded items have been shown to have higher averages amongst a higher educated sample and negatively worded items may not be read as carefully (Weems et al, 2003). Knowledge about a particular topic may also be influenced by more than just education. Krosnick & Brannon (1993) found that Americans were more knowledgeable about the Gulf War after increased media coverage, but this occurred at the expense of other issues measured by the National Election Studies. Another possibility is that education may not be as good a proxy variable for cognitive abilities as other items that are more specific to survey research. Using behavior coding from over 400 interviews, Holbrook and colleagues (2006) found that question characteristics, such as length and vocabulary, were related to comprehension, as was cultural references, but not respondent education or age. Furthermore, the respondents’ reading level and question length predicted the ability of
respondents to weigh response options while remembering the question (ibid.) Taken together, these studies indicate that satisficing behaviors are not simply present or absent given educational attainment, but that differences in wording may elicit different response styles depending on an individual’s level of education.

There are also several studies that indicate that “don’t know” responses may be indicative of more thoughtful responses. Older respondents are more likely to give “don’t know” responses than younger respondents (DeMaio, 1980; Young, 2013), although this relationship is sometimes attenuated when education is controlled for (Gergen and Back, 1966). Using an experiment on decision making and uncertainty, Sproten and colleagues (2010) found that older adults without cognitive limitations were more comfortable dealing with ambiguous situations and were also less risk averse than younger adults, although Kurnianingsih and colleagues (2015) found older adults to be less tolerant of risk and ambiguity. Another study by Helson and Wink (1992) found that middle aged women were both more confident and better tolerated ambiguity compared to college students. Aging, therefore, may make respondents more willing to accept uncertainty and to admit to ambiguous feelings, although this may not always be the case. While it is not possible to probe with secondary datasets, researchers who still interviewing respondents may find it useful to probe for more details when respondents give a “don’t know” or another ambiguous response, such as “not applicable”. Seltzer and colleagues (2012) found that younger respondents were more likely to give “don’t know” responses to a series of vignettes about intergenerational co-residence and economic necessity, they also found these respondents also had more concern about quality of family relationships. The “don’t know” responses were given, at least in part, because respondents did not feel they had enough information or the ability to give the opinions necessary for the study.
Hypotheses

The study of marital quality relies on subjective attitudes, such as feelings of happiness or dissatisfaction. Repeated measures would seem likely to lead to greater crystallization of attitudes as well as greater opinionation (Sturgis et al, 2009). Attitudes regarding spousal conflict would be most vulnerable to social desirability, although it is difficult to state a priori if panel conditioning would either lead to more admissions of marital problems or if respondents may exhibit fewer indication of problems to appear to have a better marriage as time in sample increases and, ostensibly, commitment to the survey. In this study, I test for the presence of panel conditioning on a six wave, 20 year panel study of married adults in the United States.

The hypotheses that motivate this study are as follows:

H1: The percentage of don’t know responses and refusals for the same set of survey items will change over time. Decreases in these measures would be evidence of opinionation. Increases in refusals would be consistent with social desirability bias while decreases in don’t know responses may indicate more thoughtfulness.

H2: Consistent with a crystallization effect, I expect that the variability of scales measuring marital happiness and spousal interaction, which measure positive aspects of the marriage, will decrease as time in sample increases.

H3: The variability of scales measuring marital instability, spousal disagreement, and marital problems, which measure negative aspects of the marriage, will change as time in sample increases. Decreases in variation would be consistent with either crystallization or social desirability bias increasing over time.

Methods
The dataset used for this paper is the Marital Instability over the Life Course study. This data set was originally collected in 1980, and had five follow-ups: 1983, 1988, 1992-1994, 1997, and 2000 (Booth, et.al, 2000). The sample is of persons married in 1980, and the first wave sample size is 2,033. The sample was a random digit dial, and all interviews were conducted over telephone. In addition to being currently married, the sample was also restricted to people who were under 55, and also had spouses under the age of 55. There were 986 respondents who completed all six waves of the survey, although 14 of these cases were partial interviews, and were dropped from this study as they had not received most of the attitudinal questions. There were 723 respondents who stayed in all waves and were married to the same person throughout the study, and had never been separated. Since these respondents would have received the attitudinal questions consistently, they are the only cases used in this analysis.

Three types of dependent variables were used to test for a panel conditioning effect. The first two were measures of the frequency of occurrence of don’t know responses and the frequency of occurrence of refusals for the same set of items in each wave. These were used to test for an opinionation effect. The third set of outcomes were a set of measures of inter-item scale variability that were assessed for each respondent at each wave and were used to test for patterns of change consistent with an attitude crystallization conditioning effect. These scale variability measures were created for the five marital quality scales.

Changes in don’t know and refusal rates were estimated with fixed effects models. I use a fixed effects model to capture variation that occurs within individuals. In this approach respondents serve as their own control and stable characteristics that were not explicitly measured will not influence the model (Johnson, 1988; Johnson, 2005). Missing values were imputed for the independent variables in the model. This was done by multiple imputation using
the mi procedures with chained equations in Stata 13 with 25 imputed datasets. (StataCorp LP, 2009).

Assessment of change in scale variance was also conducted with fixed effects models, using a measure of the sum of the absolute deviation of each scale item from the overall mean of the scale for each respondent in each wave. For each respondent, a mean of the scale items was calculated, and then subtracted from each item score. The absolute value was taken of each difference score and these were summed. For example, assume a scale has 10 items with response categories ranging from 1 to 3. A respondent with a mean score of 2 could obtain this by choosing the 2 response for each item. However, a mean of two could also be obtained by a respondent who answer 1 to 5 items and 3 to the other 5 items. The variability score for the first respondent would be 0 as all item responses are consistent with the mean. The second respondent would have a variability of 10 (each item is 1 score away from the mean). Because of possible floor and ceiling effects on the variability score, in all analyses the mean score is included as a control.

By allowing the mean to vary by both wave and individual, and controlling for these changes in the fixed effects models, the relationship of the deviation scores to time should capture only whether the respondent has greater or lesser variation in responding to the items of the scale.

Variables: The frequency of don’t know and of refusals were estimated in a similar manner. These variables were calculated by counting all of the times the respondent provided a “don’t know” or refused response to a survey item. Each of these sums was divided by the total number of variables with either a valid response or a don’t know or refusal. Variables that were
skipped or inapplicable were not included in the denominator. For ease of interpretation, the rates were multiplied by 100 to form percentages. The questions used to calculate these measures were those asked in every wave, and are generally questions from the household roster, questions regarding general health, job satisfaction, and income, as well as the scales. The items used are listed in Appendix 1.

The deviation scores were calculated on the items included in four scales that were available in all waves. Four scales measured various dimensions of marital quality and were central to the theme of the survey. By capturing the positive and negative dimensions, these scales increased the nuance of the analyses of marital attitudes, processes, and the impact of changes on and because of marital quality (Johnson et al, 1986). Both the 11 item marital happiness scale and the 5 item spousal interactions scale measure the positive dimensions of marriage. The 11 item marital problems scale measures whether the respondents or their spouses thought jealousy, moodiness, lack of communication or other matters were problematic in the marriage. The 27 item marital instability scale, also called the divorce proneness scale, assesses how often the respondent had considered divorce or taken steps toward dissolving the marriage, such as thinking about or talking to their spouse about divorce, leaving home or filing for divorce.

The main independent variable of interest is the wave of the survey, and it is coded in years: 1980, 1983, 1988, 1992, 1997 and 2000. For the deviation score models, the mean of the respective scale for each respondent in each wave of the survey is included in the analysis model to control for differences in scale variance that reflect the mean scale score.
Other independent variables are also used to explore other factors related to crystallization of attitudes or to control for other changes over time that might affect change in the variability among scale items. Family income was recoded into similar categories \((1=less\ than\ \$5000,\ 2=\$5,001\ to\ \$9999,\ 3=\$10000\ to\ \$14999,\ 4=\$15000\ to\ \$19999,\ 5=\$20000\ to\ \$24999,\ 6=\$25000\ to\ \$29999,\ 7=\$30000\ to\ \$39999,\ 8=\$40000\ to\ \$49999,\ 9=\$50000\ to\ \$59999,\ 10=\$60000\ or\ more)\) and then recoded again into the midpoint value for each category and adjusted for inflation using the Consumer Price Index (Bureau of Labor Statistics, 2015), with a base year of 2000. The log of this variable was included in the analyses. Another demographic variable included in the model is years of education. For the deviation models, this variable is recoded into an ordinal variable for ease of interpretation \((1=less\ than\ high\ school,\ 2=\ high\ school\ graduate,\ 3=\ some\ college,\ 4=\ 4\ or\ more\ years\ of\ college)\). As age increases in the same intervals as time between waves, the time-varying measure of age cannot be included. In its place, an interaction term with the age of the respondent at the start of the survey (assessed at wave 1) and the wave variable is also included. This interaction term will allow a test of the whether conditioning varies by the respondent age. The respondent’s gender is indicated with a dummy variable \((0=\text{male},\ 1=\text{female})\) and included in the model as an interaction with the wave.

Results

Descriptives

Table 3-1, on the next page, shows the descriptive statistics for the longitudinal measures used in this study. There are two sets of opinionation variables shown. The first set is the percentage of don’t knows, refusals, and answered questions for all items in the survey wave that were repeated in each wave. The items included are those in the household roster, the marital quality scales, income, and a several other attitudinal variables. (A list of the items included can
be found in Appendix A). The second set shows the opinionation rates for the attitudinal questions asked in all waves, omitting, for example, the items in the household roster. There is little difference between the two rates. Respondents generally answered the bulk of the questions, with an average observation having complete information for 99.27% of the variables, and the majority of the missing came from don’t know responses, as opposed to refusals.

Table 3-1. Descriptive statistics for variables used in the analysis models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean or %</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opinionation variables-q's from all waves</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of don't knows</td>
<td>5226</td>
<td>0.60</td>
<td>1.29</td>
<td>0.00</td>
<td>21.43</td>
</tr>
<tr>
<td>Percentage of refusals</td>
<td>5226</td>
<td>0.13</td>
<td>0.81</td>
<td>0.00</td>
<td>16.00</td>
</tr>
<tr>
<td>Percentage of answered q's</td>
<td>5226</td>
<td>99.27</td>
<td>1.59</td>
<td>80.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Opinionation variables- attitudinal q's</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of don't knows</td>
<td>5226</td>
<td>0.54</td>
<td>1.44</td>
<td>0.00</td>
<td>25.00</td>
</tr>
<tr>
<td>Percentage of refusals</td>
<td>5226</td>
<td>0.07</td>
<td>0.66</td>
<td>0.00</td>
<td>16.00</td>
</tr>
<tr>
<td>Percentage of answered q's</td>
<td>5226</td>
<td>99.39</td>
<td>1.64</td>
<td>80.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Demographic variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>5222</td>
<td>14.18</td>
<td>2.75</td>
<td>1.00</td>
<td>28.00</td>
</tr>
<tr>
<td>Age in 1980</td>
<td>5226</td>
<td>36.78</td>
<td>8.93</td>
<td>20.00</td>
<td>57.00</td>
</tr>
<tr>
<td>Family income (logged)</td>
<td>5057</td>
<td>10.86</td>
<td>0.93</td>
<td>20.00</td>
<td>57.00</td>
</tr>
<tr>
<td>Female</td>
<td>5226</td>
<td>64%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White (all other races are reference)</td>
<td>5178</td>
<td>93%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Obs is observations in all waves; data were in long format for this analysis.

The demographic variables in this analysis are education, age, family income, and gender. Due to the lack of variability, as 93% of the sample is white, race is not used in this study. Between lower rates of marriage for African-Americans and higher rates of attrition, this sample is highly racially homogenous, which is a limitation of this study.

Don’t Know Responses

The relationship between time and refusals were analyzed separately from the relationship between time and don’t know responses. There was no relationship between
duration of the study and refusals, therefore only the analysis of don’t know responses is shown.
Table 3-2 shows the results of the don’t know fixed effects analysis. Hypothesis 1 states that increasing opinionation should lead to decreases in don’t know responses and refusals over time.
The fixed effect model in Table 3-2 show the covariates that predict don’t know responses to attitudinal items asked in all six waves. In Model 1, when time, as measured by the wave of the survey, is regressed onto the respondents’ percentage of don’t knows, there is a slight positive relationship (b=0.007, p<0.01). In Model 2 when a gender interaction was added to the model, women were not more likely than men to give don’t know responses as time in the sample progressed.

Table 3-2. Fixed Effects Regression of DK Responses for Attitudinal Items Asked in all Waves (N=871 Respondents, 5,226 Observations)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>0.007</td>
<td>0.004</td>
<td>-0.034</td>
<td>**</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.010)</td>
<td>**</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Wave X female</td>
<td></td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X age</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td>-1.772</td>
<td></td>
<td>17.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.841)</td>
<td></td>
<td>(7.923)</td>
</tr>
<tr>
<td>Wave X education</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Age X education</td>
<td></td>
<td></td>
<td></td>
<td>-0.509</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.203)</td>
<td></td>
</tr>
<tr>
<td>Wave X education X age</td>
<td></td>
<td></td>
<td></td>
<td>0.257</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.102)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-14.032</td>
<td>**</td>
<td>-14.032</td>
<td>**</td>
<td>-14.032</td>
</tr>
</tbody>
</table>

*p<.06  **p<.05  ***p<.01  ****p<.001
Notes: *a The coefficient and standard error have been multiplied by 1000 to show the effect size. Standard errors in parentheses; Imputations done in Stata (m=25)
The effect the interaction of respondent’s age at wave 1 and the duration of the survey was examined in Model 3. The results were significant and show that as the survey progresses, the effect of age increases the percentage of don’t know responses. Education and the interaction of wave with education were added in Model 4 but were not statistically significant. Lastly, in Model 5, the model was estimated including a three-way interaction of wave, education and age. In this model the three-way interaction was statistically significant.

The interaction effect is clarified by graphs of education, age, and time, as plotted in Figures 3-1 and 3-2. Figure 3-1 shows the interaction between time and age as predictors of don’t know responses for high school graduates and Figure 3-2 shows the relationship for college graduates. For respondents with a high school education, the percentage of “don’t know” responses increases with the duration of the survey. Among college educated respondents, however, younger respondents actually gave fewer “don’t know” responses as time in the study increased; the older respondents were predicted to give the most don’t know responses. College educated respondents at the average age in wave 1 (~37 years) had a pattern consistent with average aged high school educated responses.

![Figure 3-1. Percentage of "Don't Know" Responses for High School Graduates](image1)

![Figure 3-2. Percentage of "Don't Know" Responses for College Graduates](image2)
Overall the patterns of effects observed in these models do not appear to be consistent with an opinionation panel conditioning effect. The percentage of “don’t know” responses increases with time in the panel. These results are not entirely consistent with a satisficing explanation. If cognitive burden was an issue, we should see a lower prevalence of “don’t know” responses amongst more educated respondents, but college educated respondents tend to give more “don’t know” responses in the initials years of the survey. Although the increasing rates of “don’t know” responses for the high-school educated respondents could be consistent with respondents answering “don’t know” more frequently to move past questions they do not want to contemplate due to cognitive burden, the increasing rates for older, college educated respondents is more consistent with the idea that age and education make respondents more tolerant of ambiguity and more willing to admit uncertainty. The only group in data to show a slight decrease are college graduates, and even this slope is closer to no effect than to a decline. I find no support for hypothesis 1.

*Analysis of Marital Quality*

Before turning to the analysis of the deviation scales, I present several figures to highlight the trends in reliability and mean scale change for the total survey. Figure 3-3, on the next page, shows the alpha reliability for the scales. Three of the four scales increase during the survey, although spousal interaction experiences a drop by the final wave, with reliability falling close to the estimates of the first three waves. Spousal interaction also had the lowest alpha of the scales, with a reliability of less than 0.7. Marital happiness and marital instability were the most reliable scales, with alphas over 0.8 throughout the survey, and the marital problems scale measured above 0.7, an acceptable score.
Figures 3-4 and 3-5, on the next page, show the means of the scales over time. Marital happiness and spousal interaction decreased in the initial waves. Spousal interaction increased by the fifth wave, while happiness increased in the last wave. The marital problems scale is fairly steady during the first four waves, then declining in the last two. Marital instability increases a great deal between the second and fourth wave before declining somewhat in the last two waves.
The next two hypotheses focus on the detection of any crystallization effect over the course of the panel. To measure crystallization I examine change in the variability of the items in the marital quality. In these analyses, the means are controlled for using curvilinear terms. The curvilinearity is the result of those who give the same answer option for each scale, known as straightlining (Krosnick, 1991), having no variability compared to people who give different responses to the questions in the scale. While controlling for the mean is important in order to capture changes in the score over time, which are assumed to be changes in attitudes in this study, the terms representing the means are not interpreted, as this study focuses on the changes in variation, which after controlling for real change, should be indicative of panel conditioning.

Table 3-3, on the next page, shows the relationships of time, education, and gender to the deviation scores for the spousal interaction and marital happiness scales, respectively. The first model shows the relationship of time to the deviation scores, controlling for the mean value of the scale, and this relationship is graphed in Figure 3-6. For spousal interaction, there is a marginally significant increase in variability for the second wave, followed by a significant
increase. The second model shows the contribution of schooling, treated as a time invariant variable. The interaction with time shows that those with less than a high school education have a relatively linear decrease, while those with a bachelor’s degree actually have a slight increase in variability in the second wave, followed by a slower decrease. Furthermore, a higher education is associated with lower variability, which is contradictory to a satisficing or cognitive demand theory relationship to conditioning. Model 3 shows a slight but significant increase in variability for older respondents (b=0.002, p<.05) for the spousal interaction scale. Men show significantly greater variation in their answers to the spousal interaction scale in earlier waves, but this declines in later waves. For women, the trend is the opposite, with lower variability in later waves but a positive association between time and variability in answering spousal interaction items in later waves.

Table 3-3. Fixed Effects Regression of Deviation Scores for Spousal Interactions (N=722 Respondents, 4,227 Observations)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>0.056</td>
<td>-0.170</td>
<td>0.055</td>
<td>0.133 **</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.096)</td>
<td>(0.030)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Wave squared</td>
<td>-0.030 ***</td>
<td>0.005</td>
<td>-0.030 ***</td>
<td>-0.047 ***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.019)</td>
<td>(0.006)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Wave X education</td>
<td>0.079 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave squared X education</td>
<td>-0.013 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X age (centered)</td>
<td></td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave squared X age (centered)</td>
<td>0.002 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X female</td>
<td></td>
<td></td>
<td>-0.125 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.060)</td>
<td></td>
</tr>
<tr>
<td>Wave squared X female</td>
<td></td>
<td></td>
<td>0.027 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>Scale mean</td>
<td>-0.420</td>
<td>-0.435</td>
<td>-0.199</td>
<td>-0.523</td>
</tr>
<tr>
<td></td>
<td>(4.193)</td>
<td>(4.192)</td>
<td>(4.183)</td>
<td>(4.192)</td>
</tr>
<tr>
<td>Mean (squared)</td>
<td>-0.249</td>
<td>-0.258</td>
<td>-0.386</td>
<td>-0.190</td>
</tr>
<tr>
<td></td>
<td>(2.454)</td>
<td>(2.453)</td>
<td>(2.448)</td>
<td>(2.453)</td>
</tr>
<tr>
<td>Mean (cubic)</td>
<td>0.710</td>
<td>0.716</td>
<td>0.746</td>
<td>0.696</td>
</tr>
</tbody>
</table>

56
For marital happiness, featured in Table 3-4, there is a slight decrease in deviation. Model 1 shows the effect of time on the scale, controlling for mean happiness, and is graphed in Figure 3-7. In Model 2, when education is interacted with time. The interaction between education and time shows that there is a slight decline in deviation for those with a college education, but those who never went to college have a steep decline until the fourth wave, when the deviation flattens and then increases slightly, although is less than the variance for those who went to college. Age and gender are not significantly related to variability.

Table 3-4. Fixed Effects Regression of Deviation Scores for Marital Happiness (N=722 Respondents, 4,227 Observations)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>-0.058</td>
<td>-0.229**</td>
<td>-0.058*</td>
<td>-0.094*</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.079)</td>
<td>(0.025)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Wave squared</td>
<td>0.006</td>
<td>0.034*</td>
<td>0.006</td>
<td>0.014</td>
</tr>
</tbody>
</table>
Table 3-5 shows the results for the deviation analyses of marital problems. As shown in Figure 3-8, on the next page, there is a small increase in variability for the first three waves, and then a decline for the last three waves, both of which are significant in Model 1. There is a very small difference in level of variability by education in the later waves, with more education
respondents having slightly more variability in their scores. The relationship of age and time is slightly more complex, with respondents younger than the mean age of 36.8 there is a slightly bigger increase in variability between the first and third waves, and a larger decrease in variability afterward. Those who are older than the mean age have almost no increase in variability in the first four waves, with a slow decrease in variability for the last two waves.

There is a similar trend by gender, with women having a nearly flat trend in variability in the first three waves, with a slow decrease thereafter, although this is only a marginally significant effect, while men show small but significant increase in the first three waves and a decrease in the last three waves.

Table 3-5. Fixed Effects Regression of Deviation Scores for Marital Problems (N=722 Respondents, 4,227 Observations)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>0.029 ***</td>
<td>0.031</td>
<td>0.029 ***</td>
<td>0.043 ***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.025)</td>
<td>(0.007)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Wave squared</td>
<td>-0.009 ***</td>
<td>-0.010 *</td>
<td>-0.009 ***</td>
<td>-0.012 ***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.005)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Wave X education</td>
<td>-0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave squared X education</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X age (centered)</td>
<td></td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave squared X age (centered)</td>
<td>0.000 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X female</td>
<td></td>
<td></td>
<td>-0.022</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Wave squared X female</td>
<td></td>
<td></td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Scale mean</td>
<td>25.788 ***</td>
<td>25.790 ***</td>
<td>25.785 ***</td>
<td>25.806 ***</td>
</tr>
<tr>
<td></td>
<td>(0.277)</td>
<td>(0.277)</td>
<td>(0.277)</td>
<td>(0.277)</td>
</tr>
<tr>
<td>Mean (squared)</td>
<td>-27.895 ***</td>
<td>-27.911 ***</td>
<td>-27.863 ***</td>
<td>-28.067 ***</td>
</tr>
<tr>
<td></td>
<td>(2.499)</td>
<td>(2.501)</td>
<td>(2.497)</td>
<td>(2.499)</td>
</tr>
<tr>
<td>Mean (cubic)</td>
<td>10.968</td>
<td>11.010</td>
<td>10.750</td>
<td>11.617</td>
</tr>
<tr>
<td></td>
<td>(8.188)</td>
<td>(8.192)</td>
<td>(8.180)</td>
<td>(8.188)</td>
</tr>
<tr>
<td>Mean (quartic)</td>
<td>-20.471</td>
<td>-20.518</td>
<td>-20.025</td>
<td>-21.426</td>
</tr>
<tr>
<td></td>
<td>(10.915)</td>
<td>(10.920)</td>
<td>(10.904)</td>
<td>(10.916)</td>
</tr>
<tr>
<td>Mean (quintic)</td>
<td>11.623 *</td>
<td>11.645 *</td>
<td>11.358 *</td>
<td>12.092 *</td>
</tr>
</tbody>
</table>
Table 3-6 shows the results for the marital instability scale. Deviations are flat between the first two waves, but increase thereafter, controlling only for the mean of the scale, as shown in Model 1, below, and Figure 3-9 on the next page. Education, age, and gender are not significantly related with changes in deviation as time-in-sample increases.

Table 3-6. Fixed Effects Regression of Deviation Scores for Marital Instability (N=722 Respondents, 4,227 Observations)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>-0.013</td>
<td>0.039</td>
<td>-0.013</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.044)</td>
<td>(0.013)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Wave squared</td>
<td>0.010***</td>
<td>-0.002</td>
<td>0.010***</td>
<td>0.010*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Wave X education</td>
<td>-0.018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave squared X education</td>
<td>0.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X age (centered)</td>
<td></td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave squared X age (centered)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wave X female</td>
<td></td>
<td></td>
<td></td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.028)</td>
</tr>
</tbody>
</table>
Wave squared X female

<table>
<thead>
<tr>
<th></th>
<th>Scale mean</th>
<th>Mean (squared)</th>
<th>Mean (cubic)</th>
<th>Mean (quartic)</th>
<th>Mean (quintic)</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>56.128 ***</td>
<td>56.100 ***</td>
<td>56.119 ***</td>
<td>56.126 ***</td>
<td>56.126 ***</td>
<td>56.126 ***</td>
</tr>
<tr>
<td></td>
<td>(0.916)</td>
<td>(0.916)</td>
<td>(0.917)</td>
<td>(0.916)</td>
<td>(0.916)</td>
<td>(0.916)</td>
</tr>
<tr>
<td></td>
<td>-77.228 ***</td>
<td>-77.022 ***</td>
<td>-77.181 ***</td>
<td>-77.213 ***</td>
<td>-77.213 ***</td>
<td>-77.213 ***</td>
</tr>
<tr>
<td></td>
<td>81.238 ***</td>
<td>80.740 ***</td>
<td>81.141 ***</td>
<td>81.210 ***</td>
<td>81.210 ***</td>
<td>81.210 ***</td>
</tr>
<tr>
<td></td>
<td>46.299 ***</td>
<td>46.084 ***</td>
<td>46.268 ***</td>
<td>46.291 ***</td>
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<td>46.291 ***</td>
</tr>
<tr>
<td></td>
<td>-0.161 ***</td>
<td>-0.161 ***</td>
<td>-0.161 ***</td>
<td>-0.161 ***</td>
<td>-0.161 ***</td>
<td>-0.161 ***</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.037)</td>
</tr>
</tbody>
</table>

\[ p < .06 \quad * p < .05 \quad ** p < .01 \quad *** p < .001 \]

Discussion & Conclusion

Hypothesis 1 stated that don’t know and refusal rates would change over the course of the survey. The lack of differentiation in refusal rates is evidence that social desirability bias may not be of concern, but the trend of don’t know responses may be interpreted in one of two ways. It is possible that older respondents in the survey had more difficulty recalling information and this led to increases in don’t know responses even for attitudinal items. For the variability models, only one of the five scales showed a real difference in relation to education. For spousal interaction, a higher education was associated with lower variability. If respondents were simply
giving similar answers to reduce burden, which would be consistent with satisficing and concerns about cognitive burden (Krosnick, 1996), then this trend would be reversed and more scales should have significant associations with education. The second explanation is that respondents may actually have the higher rates of don’t know responses because they are thinking about things more deeply. They may also feel more trust with their interviewer, and were therefore more willing to admit that they do not know the answer to the question.

Hypothesis 2 stated that the variability of scales measuring marital happiness and spousal interaction will decrease, and the models show that there is a general decrease, although there is also a curvilinear relationship in all of the deviation analyses. This decrease would most likely be due to crystallization, given the lack of association with education.

Hypothesis 3 stated that the variability of the marital problems and marital instability scale would also change over time, but no a priori expectation of the type of change was made. For marital problems, the variability decreased over time, which is consistent with either a crystallization effect or a social desirability effect. For marital problems, the mean of the marital problems scale declines in the later waves. Older respondents were more likely to have a decrease in the deviations of the marital problems scale. It is possible that respondents either have fewer problems in a relationship as the duration increases, either by settling issues or accepting issues and letting go of problems. It is also possible that the marital problems scale was uniquely vulnerable to social desirability bias as respondents stayed in the survey and perhaps cared more about interviewer perceptions. If managing interviewer perceptions was the primary goal, however, the increasing variability in marital instability is more difficult to explain. Given the large increase in the mean values of marital instability between the second and third wave, it is possible that respondents became more honest with interviewers about the
steps taken toward separation or divorce. This analysis relied on respondents who stayed in the same marriage and completed the survey, in order to control for remarriage, divorce, or not answering questions in every wave, so the declining means of marital instability and marital problems is not the result of marital dissolution or attrition. Another explanation for the increasing variance in marital instability is that the process of the survey led respondents to reflect on their marital quality more, and this lead to an increase in marital instability. This would be consistent with the findings of Bussell and colleagues (1995).

Panel conditioning is highly contextual, and the results of this study show how different questions have unique vulnerability to different types of conditioning. While marital happiness and spousal interaction seemed to have resulted in crystallization, marital problems and marital instability may have led to reactivity. As a whole, respondents had a slight increase in don’t know responses, which may have been the result of deeper reflection of attitudes or a willingness to admit uncertainty.

While there is evidence of panel conditioning, future work is necessary to determine the impact of the effect. A thorough investigation of the impact of panel conditioning on attitudinal measures would need to include an experiment in which a subset of respondents are not given important scales in select waves so that comparisons could be made to respondents who are given the scale in all waves (Sturgis et al, 2009; Warren & Halpern-Manners, 2012). Another option would be to use refreshment samples with more than one wave and restrict the analysis to those who have not attrited, in order to control for the confounding effect of conditioning and attrition in panels (Warren & Halpern-Manners, 2012), which is a limitation of this study. These options may, however, prove costly for researchers who would either need to collect new observations or introduce missingness on key scales, which is not generally recommended even
with modern methods of imputation (Schafer & Graham, 2002). Another possibility may be to use a planned missing design to skip a number of items in the same scale, as multiple imputation can effectively recover the mean of the scale as long as a few of the items have been answered (Johnson et al, 2011). If enough items are skipped, perhaps all but one or two key items on a small subset of respondents, it may be possible to assess whether or not conditioning exists without sacrificing the ability to draw some inferences on all of the cases.

The impact of panel conditioning on marital quality is an important area of inquiry for family researchers who may introduce some sort of reactivity bias during observation. While definitive proof of panel conditioning tends to require an experiment or new data, it is possible to explore opinionation as well as the reliability and variance of scales using fairly common analyses for longitudinal data. I found that there is some evidence of crystallization of attitudes when it comes to the positive dimensions of marital quality, marital happiness and spousal interaction. Marital stability has been found to increase along with duration (White and Booth, 1991), although researchers have long known that there is some variability in marital quality on any given day (Karney and Bradbury, 2004). Future studies may wish to consider that there is a panel conditioning effect, and that stability of marriages is due to reactivity (Bussell et al, 1995) or perhaps even satisficing (Krosnick, 1996), although I found only evidence for the former in this particular study. Of course, it should also be heartening for researchers that estimates of marital problems and marital instability seem to have trajectories that indicate more honesty of opinions, although an experiment to test this in a current survey would yield more concrete evidence of greater trust or honesty by the respondent. Even if adjustment in the presence of panel conditioning may not be possible for current studies, understanding the prevalence and
severity of the conditioning is beneficial for all studies, and may be especially helpful for those researchers planning to field studies.
Chapter 4
The Utility of Refreshment Samples in Adjusting for Attrition

Longitudinal panel datasets allow researchers to study change and life course events with a dataset that helps establish temporal ordering of variables and yields more valid inferences, yet this research also poses a unique set of challenges. One of the most common problems with panel data is the attrition of respondents from the sample. Estimates of change may be biased due to the loss of cases if they differ from those remaining in the sample. Attrition from the study over time is a common problem for all longitudinal panel studies, although less than a quarter of social science papers attempted any method to correct for attrition (Ahern and Le Brocque, 2005). These researchers either fail to acknowledge attrition or assume that attrition is only problematic if a relatively large amount of respondents are lost, rather than considering the mechanism of missingness (Ahern and Le Brocque, 2005).

Researchers have used several strategies to assess and adjust for possible biases introduced by attrition. A common approach has been to weight the data so that the distributions of a set of characteristics in the sample match those in another, more representative sample such as the Census or the American Community Survey (Battaglia et al, 2009). Weights have proved useful in cross-sectional studies adjusting for differences between a sample and a population due to nonresponse, but may be more problematic when used to adjust longitudinal data for attrition. If the researcher only uses respondents who remained in the sample at all data collection waves then attrition weights may effectively adjust for the attrition effect, although the use of weights can substantially increase standard errors of the estimates. If the researcher uses a method that retains respondents from all the waves, such as pooled-time series fixed or random effects
models (Allison, 2009; Johnson, 1995) then attrition weights would not be useful and would likely increase bias (Young & Johnson 2015).

Another strategy is to impute the data caused by attrition. As multiple imputation becomes increasingly easy to use, researchers have begun to rely on multiple imputation to adjust for item-level missingness (Johnson & Young, 2013). In the case of attrition, when an entire wave is missing for the observation, combining samples to multiply impute missing data may also have merits in order to better adjust the imputation and yield more accurate results in the final statistical analysis. For some, this may mean using a second survey for adjustment (Reiter, 2008; Van Hook et al, 2014). Another strategy found in several panel studies is to field a new sample, called a refreshment sample, which is representative of the same population and is fielded at the same time as the panel wave (Bailar, 1975; Deng et al, 2013; Hausman & Wise, 1979; Hirano et. al, 2001; Guisti & Little, 2011). Recruiting new respondents from the same target population as an existing panel gives the research the ability to judge whether or not estimates from the initial sample are still representative (Lynn, 2009). In some cases, the survey design calls for a rotating panel, in which new panels are drawn, and older panels are eventually retired, although there is overlap between the new and old samples (Lynn, 2009). Prominent examples of refreshment or rotating panels include the Current Population Survey (CPS), the National Educational Longitudinal Survey (NELS), and the General Social Survey (GSS).

The purpose of this study is to test the efficacy of using refreshment panels to adjust for attrition. A few papers have found that refreshment panels may be useful, but these articles have tended to rely on short duration panels, which have a new survey every month or every few months (Bailar, 1975; Deng et al, 2013; Hirano et. al, 2001, Guisti & Little, 2011). Using a simulation study to assess the bias from the true score model, I compares cross-sectional and
fixed effects regression models with two different dependent variables that offer unique challenges, using the same data, the General Social Survey (GSS) 2006-2010.

Literature Review

Given that there are widely used datasets with refreshment samples available, one might expect the use of these samples to test for attrition effects would be of interest in many different studies. Yet, outside of methodological research focused specifically on the usefulness of refreshment panels, there seems to be few mentions of this design. In some cases, researchers may acknowledge attrition and the existence of the refreshment sample, but never explicitly states how the refreshment panel is used to aid in this analysis or what specific steps the researcher took to explore whether mechanisms for attrition were MAR or MNAR in a particular study (Schrapler, 2004; Nelson & Weinberg, 1997). Of course, some researchers do analyze and adjust for attrition. Dahlberg and colleagues (2012) used the Swedish National Election Studies Program, a 2 year rotating panel. They were able to adjust for attrition with an instrumental variable approach analyzing inflows of immigrants under a refugee placement program. In another study Kim (2007) uses the Current Population Survey (CPS) to estimate wage growth assimilation of foreign born workers by using the weighting process proffered by Hirano and colleagues (2001) to account for differing assumptions of the population composition during the first and second measurements. Kim (2007) relies on the refreshment panels in the CPS to estimate individual weights that account for both attrition and migration by matching the refreshment panel respondents to the existing panel. The use of these procedures, however, requires a high degree of statistical proficiency to carry-out or rely on assumptions that the propensity to respond in the refreshment panel is the same as the original panel. While these methods or assumptions are not widely used by social scientists outside of economics, the ability
to use imputation to adjust for missing data is increasing. The use of refreshment panels in
imputation, even without weighting procedures, may have certain advantages in increasing the
efficiency of the standard errors (Deng, 2013) although there is also the potential for inflation of
the errors (Reiter, 2008).

Attrition is a special case of missing data, in which the researcher has some information
on the respondent from one or more interviews, but loses an entire case for at least one wave
when the respondent is not re-interviewed. Data lost through attrition can still be classified by the
same three mechanisms applied to other sources of missing data (Allison, 2001). Data may be
missing completely at random (MCAR), missing at random (MAR), and missing not at random
(MNAR). When data are MCAR, it is almost always because the survey design randomly assigns
questions to some respondents and not others; this is known as a planned missing design or
matrix sampling (Schaefer & Graham, 2002). MAR occurs when a missing value is related to an
observed value in a dataset, which can then be used to adjust for the missingness in multiple
imputation (Allison, 2001; Acock, 2005; Schafer & Graham, 2006). For MNAR, or informative
missingness, both the missing observations and the variables or observations that could adjust for
it are missing from the dataset.

Although many researchers may not explicitly investigate the impact of attrition on the
model of interest, it is possible that there is an attempt to correct for attrition bias through the use
of weights provided with the dataset. These weights usually correct for attrition based on a few
key demographic indicators, usually using Census data, but as joint-distribution tables quickly
become cumbersome with each added variable, a weight released in a public use dataset may not
take into account all of the covariates that adjust for attrition in a MAR framework (Battaglia et
al., 2009). In the GSS, the multi-stage sampling leads to a cross-sectional weight that is based on
a stratification weight that corrects for non-response and therefore deviates slightly from the sampling frame, which is the non-institutionalized population of adults in the United States (Smith et al, 2011). The panels are re-weighted for attrition using a logistic model that takes into account the number of adults in the household, whether or not the respondent was born in the United States, and race, and then uses the inverse of this propensity to respond as the panel weight (ibid.). Adjustment for attrition based on demographic variables may be insufficient to correct for bias, but is relied upon because of the availability of population level data such as the Census or American Community survey, but researchers may not have the ability to assess attrition on time varying covariates (Vandecasteele & Debels, 2007; Ahern & Le Brocque, 2005).

