Essays in Applied Microeconomics

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ABSTRACT

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This dissertation consists of three essays in applied microeconomics. The first chapter looks at whether the Social Security claiming behavior of husbands respond to the presence of Social Security spouse and survivor benefits paid to wives based on his earnings record. I separately estimate the claiming response to incentives for each of the three types of Social Security benefits: retired worker, spousal, and survivor. This approach departs from the previous literature, which estimates behavioral responses to household incentives. I begin by documenting that failure to maximize household Social Security wealth results in a financial burden borne primarily by the wife. I next estimate husbands' behavioral response to Social Security benefit incentives, with my focus exclusively upon incentives due to the actuarial adjustment from delayed claiming. Variation in incentives comes from rule changes to the Social Security benefit calculation, in addition to the age difference between spouses and the relative strength of the wife's labor force history. I find while husbands are responsive to their own benefit incentives, they are barely responsive to household, spousal, and survivor benefit incentives. A variety of robustness checks looking at segments of the population predicted to be more responsive to incentives provide very similar results to main specification.

The second chapter examines the incidence of health insurance coverage for displaced workers during the periods preceding and subsequent to job displacement. Most individuals lose health insurance coverage upon job separation. There is concern that individuals are unable to recover insurance coverage following separation. I find within 18 months following job loss the level of health insurance coverage returns to pre-displacement level. Furthermore, I find that obtaining insurance coverage upon reemployment does not impact wages.

The third chapter first examines how much of the fall in poverty among elderly women can be attributed to changes in the distributions of age, marital status, and education of elderly women using the Current Population Survey. Increased educational attainment has put tremendous downward pressure on the poverty rate driven primarily by the shift of high school dropouts to those with a high school diploma. I also find poverty would be slightly lower in the absence of changes to the age distribution and no direct impact on poverty levels due to the changes in distribution of marital status. I also investigate the role of both labor force participation and marital status over the life-cycle on old age outcomes using survey data matched to administrative earnings records from the Census Bureau. I find even after controlling for Social Security and marital status over prime-age years, lifetime earnings and labor force experience still has a significant impact on poverty incidence of elderly women. Projecting poverty for cohorts who have not reached old age, I find increased wages and LFP over the life-cycle places large downward pressure on predicted poverty. However, this is largely tempered by the increased volatility in marital status. This will be an upper bound of poverty if the relationship between previous marital status and poverty weakens over time.

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Dedication

To my whole family, you provided me with support and

love throughout this whole process

And to Kevin, for your love and making me remember

the important things in life

Chapter 1: How Does Social Security Claiming Respond to Incentives? Considering Husbands' and Wives' Benefits Separately

1.1 Introduction

Almost half of men claim Social Security retired worker benefits from Social Security at age 62, the first year of eligibility. This behavior is not consistent with financial or simple utility maximization (Coile et al, 2002; Sass and Sun, 2009). This choice does not drastically impact their own expected lifetime benefits, but it can have a large impact on the benefits their wives receive. Husbands' claiming age impacts wives since any early claiming reduces the maximum level of the survivor benefit the wife can receive, up to a 17.5% reduction of the base monthly benefit paid to surviving spouses due to the widow(er)'s limit provision (Weaver, 2001). His behavior also impacts his wife's benefit because she may not receive spouse benefits until after the husband begins to receive his own retired worker benefits. Most married women find themselves in this position, circumstances which will continue in the years to come (Levine et al, 2000). This dependence remains in the face of a large increase in the fraction of women eligible for their own Social Security benefit. Over the past 50 years, the fraction of female Social Security recipients eligible for their own benefit has almost doubled to 73% in 2009. However, more than 50% of current female recipients are receiving dependent benefits, either spouse or widow benefits. Less than 10% of recent female Social Security recipients have a retired worker benefit larger than their potential survivor benefit and therefore are unaffected by their husbands' claiming date[1]. This suggests that even the women who have driven the female labor force revolution will still be dependent on their husbands in old age.

[1] Author's calculation.

Since Social Security is a near universal public pension program, it differs from other public programs in that the take-up decision is not the traditional yes-no question but one of timing. Each individual chooses an age between 62 and 70 to begin benefit receipt. For each individual, the age that maximizes expected household lifetime benefits is typically between 62 and 65. However, maximizing worker benefits predicts different behavior than maximizing household benefits. In many cases, household expected lifetime benefits are increased by delayed claiming but this not true for men's retired worker benefits.

Little attention has been given to Social Security benefit claiming as the literature has focused on retirement behavior and labor supply in old age. However, there are compelling arguments to look at claiming separate from retirement. First, Social Security comprises a large portion of income for a many Americans, and we know very little about what drives the decision to claim benefits. In an era of near-certain Social Security reform, we need to better understand how individuals and households respond to the Social Security system. There are multiple parameters of the Social Security to be considered for reform and evaluating behavioral response to incentives resulting from the program overall does not help us understand which channel drives behavior. There are also implications for the solvency of the program as money "left on the table" by households is money which remains in the Social Security Trust Fund.

The decision to begin receipt of benefits is purely financial when viewed in isolation from labor supply. Many chose to claim and retire concurrently but this is not necessary. The decision of when to claim benefits impacts the household budget constraint today and in the future even after one's death due to survivor benefits. Typically, women outlive their husband since most are younger than their husband and women live longer lives. As widows, women's economic well-being is in part determined by survivor benefits from Social Security and any bequests. Survivor benefits depend on a choice the husband made before he died in most cases; he plays a role is determining her well-being far in advance.

There are two more practical arguments to focus my attention on the choice of claiming age. First, the date of claiming is concrete. I can measure the day benefits are received whereas retirement is a flexible definition to both researchers and individuals, which likely do not coincide. Second, claiming also allows us to analyze the full [eligible] population, where the retirement literature is limited to those working or with a career.

The role of financial incentives has been thoroughly examined in the retirement literature but only recently has the literature started to think about the relationship between these incentives and claiming. Coile et al (2002) is arguably the most thorough examination of the claiming decision to date. Since their study, Hurd et al (2004) and Delavande et al (2006) have found favorable expected mortality leads to slightly delayed claiming. This is expected as personal beliefs about mortality change the time period over which benefits will be received. Sass et al (2007) asked whether early claiming is due to ignorance or selfishness on the part of the husbands but do not find conclusive evidence of either hypothesis. In addition, a few structural studies of retirement, such as Gustman and Steinmeier (2005) and Rust and Phelan (1997), have incorporated claiming into models of retirement to help explain the spike in retirement at ages 62 and 65.

This study focuses on the role of financial incentives from Social Security in the claiming decision. I first define incentives in terms of total expected lifetime wealth from Social Security, Social Security Wealth (SSW) following the literature. This value depends on age at claiming due to an actuarial adjustment applied to monthly benefits at the date of initial receipt. The incentives measure how SSW changes with benefit claiming age. Household Social Security benefits contain multiple pieces. Each member of the household, husband and wife, can receive their own retired worker benefit and the dependent spouse can receive spouse and survivor benefits if they exceed her own retired worker benefit. The implicit assumption made by previous literature is husbands consider his own benefit and any benefits received by his spouse equally when deciding when to claim benefits or retire. However, it seems plausible that he might respond differently to each type of benefit. The existence of this possibility has not been mentioned in the retirement literature. This research extends the previous literature on claiming behavior and introduces heterogeneity in the response to financial incentives that varies by type of benefit received. This approach can be applied to studies of retirement in the future.

Most previous research uses the variation from all benefit rules together to identify how claiming [or retirement] responds to Social Security benefit incentives with the exception of Liebman et al (2009)[2]. As noted by previous studies, most of the variation in incentives can be explained by earnings history. This is particularly true once I separate incentives by type. Therefore, I must rely heavily on changes to the Social Security benefit formulas for exogenous variation in incentives in combination with the typical approach which relies on a control function. These rules impact both the normal retirement age (NRA) and the delayed retirement credit (DRC). The new laws create eleven birth cohort groups in the male population, each facing a different set of rules[3]. Changes in the NRA increases the penalty to early claiming and the increase in DRC increase the return to delay past the NRA. Variation in the birth year of each spouse creates distinct incentives for identical couples born in different birth years.

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[2] Liebman et al (2009) identify 12 rules in the Social Security benefit formulas that could be used for identification of a response to benefit rules. They use 5 rules in their study for identification which apply to labor supply incentives.

[3] Likewise, the rules split the wives' into 13 groups based on changes to her NRA, creating a total of 143 husband-wife birth year pairs with a unique set of rules.

The empirical analysis considers men born between 1922 and 1940. I include those unmarried at claiming in the base model which may sound puzzling since our underlying motivation is how husbands' behavior impacts wives' outcomes. This logic is this: if husbands only consider their own benefits and not spouse or survivor benefits when deciding when to claim, then there should be no difference in behavior between married and unmarried men. The non-married men are a control group. There are other differences by marital status, such as joint consumption of leisure that could impact claiming, perhaps, but a thorough examination is left for future research. Since there is evidence of retirement and claiming coordination, I estimate the model on a subsample of those who have exited the labor force prior to age 62. These results may be a cleaner estimate of the claiming response, but we also may be estimating a different behavioral response since this group has chosen to leave the labor force early and can fund early retirement.

Financial maximization suggests if there is a large gain [penalty] to delay claiming, an individual is more [less] likely to delay. Therefore, if behavior is consistent with financial maximization, the coefficient for Social Security incentives would be negative. I do not see a large response to the incentives from household benefits; mostly the coefficient is small and insignificant. The coefficient on the incentive measure for the retired worker benefit is negative and significant in all models where benefit incentives are entered separately. The estimates of the response to incentives due to spouse or survivor benefits are small in all models and are insignificant in most cases. The coefficient on worker incentives from the retired subsample is larger than the full sample. The early retirees may be more responsive to incentives due to a lack of credit constraints[4].

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[4] Coile et al (2002) find in the New Beneficiary Data System (NBDS) approximately 90% of early retirees claim benefits by their 63rd birthday.

It is plausible the estimates capture segments of the population who are more likely to consider financial incentives in decision making or who understand the incentives better. Chan and Stevens (2008) find for private pension incentives the full sample estimate is driven solely by those who fully understand the incentives they face. Furthermore, incentives are calculated using population life tables, so I will mis-measure the true incentives. A full treatment of this measurement error is out of the scope of this paper and left for future work. To address these concerns, I estimate the model on subsamples where measured incentives are closer to the true incentives perceived by individuals. Furthermore, individuals who differ along health dimensions might respond differently to incentives. They face different incentives due to varied mortality prospects. Those who we observe to live longer likely have private information about their health and may also be more responsive to incentives. Finally, I want to consider a role for joint leisure in the claiming decision since it has proved to be an important factor in determining couples' retirement decisions. I allow for heterogeneous responses to incentives by health status, by education, and by wife's labor force status. This allows each group to have different response to incentives in addition to the differences in claiming by observed characteristics. I find that education and wife's labor force status, a proxy for joint leisure, impact the claiming decision directly but do not impact the response to financial incentives.

The structure for the remainder of the paper is as follows: Section 1.2 provides background on Social Security benefits, women in Social Security, and previous literature, Section 1.3 details the data and compares SSW maximizing claiming age with actual claiming behavior, Section 1.4 provides empirical specification and results and Section 1.5 concludes.

1.2. Background

1.2.1 Overview of Social Security Benefits

There are three main types of old age benefits provided by the Old Age, Survivor, and Disability Insurance (OASDI) program: retired worker, spouse, and survivor benefits. Individuals are eligible for retired worker benefits if they have 40 quarters of covered earnings over their lifetime. The first calculation to determine monthly benefits is the averaged indexed monthly earnings (AIME), an average of the highest 35 years of earnings indexed to average wages in each year. This calculation includes zeros if fewer than 35 years contain positive earnings, a penalty for those without a complete work history. However, a progressive formula transforms AIME into the primary insurance amount (PIA) so those with lower lifetime average earnings experience a higher replacement rate than those with the higher earnings. The PIA is the level of monthly benefits received if the worker claims their benefits at the normal retirement age (NRA). Retired worker benefits can be claimed beginning at age 62, with a penalty for claiming between age 62 and the NRA. In addition, there is a reward for claiming after the NRA, the delayed retirement credit (DRC) that varies by birth cohort.