The use of weights has the obvious benefits of providing a check on the representativeness and quality of the sample, without requiring a high degree of statistical theory to use this correction. There are, unfortunately, several problems that limit the ability of weights to effectively correct attrition bias. Constructing weights from variables that change over time, such as attitudinal variables in a longitudinal context, may introduce untestable assumptions (Graham & Collins, 1991). This issue results from unobserved heterogeneity in change, in which the mechanism that differentiates rates of change in time varying covariates is missing from the panel (ibid.). This biases both point estimates from later waves of panels, or between person differences, as well as the estimates of change, or within individual effects.

Unobserved heterogeneity is also problematic with another method for dealing with attrition, the use of fixed-effects models. With fixed effects models, any stable trait will be excluded from the model, and each individual serves as his or her own control in the analysis of
change (Allison, 2009; Johnson, 1995). While stable traits are unaffected by missingness in fixed effects models, spurious effects due to time-varying covariates are still problematic.

**The Utility of Refreshment Samples**

Refreshment samples provide both an increased number of observations for researchers to recover lost statistical power, and provide the researcher with a comparison group to evaluate bias not just on demographic variables, but on attitudinal and other variables specific to the initial panel’s questionnaire. It is possible that the researcher may find that bias is not evident on these measures and that attrition could be treated as MAR, in which case a simple comparison offers researchers a great deal of confidence in moving ahead with analyses of panel studies subject to attrition.

The idea that refreshment samples may be useful in adjusting for attrition dates back to the 1970’s. Hausman and Wise (1979) used a probit model to create a variable to correct for attrition in a study of income disparities due to race in the Gary Income Maintenance Experiment. This technique is similar to the two-step Heckman adjustment. The Hausman and Wise model underestimates the impact of attrition on time varying covariates, and also suffers from multi-collinearity problems due the overlapping of independent variables in both the probit and substantive model (Ridder, 1992), although time constant covariates are not biased (see also Beckett et al 1988 and Nijman & Verbeek, 1990).

Statisticians have combined weighting strategies with imputation to decrease the bias of attrition. Hirano and colleagues (2001) provide a framework for the Additive Non-ignorable (AN) model using two-wave panel data by developing inverse propensity weights on marginal distributions of a refreshment panel, and subsequently imputing the data based on this joint
distribution, which allows for unbiased estimates if the MAR assumption holds (see also Deng et al, 2013). This model has been extended to three wave panels (Tunali et al, 2012).

Another option that may be more accessible to applied researchers in the social sciences is the use of the refreshment sample to inform the imputation. Some researchers may rely on the presence of the refreshment sample to correct for attrition by simply adding in the new observations to the analysis or by imputing and analyzing the original panel and the refreshment sample together (e.g., Van Wissen and Meurs, 1989; Heeringa, 1997; Thompson et al., 2006). This may lead to bias if, for example, the mechanism for attrition is related to a time varying measure that a refreshment cross-section may not capture and is not recommended (Deng, 2013; Reiter, 2008) More frequently, the refreshment sample is included in the imputation only, but not in the estimation of the models. This is called the P-only model, and may lead to positive bias in the variance estimator, such as the standard errors for regression models, as the imputation is conditioned on all of the cases (Reiter, 2008; Rubin, 1987). More recent research has found that, while there was a positive bias on a model predicting campaign interest, the bias was relatively small (Deng, 2013; Guisti & Little, 2011).

In this paper, I will present a framework for the use of multiple imputation, a procedure now commonly used amongst a wider range of social scientists to deal with missing data, in conjunction with refreshment samples to both identify and adjust for attrition in longitudinal panels subject to attrition. I compare how using the refreshment sample to either construct weights or to use in an imputation may adjust for attrition by using a simulation study. The main dataset for analysis is the General Social Survey 2006 panel, which has observations from 2006, 2008, and 2010. I use the General Social Survey 2008 panel, with observations in 2008 and 2010, as well as the 2010 General Social Survey as refreshment samples. I use six strategies: the
listwise model, raked weight model, inverse-propensity weight (IPW) model, the imputation of the three waves of the GSS 2006 panel without the refreshment samples, the imputation of the GSS 2006 panel with the first two waves of the GSS 2008 panel, and a final imputation with the GSS 2006 panel, the 2008 panel, and the 2010 cross-section. The last two strategies are both variations on the P-only model, as the refreshment sample is included in the imputation but only the panel is used in the analysis model. I compare the b-coefficients and standard errors of both an OLS regression of 2010 variables from the 2006 panel as well as a fixed effects model of the 2006 panel using all three available waves of data. I show that, while there is a positive bias in the standard errors, they are often comparable to or an improvement upon the listwise model and imputation with the refreshment panel generally improves upon the weighted models.

Methods

The dataset used for this analysis is the General Social Survey (GSS). Although this survey has been a cross-sectional design since its introduction in 1976, it is currently a rotating panel design, as illustrated in Figure 4-1. Beginning in 2006, the GSS launched a longitudinal design and 2,000 respondents were selected for re-interview. Of the respondents selected, nearly 77% were successfully re-interviewed in 2008, and nearly 64% of the first wave respondents were still in the sample by the third wave. Those who left the sample in 2008 and 2010 are attritors, while those who remain in the sample for re-interview are called stayers. In 2008, the GSS interviewed an additional 2,023 individuals, who were then re-interviewed in 2010 and 2012. The GSS design calls for each panel to be followed for three waves with no further follow-up.
In order to compare different weighting and imputation strategies, I selected two substantive dependent variables to evaluate—support for gay marriage and self-rated health. Support for gay marriage is notable for having shown increasing levels of support from 2006 to 2010 (Baunauch, 2012). As support for marriage equality is strongest amongst younger persons (ibid.) who are also more likely to attrite (Olson & Witt, 2011), failure to correct for attrition may yield estimates too low to appropriately assess the rise in support. Self-rated health was selected as it is a variable that has been found to be correlated with attrition (Goldberg et al, 2006; Gray et al, 1996).

Figures 4-2 and 4-3, below, illustrates this issue. Figure 4-2 shows the support for gay marriage for the 2006 panel, which generally decreases by age yet increases from 2006 to 2010. When two new sets of respondents, one from 2008 and another set from 2010 are combined,
however, there is small upward shift in the average support for gay marriage. Self-rated health, shown in Figure 4-3, has the same general trends for each age group with and without the refreshment panel, although there is a slight upward bias in the 2006 panel by the final wave, perhaps due to those with serious illnesses refusing the survey or possibly due to death. When the researcher does not have reason to believe the dependent variable should change in the population, we should also expect that refreshment samples will give us more leverage in adjusting for attrition.

Figure 4-2. Average Support for Gay Marriage by Age and GSS Panel.

Figure 4-3. Average Self-rated Health by Age and GSS Panel.
Variables: As shown in Table 4-1, several variables were used in this analysis, and the two dependent variables do not share all of the same predictors. The item measuring support for gay marriage is identical in the three waves and worded: “Do you agree or disagree? Homosexual couples should have the right to marry one another.” The variable is coded so that 1=strongly agree, 2=agree, 3=neither agree nor disagree, 4=disagree, 5=disagree. Self-rated health, also identical in each wave is worded: “Would you say that in general your health is excellent, very good, good, fair, or poor?” The response categories are coded 1=poor, 2=fair, 3=good, 4=excellent.

Table 4-1. Variables in the Analyses by Dependent Variable and Method (OLS Regression or Fixed Effects)

<table>
<thead>
<tr>
<th></th>
<th>Self-Rated Health</th>
<th>Support for Gay Marriage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS Regression</td>
<td>Fixed Effects</td>
</tr>
<tr>
<td>Happiness</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Satisfied with finances</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Political Views</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Religiosity</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Tolerance of Homosexuals</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Age squared</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Other race</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Income (log)</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Never married</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Divorced/widowed/separated</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Wave</td>
<td>X</td>
<td></td>
</tr>
</tbody>
</table>

I selected a set of time varying and time invariant predictors to include in the regression models. Two time varying attitudes predicted self-rated health, happiness and satisfaction with finances. Happiness was ascertained from the question “Taken all together, how would you say
things are these days—would you say that you are very happy, pretty happy, or not too happy?” and this variable was coded so that 1=not too happy, 2=pretty happy, 3=very happy. For satisfaction with finances, the question was worded: “We are interest in how people are getting along financially these days. So far as you and your family are concerned, would you say that you are pretty well satisfied with your financial situation, more or less satisfied, or not satisfied at all?” The variable was coded so that 1=not satisfied at all, 2=more or less satisfied, 3=pretty well satisfied.

The self-rated health model also includes marital status, with one dummy variable measuring whether or not the respondent in the current wave has never married and another measuring whether or not the respondent is divorced, widowed, or separated. Married individuals are the omitted group.

I used three attitudinal variables to predict support for gay marriage. Political views are coded from the question “We hear a lot of talk these days about liberals and conservatives. I’m going to show you a seven-point scale on which the political views that people might hold are arranged from extremely liberal--point 1--to extremely conservative--point 7. Where would you place yourself on this scale?” and is coded so that 1=extremely liberal, 7=extremely conservative. A religiosity scale was constructed from nine items: attendance of religious services (0=never, 8=several times per week), biblical literalism (1=actual word, 3=ancient book), degree of fundamentalism of respondents religion (1=fundamentalism, 3=liberal), belief in God (1= no belief in God, 6=no doubts about God’s existence), frequency of prayer (1=several times a day, 6= never) whether or not the respondent approves of the laws disallowing prayer in school, whether or not the respondent believes in life after death, whether or not the respondent is born again, and whether or not the respondent has ever tried to
encourage belief in Jesus Christ. Where necessary, items were recoded so that numerically higher responses indicated greater religiosity and the scale was standardized due to the different variances of the measures. These items had an alpha of 0.8305 in the true model and all waves and panels combined. When estimated separately, the alphas ranged from 0.8267 to 0.8430.

A second scale measuring social distance from homosexuals was constructed from three dichotomous items. All items start with the prompt “And what about a man who admits that he is a homosexual?” and then ask whether or not the man should be allowed to teach college, make a speech in the respondent’s community, and whether or not he should have a book about the favorability of homosexuality in the respondent’s public library. These items had an alpha of 0.7242 in the true model and all waves and panels combined. When estimated separately, the alphas ranged from 0.6596 to 0.7442.

Education and family income are in all models. Education is measured in years of schooling. Yearly personal income is coded: 1= less than $1000, 2= $1000 to $2999, 3= $3000 to $3999, 4= $4000 to $4999, 5= $5000 to $5999, 6= $6000 to $6999, 7= $7000 to $7999, 8= $8000 to $9999, 9= $10000 to $12499, 10= $12500 to $14999, 11= $15000 to $17499, 12= $17500 to $19999, 13= $20000 to $22499, 14= $22500 to $24999, 15= $25000 to $29999, 16= $30000 to $34999, 17= $35000 to $39999, 18= $40000 to $49999, 19= $50000 to $59999, 20= $60000 to $74999, 21= $75000 to $89999, 22= $90000 to $109999, 23= $110000 to $129999, 24= $130000 to $149999, 25= $150000 or more. For the analysis models, income was recoded into the dollar amounts at the midpoint of each category and transformed to the log of income.

The cross sectional models also include race and gender, as they are important time invariant characteristics. Gender was coded so that men were the reference group to females. For
race, white served as the reference category and separate dummy variables were entered into the model for African American, non-white Hispanics, and those of another race. For the cross-sectional model of support for gay marriage, dummy variables were also used to include religious affiliation, with Protestants as the reference group and Catholics, the non-religious, and those of another religion as dummy variables.

Simulation Strategy

In order to assess the bias introduced by attrition, and the efficacy of the imputation and weighting strategies, I used a simulation. Figure 4-4 shows the major steps of the simulation, and the bulk of the code is included in Appendix C\(^1\). The simulation strategy, allows for the creation of a true score dataset, in which all cases have a plausible value for each variable. I also simulate attrition through a multiple step process and create 500 datasets to compare methods for adjusting attrition.

In the following sections I explain the simulation in more detail, but I first offer an overview, as shown in Figure 4-5. The first three steps of the simulation form the datasets that will be the basis for the simulation. Steps 4 through 6 focus on the three different multiple imputation strategies used, in steps 7 through 10 the estimates of the OLS regression models are created and saved, and in steps 11 through 14 the estimates from the fixed effects models are created and saved. In step 15, the estimates from the OLS regression are combined and analyzed, and the fixed effects models are compared in step 16. Steps 4 through 16 are repeated for each dependent variable.

---

\(^1\) The code pertinent to the simulation has been provided; the code to clean the datasets is available upon request.
Figure 4-5 Flowchart of simulation

Step 1: Singly impute item and unit missingness. & drop the original dataset, keeping the single imputation with no missingness.

Step 2: Create propensity to attrite for 2008 and 2010. Generate the inverse propensity weight.

Step 3: Create true score variables. Set the original variables to missing if the propensity to attrite is greater than a randomly generated number. Generate the raked weight.

Step 4: Multiply impute only the 2006 panel, using all waves in a wide format.

Step 5: Multiply impute the 2006 and 2008 panels, using all waves in a wide format.

Step 6: Multiply impute all GSS panels, using all waves in a wide format.

Step 7: Run true score, listwise, IPW and raked weight OLS models.

Step 8: Run OLS imputation models.

Step 9: Run OLS 2008 imputation models.

Step 10: Run OLS imputation all models.

Step 11: Run true score, listwise, IPW and raked weight fixed effects.

Step 12: Run fixed effects imputation models.

Step 13: Run fixed effects 2008 imputation models.

Step 14: Run fixed effects imputation all models.

Step 15: Combine estimates of the OLS models and analyze results

Step 16: Combine estimates of the fixed effects models and analyze results

Repeat steps 3-16 500 times

Repeat steps 7-16 for each dependent
Simulation Strategy: Preparing the Datasets

The first three steps of the simulation prepare and create the initial 500 datasets that form the basis of the comparison of methods of adjusting for attrition. The first step is the single imputation to create a complete dataset that had neither item nor unit missingness. Imputing the item missingness isolates the attrition effect when comparing the different strategies to correct for missingness. For example, if item missingness existed on income, which is common, then the listwise model would have been biased by both the attrition and the item missingness for income, while the imputation model would allow for the cases with item missingness to be estimated. Another option would be to drop all of the cases with item missingness, and while this would ensure that all the data used for the true score model would be observed values from respondents, from a practical standpoint, this would mean a large decrease in sample size and statistical power. The 2006 panel would have had 318 respondents before simulated attrition was introduced, as opposed to the 1,604 cases that were ultimately used for the 2006 panel. While single imputation is generally an unacceptable model for handling missingness, the problem of having biased standard errors is not a problem in this study, as the single imputation was only meant to fill in the dataset for the simulation. Therefore, estimates from this study should only be used for inferences of the validity of using refreshment panels in missing data, and should not be used to make claims about the substantive relationships of the independent variables to the dependent variables.

I imputed each panel separately, so the 2006 panel was imputed in wide format, using variables from 2006, 2008, and 2010. The 2008 panel was imputed using variables from 2008 and 2010. The 2010 panel was imputed using only the 2010 data. When data are imputed, plausible values are used to fill in for missing values (Allison, 2001). The plausible values are
drawn from the distribution of the observed values for the variable, and conditioned on the predictors the researcher includes in the imputation model. Imputing the datasets separately at this stage of the simulation means that, if the distributions of the variables differ between the panels, the initial dataset is not influenced by differences in the distributions of the datasets.

These three panels were then combined into a single dataset. The original dataset, which contains item and unit missingness is dropped and the single imputation dataset then becomes the source for the true score model. Because the true score model contains values for all variables, it is possible to compare how accurate the methods are at correcting for attrition by comparing the models estimated with different techniques to correct for attrition to what the models should estimate had all data been present.

Since the single imputation gets rid of all missingness, I have to simulate attrition or unit missingness. In step 2, I used logistic regression to estimate the propensity for attrition (see Figure 1, page 9 for the number of attritors in the GSS). Independent variables for the logistic are age, gender, race, marital status, region, education, logged income, the number of hours worked, whether or not the respondent lived in a metropolitan area, whether or not the respondent owned their own home, respondent health, the number of adults, infants, teens and children in the home, the respondent’s political views, their religiosity, and the social distance scale for homosexuals. The model also included the length of the interview and the experience of the interviewer, measured in years. Most of these variables, especially the demographic measures, are known correlates of attrition (Booth and Johnson, Olson and Witt 2011). Other variables, such as political views, religiosity, and the social distance scale were included to ensure that any relationship between these independent variables and attrition would be captured, although these variables were not significantly related to attrition. The same variables were used to predict
attrition for three separate scenarios: the attrition of the 2006 panel respondents in 2008, the attrition of the 2006 panel respondents in 2010, and the attrition of the 2008 panel respondents in 2010. I also create the inverse propensity weight (IPW) at this stage by dividing 1 by the propensity to attrite created in step three. This means that every case has the same IPW in every dataset, although the weight itself will vary depending on who stays in the sample.

Once the propensity to attrite was estimated, I moved on to the third step of the simulation by dropping the attritors from the model and used only cases that had responded in all applicable waves. If the original attritors are not dropped, the simulation tends to drop the same number and set of cases, given that these cases have a higher likelihood to attrite. The remaining cases are then copied into variables that are labelled as true score variables.

At this point, the simulation generates a random number and those with an attrition propensity value greater than the random number are set to missing at the applicable wave. This process repeated 500 times. All datasets contain the true score variables as well as the variables with simulated attrition that need to be adjusted. I also create the raked weight. The raked weights were constructed with the ipfweight command in Stata 13 by using the 2010 only cross-section as the marginals that the 2006 and 2008 panels should have if the variables included in the raking algorithm were not biased by attrition. The weight constructed took into account demographic information from the education, race, gender and age variables. Education and age were collapsed into categories in order to ensure convergence of the command (Battaglia, 2009). Educational attainment was recoded so that the categories would reflect less than 12 years of school, 12 years of schooling, 13 to 15 years of schooling, 16 years of schooling, and 17 or more years of schooling. Age was collapsed into four categories: 18-30, 31-50, 51-70, and 71-89.
Table 4-2 highlights the methods for handling missingness and addressed the important steps in the simulation for each model. At this point in the simulation, the true score variables are created, as well as the variables that will be used to test the listwise, weighted and imputed methods for handling missingness. The weight for the IPW model is also created.

Table 4-2. Types missing data and method of handling missingness

<table>
<thead>
<tr>
<th>Attrition (Unit Missingness)</th>
<th>Method of Handling Missing Data</th>
<th>Important Simulation Steps:</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>No</td>
<td>3: True score variables generated</td>
</tr>
<tr>
<td></td>
<td>N/A</td>
<td>7: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>11: Fixed effects models generated</td>
</tr>
<tr>
<td>Listwise</td>
<td>Yes</td>
<td>3: Attrition is introduced</td>
</tr>
<tr>
<td></td>
<td>Complete Case Analysis</td>
<td>7: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>11: Fixed effects models generated</td>
</tr>
<tr>
<td>IPW</td>
<td>Yes</td>
<td>2: inverse propensity weight created</td>
</tr>
<tr>
<td></td>
<td>Logistic regression used to estimate propensity of response; inverse propensity is a weight.</td>
<td>3: Attrition is introduced</td>
</tr>
<tr>
<td></td>
<td></td>
<td>7: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>11: Fixed effects models generated</td>
</tr>
<tr>
<td>Rake Weight</td>
<td>Yes</td>
<td>3: Attrition is introduced</td>
</tr>
<tr>
<td></td>
<td>Raking algorithm from Stata .ado used to create a weight.</td>
<td>3: Raked weight created for each simulated dataset</td>
</tr>
<tr>
<td></td>
<td></td>
<td>7: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>11: Fixed effects models generated</td>
</tr>
<tr>
<td>Imputation</td>
<td>Yes</td>
<td>3: Attrition is introduced</td>
</tr>
<tr>
<td></td>
<td>Multiple imputation the 2006 panel</td>
<td>4: Imputation of 2006 panel only</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>12: Fixed effects models generated</td>
</tr>
<tr>
<td>Imputation 2008</td>
<td>Yes</td>
<td>3: Attrition is introduced</td>
</tr>
<tr>
<td></td>
<td>Multiple imputation of the 2006 panel and the 2008 panel</td>
<td>9: Imputation of 2006 &amp; 2008 datasets simultaneously</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>13: Fixed effects models generated</td>
</tr>
<tr>
<td>Imputation all</td>
<td>Yes</td>
<td>3: Attrition is introduced</td>
</tr>
<tr>
<td></td>
<td>Multiple imputation of all three GSS panels</td>
<td>6: Imputation f all GSS panels</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10: OLS models generated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>14: Fixed effects models generated</td>
</tr>
</tbody>
</table>
Simulation Strategy: Multiple Imputation Strategy

The first three steps of the simulation focus on setting up the basic datasets and creating attrition. In each of these 500 datasets, the major difference is the cases that are made into attritors. In the next three steps, steps 4 through 6, the simulation I construct a method for dealing with attrition that will differ for each of the 500 datasets.

I employed three imputation strategies. In the first strategy, which is created in step 4 of the simulation, only the original panel is used for the imputation of variables, with attitudinal and demographic variables from all three waves included. In the second strategy, which is created in step 5, the 2008 panel is used in the imputation, but not in the analysis. The 2008 panel acts as a refreshment sample with two waves in this study. I deleted the 2008 attritors before the imputation. This allows me to compare the stayers of the 2006 panel to the stayers of the 2008 panel, which may help control for unknown correlates of attrition unless a different mechanism caused attrition in the two different panels. While not a foolproof strategy, it does offer some leverage over the problem of unobserved heterogeneity of change and attrition.

In the third strategy, which is created in step 6 of the simulation, the 2008 and 2010 samples are used for the imputation. The 2008 panel has observations for both 2008 and 2010, while the 2010 panel is really more of a cross-section in this analysis, as the 2010 panel contributes only observations from the 2010 wave of interviews. I imputed 30 datasets using Stata 13’s MI procedure with the chained option (StataCorp LP, 2009). Beginning with Stata 12, the mi procedure had the option to use the imputation of chained regression equations, which requires fewer assumptions about the pattern of missing information than monotonic equations (Royston, 2005). I imputed in a wide data structure, meaning that a respondent with multiple
years of available data had all variables arranged in a single row in the dataset. Although panel
data is often analyzed in a long format or person-year data structure, this does not allow MI to
capture the correlation of the respondent’s answers in multiple years, and also violates the
independent random samples assumption (Allison, 2001; Berry 1993).

*Simulation Strategy: Analysis*

Once the weights are created and the simulated datasets have been multiply imputed, I
analyzed the models. The simulation saved estimates for the b-coefficients and the standard
erors for each model type, either OLS or fixed effects, and for each dependent variable, either
health or support for gay marriage. This leads to four final datasets for analysis. I used six
strategies for handling attrition: listwise deletion, inverse propensity weight (IPW), raked weight,
imputation of the 2006 panel (imputation), imputation of the 2006 and 2008 panels (imputation 2008), and imputation of all GSS panels (imputation all). Each of these six models is subtracted
from their true-score counterpart. For example, the mean of age when cases are listwise deleted
is subtracted from the mean of age for the true score model. This gives the bias of listwise
deletion for each of the 500 datasets for the mean of age. I report the average of the bias over the
500 datasets. I also report the range of the standard errors for each of the 500 simulated datasets
for the listwise and imputation all methods using boxplots.

**Results**

*Bias of Averages (Univariate Measures)*

In order to assess how close each strategy came to the true score model, the following
tables focus on the bias. For example, the mean score for self-rated health was calculated for
each of the 500 datasets. The averages were compiled and the mean of the averages was
subtracted from the true mean for self-rated health.
As shown in Table 4-3, on the next page, the bias was generally less than a tenth of a point. Age squared did have larger scores, with the rake weight average nearly 495 points below the true score mean. The bias for the age term was much lower, with a range of less than 2 years, meaning that over 500 simulations, all of the datasets had an average age within 2 years of the true score average.

The raked weight constructed from the refreshment panel failed to adjust for bias for the means of the demographic variables compared to the listwise model. While the inverse propensity weight (IPW) was also an improvement over the raked weight, the listwise model outperforms the IPW model as well. The time invariant demographic variables did not have any bias in the imputed models, because this study assumes no item-missing data, and therefore the bias was caused only by attrition. The three imputation models also perform better than the listwise and the weighted models on the attitudinal measures, all of which have missing data due to the attrition assumptions of the simulation. All three imputation strategies were superior to the weighted and listwise models, and using both the 2008 and 2010 refreshment samples generally improved the estimates of the means.
Table 4-3. Univariate Bias of the Means from year 2010, both the Average and the Range.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Listwise Mean Bias</th>
<th>Listwise Range of Bias</th>
<th>IPW Mean Bias</th>
<th>IPW Range of Bias</th>
<th>Rake Weight Mean Bias</th>
<th>Rake Weight Range of Bias</th>
<th>Imputation Mean Bias</th>
<th>Imputation Range of Bias</th>
<th>Imputation 2008 Mean Bias</th>
<th>Imputation 2008 Range of Bias</th>
<th>Imputation all(^c) Mean Bias</th>
<th>Imputation all(^c) Range of Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support for gay marriage</td>
<td>-0.013</td>
<td>0.195</td>
<td>-0.020</td>
<td>0.199</td>
<td>-0.058</td>
<td>0.208</td>
<td>-0.004</td>
<td>0.155</td>
<td>-0.005</td>
<td>0.145</td>
<td>0.000</td>
<td>0.144</td>
</tr>
<tr>
<td>Health</td>
<td>0.014</td>
<td>0.099</td>
<td>0.034</td>
<td>0.085</td>
<td>0.019</td>
<td>0.104</td>
<td>0.000</td>
<td>0.093</td>
<td>-0.002</td>
<td>0.090</td>
<td>-0.008</td>
<td>0.084</td>
</tr>
<tr>
<td>Political Views</td>
<td>0.013</td>
<td>0.174</td>
<td>0.050</td>
<td>0.182</td>
<td>-0.052</td>
<td>0.189</td>
<td>-0.005</td>
<td>0.155</td>
<td>0.001</td>
<td>0.153</td>
<td>0.003</td>
<td>0.150</td>
</tr>
<tr>
<td>Religiosity</td>
<td>0.007</td>
<td>0.086</td>
<td>0.024</td>
<td>0.088</td>
<td>-0.026</td>
<td>0.087</td>
<td>-0.001</td>
<td>0.035</td>
<td>0.000</td>
<td>0.038</td>
<td>0.002</td>
<td>0.037</td>
</tr>
<tr>
<td>Social Distance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homosexuals</td>
<td>0.017</td>
<td>0.078</td>
<td>0.047</td>
<td>0.075</td>
<td>0.007</td>
<td>0.104</td>
<td>0.001</td>
<td>0.071</td>
<td>0.002</td>
<td>0.071</td>
<td>-0.005</td>
<td>0.071</td>
</tr>
<tr>
<td>Happiness</td>
<td>0.012</td>
<td>0.086</td>
<td>0.034</td>
<td>0.081</td>
<td>-0.009</td>
<td>0.110</td>
<td>0.000</td>
<td>0.070</td>
<td>0.000</td>
<td>0.066</td>
<td>-0.006</td>
<td>0.071</td>
</tr>
<tr>
<td>Satisfied with finances</td>
<td>0.014</td>
<td>0.102</td>
<td>0.045</td>
<td>0.103</td>
<td>-0.044</td>
<td>0.104</td>
<td>0.000</td>
<td>0.109</td>
<td>0.002</td>
<td>0.101</td>
<td>0.003</td>
<td>0.097</td>
</tr>
<tr>
<td>Never married</td>
<td>-0.014</td>
<td>0.043</td>
<td>-0.042</td>
<td>0.038</td>
<td>0.054</td>
<td>0.061</td>
<td>-0.001</td>
<td>0.026</td>
<td>0.000</td>
<td>0.026</td>
<td>0.002</td>
<td>0.022</td>
</tr>
<tr>
<td>Divorced/widowed/separated</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.098</td>
<td>1.978</td>
<td>0.729</td>
<td>1.882</td>
<td>-5.141</td>
<td>6.34</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Age squared</td>
<td>-4.457</td>
<td>202.602</td>
<td>40.318</td>
<td>197.529</td>
<td>-494.834</td>
<td>60.793</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Female</td>
<td>0.015</td>
<td>0.060</td>
<td>0.046</td>
<td>0.057</td>
<td>-0.056</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Black</td>
<td>-0.001</td>
<td>0.047</td>
<td>-0.006</td>
<td>0.047</td>
<td>0.003</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.019</td>
<td>0.044</td>
<td>-0.046</td>
<td>0.027</td>
<td>0.041</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Other race</td>
<td>-0.002</td>
<td>0.020</td>
<td>-0.005</td>
<td>0.018</td>
<td>0.017</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: Bias is calculated by averaging the means for each variable for each of the 500 simulated datasets, then differenced from the true mean.

\(a\) This model is the multiple imputation of the 2006 panel only, using data from the year 2010.

\(b\) This model is the multiple imputation of the 2006 and 2008 panel, but only uses the 2006 panel in the analysis.

\(c\) This model is the multiple imputation of all panels for all eligible years, but only uses the 2006 panel in the analysis.
Support for Gay Marriage

Table 4-4, on the next page, shows the bias for b-coefficients and standard errors for the OLS regression of support for gay marriage. This table contains the 2010 measures of the 2006 panel. The bias is calculated by subtracting the b-coefficient or standard error from the respective true score statistic. The table presents both mean bias and range of bias for the five models: listwise, inverse propensity weight (IPW), raked weight, imputation of only the 2006 panel (imputation), imputation of the 2006 and 2008 panel (imputation 2008), and the imputation of all three panels (imputation all). In all models, however, only the 2006 panel is analyzed.

The two weighted models tend to fare worse on both the bias of b-coefficient and the inflation of standard errors. The increased standard errors is a common disadvantage of using weights (Battaglia, 2009; Winship & Radbill, 1994). Estimates for those of another race were particularly bad, as the listwise model had an average b-coefficient bias of 0.036 (SE bias=0.053) while propensity weight model has an average bias of 0.07 (SE bias=0.058) and the raked weight had an average bias of 0.153 (SE bias=0.089). The ranges are even worse, as the range of bias for the listwise model was about 0.8 points but for the raked weight, was 1.2 points. The dependent variable has a five point range. The weights did not improve the bias of the coefficients.

For the three attitudinal variables, which would be the most difficult for a researcher estimate the potential for bias in a non-simulation the study, the listwise model general outperforms in terms of average bias of both b-coefficients and standard errors, which the exception of the religiosity variable, where the raked weight b-coefficient bias is slightly smaller (b_{listwise}=0.12, b_{rakewt}=0.007). The bias of standard errors, both the range and average, are always larger for the weighted models.
For the imputation modes, the 2006 only imputation tends to have similar estimates of bias for both the b-coefficients and the standard errors, and often offers a slight improvement. For example, the average b-coefficient bias for religiosity is -0.012 for the listwise model (SE bias=0.016) while the imputation 2006 model has an average b-coefficient bias of -0.01 (SE=0.015). For the refreshment models, there is a tendency for slightly greater bias of the coefficients, however, both the mean bias and range of bias shrinks for the standard errors.

Consistent with the work of Rubin (1987) and Reiter (2008), the standard errors were inflated. I also find that the inflation of the standard errors is smaller than the listwise model. This trend is illustrated by Figure 4-5 on page 22, which shows the box graphs of the standard error bias for the listwise model and the imputation all (all refreshment panel) model. The bias of errors for age squared were comparable, but for all other variables, most of the 500 simulated imputation all standard errors were closer to the true standard error than the median estimate for the listwise models.
<table>
<thead>
<tr>
<th></th>
<th>Listwise</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Imputation a</th>
<th></th>
<th></th>
<th></th>
<th>Imputation 2008 b</th>
<th>Imputation all c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
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<tr>
<td></td>
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<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
</tr>
<tr>
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<td>0.008</td>
<td>0.060</td>
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<td>0.082</td>
<td>0.000</td>
<td>0.056</td>
<td>0.002</td>
<td>0.048</td>
<td>-0.001</td>
<td>0.041</td>
<td>0.004</td>
<td>0.005</td>
<td>0.002</td>
</tr>
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<td>Income (log)</td>
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<td>0.192</td>
<td>-0.023</td>
<td>0.174</td>
<td>0.023</td>
<td>0.215</td>
<td>-0.006</td>
<td>0.173</td>
<td>-0.010</td>
<td>0.137</td>
<td>-0.017</td>
<td>0.113</td>
<td>0.010</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td>Political Views</td>
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<td>0.116</td>
<td>0.014</td>
<td>0.115</td>
<td>0.009</td>
<td>0.140</td>
<td>0.001</td>
<td>0.117</td>
<td>0.009</td>
<td>0.102</td>
<td>0.027</td>
<td>0.086</td>
<td>0.005</td>
<td>0.009</td>
<td>0.004</td>
</tr>
<tr>
<td>Religiosity</td>
<td>-0.012</td>
<td>0.238</td>
<td>-0.028</td>
<td>0.255</td>
<td>0.007</td>
<td>0.294</td>
<td>-0.010</td>
<td>0.243</td>
<td>-0.001</td>
<td>0.187</td>
<td>-0.046</td>
<td>0.147</td>
<td>0.010</td>
<td>0.015</td>
<td>0.015</td>
</tr>
<tr>
<td>Social Distance</td>
<td>-0.004</td>
<td>0.244</td>
<td>-0.005</td>
<td>0.266</td>
<td>-0.005</td>
<td>0.297</td>
<td>0.001</td>
<td>0.255</td>
<td>0.006</td>
<td>0.202</td>
<td>0.001</td>
<td>0.182</td>
<td>0.005</td>
<td>0.010</td>
<td>0.015</td>
</tr>
<tr>
<td>Homosexuals</td>
<td>0.015</td>
<td>0.012</td>
<td>0.021</td>
<td>0.018</td>
<td>0.023</td>
<td>0.026</td>
<td>0.016</td>
<td>0.030</td>
<td>0.012</td>
<td>0.018</td>
<td>0.010</td>
<td>0.015</td>
<td>0.005</td>
<td>0.015</td>
<td>0.015</td>
</tr>
<tr>
<td>Age</td>
<td>-0.005</td>
<td>0.070</td>
<td>-0.012</td>
<td>0.069</td>
<td>0.003</td>
<td>0.073</td>
<td>-0.003</td>
<td>0.062</td>
<td>0.000</td>
<td>0.049</td>
<td>0.008</td>
<td>0.038</td>
<td>0.003</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Age squared</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Female</td>
<td>-0.013</td>
<td>0.358</td>
<td>-0.036</td>
<td>0.307</td>
<td>0.025</td>
<td>0.401</td>
<td>-0.022</td>
<td>0.304</td>
<td>-0.004</td>
<td>0.248</td>
<td>0.033</td>
<td>0.226</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Black</td>
<td>0.001</td>
<td>0.587</td>
<td>-0.007</td>
<td>0.576</td>
<td>-0.012</td>
<td>0.554</td>
<td>-0.007</td>
<td>0.504</td>
<td>-0.068</td>
<td>0.496</td>
<td>-0.022</td>
<td>0.400</td>
<td>0.027</td>
<td>0.034</td>
<td>0.015</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.006</td>
<td>0.713</td>
<td>0.001</td>
<td>0.674</td>
<td>0.045</td>
<td>0.823</td>
<td>-0.017</td>
<td>0.665</td>
<td>-0.055</td>
<td>0.424</td>
<td>-0.042</td>
<td>0.404</td>
<td>0.048</td>
<td>0.042</td>
<td>0.025</td>
</tr>
<tr>
<td>Other race</td>
<td>0.036</td>
<td>0.822</td>
<td>0.070</td>
<td>0.820</td>
<td>0.153</td>
<td>1.202</td>
<td>0.024</td>
<td>0.801</td>
<td>-0.100</td>
<td>0.700</td>
<td>-0.025</td>
<td>0.568</td>
<td>0.053</td>
<td>0.084</td>
<td>0.029</td>
</tr>
</tbody>
</table>

Notes: Bias is calculated by subtracting the b-coefficient or standard error for each of the 500 simulated datasets from the true score.

a This model is the multiple imputation of the 2006 panel only, using data from the year 2010.

b This model is the multiple imputation of the 2006 and 2008 panel, but only uses the 2006 panel in the analysis of 2010 variables.

c This model is the multiple imputation of all panels but only uses the 2006 panel in the analysis of 2010 variables.
Figure 4-5. Box Graphs of Bias of SE’s OLS Regression of Support for Gay Marriage

Note: Only the 2006 panel is used in the analysis.
Another way to assess the impact of bias is to assess the accuracy of the significance tests. I used an alpha of 0.05 to compare the percentage of accurate tests for the five models to the true score model. Table 4-5, below, shows that significance testing was robust for most variables, although logged income and the dummy variables black and other race were often incorrect. The raked weight model had the most success at predicting the significant relationship between income (logged) and support for gay marriage, although only 46% of the 500 simulations captured this relationship. The rake weight model was also the most successful at capturing the significant relationship for respondents of another race, as compared to whites, although the success rate was only 53%. For the dummy variable for black respondents, 57% of the listwise and 58% of the three panel imputation accurately predicted the significant relationship.

<table>
<thead>
<tr>
<th>Variable</th>
<th>True</th>
<th>Listwise</th>
<th>IPW</th>
<th>Rake Weight</th>
<th>Imputationa</th>
<th>Imputation 2008b</th>
<th>Imputation allc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>ns</td>
<td>100%</td>
<td>100%</td>
<td>99%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Income (log)</td>
<td>sig</td>
<td>21%</td>
<td>5%</td>
<td>46%</td>
<td>23%</td>
<td>18%</td>
<td>10%</td>
</tr>
<tr>
<td>Political Views</td>
<td>sig</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Religiosity</td>
<td>sig</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Social Distance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homosexuals</td>
<td>sig</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Age</td>
<td>ns</td>
<td>99%</td>
<td>98%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Age squared</td>
<td>ns</td>
<td>89%</td>
<td>79%</td>
<td>98%</td>
<td>91%</td>
<td>98%</td>
<td>100%</td>
</tr>
<tr>
<td>Female</td>
<td>sig</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Black</td>
<td>sig</td>
<td>57%</td>
<td>33%</td>
<td>35%</td>
<td>54%</td>
<td>25%</td>
<td>58%</td>
</tr>
<tr>
<td>Hispanic</td>
<td>ns</td>
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<td>93%</td>
<td>88%</td>
<td>96%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Other race</td>
<td>sig</td>
<td>46%</td>
<td>49%</td>
<td>53%</td>
<td>41%</td>
<td>14%</td>
<td>32%</td>
</tr>
</tbody>
</table>

Notes: ns denotes a p>0.05 while sig denotes p<0.05.

a This model is the multiple imputation of the 2006 panel only, using data from the year 2010.
b This model is the multiple imputation of the 2006 and 2008 panel, but only uses the 2006 panel in the analysis.
c This model is the multiple imputation of all panels, but only uses the 2006 panel in the analysis.
Similar to the OLS regression, the fixed effects model offers little support for the use of weights. As shown in Table 4-6, on the next page, the listwise b-coefficients and standard errors are closer to the true model than the weighted model. Although the raked weight coefficients may be slightly less biased on average, the range tends to be greater. The religiosity coefficient, for example, for the rake weight model has an average b-coefficient bias of -0.027 as opposed to -0.046 for the listwise model. Even in this case, however, the range of coefficient bias is just under 0.6 for the rake weight model and about 0.33 points for the listwise model. While the average listwise coefficient was more biased, there is a smaller range of bias overall. Using all three panels in the imputation did decrease the average bias and range of bias for the b-coefficients for logged income.
Table 4-6. Bias of b-Coefficient and Standard Errors, both average and range, for Fixed Effects Regression of Support for Gay Marriage

<table>
<thead>
<tr>
<th></th>
<th>Listwise</th>
<th>IPW</th>
<th>Rake Weight</th>
<th>Imputation&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Imputation 2008&lt;sup&gt;b&lt;/sup&gt;</th>
<th>Imputation all&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
<td>Mean Bias</td>
<td>Range of Bias</td>
</tr>
<tr>
<td>b-coef</td>
<td>(SE)</td>
<td>(SE)</td>
<td>(SE)</td>
<td>(SE)</td>
<td>(SE)</td>
<td>(SE)</td>
</tr>
<tr>
<td>Wave</td>
<td>-0.002</td>
<td>0.035</td>
<td>-0.006</td>
<td>0.037</td>
<td>0.003</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
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<td>0.082</td>
<td>0.013</td>
<td>0.076</td>
<td>-0.018</td>
<td>0.124</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.007)</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Income (log)</td>
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<td>0.129</td>
<td>-0.023</td>
<td>0.135</td>
<td>0.023</td>
<td>0.188</td>
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<tr>
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<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.012)</td>
<td>(0.014)</td>
<td>(0.016)</td>
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</tr>
<tr>
<td>Political Views</td>
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<td>-0.005</td>
<td>0.078</td>
<td>0.002</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.011)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Religiosity</td>
<td>-0.046</td>
<td>0.325</td>
<td>-0.094</td>
<td>0.337</td>
<td>-0.027</td>
<td>0.584</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.009)</td>
<td>(0.027)</td>
<td>(0.018)</td>
<td>(0.053)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Social Distance</td>
<td>0.009</td>
<td>0.158</td>
<td>0.028</td>
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<td>0.036</td>
<td>0.240</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.012)</td>
<td>(0.008)</td>
<td>(0.022)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Homosexuals</td>
<td>0.003</td>
<td>0.164</td>
<td>-0.007</td>
<td>0.145</td>
<td>0.001</td>
<td>0.182</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.008)</td>
<td>(0.013)</td>
<td>(0.008)</td>
<td>(0.015)</td>
<td>(0.008)</td>
</tr>
</tbody>
</table>

Notes: Bias is calculated by subtracting the b-coefficient or standard error for each of the 500 simulated datasets from the true score.

<sup>a</sup> This model is the multiple imputation of the 2006 panel only, using data from the year 2006, 2008, 2010.

<sup>b</sup> This model is the multiple imputation of the 2006 and 2008 panel, all eligible years, but only uses the 2006 panel in the analysis.

<sup>c</sup> This model is the multiple imputation of all panels for all eligible years, but only uses the 2006 panel in the analysis.
Figure 4-6. Box Graphs of Bias of SE’s
Fixed Effects Regression of Support for Gay Marriage

Note: Only the 2006 panel is used in the analysis.
The refreshment panel did not adjust the standard errors as efficiently as the listwise model, as illustrated by Figure 4-6, on the previous page. The box graphs show that the inclusion of all panels in the imputation was less consistent in assessing the standard errors, particularly for religiosity. Although the bias for the coefficients and standard errors are generally larger for the all refreshment imputation, this model tended to more accurately assess the significance of relationship, as shown below in Table 4-7. The refreshment imputation with three panels did the best job of predicting a successful relationship for political views, with a success rate of 87%, and the 2008 imputation, was successful 72% of the time.

Table 4-7. Percent of t-tests correct for Fixed Effects Regression of Support for Gay Marriage.

<table>
<thead>
<tr>
<th>Wave</th>
<th>True</th>
<th>Listwise</th>
<th>IPW</th>
<th>Rake Weight</th>
<th>Imputation&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Imputation 2008&lt;sup&gt;b&lt;/sup&gt;</th>
<th>Imputation all&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>sig</td>
<td>100%</td>
<td>100%</td>
<td>98%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Education</td>
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<td>92%</td>
<td>99%</td>
<td>99%</td>
<td>92%</td>
<td>95%</td>
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<td>ns</td>
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<td>100%</td>
<td>96%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Political Views</td>
<td>sig</td>
<td>59%</td>
<td>28%</td>
<td>33%</td>
<td>53%</td>
<td>72%</td>
<td>87%</td>
</tr>
<tr>
<td>Religiosity</td>
<td>sig</td>
<td>87%</td>
<td>47%</td>
<td>54%</td>
<td>90%</td>
<td>95%</td>
<td>97%</td>
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<td>100%</td>
<td>99%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Homosexuals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: ns denotes a p>0.05 while sig denotes p<0.05.

<sup>a</sup> This model is the multiple imputation of the 2006 panel only, using data from all waves.

<sup>b</sup> This model is the multiple imputation of the 2006 and 2008 panel, but only analyses the 2006 panel.

<sup>c</sup> This model is the multiple imputation of all panels, but only analyses the 2006 panel.

**Self-Rated Health**

Table 4-8, on the next page, shows the results for the OLS regression of health. This table contains the 2010 measures of the 2006 panel. The bias is calculated by subtracting the b-coefficient or standard error from the respective true score statistic. The table presents both mean bias and range of bias for the five models: listwise, inverse propensity weight (IPW), raked weight, imputation of only the 2006 panel (imputation), imputation of the 2006 and 2008 panel.
(imputation 2008), and the imputation of all three panels (imputation all). In all models, however, only the 2006 panel is analyzed.

Table 8 shows the bias of both the b-coefficients and the standard errors of the two weighted models are generally larger than the listwise model, with the raked weights having a larger range of bias for all variables except age and age squared, which are about the same as the listwise.

The imputation model performed similar to the listwise model, while the both of the refreshment imputation models performed slightly better on the range of bias for the b-coefficients and standard errors. Boxplots in Figure 4-7, on page 28, show that the errors for age squared are similar, but for all other variables, the majority of standard errors for the 500 simulated datasets were less than the median standard error estimates for the listwise model.
<table>
<thead>
<tr>
<th></th>
<th>Listwise Mean Bias (SE)</th>
<th>IPW Mean Bias (SE)</th>
<th>Rake Weight Mean Bias (SE)</th>
<th>Imputation Mean Bias (SE)</th>
<th>Imputation 2008 Mean Bias (SE)</th>
<th>Imputation all Mean Bias (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range of Bias</td>
<td>Range of Bias</td>
<td>Range of Bias</td>
<td>Range of Bias</td>
<td>Range of Bias</td>
<td>Range of Bias</td>
</tr>
<tr>
<td>b-coef</td>
<td>0.000 (0.002)</td>
<td>0.002 (0.004)</td>
<td>0.004 (0.005)</td>
<td>0.000 (0.002)</td>
<td>-0.002 (0.003)</td>
<td>0.000 (0.001)</td>
</tr>
<tr>
<td>Other race</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.002 (0.007)</td>
<td>-0.009 (0.011)</td>
<td>-0.010 (0.012)</td>
<td>-0.003 (0.007)</td>
<td>-0.003 (0.013)</td>
<td>-0.002 (0.004)</td>
</tr>
<tr>
<td>Age</td>
<td>0.004 (0.007)</td>
<td>0.017 (0.011)</td>
<td>-0.013 (0.012)</td>
<td>0.002 (0.007)</td>
<td>0.002 (0.013)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td>Age squared</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.001 (0.002)</td>
<td>0.003 (0.003)</td>
<td>0.002 (0.003)</td>
<td>0.001 (0.003)</td>
<td>0.002 (0.003)</td>
<td>0.001 (0.000)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.009 (0.017)</td>
<td>-0.029 (0.019)</td>
<td>0.041 (0.020)</td>
<td>-0.011 (0.014)</td>
<td>-0.001 (0.013)</td>
<td>-0.007 (0.013)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.037 (0.031)</td>
<td>0.073 (0.037)</td>
<td>0.012 (0.036)</td>
<td>0.023 (0.025)</td>
<td>0.023 (0.037)</td>
<td>0.018 (0.028)</td>
</tr>
<tr>
<td>Other race</td>
<td>-0.002 (0.035)</td>
<td>-0.009 (0.050)</td>
<td>-0.124 (0.056)</td>
<td>0.000 (0.063)</td>
<td>0.027 (0.048)</td>
<td>0.023 (0.037)</td>
</tr>
<tr>
<td>Happiness</td>
<td>0.044 (0.051)</td>
<td>0.197 (0.052)</td>
<td>0.051 (0.056)</td>
<td>0.027 (0.060)</td>
<td>0.027 (0.057)</td>
<td>0.023 (0.039)</td>
</tr>
</tbody>
</table>

Notes: Bias is calculated by subtracting the b-coefficient or standard error for each of the 500 simulated datasets from the true score.

a This model is the multiple imputation of the 2006 panel only, analyzing data from the year 2010.
b This model is the multiple imputation of the 2006 and 2008 panel, but only uses the 2006 panel in the analysis.
c This model is the multiple imputation of all panels, but only uses the 2006 panel in the analysis.
Table 4-9, on the next page, shows the accuracy of the significance testing. Most variables were robust to the method used, except for income and the dummy variable for Black respondents. For income, the imputation all model accurately predicted significance 77% of the
time, while the listwise model was only accurately 38% times and the weighted models were accurate in only 14% of the 500 simulations. The trend is reversed for the dummy variable Black, which was accurate in less than a fifth of the simulations using both refreshment panels in the imputation, but was most accurate in nearly 50% of the IPW models and in 34% of the listwise models.

Table 4.9. Percent of t-tests correct for OLS Regression of Self-Rated Health.

<table>
<thead>
<tr>
<th>Variable</th>
<th>True</th>
<th>Listwise</th>
<th>IPW</th>
<th>Rake Weight</th>
<th>Imputation</th>
<th>Imputation 2008</th>
<th>Imputation all</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education sig</td>
<td>98%</td>
<td>99%</td>
<td>96%</td>
<td>99%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Income (log) sig</td>
<td>38%</td>
<td>14%</td>
<td>14%</td>
<td>35%</td>
<td>54%</td>
<td>77%</td>
<td></td>
</tr>
<tr>
<td>Happiness sig</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Satisfied with finances</td>
<td>85%</td>
<td>82%</td>
<td>86%</td>
<td>80%</td>
<td>90%</td>
<td>96%</td>
<td></td>
</tr>
<tr>
<td>Never married ns</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Divorced/widowed ns</td>
<td></td>
<td>97%</td>
<td>96%</td>
<td>98%</td>
<td>98%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Age ns</td>
<td>85%</td>
<td>91%</td>
<td>89%</td>
<td>85%</td>
<td>84%</td>
<td>91%</td>
<td></td>
</tr>
<tr>
<td>Age squared ns</td>
<td>99%</td>
<td>99%</td>
<td>99%</td>
<td>99%</td>
<td>100%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Female ns</td>
<td>97%</td>
<td>97%</td>
<td>98%</td>
<td>99%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Black sig</td>
<td>34%</td>
<td>48%</td>
<td>10%</td>
<td>40%</td>
<td>39%</td>
<td>18%</td>
<td></td>
</tr>
<tr>
<td>Hispanic ns</td>
<td>100%</td>
<td>99%</td>
<td>98%</td>
<td>100%</td>
<td>99%</td>
<td>98%</td>
<td></td>
</tr>
<tr>
<td>Other race ns</td>
<td>81%</td>
<td>87%</td>
<td>58%</td>
<td>77%</td>
<td>87%</td>
<td>88%</td>
<td></td>
</tr>
</tbody>
</table>

Notes: ns denotes p>0.05 while sig denotes p<0.05.

a This model is the multiple imputation of the 2006 panel only, using data from the year 2010.
b This model is the multiple imputation of the 2006 and 2008 panel, but only uses the 2006 panel in the analysis.
c This model is the multiple imputation of all panels, but only uses the 2006 panel in the analysis.

Table 4-10, on the next page, shows the results for the fixed effects model for health. Similar to the model for support for gay marriage, the weighted and imputation models do not offer an improvement over the listwise model in terms of decreasing bias, either for the coefficients or the standard errors.
<table>
<thead>
<tr>
<th></th>
<th>Listwise</th>
<th>IPW</th>
<th>Rake Weight</th>
<th>Imputation&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Imputation 2008&lt;sup&gt;b&lt;/sup&gt;</th>
<th>Imputation all&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Range of Bias</td>
<td>Mean</td>
<td>Range of Bias</td>
<td>Mean</td>
<td>Range of Bias</td>
</tr>
<tr>
<td></td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
<td>b-coef</td>
<td>(SE)</td>
</tr>
<tr>
<td>Wave</td>
<td>-0.001</td>
<td>0.021</td>
<td>-0.004</td>
<td>0.021</td>
<td>0.002</td>
<td>0.030</td>
</tr>
<tr>
<td>Education</td>
<td>0.005</td>
<td>0.057</td>
<td>0.019</td>
<td>0.054</td>
<td>0.002</td>
<td>0.092</td>
</tr>
<tr>
<td>Income (log)</td>
<td>0.047</td>
<td>0.032</td>
<td>0.008</td>
<td>0.011</td>
<td>0.009</td>
<td>0.013</td>
</tr>
<tr>
<td>Happiness</td>
<td>0.001</td>
<td>0.101</td>
<td>0.006</td>
<td>0.094</td>
<td>-0.011</td>
<td>0.111</td>
</tr>
<tr>
<td>Satisfied with finances</td>
<td>0.005</td>
<td>0.069</td>
<td>0.004</td>
<td>0.063</td>
<td>0.009</td>
<td>0.114</td>
</tr>
<tr>
<td>Never married</td>
<td>0.015</td>
<td>0.412</td>
<td>0.009</td>
<td>0.431</td>
<td>-0.033</td>
<td>0.554</td>
</tr>
<tr>
<td>Divorced/widowed/separated</td>
<td>0.002</td>
<td>0.224</td>
<td>-0.014</td>
<td>0.209</td>
<td>0.135</td>
<td>0.024</td>
</tr>
</tbody>
</table>

Notes: Bias is calculated by subtracting the b-coefficient or standard error for each of the 500 simulated datasets from the true score.

<sup>a</sup> This model is the multiple imputation of the 2006 panel only, using data from the year 2006, 2008, 2010.

<sup>b</sup> This model is the multiple imputation of the 2006 and 2008 panel, all eligible years, but only uses the 2006 panel in the analysis.

<sup>c</sup> This model is the multiple imputation of all panels for all eligible years, but only uses the 2006 panel in the analysis.
Figure 4-8 shows the standard error bias for the listwise and imputation all model. The standard errors are similar for both models, although the refreshment imputation had a larger range for the bias. The refreshment imputation was not beneficial in this analysis. Another way to look at the strategies is to compare the accuracy of the significance tests. Table 4-11 shows the
slight improvement of the listwise model for most variables. The listwise model was most beneficial when estimating the relationship between health and satisfaction with finances, which was accurately predicted 53% of the time for the listwise models and closer to a third of the time for the rest of the models. The rest of variables were generally robust, although the rake weight model only captured the significant relationship between the wave of the survey and health in 46% of the simulations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>True</th>
<th>Listwise</th>
<th>IPW</th>
<th>Rake Weight</th>
<th>Imputation</th>
<th>Imputation 2008</th>
<th>Imputation all</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>sig</td>
<td>96%</td>
<td>99%</td>
<td>46%</td>
<td>91%</td>
<td>96%</td>
<td>98%</td>
</tr>
<tr>
<td>Education</td>
<td>ns</td>
<td>99%</td>
<td>98%</td>
<td>99%</td>
<td>99%</td>
<td>100%</td>
<td>96%</td>
</tr>
<tr>
<td>Income (log)</td>
<td>ns</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Happiness</td>
<td>sig</td>
<td>100%</td>
<td>100%</td>
<td>99%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Satisfied with finances</td>
<td>sig</td>
<td>53%</td>
<td>37%</td>
<td>37%</td>
<td>37%</td>
<td>34%</td>
<td>38%</td>
</tr>
<tr>
<td>Never married</td>
<td>ns</td>
<td>95%</td>
<td>99%</td>
<td>99%</td>
<td>97%</td>
<td>96%</td>
<td>96%</td>
</tr>
<tr>
<td>Divorced/widowed/separated</td>
<td>ns</td>
<td>96%</td>
<td>96%</td>
<td>100%</td>
<td>94%</td>
<td>98%</td>
<td>96%</td>
</tr>
</tbody>
</table>

Notes: ns denotes a p>0.05 while sig denotes p<0.05.

* This model is the multiple imputation of the 2006 panel only, using data from all waves.

b This model is the multiple imputation of the 2006 and 2008 panel, but only analyses the 2006 panel.

c This model is the multiple imputation of all panels, but only analyses the 2006 panel.

Discussion & Conclusion

In this study, I tested the veracity of using refreshment samples to adjust for attrition using a simulation of the General Social Survey. Using the refreshment sample to construct either an inverse propensity weight or a raked weight was not beneficial. While standard errors were going to be inflated, there was no decrease in bias of the b-coefficients or means and, in many cases, the bias was actually worse than the listwise model. As weights are usually created when datasets, such as the General Social Survey, it is possible that researchers rely on the use of a weight to correct for attrition. While researchers may believe that the increase in standard
errors, or the decrease in efficiency, is the cost of lowering bias of the estimates, such as the b-coefficients, refreshment panel imputation may provide a preferable alternative, although there are limited circumstances to the benefits of the adjustment.

By using the refreshment samples in the imputation only, and not in the analyses, I used what is sometimes referred to as the P-only model (Deng, 2013; Reiter, 2008). The major criticism of the P-only model is that the standard errors are biased due to the failure to include all cases in the analysis that were included in the imputation (Reiter, 2008; Rubin, 1987). The use of the refreshment panels in the imputation did lead to a positive bias in the standard errors but the inflation was generally better than the listwise model as well as the imputation of only the 2006 panel. The use of only the 2008 refreshment sample in the imputation did not prove beneficial in adjusting the scores of attritors even though two waves were observed for this sample.

The cross-sectional models benefited most from the use of both of the refreshment panels. The fixed effects health models did not benefit from the inclusion of the refreshment panel, and the listwise models were the most accurate. For support for gay marriage, the refreshment imputation generally had more accurate significance tests for the religiosity and political views covariates. In absolute terms, the bias for the health models tended to be smaller for all the strategies, but the bias tended to be less than 0.1 for most variables for either model.

While the GSS panels were combined for the multiple imputations in the simulation, only the 2006 dataset was analyzed. Combining the 2008 and 2010 refreshment samples in the analysis led to substantial bias in the b-coefficients and the means for all methods of handling missing data. The bias of these coefficients, not shown in this paper, were far greater than the decrease in the standard errors.

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In this study, I found that the use of refreshment samples may be beneficial in some circumstances, particularly when predicting a cross-sectional model while using later waves of a longitudinal dataset that has been subject to attrition. The use of refreshment samples when dependent variables are not subject to large changes in short periods of time, such as health, may not be beneficial. I found that support for gay marriage, an attitude that has been changing in the United States during the last decade (Baunach, 2012) was improved by the inclusion of the refreshment panel in the imputation. Future research should focus on the ability of the refreshment imputation to deal with changing attitudes. Is there a certain amount of change that is too great for a refreshment panel to adjust? Another important avenue for research is the use of refreshment imputation in mixed effects models, when group effects are also taken into account.

In conclusion, while refreshment panels may not be suitable for the creation of raked weights, their use in the imputation step is beneficial for cross-sectional models based off of panel data that has been subject to attrition. Researchers who rely on created weights to adjust for attrition should consider multiple imputation. In this study, I found that even imputing the entire 2006 GSS panel could be similar to the IPW and raked weight in the case of the fixed effects model, and tended to perform slightly better on the significance tests for the OLS regressions, although the improvement was small. When available, the use of the refreshment panels for imputation should be considered for OLS regressions, and would not harm fixed effects models.
Chapter 5

Conclusion

The use of panel studies, in which the same people are interviewed at least twice in two different time periods, provides researchers with the ability to explore a multitude of issues. Researchers can explore change over time, better establish temporal order of events, and have the option to use a wide array of models that are only possible with longitudinal survey data (Johnson, 1988; Toon, 2000). While longitudinal datasets give researchers a great deal of leverage to study many important issues, they also come with greater challenges in ensuring quality data and accurate results.

In this study, I have explored the important problems of attrition and panel conditioning in longitudinal panel datasets. I have demonstrated ways that researchers may use widely used statistical models, such as fixed effects analysis (Allison, 2009; Johnson, 2005), to explore attrition and panel conditioning. I also show how the use of refreshment samples may inform imputation, under limited circumstances. These results will be of use to those using panel datasets who wish to explore potential bias related to the panel.

I analyzed the impact of attrition by comparing two datasets, the NLSY and the MILC. I demonstrated that the trajectories of marital happiness are not impacted by attrition for the NLSY. The MILC, however, does have a higher level of predicted happiness when only those who complete the survey, the stayers, are analyzed, and the level of happiness is higher for all available data from the MILC when compared to the NLSY. That the stayers are higher than the full sample MILC even though this is not true for the NLSY points to some sort of selective attrition effect that occurs in the MILC, perhaps due to this survey’s focus on marital quality. For
the MILC respondents, who are asked dozens of questions about their marital quality, answering questions about a marriage that is unhappy or having several problems could result in an unpleasant experience for the respondent, and perhaps make them unwilling to go through the process at a later time. The NLSY respondents, who get asked questions related to employment and education, and only a few questions on marital quality, should not have as difficult time sitting through the entire survey if their marriages are struggling. Although respondents in the MILC had a higher level of happiness, however, the fixed effects model still showed similar trajectories in happiness, with a steep decline in early years, followed by a slowing of the decline, and finally an increase in happiness in the later years of the marriage.

I assessed the presence of panel conditioning, focusing on evidence for opinionation, crystallization of attitudes, and social desirability bias. Opinionation is often assessed through the prevalence of don’t know and refusal responses in latter waves of the surveys. While refusals were not significantly changed over time in the survey, there is an increase in don’t know responses. This is evidence against opinionation. By studying the variation in answers to four separate scales related to marital quality, I found decreasing variability in the measures of positive dimensions of quality, spousal interaction and marital happiness. This is consistent with crystallization of attitudes, which occurs when respondents become more certain of their attitudes over time. For the negative dimensions of marital quality, marital problems and marital instability, the trajectories are not consistent. While marital problems also show a decreasing variation, the variation of the answers for the marital instability scale increases with time in sample. The increasing variation in marital instability is evidence against social desirability, as is the increasing rate of don’t knows, as respondents would likely try to give consistently positive impressions of their marriages and would also give interviewers the impression that they were
knowledgeable about the questions they were asked. There was also a noticeable increase in the mean of the marital instability scale after the first wave, which may be evidence that respondents were thinking more deeply about their marriages, consistent with the findings of Bussell and colleagues (1995).

I used a simulation to compare methods for adjusting for attrition, including the use of weights and imputation with and without a refreshment panel. I used what is sometimes referred to as the P-only model, when the researcher includes the refreshment sample in the imputation, but does not include the sample in the actual analysis of the data (Deng, 2013; Reiter, 2008). The major criticism of the P-only model is that the standard errors are biased due to the failure to include all cases in the analysis that were included in the imputation (Reiter, 2008; Rubin, 1987). I tested models of self-rated health and support for gay marriage. I found that the use of the refreshment panels in the imputation did lead to a positive bias in the standard errors but the inflation was generally better than the listwise model as well as the imputation of only the 2006 panel when using OLS regression, and led to more accurate significance tests. Although the simulation showed greater variability in the inflation of standard errors in the P-only fixed effects model for support for gay marriage compared to the listwise model, the significance tests were generally more accurate for two time varying covariates, religiosity and political views. The use of the P-only model was not beneficial when estimating the changes in individual health using fixed effects analysis.

The major contribution of this dissertation is the use of common analysis techniques to explore problems in panel datasets. By using two different datasets with different research themes, it is possible to assess attrition bias. The proliferation of large, nationally representative
datasets may give researchers the ability to understand whether or not there is a selection bias that impacts datasets with more focused research questions.

The presence of panel conditioning may not be something the research can adjust for, but it is important to explore these issues. For those who believe they will have another follow-up, analyzing panel conditioning may highlight the need for different questions or even an experimental planned missing design to analyze whether respondents are displaying signs of reactivity. Researchers who are using secondary data may also find it useful to understand the potential bias in the panel, if for no other reason than to better ascertain potential limitations of their data for generalization.

The use of refreshment samples in imputations may be beneficial when the researcher is analyzing cross-sectional model. More research is necessary to understand the benefits in longitudinal models, as well as how well imputation adjusts when there is a large change in attitudes over time. Although my analysis focused on a refreshment sample with overlapping questions, it is possible that other researchers may wish to look at different datasets to see if they can adjust their imputation using variables not found in the original dataset. Van Hook and colleagues (2015) have already used this strategy to adjust for the imputation of undocumented workers.

Ensuring data quality is important to social science researchers, who cannot rely on experiments to answer many of our research questions. Researchers who use panel datasets may need to take extra steps and consider how repeated interviews may impact our respondents. While we may not always be able to correct the problems we encounter, understanding the potential for bias may help us find new techniques, such as using additional datasets in
imputation, or encourage more research in the data collection phase to try to lessen respondent reactivity.
References


http://www.bls.gov/cpi/#tables


Reiter, J. P. 2008. Multiple imputation when records used for imputation are not used or disseminated for analysis. Biometrika 95: 933–946.


Yan, T. and K. Copeland. 2010. Panel conditioning in the Consumer Expenditure Quarterly Interview survey. Section on Survey Research Methods-JSM.


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Appendix A. Question Wording of Scales

Marital Happiness:

How happy are you with the amount of understanding you receive from your (husband/wife)?
How happy are you with the amount of love and affection you receive?
How happy are you with the extent to which you and your spouse agree about things?
How happy are you with your sexual relationship?
How happy are you with your spouse as someone who takes care of things around the house?
How happy are you with your spouse as someone to do things with?
How happy are you with your spouse's faithfulness to you?
Taking all things together, how would you describe your marriage?
Response options: 1=very happy, 2=pretty happy, 3=not too happy

Compared to other marriages you know about, do you think your marriage is better than most, about the same as most, or not as good as most?
Comparing your marriage to three years ago, is your marriage getting better, staying the same, or getting worse?
Response options: 1=better, 2=same, 3=not as good as most

Would you say the feelings of love you have for your (husband/wife) are extremely strong, very strong, pretty strong, not too strong, or not strong at all?
Response options: 1=extremely strong, 2=very strong, 3=pretty strong, 4=not too strong, 5=not strong at all

Marriage Problems

I'd like to mention a number of problem areas. Have you had a problem in your marriage because one of you gets angry easily?
Has feelings that are easily hurt?
Is jealous?
Is domineering?
Have you had a problem in your marriage because one of you is critical?
Is moody?
Won't talk to the other?
Has had a sexual relationship with someone else?
Has irritating habits?
Have you had a problem in your marriage because one of you is not at home enough?
Spends money foolishly?
Drinks or uses drugs?
Has been in trouble with the law?
Response options: 1=no, 2=yes, spouse, 3=yes, self; 4=both

Spousal Interaction

I am going to mention some of the things couples sometimes do together. For each one, I would like you to tell me how often you and your spouse do this together. How often do you eat your main meal together?
How often do you go shopping together?
How often do you visit friends together?
How often do you work together on projects around the house?
When you go out--say, to play cards, bowling, or a movie--how often do you do this together?
Response options: 1=almost always, 2=usually, 3=occasionally, 4=never

Marital Instability

Sometimes married people think they would enjoy living apart from their spouse. How often do you feel this way?
Response: 1=very often, 2=often, 3=occasionally, 4=never

Even people who get along quite well with their spouse sometimes wonder whether their marriage is working out. Have you ever thought your marriage might be in trouble?
Have you thought this within the last three years?
Do you feel this way now?
Have you ever talked with family members, friends, clergy, counselors, or social workers about problems in your marriage?
Have you talked with them about your marital problems within the last three years?
Have you talked with them recently?
As far as you know has your (husband/wife) talked with relatives, friends, or a counselor about problems either of you are having with your marriage?
Has (he/she) talked with any of them within the last three years?
Has (he/she) done so recently?
As far as you know, has your spouse ever thought your marriage was in trouble?
Has (he/she) thought this way in the last three years?
Does (he/she) feel this way now?
Has the thought of getting a divorce or separation crossed your mind (in the last three years)?
Are you thinking about it now?
As far as you know, has the thought of divorce or a separation crossed your (husband's/wife's) mind (in the last three years)?
Is (he/she) thinking about it now?
Have you or your (husband/wife) ever seriously suggested the idea of divorce?
Has this been within the last three years?
Has this been recently?
Did you talk about consulting an attorney?
Have you talked about filing?
Have you or your (husband/wife) consulted an attorney about a divorce or separation?
Have you or your (husband/wife) filed a divorce or separation petition?
Because of problems people are having with their marriage they sometimes leave home either for a short time or as a trial separation. Has this ever happened in your marriage?
Has this happened in the last three years?
Response options: 1=yes 2=no
Appendix B. List of Variable Labels Included in Don’t Know and Refusal Analyses