Claiming age determines the actuarial adjustment applied to the PIA to calculate monthly benefits. Those that claim at their NRA receive their PIA as their monthly payment. For each month prior to NRA benefits are claimed up to 36 months, a penalty of 5/9 of 1% is applied to the PIA. Those born 1937 and earlier receive 80% of their PIA if they claim benefits at age 62 and 0 months. For those born 1938 and later, the early entitlement age is more than 36 months prior to the NRA. If someone in this cohort claims prior to 36 months before the NRA, they are penalized an additional 5/12 of one percent per extra month of claiming early past 36 months.

For example, those born in 1939 have a NRA of 65 years and 4 months. If they claim at 62 and 2 months, they are penalized [20% + 2*(5/12)%)] for a total penalty of 20.83%.

Since Social Security was founded in an era of one-earner families, a spousal benefit, equal to half of her husband's benefit, was included since many wives did not have a benefit based on their own work history[5]. Penalties apply to the monthly benefit if the spouse claims prior to her NRA, but the husband's claiming age does not impact the level of the spouse benefit directly. His claiming age only impacts her spouse benefits because she cannot claim spouse benefits until after her husband claims his retired worker benefit. To ease in following discussion, I refer to the ratio [Wife PIA/Husband PIA] as the "PIA ratio". Wives expect to receive a spouse benefit if the PIA ratio is below 0.5[6]. Spouse benefits are also subject to an actuarial adjustment. However, it is the wife's claiming age which impacts the determination of MBA. The spouse benefit, equal to 0.5*Husband's PIA, is penalized (25/36)% for each month prior to the NRA up to 36 months and 5/12% for each month of early claiming greater than 36.

When the primary earner dies, the survivor is entitled to a benefit equal to that received by the deceased. Survivor benefits can be claimed beginning at age 60. If the deceased claimed their own benefit early, then penalties carry over to survivor benefit. In addition, if the deceased delayed claiming past the normal retirement age, the credits applied to their monthly benefit will carry over to the survivor benefit. Survivor benefit calculation is the most involved, as both the husband's and wife's claiming age determines the MBA. The claiming age of her husband sets a maximum value for the survivor benefit. The formula for survivor benefits is:

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[5] I use husband and wife since this is the typical arrangement. Of course, husbands are entitled to a spouse benefit as well. Less than 2 % of male beneficiaries receive spouse or survivor benefits.

[6] The cutoff for spouse benefits in general is 0.5 but is only practically relevant if she claims spouse benefits at her NRA. If she claims her own benefits before age 65, the relevant threshold decreases.

$$\text{Actuarial Adjustment} = \begin{cases} Min\{\text{Husband's PIA} * \max(\text{Husband's actuarial adjustment},\ 0.825), \\ \quad \text{Husband's PIA} * \text{Wife's actuarial adjustment}\} \text{ if Husband's claiming age} < 65 \\ \text{Husband's PIA} * \text{Husband's actuarial adjustment} * \text{Wife's actuarial adjustment} \\ \quad \text{if Husband's claiming age} \geq 65 \ \& \ \text{Wife's claiming age} < 65 \\ \text{Husband's PIA} * \text{Husband's actuarial adjustment} \\ \quad \text{if Husband's claiming age} \geq 65 \ \& \ \text{Wife's claiming age} \geq 65 \end{cases}$$

The first line describes the benefit if the husband claims early. He creates a ceiling for the maximum benefit she can receive. If he claims at the EEA, there is a special provision so that the cap is 82.5% of her husband's PIA. The second and third lines detail the adjustment when he delays claiming past his NRA. His delay increases the base survivor benefit, but if she claims prior to her NRA, penalties apply.

1.2.2 Calculation of Household Social Security Wealth

In order to calculate incentives, I first calculate expected lifetime Social Security benefits, Social Security Wealth (SSW) for each potential claiming age. The expected monthly payment incorporates the PIA and actuarial adjustments, including all retired worker benefits, spouse and survivor benefits the wife expects to receive. All calculations assume the wife claims as soon as possible. Adding in her choice of claiming age complicates the process an immense amount and should have little effect in practical terms given most women should claim at age 62 to maximize SSW. This conclusion comes from my calculations and the results of Sass et al (2007)[7]. If she is eligible for her own benefits, she begins receipt at age 62. She is permitted to switch to the spouse benefit when her husband claims if it is larger than her own retired worker benefit. These are the same assumptions used by Leibman et al (2009). The other event which permits a change of benefit type is the death of her spouse. Once household total monthly payments are

[7] Less than 10% of women have a PIA ratio greater than her husband. All women with a PIA ratio less than 1 should claim at 62 to maximize their own benefits (author's calculation).

calculated, I discount the lifetime stream to the present [age 62]. I follow the literature and use a 3% annual discount rate[8]. For the probability of surviving to each future period, I use sex-specific mortality tables from the Social Security Administration from 1980, 1990, and 2000 since the sample turns 62 between 1984 and 2002. There are well-known differences by race and education. Therefore, I adjust the population life tables using adjustments from Brown et al (2002).

For an individual (male) worker with an average life expectancy, claiming age has little impact on his expected lifetime worker benefits. Figure 1.1 presents expected lifetime worker benefits and how they vary with claiming age. For exposition, I use the life table from 1990, NRA of 65, and a DRC of 6.5. These rules apply for those born in 1936 or 1937. Between age 62 and 64, expected benefits change little. After the NRA, there is a steep decline due to a less than actuarially fair DRC.

Household SSW can be impacted a great deal by his choice of claiming age, in contrast to retired worker benefits. The impact of husband's claiming age on household SSW is shown in Figure 1.2 for two hypothetical couples where the wife is 3 years younger than her husband[9]. In the first couple, the wife is not eligible for her own benefits, recreating the presentation from Coile et al (2002). The wife in the second couple has a PIA large enough to make the spouse benefit irrelevant. Starting at the bottom of the figure, where the wife is not entitled to her own benefits, household benefits contain the husband's retired worker benefits, spouse and survivor benefits. After age 63, expected worker benefits begin to fall, as seen in Figure 1.1. From age 62 and 2 months, survivor benefits increase monotonically as the husband's claim age increases.

[8] Those using 3% include Liebman et al (2009), Mastrobuoni (2010), and Coile et al (2002). The impact of discount rate on household benefits can be found in Appendix Figures A1 and A2. Any increase in discount rate increases incentives to claim at age 62.
[9] Wives are on average 3 years younger than their husband.

The wife cannot receive spouse benefits until her husband claims his own benefits, so there is a fall in spouse benefits after age 65 while she waits for him to claim. The combination of declining spouse and worker benefits outweigh the increase in survivor benefits when claiming is delayed past age 65. For the second couple, where her PIA is larger than half of her husband's PIA, the increase in SSW between ages 62 and 65 is due to survivor benefits increasing faster than his worker benefits are falling. However, after he turns 65, his benefits fall more drastically so this decline offsets the increase in survivor benefits. These descriptions are consistent with the findings from Sass et al (2007). Figures detailing spouse and survivor benefits by husband's claiming age for the two couples can be found in Appendix Figures A3 and A4.

1.2.3 Women and Social Security

Given the large increase in the labor force participation (LFP) of women and the dramatic narrowing of the gender wage gap, we might presume women are more self-sufficient when they reach old age. With these changes, women are more independent of their husbands in determining their economic well-being while of working-age. Increased market wages and narrowing of the gender gap increase bargaining power in household financial decision-making (Pollak 2005, Knowles 2007). Due to Social Security rules, however, wives remain dependent on husbands in old-age (Levine et al, 2000). Even while women have increased their LFP and received higher wages, the husband works more years in most couples, between maternity leave and child rearing, and receives higher wages. As a result, most women end up relying on one if not both types of these benefits.

One direct result of the increase in female LFP is the increase in the fraction of wives eligible for their own benefit. Figure 1.3 presents the fraction of female recipients by type of benefit received. There has been an increase in the fraction of women eligible for their own benefit over the past 50 years. In 1940, less than half of women recipients of Social Security were eligible for their own retired worker benefit, with fewer than 40 quarters of covered earnings. Almost three-quarters of current female beneficiaries are eligible to receive a benefit based on their own work history. However, the fraction of women still receiving dependent benefits is still over 50%.[10] From 1940 through the early 1990s, the fraction of women receiving spouse or survivor benefits hovered around 60%. Only since the mid-1990s has this fraction begun to fall.

Looking at females eligible for their own and dependent benefits, I examine how reliant these women are on the spouse and survivor benefits. Using data from SSA, I compare the benefits received by female dual beneficiaries, those eligible for both their own and spouse or survivor benefit, to those she would have received due to only her own retired worker benefits. As this ratio approaches 1, women are no longer dependent on their husbands for the respective benefit. Figure 1.4 shows the ratio increasing from 1995 to the present for those that are receiving spouse benefits. However, there was an initial decline from 1986 to 1995, probably due to a change in sample composition. As more women are eligible for benefits, the average lifetime earnings will fall as the newly eligibles have lower lifetime earnings. If the inflow to the sample from the bottom of the earnings distribution is larger than the outflow of women who are no longer dependent on spouse benefits, we would expect to see this fall. This is likely true for the earlier period, as it coincides more with the beginning of the female labor force revolution. We do not see an analogous fall and rise for survivor benefits. The most likely explanation for this is beneficiaries receiving survivor benefits are older than those receiving spousal benefits.

[10] Mostly these are women receiving survivor benefits, only 20% of female beneficiaries receive spouse benefits.

Therefore, we would expect a rise in the future as women with stronger worker histories begin to receive survivor benefits[11].

1.2.4 Related Literature

There is not a large literature on Social Security benefit claiming so this review highlights the few results on claiming and discusses a few relevant studies of the retirement response to Social Security incentives.

Arguably the most complete study of claiming to date, Coile et al (2002) present results of a financial maximization for married couples where the wife is not entitled to her own benefit and for single males. Their results highlight the role of longevity, earnings history, discount rate, and age difference with wife in determining optimal claiming age. All but earnings history play a central role in determining the age which maximizes household SSW. In addition, they present a simple utility model for single men who have already retired to make predictions about the impact of wealth and risk aversion on the claiming decision. Their results suggest claiming behavior is generally consistent with the predictions of financial maximization and utility maximization in the cross section, finding marital status is the primary inconsistency in the cross-section. Important to note as we move forward is that the presence of risk aversion [value of insurance provided by Social Security] increases the optimal age from the maximizing SSW benchmark. Sun and Webb (2009) also find this role of risk aversion as their analysis expands the work of Coile et al (2002) to include married couples and wives eligible for their own benefit. Their results suggest the presence of a working wife does not change the conclusion that husbands should delay longer due to the value of the annuity provided.

[11] Another factor that would impact these facts is any changes in the correlation between mortality of the husband and wife might cause different patterns for spouse and survivor benefits if the trends are different for high- and low-wage women.

Sass et al (2007) aim to evaluate why married men claim their benefits so early. They propose two theories, caddishness and ignorance. First, they calculate the optimal claiming delay for couples in Health and Retirement Survey (HRS) and focus on the fact that the loss from early claiming is primarily through the survivor benefits. To evaluate their hypotheses, they use demographic characteristics, measures of financial knowledge, and questions about household decision-making from the HRS to see if their theories can be confirmed. They find the only measures of educational attainment are correlated with claiming at age 62. This is consistent with an ignorance story but does not confirm either of their hypotheses.