Sex of respondent
Age of respondent
Respondent's years of schooling
Sex of spouse
Age of spouse
Spouse's years of schooling
Person3's relationship to respondent
Sex of person3
Age of person3
Marital status of person3
Person3's years of schooling
Person4's relationship to respondent
Sex of person4
Age of person4
Marital status of person4
Person4's years of schooling
Person5's relationship to respondent
Sex of person5
Age of person5
Marital status of person5
Person5's years of schooling
Person6's relationship to respondent
Sex of person6
Age of person6
Marital status of person6
Person6's years of schooling
Person7's relationship to respondent
Sex of person7
Age of person7
Marital status of person7
Person7's years of schooling
Person8's relationship to respondent
Sex of person8
Age of person8
Marital status of person8
Person8's years of schooling
Person9's relationship to respondent
Sex of person9
Age of person9
Marital status of person9
Person9's years of schooling
Person10's relationship to respondent
Sex of person10
Age of person10
Marital status of person10
Person10's years of schooling
Living in urban, farm or country
Things interesting as they were
Gotten expected out of life
Not enough time left to achieve
Feeling of non-control of life
Number of marriages
Age at first marriage
First marriage intact?
Reason for first marriage end
Age at first marriage end
Age at second marriage
Second marriage intact?
Reason for second marriage end
Age at second marriage end
Age at third marriage
Third marriage intact?
Reason for third marriage end
Age at third marriage end
Age at fourth marriage
Spouse's number of marriages
Spouse's age at first marriage
Spouse's first marriage intact?
Reason spouse's first marriage ended
Age at spouse's first marriage end
Spouse's age at second marriage
Spouse's second marriage intact
Reason spouse's second marriage ended
Age at spouse's second marriage end
Spouse's age at third marriage
Spouse's third marriage intact?
Reason spouse's third marriage ended
Age at spouse's third marriage end
Age at spouse's fourth marriage
Knew spouse before age twelve?
Talk to spouse in school?
Played with spouse when children
How many months dating spouse before marriage
Live with spouse before marriage?
Parents unhappy with spouse choice?
Parents get along now with spouse
In-laws unhappy with marriage?
In-laws get along now with respondent?
Total number of children
Number of children-this marriage
Intended children-next 3 years
W pregnant now
Number of children desired
Respondent's religion
Respondent's denomination
Spouse's religion the same?
Spouse's denomination
Frequency of churchgoing together
Degree religion influences life
Degree spouse's religion influences life
R and s same religion when began dating?
Type of housing
Number of rooms in household
Home-own, renting, buying?
Year home bought
Current dollar value of home
Respondent's race
Father's years of schooling
Father-in-law's years of schooling
Time mother worked when r grew up
Mother's work: part or full-time
Mother's years of schooling
Time s's mother worked-when s grew
S's mother's work: part or full-time
Spouse's mother's years of schooling
Husband's work status
Number of men-colleagues
Number of hours husband works
Husband's job-irregular hours
Husband's job-shift work
Husband's job-evening meetings?
Husband's job-overnight trips?
Husband's job-interfere with family life
Husband's job satisfaction
Time husband couldn’t support family financially
Husband couldn’t support-past 3 years
Wife paid employee before marriage?
Wife worked after marriage?
Wife's post-marriage work: time spent
Wife working at start of marriage?
Wife works-to make ends meet
Wife works-get money for better things
Wife works-wants a career
Wife works-for feeling of accomplishment
Wife works-get away from family, children
Wife works-does not like staying at home
Wife works-likes contact with people
Wife works-for financial independence
Wife working for pay now?
Wife's job associated with husband's
Wife working: part or full-time
Wife's job-irregular hours
Wife's job-shift work
Wife's job-evening meetings
Wife's job-overnight trips
Wife's job-regular non-work periods
Wife's job-number of hours
Wife's job-hours away from home
Wife's job satisfaction
Wife's number of months on current job
Wife's job-number of women workers
Wife's job-affect quality of marriage
R's feeling re: wife working
W's job concern: come home irritable
W's job concern: no time to do h things
W's job concern: no time care for house
W's job concern: meeting too many men
W's job concern: no time do things together
W's job concern: take proper care of kids
Last 3 years-rely on wife’s income
Last 3 years-time wife didn't work
Latest job-months since started work
Latest job-months since last job?
Reason to start work-husband suggested
Reason to start work-to make ends meet
Reason to start work-money for good thin
Reason to start work-career
Reason to start work-accomplishment
Reason to start work-get away from family
Reason to start work-dislike stay at home
Reason to start work-contact with people
Reason to start work-financial independence
Reason to start work-other
Wife changed from part to full-time work
How long wife changed part to fulltime w
Wife change fulltime: different job?
Wife change fulltime: different assignment
Wife change fulltime: husband suggested extra hours
Wife change fulltime: to make ends meet
Wife change fulltime: get good things
Wife change fulltime: wanted career
Wife change fulltime: accomplishment
Wife change fulltime: get away from family
Wife change fulltime: dislike stay home
Wife change fulltime: like people contact
Wife change fulltime: financial independence
Wife change fulltime: other reasons
Wife change full to part-time work
Wife change part-time work: how long ago?
Wife change part-time: get different job
Wife change part-time: employer cut hours
Wife change part-time: have, care children
Wife change part-time: strain on family, marriage
Wife change part-time: husband said too much work
Wife change part-time: spend more time home
Wife change part-time: laid-off, on strike
Wife change part-time: disliked job
Wife change part-time: other reasons
Last year wife worked
How many months since wife worked
Wife stop work: have, take care of children
Wife stop work: strain family, marriage
Wife stop work: h didn't want her to work
Wife stop work: to spend more time at home
Wife stop work: laid off or on strike
Wife stop work: disliked job
Wife stop work: other reason
Most recent change: stopped working
Most recent change: started after absence
Most recent change: working more hours
Most recent change: working less hours
Most recent change: no change in situation
Wife wants to return to work
Wife wants work again: make ends meet
Wife wants work again: get better things
Wife wants work again: career
Wife wants work again: accomplishment
Wife wants work again: get away from home
Wife wants work again: boredom at home
Wife wants work again: likes contact with people
Wife wants work again: financial independence
Wife wants work again: other reasons
Wife doesn't work: to take care of husband
Wife doesn't work: husband disapproves
Wife doesn't work: health problems
Wife doesn't work: no jobs available
Wife doesn't work: to have, care for child
Difficult for wife to find job now?
Wife has training or job experience?
Wife's training, job experience: type
Husband's feeling re: wife working fulltime now
Husband suggest wife’s going back to work good idea
Husband dislike wife’s return work: take care children
Husband dislike wife’s return work: loss of service
Husband dislike wife’s return work: wouldn't pay enough
Husband dislike wife’s return work: wife should stay home
Husband dislike wife’s return work: other reason
How would h feel about w work part-time
If wife had choice: work full-time, part-time, not at all
Wife's most imp task: caring of children
Husband should earn larger pay than wife
Shouldn't worry husband if wife’s job has overnight stay
If wife works full-time husband must share home chores
If jobs scarce, supported wives shouldn’t work
Working mothers have good relationships with children
Even if wife works, husband must be mainly responsible to provide
Always help people in trouble
Get even not forget and forgive
Good listener to everybody
Insist on having things own way
Degree of happiness
Main meal together?
Go shopping together?
Visit friends together?
Work around home together?
Go out-cards, bowling, movies-together?
Time spent together change since work change
Increase or decrease in time spent with s since work change
Close friends who are not relatives?
Number of close friends not relatives?
How well friends get along with spouse?
Number of r's close friends also spouse?
Increase or decrease friends since work change
Recent spouse suggest make new friends
Recent r suggest s make new friends
Membership in groups and clubs
Number of memberships
How many clubs and groups do you and spouse belong to
Changes in membership: since wife’s work changed
Membership in self-help groups since marrie
Amount of chores actually done by R
Chore division-fair or you do more?
Chore division-spouse thinks fair?
Chore division-arguments with spouse?
Chore division arguments: change with wife’s work cha
Chore division responsibility: change with w work change
Chore division responsibility change: husband does more?
Chore division responsibility change: husband does less?
Chore division responsibility change: kids do more
Chore division responsibility change: make do with less?
Chore division responsibility change: others do it?
Child care-amount usually done by R?
Child care-fair or you do more than share?
Child care-spouse thinks fair?
Child care-arguments re sharing of work?
Child care argument: change since wife's work change
Child care responsibility: change since wife work
Child care responsibility change: husband does more
Child care responsibility change: husband does less
Child care responsibility change: kids do more
Child care responsibility change: do with less
Child care responsibility change: others do it
Degree respondent misses spouse when away
R upset if staying all day with family?
Perceived frequency: enjoy living apart from spouse
Perceived frequency: enjoy live away from child(ren)
Perceived amount of problems from children
Decisions: any where R has the final word
Decisions: any where spouse has the final word
Decisions overall: whose word final most?
Decision overall: R satisfied with influence
R decision influence-change since wife’s work changed
Frequency of disagreements with spouse
Disagreements: frequency change since wife work cha
Change in frequency of disagreements: more or less
Quarrels: frequency in past two months
Spouse abuse occurrence
Frequency of spouse abuse in last 3 year
Health: self-rating
Health condition-strain on marriage?
Health problems restrict household work?
Health problems-strain on marriage?
Nervous, unhappy, irritable, etc.
Nervous, irritable, unhappy, etc.recently
Mental problems led to fewer activities
Mental problems strain on marriage
Spouse’s health rating
Spouse health-strain on marriage?
Spouse health problem restrict household work
Spouse health problems-strain on marriage
Spouse nervous, unhappy, irritable etc.
Spouse nervous, unhappy irritable etc. recently
Spouse mental problems led to cut activities
Spouse mental problems strain on marriage
Satisfaction: extent of s understanding?
Satisfaction: amount love, affection received
Satisfaction: agreement with spouse
Satisfaction: sexual relationship
Satisfaction: getting along with children
Satisfaction: spouse as breadwinner
Satisfaction: spouse takes care of home
Satisfaction: spouse as someone to do things
Satisfaction: spouse’s faithfullness
Satisfaction: financial situation
Satisfaction: with home
Marriage positive, negative: social life
Marriage positive, negative: finances
Marriage positive, negative: peace of mind
Marriage posit, negative: get along children
Marriage positive, negative: job chances
1 partner give more than other to marriage
Spouse or respondent gives more to marriage
Marriage problem: get angry easily
Marriage problem: easily hurt feelings
Marriage problem: is jealous
Marriage problem: is domineering
Marriage problem: is critical
Marriage problem: is moody
Marriage problem: one not talking to other
Marriage problem: sex relations with other
Marriage problem: has irritating habits
Marriage problem: one not at home enough
Marriage problem: spends money foolishly
Marriage problem: drinks, uses drugs
Marriage problem: been in trouble with la
Marriage problem: abusive to children
If doing all over again: marry spouse, someone else, or no one
Before marriage doubts about this best?
Marriage overall: R degree of happiness
Compared to other marriages: better or worse
R ever thought marriage in trouble
When r first felt marriage in trouble
R felt marriage in trouble last 3 years
R feels marriage in trouble now
Talk to spouse re marriage problems
Talk to significant others about marital problem
R talk to others about marital problems
R talk to family about marital problems
R talk to friends about marital problems
R talk to clergy, doctor about marital problems
R talk to others re marital problems
R others talk re marital problems recent
Spouse talk to others re marital problem
Spouse talk to others about marital problems
Spouse talk to others about marital problems recently
Has spouse thought marriage in trouble?
Spouse thought marriage in trouble
Spouse thinks marriage in trouble now?
Past 3 years thought of divorce, separation
R thinking about divorce, separation now?
R thinks divorce, separation good idea?
Has spouse thought of divorce, separation
Spouse thinking of divorce, separation no
Spouse thinks divorce, separation good idea?
Divorce suggested?
Divorce suggested: last 3 years?
Divorce suggested: recently?
Divorce suggested: more than once?
Divorce: who began most recent talk?
Divorce talk: R speak favoring the idea?
Divorce talk: Spouse speak favoring the idea?
Divorce talk: Spouse more, less strong than R?
Divorce talk: consulting attorney
Divorce talk: discuss child custody
Divorce talk: dividing up the property
Divorce talk: of problems of living apart
Divorce talk: about filing
Divorce: R or spouse consult attorney?
R or spouse file a divorce, separation petition
Fate of divorce, separation petition
Divorce, separation discussed with family
Family approve idea of divorce, separation
Discuss divorce, separate with a close pa
Pal approve, disapprove: divorce, separation
Trial separation: occurrence
Trial separation: past 3 years?
Frequency trial separation past 3 years
Trial separation: who left last time?
Trial separation: how long?
Compared to 3yrs ago marriage better?
Future of marriage
Strength of feelings of love for spouse
Strength of spouse's love for respondent
R's parents divorced, permanent separated
State of r's parents' marriage
Spouse's parents divorced, permanent separated
R siblings divorced, separated, in process
R friends divorced, separated, in process?
If marital breakup: earn enough money?
If marital breakup: spouse earn enough money?
If marital breakup: handle children on own
If marital breakup: spouse handle children own
If marital breakup: can live apart from child?
If marital breakup: spouse can live apart from child
If marital breakup: can R live without s
If marital breakup: can spouse live without R
If marital breakup: can R rely on relatives
If marital breakup: can spouse rely relatives
If marital breakup: R can find other spouse
R's attractiveness compared to spouse
R's intelligence compared to spouse
Couples able to get divorced too easily
Alright if marriage doesn’t work out
Individual happiness more important than bad marriage
Spouse disabled, other should stay; even unhappy
Marriage for life, even if couple unhappy
Parents fight; separation-better for child
Spouse and R congruence of views re divorce
Family income more or less than $20000
Total 1979 family income less $20000
Total 1979 family income more $20000
Respondent's contribution percentage
Spouse's contribution percentage
Income from public assistance programs?
Social security benefits
Financial situation better or worse?
Financial situation since w work change
Joint property
Value of joint property
Appendix C: Simulation Code

The following is the code for the imputation. The first three steps focus on creating the datasets necessary for the simulation as well as constructing the two weights used to test the weighting strategy to adjust for attrition. Steps four through six identify the multiple imputation models used to adjust for attrition. Steps seven through thirteen run the means and regressions for the comparison of the results. While I have included syntax specifying only one change directory (cd) command, I strongly suggest using multiple computers for steps eight through thirteen, as this will reduce simulation time by several days or weeks, depending on how quickly Stata can run the imputation and analysis models.

Step 1: Single imputation
/
This simulation uses three datasets from the General Social Survey (GSS):
The 2006 GSS panel, with observations from 2006, 2008, and 2010
The 2008 GSS panel, with observations from 2008 and 2010
The 2010 GSS panel, with observations from 2010 only.
These datasets were cleaned separately and then combined and checked again to ensure that the variables were named and labelled consistently. Please contact the author for this section of the code.

The code for the rest of the simulation is presented below.
*/

/*
The first step is to separate the datasets and singly impute to get rid of item and unit missing for the simulation. The panels were imputed separately in this step.
*/

use "gss for single impute.dta", clear
*Imputing all available waves of the 2006 panel:
keep if startyr==2006

mi set flong
mi register impute attend2006-
race

mi impute chained (regress) age educ* childs* loginc* hrs* intyrs* lngthinv* ///
(mlogit) race (logit) female ///
, augment force add(1) rseed(429)

foreach var of varlist age educ* childs* hrs* lngthinv* {
replace `var' = round(`var')
}


mi impute chained (mlogit) marital* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (mlogit) relig* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (mlogit) region* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (mlogit) wrkstat* ///
= i.race age female educ* loginc* hrs* ///
, augment force replace rseed(429) burnin(1)

mi impute chained (regress) attend* polviews* ///
(ologit) god* marhomo* bible* ///
fund* homosex* prays* health* satfin* happy* adults* babies* ///
preteen* teens* metro* ///
= age educ* i.race female loginc* hrs* i.marital2006 i.marital2008 i.marital2010 ///
i.relig2006 i.relig2008 i.relig2010 i.wrkstat2006 i.wrkstat2008 i.wrkstat2010 ///
i.region2006 i.region2008 i.region2010 ///
, augment force replace rseed(429) burnin(1)

foreach var of varlist attend* polviews* {
    replace `var' = round(`var')
}

mi impute chained (logit) colhomo2006 colhomo2008 colhomo2010 ///
dwelown2006 dwelown2008 dwelown2010 ///
mode2006 mode2008 mode2010 ///
= age educ* i.race female loginc* hrs* i.marital2006 i.marital2008 i.marital2010 ///
i.relig2006 i.relig2008 i.relig2010 i.wrkstat2006 i.wrkstat2008 i.wrkstat2010 ///
i.region2006 i.region2008 i.region2010 ///
, augment force replace rseed(429) burnin(1)

mi unset
*This will drop the unimputed dataset, creating a dataset with plausible values
*for all cases & variables
drop if mi_m==0

save "2006 single impute.dta", replace

use "gss for single impute.dta", clear

*Imputing the 2008 panel
keep if startyr==2008

*There are no valid observations for 2006 for this panel, and so the
*time varying covariates for this year are dropped. They are all missing
*values that exist only because the panels were combined during cleaning.

mi set flong
mi register impute attend2008= race

mi impute chained (regress) age educ* childs* loginc* hrs* intyrs* lngthinv* ///
(mlogit) race (logit) female ///
, augment force add(1) rseed(429)

foreach var of varlist age educ* childs* hrs* lngthinv* {
replace `var' = round(`var')
}

mi impute chained (mlogit) marital* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (mlogit) relig* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (mlogit) region* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (mlogit) wrkstat* ///
= i.race age female educ* loginc* hrs* ///
, augment force replace rseed(429) burnin(1)
mi impute chained (regress) attend* polviews* ///
(ologit) god* marhomo* bible* ///
fund* homosex* prays* health* satfin* happy* adults* babies* ///
preteen* teens* metro* ///
= age educ* i.race female loginc* hrs* i.marital2008 i.marital2010 ///
i.relig2008 i.relig2010 i.wrkstat2008 i.wrkstat2010 ///
i.region2008 i.region2010 ///
, augment force replace rseed(429) burnin(1)

foreach var of varlist attend* polviews* {
replace `var' = round(`var')
}

mi impute chained (logit) colhomo2008 colhomo2010 ///
dwelown2008 dwelown2010 ///
libhomo2008 libhomo2010 prayer2008 prayer2010 ///
postlife2008 postlife2010 reborn2008 reborn2010 ///
savesoul2008 savesoul2010 spkhomo2008 spkhomo2010 ///
mode2008 mode2010 ///
= age educ* i.race female loginc* hrs* i.marital2008 i.marital2010 ///
i.relig2008 i.relig2010 i.wrkstat2008 i.wrkstat2010 ///
i.region2008 i.region2010 ///
, augment force replace rseed(429) burnin(1)

mi unset

*This will drop the unimputed dataset, creating a dataset with plausible values
*for all cases & variables
drop if mi_m==0

save "2008 single impute.dta", replace

use "gss for single impute.dta", clear

keep if startyr==2010

*There are only valid observations for the year 2010 in this panel, and so only
*the time varying covariates for this year are kept. Variables from 2006 and
*2008 only exist because the panels were combined during cleaning.
mi set flong
mi register impute attend2010- race

mi impute chained (regress) age educ* childs* loginc* hrs* intyrs* lngthinv* ///
(mlogit) race (logit) female ///
, augment force add(1) rseed(429)

foreach var of varlist age educ* childs* hrs* lngthinv* {
    replace `var' = round(`var')
}

mi impute chained (mlogit) marital* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)

mi impute chained (mlogit) relig* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)

mi impute chained (mlogit) region* ///
= i.race age female educ* loginc* ///
, augment force replace rseed(429) burnin(1)

mi impute chained (mlogit) wrkstat* ///
= i.race age female educ* loginc* hrs* ///
, augment force replace rseed(429) burnin(1)

mi impute chained (regress) attend* polviews* ///
(ologit) god* marhomo* bible* ///
fund* homosexual* prays* health* satfin* happy* adults* babies* ///
preteen* teens* metro* ///
= age educ* i.race female loginc* hrs* i.marital2010 ///
i.relig2010 i.wrkstat2010 ///
i.region2010 ///
, augment force replace rseed(429) burnin(1)

foreach var of varlist attend* polviews* {
    replace `var' = round(`var')
}

mi impute chained (logit) colhomo2010 ///
dwelown2010 ///
libhomo2010 prayer2010 ///
postlife2010 reborn2010 ///
savesoul2010 spkhomo2010 ///
mode2010 ///
= age educ* i.race female loginc* hrs* i.marital2010 ///
i.relig2010  i.wrkstat2010 ///
i.region2010 ///
, augment force replace rseed(429) burnin(1)

mi unset

*This will drop the unimputed dataset, creating a dataset with plausible values
*for all cases & variables
drop if mi_m==0

save "2010 single impute.dta", replace

*Combining the singly imputed datasets
use "2006 single impute.dta", clear
append using "2008 single impute.dta"
append using "2010 single impute.dta"

save "gss.dta", replace
Step 2: Predicting the propensity to attrite

keep if startyr==2006

foreach var of varlist ///
    age2006 female race marital2006 region2006 ///
    intyrs2006 lngthinv2006 mode2006 adults2006 babies2006 ///
    preteen2006 teens2006 gaytolerance2006 religiosity2006 marhomo2006 {
    gen i_`var' = `var'
}

save "pr(attrition 2006)", replace

*2006 sample only (original sample)

logit attrite2008 ///
    c.i_age##c.i_age##c.i_age i_female i.i_race i.i_marital2006 i.i_region2006 ///
    i.educ2006 i.loginc2006 i.hrs2006 i.metro2006 ///
    i.dwelown2006 i.health2006 i.intyrs2006 ///
    c.i.lngthinv2006 i.mode2006 i.adults2006 i.babies2006 ///
    i.preteen2006 i.teens2006 i.gaytolerance2006 i.religiosity2006 i.marhomo2006

predict attritMAR2008
sum attritMAR2008 attrite2008
* The probability of attrition ranges from 5% to ~69%
keep vid id startyr attritMAR2008
save "pr(attrition2008) startyr==2006.dta", replace

*Predicting attrition in 2010 for the 2006 sample
*Exiting those who attrited in 2008
use "gss.dta", replace
foreach var of varlist ///
    age2008 female race marital2008 region2008 ///
    gen i_`var' = `var'
}

logit attrite2010 ///
    c.i_age##c.i_age##c.i_age i_female i.i_race i.i_marital2008 i.i_region2008 ///
    i.educ2008 i.loginc2008 i.hrs2008 i.metro2008 ///
    i.dwelown2008 i.health2008 i.intyrs2008 ///
    c.i.lngthinv2008 i.mode2008 i.adults2008 i.babies2008 ///
predict attritMAR2010
sum attritMAR2010 attrite2010
* The probability of attrition ranges from ~4% to ~65%
keep vid id startyr attritMAR2010
save "pr(attrition2010) startyr==2006.dta", replace

*And the pr(attrition2010) for the 2008 sample
use "gss.dta", replace
keep if startyr==2008

foreach var of varlist ///
    age2008 female race marital2008 region2008 ///
    gen i_`var' = `var'
}

logit attrite2010 ///
c.i_age##c.i_age##c.i_age i.i_female i.i_marital2008 i.i_region2008 ///
i.i_educ2008 i.i_loginc2008 i.i_hrs2008 i.i_metro2008 ///
i.i_dwelown2008 i.i_health2008 i.i_intyrs2008 ///
c.i_lngthinv2008 i.i_mode2008 i.i_adults2008 i.i_babies2008 ///
i.i_preteen2008 i.i_teens2008 i.i_gaytolerance2008 i.i_religiosity2008 i.i_marhomo2008

predict attritMAR2010_08sample
sum attritMAR2010 attrite2010
* The probability of attrition ranges from ~5% to ~57%
keep vid id startyr attritMAR2010
save "pr(attrition2010) startyr==2008.dta", replace

*3. Drop imputations, keep pr(attrition)
use "gss.dta", replace
merge 1:1 id using "pr(attrition2008) startyr==2006.dta"
drop _merge
merge 1:1 id using "pr(attrition2010) startyr==2006.dta"
drop _merge
merge 1:1 id using "pr(attrition2010) startyr==2008.dta"
drop _merge
*4 Making complete cases dataset:
drop if attrite2008==1 | attrite2010==1
***Making ipweights

*pwt2006 is the predicted prob. for the 2006 sample
*averaging probs, not advisable but multiplicative wt is wrong
gen pwt2006 = 1/((attritMAR2008 + attritMAR2010) / 2)

*pwt2008 is for the 2008 sample
gen pwt2008 = 1/attritMAR2010_08sample

sum pwt*
*graph box pwt2006
*graph box pwt2008
*range of pwt2006 is well over 300!
gen pwt2006_trim = pwt2006
recode pwt2006_trim 15/max=15 if !missing(pwt2006)
sum pwt*

gen fwt = pwt2006_trim
replace fwt = pwt2008 if startyr==2008
replace fwt = wtnr2010 if startyr==2010

trimmean fwt, percent(10) ceiling gen(fwttrim)
egen fwtmean = mean(fwt)
egen fwtstd = sd(fwt)
egen fwtiqr = iqr(fwt)
sum fwt*
egen fwttrim = fwt
replace fwttrim = fwtmean + 3*fwtstd if fwttrim > fwtmean + 3*fwtstd
Step 3: Creating 500 datasets with simulated attrition

foreach num of numlist 1/500{
    use "C:\Simulations\Refresher imputation\sim\data sim.dta", clear
    *Creating propensity of stayers to attrite & making missing variables
    *I need 23% attrition
    generate mi2006_2008 = 1
    replace mi2006_2008 = 0 if (attritMAR2008+.016)>(runiform())
    tab mi2006_2008 if startyr==2006
    *I need 17% of stayers or 36% cumulative
    gen mi2006_2010 = 1
    replace mi2006_2010 = 0 if (attritMAR2010+.01)>(runiform())
    tab mi2006_2010 if startyr==2006 & mi2006_2008 == 1
    *I need 22% attrition
    gen mi2008_2010 = 1
    replace mi2008_2010 = 0 if (attritMAR2010_08sample+.01)>(runiform())
    *getting 23%
    tab mi2008_2010 if startyr==2008

    *Creating true variables
    foreach var of varlist divwidsep2006 divwidsep2008 divwidsep2010 ///
        nevmarried2006 nevmarried2008 nevmarried2010 ///
        polviews2006 polviews2008 polviews2010 ///
        gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
        health2006 health2008 health2010 {
            gen tr_`var' = `var'
        }
}

foreach var of varlist divwidsep2008 divwidsep2010 nevmarried2008 nevmarried2010 ///
        south2008 south2010 catholic2008 catholic2010 ///
        norelig2008 norelig2010 otherrelig2008 otherrelig2010 ///
        educ2008 educ2010 loginc2008 loginc2010 ///
        polviews2008 polviews2010 ///
        happy2008 happy2010 satfin2008 satfin2010 ///
        religiosity2008 religiosity2010 marhomo2008 marhomo2010 ///
        gaytolerance2008 gaytolerance2010 health2008 health2010 {
            replace `var' =. if mi2006_2008==0 & startyr==2006

foreach var of varlist \\
divwidsep2010 nevmarried2010 \\
south2010 catholic2010 \\
norelig2010 otherrelig2010 \\
educ2010 loginc2010 \\
polviews2010 \\
happy2010 satfin2010 \\
religiosity2010 marhomo2010 \\
gaytolerance2010 health2010 
    replace `var' =. if mi2006_2010==0 & startyr==2006 
} 

foreach var of varlist \\
divwidsep2010 nevmarried2010 \\
south2010 catholic2010 \\
norelig2010 otherrelig2010 \\
educ2010 loginc2010 \\
polviews2010 \\
happy2010 satfin2010 \\
religiosity2010 marhomo2010 \\
gaytolerance2010 health2010 
    replace `var' =. if mi2008_2010==0 & startyr==2008 
} 

gen edcat2006=educ2006 
recode edcat2006 8/11=1 12=2 13/15=3 16=4 17/20=5 

gen edcat2008=educ2008 
recode edcat2008 8/11=1 12=2 13/15=3 16=4 17/20=5 

gen edcat2010=educ2010 
recode edcat2010 8/11=1 12=2 13/15=3 16=4 17/20=5 

*************Making weights**********

ipfweight female race agecat2010 edcat2010 if startyr==2006, gen(rakedwgt1) \\
val(46.5 53.5 67.0 14.7 13.1 5.3 26.4 35.4 29.4 8.8 16.8 27.0 28.1 15.6 12.5) \\
maxiter(50) tol(.01)

ipfweight female race agecat2010 edcat2010 if startyr==2008, gen(rakedwgt2) \\
val(46.5 53.5 67.0 14.7 13.1 5.3 26.4 35.4 29.4 8.8 16.8 27.0 28.1 15.6 12.5) \\
maxiter(50) tol(.01)
gen rakedwgt=rakedwgt1
replace rakedwgt=rakedwgt2 if startyr==2008
replace rakedwgt=wtnr2010 if startyr==2010

* Sample size
sum mi2006_2008 if mi2006_2008==1 & startyr==2006
gen samplesize1=r(N)
gen samplesize2=r(N)
sum mi2008_2010 if mi2008_2010==1 & startyr==2008
gen samplesize3=r(N)
sum startyr if startyr==2010
gen samplesize4=r(N)

gen stayer=1
replace stayer=0 if startyr==2006 & (mi2006_2008==0 | mi2006_2010==0) | startyr==2008 & mi2008_2010==0

keep tr_* age* childs* educ* loginc* mode* polviews* dwellown* startyr ///
religiosity* marhomo* gaytolerance* health* happy* satfin* ///
female white black hispanic othrace ///
divwidsep* nevmarried* south* catholic* norelig* otherrelig* ///
stayer fwt rakedwgt samplesize* drop

drop agecat*
cd "C:\Simulations\Refresher imputation\sim\seed files"
save dataset`num', replace
}
Steps 4-6: Syntax for creating the 500 imputed, 2008 refreshment, and all refreshment panel imputation datasets

*Step 4: creating the imputed datasets
foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\seed files"
    use dataset`num', clear
    gen id = _n
    gen fwtflag=1 if missing(fwt)
    gen rakedwgtflag=1 if missing(rakedwgt)
    *2006
    keep if startyr==2006
    mi set flong
    mi register imputed ///
    female white black hispanic othrace ///
    dwelown2006 dwelown2008 dwelown2010 ///
    childs2006 childs2008 childs2010 ///
    religiosity2006 religiosity2008 religiosity2010 ///
    gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
    nevmarried2006 nevmarried2008 nevmarried2010 ///
    divwidsep2006 divwidsep2008 divwidsep2010 ///
    fwt rakedwgt

    mi impute chained (regress) ///
    female white black hispanic othrace ///
    dwelown2006 dwelown2008 dwelown2010 ///
    childs2006 childs2008 childs2010 ///
    religiosity2006 religiosity2008 religiosity2010 ///
    gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
    nevmarried2006 nevmarried2008 nevmarried2010 ///
    divwidsep2006 divwidsep2008 divwidsep2010 ///
fwt rakedwgt ///
   , augment force add(30) rseed(429)
replace fwt=1 if fwtflag==1
replace rakedwgt=1 if rakedwgtflag==1
   cd "C:\Simulations\Refresher imputation\sim\2006"
save 2006imp`num', replace
}

*Step 5: 2008 refreshment imputation
foreach num of numlist 1/500{
   cd "C:\Simulations\Refresher imputation\sim\seed files"
use dataset`num', clear
drop if drop==1
drop if startyr==2010
gen id = _n
gen fwtflag=1 if missing(fwt)
gen rakedwgtflag=1 if missing(rakedwgt)

   mi set f
   long
   mi register imputed ///
   female white black hispanic othrace ///
   dwelown2006 dwelown2008 dwelown2010 ///
   childs2006 childs2008 childs2010 ///
   religiosity2006 religiosity2008 religiosity2010 ///
   gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
   nevmarried2006 nevmarried2008 nevmarried2010 divwidsep2006 divwidsep2008
   divwidsep2010 ///
   fwt rakedwgt

   mi impute chained (regress) ///
   female white black hispanic othrace ///
   dwelown2006 dwelown2008 dwelown2010 ///
   childs2006 childs2008 childs2010 ///
   religiosity2006 religiosity2008 religiosity2010 ///
gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
nevmarried2006 nevmarried2008 nevmarried2010 divwidsep2006 divwidsep2008
divwidsep2010 ///
fwt rakedwgt ///
, augment force add(30) rseed(429)
replace fwt=1 if fwtflag==1
replace rakedwgt=1 if rakedwgtflag==1
    cd "C:\Simulations\Refresher imputation\sim\ref"
save ref2008imp`num', replace
}

*Step 6: imputation all
* imputation with all three panels
foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\seed files"
    use dataset`num', clear

    gen id = _n
    gen fwtflag=1 if missing(fwt)
gen rakedwgtflag=1 if missing(rakedwgt)

    mi set flong
    mi register imputed ///
    female white black hispanic othrace ///
dwelown2006 dwelown2008 dwelown2010 ///
childs2006 childs2008 childs2010 ///
religiosity2006 religiosity2008 religiosity2010 ///
gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
nevmarried2006 nevmarried2008 nevmarried2010 divwidsep2006 divwidsep2008
divwidsep2010 ///
fwt rakedwgt

    mi impute chained (regress) ///
female white black hispanic othrace ///
dwelown2006 dwelown2008 dwelown2010 ///
childs2006 childs2008 childs2010 ///
religiosity2006 religiosity2008 religiosity2010 ///
gaytolerance2006 gaytolerance2008 gaytolerance2010 ///
nevmarried2006 nevmarried2008 nevmarried2010 divwidsep2006 divwidsep2008
divwidsep2010 ///
fwt rakedwgt ///
    , augment force add(30) rseed(429)
replace fwt=1 if fwtflag==1
replace rakedwgt=1 if rakedwgtflag==1
    cd "C:\Simulations\Refresher imputation\sim\ref"
save refimp\num', replace
}

}
Step 7: True, listwise, IPW, and raked weight OLS models (DV is support for gay marriage)

foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\seed files"
    use dataset num', clear
    keep if startyr==2006
    *true score
    *means
    mean tr_marhomo2010 ///
    tr_educ2010 tr_loginc2010 tr_polviews2010 tr_religiosity2010 ///
    tr_gaytolerance2010 age2010 agesq2010 female black hispanic othrace
    qui gen t_2006_m_marhomo = _b[tr_marhomo2010]
    qui gen t_2006_m_educ = _b[tr_educ2010]
    qui gen t_2006_m_loginc = _b[tr_loginc2010]
    qui gen t_2006_m_polviews = _b[tr_polviews2010]
    qui gen t_2006_m_religiosity = _b[tr_religiosity2010]
    qui gen t_2006_m_gaytolerance = _b[tr_gaytolerance2010]
    qui gen t_2006_m_age = _b[age2010]
    qui gen t_2006_m_agesq = _b[agesq2010]
    qui gen t_2006_m_female = _b[female]
    qui gen t_2006_m_black = _b[black]
    qui gen t_2006_m_hispanic = _b[hispanic]
    qui gen t_2006_m_othrace = _b[othrace]
    *regression:
    reg tr_marhomo2010 ///
    tr_educ2010 tr_loginc2010 tr_polviews2010 tr_religiosity2010 ///
    tr_gaytolerance2010 age2010 agesq2010 female black hispanic othrace
    *Save b-coefficients
    qui gen t_2006_b_educ = _b[tr_educ2010]
    qui gen t_2006_b_loginc = _b[tr_loginc2010]
    qui gen t_2006_b_polviews = _b[tr_polviews2010]
    qui gen t_2006_b_religiosity = _b[tr_religiosity2010]
    qui gen t_2006_b_gaytolerance = _b[tr_gaytolerance2010]
    qui gen t_2006_b_age = _b[age2010]
    qui gen t_2006_b_agesq = _b[agesq2010]
    qui gen t_2006_b_female = _b[female]
    qui gen t_2006_b_black = _b[black]
    qui gen t_2006_b_hispanic = _b[hispanic]
    qui gen t_2006_b_othrace = _b[othrace]
    *Save standard errors
    qui gen t_2006_se_educ = _se[tr_educ2010]
qui gen t_2006_se_loginc = _se[tr_loginc2010]
qui gen t_2006_se_polviews = _se[tr_polviews2010]
qui gen t_2006_se_religiosity = _se[tr_religiosity2010]
qui gen t_2006_se_gaytolerance = _se[tr_gaytolerance2010]
qui gen t_2006_se_age = _se[age2010]
qui gen t_2006_se_agesq = _se[agesq2010]
qui gen t_2006_se_female = _se[female]
qui gen t_2006_se_black = _se[black]
qui gen t_2006_se_hispanic = _se[hispanic]
qui gen t_2006_se_othrace = _se[othrace]

*listwise:

*means
mean marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace
qui gen l_2006_m_marhomo = _b[marhomo2010]
qui gen l_2006_m_educ = _b[educ]
qui gen l_2006_m_loginc = _b[loginc]
qui gen l_2006_m_polviews = _b[polviews]
qui gen l_2006_m_religiosity = _b[religiosity]
qui gen l_2006_m_gaytolerance = _b[gaytolerance]
qui gen l_2006_m_age = _b[age2010]
qui gen l_2006_m_agesq = _b[agesq2010]
qui gen l_2006_m_female = _b[female]
qui gen l_2006_m_black = _b[black]
qui gen l_2006_m_hispanic = _b[hispanic]
qui gen l_2006_m_othrace = _b[othrace]

*regression:
reg marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace

*Save b-coefficients
qui gen l_2006_b_educ = _b[educ]
qui gen l_2006_b_loginc = _b[loginc]
qui gen l_2006_b_polviews = _b[polviews]
qui gen l_2006_b_religiosity = _b[religiosity]
qui gen l_2006_b_gaytolerance = _b[gaytolerance]
qui gen l_2006_b_age = _b[age2010]
qui gen l_2006_b_agesq = _b[agesq2010]
qui gen l_2006_b_female = _b[female]
qui gen l_2006_b_black = _b[black]
qui gen l_2006_b_hispanic = _b[hispanic]
qui gen l_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen l_2006_se_educ = _se[educ]
qui gen l_2006_se_loginc = _se[loginc]
qui gen l_2006_se_polviews = _se[polviews]
qui gen l_2006_se_religiosity = _se[religiosity]
qui gen l_2006_se_gaytolerance = _se[gaytolerance]
qui gen l_2006_se_age = _se[age2010]
qui gen l_2006_se_agesq = _se[agesq2010]
qui gen l_2006_se_female = _se[female]
qui gen l_2006_se_black = _se[black]
qui gen l_2006_se_hispanic = _se[hispanic]
qui gen l_2006_se_othrace = _se[othrace]

*Weighted models

*IPW version
svyset [pweight=fwt]

*Means
svy: mean marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace
qui gen p_2006_m_marhomo = _b[marhomo2010]
qui gen p_2006_m_educ = _b[educ]
qui gen p_2006_m_loginc = _b[loginc]
qui gen p_2006_m_polviews = _b[polviews]
qui gen p_2006_m_religiosity = _b[religiosity]
qui gen p_2006_m_gaytolerance = _b[gaytolerance]
qui gen p_2006_m_age = _b[age2010]
qui gen p_2006_m_agesq = _b[agesq2010]
qui gen p_2006_m_female = _b[female]
qui gen p_2006_m_black = _b[black]
qui gen p_2006_m_hispanic = _b[hispanic]
qui gen p_2006_m_othrace = _b[othrace]

*regression:
svy: reg marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace

*Save b-coefficients
*Save b-coefficients
qui gen p_2006_b Educ = _b[educ2010]
qui gen p_2006_b Loginc = _b[loginc2010]
qui gen p_2006_b Polviews = _b[polviews2010]
qui gen p_2006_b Religiosity = _b[religiosity2010]
qui gen p_2006_b Gaytolerance = _b[gaytolerance2010]
qui gen p_2006_b Age = _b[age2010]
qui gen p_2006_b Agesq = _b[agesq2010]
qui gen p_2006_b Female = _b[female]
qui gen p_2006_b Black = _b[black]
qui gen p_2006_b Hispanic = _b[hispanic]
qui gen p_2006_b Othrace = _b[othrace]

*Save standard errors
qui gen p_2006_se Educ = _se[educ2010]
qui gen p_2006_se Loginc = _se[loginc2010]
qui gen p_2006_se Polviews = _se[polviews2010]
qui gen p_2006_se Religiosity = _se[religiosity2010]
qui gen p_2006_se Gaytolerance = _se[gaytolerance2010]
qui gen p_2006_se Age = _se[age2010]
qui gen p_2006_se Agesq = _se[agesq2010]
qui gen p_2006_se Female = _se[female]
qui gen p_2006_se Black = _se[black]
qui gen p_2006_se Hispanic = _se[hispanic]
qui gen p_2006_se Othrace = _se[othrace]

*Raked weight model, using weight created from 2010 GSS panel marginals
svyset [pweight=rakedwgt]

*Means
svy: mean marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace
qui gen w_2006_m_Marhomo = _b[marhomo2010]
qui gen w_2006_m_Educ = _b[educ]
qui gen w_2006_m_Loginc = _b[loginc]
qui gen w_2006_m_Polviews = _b[polviews]
qui gen w_2006_m_Religiosity = _b[religiosity]
qui gen w_2006_m_Gaytolerance = _b[gaytolerance]
qui gen w_2006_m_Age = _b[age2010]
qui gen w_2006_m_Agesq = _b[agesq2010]
qui gen w_2006_m_Female = _b[female]
qui gen w_2006_m_Black = _b[black]
qui gen w_2006_m_Hispanic = _b[hispanic]
qui gen w_2006_m_Othrace = _b[othrace]
*regression:
svy: reg marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace if startyr==2006

*Save b-coefficients
*Save b-coefficients
qui gen w_2006_b_educ = _b[educ2010]
qui gen w_2006_b_loginc = _b[loginc2010]
qui gen w_2006_b_polviews = _b[polviews2010]
qui gen w_2006_b_religiosity = _b[religiosity2010]
qui gen w_2006_b_gaytolerance = _b[gaytolerance2010]
qui gen w_2006_b_age = _b[age2010]
qui gen w_2006_b_agesq = _b[agesq2010]
qui gen w_2006_b_female = _b[female]
qui gen w_2006_b_black = _b[black]
qui gen w_2006_b_hispanic = _b[hispanic]
qui gen w_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen w_2006_se_educ = _se[educ2010]
qui gen w_2006_se_loginc = _se[loginc2010]
qui gen w_2006_se_polviews = _se[polviews2010]
qui gen w_2006_se_religiosity = _se[religiosity2010]
qui gen w_2006_se_gaytolerance = _se[gaytolerance2010]
qui gen w_2006_se_age = _se[age2010]
qui gen w_2006_se_agesq = _se[agesq2010]
qui gen w_2006_se_female = _se[female]
qui gen w_2006_se_black = _se[black]
qui gen w_2006_se_hispanic = _se[hispanic]
qui gen w_2006_se_othrace = _se[othrace]

gen rowkeep = _n
keep if rowkeep ==`num'
*keep rowkeep t_2006_m_marhomo-w_all_se_othrace
keep rowkeep t_2006_m_marhomo-w_2006_se_othrace
cd "C:\Simulations\Refresher imputation\gay to\x sect\true list wt"
save t_l_p_w_x`num'.dta, replace
}

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Step 11: True, listwise, IPW and raked weight fixed effects models (DV is support for gay marriage)

foreach num of numlist 1/50{
    cd "C:\Simulations\Refresher imputation\sim\seed files"
    use dataset`num', clear
    keep if startyr==2006
    gen id=_n
    reshape long tr_marhomo tr_nevmarried tr_south tr_catholic tr_norelig ///
    tr_otherrelig tr_educ tr_loginc tr_polviews tr_religiosity ///
    tr_gaytolerance tr_blkwhite ///
    marhomo nevmarried south catholic norelig ///
    otherrelig educ loginc polviews religiosity ///
    gaytolerance, i(id) j(wave)
    
    *2006
    xtset id wave, delta(2)
    
    *Save b-coefficients
    qui gen t_2006_b_wave = _b[wave]
    qui gen t_2006_b_educ = _b[tr_educ]
    qui gen t_2006_b_loginc = _b[tr_loginc]
    qui gen t_2006_b_polviews = _b[tr_polviews]
    qui gen t_2006_b_religiosity = _b[tr_religiosity]
    qui gen t_2006_b_gaytolerance = _b[tr_gaytolerance]
    
    *Save standard errors
    qui gen t_2006_se_wave = _se[wave]
    qui gen t_2006_se_educ = _se[tr_educ]
    qui gen t_2006_se_loginc = _se[tr_loginc]
    qui gen t_2006_se_polviews = _se[tr_polviews]
    qui gen t_2006_se_religiosity = _se[tr_religiosity]
    qui gen t_2006_se_gaytolerance = _se[tr_gaytolerance]
    
    *listwise
    *2006
    xtreg marhomo ///
    educ loginc polviews religiosity ///
    gaytolerance wave if startyr==2006, fe
*Save b-coefficients
qui gen l_2006_b_wave  = _b[wave]
qui gen l_2006_b_educ  = _b[educ]
qui gen l_2006_b_loginc = _b[loginc]
qui gen l_2006_b_polviews = _b[polviews]
qui gen l_2006_b_religiosity = _b[religiosity]
qui gen l_2006_b_gaytolerance = _b[gaytolerance]

*Save standard errors
qui gen l_2006_se_wave  = _se[wave]
qui gen l_2006_se_educ  = _se[educ]
qui gen l_2006_se_loginc = _se[loginc]
qui gen l_2006_se_polviews = _se[polviews]
qui gen l_2006_se_religiosity = _se[religiosity]
qui gen l_2006_se_gaytolerance = _se[gaytolerance]

xtreg marhomo  ///
educ loginc polviews religiosity ///
gaytolerance  wave if startyr==2006 [pweight=fwt] , fe

*Save b-coefficients
qui gen p_2006_b_wave  = _b[wave]
qui gen p_2006_b_educ  = _b[educ]
qui gen p_2006_b_loginc = _b[loginc]
qui gen p_2006_b_polviews = _b[polviews]
qui gen p_2006_b_religiosity = _b[religiosity]
qui gen p_2006_b_gaytolerance = _b[gaytolerance]

*Save standard errors
qui gen p_2006_se_wave  = _se[wave]
qui gen p_2006_se_educ  = _se[educ]
qui gen p_2006_se_loginc = _se[loginc]
qui gen p_2006_se_polviews = _se[polviews]
qui gen p_2006_se_religiosity = _se[religiosity]
qui gen p_2006_se_gaytolerance = _se[gaytolerance]

**Raked weight
xtreg marhomo  ///
educ loginc polviews religiosity ///
gaytolerance  wave if startyr==2006 [pweight=rakedwgt] , fe
*Save b-coefficients
qui gen w_2006_b_wave = _b[wave]
qui gen w_2006_b_educ = _b[educ]
qui gen w_2006_b_loginc = _b[loginc]
qui gen w_2006_b_polviews = _b[polviews]
qui gen w_2006_b_religiosity = _b[religiosity]
qui gen w_2006_b_gaytolerance = _b[gaytolerance]

*Save standard errors
qui gen w_2006_se_wave = _se[wave]
qui gen w_2006_se_educ = _se[educ]
qui gen w_2006_se_loginc = _se[loginc]
qui gen w_2006_se_polviews = _se[polviews]
qui gen w_2006_se_religiosity = _se[religiosity]
qui gen w_2006_se_gaytolerance = _se[gaytolerance]

gen rowkeep = _n
keep if rowkeep == `num'
*keep rowkeep t_2006_b_wave-w_2_all_se_gaytolerance
keep rowkeep t_2006_b_wave-w_2006_se_gaytolerance
cd "C:\Simulations\Refresher imputation\gay tolpanel\true list wt"
save t_l_p_w_longitudinal\num\num'.dta, replace

}
Steps 8 & 12: Imputation model (DV is support for gay marriage)

foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\2006"
    use 2006imp`num', clear
    mi export ice
    save icesim, replace
    use icesim, clear

    micombine mean marhomo2010 ///
    educ2010 loginc2010 polviews2010 religiosity2010 ///
    gaytolerance2010 age2010 agesq2010 female black hispanic othrace
    qui gen i_2006_m_marhomo = _b[marhomo2010]
    qui gen i_2006_m_educ = _b[educ]
    qui gen i_2006_m_loginc = _b[loginc]
    qui gen i_2006_m_polviews = _b[polviews]
    qui gen i_2006_m_religiosity = _b[religiosity]
    qui gen i_2006_m_gaytolerance = _b[gaytolerance]
    qui gen i_2006_m_age = _b[age2010]
    qui gen i_2006_m_agesq = _b[agesq2010]
    qui gen i_2006_m_female = _b[female]
    qui gen i_2006_m_black = _b[black]
    qui gen i_2006_m_hispanic = _b[hispanic]
    qui gen i_2006_m_othrace = _b[othrace]

*all
    micombine reg marhomo2010 ///
    educ2010 loginc2010 polviews2010 religiosity2010 ///
    gaytolerance2010 age2010 agesq2010 female black hispanic othrace

*Save b-coefficients
    qui gen i_2006_b_educ = _b[educ]
    qui gen i_2006_b_loginc = _b[loginc]
    qui gen i_2006_b_polviews = _b[polviews]
    qui gen i_2006_b_religiosity = _b[religiosity]
    qui gen i_2006_b_gaytolerance = _b[gaytolerance]
    qui gen i_2006_b_age = _b[age2010]
    qui gen i_2006_b_agesq = _b[agesq2010]
    qui gen i_2006_b_female = _b[female]
    qui gen i_2006_b_black = _b[black]
    qui gen i_2006_b_hispanic = _b[hispanic]
qui gen i_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen i_2006_seEduc = _se[educ]
qui gen i_2006_seLoginc = _se[loginc]
qui gen i_2006_sePolviews = _se[polviews]
qui gen i_2006_seReligiosity = _se[religiosity]
qui gen i_2006_seGaytolerance = _se[gaytolerance]
qui gen i_2006_seAge = _se[age2010]
qui gen i_2006_seAgesq = _se[agesq2010]
qui gen i_2006_seFemale = _se[female]
qui gen i_2006_seBlack = _se[black]
qui gen i_2006_seHispanic = _se[hispanic]
qui gen i_2006_seOthrace = _se[othrace]

*Save standard errors
qui gen i_p_2006_seEduc = _se[educ]
qui gen i_p_2006_seLoginc = _se[loginc]
qui gen i_p_2006_sePolviews = _se[polviews]
qui gen i_p_2006_seReligiosity = _se[religiosity]
qui gen i_p_2006_seGaytolerance = _se[gaytolerance]
qui gen i_p_2006_seAge = _se[age2010]
qui gen i_p_2006_seAgesq = _se[agesq2010]
qui gen i_p_2006_seFemale = _se[female]
qui gen i_p_2006_seBlack = _se[black]
qui gen i_p_2006_seHispanic = _se[hispanic]
qui gen i_p_2006_seOthrace = _se[othrace]

micombine reg marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace [pweight=rakedwgt]

*Save b-coefficients
qui gen i_w_2006_bEduc = _b[educ]
qui gen i_w_2006_bLoginc = _b[loginc]
qui gen i_w_2006_bPolviews = _b[polviews]
qui gen i_w_2006_bReligiosity = _b[religiosity]
qui gen i_w_2006_bGaytolerance = _b[gaytolerance]
qui gen i_w_2006_bAge = _b[age2010]
qui gen i_w_2006_bAgesq = _b[agesq2010]
qui gen i_w_2006_bFemale = _b[female]
qui gen i_w_2006_bBlack = _b[black]
qui gen i_w_2006_bHispanic = _b[hispanic]
qui gen i_w_2006_bOthrace = _b[othrace]
*Save standard errors
qui gen i_w_2006_se_educ = _se[educ]
qui gen i_w_2006_se_loginc = _se[loginc]
qui gen i_w_2006_se_polviews = _se[polviews]
qui gen i_w_2006_se_religiosity = _se[religiosity]
qui gen i_w_2006_se_gaytolerance = _se[gaytolerance]
qui gen i_w_2006_se_age = _se[age2010]
qui gen i_w_2006_se_agesq = _se[agesq2010]
qui gen i_w_2006_se_female = _se[female]
qui gen i_w_2006_se_black = _se[black]
qui gen i_w_2006_se_hispanic = _se[hispanic]
qui gen i_w_2006_se_othrace = _se[othrace]
*/
gen rowkeep = _n
keep if rowkeep == `num'
*keep rowkeep i_2006_m_marhomo-i_w_2006_se_othrace
keep rowkeep i_2006_m_marhomo-i_2006_se_othrace

cd "C:\Simulations\Refresher imputation\gay tol\sect\imputed"
save i_2006x`num'.dta, replace
}
foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\2006"
    use 2006imp`num', clear
    mi reshape long marhomo nevmarried south catholic norelig ///
    otherrelig educ loginc polviews religiosity ///
    gaytolerance , i(id) j(wave)
    mi xtset id wave, delta(2)
    mi export ice
    save icesim, replace
    use icesim, clear

    micombine xtreg marhomo ///
        educ loginc polviews religiosity ///
        gaytolerance wave , fe

*Save b-coefficients
qui gen i_2006_b_wave = _b[wave]
qui gen i_2006_b_educ = _b[educ]
qui gen i_2006_b_loginc = _b[loginc]
qui gen i_2006_b_polviews = _b[polviews]
qui gen i_2006_b_religiosity = _b[religiosity]
qui gen i_2006_b_gaytolerance = _b[gaytolerance]

*Save standard errors

qui gen i_2006_se_wave = _se[wave]
qui gen i_2006_se_educ = _se[educ]
qui gen i_2006_se_loginc = _se[loginc]
qui gen i_2006_se_polviews = _se[polviews]
qui gen i_2006_se_religiosity = _se[religiosity]
qui gen i_2006_se_gaytolerance = _se[gaytolerance]

gen rowkeep = _n
keep if rowkeep == `num'
*keep rowkeep i_2006_b_wave- i_w_2006_se_gaytolerance
keep rowkeep i_2006_b_wave- i_2006_se_gaytolerance

cd "C:\Simulations\Refresher imputation\gay tol\panel\imputed"
save i_2006longitudinal`num'.dta, replace
}
Steps 9-10 & 12-13: Refreshment imputation models (DV is support for gay marriage)

foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\ref"
    use refimp`num', clear
    keep if startyr==2006
    *all
    mi reshape long marhomo nevmarried south catholic norelig ///
    otherrelig educ loginc polviews religiosity ///
    gaytolerance blkwhite, i(id) j(wave)
    mi xtset id wave, delta(2)

    mi export ice
    save icesim, replace
    use icesim, clear

    micombine xtreg marhomo ///
    educ loginc polviews religiosity ///
    gaytolerance wave , fe

    *Save b-coefficients
    qui gen r_b_wave = _b[wave]
    qui gen r_b_educ = _b[educ]
    qui gen r_b_loginc = _b[loginc]
    qui gen r_b_polviews = _b[polviews]
    qui gen r_b_religiosity = _b[religiosity]
    qui gen r_b_gaytolerance = _b[gaytolerance]

    *Save standard errors
    qui gen r_se_wave = _se[wave]
    qui gen r_se_educ = _se[educ]
    qui gen r_se_loginc = _se[loginc]
    qui gen r_se_polviews = _se[polviews]
    qui gen r_se_religiosity = _se[religiosity]
    qui gen r_se_gaytolerance = _se[gaytolerance]

    *cd "C:\Simulations\Refresher imputation\gay tol\panel\imputed"
    save r_longitudinal`num`.dta, replace
}

foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\ref"
    use refimp`num', clear

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keep if startyr==2006
save temp, replace
mi export ice
save icesim, replace
use icesim, clear

micombine mean marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace
qui gen r_2006_m_marhomo = _b[marhomo2010]
qui gen r_2006_m_educ  = _b[educ] 
qui gen r_2006_m_loginc = _b[loginc]
qui gen r_2006_m_polviews = _b[polviews]
qui gen r_2006_m_religiosity = _b[religiosity]
qui gen r_2006_m_gaytolerance = _b[gaytolerance]
qui gen r_2006_m_age  = _b[age2010]
qui gen r_2006_m_agesq = _b[agesq2010]
qui gen r_2006_m_female  = _b[female]
qui gen r_2006_m_black  = _b[black]
qui gen r_2006_m_hispanic  = _b[hispanic]
qui gen r_2006_m_othrace = _b[othrace]

*all
micombine reg marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace
*Save b-coefficients
qui gen r_2006_b_educ  = _b[educ]
qui gen r_2006_b_loginc = _b[loginc]
qui gen r_2006_b_polviews = _b[polviews]
qui gen r_2006_b_religiosity = _b[religiosity]
qui gen r_2006_b_gaytolerance = _b[gaytolerance]
qui gen r_2006_b_age  = _b[age2010]
qui gen r_2006_b_agesq = _b[agesq2010]
qui gen r_2006_b_female  = _b[female]
qui gen r_2006_b_black  = _b[black]
qui gen r_2006_b_hispanic  = _b[hispanic]
qui gen r_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen r_2006_se_educ = _se[educ]
qui gen r_2006_se_loginc = _se[loginc]
qui gen r_2006_se_polviews = _se[polviews]
qui gen r_2006_se_religiosity = _se[religiosity]
qui gen r_2006_se_gaytolerance = _se[gaytolerance]
qui gen r_2006_se_age = _se[age2010]
qui gen r_2006_se_agesq = _se[agesq2010]
qui gen r_2006_se_female = _se[female]
qui gen r_2006_se_black = _se[black]
qui gen r_2006_se_hispanic = _se[hispanic]
qui gen r_2006_se_othrace = _se[othrace]

gen rowkeep =_n
keep if rowkeep ==`num'
*keep rowkeep r_2006_m_marhomo-r_w_2006_se_othrace

foreach num of numlist 1/500{
*cd "C:\Simulations\Refresher imputation\gay tol\x sect\imputed"
save r_2006_x`num'.dta, replace
}

cd "C:\Simulations\Refresher imputation\sim\ref"
cd "\redmond\Profiles\Desktop\vlr124\sims"
use ref2008imp`num', clear
keep if startyr==2006
save temp, replace
mi export ice
save icesim, replace
use icesim, clear

micombine mean marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace
qui gen r8_2006_m_marhomo = _b[marhomo2010]
qui gen r8_2006_m_educ = _b[educ]
qui gen r8_2006_m_loginc = _b[loginc]
qui gen r8_2006_m_polviews = _b[polviews]
qui gen r8_2006_m_religiosity = _b[religiosity]
qui gen r8_2006_m_gaytolerance = _b[gaytolerance]
qui gen r8_2006_m_age = _b[age2010]
qui gen r8_2006_m_agesq = _b[agesq2010]
qui gen r8_2006_m_female = _b[female]
gen r8_2006_m_black = _b[black]
gen r8_2006_m_hispanic = _b[hispanic]
gen r8_2006_m_othrace = _b[othrace]

*all
micombine reg marhomo2010 ///
educ2010 loginc2010 polviews2010 religiosity2010 ///
gaytolerance2010 age2010 agesq2010 female black hispanic othrace

*Save b-coefficients
gen r8_2006_b_educ = _b[educ]
gen r8_2006_b_loginc = _b[loginc]
gen r8_2006_b_polviews = _b[polviews]
gen r8_2006_b_religiosity = _b[religiosity]
gen r8_2006_b_gaytolerance = _b[gaytolerance]
gen r8_2006_b_age = _b[age2010]
gen r8_2006_b_agesq = _b[agesq2010]
gen r8_2006_b_female = _b[female]
gen r8_2006_b_black = _b[black]
gen r8_2006_b_hispanic = _b[hispanic]
gen r8_2006_b_othrace = _b[othrace]

*Save standard errors
gen r8_2006_se_educ = _se[educ]
gen r8_2006_se_loginc = _se[loginc]
gen r8_2006_se_polviews = _se[polviews]
gen r8_2006_se_religiosity = _se[religiosity]
gen r8_2006_se_gaytolerance = _se[gaytolerance]
gen r8_2006_se_age = _se[age2010]
gen r8_2006_se_agesq = _se[agesq2010]
gen r8_2006_se_female = _se[female]
gen r8_2006_se_black = _se[black]
gen r8_2006_se_hispanic = _se[hispanic]
gen r8_2006_se_othrace = _se[othrace]

gen rowkeep = _n
keep if rowkeep ==`num'
keep rowkeep r8_2006_m_marhomo-r8_2006_se_othrace
*cd "C:\Simulations\Refresher imputation\gay tol\x sect\imputed"
save r8_2006_x`num'.dta, replace
}

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foreach num of numlist 1/500{
  *cd "C:\Simulations\Refresher imputation\sim\ref"
  cd "\redmond\Profiles\Desktop\vlr124\sims"
  use ref2008imp`num', clear
  keep if startyr==2006
  *all
  mi reshape long marhomo nevmarried south catholic norelig ///
  otherrelig educ loginc polviews religiosity ///
  gaytolerance blkwhite, i(id) j(wave)
  mi xtset id wave, delta(2)

  save temp, replace
  mi export ice
  save icesim, replace
  use icesim, clear

  micombine xtreg marhomo ///
  educ loginc polviews religiosity ///
  gaytolerance wave , fe

  *Save b-coefficients
  qui gen r8_b_wave = _b[wave]
  qui gen r8_b_educ = _b[educ]
  qui gen r8_b_loginc = _b[loginc]
  qui gen r8_b_polviews = _b[polviews]
  qui gen r8_b_religiosity = _b[religiosity]
  qui gen r8_b_gaytolerance = _b[gaytolerance]

  *Save standard errors
  qui gen r8_se_wave = _se[wave]
  qui gen r8_se_educ = _se[educ]
  qui gen r8_se_loginc = _se[loginc]
  qui gen r8_se_polviews = _se[polviews]
  qui gen r8_se_religiosity = _se[religiosity]
  qui gen r8_se_gaytolerance = _se[gaytolerance]

  gen rowkeep = _n
  keep if rowkeep ==`num'

  keep rowkeep r8_b_wave- r8_se_gaytolerance

  save r8_longitudinal`num'.dta, replace
}
Step 7: True, listwise, IPW, and raked weight OLS models (DV is self-rated health)

**********True, listwise & weighted

***************Making X-section Variables***************

foreach num of numlist 1/500{
  cd "C:\Simulations\Refresher imputation\sim\seed files"
  use dataset`num', clear
  *Do I need sd for means and regs? how would I do that for longitudinal data?
  *true score
  *means
  *2006
  mean tr_health2010 ///
  tr_educ2010 tr_loginc2010 tr_happy2010 tr_satfin2010 ///
  tr_nevmarried2010 tr_divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006
  qui gen t_2006_m_health = _b[tr_health2010]
  qui gen t_2006_m_educ  = _b[tr_educ2010]
  qui gen t_2006_m_loginc = _b[tr_loginc2010]
  qui gen t_2006_m_happy = _b[tr_happy2010]
  qui gen t_2006_m_satfin = _b[tr_satfin2010]
  qui gen t_2006_m_nevmarried = _b[tr_nevmarried2010]
  qui gen t_2006_m_divwidsep = _b[tr_divwidsep2010]
  qui gen t_2006_m_age  = _b[age2010]
  qui gen t_2006_m_agesq = _b[agesq2010]
  qui gen t_2006_m_female = _b[female]
  qui gen t_2006_m_black = _b[black]
  qui gen t_2006_m_hispanic = _b[hispanic]
  qui gen t_2006_m_othrace = _b[othrace]

*regressions:
*2006
  reg tr_health2010 ///
  tr_educ2010 tr_loginc2010 tr_happy2010 tr_satfin2010 ///
  tr_nevmarried2010 tr_divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006

*Save b-coefficients
  qui gen t_2006_b_educ = _b[tr_educ2010]
  qui gen t_2006_b_loginc = _b[tr_loginc2010]
  qui gen t_2006_b_happy = _b[tr_happy2010]
qui gen t_2006_b_satfin = _b[tr_satfin2010]  
qui gen t_2006_b_nevmarried = _b[tr_nevmarried2010]  
qui gen t_2006_b_divwidsep = _b[tr_divwidsep2010]  
qui gen t_2006_b_age = _b[age2010]  
qui gen t_2006_b_agesq = _b[agesq2010]  
qui gen t_2006_b_female = _b[female]  
qui gen t_2006_b_black = _b[black]  
qui gen t_2006_b_hispanic = _b[hispanic]  
qui gen t_2006_b_othrace = _b[othrace]

*Save standard errors  
qui gen t_2006_se_educ = _se[tr_educ2010]  
qui gen t_2006_se_loginc = _se[tr_loginc2010]  
qui gen t_2006_se_happy = _se[tr_happy2010]  
qui gen t_2006_se_satfin = _se[tr_satfin2010]  
qui gen t_2006_se_nevmarried = _se[tr_nevmarried2010]  
qui gen t_2006_se_divwidsep = _se[tr_divwidsep2010]  
qui gen t_2006_se_age = _se[age2010]  
qui gen t_2006_se_agesq = _se[agesq2010]  
qui gen t_2006_se_female = _se[female]  
qui gen t_2006_se_black = _se[black]  
qui gen t_2006_se_hispanic = _se[hispanic]  
qui gen t_2006_se_othrace = _se[othrace]

*listwise:

*means  
*2006  
mean health2010 ///  
educ2010 loginc2010 happy2010 satfin2010 ///  
nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace if  
startyr==2006
qui gen l_2006_m_health = _b[health2010]  
qui gen l_2006_m_educ = _b[educ]  
qui gen l_2006_m_loginc = _b[loginc]  
qui gen l_2006_m_happy = _b[happy]  
qui gen l_2006_m_satfin = _b[satfin]  
qui gen l_2006_m_nevmarried = _b[nevmarried]  
qui gen l_2006_m_divwidsep = _b[divwidsep2010]  
qui gen l_2006_m_age = _b[age2010]  
qui gen l_2006_m_agesq = _b[agesq2010]  
qui gen l_2006_m_female = _b[female]  
qui gen l_2006_m_black = _b[black]  
qui gen l_2006_m_hispanic = _b[hispanic]  

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qui gen l_2006_m_othrace = _b[othrace]

*regressions:
*2006
reg health2010 ///
educ2010 loginc2010 happy2010 satfin2010 ///
nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006

*Save b-coefficients
qui gen l_2006_b_educ = _b[educ]
qui gen l_2006_b_loginc = _b[loginc]
qui gen l_2006_b_happy = _b[happy]
qui gen l_2006_b_satfin = _b[satfin]
qui gen l_2006_b_nevmarried = _b[nevmarried]
qui gen l_2006_b_divwidsep = _b[divwidsep2010]
qui gen l_2006_b_age = _b[age2010]
qui gen l_2006_b_agesq = _b[agesq2010]
qui gen l_2006_b_female = _b[female]
qui gen l_2006_b_black = _b[black]
qui gen l_2006_b_hispanic = _b[hispanic]
qui gen l_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen l_2006_se_educ = _se[educ]
qui gen l_2006_se_loginc = _se[loginc]
qui gen l_2006_se_happy = _se[happy]
qui gen l_2006_se_satfin = _se[satfin]
qui gen l_2006_se_nevmarried = _se[nevmarried]
qui gen l_2006_se_divwidsep = _se[divwidsep2010]
qui gen l_2006_se_age = _se[age2010]
qui gen l_2006_se_agesq = _se[agesq2010]
qui gen l_2006_se_female = _se[female]
qui gen l_2006_se_black = _se[black]
qui gen l_2006_se_hispanic = _se[hispanic]
qui gen l_2006_se_othrace = _se[othrace]

*Weighted models

*IPW version
*fwt is the propensity wts for 2006 & 2008 which I estimated from the single
*imputation (2006 wt has the enormous range) and the 2010 wt that NORC made
svyset [pweight=fwt]

*Means
*2006
svy: mean health2010
   educ2010 loginc2010 happy2010 satfin2010
   nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006
qui gen p_2006_m_health = _b[health2010]
qui gen p_2006_m_educ  = _b[educ]
qui gen p_2006_m_loginc = _b[loginc]
qui gen p_2006_m_happy = _b[happy]
qui gen p_2006_m_satfin = _b[satfin]
qui gen p_2006_m_nevmarried = _b[nevmarried]
qui gen p_2006_m_divwidsep = _b[divwidsep2010]
qui gen p_2006_m_age  = _b[age2010]
qui gen p_2006_m_agesq = _b[agesq2010]
qui gen p_2006_m_female = _b[female]
qui gen p_2006_m_black = _b[black]
qui gen p_2006_m_hispanic = _b[hispanic]
qui gen p_2006_m_othrace = _b[othrace]

*regressions:
*2006
svy: reg health2010
   educ2010 loginc2010 happy2010 satfin2010
   nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006
qui gen p_2006_b_educ  = _b[educ2010]
qui gen p_2006_b_loginc = _b[loginc2010]
qui gen p_2006_b_happy = _b[happy2010]
qui gen p_2006_b_satfin = _b[satfin2010]
qui gen p_2006_b_nevmarried = _b[nevmarried2010]
qui gen p_2006_b_divwidsep = _b[divwidsep2010]
qui gen p_2006_b_age  = _b[age2010]
qui gen p_2006_b_agesq = _b[agesq2010]
qui gen p_2006_b_female = _b[female]
qui gen p_2006_b_black = _b[black]
qui gen p_2006_b_hispanic = _b[hispanic]
qui gen p_2006_b_othrace = _b[othrace]

*Save b-coefficients
*Save b-coefficients
qui gen p_2006_b_educ  = _b[educ2010]
qui gen p_2006_b_loginc = _b[loginc2010]
qui gen p_2006_b_happy = _b[happy2010]
qui gen p_2006_b_satfin = _b[satfin2010]
qui gen p_2006_b_nevmarried = _b[nevmarried2010]
qui gen p_2006_b_divwidsep = _b[divwidsep2010]
qui gen p_2006_b_age  = _b[age2010]
qui gen p_2006_b_agesq = _b[agesq2010]
qui gen p_2006_b_female = _b[female]
qui gen p_2006_b_black = _b[black]
qui gen p_2006_b_hispanic = _b[hispanic]
qui gen p_2006_b_othrace = _b[othrace]

*Save standard errors
**Raked weights**
*The weights I made raking everything together; have not
* figured out how to distinguish between the waves, in creating this weight

svyset [pweight=rakedwgt]

*Means
*2006

svy: mean health2010 ///
educ2010 loginc2010 happy2010 satfin2010 ///
nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006
qui gen w_2006_m_health = _b[health2010]
qui gen w_2006_m_educ = _b[educ]
qui gen w_2006_m_loginc = _b[loginc]
qui gen w_2006_m_happy = _b[happy]
qui gen w_2006_m_satfin = _b[satfin]
qui gen w_2006_m_nevmarried = _b[nevmarried]
qui gen w_2006_m_divwidsep = _b[divwidsep2010]
qui gen w_2006_m_age = _b[age2010]
qui gen w_2006_m_agesq = _b[agesq2010]
qui gen w_2006_m_female = _b[female]
qui gen w_2006_m_black = _b[black]
qui gen w_2006_m_hispanic = _b[hispanic]
qui gen w_2006_m_othrace = _b[othrace]

*regressions:
*2006
svy: reg health2010 ///
educ2010 loginc2010 happy2010 satfin2010 ///
nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace if startyr==2006

*Save b-coefficients
*Save b-coefficients
qui gen w_2006_b_educ  = _b[educ2010]
qui gen w_2006_b_loginc  = _b[loginc2010]
qui gen w_2006_b_happy  = _b[happy2010]
qui gen w_2006_b_satfin  = _b[satfin2010]
qui gen w_2006_b_nevmarried  = _b[nevmarried2010]
qui gen w_2006_b_divwidsep  = _b[divwidsep2010]
qui gen w_2006_b_age  = _b[age2010]
qui gen w_2006_b_agesq  = _b[agesq2010]
qui gen w_2006_b_female  = _b[female]
qui gen w_2006_b_black  = _b[black]
qui gen w_2006_b_hispanic  = _b[hispanic]
qui gen w_2006_b_othrace  = _b[othrace]

*Save standard errors
qui gen w_2006_se_educ  = _se[educ2010]
qui gen w_2006_se_loginc  = _se[loginc2010]
qui gen w_2006_se_happy  = _se[happy2010]
qui gen w_2006_se_satfin  = _se[satfin2010]
qui gen w_2006_se_nevmarried  = _se[nevmarried2010]
qui gen w_2006_se_divwidsep  = _se[divwidsep2010]
qui gen w_2006_se_age  = _se[age2010]
qui gen w_2006_se_agesq  = _se[agesq2010]
qui gen w_2006_se_female  = _se[female]
qui gen w_2006_se_black  = _se[black]
qui gen w_2006_se_hispanic  = _se[hispanic]
qui gen w_2006_se_othrace  = _se[othrace]

gen rowkeep = _n
keep if rowkeep ==`num'
keep rowkeep t_2006_m_health-w_2006_se_othrace

cd "C:\Simulations\Refresher imputation\health\x sect\true list wt"
save t_L_p_w_x'num'.dta, replace
}
Step 11: True, listwise, IPW and raked weight fixed effects models (DV is self-rated health)

***************Making Longitudinal Models***************

foreach num of numlist 1/500{
  cd "C:\Simulations\Refresher imputation\sim\seed files"
  use dataset `num', clear
  keep if startyr==2006
  gen id=_n
  reshape long tr_health ///
  tr_educ tr_loginc tr_happy tr_satfin ///
  tr_nevmarried tr_divwidsep ///
  health ///
  educ loginc happy satfin ///
  nevmarried divwidsep , i(id) j(wave)

  xtset id wave, delta(2)

  *2006
  xtreg tr_health ///
  tr_educ tr_loginc tr_happy tr_satfin ///
  tr_nevmarried tr_divwidsep wave if startyr==2006, fe

  *Save b-coefficients
  qui gen t_2006_b_wave  = _b[wave]
  qui gen t_2006_b_educ  = _b[tr_educ]
  qui gen t_2006_b_loginc = _b[tr_loginc]
  qui gen t_2006_b_happy  = _b[tr_happy]
  qui gen t_2006_b_satfin  = _b[tr_satfin]
  qui gen t_2006_b_nevmarried = _b[tr_nevmarried]
  qui gen t_2006_b_divwidsep  = _b[tr_divwidsep]

  *Save standard errors
  qui gen t_2006_se_wave  = _se[wave]
  qui gen t_2006_se_educ  = _se[tr_educ]
  qui gen t_2006_se_loginc = _se[tr_loginc]
  qui gen t_2006_se_happy  = _se[tr_happy]
  qui gen t_2006_se_satfin  = _se[tr_satfin]
  qui gen t_2006_se_nevmarried = _se[tr_nevmarried]
  qui gen t_2006_se_divwidsep  = _se[tr_divwidsep]

  *listwise
  *2006
  xtreg health ///
educ loginc happy satfin ///
nevmarried divwidsep wave if startyr==2006, fe

*Save b-coefficients
qui gen l_2006_b_wave = _b[wave]
qui gen l_2006_b EDUC = _b[educ]
qui gen l_2006_b_loginc = _b[loginc]
qui gen l_2006_b_happy = _b[happy]
qui gen l_2006_b_satfin = _b[satfin]
qui gen l_2006_b_nevmarried = _b[nevmarried]
qui gen l_2006_b_divwidsep = _b[divwidsep]

*Save standard errors
qui gen l_2006_se_wave = _se[wave]
qui gen l_2006_se_educ = _se[educ]
qui gen l_2006_se_loginc = _se[loginc]
qui gen l_2006_se_happy = _se[happy]
qui gen l_2006_se_satfin = _se[satfin]
qui gen l_2006_se_nevmarried = _se[nevmarried]
qui gen l_2006_se_divwidsep = _se[divwidsep]

xtreg health ///
educ loginc happy satfin ///
nevmarried divwidsep wave if startyr==2006 [pweight=fwt] , fe

*Save b-coefficients
qui gen p_2006_b_wave = _b[wave]
qui gen p_2006_b_educ = _b[educ]
qui gen p_2006_b_loginc = _b[loginc]
qui gen p_2006_b_happy = _b[happy]
qui gen p_2006_b_satfin = _b[satfin]
qui gen p_2006_b_nevmarried = _b[nevmarried]
qui gen p_2006_b_divwidsep = _b[divwidsep]

*Save standard errors
qui gen p_2006_se_wave = _se[wave]
qui gen p_2006_se_educ = _se[educ]
qui gen p_2006_se_loginc = _se[loginc]
qui gen p_2006_se_happy = _se[happy]
qui gen p_2006_se_satfin = _se[satfin]
qui gen p_2006_se_nevmarried = _se[nevmarried]
qui gen p_2006_se_divwidsep = _se[divwidsep]
**Raked weight**

_xtreg health ///
educ loginc happy satfin ///
nevmarried divwidsep wave if startyr==2006 [pweight=rakedwgt] , fe

*Save b-coefficients*
qui gen w_2006_b_wave = _b[wave]
qui gen w_2006_b_educ = _b[educ]
qui gen w_2006_b_loginc = _b[loginc]
qui gen w_2006_b_happy = _b[happy]
qui gen w_2006_b_satfin = _b[satfin]
qui gen w_2006_b_nevmarried = _b[nevmarried]
qui gen w_2006_b_divwidsep = _se[divwidsep]

*Save standard errors*
qui gen w_2006_se_wave = _se[wave]
qui gen w_2006_se_educ = _se[educ]
qui gen w_2006_se_loginc = _se[loginc]
qui gen w_2006_se_happy = _se[happy]
qui gen w_2006_se_satfin = _se[satfin]
qui gen w_2006_se_nevmarried = _se[nevmarried]
qui gen w_2006_se_divwidsep = _se[divwidsep]

gen rowkeep = _n
keep if rowkeep ==`num'
keep rowkeep t_2006_b_wave-w_2006_se_divwidsep
cd "C:\Simulations\Refresher imputation\health\panel\true list wt"
save t_l_p_w_longitudinal`num'.dta, replace

}
Steps 8 & 12: Imputation model (DV is self-rated health)

foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim2006"
    use 2006imp`num', clear

    mi export ice
    save icesim, replace
    use icesim, clear

    micombine mean health2010 ///
    educ2010 loginc2010 happy2010 satfin2010 ///
    nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace
    qui gen i_2006_m_health = _b[health2010]
    qui gen i_2006_m_educ  = _b[educ]
    qui gen i_2006_m_loginc  = _b[loginc]
    qui gen i_2006_m_happy  = _b[happy]
    qui gen i_2006_m_satfin  = _b[satfin]
    qui gen i_2006_m_nevmarried  = _b[nevmarried]
    qui gen i_2006_m_divwidsep  = _b[divwidsep]
    qui gen i_2006_m_age  = _b[age2010]
    qui gen i_2006_m_agesq  = _b[agesq2010]
    qui gen i_2006_m_female  = _b[female]
    qui gen i_2006_m_black  = _b[black]
    qui gen i_2006_m_hispanic  = _b[hispanic]
    qui gen i_2006_m_othrace  = _b[othrace]

*all
    micombine reg health2010 ///
    educ2010 loginc2010 happy2010 satfin2010 ///
    nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace

*Save b-coefficients
    qui gen i_2006_b_educ  = _b[educ]
    qui gen i_2006_b_loginc  = _b[loginc]
    qui gen i_2006_b_happy  = _b[happy]
    qui gen i_2006_b_satfin  = _b[satfin]
    qui gen i_2006_b_nevmarried  = _b[nevmarried]
    qui gen i_2006_b_divwidsep  = _b[divwidsep]
    qui gen i_2006_b_age  = _b[age2010]
    qui gen i_2006_b_agesq  = _b[agesq2010]
    qui gen i_2006_b_female  = _b[female]
qui gen i_2006_b_black = _b[black]
qui gen i_2006_b_hispanic = _b[hispanic]
qui gen i_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen i_2006_se_educ = _se[educ]
qui gen i_2006_se_loginc = _se[loginc]
qui gen i_2006_se_happy = _se[happy]
qui gen i_2006_se_satfin = _se[satfin]
qui gen i_2006_se_nevmarried = _se[nevmarried]
qui gen i_2006_se_divwidsep = _se[divwidsep]
qui gen i_2006_se_age = _se[age2010]
qui gen i_2006_se_agesq = _se[agesq2010]
qui gen i_2006_se_female = _se[female]
qui gen i_2006_se_black = _se[black]
qui gen i_2006_se_hispanic = _se[hispanic]
qui gen i_2006_se_othrace = _se[othrace]

gen rowkeep = _n
keep if rowkeep ==`num'
keep rowkeep i_2006_m_health-i_2006_se_othrace
cd "C:\Simulations\Refresher imputation\health\x sect\imputed"
save i_2006x`num'.dta, replace
}

foreach num of numlist 1/500{
cd "C:\Simulations\Refresher imputation\sim\2006"
use 2006imp`num', clear

mi reshape long health nevmarried divwidsep ///
educ loginc happy satfin ///
    , i(id) j(wave)
mi xtset id wave, delta(2)

mi export ice
save icesim, replace
use icesim, clear

micombine xtreg health ///
educ loginc happy satfin ///
nevmarried divwidsep wave , fe

*Save b-coefficients
qui gen i_2006_b_wave = _b[wave]
*Save standard errors*

```stata
qui gen i_2006_se_wave = _se[wave]
qui gen i_2006_se_educ = _se[educ]
qui gen i_2006_se_loginc = _se[loginc]
qui gen i_2006_se_happy = _se[happy]
qui gen i_2006_se_satfin = _se[satfin]
qui gen i_2006_se_nevmarried = _se[nevmarried]
qui gen i_2006_se_divwidsep = _se[divwidsep]
```

```stata
gen rowkeep = n
keep if rowkeep ==`num'
keep rowkeep i_2006_b_wave- i_2006_se_divwidsep

cd "C:\Simulations\Refresher imputation\health\panel\imputed"
save i_2006longitudinal`num'.dta, replace
```

Steps 9-10 & 12-13: Refreshment imputation models (DV is self-rated health)

```stata
foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\2006"
    use refimp`num', clear
    keep if startyr==2006
    *all
    mi reshape long health nevmarried ///
    divwidsep educ loginc happy satfin ///
    , i(id) j(wave)
    mi xtset id wave, delta(2)
    mi export ice
    save icesim, replace
    use icesim, clear

    micombine xtreg health ///
    educ loginc happy satfin ///
    nevmarried divwidsep wave , fe

    *Save b-coefficients
    qui gen r_b_wave = _b[wave]
    qui gen r_b_educ = _b[educ]
    qui gen r_b_loginc = _b[loginc]
    qui gen r_b_happy = _b[happy]
    qui gen r_b_satfin = _b[satfin]
    qui gen r_b_nevmarried = _b[nevmarried]
    qui gen r_b_divwidsep = _b[divwidsep]
    *Save standard errors
    qui gen r_se_wave = _se[wave]
    qui gen r_se_educ = _se[educ]
    qui gen r_se_loginc = _se[loginc]
    qui gen r_se_happy = _se[happy]
    qui gen r_se_satfin = _se[satfin]
    qui gen r_se_nevmarried = _se[nevmarried]
    qui gen r_se_divwidsep = _se[divwidsep]

    gen rowkeep =_n
    keep if rowkeep ==`num'
    keep rowkeep r_b_wave- r_w_se_divwidsep

    save r_longitudinal`num'.dta, replace
```
foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim\2006"
    use refimp`num', clear
    keep if startyr==2006
    save temp, replace
    mi export ice
    save icesim, replace
    use icesim, clear
    micombine mean health2010 ///
    educ2010 loginc2010 happy2010 satfin2010 ///
    nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace
    qui gen r_2006_m_health = _b[health2010]
    qui gen r_2006_m_educ = _b[educ]
    qui gen r_2006_m_loginc = _b[loginc]
    qui gen r_2006_m_happy = _b[happy]
    qui gen r_2006_m_satfin = _b[satfin]
    qui gen r_2006_m_nevmarried = _b[nevmarried]
    qui gen r_2006_m_age = _b[age2010]
    qui gen r_2006_m_agesq = _b[agesq2010]
    qui gen r_2006_m_female = _b[female]
    qui gen r_2006_m_black = _b[black]
    qui gen r_2006_m_hispanic = _b[hispanic]
    qui gen r_2006_m_othrace = _b[othrace]
    *all
    micombine reg health2010 ///
    educ2010 loginc2010 happy2010 satfin2010 ///
    nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace
    *Save b-coefficients
    qui gen r_2006_b_educ = _b[educ]
    qui gen r_2006_b_loginc = _b[loginc]
    qui gen r_2006_b_happy = _b[happy]
    qui gen r_2006_b_satfin = _b[satfin]
    qui gen r_2006_b_nevmarried = _b[nevmarried]
    qui gen r_2006_b_divwidsep = _b[divwidsep]
qui gen r_2006_b_age = _b[age2010]
qui gen r_2006_b_agesq = _b[agesq2010]
qui gen r_2006_b_female = _b[female]
qui gen r_2006_b_black = _b[black]
qui gen r_2006_b_hispanic = _b[hispanic]
qui gen r_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen r_2006_se_educ = _se[educ]
qui gen r_2006_se_loginc = _se[loginc]
qui gen r_2006_se_happy = _se[happy]
qui gen r_2006_se_satfin = _se[satfin]
qui gen r_2006_se_nevmarried = _se[nevmarried]
qui gen r_2006_se_divwidsep = _se[divwidsep]
qui gen r_2006_se_age = _se[age2010]
qui gen r_2006_se_agesq = _se[agesq2010]
qui gen r_2006_se_female = _se[female]
qui gen r_2006_se_black = _se[black]
qui gen r_2006_se_hispanic = _se[hispanic]
qui gen r_2006_se_othrace = _se[othrace]

gen rowkeep = _n
keep if rowkeep ==`num'
keep rowkeep r_2006_m_health-r_w_2006_se_othrace
save r_2006_x`num'.dta, replace
}

foreach num of numlist 1/500{
  cd "C:\Simulations\Refresher imputation\sim\2006"
  use ref2008imp`num', clear
  keep if startyr==2006
  *all
  mi reshape long health nevmarried ///
divwidsep educ loginc happy satfin ///
  , i(id) j(wave)
  mi xtset id wave, delta(2)

  save temp, replace
  mi export ice
  save icesim, replace
  use icesim, clear

  micombine xtreg health ///
}
educ loginc happy satfin ///
nevmarried divwidsep wave , fe

*Save b-coefficients
qui gen r8_b_wave  = _b[wave]
qui gen r8_b_educ  = _b[educ]
qui gen r8_b_loginc = _b[loginc]
qui gen r8_b_happy  = _b[happy]
qui gen r8_b_satfin = _b[satfin]
qui gen r8_b_nevmarried = _b[nevmarried]
qui gen r8_b_divwidsep = _b[divwidsep]

*Save standard errors
qui gen r8_se_wave  = _se[wave]
qui gen r8_se_educ  = _se[educ]
qui gen r8_se_loginc = _se[loginc]
qui gen r8_se_happy  = _se[happy]
qui gen r8_se_satfin = _se[satfin]
qui gen r8_se_nevmarried = _se[nevmarried]
qui gen r8_se_divwidsep = _se[divwidsep]

gen rowkeep = _n
keep if rowkeep ==`num'
keep rowkeep r8_b_wave- r8_se_divwidsep
save r8_longitudinal`num'.dta, replace
}
foreach num of numlist 1/500{
    cd "C:\Simulations\Refresher imputation\sim2006"
    use ref2008imp`num', clear
    keep if startyr==2006
    save temp, replace
    mi export ice
    save icesim, replace
    use icesim, clear
    micombine mean health2010 //
    educ2010 loginc2010 happy2010 satfin2010 //
    nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace
    qui gen r8_2006_m_health = _b[health2010]
    qui gen r8_2006_m_educ  = _b[educ]
    qui gen r8_2006_m_loginc = _b[loginc]
    qui gen r8_2006_m_happy  = _b[happy]
    qui gen r8_2006_m_satfin = _b[satfin]
    qui gen r8_2006_m_nevmarried = _b[nevmarried]

qui gen r8_2006_m_divwidsep = _b[divwidsep]
qui gen r8_2006_m_age = _b[age2010]
qui gen r8_2006_m_agesq = _b[agesq2010]
qui gen r8_2006_m_female = _b[female]
qui gen r8_2006_m_black = _b[black]
qui gen r8_2006_m_hispanic = _b[hispanic]
qui gen r8_2006_m_othrace = _b[othrace]

*all
micombine reg health2010 ///
educ2010 loginc2010 happy2010 satfin2010 ///
nevmarried2010 divwidsep2010 age2010 agesq2010 female black hispanic othrace

*Save b-coefficients
qui gen r8_2006_b_educ = _b[educ]
qui gen r8_2006_b_loginc = _b[loginc]
qui gen r8_2006_b_happy = _b[happy]
qui gen r8_2006_b_satfin = _b[satfin]
qui gen r8_2006_b_nevmarried = _b[nevmarried]
qui gen r8_2006_b_divwidsep = _b[divwidsep]
qui gen r8_2006_b_age = _b[age2010]
qui gen r8_2006_b_agesq = _b[agesq2010]
qui gen r8_2006_b_female = _b[female]
qui gen r8_2006_b_black = _b[black]
qui gen r8_2006_b_hispanic = _b[hispanic]
qui gen r8_2006_b_othrace = _b[othrace]

*Save standard errors
qui gen r8_2006_se_educ = _se[educ]
qui gen r8_2006_se_loginc = _se[loginc]
qui gen r8_2006_se_happy = _se[happy]
qui gen r8_2006_se_satfin = _se[satfin]
qui gen r8_2006_se_nevmarried = _se[nevmarried]
qui gen r8_2006_se_divwidsep = _se[divwidsep]
qui gen r8_2006_se_age = _se[age2010]
qui gen r8_2006_se_agesq = _se[agesq2010]
qui gen r8_2006_se_female = _se[female]
qui gen r8_2006_se_black = _se[black]
qui gen r8_2006_se_hispanic = _se[hispanic]
qui gen r8_2006_se_othrace = _se[othrace]

gen rowkeep = _n
keep if rowkeep == `num'
keep rowkeep r8_2006_m_health-r8_2006_se_othrace
save r8_2006_x`num'.dta, replace
}

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Step 14: Combining datasets and analyzing OLS regression of support for gay marriage

*Putting Results together

cd "C:\Simulations\Refresher imputation\gay tol\x sect\true list wt"

**True, listwist and weighted x-sectionals

use t_l_p_w_x1, clear
foreach num of numlist 2/500{
append using t_l_p_w_x`num'
}save "C:\Simulations\Refresher imputation\gay tol\results\t_l_p_w_xtotal1.dta", replace clear

*Imputed 2006 only cross-section

cd "C:\Simulations\Refresher imputation\gay tol\x sect\imputed"

use i_2006x1
foreach num of numlist 2/500{
append using i_2006x`num'
}save "C:\Simulations\Refresher imputation\gay tol\results\i_2006xtotal1.dta", replace

*2006 cross section with refresher imputation adjustment

clear
cd "C:\Simulations\Refresher imputation\gay tol\x sect\imputed"

use r_2006_x1
foreach num of numlist 2/500{
append using r_2006_x`num'
}save "C:\Simulations\Refresher imputation\gay tol\results\r_2006xtotal1.dta", replace

*All data cross section

clear
cd "C:\Simulations\Refresher imputation\gay tol\x sect\imputed"

use r_all_x1
foreach num of numlist 2/500{
append using r_all_x`num'
}save "C:\Simulations\Refresher imputation\gay tol\results\r_allxtotal1.dta", replace

*Making the cross-sectional dataset

cd "C:\Simulations\Refresher imputation\gay tol\results"

use t_l_p_w_xtotal1, clear
merge 1:1 rowkeep using i_2006xtotal1
drop_merge
merge 1:1 rowkeep using r_2006xtotal1
drop_merge
save x.dta, replace
sum *, sep(0)
gen d_l_2006_b_educ = l_2006_b_educ - t_2006_b_educ
gen d_l_2006_b_loginc = l_2006_b_loginc - t_2006_b_loginc
gen d_l_2006_b_polviews = l_2006_b_polviews - t_2006_b_polviews
gen d_l_2006_b_religiosity = l_2006_b_religiosity - t_2006_b_religiosity
gen d_l_2006_b_gaytolerance = l_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_l_2006_b_age = l_2006_b_age - t_2006_b_age
gen d_l_2006_b_agesq = l_2006_b_agesq - t_2006_b_agesq
gen d_l_2006_b_female = l_2006_b_female - t_2006_b_female
gen d_l_2006_b_black = l_2006_b_black - t_2006_b_black
gen d_l_2006_b_hispanic = l_2006_b_hispanic - t_2006_b_hispanic
gen d_l_2006_b_othrace = l_2006_b_othrace - t_2006_b_othrace

gen d_l_2006_se_educ = l_2006_se_educ - t_2006_se_educ
gen d_l_2006_se_loginc = l_2006_se_loginc - t_2006_se_loginc
gen d_l_2006_se_polviews = l_2006_se_polviews - t_2006_se_polviews
gen d_l_2006_se_religiosity = l_2006_se_religiosity - t_2006_se_religiosity
gen d_l_2006_se_gaytolerance = l_2006_se_gaytolerance - t_2006_se_gaytolerance
gen d_l_2006_se_age = l_2006_se_age - t_2006_se_age
gen d_l_2006_se_agesq = l_2006_se_agesq - t_2006_se_agesq
gen d_l_2006_se_female = l_2006_se_female - t_2006_se_female
gen d_l_2006_se_black = l_2006_se_black - t_2006_se_black
gen d_l_2006_se_hispanic = l_2006_se_hispanic - t_2006_se_hispanic
gen d_l_2006_se_othrace = l_2006_se_othrace - t_2006_se_othrace

gen d_p_2006_b_educ = p_2006_b_educ - t_2006_b_educ
gen d_p_2006_b_loginc = p_2006_b_loginc - t_2006_b_loginc
gen d_p_2006_b_polviews = p_2006_b_polviews - t_2006_b_polviews
gen d_p_2006_b_religiosity = p_2006_b_religiosity - t_2006_b_religiosity
gen d_p_2006_b_gaytolerance = p_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_p_2006_b_age = p_2006_b_age - t_2006_b_age
gen d_p_2006_b_agesq = p_2006_b_agesq - t_2006_b_agesq
gen d_p_2006_b_female = p_2006_b_female - t_2006_b_female
gen d_p_2006_b_black = p_2006_b_black - t_2006_b_black
gen d_p_2006_b_hispanic = p_2006_b_hispanic - t_2006_b_hispanic
gen d_p_2006_b_othrace = p_2006_b_othrace - t_2006_b_othrace

gen d_p_2006_se_educ = p_2006_se_educ - t_2006_se_educ
gen d_p_2006_se_loginc = p_2006_se_loginc - t_2006_se_loginc
gen d_p_2006_se_polviews = p_2006_se_polviews - t_2006_se_polviews
gen d_p_2006_se_religiosity = p_2006_se_religiosity - t_2006_se_religiosity
gen d_p_2006_se_gaytolerance = p_2006_se_gaytolerance - t_2006_se_gaytolerance
gen d_p_2006_se_age = p_2006_se_age - t_2006_se_age
gen d_p_2006_se_agesq = p_2006_se_agesq - t_2006_se_agesq
gen d_p_2006_se_female = p_2006_se_female - t_2006_se_female
gen d_p_2006_se_black = p_2006_se_black - t_2006_se_black
gen d_p_2006_se_hispanic = p_2006_se_hispanic - t_2006_se_hispanic
gen d_p_2006_se_othrace = p_2006_se_othrace - t_2006_se_othrace
gen d_w_2006_b_educ = w_2006_b_educ - t_2006_b_educ
gen d_w_2006_b_loginc = w_2006_b_loginc - t_2006_b_loginc
gen d_w_2006_b_polviews = w_2006_b_polviews - t_2006_b_polviews
gen d_w_2006_b_religiosity = w_2006_b_religiosity - t_2006_b_religiosity
gen d_w_2006_b_gaytolerance = w_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_w_2006_b_age = w_2006_b_age - t_2006_b_age
gen d_w_2006_b_agesq = w_2006_b_agesq - t_2006_b_agesq
gen d_w_2006_b_female = w_2006_b_female - t_2006_b_female
gen d_w_2006_b_black = w_2006_b_black - t_2006_b_black
gen d_w_2006_b_hispanic = w_2006_b_hispanic - t_2006_b_hispanic
gen d_w_2006_b_othrace = w_2006_b_othrace - t_2006_b_othrace
gen d_w_2006_se_educ = w_2006_se_educ - t_2006_se_educ
gen d_w_2006_se_loginc = w_2006_se_loginc - t_2006_se_loginc
gen d_w_2006_se_polviews = w_2006_se_polviews - t_2006_se_polviews
gen d_w_2006_se_religiosity = w_2006_se_religiosity - t_2006_se_religiosity
gen d_w_2006_se_gaytolerance = w_2006_se_gaytolerance - t_2006_se_gaytolerance
gen d_w_2006_se_age = w_2006_se_age - t_2006_se_age
gen d_w_2006_se_agesq = w_2006_se_agesq - t_2006_se_agesq
gen d_w_2006_se_female = w_2006_se_female - t_2006_se_female
gen d_w_2006_se_black = w_2006_se_black - t_2006_se_black
gen d_w_2006_se_hispanic = w_2006_se_hispanic - t_2006_se_hispanic
gen d_w_2006_se_othrace = w_2006_se_othrace - t_2006_se_othrace
gen d_i_2006_b_educ = i_2006_b_educ - t_2006_b_educ
gen d_i_2006_b_loginc = i_2006_b_loginc - t_2006_b_loginc
gen d_i_2006_b_polviews = i_2006_b_polviews - t_2006_b_polviews
gen d_i_2006_b_religiosity = i_2006_b_religiosity - t_2006_b_religiosity
gen d_i_2006_b_gaytolerance = i_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_i_2006_b_age = i_2006_b_age - t_2006_b_age
gen d_i_2006_b_agesq = i_2006_b_agesq - t_2006_b_agesq
gen d_i_2006_b_female = i_2006_b_female - t_2006_b_female
gen d_i_2006_b_black = i_2006_b_black - t_2006_b_black
gen d_i_2006_b_hispanic = i_2006_b_hispanic - t_2006_b_hispanic
gen d_i_2006_b_othrace = i_2006_b_othrace - t_2006_b_othrace
gen d_i_2006_se_educ = i_2006_se_educ - t_2006_se_educ
gen d_i_2006_se_loginc = i_2006_se_loginc - t_2006_se_loginc
gen d_i_2006_se_polviews = i_2006_se_polviews - t_2006_se_polviews
gen d_i_2006_se_religiosity = i_2006_se_religiosity - t_2006_se_religiosity
gen d_i_2006_se_gaytolerance = i_2006_se_gaytolerance - t_2006_se_gaytolerance
gen d_i_2006_se_age = i_2006_se_age - t_2006_se_age
gen d_i_2006_se_agesq = i_2006_se_agesq - t_2006_se_agesq
gen d_i_2006_se_female = i_2006_se_female - t_2006_se_female
gen d_i_2006_se_black = i_2006_se_black - t_2006_se_black
gen d_i_2006_se_hispanic = i_2006_se_hispanic - t_2006_se_hispanic
gen d_i_2006_se_othrace = i_2006_se_othrace - t_2006_se_othrace
gen d\_r8\_2006\_b\_educ = r8\_2006\_b\_educ - t\_2006\_b\_educ
gen d\_r8\_2006\_b\_loginc = r8\_2006\_b\_loginc - t\_2006\_b\_loginc
gen d\_r8\_2006\_b\_polviews = r8\_2006\_b\_polviews - t\_2006\_b\_polviews
gen d\_r8\_2006\_b\_religiosity = r8\_2006\_b\_religiosity - t\_2006\_b\_religiosity
gen d\_r8\_2006\_b\_gaytolerance = r8\_2006\_b\_gaytolerance - t\_2006\_b\_gaytolerance
gen d\_r8\_2006\_b\_age = r8\_2006\_b\_age - t\_2006\_b\_age
gen d\_r8\_2006\_b\_agesq = r8\_2006\_b\_agesq - t\_2006\_b\_agesq
gen d\_r8\_2006\_b\_female = r8\_2006\_b\_female - t\_2006\_b\_female
gen d\_r8\_2006\_b\_black = r8\_2006\_b\_black - t\_2006\_b\_black
gen d\_r8\_2006\_b\_hispanic = r8\_2006\_b\_hispanic - t\_2006\_b\_hispanic
gen d\_r8\_2006\_b\_othrace = r8\_2006\_b\_othrace - t\_2006\_b\_othrace

gen d\_r8\_2006\_se\_educ = r8\_2006\_se\_educ - t\_2006\_se\_educ
gen d\_r8\_2006\_se\_loginc = r8\_2006\_se\_loginc - t\_2006\_se\_loginc
gen d\_r8\_2006\_se\_polviews = r8\_2006\_se\_polviews - t\_2006\_se\_polviews
gen d\_r8\_2006\_se\_religiosity = r8\_2006\_se\_religiosity - t\_2006\_se\_religiosity
gen d\_r8\_2006\_se\_gaytolerance = r8\_2006\_se\_gaytolerance - t\_2006\_se\_gaytolerance
gen d\_r8\_2006\_se\_age = r8\_2006\_se\_age - t\_2006\_se\_age
gen d\_r8\_2006\_se\_agesq = r8\_2006\_se\_agesq - t\_2006\_se\_agesq
gen d\_r8\_2006\_se\_female = r8\_2006\_se\_female - t\_2006\_se\_female
gen d\_r8\_2006\_se\_black = r8\_2006\_se\_black - t\_2006\_se\_black
gen d\_r8\_2006\_se\_hispanic = r8\_2006\_se\_hispanic - t\_2006\_se\_hispanic
gen d\_r8\_2006\_se\_othrace = r8\_2006\_se\_othrace - t\_2006\_se\_othrace
gen d_l_2006_m_marhomo = l_2006_m_marhomo - t_2006_m_marhomo
gen d_l_2006_m_educ = l_2006_m_educ - t_2006_m_educ
gen d_l_2006_m_loginc = l_2006_m_loginc - t_2006_m_loginc
gen d_l_2006_m_polviews = l_2006_m_polviews - t_2006_m_polviews
gen d_l_2006_m_religiosity = l_2006_m_religiosity - t_2006_m_religiosity
gen d_l_2006_m_gaytolerance = l_2006_m_gaytolerance - t_2006_m_gaytolerance
gen d_l_2006_m_age = l_2006_m_age - t_2006_m_age
gen d_l_2006_m_agesq = l_2006_m_agesq - t_2006_m_agesq
gen d_l_2006_m_female = l_2006_m_female - t_2006_m_female
gen d_l_2006_m_black = l_2006_m_black - t_2006_m_black
gen d_l_2006_m_hispanic = l_2006_m_hispanic - t_2006_m_hispanic
gen d_l_2006_m_othrace = l_2006_m_othrace - t_2006_m_othrace

gen d_p_2006_m_marhomo = p_2006_m_marhomo - t_2006_m_marhomo
gen d_p_2006_m_educ = p_2006_m_educ - t_2006_m_educ
gen d_p_2006_m_loginc = p_2006_m_loginc - t_2006_m_loginc
gen d_p_2006_m_polviews = p_2006_m_polviews - t_2006_m_polviews
gen d_p_2006_m_religiosity = p_2006_m_religiosity - t_2006_m_religiosity
gen d_p_2006_m_gaytolerance = p_2006_m_gaytolerance - t_2006_m_gaytolerance
gen d_p_2006_m_age = p_2006_m_age - t_2006_m_age
gen d_p_2006_m_agesq = p_2006_m_agesq - t_2006_m_agesq
gen d_p_2006_m_female = p_2006_m_female - t_2006_m_female
gen d_p_2006_m_black = p_2006_m_black - t_2006_m_black
gen d_p_2006_m_hispanic = p_2006_m_hispanic - t_2006_m_hispanic
gen d_p_2006_m_othrace = p_2006_m_othrace - t_2006_m_othrace

gen d_w_2006_m_marhomo = w_2006_m_marhomo - t_2006_m_marhomo
gen d_w_2006_m_educ = w_2006_m_educ - t_2006_m_educ
gen d_w_2006_m_loginc = w_2006_m_loginc - t_2006_m_loginc
gen d_w_2006_m_polviews = w_2006_m_polviews - t_2006_m_polviews
gen d_w_2006_m_religiosity = w_2006_m_religiosity - t_2006_m_religiosity
gen d_w_2006_m_gaytolerance = w_2006_m_gaytolerance - t_2006_m_gaytolerance
gen d_w_2006_m_age = w_2006_m_age - t_2006_m_age
gen d_w_2006_m_agesq = w_2006_m_agesq - t_2006_m_agesq
gen d_w_2006_m_female = w_2006_m_female - t_2006_m_female
gen d_w_2006_m_black = w_2006_m_black - t_2006_m_black
gen d_w_2006_m_hispanic = w_2006_m_hispanic - t_2006_m_hispanic
gen d_w_2006_m_othrace = w_2006_m_othrace - t_2006_m_othrace

gen d_i_2006_m_marhomo = i_2006_m_marhomo - t_2006_m_marhomo
gen d_i_2006_m_educ = i_2006_m_educ - t_2006_m_educ
gen d_i_2006_m_loginc = i_2006_m_loginc - t_2006_m_loginc
gen d_i_2006_m_polviews = i_2006_m_polviews - t_2006_m_polviews
gen d_i_2006_m_religiosity = i_2006_m_religiosity - t_2006_m_religiosity
gen d_i_2006_m_gaytolerance = i_2006_m_gaytolerance - t_2006_m_gaytolerance
gen d_i_2006_m_age = i_2006_m_age - t_2006_m_age
gen d_i_2006_m_agesq = i_2006_m_agesq - t_2006_m_agesq
gen d_i_2006_m_female = i_2006_m_female - t_2006_m_female
gen d_i_2006_m_black = i_2006_m_black - t_2006_m_black
gen d_i_2006_m_hispanic = i_2006_m_hispanic - t_2006_m_hispanic
gen d_i_2006_m_othrace = i_2006_m_othrace - t_2006_m_othrace

gen d_r8_2006_m_marhomo = r8_2006_m_marhomo - t_2006_m_marhomo
gen d_r8_2006_m_educ = r8_2006_m_educ - t_2006_m_educ
gen d_r8_2006_m_loginc = r8_2006_m_loginc - t_2006_m_loginc
gen d_r8_2006_m_polviews = r8_2006_m_polviews - t_2006_m_polviews
gen d_r8_2006_m_religiosity = r8_2006_m_religiosity - t_2006_m_religiosity
gen d_r8_2006_m_gaytolerance = r8_2006_m_gaytolerance - t_2006_m_gaytolerance
gen d_r8_2006_m_age = r8_2006_m_age - t_2006_m_age
gen d_r8_2006_m_agesq = r8_2006_m_agesq - t_2006_m_agesq
gen d_r8_2006_m_female = r8_2006_m_female - t_2006_m_female
gen d_r8_2006_m_black = r8_2006_m_black - t_2006_m_black
gen d_r8_2006_m_hispanic = r8_2006_m_hispanic - t_2006_m_hispanic
gen d_r8_2006_m_othrace = r8_2006_m_othrace - t_2006_m_othrace

gen d_r_2006_m_marhomo = r_2006_m_marhomo - t_2006_m_marhomo
gen d_r_2006_m_educ = r_2006_m_educ - t_2006_m_educ
gen d_r_2006_m_loginc = r_2006_m_loginc - t_2006_m_loginc
gen d_r_2006_m_polviews = r_2006_m_polviews - t_2006_m_polviews
gen d_r_2006_m_religiosity = r_2006_m_religiosity - t_2006_m_religiosity
gen d_r_2006_m_gaytolerance = r_2006_m_gaytolerance - t_2006_m_gaytolerance
gen d_r_2006_m_age = r_2006_m_age - t_2006_m_age
gen d_r_2006_m_agesq = r_2006_m_agesq - t_2006_m_agesq
gen d_r_2006_m_female = r_2006_m_female - t_2006_m_female
gen d_r_2006_m_black = r_2006_m_black - t_2006_m_black
gen d_r_2006_m_hispanic = r_2006_m_hispanic - t_2006_m_hispanic
gen d_r_2006_m_othrace = r_2006_m_othrace - t_2006_m_othrace

*Getting results for Table 4-4 *
sum d_l_2006_b_educ - d_r_2006_m_othrace, sep(0)

*Boxplots for figure 4-5 *
graph box d_l_2006_se_educ d_r_2006_se_educ d_l_2006_se_loginc d_r_2006_se_loginc ///
d_l_2006_se_polviews d_r_2006_se_polviews ///
d_l_2006_se_age d_r_2006_se_age d_l_2006_se_agesq d_r_2006_se_agesq ///
, graphregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
plotregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
ylabel(nogrid)

graph box d_l_2006_se_religiosity d_r_2006_se_religiosity d_l_2006_se_gaytolerance d_r_2006_se_gaytolerance ///
d_l_2006_se_female d_r_2006_se_female d_l_2006_se_black d_r_2006_se_black ///
**Significance tests**

gen tval_t_2006_b_educ = abs(t_2006_b_educ / t_2006_se_educ)
gen tval_t_2006_b_loginc = abs(t_2006_b_loginc / t_2006_se_loginc)
gen tval_t_2006_b_polviews = abs(t_2006_b_polviews / t_2006_se_polviews)
gen tval_t_2006_b_religiosity = abs(t_2006_b_religiosity / t_2006_se_religiosity)
gen tval_t_2006_b_gaytolerance = abs(t_2006_b_gaytolerance / t_2006_se_gaytolerance)
gen tval_t_2006_b_age = abs(t_2006_b_age / t_2006_se_age)
gen tval_t_2006_b_agesq = abs(t_2006_b_agesq / t_2006_se_agesq)
gen tval_t_2006_b_female = abs(t_2006_b_female / t_2006_se_female)
gen tval_t_2006_b_black = abs(t_2006_b_black / t_2006_se_black)
gen tval_t_2006_b_hispanic = abs(t_2006_b_hispanic / t_2006_se_hispanic)
gen tval_t_2006_b_othrace = abs(t_2006_b_othrace / t_2006_se_othrace)

gen tval_l_2006_b_educ = abs(l_2006_b_educ / l_2006_se_educ)
gen tval_l_2006_b_loginc = abs(l_2006_b_loginc / l_2006_se_loginc)
gen tval_l_2006_b_polviews = abs(l_2006_b_polviews / l_2006_se_polviews)
gen tval_l_2006_b_religiosity = abs(l_2006_b_religiosity / l_2006_se_religiosity)
gen tval_l_2006_b_gaytolerance = abs(l_2006_b_gaytolerance / l_2006_se_gaytolerance)
gen tval_l_2006_b_age = abs(l_2006_b_age / l_2006_se_age)
gen tval_l_2006_b_agesq = abs(l_2006_b_agesq / l_2006_se_agesq)
gen tval_l_2006_b_female = abs(l_2006_b_female / l_2006_se_female)
gen tval_l_2006_b_black = abs(l_2006_b_black / l_2006_se_black)
gen tval_l_2006_b_hispanic = abs(l_2006_b_hispanic / l_2006_se_hispanic)
gen tval_l_2006_b_othrace = abs(l_2006_b_othrace / l_2006_se_othrace)

gen tval_p_2006_b_educ = abs(p_2006_b_educ / p_2006_se_educ)
gen tval_p_2006_b_loginc = abs(p_2006_b_loginc / p_2006_se_loginc)
gen tval_p_2006_b_polviews = abs(p_2006_b_polviews / p_2006_se_polviews)
gen tval_p_2006_b_religiosity = abs(p_2006_b_religiosity / p_2006_se_religiosity)
gen tval_p_2006_b_gaytolerance = abs(p_2006_b_gaytolerance / p_2006_se_gaytolerance)
gen tval_p_2006_b_age = abs(p_2006_b_age / p_2006_se_age)
gen tval_p_2006_b_agesq = abs(p_2006_b_agesq / p_2006_se_agesq)
gen tval_p_2006_b_female = abs(p_2006_b_female / p_2006_se_female)
gen tval_p_2006_b_black = abs(p_2006_b_black / p_2006_se_black)
gen tval_p_2006_b_hispanic = abs(p_2006_b_hispanic / p_2006_se_hispanic)
gen tval_p_2006_b_othrace = abs(p_2006_b_othrace / p_2006_se_othrace)

gen tval_w_2006_b_educ = abs(w_2006_b_educ / w_2006_se_educ)
gen tval_w_2006_b_loginc = abs(w_2006_b_loginc / w_2006_se_loginc)
gen tval_w_2006_b_polviews = abs(w_2006_b_polviews / w_2006_se_polviews)
gen tval_w_2006_b_religiosity = abs(w_2006_b_religiosity / w_2006_se_religiosity)
gen tval_w_2006_b_gaytolerance = abs(w_2006_b_gaytolerance / w_2006_se_gaytolerance)
gen tval_w_2006_b_age = abs(w_2006_b_age / w_2006_se_age)
gen tval_w_2006_b_agesq = abs(w_2006_b_agesq / w_2006_se_agesq)
gen tval_w_2006_b_female = abs(w_2006_b_female / w_2006_se_female)
gen tval_w_2006_b_black = abs(w_2006_b_black / w_2006_se_black)
gen tval_w_2006_b_hispanic = abs(w_2006_b_hispanic / w_2006_se_hispanic)
gen tval_w_2006_b_othrace = abs(w_2006_b_othrace / w_2006_se_othrace)

gen tval_i_2006_b_educ = abs(i_2006_b_educ / i_2006_se_educ)
gen tval_i_2006_b_loginc = abs(i_2006_b_loginc / i_2006_se_loginc)
gen tval_i_2006_b_polviews = abs(i_2006_b_polviews / i_2006_se_polviews)
gen tval_i_2006_b_religiosity = abs(i_2006_b_religiosity / i_2006_se_religiosity)
gen tval_i_2006_b_gaytolerance = abs(i_2006_b_gaytolerance / i_2006_se_gaytolerance)
gen tval_i_2006_b_age = abs(i_2006_b_age / i_2006_se_age)
gen tval_i_2006_b_agesq = abs(i_2006_b_agesq / i_2006_se_agesq)
gen tval_i_2006_b_female = abs(i_2006_b_female / i_2006_se_female)
gen tval_i_2006_b_black = abs(i_2006_b_black / i_2006_se_black)
gen tval_i_2006_b_hispanic = abs(i_2006_b_hispanic / i_2006_se_hispanic)
gen tval_i_2006_b_othrace = abs(i_2006_b_othrace / i_2006_se_othrace)

gen tval_r8_2006_b_educ = abs(r8_2006_b_educ / r8_2006_se_educ)
gen tval_r8_2006_b_loginc = abs(r8_2006_b_loginc / r8_2006_se_loginc)
gen tval_r8_2006_b_polviews = abs(r8_2006_b_polviews / r8_2006_se_polviews)
gen tval_r8_2006_b_religiosity = abs(r8_2006_b_religiosity / r8_2006_se_religiosity)
gen tval_r8_2006_b_gaytolerance = abs(r8_2006_b_gaytolerance / r8_2006_se_gaytolerance)
gen tval_r8_2006_b_age = abs(r8_2006_b_age / r8_2006_se_age)
gen tval_r8_2006_b_agesq = abs(r8_2006_b_agesq / r8_2006_se_agesq)
gen tval_r8_2006_b_female = abs(r8_2006_b_female / r8_2006_se_female)
gen tval_r8_2006_b_black = abs(r8_2006_b_black / r8_2006_se_black)
gen tval_r8_2006_b_hispanic = abs(r8_2006_b_hispanic / r8_2006_se_hispanic)
gen tval_r8_2006_b_othrace = abs(r8_2006_b_othrace / r8_2006_se_othrace)

gen tval_r_2006_b_educ = abs(r_2006_b_educ / r_2006_se_educ)
gen tval_r_2006_b_loginc = abs(r_2006_b_loginc / r_2006_se_loginc)
gen tval_r_2006_b_polviews = abs(r_2006_b_polviews / r_2006_se_polviews)
gen tval_r_2006_b_religiosity = abs(r_2006_b_religiosity / r_2006_se_religiosity)
gen tval_r_2006_b_gaytolerance = abs(r_2006_b_gaytolerance / r_2006_se_gaytolerance)
gen tval_r_2006_b_age = abs(r_2006_b_age / r_2006_se_age)
gen tval_r_2006_b_agesq = abs(r_2006_b_agesq / r_2006_se_agesq)
gen tval_r_2006_b_female = abs(r_2006_b_female / r_2006_se_female)
gen tval_r_2006_b_black = abs(r_2006_b_black / r_2006_se_black)
gen tval_r_2006_b_hispanic = abs(r_2006_b_hispanic / r_2006_se_hispanic)
gen tval_r_2006_b_othrace = abs(r_2006_b_othrace / r_2006_se_othrace)
gen s_t_2006_b_educ=1 if tval_t_2006_b_educ>1.96
gen s_t_2006_b_loginc=1 if tval_t_2006_b_loginc>1.96
gen s_t_2006_b_polviews=1 if tval_t_2006_b_polviews>1.96
gen s_t_2006_b_religiosity=1 if tval_t_2006_b_religiosity>1.96
gen s_t_2006_b_gaytolerance=1 if tval_t_2006_b_gaytolerance>1.96
gen s_t_2006_b_age=1 if tval_t_2006_b_age>1.96
gen s_t_2006_b_agesq=1 if tval_t_2006_b_agesq>1.96
gen s_t_2006_b_female=1 if tval_t_2006_b_female>1.96
gen s_t_2006_b_black=1 if tval_t_2006_b_black>1.96
gen s_t_2006_b_hispanic=1 if tval_t_2006_b_hispanic>1.96
gen s_t_2006_b_othrace=1 if tval_t_2006_b_othrace>1.96

gen s_l_2006_b_educ=1 if tval_l_2006_b_educ>1.96
gen s_l_2006_b_loginc=1 if tval_l_2006_b_loginc>1.96
gen s_l_2006_b_polviews=1 if tval_l_2006_b_polviews>1.96
gen s_l_2006_b_religiosity=1 if tval_l_2006_b_religiosity>1.96
gen s_l_2006_b_gaytolerance=1 if tval_l_2006_b_gaytolerance>1.96
gen s_l_2006_b_age=1 if tval_l_2006_b_age>1.96
gen s_l_2006_b_agesq=1 if tval_l_2006_b_agesq>1.96
gen s_l_2006_b_female=1 if tval_l_2006_b_female>1.96
gen s_l_2006_b_black=1 if tval_l_2006_b_black>1.96
gen s_l_2006_b_hispanic=1 if tval_l_2006_b_hispanic>1.96
gen s_l_2006_b_othrace=1 if tval_l_2006_b_othrace>1.96

gen s_p_2006_b_educ=1 if tval_p_2006_b_educ>1.96
gen s_p_2006_b_loginc=1 if tval_p_2006_b_loginc>1.96
gen s_p_2006_b_polviews=1 if tval_p_2006_b_polviews>1.96
gen s_p_2006_b_religiosity=1 if tval_p_2006_b_religiosity>1.96
gen s_p_2006_b_gaytolerance=1 if tval_p_2006_b_gaytolerance>1.96
gen s_p_2006_b_age=1 if tval_p_2006_b_age>1.96
gen s_p_2006_b_agesq=1 if tval_p_2006_b_agesq>1.96
gen s_p_2006_b_female=1 if tval_p_2006_b_female>1.96
gen s_p_2006_b_black=1 if tval_p_2006_b_black>1.96
gen s_p_2006_b_hispanic=1 if tval_p_2006_b_hispanic>1.96
gen s_p_2006_b_othrace=1 if tval_p_2006_b_othrace>1.96

gen s_w_2006_b_educ=1 if tval_w_2006_b_educ>1.96
gen s_w_2006_b_loginc=1 if tval_w_2006_b_loginc>1.96
gen s_w_2006_b_polviews=1 if tval_w_2006_b_polviews>1.96
gen s_w_2006_b_religiosity=1 if tval_w_2006_b_religiosity>1.96
gen s_w_2006_b_gaytolerance=1 if tval_w_2006_b_gaytolerance>1.96
gen s_w_2006_b_age=1 if tval_w_2006_b_age>1.96
gen s_w_2006_b_agesq=1 if tval_w_2006_b_agesq>1.96
gen s_w_2006_b_female=1 if tval_w_2006_b_female>1.96
gen s_w_2006_b_black=1 if tval_w_2006_b_black>1.96
gen s_w_2006_b_hispanic=1 if tval_w_2006_b_hispanic>1.96
gen s_w_2006_b_othrace=1 if tval_w_2006_b_othrace>1.96

gen s_i_2006_b_educ=1 if tval_i_2006_b_educ>1.96
gen s_i_2006_b_loginc=1 if tval_i_2006_b_loginc>1.96
gen s_i_2006_b_polviews=1 if tval_i_2006_b_polviews>1.96
gen s_i_2006_b_religiosity=1 if tval_i_2006_b_religiosity>1.96
gen s_i_2006_b_gaytolerance=1 if tval_i_2006_b_gaytolerance>1.96
gen s_i_2006_b_age=1 if tval_i_2006_b_age>1.96
gen s_i_2006_b_agesq=1 if tval_i_2006_b_agesq>1.96
gen s_i_2006_b_female=1 if tval_i_2006_b_female>1.96

foreach var of varlist s_t_2006_b_educ - s_r_2006_b_othrace {
    replace `var' =0 if missing(`var')
}