Two studies directly examine the claiming response to Social Security incentives. Panis et al. (2002) aim to predict the behavioral impact of changes to the Social Security early entitlement age (EEA) and NRA. Their claiming model estimates the response to option value (OV) [option value of utility to be gained by delaying] and peak value (PV) [option value of financial gain from delayed claiming] measures, in addition to a multinomial OV to incorporate disability claims. They estimate the response of both retirement and claiming to Social Security incentives to enable prediction following the empirical approach of Coile and Gruber (2007). They find claiming is more responsive to Social Security incentives than retirement. The second study is Mastrobuoni (2011) who looks at the impact of the introduction of Social Security statement (SSS). He uses the SSS introduction as a natural experiment approach for identification to look at how information impacts knowledge of benefits and the response to incentives. In his base model using the Survey of Income and Program Participation, a $1,000 increase in annual SSW decreases the hazard rate 0.74 percentage points[12]. This is similar to Panis et al's (2002) results using HRS. To my knowledge, he is the first to allow the response to

[12] An early version of this paper (2007) uses claiming as the dependent variable while subsequent versions use retirement.

incentives vary by observable characteristics.[13] Allowing the response to incentives to vary by marital status and whether wife is independent or dependent, he finds that husbands whose wives are independent are more responsive to incentives. He expects men whose wives are dependent to be more responsive which is not what he finds[14]. His rationale is households with dependent wives are paid more benefits from the husband's earnings record and therefore he expects this group to be more responsive to incentives. The results show prior to the Statement introduction those with independent wives were more responsive than those with dependent wives, but after the introduction they respond the same.[15] However, the husband's claiming choice has little impact on the spouse benefits so there may be little practical difference in the expected impact for independent and dependent wives.

Many studies have sought to understand the role of Social Security in retirement decisions. I do not review the entire literature but mention two recent studies. Coile and Gruber (2007) investigate the role of Social Security financial incentives on the retirement decision. They use a variety of incentives measures on HRS data. The primary challenge in studying the retirement response to Social Security benefits is the variables that determine Social Security incentives, a function of work history, will also impact the retirement decision likely creating omitted variables bias. They demonstrate the wide range of incentive values in the data and show measures of work history can explain about half of the variation in household incentive measures. They find retirement responds to several measures of household Social Security

[13] Chan and Stevens (2008) allow the response to private pension incentives to vary between those that understand the incentives and those that do not.
[14] He defines dependent as couples with a PIA ratio below 0.5, and independent as couples with a PIA ratio above 0.5.
[15] The incentives are larger at most ages for those with 'dependent' wives, but it is not clear why men should respond to $1000 increase in the household SSW differently.

incentives and highlight the importance of taking into account the full option value instead of the annual gain, whether measured in terms of utility or dollars.

More recently, Liebman et al (2009) investigate both the intensive and extensive labor supply response to Social Security work incentives. They only allow changes in incentives due to continued work and not delayed claiming. In order to be more confident that their estimates are driven by the discontinuities in benefit formulas and are free of bias from individual heterogeneity, they develop an in-depth approach to identifying the ideal control function before proceeding to their final estimation. This allows them to compare individuals on each side of the discontinuities created by the Social Security benefit rules in a framework with uncertainty. They reject the hypothesis that labor supply is completely unresponsive to the Social Security incentives.

There is a large body of evidence which suggests behavior in old age is responsive to Social Security, including both benefit claiming and retirement. However, we still do not have a strong grasp of how decision making occurs. We do not know what program parameters matter which has policy implications nor do we have a strong sense of how married couples differ in their behavior, since they are treated very differently by the program.

1.3 Data

1.3.1 Overview

The data utilized in this study is an administrative dataset which merges (1) a pared down version of the Survey of Income and Program Participation (SIPP) data from the 1990s (1990-1993, 1996), (2) the Summary Earnings Records (SER) and Detailed Earnings Records (DER) from the Internal Revenue Service, and (3) the Master Beneficiary Record (MBR) from the

Social Security Administration[16]. This project is housed at the Census Bureau. The project's goal was to merge demographic variables to the administrative data. In most cases, administrative data is missing this key information. Since not all individuals from the SIPP can be matched to administrative data, missing values are imputed to the final data. Four different imputations are performed, and final estimates must average the four sets of results and calculate standard errors to account for the imputation. These datasets are referred to as the Gold Standard files. Details on this process are specified in Abowd et al (2006).

This data is nearly ideal for the current study. Included in the data are birth date, OASDI claiming date and type of initial benefit, marital history, death date, earnings history, and a link to current spouse. It is possible to determine whether men were married at the time of claiming, regardless of his current marital status. This is important because we do not want to treat a man who was married as single as we will misrepresent the incentives he faced. It is also necessary remove those who received disability benefits (DI) prior to age 62 since they do not face a claiming decision at age 62 and are automatically rolled into the old age program. The sample used for analysis includes all males born between 1922 and 1940. Those born prior to 1922 faced different Social Security rules, making calculations from the available data impossible. The last year we observe claiming is 2002. The youngest cohort is born in 1940, and they reach their EEA in 2002. I am able to include them in the analysis since we observe their decision at age 62.

The sample contains 13,753 men who received retired worker benefits as their initial benefits from OASDI. Table 1.1 contains summary statistics for the analytical sample. The average lifetime retired worker benefits are $129,829. Almost 70% of households containing a

[16] An application for the publicly available data can be found at http://www.census.gov/sipp/synth_data.html. Questions can be directed to hhes.synthetic.data.use.list@census.gov.

married couple expect to receive survivor benefits, and about 45% expect to receive spouse benefits. These values are taken when men are 62 years old. Approximately three-quarters were married when they claimed retired worker benefits and about one quarter of men exit the labor force before age 62. On average, wives are 3.9 years younger than their husbands. Finally, I trim outliers that look like data errors, those who have wives more than 40 years older (10 observations) or those who have PIA ratios above 50 (5 observations)[17].

Figure 1.5 graphs the empirical claiming distribution of men, by whether they were married at the time of claiming. As reported in official data, almost half of men claim benefits as soon as they are eligible. Due to a technical rule, most individuals are not eligible until they are 62 years and 1 month old. Furthermore, we see another spike at age 65 with very few individuals claiming after this age. One quarter of men claim between ages 63 and 65, while less than 5% claim after they turn 65. Those not married are more likely to claim before age 62.5 than those married but married men are slightly more likely to claim around age 65. This is consistent with the predictions from financial maximization, but weak evidence at best.

The key question underlying this analysis is whether the presence of a wife and her benefits causes different behavior. If singles claim in similar patterns to married men, we would predict the presence of dependent benefits plays no role in the claiming decision. Evidence from Coile et al (2002) suggests claiming differences by marital status are not consistent with financial maximization. Financial maximization predicts that married men should claim later than unmarried men, but they do not find that this holds in the cross section. In a multivariate regression, they find that married men claim earlier than single men. Looking at the raw data in

[17] Ibid.

Figure 1.5, I cannot confirm this result. This study answers whether differences in claiming by marital status is due to the presence of dependent benefits.

1.3.2 Benefits Lost

Before turning to formal analyses, I document the implications of observed claiming behavior. For each couple in the sample, I compare potential benefits available to the household to the expected paid benefits that result from claiming choices. For potential benefits, I calculate the husband's claiming age which maximizes household SSW. This data is the best available to perform this exercise. Most datasets do not include full earnings history for both spouses, and those that do, such as the matched HRS, are significantly smaller. Sass et al (2007) calculate SSW maximizing delay for husbands and wives but they can only calculate a PIA ratio for only 141 couples[18]. In contrast, the current data contains over 10,000 matched couples and includes both spouses' earnings histories needed to calculate the PIA ratio. Figure 1.6 graphs the distribution of the claiming age which maximizes household SSW for married men. These values are taken at annual intervals due to Census Bureau procedure to protect anonymity. Other than cohort variation in the rules, the PIA ratio and the age difference between spouses provide the remaining variation to determine the SSW maximizing claiming age.[19] Assuming wives claim as soon as possible, more than 60% of husbands should claim at age 65 to maximize household SSW. This is primarily due to the less than fair delayed retirement credit (DRC) for older cohorts. The DRC has been increasing beginning with those born in 1925 but does not reach a more actuarially fair level until the 1939 cohort. The gain to delay past age 65 is very small for older cohorts. For cohorts with the most favorable DRC, there is very small mass of

[18] Their study also requires labor force exit prior to age 62.
[19] The distribution of PIA ratio can be found in Appendix Figure A5.

those whose SSW maximizing claiming age is at the NRA. Less than 10% of husbands should claim before age 63, far less than the observed 50% seen in Figure 5.

Looking back at Figure 1.5, the empirical claiming distribution, there is no concentration near age 65 as would be expected if men were maximizing household SSW. Since it appears unlikely financial maximization of household SSW is a large part of the claiming decision, we want to know what are the costs associated with actual claiming behavior. To do this, I look at how much money is 'left on the table' as a result of early claiming.[20] Sass et al (2007) explore this question for the HRS. The Synthetic SIPP allows us broaden the sample to include older cohorts. I first look at how much household wealth is "lost" due to early claiming by comparing the maximum available SSW and benefits received as a result of actual behavior.[21] Figure 1.7 graphs the distribution of total benefits lost for married couples. About 20% of couples lose at least $5,000 and about 5% lose at least $20,000 [in 2003 dollars]. This may not seem like a large loss, but the numbers hide two key points. First is who bears the burden and second is what does this mean in terms of monthly benefits. To answer this first question, I group the benefits in the following way: (1) husband's retired worker benefits, (2) spouse benefits and wife's retired worker benefits received while husband is alive, and (3) survivor benefits and wife's retired worker benefits received while husband dead. The rationale for this grouping is both spouse and survivor benefits are substitutes for the wife's retired worker benefits. To see why consider couples where the wife's PIA is approximately half of her husband's. If it is slightly less than half, she would want to receive the spouse benefit once eligible, since 0.5*Husband PIA is larger than 0.49*Own PIA. If her PIA is slightly larger than half of her husband's PIA then she would not want to receive spouse benefits. In both cases, the total amount of benefits paid to the

[20] I use the term "claim early" to refer to behavior not maximizing SSW. Obviously, there are individuals claiming late who should claim early, but overwhelmingly, the reverse occurs.
[21] Potential benefits are calculated using 3-month intervals instead of the annual intervals reported in Figure 6.

household will be the same. These couples are nearly identical in terms of SSW and I want to treat them as such. The same logic holds for survivor benefits. I refer to benefits paid to the wife while her husband is alive as "wife benefits" and benefits we expect to be paid to the wife after her husband dies as "survivor benefits".

Figure 1.8 graphs the distribution of benefits lost by type of benefit [worker,"wife", and "survivor"]. The distribution for lost wife and survivor benefits only include couples that expect to receive each type of benefit given their age difference and PIA ratio. More than three quarters of husbands are gain expected worker benefits due to choice of claiming age, compared to the benefits he would expect to receive if he maximized household SSW. These extra worker benefits are not large, with approximately 5% gaining more than $5,000 in expected lifetime worker benefits. One potential explanation for this finding is the majority of husbands respond only to their own benefit incentives. Most husbands would maximize their worker benefits if they claimed between ages 62 and 63. Since the SSW maximizing delay for most husbands is around age 65 to maximize household benefits and between ages 62 and 63 to maximize own benefits, we see husbands slightly gaining from their choice of claiming age[22].

Since worker benefits are barely affected by the choice of claiming age, wives must bear the majority of costs associated with early claiming. About one-third of wives lose more than $5,000 in expected lifetime survivor benefits, while more than 5% lose more than $10,000. It is difficult to conceptualize how big these numbers are in a practical sense because they take into account probability of individuals being alive at every year in the future. To answer the second question about the impact on monthly benefits, I compare the survivor benefit received under

[22] It is important to keep in mind that these values are for average life expectancy. If an individual believes he will die sooner than average, he should claim benefits earlier and as a result will attain greater lifetime benefits than if he delayed.

actual husband behavior and hypothetical behavior. Figure 1.9 graphs survivor benefits under three different scenarios. The first is given actual claiming behavior. The second and third scenarios use two alternate claiming possibilities: the age which maximizes SSW and age 68. Given actual claiming and assuming the husband passes away after the widow turns 65, approximately 25% of widows would find themselves living below the poverty line if she had no other income[23]. In contrast, if husbands claimed at the age that maximized household benefits, less than 20% would be below the poverty line. If he claimed at age 68, later than the age that typically maximizes SSW, less than 15% would be in poverty. Not all widows rely solely on Social Security for their income but for many Social Security plays a large role, particularly at the lower end of the income distribution. In 2008, almost half of unmarried female beneficiaries, including widows, received more than 90% of their income from Social Security (Social Security Administration, 2010a).