*Results for Table 4-5
sum s_*, sep(0)
Step 15: Combining datasets and analyzing Fixed Effects regression of support for gay marriage

cd "C:\Simulations\Refresher imputation\gay tol\panel\true list wt"
use t_1_p_w_longitudinal1, clear
foreach num of numlist 2/500 {
append using t_1_p_w_longitudinal\num'
}
save "C:\Simulations\Refresher imputation\gay tol\results\t_1_p_w_longitudinaltotal1.dta", replace

cd "C:\Simulations\Refresher imputation\gay tol\panel\imputed"/
use i_2006longitudinal1, clear
foreach num of numlist 2/500 {
append using i_2006longitudinal\num'
}
save "C:\Simulations\Refresher imputation\gay tol\results\i_2006longitudinaltotal1.dta", replace

use r_longitudinal1
foreach num of numlist 2/500 {
append using r_longitudinal\num'
}
save "C:\Simulations\Refresher imputation\gay tol\results\r_longitudinaltotal1.dta", replace

cd "C:\Simulations\Refresher imputation\gay tol\results\"
use t_1_p_w_longitudinaltotal1
merge 1:1 rowkeep using i_2006longitudinaltotal1
drop _merge
merge 1:1 rowkeep using r_longitudinaltotal1
drop _merge

sum *, sep(0)
save l.dta, replace

gen d_1_2006_b_wave = l_2006_b_wave - t_2006_b_wave
gen d_1_2006_b_educ = l_2006_b_educ - t_2006_b_educ
gen d_1_2006_b_loginc = l_2006_b_loginc - t_2006_b_loginc
gen d_1_2006_b_polviews = l_2006_b_polviews - t_2006_b_polviews
gen d_1_2006_b_religiosity = l_2006_b_religiosity - t_2006_b_religiosity
gen d_1_2006_b_gaytolerance = l_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_1_2006_se_wave = l_2006_se_wave - t_2006_se_wave
gen d_1_2006_se_educ = l_2006_se_educ - t_2006_se_educ
gen d_1_2006_se_loginc = l_2006_se_loginc - t_2006_se_loginc
gen d_1_2006_se_polviews = l_2006_se_polviews - t_2006_se_polviews

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gen d_l_2006_se_religiosity = l_2006_se_religiosity - t_2006_se_religiosity
gen d_l_2006_se_gaytolerance = l_2006_se_gaytolerance - t_2006_se_gaytolerance

gen d_p_2006_b_wave = p_2006_b_wave - t_2006_b_wave
gen d_p_2006_b_educ = p_2006_b_educ - t_2006_b_educ
gen d_p_2006_b_loginc = p_2006_b_loginc - t_2006_b_loginc
gen d_p_2006_b_polviews = p_2006_b_polviews - t_2006_b_polviews
gen d_p_2006_b_religiosity = p_2006_b_religiosity - t_2006_b_religiosity
gen d_p_2006_b_gaytolerance = p_2006_b_gaytolerance - t_2006_b_gaytolerance

gen d_p_2006_se_wave = p_2006_se_wave - t_2006_se_wave
gen d_p_2006_se_educ = p_2006_se_educ - t_2006_se_educ
gen d_p_2006_se_loginc = p_2006_se_loginc - t_2006_se_loginc
gen d_p_2006_se_polviews = p_2006_se_polviews - t_2006_se_polviews
gen d_p_2006_se_religiosity = p_2006_se_religiosity - t_2006_se_religiosity
gen d_p_2006_se_gaytolerance = p_2006_se_gaytolerance - t_2006_se_gaytolerance

gen d_w_2006_b_wave = w_2006_b_wave - t_2006_b_wave
gen d_w_2006_b_educ = w_2006_b_educ - t_2006_b_educ
gen d_w_2006_b_loginc = w_2006_b_loginc - t_2006_b_loginc
gen d_w_2006_b_polviews = w_2006_b_polviews - t_2006_b_polviews
gen d_w_2006_b_gaytolerance = w_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_w_2006_se_wave = w_2006_se_wave - t_2006_se_wave
gen d_w_2006_se_educ = w_2006_se_educ - t_2006_se_educ
gen d_w_2006_se_loginc = w_2006_se_loginc - t_2006_se_loginc
gen d_w_2006_se_polviews = w_2006_se_polviews - t_2006_se_polviews
gen d_w_2006_se_religiosity = w_2006_se_religiosity - t_2006_se_religiosity
gen d_w_2006_se_gaytolerance = w_2006_se_gaytolerance - t_2006_se_gaytolerance

gen d_i_2006_b_wave = i_2006_b_wave - t_2006_b_wave
gen d_i_2006_b_educ = i_2006_b_educ - t_2006_b_educ
gen d_i_2006_b_loginc = i_2006_b_loginc - t_2006_b_loginc
gen d_i_2006_b_polviews = i_2006_b_polviews - t_2006_b_polviews
gen d_i_2006_b_gaytolerance = i_2006_b_gaytolerance - t_2006_b_gaytolerance
gen d_i_2006_se_wave = i_2006_se_wave - t_2006_se_wave
gen d_i_2006_se_educ = i_2006_se_educ - t_2006_se_educ
gen d_i_2006_se_loginc = i_2006_se_loginc - t_2006_se_loginc
gen d_i_2006_se_polviews = i_2006_se_polviews - t_2006_se_polviews
gen d_i_2006_se_religiosity = i_2006_se_religiosity - t_2006_se_religiosity
gen d_i_2006_se_gaytolerance = i_2006_se_gaytolerance - t_2006_se_gaytolerance

gen d_r8_b_wave = r8_b_wave - t_2006_b_wave
gen d_r8_b_educ = r8_b_educ - t_2006_b_educ
gen d_r8_b_loginc = r8_b_loginc - t_2006_b_loginc
gen d_r8_b_polviews = r8_b_polviews - t_2006_b_polviews
gen d_r8_b_religiosity = r8_b_religiosity - t_2006_b_religiosity
gen d_r8_b_gaytolerance = r8_b_gaytolerance - t_2006_b_gaytolerance
gen d_r8_se_wave = r8_se_wave - t_2006_se_wave
gen d_r8_se_educ = r8_se_educ - t_2006_se_educ
gen d_r8_se_loginc = r8_se_loginc - t_2006_se_loginc
gen d_r8_se_polviews = r8_se_polviews - t_2006_se_polviews
gen d_r8_se_religiosity = r8_se_religiosity - t_2006_se_religiosity
gen d_r8_se_gaytolerance = r8_se_gaytolerance - t_2006_se_gaytolerance

gen d_r_b_wave = r_b_wave - t_2006_b_wave
gen d_r_b_educ = r_b_educ - t_2006_b_educ
gen d_r_b_loginc = r_b_loginc - t_2006_b_loginc
gen d_r_b_polviews = r_b_polviews - t_2006_b_polviews
gen d_r_b_religiosity = r_b_religiosity - t_2006_b_religiosity
gen d_r_b_gaytolerance = r_b_gaytolerance - t_2006_b_gaytolerance

gens d_r_se_wave = r_se_wave - t_2006_se_wave
gen d_r_se_educ = r_se_educ - t_2006_se_educ
gen d_r_se_loginc = r_se_loginc - t_2006_se_loginc
gen d_r_se_polviews = r_se_polviews - t_2006_se_polviews
gen d_r_se_religiosity = r_se_religiosity - t_2006_se_religiosity
gen d_r_se_gaytolerance = r_se_gaytolerance - t_2006_se_gaytolerance

*Getting results for Table 4-6

sum d_l_2006_b_wave-d_r_se_gaytolerance, sep(0)

*Boxplots for Figure 4-6

graph box d_l_2006_se_wave d_r_se_wave d_l_2006_se_educ d_r_se_educ d_l_2006_se_loginc
d_r_se_loginc ///
d_l_2006_se_polviews d_r_se_polviews d_l_2006_se_religiosity ///
d_r_se_religiosity d_l_2006_se_gaytolerance d_r_se_gaytolerance ///
, graphregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
plotregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
ylabel(,nogrid)

**Significance tests

gen tval_t_2006_b_wave = abs(t_2006_b_wave / t_2006_se_wave)
gen tval_t_2006_b_educ = abs(t_2006_b_educ / t_2006_se_educ)
gen tval_t_2006_b_loginc = abs(t_2006_b_loginc / t_2006_se_loginc)
gen tval_t_2006_b_polviews = abs(t_2006_b_polviews / t_2006_se_polviews)
gen tval_t_2006_b_religiosity = abs(t_2006_b_religiosity / t_2006_se_religiosity)
gen tval_t_2006_b_gaytolerance = abs(t_2006_b_gaytolerance / t_2006_se_gaytolerance)
gen tval_l_2006_b_wave = abs(l_2006_b_wave / l_2006_se_wave)
gen tval_l_2006_b_educ = abs(l_2006_b_educ / l_2006_se_educ)
gen tval_l_2006_b_loginc = abs(l_2006_b_loginc / l_2006_se_loginc)
gen tval_l_2006_b_polviews = abs(l_2006_b_polviews / l_2006_se_polviews)
gen tval_l_2006_b_religiosity = abs(l_2006_b_religiosity / l_2006_se_religiosity)
gen tval_l_2006_b_gaytolerance = abs(l_2006_b_gaytolerance / l_2006_se_gaytolerance)

gen tval_p_2006_b_wave = abs(p_2006_b_wave / p_2006_se_wave)
gen tval_p_2006_b_educ = abs(p_2006_b_educ / p_2006_se_educ)
gen tval_p_2006_b_loginc = abs(p_2006_b_loginc / p_2006_se_loginc)
gen tval_p_2006_b_polviews = abs(p_2006_b_polviews / p_2006_se_polviews)
gen tval_p_2006_b_religiosity = abs(p_2006_b_religiosity / p_2006_se_religiosity)
gen tval_p_2006_b_gaytolerance = abs(p_2006_b_gaytolerance / p_2006_se_gaytolerance)

gen tval_w_2006_b_wave = abs(w_2006_b_wave / w_2006_se_wave)
gen tval_w_2006_b_educ = abs(w_2006_b_educ / w_2006_se_educ)
gen tval_w_2006_b_loginc = abs(w_2006_b_loginc / w_2006_se_loginc)
gen tval_w_2006_b_polviews = abs(w_2006_b_polviews / w_2006_se_polviews)
gen tval_w_2006_b_religiosity = abs(w_2006_b_religiosity / w_2006_se_religiosity)
gen tval_w_2006_b_gaytolerance = abs(w_2006_b_gaytolerance / w_2006_se_gaytolerance)

gen tval_i_2006_b_wave = abs(i_2006_b_wave / i_2006_se_wave)
gen tval_i_2006_b_educ = abs(i_2006_b_educ / i_2006_se_educ)
gen tval_i_2006_b_loginc = abs(i_2006_b_loginc / i_2006_se_loginc)
gen tval_i_2006_b_polviews = abs(i_2006_b_polviews / i_2006_se_polviews)
gen tval_i_2006_b_religiosity = abs(i_2006_b_religiosity / i_2006_se_religiosity)
gen tval_i_2006_b_gaytolerance = abs(i_2006_b_gaytolerance / i_2006_se_gaytolerance)

gen tval_r8_b_wave = abs(r8_b_wave / r8_se_wave)
gen tval_r8_b_educ = abs(r8_b_educ / r8_se_educ)
gen tval_r8_b_loginc = abs(r8_b_loginc / r8_se_loginc)
gen tval_r8_b_polviews = abs(r8_b_polviews / r8_se_polviews)
gen tval_r8_b_religiosity = abs(r8_b_religiosity / r8_se_religiosity)
gen tval_r8_b_gaytolerance = abs(r8_b_gaytolerance / r8_se_gaytolerance)

gen tval_r_b_wave = abs(r_b_wave / r_se_wave)
gen tval_r_b_educ = abs(r_b_educ / r_se_educ)
gen tval_r_b_loginc = abs(r_b_loginc / r_se_loginc)
gen tval_r_b_polviews = abs(r_b_polviews / r_se_polviews)
gen tval_r_b_religiosity = abs(r_b_religiosity / r_se_religiosity)
gen tval_r_b_gaytolerance = abs(r_b_gaytolerance / r_se_gaytolerance)

gen s_t_2006_b_wave=1 if tval_t_2006_b_wave>1.96
gen s_t_2006_b_educ=1 if tval_t_2006_b_educ>1.96
gen s_t_2006_b_loginc=1 if tval_t_2006_b_loginc>1.96
gen s_t_2006_b_polviews=1 if tval_t_2006_b_polviews>1.96
gen s_t_2006_b_religiosity=1 if tval_t_2006_b_religiosity>1.96
gen s_t_2006_b_gaytolerance=1 if tval_t_2006_b_gaytolerance>1.96
gen s_l_2006_b_wave=1 if tval_l_2006_b_wave>1.96
gen s_l_2006_b_educ=1 if tval_l_2006_b_educ>1.96
gen s_l_2006_b_loginc=1 if tval_l_2006_b_loginc>1.96
gen s_l_2006_b_polviews=1 if tval_l_2006_b_polviews>1.96
gen s_l_2006_b_religiosity=1 if tval_l_2006_b_religiosity>1.96
gen s_l_2006_b_gaytolerance=1 if tval_l_2006_b_gaytolerance>1.96

gen s_p_2006_b_wave=1 if tval_p_2006_b_wave>1.96
gen s_p_2006_b_educ=1 if tval_p_2006_b_educ>1.96
gen s_p_2006_b_loginc=1 if tval_p_2006_b_loginc>1.96
gen s_p_2006_b_polviews=1 if tval_p_2006_b_polviews>1.96
gen s_p_2006_b_religiosity=1 if tval_p_2006_b_religiosity>1.96
gen s_p_2006_b_gaytolerance=1 if tval_p_2006_b_gaytolerance>1.96

gen s_w_2006_b_wave=1 if tval_w_2006_b_wave>1.96
gen s_w_2006_b_educ=1 if tval_w_2006_b_educ>1.96
gen s_w_2006_b_loginc=1 if tval_w_2006_b_loginc>1.96
gen s_w_2006_b_polviews=1 if tval_w_2006_b_polviews>1.96
gen s_w_2006_b_religiosity=1 if tval_w_2006_b_religiosity>1.96
gen s_w_2006_b_gaytolerance=1 if tval_w_2006_b_gaytolerance>1.96

gen s_i_2006_b_wave=1 if tval_i_2006_b_wave>1.96
gen s_i_2006_b_educ=1 if tval_i_2006_b_educ>1.96
gen s_i_2006_b_loginc=1 if tval_i_2006_b_loginc>1.96
gen s_i_2006_b_polviews=1 if tval_i_2006_b_polviews>1.96
gen s_i_2006_b_religiosity=1 if tval_i_2006_b_religiosity>1.96
gen s_i_2006_b_gaytolerance=1 if tval_i_2006_b_gaytolerance>1.96

gen s_r8_b_wave=1 if tval_r8_b_wave>1.96
gen s_r8_b_educ=1 if tval_r8_b_educ>1.96
gen s_r8_b_loginc=1 if tval_r8_b_loginc>1.96
gen s_r8_b_polviews=1 if tval_r8_b_polviews>1.96
gen s_r8_b_religiosity=1 if tval_r8_b_religiosity>1.96
gen s_r8_b_gaytolerance=1 if tval_r8_b_gaytolerance>1.96

gen s_r_b_wave=1 if tval_r_b_wave>1.96
gen s_r_b_educ=1 if tval_r_b_educ>1.96
gen s_r_b_loginc=1 if tval_r_b_loginc>1.96
gen s_r_b_polviews=1 if tval_r_b_polviews>1.96
gen s_r_b_religiosity=1 if tval_r_b_religiosity>1.96
gen s_r_b_gaytolerance=1 if tval_r_b_gaytolerance>1.96

foreach var of varlist s_t_2006_b_wave-s_r_b_gaytolerance {
    replace `var' =0 if missing(`var')
}

*Results for Table 4-7

sum s_*, sep(0)
Step 14: Combining datasets and analyzing OLS regression of self-rated health

*Putting Results together

cd "C:\Simulations\Refresher imputation\health\x sect\true list wt"

**True, listwist and weighted x-sectionals

use t_l_p_w_x1, clear
foreach num of numlist 2/500{
append using t_l_p_w_x`num'
}
save "C:\Simulations\Refresher imputation\health\results\t_l_p_w_xtotal1.dta", replace
clear

*Imputed 2006 only cross-section

cd "C:\Simulations\Refresher imputation\health\x sect\imputed"

use i_2006x1
foreach num of numlist 2/500{
append using i_2006x`num'
}
save "C:\Simulations\Refresher imputation\health\results\i_2006xtotal1.dta", replace

clear

do

*2006 cross section with refresher imputation adjustment

cd "C:\Simulations\Refresher imputation\health\x sect\imputed"

use r_2006_x1
foreach num of numlist 2/500{
append using r_2006_x`num'
}
save "C:\Simulations\Refresher imputation\health\results\r_2006xtotal1.dta", replace

clear

do

*All data cross section

cd "C:\Simulations\Refresher imputation\health\x sect\imputed"

use r_all_x1
foreach num of numlist 2/500{
append using r_all_x`num'
}
save "C:\Simulations\Refresher imputation\health\results\r_allxtotal1.dta", replace

clear

do

*Making the cross-sectional dataset

cd "C:\Simulations\Refresher imputation\health\results"

use t_l_p_w_xtotal1, clear
merge 1:1 rowkeep using i_2006xtotal1
drop _merge
merge 1:1 rowkeep using r_2006xtotal1
drop _merge
save x.dta, replace
sum *, sep(0)

```
gen d_l_2006_b_educ = l_2006_b_educ - t_2006_b_educ
gen d_l_2006_b_loginc = l_2006_b_loginc - t_2006_b_loginc
gen d_l_2006_b_happy = l_2006_b_happy - t_2006_b_happy
gen d_l_2006_b_satfin = l_2006_b_satfin - t_2006_b_satfin
gen d_l_2006_b_nevmarried = l_2006_b_nevmarried - t_2006_b_nevmarried
gen d_l_2006_b_divwidsep = l_2006_b_divwidsep - t_2006_b_divwidsep
gen d_l_2006_b_age = l_2006_b_age - t_2006_b_age
gen d_l_2006_b_agesq = l_2006_b_agesq - t_2006_b_agesq
```

```
gen d_l_2006_b_female = l_2006_b_female - t_2006_b_female
gen d_l_2006_b_black = l_2006_b_black - t_2006_b_black
gen d_l_2006_b_hispanic = l_2006_b_hispanic - t_2006_b_hispanic
gen d_l_2006_b_othrace = l_2006_b_othrace - t_2006_b_othrace
```

```
gen d_l_2006_se_educ = l_2006_se_educ - t_2006_se_educ
gen d_l_2006_se_loginc = l_2006_se_loginc - t_2006_se_loginc
```

```
gen d_l_2006_se_happy = l_2006_se_happy - t_2006_se_happy
gen d_l_2006_se_satfin = l_2006_se_satfin - t_2006_se_satfin
gen d_l_2006_se_nevmarried = l_2006_se_nevmarried - t_2006_se_nevmarried
gen d_l_2006_se_divwidsep = l_2006_se_divwidsep - t_2006_se_divwidsep
```

```
gen d_l_2006_se_age = l_2006_se_age - t_2006_se_age
gen d_l_2006_se_agesq = l_2006_se_agesq - t_2006_se_agesq
```

```
gen d_l_2006_se_female = l_2006_se_female - t_2006_se_female
gen d_l_2006_se_black = l_2006_se_black - t_2006_se_black
gen d_l_2006_se_hispanic = l_2006_se_hispanic - t_2006_se_hispanic
gen d_l_2006_se_othrace = l_2006_se_othrace - t_2006_se_othrace
```

```
gen d_p_2006_b_educ = p_2006_b_educ - t_2006_b_educ
gen d_p_2006_b_loginc = p_2006_b_loginc - t_2006_b_loginc
```

```
gen d_p_2006_b_happy = p_2006_b_happy - t_2006_b_happy
gen d_p_2006_b_satfin = p_2006_b_satfin - t_2006_b_satfin
```

```
gen d_p_2006_b_nevmarried = p_2006_b_nevmarried - t_2006_b_nevmarried
```

```
gen d_p_2006_b_divwidsep = p_2006_b_divwidsep - t_2006_b_divwidsep
```

```
gen d_p_2006_b_age = p_2006_b_age - t_2006_b_age
gen d_p_2006_b_agesq = p_2006_b_agesq - t_2006_b_agesq
```

```
gen d_p_2006_b_female = p_2006_b_female - t_2006_b_female
gen d_p_2006_b_black = p_2006_b_black - t_2006_b_black
gen d_p_2006_b_hispanic = p_2006_b_hispanic - t_2006_b_hispanic
gen d_p_2006_b_othrace = p_2006_b_othrace - t_2006_b_othrace
```

```
gen d_p_2006_se_educ = p_2006_se_educ - t_2006_se_educ
```

```
gen d_p_2006_se_loginc = p_2006_se_loginc - t_2006_se_loginc
```

```
gen d_p_2006_se_happy = p_2006_se_happy - t_2006_se_happy
des
```

```
gen d_p_2006_se_satfin = p_2006_se_satfin - t_2006_se_satfin
```

```
gen d_p_2006_se_nevmarried = p_2006_se_nevmarried - t_2006_se_nevmarried
```

```
gen d_p_2006_se_divwidsep = p_2006_se_divwidsep - t_2006_se_divwidsep
```

```
gen d_p_2006_se_age = p_2006_se_age - t_2006_se_age
```
gen d_p_2006_se_agesq = p_2006_se_agesq - t_2006_se_agesq
gen d_p_2006_se_female = p_2006_se_female - t_2006_se_female
gen d_p_2006_se_black = p_2006_se_black - t_2006_se_black
gen d_p_2006_se_hispanic = p_2006_se_hispanic - t_2006_se_hispanic
gen d_p_2006_se_othrace = p_2006_se_othrace - t_2006_se_othrace

gen d_w_2006_b_educ = w_2006_b_educ - t_2006_b_educ
gen d_w_2006_b_loginc = w_2006_b_loginc - t_2006_b_loginc
gen d_w_2006_b_happy = w_2006_b_happy - t_2006_b_happy
gen d_w_2006_b_satfin = w_2006_b_satfin - t_2006_b_satfin
gen d_w_2006_b_nevmarried = w_2006_b_nevmarried - t_2006_b_nevmarried
gen d_w_2006_b_divwidsep = w_2006_b_divwidsep - t_2006_b_divwidsep

gen d_w_2006_b_age = w_2006_b_age - t_2006_b_age
gen d_w_2006_b_agesq = w_2006_b_agesq - t_2006_b_agesq
gen d_w_2006_b_female = w_2006_b_female - t_2006_b_female
gen d_w_2006_b_black = w_2006_b_black - t_2006_b_black
gen d_w_2006_b_hispanic = w_2006_b_hispanic - t_2006_b_hispanic

gen d_w_2006_se_educ = w_2006_se_educ - t_2006_se_educ
gen d_w_2006_se_loginc = w_2006_se_loginc - t_2006_se_loginc
gen d_w_2006_se_happy = w_2006_se_happy - t_2006_se_happy
gen d_w_2006_se_satfin = w_2006_se_satfin - t_2006_se_satfin

gen d_w_2006_se_nevmarried = w_2006_se_nevmarried - t_2006_se_nevmarried
gen d_w_2006_se_divwidsep = w_2006_se_divwidsep - t_2006_se_divwidsep

gen d_w_2006_se_age = w_2006_se_age - t_2006_se_age
gen d_w_2006_se_agesq = w_2006_se_agesq - t_2006_se_agesq
gen d_w_2006_se_female = w_2006_se_female - t_2006_se_female
gen d_w_2006_se_black = w_2006_se_black - t_2006_se_black
gen d_w_2006_se_hispanic = w_2006_se_hispanic - t_2006_se_hispanic

gen d_w_2006_se_othrace = w_2006_se_othrace - t_2006_se_othrace

gen d_i_2006_b_educ = i_2006_b_educ - t_2006_b_educ
gen d_i_2006_b_loginc = i_2006_b_loginc - t_2006_b_loginc
gen d_i_2006_b_happy = i_2006_b_happy - t_2006_b_happy

gen d_i_2006_b_nevmarried = i_2006_b_nevmarried - t_2006_b_nevmarried

gen d_i_2006_b_divwidsep = i_2006_b_divwidsep - t_2006_b_divwidsep

gen d_i_2006_b_age = i_2006_b_age - t_2006_b_age
gen d_i_2006_b_agesq = i_2006_b_agesq - t_2006_b_agesq

gen d_i_2006_b_female = i_2006_b_female - t_2006_b_female

200
gen d_i_2006_se_satfin = i_2006_se_satfin - t_2006_se_satfin
gen d_i_2006_se_nevmarried = i_2006_se_nevmarried - t_2006_se_nevmarried
gen d_i_2006_se_divwidsep = i_2006_se_divwidsep - t_2006_se_divwidsep
gen d_i_2006_se_age = i_2006_se_age - t_2006_se_age
gen d_i_2006_se_agesq = i_2006_se_agesq - t_2006_se_agesq
gen d_i_2006_se_female = i_2006_se_female - t_2006_se_female
gen d_i_2006_se_black = i_2006_se_black - t_2006_se_black
gen d_i_2006_se_hispanic = i_2006_se_hispanic - t_2006_se_hispanic
gen d_i_2006_se_othrace = i_2006_se_othrace - t_2006_se_othrace

gen d_r8_2006_b_educ = r8_2006_b_educ - t_2006_b_educ
gen d_r8_2006_b_loginc = r8_2006_b_loginc - t_2006_b_loginc
gen d_r8_2006_b_happy = r8_2006_b_happy - t_2006_b_happy
gen d_r8_2006_b_satfin = r8_2006_b_satfin - t_2006_b_satfin
gen d_r8_2006_b_nevmarried = r8_2006_b_nevmarried - t_2006_b_nevmarried
gen d_r8_2006_b_divwidsep = r8_2006_b_divwidsep - t_2006_b_divwidsep
gen d_r8_2006_b_age = r8_2006_b_age - t_2006_b_age
gen d_r8_2006_b_agesq = r8_2006_b_agesq - t_2006_b_agesq
gen d_r8_2006_b_female = r8_2006_b_female - t_2006_b_female
gen d_r8_2006_b_black = r8_2006_b_black - t_2006_b_black
gen d_r8_2006_b_hispanic = r8_2006_b_hispanic - t_2006_b_hispanic
gen d_r8_2006_b_othrace = r8_2006_b_othrace - t_2006_b_othrace

gen d_r_2006_b_educ = r_2006_b_educ - t_2006_b_educ
gen d_r_2006_b_loginc = r_2006_b_loginc - t_2006_b_loginc
gen d_r_2006_b_happy = r_2006_b_happy - t_2006_b_happy
gen d_r_2006_b_satfin = r_2006_b_satfin - t_2006_b_satfin
gen d_r_2006_b_nevmarried = r_2006_b_nevmarried - t_2006_b_nevmarried
gen d_r_2006_b_divwidsep = r_2006_b_divwidsep - t_2006_b_divwidsep
gen d_r_2006_b_age = r_2006_b_age - t_2006_b_age
gen d_r_2006_b_agesq = r_2006_b_agesq - t_2006_b_agesq
gen d_r_2006_b_female = r_2006_b_female - t_2006_b_female
gen d_r_2006_b_black = r_2006_b_black - t_2006_b_black
gen d_r_2006_b_hispanic = r_2006_b_hispanic - t_2006_b_hispanic
gen d_r_2006_b_othrace = r_2006_b_othrace - t_2006_b_othrace
gen d_r_2006_se_educ = r_2006_se_educ - t_2006_se_educ
gen d_r_2006_se_loginc = r_2006_se_loginc - t_2006_se_loginc
gen d_r_2006_se_happy = r_2006_se_happy - t_2006_se_happy
gen d_r_2006_se_satfin = r_2006_se_satfin - t_2006_se_satfin
gen d_r_2006_se_nevmarried = r_2006_se_nevmarried - t_2006_se_nevmarried
gen d_r_2006_se_divwidsep = r_2006_se_divwidsep - t_2006_se_divwidsep
gen d_r_2006_se_age = r_2006_se_age - t_2006_se_age
gen d_r_2006_se_agesq = r_2006_se_agesq - t_2006_se_agesq
gen d_r_2006_se_female = r_2006_se_female - t_2006_se_female
gen d_r_2006_se_black = r_2006_se_black - t_2006_se_black
gen d_r_2006_se_hispanic = r_2006_se_hispanic - t_2006_se_hispanic
gen d_r_2006_se_othrace = r_2006_se_othrace - t_2006_se_othrace

gen d_l_2006_m_health = l_2006_m_health - t_2006_m_health
gen d_l_2006_m_educ = l_2006_m_educ - t_2006_m_educ
gen d_l_2006_m_loginc = l_2006_m_loginc - t_2006_m_loginc
gen d_l_2006_m_happy = l_2006_m_happy - t_2006_m_happy
gen d_l_2006_m_satfin = l_2006_m_satfin - t_2006_m_satfin
gen d_l_2006_m_nevmarried = l_2006_m_nevmarried - t_2006_m_nevmarried
gen d_l_2006_m_divwidsep = l_2006_m_divwidsep - t_2006_m_divwidsep
gen d_l_2006_m_age = l_2006_m_age - t_2006_m_age
gen d_l_2006_m_agesq = l_2006_m_agesq - t_2006_m_agesq
gen d_l_2006_m_female = l_2006_m_female - t_2006_m_female
gen d_l_2006_m_black = l_2006_m_black - t_2006_m_black
gen d_l_2006_m_hispanic = l_2006_m_hispanic - t_2006_m_hispanic
gen d_l_2006_m_othrace = l_2006_m_othrace - t_2006_m_othrace

gen d_p_2006_m_health = p_2006_m_health - t_2006_m_health
gen d_p_2006_m_educ = p_2006_m_educ - t_2006_m_educ
gen d_p_2006_m_loginc = p_2006_m_loginc - t_2006_m_loginc
gen d_p_2006_m_happy = p_2006_m_happy - t_2006_m_happy
gen d_p_2006_m_satfin = p_2006_m_satfin - t_2006_m_satfin
gen d_p_2006_m_nevmarried = p_2006_m_nevmarried - t_2006_m_nevmarried
gen d_p_2006_m_divwidsep = p_2006_m_divwidsep - t_2006_m_divwidsep
gen d_p_2006_m_age = p_2006_m_age - t_2006_m_age
gen d_p_2006_m_agesq = p_2006_m_agesq - t_2006_m_agesq
gen d_p_2006_m_female = p_2006_m_female - t_2006_m_female
gen d_p_2006_m_black = p_2006_m_black - t_2006_m_black
gen d_p_2006_m_hispanic = p_2006_m_hispanic - t_2006_m_hispanic
gen d_p_2006_m_othrace = p_2006_m_othrace - t_2006_m_othrace

gen d_w_2006_m_health = w_2006_m_health - t_2006_m_health
gen d_w_2006_m_educ = w_2006_m_educ - t_2006_m_educ
gen d_w_2006_m_loginc = w_2006_m_loginc - t_2006_m_loginc
gen d_w_2006_m_happy = w_2006_m_happy - t_2006_m_happy
gen d_w_2006_m_satfin = w_2006_m_satfin - t_2006_m_satfin
gen d_w_2006_m_nevmarried = w_2006_m_nevmarried - t_2006_m_nevmarried
gen d_w_2006_m_divwidsep = w_2006_m_divwidsep - t_2006_m_divwidsep
gen d_w_2006_m_age = w_2006_m_age - t_2006_m_age
gen d_w_2006_m_agesq = w_2006_m_agesq - t_2006_m_agesq
gen d_w_2006_m_female = w_2006_m_female - t_2006_m_female
gen d_w_2006_m_black = w_2006_m_black - t_2006_m_black
gen d_w_2006_m_hispanic = w_2006_m_hispanic - t_2006_m_hispanic
gen d_w_2006_m_othrace = w_2006_m_othrace - t_2006_m_othrace

gen d_i_2006_m_health = i_2006_m_health - t_2006_m_health
gen d_i_2006_m_educ = i_2006_m_educ - t_2006_m_educ
gen d_i_2006_m_loginc = i_2006_m_loginc - t_2006_m_loginc
gen d_i_2006_m_happy = i_2006_m_happy - t_2006_m_happy
gen d_i_2006_m_satfin = i_2006_m_satfin - t_2006_m_satfin
gen d_i_2006_m_nevmarried = i_2006_m_nevmarried - t_2006_m_nevmarried
gen d_i_2006_m_divwidsep = i_2006_m_divwidsep - t_2006_m_divwidsep
gen d_i_2006_m_age = i_2006_m_age - t_2006_m_age
gen d_i_2006_m_agesq = i_2006_m_agesq - t_2006_m_agesq
gen d_i_2006_m_female = i_2006_m_female - t_2006_m_female
gen d_i_2006_m_black = i_2006_m_black - t_2006_m_black
gen d_i_2006_m_hispanic = i_2006_m_hispanic - t_2006_m_hispanic
gen d_i_2006_m_othrace = i_2006_m_othrace - t_2006_m_othrace

gen d_r8_2006_m_health = r8_2006_m_health - t_2006_m_health
gen d_r8_2006_m_educ = r8_2006_m_educ - t_2006_m_educ
gen d_r8_2006_m_loginc = r8_2006_m_loginc - t_2006_m_loginc
gen d_r8_2006_m_happy = r8_2006_m_happy - t_2006_m_happy
gen d_r8_2006_m_satfin = r8_2006_m_satfin - t_2006_m_satfin
gen d_r8_2006_m_nevmarried = r8_2006_m_nevmarried - t_2006_m_nevmarried
gen d_r8_2006_m_divwidsep = r8_2006_m_divwidsep - t_2006_m_divwidsep
gen d_r8_2006_m_age = r8_2006_m_age - t_2006_m_age
gen d_r8_2006_m_agesq = r8_2006_m_agesq - t_2006_m_agesq
gen d_r8_2006_m_female = r8_2006_m_female - t_2006_m_female
gen d_r8_2006_m_black = r8_2006_m_black - t_2006_m_black
gen d_r8_2006_m_hispanic = r8_2006_m_hispanic - t_2006_m_hispanic
gen d_r8_2006_m_othrace = r8_2006_m_othrace - t_2006_m_othrace

gen d_r_2006_m_health = r_2006_m_health - t_2006_m_health
gen d_r_2006_m_educ = r_2006_m_educ - t_2006_m_educ
gen d_r_2006_m_loginc = r_2006_m_loginc - t_2006_m_loginc
gen d_r_2006_m_happy = r_2006_m_happy - t_2006_m_happy
gen d_r_2006_m_satfin = r_2006_m_satfin - t_2006_m_satfin
gen d_r_2006_m_nevmarried = r_2006_m_nevmarried - t_2006_m_nevmarried
gen d_r_2006_m_divwidsep = r_2006_m_divwidsep - t_2006_m_divwidsep
gen d_r_2006_m_age = r_2006_m_age - t_2006_m_age

gen d_r_2006_m_agesq = r_2006_m_agesq - t_2006_m_agesq

gen d_r_2006_m_female = r_2006_m_female - t_2006_m_female

gen d_r_2006_m_black = r_2006_m_black - t_2006_m_black

gen d_r_2006_m_hispanic = r_2006_m_hispanic - t_2006_m_hispanic

gen d_r_2006_m_othrace = r_2006_m_othrace - t_2006_m_othrace

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gen d_r_2006_m_agesq = r_2006_m_agesq - t_2006_m_agesq
gen d_r_2006_m_female = r_2006_m_female - t_2006_m_female
gen d_r_2006_m_black = r_2006_m_black - t_2006_m_black
gen d_r_2006_m_hispanic = r_2006_m_hispanic - t_2006_m_hispanic
gen d_r_2006_m_othrace = r_2006_m_othrace - t_2006_m_othrace