1.4. Empirical analysis

1.4.1 Empirical Approach

The empirical approach estimates a reduced form model of claiming. Mastrobuoni (2007) and Panis (2002) use this model for claiming, and the retirement literature estimating reduced form equations primarily presents this type of model with retirement as the outcome variable. Coile and Gruber (2007) estimate a probit model using Social Security benefits and financial incentives as their key independent variables, adapting the previous work of Stock and Wise (1990) who developed an option value model of retirement into financial terms. Given the link

[23] Annual threshold for the aged determined by the Census Bureau. http://www.census.gov/hhes/www/poverty/histpov/hstpov1.html

between claiming and retirement (Coile et al, 2002), I regress an indicator for benefit claiming at age *a* on Social Security incentives at age *a* and control variables.

$$Pr(Claim_a) = \alpha + \beta \cdot Incentive_a + \gamma \cdot X_{ia} + g(Z_{ia}) + \tau + \varepsilon_{ia}$$

I use a linear probability model to estimate this model[24]**.** The variables changing over time are the incentives from Social Security, age, and year. I control for age using a dummy variable for each age in the sample omitting age 62. Once an individual has claimed benefits, they are removed from the sample. This allows us to estimate a duration model using reduced form analysis. This model will then estimate hazard rates since individuals are dropped after claiming**.**

There are two measures of financial incentives, peak value (PV) and accrual (ACC), used in studies of the retirement response to financial incentives from Social Security. They measure the financial gain from delaying claiming from period *t* to some future period. ACC compares SSW in *t* to SSW in *t+1*, where PV compares SSW_t to the value at its maximum [SSW_{max}]. Almost all studies calculate total household SSW defined as benefits paid from both the husbands' and wives' earning histories and use the resulting incentives as the key independent variable[25]. Coile and Gruber (2007) developed the PV measure as an alternative to the option value measure developed by Stock and Wise (1990) but in financial terms instead of incentives measured in utility[26]. By delaying today, one retains the option to claim benefits at a later date. One drawback to financial measures is that they do not account for the disutility of work, an important feature when considering retirement incentives but less of an issue in this setup with the focus on benefit claiming. Mastrobuoni (2011) prefers the ACC measure since after age 62,

[24] Conclusions from a logit model are consistent with the results reported.
[25] The exception is Liebman et al (2010) who calculate incentives from benefits paid out on the husband's and wife's work histories separately.
[26] Warner (1978) used a concept called Cost of Leaving (COL) which is analogous to the PV measure.

PV is monotonic. He argues it is important to measure the annual change, since two individuals with the same peak value could face much different short-term incentives.

An additional advantage to the ACC measure is it is straightforward to compare across individuals for all types of benefits. When comparing two individuals, ACC calculates the annual change in SSW for each. The PV measure does not capture the timing of when the maximum value occurs for two individuals. This unknown maximum complicates the analysis of benefit-specific incentives. For a given individual, there could be three different ages correspond to maximizing each type of benefit [worker, wife and survivor]. The age that maximizes worker benefits is between age 62 and 63, and the survivor benefit is maximizes around age 70. The age which maximizes wife benefits varies with the age difference between spouses and the PIA ratio. SSW is the sum of husband's worker benefits, wife's benefits, and survivor benefits, but this linearity will not hold for the PV measure, i.e. PV of household will not equal the sum of the individual benefit PVs. However, the linearity *will* hold for the accrual measure.

$$ACC_{SSW} = ACC_{worker} + ACC_{wife} + ACC_{surv}$$

I present results using both PV and ACC for the base model but focus the remaining analysis on the accrual measure.

Focusing on household incentives implicitly assumes husbands take the total household benefits into consideration when making their claiming [or retirement] decision. This approach assumes husbands are indifferent between types of benefits received by the household over all points in time, regardless of whether he is alive when the benefits are received. This may be a strong assumption or at least one to be tested. Much variation in household benefits is in terms of the survivor benefit, which the husband may not weight as heavily as benefits received while he is alive. After noting this, it makes sense to consider each benefit separately. I break household SSW into its components and define incentive measures for each type of benefit. The key contribution of this study is measuring incentives and the behavioral responses to these measures in a piece-wise approach. It is possible husbands are more sensitive to their own benefits, or at least more sensitive to benefits received while he is alive. I compare results controlling for the household incentives to results controlling individual benefit incentives to see which model describes observed behavior better. If behavior is consistent with treating all benefits equally, the coefficients on each type of benefit would be equal. This value would be equal to the coefficient on the household incentives in the alternate model. This provides additional incentive to focus on the accrual measure in addition to the linearity mentioned earlier.

Two channels can impact the PIA as the claiming decision is delayed. One is due to the change in PIA due to continued work, where a high earnings year replaces a low earnings year[27]. The other is due to the actuarial adjustment of benefits. Liebman et al (2009) use the former source for identification since they focus on the labor supply incentives for retirement. I have done the reverse. Since claiming is the outcome variable of interest, it is important to use the financial incentives corresponding to claiming not labor force exit. Most papers combine the two channels but it is important use the appropriate incentives for each decision. Therefore, this study holds PIA fixed while changing the actuarial adjustment, focusing only on the incentives caused by a change in the claiming age not continued work. Separating the response to each channel, driven by different parameters of the Social Security program, will also be informative for reform.

[27] If next year's earnings are expected to be greater than the lowest earnings year included in AIME, then the PIA is expected to increase.

While looking for suitable variation to identify the response to Social Security incentives, studies have focused on the significant heterogeneity in household incentives. Much of this heterogeneity is driven by eligibility for different types of benefits: worker, spouse or survivor. Variation in incentives comes from the interaction of the couple's PIA ratio and age difference. This interaction creates non-linearities in lifetime benefits around thresholds associated with "eligibility" for spouse and survivor benefits[28]. Figure 1.10 shows the variation in incentives that have been used for identification used by most claiming and retirement studies. This shows how varying the PIA of the wife changes the incentives husbands face. It is easy to see how the variation in total incentives can be attributed to the spouse and survivor incentives. This is additional motivation to use the incentives associated with each benefit separately. Remaining cross sectional variation comes from earnings differences and changes in mortality between cohorts.

The analytical framework combines the work of Coile and Gruber (2007, CG07 henceforth) with Liebman et al (2009). CG07 seek to estimate the impact of Social Security incentives on retirement. They acknowledge the determinants of SSW are likely correlated with the retirement decision. They use a control function whose primary components are quartics in AIME and potential [lagged] earnings of both the individual and their spouse. Liebman et al (2009) are more explicit than CG07 in describing rules from the benefit formulas that drive model identification. They also use a control function approach but are more methodological about its construction.

Omitted variables bias is less of a concern in a model of claiming than in a model of retirement unless claiming is a one-to-one mapping of retirement. In a model of retirement, the

[28] Liebman et al (2010) are able to rely on discontinuities because they focus on the tax-benefit link and separate benefits paid on the wife's work history separately from those paid on the husband's.

factors that determine incentives [measures of earnings history] play a direct role in the retirement decision. Furthermore, the concern for unobserved heterogeneity should be less of a concern when looking at the claiming decision since there is less uncertainty in incentives due to the sample all being at least 62 years of age.[29] However, I want to be confident the estimates are driven by variation uncorrelated with individual heterogeneity. I use a control function approach like Coile and Gruber (2007), Liebman et al (2009), and others. The premise is to include all variables use to calculate incentives. I use the same interactions included in Coile and Gruber (2007) but add additional measures used by Liebman et al (2009). Following Liebman et al (2009), I also include lagged earnings back to age 30 of the worker and his spouse and quartics of ln(SSW). In addition, I include quartics of ln(Worker benefits), ln(Wife benefits) and ln(Survivor benefits). This does not exactly duplicate the full control function used in their study due to data differences but I capture the primary components and use more flexible controls by type of benefits[30]. This control function captures approximately 90% of the variation in accrual for worker benefits, but captures less than one quarter of variation in the wife and survivor incentives.

The other source of identification is due to parametric changes in the Social Security benefit formulas. This source of identification has been use previously by Song and Manchester (2007), Kopczuk and Song (2008), and Mastrobuoni (2007) among others. Most studies that rely on this variation for identification are strictly reduced form since the data analyzed do not allow the full calculation of household incentives due to missing spouse information. There are two different types of changes. The first is an increase in the normal retirement age. It is gradually increasing from age 65 to 67 beginning with the cohort born in 1938. The second change is an

[29] Most studies of retirement consider samples of individuals who are at least 50 or 55 years old.
[30] The HRS contains more measures of labor force behavior like tenure and detailed occupation and industry.

increase in the delayed retirement credit from 3% per year to 8% per year beginning with those born in 1925. Both of these changes increase the return to delaying retirement, at different points in the claiming distribution.

To illustrate, consider a husband born in 1937 who claims his benefits at the EEA. He receives 80% of his PIA as a monthly benefit[31]. An individual born in 1938 receives 79.17% if he claims at age 62 and 0 months and someone born in 1939 receives 79.33%. It is akin to multiple natural experiments. The impact of a change of NRA from age 65 to 66 on retired worker benefits can be seen in Appendix Figure 3. If benefits are claimed at age 62 when an individual's NRA is 66, 75% of the PIA is paid on a monthly basis. For these two men, ACC at age 62 is -$74 and -$1,765 respectively. As the NRA increases, the incentives to claim at age 62 fall[32].

Changes to the DRC imply two individuals with the same NRA, one born in 1924 would receive 103% of his PIA if claimed at age 66 but someone born in 1935 would receive 106% of his PIA if he claims benefits are claimed at age 66. Therefore, the incentives at age 65 are much larger for younger individual. The same rationale holds true for monthly survivor benefits, but the calculation is more involved.[33] These policy changes also apply to the wife's claiming age. Changes to her benefit calculation will impact both the level of spouse and survivor benefits. This provides additional variation due to the wide range of birth years of women married to men born between 1922 and 1940.[34]

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[31] This is true only for those who are born on the 2nd of the month. For everyone else, their EEA is 62 and 1 month so they receive 80.55% of their PIA as a monthly benefit if they claim at their EEA.
[32] See Appendix Figure A6
[33] The impact on expected survivor benefits can be found in the Appendix, Tables A7.
[34] Wives' birth years range from pre-1910 to post-1960, see Appendix Table A8 for impact on expected survivor benefits.

Focusing on the accrual measure, where variation is not driven by differences in the SSW maximizing age, much of the identification of the spouse and survivor accrual will come from changes to the wife's NRA. The actuarial adjustment to both benefits is a function of the wife's birth year. The variation in rules among wives will create variation in the exact level of benefits. Age difference between spouses will vary the importance of spouse and survivor benefits. Those with the youngest wives will have the largest weight on survivor benefits while those with older wives have a larger weight on the spouse benefit. Starting at age 65, the husband's DRC provides additional variation in the survivor incentives as noted above.

Although the claiming choice is primarily a financial decision, more than the Social Security incentives will impact the choice. Credit constraints, mortality expectations, and preferences for leisure are all factors which may influence the choice of claiming age. To allow for this possibility, I include additional control variables in the estimation to proxy for these factors. The controls include education, marital status, work-limiting disability, experience and its square, household wealth including square and cubic, and observed mortality. As mentioned previously, I control for age using dummy variables.[35] This allows for the value of leisure to change over time while accounting for any possible focal points associated with claiming at age 62 or 65. It should also help address sample selection issues that may arise if those in the sample for longer are different in unobservables from those who claim at age 62.

Most studies of retirement make some assumptions about claiming. This study of course is forced to make its own assumptions. I assume claiming is independent of the retirement decision. This appears to be a strong assumption given most men who retire after age 62 retire and claim within a 12-month period.[36] If claiming is merely a response to or part of exiting the

[35] Adding up to a quartic in age instead does not change the findings.
[36] Coile et al (2002)

labor force, I would expect a weak response of claiming to financial incentives. Since I use incentives from the actuarial adjustment and not the incentives associated with labor supply, any bias due to this assumption is less of a concern. Holding PIA fixed at age 62 to isolate the role of actuarial adjustments will understate gains to any claiming delay. Furthermore, I estimate the base model on a sample that exited the labor force by age 62. While there still may be some coordinating between retirement and claiming for this group, I expect the bias from a retirement response to be muted.

1.4.2 Results and Discussion

The table reports the coefficients from a linear probability model with claiming as the dependent variable. For the base model, I present the results for both ACC and PV. The top panel in Table 1.2 presents results from the ACC models while the bottom panel presents the results from the PV model. The first three columns estimate the models on the full sample of men born 1922 to 1940 and the second three columns look at the subsample of men who retire by age 62[37]. I also present results for household incentives in columns (1) and (4) to highlight what the approach used in the literature lacks and allow comparison to previous work. I do not find a strong claiming response to the household incentives. The coefficient on the ACC measure in (1) suggests a $1000 increase in the annual change in household SSW leads to a 0.2 percentage point reduction in the claiming hazard. This is roughly consistent with Mastrobuoni (2007) who finds no claiming response to benefit accrual for early retirees. Since this group only faces incentives due to the actuarial adjustment and no changes to PIA, the incentives used here are identical to those used in his early retiree model.

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[37] I define early retirees as those whose last year containing earnings is the year in which they turn 62. Since earnings are an annual measure, we are unable to exactly determine if individuals have exited the labor force before their 62nd birthday.

For some individuals, household incentives include only worker benefit incentives. For others, the incentives are a combination of worker, spouse, and survivor benefits. Recognizing this fact makes it harder to interpret results that estimate the response household incentives. In the remaining models found in Table 1.2, I find a strong negative response to the incentives from the retired worker benefit. In model (2), a $1,000 increase in worker incentives will reduce the hazard rate by 3.4 percentage points in the ACC model and 4.5 percentage points using the PV model. These results suggest a stronger response to the total benefits to be gained instead of the annual gain. There is no response to the incentives from either wife or survivor benefits. Models (3) and (6) combine the household and worker incentives in one model to see in one setting which measure is more important in determining male claiming. These results are consistent with the preceding models. Claiming behavior responds strongly to the worker incentives but not to any other incentives including those defined by household benefits. This is the primary message to be taken from this study. It is important to allow for the response to vary by type of benefits, for controlling for the overall incentives hides a true behavioral response. As robustness checks, I estimate (1) the model only at age 62 to look at the impact of incentives on early claiming and (2) setup a model comparing the choice to claim at age 62 compared to claiming at 65. Results from these analyses find qualitatively similar results[38].

In the early retiree sample, found in the second set of columns, there is smaller response to worker incentives than in the full sample. In general, the results are fairly consistent with the overall sample. There still is little or no response to incentives determined by household, spouse or survivor benefits. There are economic arguments to be made why early retirees may be more or less responsive to incentives. It would not be surprising if they were more responsive as this group has been able to fund retirement prior to Social Security benefits. They may be more able

[38] Results available upon request.

to respond to incentives since they are not credit constrained; they were able to fund retirement prior to age 62. When these individuals reach age 62, they face strictly a financial decision of when to claim benefits. However, they could follow a rule of thumb to claim as soon as benefits are available since they are not making a joint claiming and retirement decision. Furthermore, the early retirees are not credit constrained so Social Security benefits are likely a smaller portion of their annual income. If this is the case, maximizing SSW may not be a high priority. I am unable to determine if these estimates from the early retirees are a cleaner response to incentives and the presence of the retirement decision caused bias in the original models or if this subsample has a smaller response to retired worker incentives overall.

1.4.3 Robustness Checks

Before concluding husbands do not consider wife or survivor benefit incentives when making their claiming choice, there are a few robustness checks I want to explore. The following analyses have a few goals. The first is to identify groups in the population where there is more variation in claiming behavior, where all observations are not found at or near age 62. This ensures the base model is not solely capturing individuals claiming at 62 due to a default rule who also happen to face incentives which encourage them to do so, although the incentives to not enter the decision-making. This also may identify populations who are more likely to respond to the other incentives besides those from retired worker benefits. The second is to identify populations who either understand the incentives better or may be more likely to respond to the incentives they face. This allows me to focus on groups where the perceived incentives are closer to the calculated incentives, reducing bias from measurement error.

The first robustness check considers the health of individuals as a factor which impacts Social Security incentives since expected lifetime plays a central role in the calculation of SSW. Hurd et al (2004) and Delavande et al (2006) find those with low mortality expectations claim benefits slightly earlier than those who think they have a good chance of living to age 75. Ideally, I would like to take this one step further and ask whether the response to incentives varies by mortality expectations. Unfortunately, there are no measures of mortality expectations in the SIPP like the HRS. Instead, I use ex post mortality since it is likely to be correlated with private information held by the individual that would inform their mortality expectations. Those who do not live as long receive benefits over fewer years. Claiming benefits early maximizes the lifetime benefits of those with worse mortality prospects. I predict those in poor health [low mortality expectations] would respond less to the measured financial incentives. I look at this in two manners. The first is to interact the response to incentives with a dummy variable for whether the individual lives past his 75th birthday.[39] This approach will tell us whether the two groups respond differently to the average incentives for all individuals. Using mortality as a proxy for mortality expectations, we expect a negative coefficient on the interaction with incentives. Since measured incentives are more accurate for those who live to age 75, I estimate the model on this subsample of individuals with better mortality outcomes. These results should be less prone to measurement error.

Table 1.3 presents results using observed mortality differences. In column (1), a $1,000 increase in household SSW over the next year reduces the claiming hazard by 0.2 percentage points with no statistically significant difference for those who live longer. In column (2), there is no difference by observed mortality in the response to their own benefits incentives. In model (3), I find a small but significant effect of household incentives on claiming in addition to the

[39] Results are similar when using either age 70 or 80 as a cutoff.

strong effect of worker incentives for those who live past 75. I previously noted that those with average mortality do not experience a large variation in worker benefits by claiming age. Taking this into account, it may be plausible that the long-lived group can afford to be more responsive to dependent benefits with little cost in terms of their own benefit. The sign on the interaction between living past 75 with the survivor and spouse incentives is negative as predicted but insignificant and very small in magnitude when compared to the coefficient on the worker incentives. The coefficients on observed mortality of self and spouse are generally positive and insignificant. Model (4) estimates a coefficient on worker incentives slightly large than the full model, which is consistent with the hypothesis that the longer lived would respond more to incentives. There are no other qualitative differences in the results from these two different approaches. Given the results in column (4), it does not appear measurement error attenuates the coefficient estimates on worker incentives towards zero. A similar analysis using the wife's observed mortality is similarly inconclusive, partly because we have fewer women observed at age 75 to measure mortality[40].

A primary concern when estimating behavioral responses is whether individuals understand the program being analyzed. I implicitly assume individuals understand the rules when estimating a response to incentives. Chan and Stevens (2008) note that it is puzzling how strong the estimated behavioral response to pensions is given that most individuals do not have a full understanding of the incentives. They find the response to private pensions is solely driven by those who understand their pension. Given the complicated rules of the Social Security program it is reasonable to ask how well individuals understand the program. Leibman and Luttmer (2009) do just this. They find the median voter knows more than we think but that the spouse benefit provision is not well understood. This finding could explain the lack of economic

[40] Results available upon request.

meaningful results concerning dependent benefits from the base model. Allowing for individual information is impossible given the data, but I look at whether those we expect to have more information respond to incentives differently. The best option given the constraints of our data is to focus on differences by education[41]. Those with more education likely have lower costs to gathering the relevant information or they have a higher chance of understanding the incentives themselves.

Table 1.4 allows the response to incentives to vary by whether the husband has at least a college degree. I find those with a college degree are slightly less responsive to worker and wife's incentives but no more responsive to survivor incentives than those without a college degree. While this was not as expected, it suggests even those with less education respond to incentives and understand the incentives to some degree. The concern that only part of the population understands the benefit rules and responds to incentives does not appear to be true using educational attainment as a proxy for information. I find those with more education claim much later as expected given results from previous studies (Mastrobuoni, 2011; Sass et al, 2007). I also estimate the split model only including those with a college education. This group might have an effective discount rate in line with our calculations, again providing estimates less susceptible to measurement error. The results in (4) look very similar to the results from the early retiree sample. Given the early retirees are more likely to have higher education, this finding is not surprising.

The last robustness check I want to perform allows for a direct role of joint leisure in the response to incentives. Over the past twenty years, joint retirement has been documented for working couples and the importance of joint leisure has been stressed. Valuing joint leisure

[41] I use the cohort-differences created by the Social Security Statement utilized by Mastrobuoni (2011) as a robustness check on the synthetic data. Consistent with his findings I do not find any meaningful difference in behavior after the dissemination of information.

could be a potential explanation why men claim benefits early. If their wife is at home, they might want to retire and claim as soon as possible. Directly evaluating the role of joint leisure is difficult, but at the very least, men may respond less to financial incentives if their objective function highly weights joint leisure. I break couples into three different groups based on wives' work history. Although this is far from perfect, it will help us determine if joint leisure contributes to our base results. The first group is couples where the wife has a very weak work history defined as less than ten years of any earnings over her lifetime or not eligible for retired worker benefits[42]. For wives with more than ten years of positive earnings and who is eligible for her own benefit, I split by whether the wife is still in the labor force[43]. Approximately 15% of wives have a strong work history but have exited the labor force while 30% are still working. Studies of joint retirement are limited because they only consider couples where both spouses have a strong work history or were both in the labor force at some age, say 55. Examining claiming behavior does not face this constraint. The models are estimated for married men only; the omitted category is husbands whose wives have a weak work history. Table 1.5 presents results allowing for claiming and the response to incentives to vary by the three groups defined above. Starting with the group indicator variables [which are included in all previous models as well], husbands whose wives have a stronger work history appear more likely to claim that those whose wives have a weak work history but the differences in each model are not statistically significant. Men whose wives have left the labor market [and have a strong work history] are much less responsive to their own benefits. This is consistent with a joint leisure hypothesis because he ignores his own benefits once his wife has retired. Again, there is no response to spouse or survivor incentives. These results point to a strong role for joint leisure in the decision

[42] Those claiming their own retired worker benefit include dual beneficiaries.

[43] Alternate measures of claiming or retirement do not yield any indication that joint leisure impacts the response claiming decisions to the Social Security incentives.

of when to claim Social Security benefits and determining more precisely the role of joint leisure is an important avenue for future research.

1.5. Conclusions

This study highlights the dependence of wives on their husbands for Social Security benefits, even after the drastic increase in labor force participation and wages women have experienced over the past several decades. I explore whether the behavior of husbands is consistent with this dependence. Are men equally responsive to all household benefits, or do they respond to the incentives created by their own benefits more strongly? This is the first study to allow the response to Social Security financial incentives to vary by the type of benefit received by the different members of the household at different points in time.