*Results for Table 4-8
sum d_l_2006_b_edu - d_r_2006_m_othrace, sep(0)

*Results for Figure 4-7
graph box d_l_2006_se_educ d_r_2006_se_educ d_l_2006_se_loginc d_r_2006_se_loginc ///
d_l_2006_se_happy d_r_2006_se_happy d_l_2006_se_satfin d_r_2006_se_satfin ///
d_l_2006_se_age d_r_2006_se_age d_l_2006_se_agesq d_r_2006_se_agesq ///
, graphregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
plotregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
ylabel(,nogrid)

graph box d_l_2006_se_nevmarried d_r_2006_se_nevmarried ///
d_l_2006_se_divwidsep d_r_2006_se_divwidsep ///
d_l_2006_se_female d_r_2006_se_female d_l_2006_se_black d_r_2006_se_black ///
d_l_2006_se_hispanic d_r_2006_se_hispanic d_l_2006_se_othrace d_r_2006_se_othrace ///
, graphregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
plotregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
ylabel(,nogrid)

**Significance testing

gen tval_t_2006_b_educ = abs(t_2006_b_educ / t_2006_se_educ)
gen tval_t_2006_b_loginc = abs(t_2006_b_loginc / t_2006_se_loginc)
gen tval_t_2006_b_happy = abs(t_2006_b_happy / t_2006_se_happy)
gen tval_t_2006_b_satfin = abs(t_2006_b_satfin / t_2006_se_satfin)
gen tval_t_2006_b_nevmarried = abs(t_2006_b_nevmarried / t_2006_se_nevmarried)
gen tval_t_2006_b_divwidsep = abs(t_2006_b_divwidsep / t_2006_se_divwidsep)
gen tval_t_2006_b_age = abs(t_2006_b_age / t_2006_se_age)
gen tval_t_2006_b_agesq = abs(t_2006_b_agesq / t_2006_se_agesq)
gen tval_t_2006_b_female = abs(t_2006_b_female / t_2006_se_female)
gen tval_t_2006_b_black = abs(t_2006_b_black / t_2006_se_black)
gen tval_t_2006_b_hispanic = abs(t_2006_b_hispanic / t_2006_se_hispanic)
gen tval_t_2006_b_othrace = abs(t_2006_b_othrace / t_2006_se_othrace)

gen tval_l_2006_b_educ = abs(l_2006_b_educ / l_2006_se_educ)
gen tval_l_2006_b_loginc = abs(l_2006_b_loginc / l_2006_se_loginc)
gen tval_l_2006_b_happy = abs(l_2006_b_happy / l_2006_se_happy)
gen tval_l_2006_b_satfin = abs(l_2006_b_satfin / l_2006_se_satfin)
gen tval_l_2006_b_nevmarried = abs(l_2006_b_nevmarried / l_2006_se_nevmarried)
gen tval_l_2006_b_divwidsep = abs(l_2006_b_divwidsep / l_2006_se_divwidsep)
gen tval_l_2006_b_age = abs(l_2006_b_age / l_2006_se_age)
gen tval_l_2006_b_agesq = abs(l_2006_b_agesq / l_2006_se_agesq)
gen tval_l_2006_b_female = abs(l_2006_b_female / l_2006_se_female)
gen tval_l_2006_b_black = abs(l_2006_b_black / l_2006_se_black)
gen tval_l_2006_b_hispanic = abs(l_2006_b_hispanic / l_2006_se_hispanic)
gen tval_l_2006_b_othrace = abs(l_2006_b_othrace / l_2006_se_othrace)
gen tval_p_2006_b_educ = abs(p_2006_b_educ / p_2006_se_educ)
gen tval_p_2006_b_loginc = abs(p_2006_b_loginc / p_2006_se_loginc)
gen tval_p_2006_b_happy = abs(p_2006_b_happy / p_2006_se_happy)
gen tval_p_2006_b_nevmarried = abs(p_2006_b_nevmarried / p_2006_se_nevmarried)
gen tval_p_2006_b_divwidsep = abs(p_2006_b_divwidsep / p_2006_se_divwidsep)
gen tval_p_2006_b_age = abs(p_2006_b_age / p_2006_se_age)
gen tval_p_2006_b_agesq = abs(p_2006_b_agesq / p_2006_se_agesq)
gen tval_p_2006_b_female = abs(p_2006_b_female / p_2006_se_female)
gen tval_p_2006_b_black = abs(p_2006_b_black / p_2006_se_black)
gen tval_p_2006_b_hispanic = abs(p_2006_b_hispanic / p_2006_se_hispanic)
gen tval_p_2006_b_othrace = abs(p_2006_b_othrace / p_2006_se_othrace)
gen tval_w_2006_b_educ = abs(w_2006_b_educ / w_2006_se_educ)
gen tval_w_2006_b_loginc = abs(w_2006_b_loginc / w_2006_se_loginc)
gen tval_w_2006_b_happy = abs(w_2006_b_happy / w_2006_se_happy)
gen tval_w_2006_b_satfin = abs(w_2006_b_satfin / w_2006_se_satfin)
gen tval_w_2006_b_nevmarried = abs(w_2006_b_nevmarried / w_2006_se_nevmarried)
gen tval_w_2006_b_divwidsep = abs(w_2006_b_divwidsep / w_2006_se_divwidsep)
gen tval_w_2006_b_age = abs(w_2006_b_age / w_2006_se_age)
gen tval_w_2006_b_agesq = abs(w_2006_b_agesq / w_2006_se_agesq)
gen tval_w_2006_b_female = abs(w_2006_b_female / w_2006_se_female)
gen tval_w_2006_b_black = abs(w_2006_b_black / w_2006_se_black)
gen tval_w_2006_b_hispanic = abs(w_2006_b_hispanic / w_2006_se_hispanic)
gen tval_w_2006_b_othrace = abs(w_2006_b_othrace / w_2006_se_othrace)
gen tval_i_2006_b_educ = abs(i_2006_b_educ / i_2006_se_educ)
gen tval_i_2006_b_loginc = abs(i_2006_b_loginc / i_2006_se_loginc)
gen tval_i_2006_b_happy = abs(i_2006_b_happy / i_2006_se_happy)
gen tval_i_2006_b_satfin = abs(i_2006_b_satfin / i_2006_se_satfin)
gen tval_i_2006_b_nevmarried = abs(i_2006_b_nevmarried / i_2006_se_nevmarried)
gen tval_i_2006_b_divwidsep = abs(i_2006_b_divwidsep / i_2006_se_divwidsep)
gen tval_i_2006_b_age = abs(i_2006_b_age / i_2006_se_age)
gen tval_i_2006_b_agesq = abs(i_2006_b_agesq / i_2006_se_agesq)
gen tval_i_2006_b_female = abs(i_2006_b_female / i_2006_se_female)
gen tval_i_2006_b_black = abs(i_2006_b_black)
gen tval_i_2006_b_hispanic = abs(i_2006_b_hispanic / i_2006_se_hispanic)
gen tval_i_2006_b_othrace = abs(i_2006_b_othrace / i_2006_se_othrace)

gen tval_r8_2006_b_educ = abs(r8_2006_b_educ / r8_2006_se_educ)
gen tval_r8_2006_b_loginc = abs(r8_2006_b_loginc / r8_2006_se_loginc)
gen tval_r8_2006_b_happy = abs(r8_2006_b_happy / r8_2006_se_happy)
gen tval_r8_2006_b_satfin = abs(r8_2006_b_satfin / r8_2006_se_satfin)
gen tval_r8_2006_b_nevmarried = abs(r8_2006_b_nevmarried / r8_2006_se_nevmarried)
gen tval_r8_2006_b_divwidsep = abs(r8_2006_b_divwidsep / r8_2006_se_divwidsep)
gen tval_r8_2006_b_age = abs(r8_2006_b_age / r8_2006_se_age)
gen tval_r8_2006_b_agesq = abs(r8_2006_b_agesq / r8_2006_se_agesq)
gen tval_r8_2006_b_female = abs(r8_2006_b_female / r8_2006_se_female)
gen tval_r8_2006_b_black = abs(r8_2006_b_black / r8_2006_se_black)
gen tval_r8_2006_b_hispanic = abs(r8_2006_b_hispanic / r8_2006_se_hispanic)
gen tval_r8_2006_b_othrace = abs(r8_2006_b_othrace / r8_2006_se_othrace)

gen tval_r_2006_b_educ = abs(r_2006_b_educ / r_2006_se_educ)
gen tval_r_2006_b_loginc = abs(r_2006_b_loginc / r_2006_se_loginc)
gen tval_r_2006_b_happy = abs(r_2006_b_happy / r_2006_se_happy)
gen tval_r_2006_b_satfin = abs(r_2006_b_satfin / r_2006_se_satfin)
gen tval_r_2006_b_nevmarried = abs(r_2006_b_nevmarried / r_2006_se_nevmarried)
gen tval_r_2006_b_divwidsep = abs(r_2006_b_divwidsep / r_2006_se_divwidsep)
gen tval_r_2006_b_age = abs(r_2006_b_age / r_2006_se_age)
gen tval_r_2006_b_agesq = abs(r_2006_b_agesq / r_2006_se_agesq)
gen tval_r_2006_b_female = abs(r_2006_b_female / r_2006_se_female)
gen tval_r_2006_b_black = abs(r_2006_b_black / r_2006_se_black)
gen tval_r_2006_b_hispanic = abs(r_2006_b_hispanic / r_2006_se_hispanic)
gen tval_r_2006_b_othrace = abs(r_2006_b_othrace / r_2006_se_othrace)

gens_t_2006_b_educ=1 if tval_t_2006_b_educ>1.96

gens_t_2006_b_loginc=1 if tval_t_2006_b_loginc>1.96

gens_t_2006_b_happy=1 if tval_t_2006_b_happy>1.96

gens_t_2006_b_satfin=1 if tval_t_2006_b_satfin>1.96

gens_t_2006_b_nevmarried=1 if tval_t_2006_b_nevmarried>1.96

gens_t_2006_b_divwidsep=1 if tval_t_2006_b_divwidsep>1.96

gens_t_2006_b_age=1 if tval_t_2006_b_age>1.96

gens_t_2006_b_agesq=1 if tval_t_2006_b_agesq>1.96

gens_t_2006_b_female=1 if tval_t_2006_b_female>1.96

gens_t_2006_b_black=1 if tval_t_2006_b_black>1.96

gens_t_2006_b_hispanic=1 if tval_t_2006_b_hispanic>1.96

gens_t_2006_b_othrace=1 if tval_t_2006_b_othrace>1.96


gens_l_2006_b_educ=1 if tval_l_2006_b_educ>1.96

gens_l_2006_b_loginc=1 if tval_l_2006_b_loginc>1.96

gens_l_2006_b_happy=1 if tval_l_2006_b_happy>1.96
gen s_l_2006_b_satfin=1 if tval_l_2006_b_satfin>1.96
gen s_l_2006_b_nevmarried=1 if tval_l_2006_b_nevmarried>1.96
gen s_l_2006_b_divwidsep=1 if tval_l_2006_b_divwidsep>1.96
gen s_l_2006_b_age=1 if tval_l_2006_b_age>1.96
gen s_l_2006_b_agesq=1 if tval_l_2006_b_agesq>1.96
gen s_l_2006_b_female=1 if tval_l_2006_b_female>1.96
gen s_l_2006_b_black=1 if tval_l_2006_b_black>1.96
gen s_l_2006_b_hispanic=1 if tval_l_2006_b_hispanic>1.96
gen s_l_2006_b_othrace=1 if tval_l_2006_b_othrace>1.96

gen s_p_2006_b_educ=1 if tval_p_2006_b_educ>1.96
gen s_p_2006_b_loginc=1 if tval_p_2006_b_loginc>1.96
gen s_p_2006_b_happy=1 if tval_p_2006_b_happy>1.96
gen s_p_2006_b_satfin=1 if tval_p_2006_b_satfin>1.96
gen s_p_2006_b_nevmarried=1 if tval_p_2006_b_nevmarried>1.96
gen s_p_2006_b_divwidsep=1 if tval_p_2006_b_divwidsep>1.96
gen s_p_2006_b_age=1 if tval_p_2006_b_age>1.96
gen s_p_2006_b_agesq=1 if tval_p_2006_b_agesq>1.96
gen s_p_2006_b_female=1 if tval_p_2006_b_female>1.96
gen s_p_2006_b_black=1 if tval_p_2006_b_black>1.96
gen s_p_2006_b_hispanic=1 if tval_p_2006_b_hispanic>1.96
gen s_p_2006_b_othrace=1 if tval_p_2006_b_othrace>1.96

gen s_w_2006_b_educ=1 if tval_w_2006_b_educ>1.96
gen s_w_2006_b_loginc=1 if tval_w_2006_b_loginc>1.96
gen s_w_2006_b_happy=1 if tval_w_2006_b_happy>1.96
gen s_w_2006_b_satfin=1 if tval_w_2006_b_satfin>1.96
gen s_w_2006_b_nevmarried=1 if tval_w_2006_b_nevmarried>1.96
gen s_w_2006_b_divwidsep=1 if tval_w_2006_b_divwidsep>1.96
gen s_w_2006_b_age=1 if tval_w_2006_b_age>1.96
gen s_w_2006_b_agesq=1 if tval_w_2006_b_agesq>1.96
gen s_w_2006_b_female=1 if tval_w_2006_b_female>1.96
gen s_w_2006_b_black=1 if tval_w_2006_b_black>1.96
gen s_w_2006_b_hispanic=1 if tval_w_2006_b_hispanic>1.96

gen s_i_2006_b_educ=1 if tval_i_2006_b_educ>1.96
gen s_i_2006_b_loginc=1 if tval_i_2006_b_loginc>1.96
gen s_i_2006_b_happy=1 if tval_i_2006_b_happy>1.96
gen s_i_2006_b_satfin=1 if tval_i_2006_b_satfin>1.96
gen s_i_2006_b_nevmarried=1 if tval_i_2006_b_nevmarried>1.96
gen s_i_2006_b_divwidsep=1 if tval_i_2006_b_divwidsep>1.96
gen s_i_2006_b_age=1 if tval_i_2006_b_age>1.96
gen s_i_2006_b_agesq=1 if tval_i_2006_b_agesq>1.96

gen s_i_2006_b_hispanic=1 if tval_i_2006_b_hispanic>1.96
gen s_i_2006_b_othrace=1 if tval_i_2006_b_othrace>1.96

gen s_r8_2006_b_educ=1 if tval_r8_2006_b_educ>1.96
gen s_r8_2006_b_loginc=1 if tval_r8_2006_b_loginc>1.96
gen s_r8_2006_b_happy=1 if tval_r8_2006_b_happy>1.96
gen s_r8_2006_b_satfin=1 if tval_r8_2006_b_satfin>1.96
gen s_r8_2006_b_nevmarried=1 if tval_r8_2006_b_nevmarried>1.96
gen s_r8_2006_b_divwidsep=1 if tval_r8_2006_b_divwidsep>1.96
gen s_r8_2006_b_age=1 if tval_r8_2006_b_age>1.96
gen s_r8_2006_b_agesq=1 if tval_r8_2006_b_agesq>1.96
gen s_r8_2006_b_female=1 if tval_r8_2006_b_female>1.96
gen s_r8_2006_b_black=1 if tval_r8_2006_b_black>1.96
gen s_r8_2006_b_hispanic=1 if tval_r8_2006_b_hispanic>1.96
gen s_r8_2006_b_othrace=1 if tval_r8_2006_b_othrace>1.96

gen s_r_2006_b_educ=1 if tval_r_2006_b_educ>1.96
gen s_r_2006_b_loginc=1 if tval_r_2006_b_loginc>1.96
gen s_r_2006_b_happy=1 if tval_r_2006_b_happy>1.96
gen s_r_2006_b_satfin=1 if tval_r_2006_b_satfin>1.96
gen s_r_2006_b_nevmarried=1 if tval_r_2006_b_nevmarried>1.96
gen s_r_2006_b_divwidsep=1 if tval_r_2006_b_divwidsep>1.96
gen s_r_2006_b_age=1 if tval_r_2006_b_age>1.96
gen s_r_2006_b_agesq=1 if tval_r_2006_b_agesq>1.96
gen s_r_2006_b_female=1 if tval_r_2006_b_female>1.96
gen s_r_2006_b_black=1 if tval_r_2006_b_black>1.96
gen s_r_2006_b_hispanic=1 if tval_r_2006_b_hispanic>1.96
gen s_r_2006_b_othrace=1 if tval_r_2006_b_othrace>1.96

foreach var of varlist s_t_2006_b_educ-s_r_2006_b_othrace {
    replace `var' =0 if missing(`var')
}

*Results for Table 4-9
sum s_*, sep(0)
Step 15: Combining datasets and analyzing Fixed Effects regression of self-rated health

*Setting up longitudinal data

cd "C:\Simulations\Refresher imputation\health\panel\true list wt"
use t_l_p_w_longitudinal1, clear
foreach num of numlist 2/500{
    append using t_l_p_w_longitudinal`num'
}
save "C:\Simulations\Refresher imputation\health\results\t_l_p_w_longitudinaltotal1.dta", replace

cd "C:\Simulations\Refresher imputation\health\panel\imputed"
use i_2006longitudinal1, clear
foreach num of numlist 2/500{
    append using i_2006longitudinal`num'
}
save "C:\Simulations\Refresher imputation\health\results\i_2006longitudinaltotal1.dta", replace

use r_longitudinal1
foreach num of numlist 2/500{
    append using r_longitudinal`num'
}
save "C:\Simulations\Refresher imputation\health\results\r_longitudinaltotal1.dta", replace

cd "C:\Simulations\Refresher imputation\health\results\"
use t_l_p_w_longitudinaltotal1
merge 1:1 rowkeep using i_2006longitudinaltotal1
drop _merge
merge 1:1 rowkeep using r_longitudinaltotal1
drop _merge

sum *, sep(0)
save l.dta, replace

gen d_l_2006_b_wave = l_2006_b_wave - t_2006_b_wave
gen d_l_2006_b_educ = l_2006_b_educ - t_2006_b_educ
gen d_l_2006_b_loginc = l_2006_b_loginc - t_2006_b_loginc
gen d_l_2006_b_happy = l_2006_b_happy - t_2006_b_happy
gen d_l_2006_b_satfin = l_2006_b_satfin - t_2006_b_satfin
gen d_l_2006_b_nevmartied = l_2006_b_nevmartied - t_2006_b_nevmartied
gen d_l_2006_b_divwidsep = l_2006_b_divwidsep - t_2006_b_divwidsep

gen d_l_2006_se_wave = l_2006_se_wave - t_2006_se_wave
gen d_l_2006_se_educ = l_2006_se_educ - t_2006_se_educ
gen d_l_2006_se_loginc = l_2006_se_loginc - t_2006_se_loginc
gen d_l_2006_se_happy = l_2006_se_happy - t_2006_se_happy
gen d_l_2006_se_satfin = l_2006_se_satfin - t_2006_se_satfin
gen d_l_2006_se_nevmarried = l_2006_se_nevmarried - t_2006_se_nevmarried

gen d_p_2006_b_wave = p_2006_b_wave - t_2006_b_wave
gen d_p_2006_b_educ = p_2006_b_educ - t_2006_b_educ
gen d_p_2006_b_loginc = p_2006_b_loginc - t_2006_b_loginc
gen d_p_2006_b_happy = p_2006_b_happy - t_2006_b_happy
gen d_p_2006_b_satfin = p_2006_b_satfin - t_2006_b_satfin
gen d_p_2006_b_nevmarried = p_2006_b_nevmarried - t_2006_b_nevmarried

gen d_p_2006_se_wave = p_2006_se_wave - t_2006_se_wave
gen d_p_2006_se_educ = p_2006_se_educ - t_2006_se_educ
gen d_p_2006_se_loginc = p_2006_se_loginc - t_2006_se_loginc
gen d_p_2006_se_happy = p_2006_se_happy - t_2006_se_happy
gen d_p_2006_se_satfin = p_2006_se_satfin - t_2006_se_satfin
gen d_p_2006_se_nevmarried = p_2006_se_nevmarried - t_2006_se_nevmarried

gen d_w_2006_b_wave = w_2006_b_wave - t_2006_b_wave
gen d_w_2006_b_educ = w_2006_b_educ - t_2006_b_educ
gen d_w_2006_b_loginc = w_2006_b_loginc - t_2006_b_loginc
gen d_w_2006_b_happy = w_2006_b_happy - t_2006_b_happy
gen d_w_2006_b_satfin = w_2006_b_satfin - t_2006_b_satfin
gen d_w_2006_b_nevmarried = w_2006_b_nevmarried - t_2006_b_nevmarried

gen d_w_2006_se_wave = w_2006_se_wave - t_2006_se_wave
gen d_w_2006_se_educ = w_2006_se_educ - t_2006_se_educ
gen d_w_2006_se_loginc = w_2006_se_loginc - t_2006_se_loginc
gen d_w_2006_se_happy = w_2006_se_happy - t_2006_se_happy
gen d_w_2006_se_satfin = w_2006_se_satfin - t_2006_se_satfin
gen d_w_2006_se_nevmarried = w_2006_se_nevmarried - t_2006_se_nevmarried

gen d_i_2006_b_wave = i_2006_b_wave - t_2006_b_wave
gen d_i_2006_b_educ = i_2006_b_educ - t_2006_b_educ
gen d_i_2006_b_loginc = i_2006_b_loginc - t_2006_b_loginc
gen d_i_2006_b_happy = i_2006_b_happy - t_2006_b_happy
gen d_i_2006_b_satfin = i_2006_b_satfin - t_2006_b_satfin
gen d_i_2006_b_nevmarried = i_2006_b_nevmarried - t_2006_b_nevmarried
gen d_i_2006_b_divwidsep = i_2006_b_divwidsep - t_2006_b_divwidsep

gen d_i_2006_se_wave = i_2006_se_wave - t_2006_se_wave
gen d_i_2006_se_educ = i_2006_se_educ - t_2006_se_educ
gen d_i_2006_se_loginc = i_2006_se_loginc - t_2006_se_loginc
gen d_i_2006_se_happy = i_2006_se_happy - t_2006_se_happy
gen d_i_2006_se_satfin = i_2006_se_satfin - t_2006_se_satfin
gen d_i_2006_se_nevmarried = i_2006_se_nevmarried - t_2006_se_nevmarried
gen d_i_2006_se_divwidsep = i_2006_se_divwidsep - t_2006_se_divwidsep

...
Results for Table 4-10
sum d_l_2006_b_wave - d_r_se_divwidsep, sep(0)

Results for Figure 4-8
graph box d_l_2006_se_wave d_r_se_wave d_l_2006_se_educ d_r_se_educ ///
    d_l_2006_se_loginc d_r_se_loginc d_l_2006_se_happy d_r_se_happy ///
    d_l_2006_se_satfin d_r_se_satfin ///
    , graphregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
    plotregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
    ylabel(, nogrid)

graph box d_l_2006_se_nevmarried d_r_se_nevmarried d_l_2006_se_divwidsep
    d_r_se_divwidsep ///
    , graphregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
    plotregion(fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///
    ylabel(, nogrid)

gen tval_t_2006_b_wave = abs(t_2006_b_wave / t_2006_se_wave)
gen tval_t_2006_b_educ = abs(t_2006_b_educ / t_2006_se_educ)
gen tval_t_2006_b_loginc = abs(t_2006_b_loginc / t_2006_se_loginc)
gen tval_t_2006_b_happy = abs(t_2006_b_happy / t_2006_se_happy)
gen tval_t_2006_b_satfin = abs(t_2006_b_satfin / t_2006_se_satfin)
gen tval_t_2006_b_nevmarried = abs(t_2006_b_nevmarried / t_2006_se_nevmarried)
gen tval_t_2006_b_divwidsep = abs(t_2006_b_divwidsep / t_2006_se_divwidsep)

gen tval_l_2006_b_wave = abs(l_2006_b_wave / l_2006_se_wave)
gen tval_l_2006_b_educ = abs(l_2006_b_educ / l_2006_se_educ)
gen tval_l_2006_b_loginc = abs(l_2006_b_loginc / l_2006_se_loginc)
gen tval_l_2006_b_happy = abs(l_2006_b_happy / l_2006_se_happy)
gen tval_l_2006_b_satfin = abs(l_2006_b_satfin / l_2006_se_satfin)
gen tval_l_2006_b_nevmarried = abs(l_2006_b_nevmarried / l_2006_se_nevmarried)
gen tval_l_2006_b_divwidsep = abs(l_2006_b_divwidsep / l_2006_se_divwidsep)

gen tval_p_2006_b_wave = abs(p_2006_b_wave / p_2006_se_wave)
gen tval_p_2006_b_educ = abs(p_2006_b_educ / p_2006_se_educ)
gen tval_p_2006_b_loginc = abs(p_2006_b_loginc / p_2006_se_loginc)
gen tval_p_2006_b_happy = abs(p_2006_b_happy / p_2006_se_happy)
gen tval_p_2006_b_satfin = abs(p_2006_b_satfin / p_2006_se_satfin)
gen tval_p_2006_b_nevmarried = abs(p_2006_b_nevmarried / p_2006_se_nevmarried)
gen tval_p_2006_b_divwidsep = abs(p_2006_b_divwidsep / p_2006_se_divwidsep)

gen tval_w_2006_b_wave = abs(w_2006_b_wave / w_2006_se_wave)
gen tval_w_2006_b_educ = abs(w_2006_b_educ / w_2006_se_educ)
gen tval_w_2006_b_loginc = abs(w_2006_b_loginc / w_2006_se_loginc)
gen tval_w_2006_b_happy = abs(w_2006_b_happy / w_2006_se_happy)
gen tval_w_2006_b_satfin = abs(w_2006_b_satfin / w_2006_se_satfin)
gen tval_w_2006_b_nevmarried = abs(w_2006_b_nevmarried / w_2006_se_nevmarried)
gen tval_w_2006_b_divwidsep = abs(w_2006_b_divwidsep / w_2006_se_divwidsep)

gen tval_i_2006_b_wave = abs(i_2006_b_wave / i_2006_se_wave)
gen tval_i_2006_b_educ = abs(i_2006_b_educ / i_2006_se_educ)
gen tval_i_2006_b_loginc = abs(i_2006_b_loginc / i_2006_se_loginc)
gen tval_i_2006_b_happy = abs(i_2006_b_happy / i_2006_se_happy)
gen tval_i_2006_b_satfin = abs(i_2006_b_satfin / i_2006_se_satfin)
gen tval_i_2006_b_nevmarried = abs(i_2006_b_nevmarried / i_2006_se_nevmarried)
gen tval_i_2006_b_divwidsep = abs(i_2006_b_divwidsep / i_2006_se_divwidsep)

gen tval_r8_b_wave = abs(r8_b_wave / r8_se_wave)
gen tval_r8_b_educ = abs(r8_b_educ / r8_se_educ)
gen tval_r8_b_loginc = abs(r8_b_loginc / r8_se_loginc)
gen tval_r8_b_happy = abs(r8_b_happy / r8_se_happy)
gen tval_r8_b_satfin = abs(r8_b_satfin / r8_se_satfin)
gen tval_r8_b_nevmarried = abs(r8_b_nevmarried / r8_se_nevmarried)
gen tval_r8_b_divwidsep = abs(r8_b_divwidsep / r8_se_divwidsep)

gen tval_r_b_wave = abs(r_b_wave / r_se_wave)
gen tval_r_b_educ = abs(r_b_educ / r_se_educ)
gen tval_r_b_loginc = abs(r_b_loginc / r_se_loginc)
gen tval_r_b_happy = abs(r_b_happy / r_se_happy)
gen tval_r_b_satfin = abs(r_b_satfin / r_se_satfin)
gen tval_r_b_nevmarried = abs(r_b_nevmarried / r_se_nevmarried)
gen tval_r_b_divwidsep = abs(r_b_divwidsep / r_se_divwidsep)

gen s_t_2006_b_wave=1 if tval_t_2006_b_wave>1.96
gen s_t_2006_b_educ=1 if tval_t_2006_b_educ>1.96
gen s_t_2006_b_loginc=1 if tval_t_2006_b_loginc>1.96
gen s_t_2006_b_happy=1 if tval_t_2006_b_happy>1.96
gen s_t_2006_b_satfin=1 if tval_t_2006_b_satfin>1.96
gen s_t_2006_b_nevmarried=1 if tval_t_2006_b_nevmarried>1.96
gen s_t_2006_b_divwidsep=1 if tval_t_2006_b_divwidsep>1.96
gen s_l_2006_b_wave=1 if tval_l_2006_b_wave>1.96
gen s_l_2006_b_educ=1 if tval_l_2006_b_educ>1.96
gen s_l_2006_b_loginc=1 if tval_l_2006_b_loginc>1.96
gen s_l_2006_b_happy=1 if tval_l_2006_b_happy>1.96
gen s_l_2006_b_satfin=1 if tval_l_2006_b_satfin>1.96
gen s_l_2006_b_nevmarried=1 if tval_l_2006_b_nevmarried>1.96
gen s_l_2006_b_divwidsep=1 if tval_l_2006_b_divwidsep>1.96

gen s_p_2006_b_wave=1 if tval_p_2006_b_wave>1.96
gen s_p_2006_b_educ=1 if tval_p_2006_b_educ>1.96

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gen s_p_2006_b_loginc=1 if tval_p_2006_b_loginc>1.96
gen s_p_2006_b_happy=1 if tval_p_2006_b_happy>1.96
gen s_p_2006_b_satfin=1 if tval_p_2006_b_satfin>1.96
gen s_p_2006_b_nevmarried=1 if tval_p_2006_b_nevmarried>1.96
gen s_p_2006_b_divwidsep=1 if tval_p_2006_b_divwidsep>1.96

gen s_w_2006_b_wave=1 if tval_w_2006_b_wave>1.96
gen s_w_2006_b_educ=1 if tval_w_2006_b_educ>1.96
gen s_w_2006_b_loginc=1 if tval_w_2006_b_loginc>1.96
gen s_w_2006_b_happy=1 if tval_w_2006_b_happy>1.96
gen s_w_2006_b_satfin=1 if tval_w_2006_b_satfin>1.96
gen s_w_2006_b_nevmarried=1 if tval_w_2006_b_nevmarried>1.96
gen s_w_2006_b_divwidsep=1 if tval_w_2006_b_divwidsep>1.96

gen s_i_2006_b_wave=1 if tval_i_2006_b_wave>1.96
gen s_i_2006_b_educ=1 if tval_i_2006_b_educ>1.96
gen s_i_2006_b_loginc=1 if tval_i_2006_b_loginc>1.96
gen s_i_2006_b_happy=1 if tval_i_2006_b_happy>1.96
gen s_i_2006_b_satfin=1 if tval_i_2006_b_satfin>1.96
gen s_i_2006_b_nevmarried=1 if tval_i_2006_b_nevmarried>1.96
gen s_i_2006_b_divwidsep=1 if tval_i_2006_b_divwidsep>1.96

gen s_r8_b_wave=1 if tval_r8_b_wave>1.96
gen s_r8_b_educ=1 if tval_r8_b_educ>1.96
gen s_r8_b_loginc=1 if tval_r8_b_loginc>1.96
gen s_r8_b_happy=1 if tval_r8_b_happy>1.96
gen s_r8_b_satfin=1 if tval_r8_b_satfin>1.96
gen s_r8_b_nevmarried=1 if tval_r8_b_nevmarried>1.96
gen s_r8_b_divwidsep=1 if tval_r8_b_divwidsep>1.96

foreach var of varlist s_t_2006_b_wave-s_r_b_divwidsep {
    replace `var' =0 if missing(`var')
}

*Results for Table 4-11
sum s_*, sep(0)
Veronica Roth

Email: vlr124@psu.edu Cell Phone: (517) 449-2824

Education

2015 Doctoral student in Sociology & Demography, Pennsylvania State University
Certificates in Quantitative Methods & Survey Research
Dissertation: Detecting & Adjusting for Attrition Bias in Longitudinal Survey Panels
Chair: David Johnson
Committee Members: Paul Amato, Kurt Johnson & Eric Plutzer

2011 M.A., Pennsylvania State University, Sociology & Demography
Thesis Title: “The Inconvenience of Haphazard Samples”

2009 B.A. Michigan State University, Sociology; cum laude

Research Interests

Attrition, Longitudinal Studies, Survey Research, Split Ballot/Planned Missing Designs, Weighting,
Infertility, Attitudes toward Parenting & Marriage

Published Work

Pearce-Morris, Jennifer, Seung-won Choi, Veronica Roth, and Rebekah Young. (2014) “Substantive
Meanings of Missing Data in Family Research: Does “Don’t Know” Matter?” Marriage & Family Review
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surveys.” Proceedings of the Tenth Conference on Health Survey Research Methods. Hyattsville, MD:
National Center for Health Statistics

References

David Johnson, Professor
Department of Sociology
Phone: (814) 865-9564
Email: drj10@psu.edu

Paul Amato, Professor Emeritus
Department of Sociology
Email: pxa6@psu.edu

Kurt Johnson, Director
Survey Research Center
Phone: (814) 867-1290
Email: kdj11@psu.edu

Eric Plutzer, Professor
Department of Political Science
Phone: (814) 865-6576
Email: exp12@psu.edu