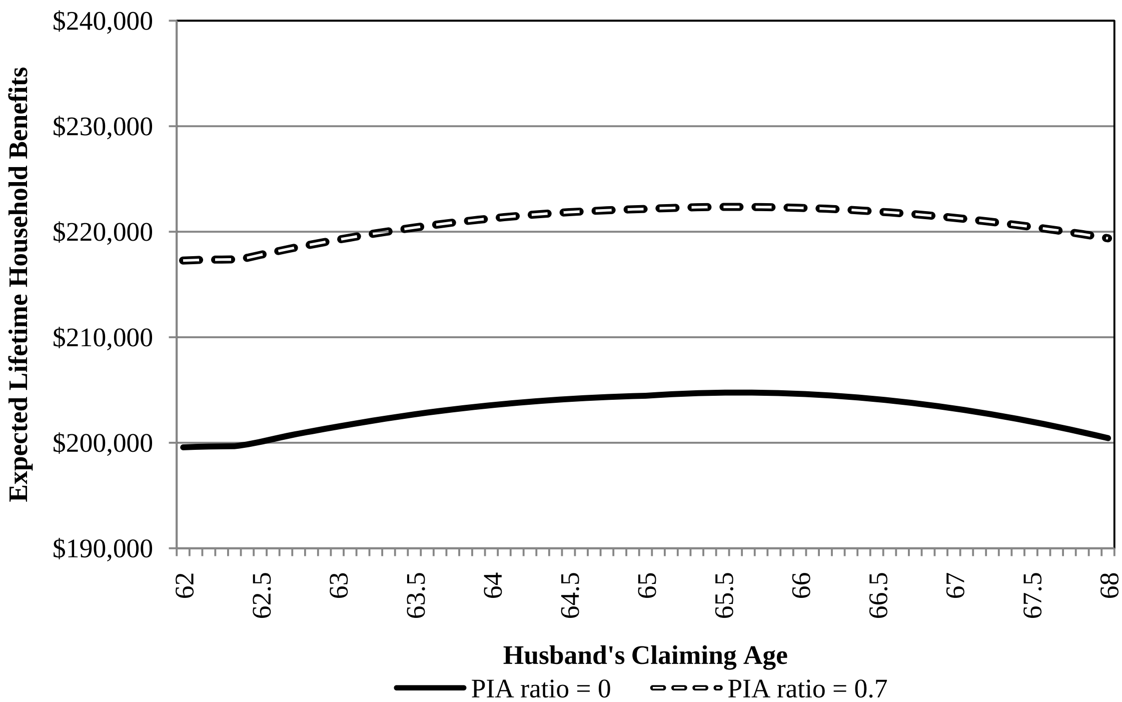
My findings suggest husbands do not treat all benefits received by the household equally. I find men are very responsive to their own benefits, but not responsive to the incentives created by dependent benefits. I estimate models trying to elicit whether responses are driven by certain segments of the population who either respond more to financial incentives or for whom the incentives are calculated more accurately. I find those who live longer are less responsive to the incentives from retired worker benefits but still not responsive to any other benefit type. Those with the most education are much more likely to claim benefits later but those with all levels of education respond to the incentives. In addition, joint leisure appears to play a role in determining claiming age where those who have a big change to their potential leisure outcomes, the retirement of his wife, having little response to their own worker incentives.

Widows' well-being is partially determined by the claiming decision of her deceased spouse. In the case of survivor benefits, claiming age of the husband can increase the benefits by up to 50%. We do not see evidence of behavior consistent with husbands prioritizing the survivor benefit. There is a chance some of this discrepancy could be due to better understanding of own benefits, as noted by Liebman and Luttmer (2009), but it is unlikely that this is the sole explanation. Future cohorts may be more responsive to all benefits as they will receive the Social Security statement for longer, and maybe as a result will learn more about survivor benefits. As it currently stands, the Social Security statement does not provide much information about either spouse or survivor benefits, so this is one avenue for information dissemination. In addition, policy circles have talked about trying to disentangle the wives' benefits from their husbands' behavior due to the substantial impact of husband's claiming age on survivor benefits. Given the results of this study, this may be an avenue to more seriously consider.

Figure 1.1. Expected Lifetime Retired Worker Benefits by Claiming Age, Men

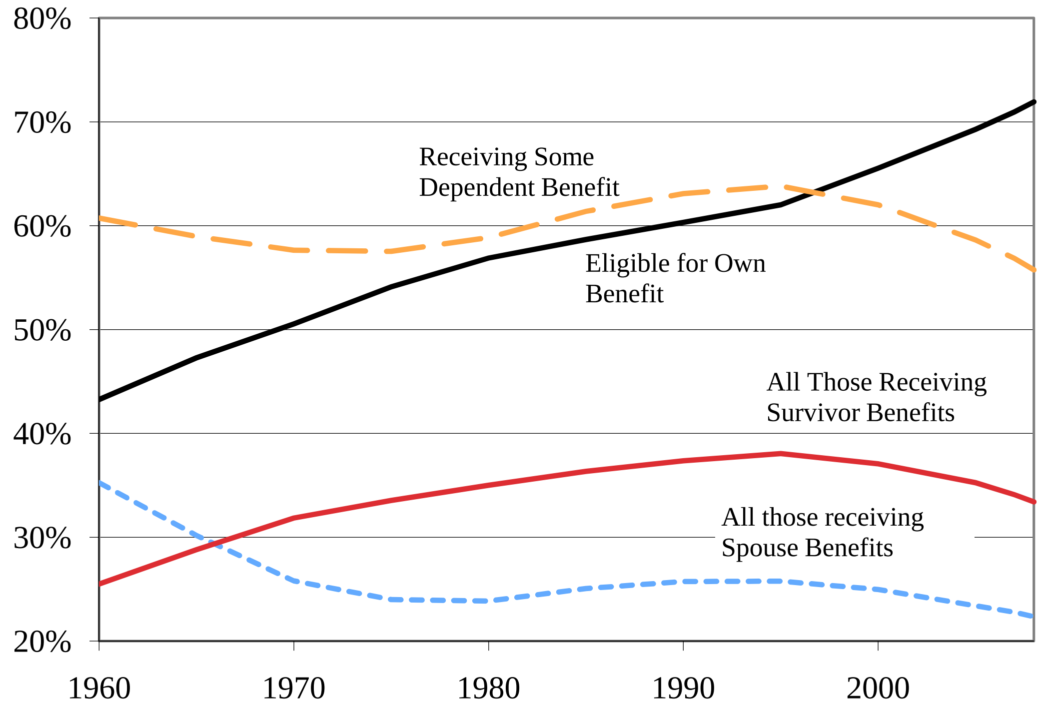
Note: For males with PIA of $963 born in 1937; NRA = 65 and DRC = 6.5%.

Figure 1.2. Expected Household Social Security Wealth (SSW)



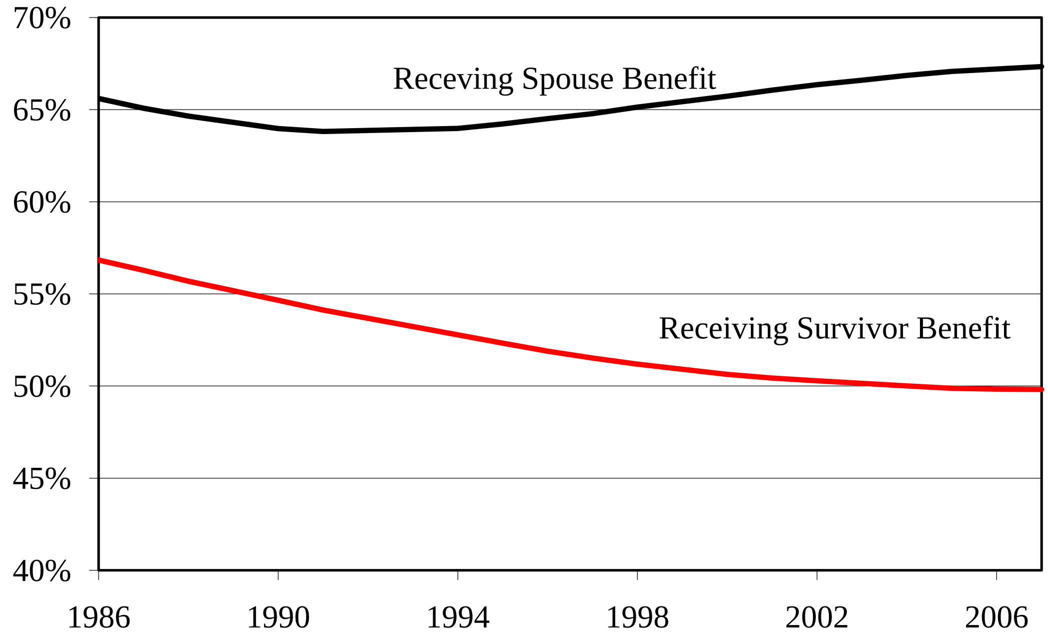
Notes: For males with PIA of $963 born in 1937; NRA = 65 and DRC = 6.5%; wife 3 years younger. PIA Ratio = Wife PIA/Husband PIA. If PIA ratio = 0, the household benefits are husband's retired worker, spouse and survivor benefits. If PIA ratio = 0.7, the household benefits are husband's retired worker, wife's retired worker, and survivor benefits.

Figure 1.3. Current Female OASI recipients, Type of Benefit



Source: Social Security Administration, various years

Figure 1.4. Fraction of Total Benefits Due to own PIA, Female Dual Beneficiaries



Note: Each series represents the ratio [Own/Wife's PIA/Dependent Benefit] where "Dependent" refers to Spouse and Survivor Benefits respectively.
Source: Social Security Administration, 2010

Figure 1.5. Empirical Distribution of Claiming Age by Marital Status at Claiming, Males

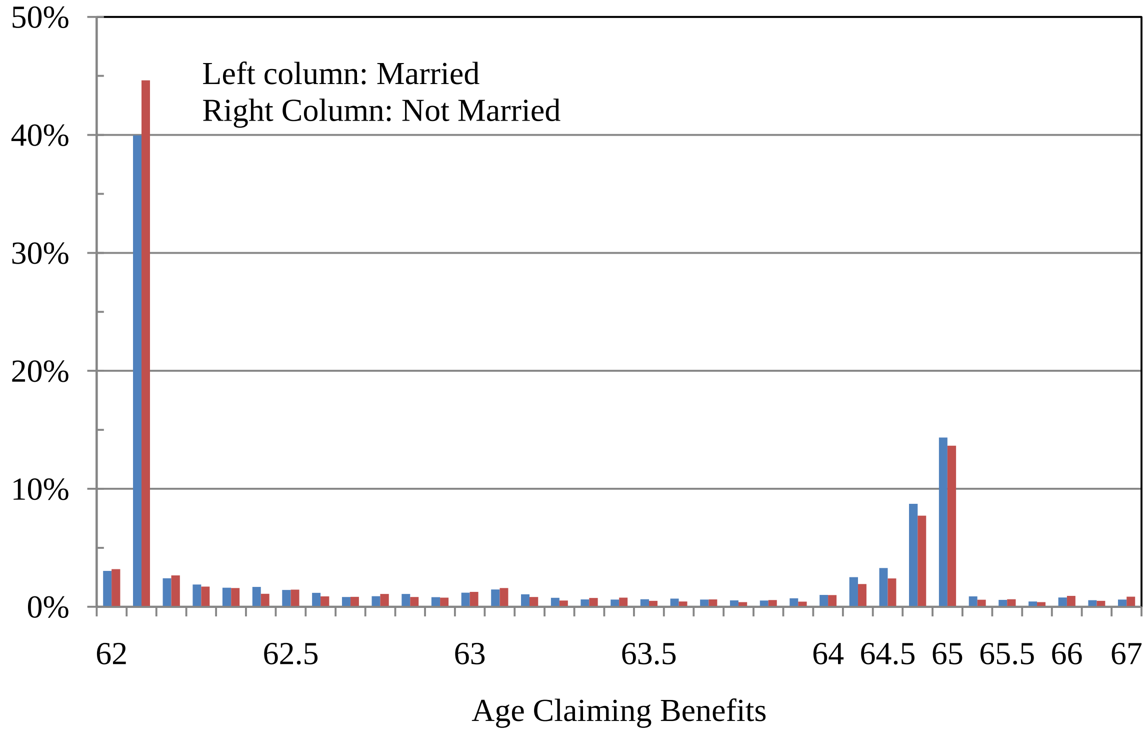


Figure 1.6. Distribution of Claiming Age that Maximizes Household SSW

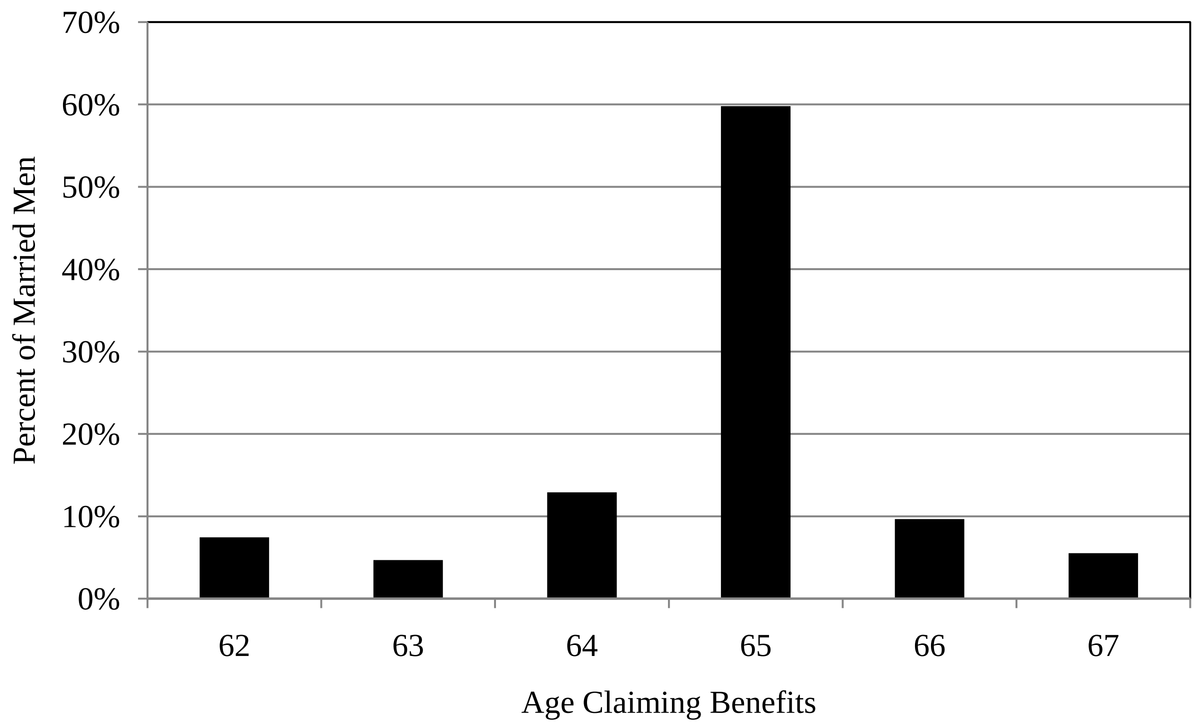


Figure 1.7. Distribution of Total Household Benefits Lost
Maximum OASI Benefits Less Actual Expected Benefits

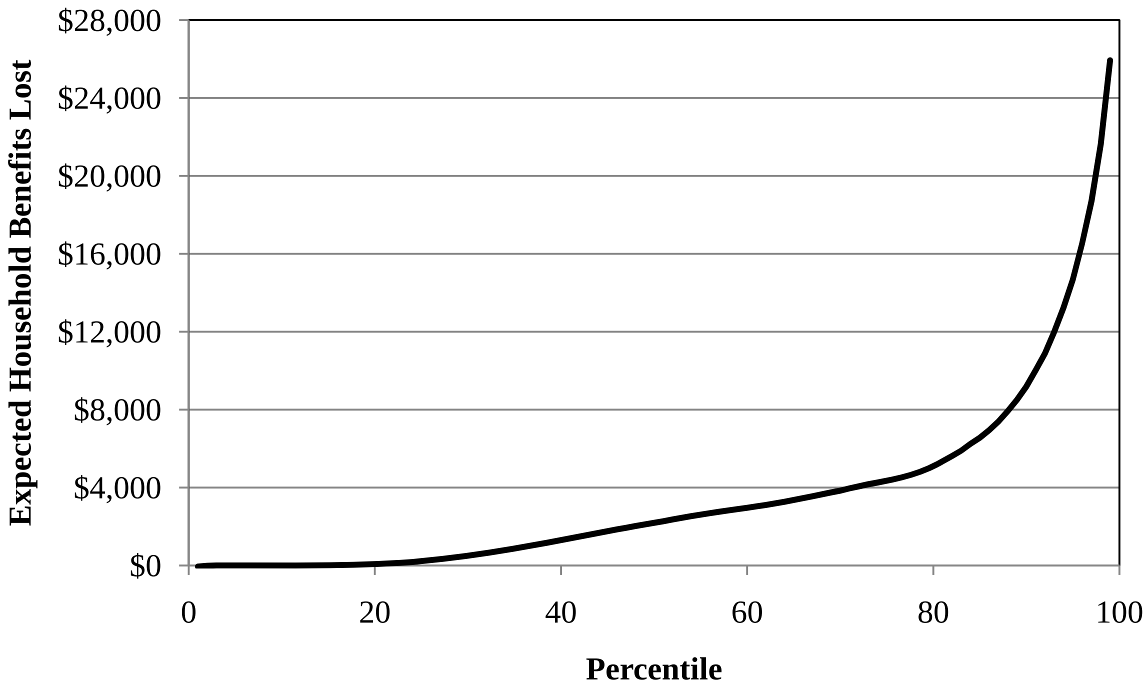
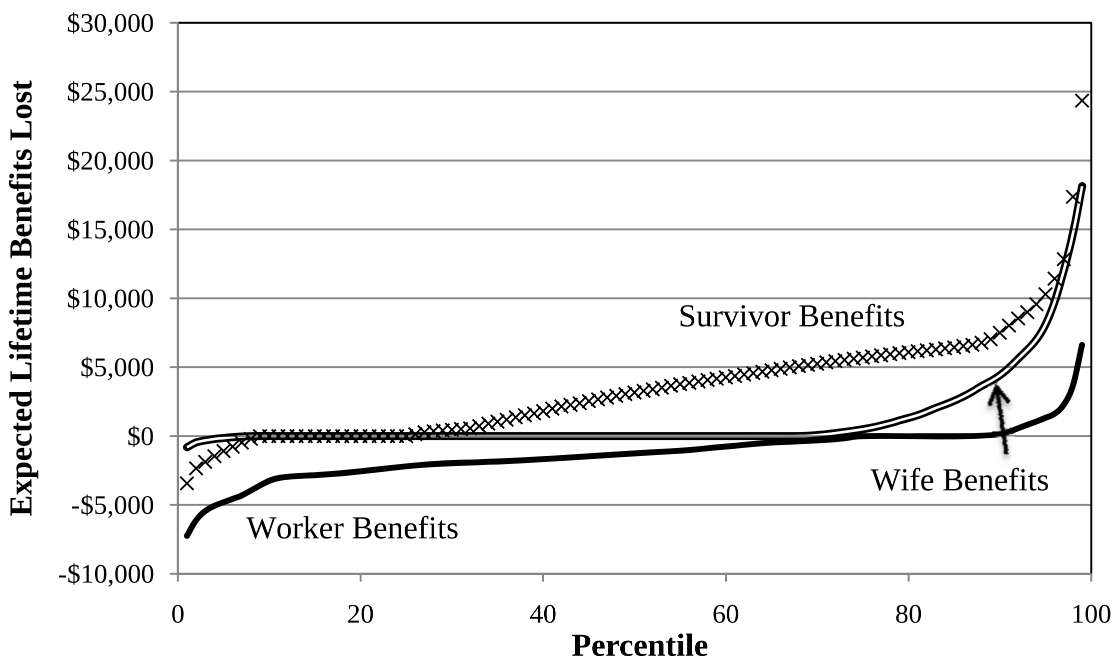


Figure 1.8. Lifetime OASI Benefits Lost, By Type
Maximum OASI Benefits Less Actual Expected Benefits



Note: Maximum Benefits are defined by the claiming age that maximizes the sum of wife & husband's worker benefits, spouse, and survivor benefits.

Figure 1.9. Actual and Potential Survivor Benefits

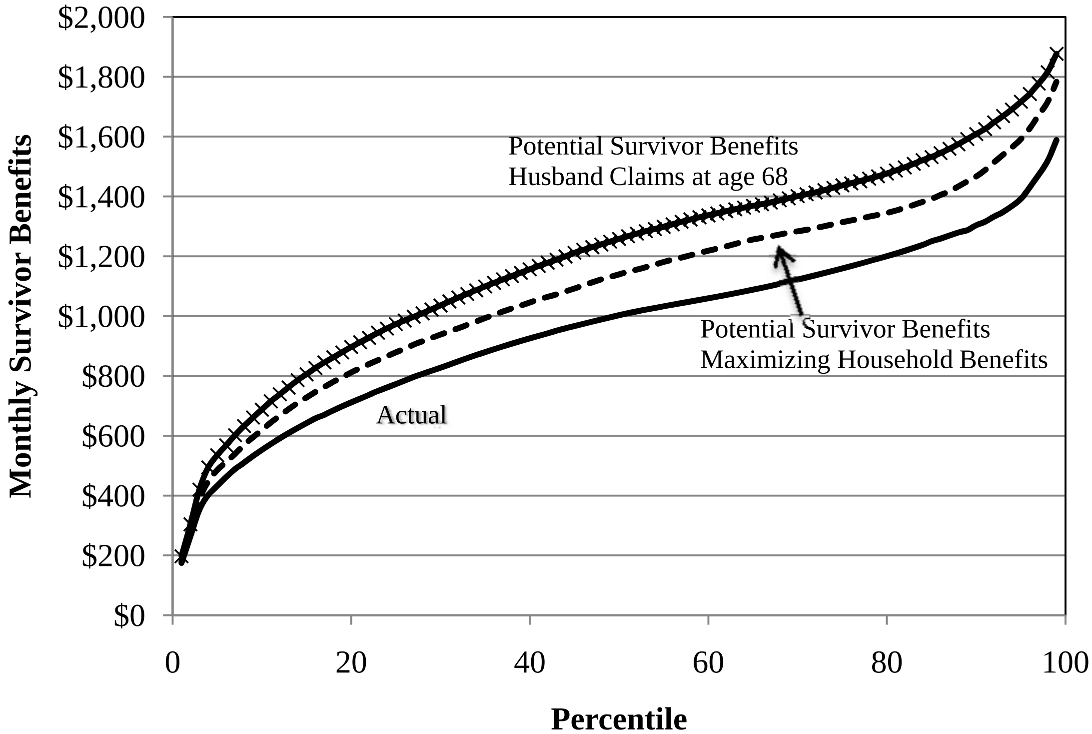
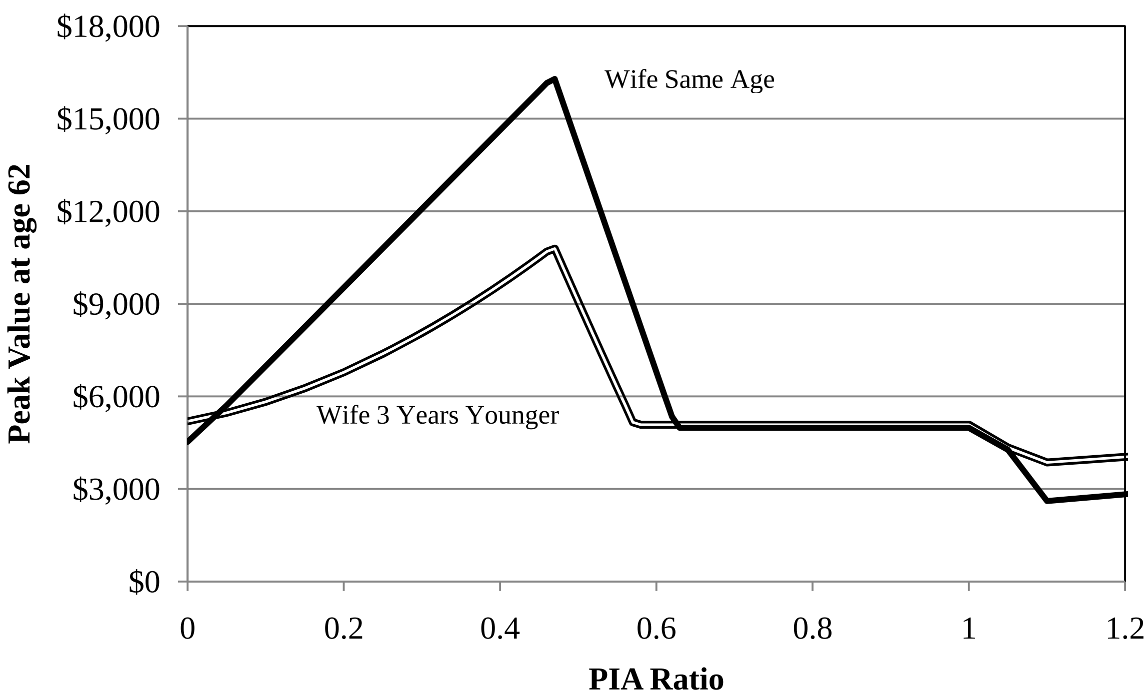


Figure 10. Household Peak Value, by PIA ratio and Age difference between Spouses



Note: PIA Ratio is the ratio of Wife's PIA to Husband's PIA

Table 1.1. Summary Statistics of Social Security Wealth, Incentives and Key explanatory variables

	Median	Mean	Std. Deviation
Expected Worker Benefits	\$133,755	\$129,829	\$43,858
Fraction Expecting Spouse benefits	---	46.9%	49.8%
Expected Spouse Benefits	\$0	\$21,612	\$25,428
Fraction Expecting Survivor benefits	---	0.6920	42.1%
Expected Survivor Benefits	\$41,178	\$36,877	\$28,167
Accrual - Worker Benefits	\$206	\$563	\$467
Accrual - Spouse Benefits	\$0	\$76	\$1,334
Accrual - Survivor Benefits	\$1,737	\$1780	\$4,004
Age Difference Between Spouses	2.71	3.9	5.6
Total Net Worth	\$141,914	\$370,958	\$739,495
Fraction Claiming Single	---	24.3%	39.4%
Fraction with at least College Degree	---	28.9%	42.9%
Fraction Retiring prior to age 62	---	32.1%	44.9%
Years with earnings before claiming	37	28.0	9.0
Years with earnings before claiming - Spouse	15	15.2	13.8
Health Limits Work	---	17.0%	32.3%
Health Limits Work – Spouse	---	19.8%	35.2%
# Individuals	13,753		

Sample: Men born between 1922 and 1940
Incentives reported at age 62

Note: $PV = SSW_{max} - SSW_{62}$
$ACC = SSW_{63} - SSW_{62}$

Table 1.2. Baseline Model Results

	(1)	(2)	(3)	(4)	(5)	(6)
Sample		Full Sample			Early Retirees	
Accrual Household	**-0.0022***** (0.0007)		**0.0004** (0.0010)	**-0.0004** (0.0011)		**-0.0003** (0.0011)
Accrual Worker		**-0.0337***** (0.0022)	**-0.0339***** (0.0019)		**-0.0121***** (0.0048)	**-0.0121***** (0.0049)
Accrual Wife		**0.0003** (0.0013)			**-0.0021** (0.0017)	
Accrual Survivor		**0.0012** (0.0008)			**0.0008** (0.0013)	
Peak Value Household	**0.0004** (0.0004)		**0.0010** (0.0004)	**0.0003** (0.0004)		**0.0007** (0.0005)
Peak Value Worker		**-0.0451***** (0.0040)	**-0.0629***** (0.0040)		**-0.0284***** (0.0089)	**-0.0230***** (0.0089)
Peak Value Wife		**0.0010**** (0.0005)			**-0.0003** (0.0007)	
Peak Value Survivor		**0.0009** (0.0006)			**0.0026***** (0.0008)	
# Observations		27,310			19,675	
# Individuals		13,753			7,643	

Source: Averaged values from 4 completed data implicates from Gold Standard data. Standard errors are calculated as detailed in Abowd et al (2006).

Note: Population mortality tables used in calculation of incentives. Control variables in each model are age dummies, education, interactions of quartics of AIME and potential earnings, own and spouse earnings starting at age 30, experience and its square, death after age 75 of self & spouse, death after age 80 of self & spouse, years since retirement (if retired), presence of work limiting disability, presence of DB/DC pension, net household wealth up to its cubic, and log(SSW), log(Worker Benefits), log(Spouse Benefits) and log(Survivor benefits) up to their cubics.

Table 1.3. Results by Husbands' Ex Post Mortality

	(1)	(2)	(3)	(4)
Sample	Full	Full	Full	Those who live to at least age 75
Accrual-Household	**-0.0020** (0.0021)		**-0.00001** (0.0007)	
*Death after age 75	**-0.0036** (0.0023)		**-0.0024*** (0.0014)	
Accrual – Worker		**-0.0206***** (0.0022)	**-0.0205** (0.0022)	**-0.0244***** (0.0041)
*Death after age 75		**-0.0011** (0.0018)	**0.0002** (0.0019)	
Accrual – Wife		**0.0011** (0.0014)		**0.0014** (0.0040)
*Death after age 75		**-0.0027** (0.0039)		
Accrual - Survivor		**-0.0005** (0.0009)		**-0.0015** (0.0013)
*Death after age 75		**-0.0014** (0.0015)		
Death after age 75	**0.0100** (0.0097)	**0.0045** (0.0116)	**0.0057** (0.0115)	n/a
Spouse's death after age 75	**0.0043** (0.0100)	**-0.0010** (0.0101)	**-0.0009** (0.0322)	**0.0025** (0.0192)
# Observations		27,042		9,466
# Individuals		13,753		4,334

Source: Averaged values from 4 completed data implicates from Gold Standard data. Standard errors are calculated as detailed in Abowd et al (2006).

Note: Control variables in each model are age dummies, education, interactions of quartics of AIME and potential earnings, own and spouse earnings starting at age 30, experience and its square, years since retirement (if retired), presence of work limiting disability, presence of DB/DC pension, net household wealth up to its cubic, and log(SSW), log(Worker Benefits), log(Spouse Benefits) and log(Survivor benefits) up to their cubics.

Table 1.4. Results by College Education

	(1)	(2)	(3)	(4)
Sample	Full	Full	Full	College Graduates
Accrual - Household	**-0.0025** (0.0025)		**-0.0015** (0.0034)	
*College	**0.0024**** (0.0012)		**0.0025*** (0.0014)	
Accrual – Worker		**-0.0374***** (0.0067)	**-0.0372***** (0.0023)	**-0.0138***** (0.0040)
*College		**0.0062***** (0.0015)	**0.0050***** (0.0016)	
Accrual – Wife		**-0.0017** (0.0015)		**0.0017** (0.0022)
*College		**0.0048**** (0.0024)		
Accrual – Survivor		**0.0008** (0.0010)		**0.0004** (0.0013)
*College		**0.0013** (0.0017)		
College	**-0.3525***** (0.0208)	**-0.3406***** (0.0198)	**-0.3424***** (0.0198)	n/a
# Observations		27,042		11,630
# Individuals		13,753		3,858

Data: Averaged values from 4 completed data implicates from Gold Standard data. Standard errors are calculated as detailed in Abowd et al (2006).

Note: Control variables in each model are age dummies, education, interactions of quartics of AIME and potential earnings, own and spouse earnings starting at age 30, experience and its square, years since retirement (if retired), presence of work limiting disability, presence of DB/DC pension, net household wealth up to its cubic, and log(SSW), log(Worker Benefits), log(Spouse Benefits) and log(Survivor benefits) up to their cubics.

Table 1.5. Results by Wife's Labor Force History

	(1)	(2)	(3)
Accrual – Household	**-0.0030** (0.0028)		**0.0008** (0.0010)
*Wife Strong LF, Exited LF	**0.0045**** (0.0019)		**-0.0022** (0.0044)
*Wife Strong LF, Still Working	**0.0015** (0.0013)		**0.0014** (0.0014)
Accrual – Worker		**-0.0279***** (0.0023)	**-0.0283***** (0.0025)
*Wife Strong LF, Exited LF		**0.0193***** (0.0044)	**0.0197***** (0.0043)
*Wife Strong LF, Still Working		**-0.0004** (0.0023)	**-0.0004** (0.0016)
Accrual – Wife Benefits		**-0.0012** (0.0020)	
*Wife Strong LF, Exited LF		**-0.0007** (0.0041)	
*Wife Strong LF, Still Working		**0.0017** (0.0028)	
Accrual – Survivor		**0.0025** (0.0013)	
*Wife Strong LF, Exited LF		**-0.0014** (0.0023)	
*Wife Strong LF, Still Working		**0.0007** (0.0016)	
Wife Strong LF, Exited LF	**-0.0259** (0.0191)	**-0.0163** (0.0244)	**-0.0185** (0.0234)
Wife Strong LF, Still Working	**-0.0117** (0.0145)	**-0.0162** (0.0171)	**-0.0176** (0.0167)
# Observations		22,770	
# Individuals		11,274	

Data: Averaged values from 4 completed data implicates from Gold Standard data. Standard errors are calculated as detailed in Abowd et al (2006).

Note: "Wife Strong LF" is wives who have at least 10 years of positive earnings and are eligible for their own retired worker benefit from SS.
Control variables in each model are age dummies, education, interactions of quartics of AIME and potential earnings, own and spouse earnings starting at age 30, experience and its square, years since retirement (if retired), presence of disability, presence of DB/DC pension, net household wealth up to its cubic, and log(SSW), log(Worker Benefits), log(Spouse Benefits) and log(Survivor benefits) up to their cubics.

Chapter 2: How does Job Loss Impact Employer-Provided Health Insurance Coverage & Wages?

Evidence from the Survey of Income and Program Participation

2.1. Introduction

Fringe benefits, including health insurance, are a prominent part of the compensation package for many employees. It is important to investigate to what extent job loss impacts access to this type of compensation, especially as health care costs continue to rise. There has been much focus on the impact of job loss on workers' wages and earnings but less attention focused on how health insurance coverage is impacted by job loss. Health insurance is a key component to economic stability as it prevents large loss of wealth in the event of a serious health shock. Workers who lose their job see a fall in their incomes of 60% before taking into account unemployment benefits. Sole earners see almost 90% income loss, and households with multiple workers see a drop of 20% in income

[1]. With such large drops in income, most households are unlikely to be able to afford out-of-pocket health care costs. Health insurance is valued both for its protection from large losses of wealth and for providing access to health care not otherwise available (Nyman, 1999).

The number of uninsured has been rising consistently over the past few decades, reaching 16.7% of the population uninsured in 2009[2]. Older individuals have higher rates of insurance, as do whites and those with higher income. While the overall insurance rate recently remained flat, coverage from private insurance fell from 73.2% in 1990 to 63.9% in 2009. Eligibility for insurance has fallen over time due in part to the increase in part-time and contract workers[3]. In

[1] Congressional Budget Office (2004)
[2] Statistical Abstract of the United States, various years. Years prior to 1987 published a different statistic on uninsured individuals not directly comparable.
[3] Farber and Levy (2000).

addition, families are spending more of their personal income on health during this time as well. The annual premium for a family now averages over $13,000 with employee contributions around $4,000[4]. It is likely that due to the rising costs, families will start to opt out of coverage because they cannot afford it (Andersson et al, 2011).

Job loss impacts health insurance since most individuals gain coverage to insurance through their employer. Tax preferences for health insurance premiums paid by employers is responsible for this relationship. More that 80% of employed workers have private health insurance in their own name through their own employer[5]. Individuals will eventually lose access to coverage after they lose their job. For primary earners, this loss of coverage will impact their family as well. Two-thirds of children are covered by an adult in the household and approximately half of adults with private coverage are covered through another individual's plan[6]. Since individuals lose coverage with their job, job loss carries additional costs besides reduced income. Access to health insurance might also increase health outcomes in the long run. Currently, there is not much conclusive evidence about the relationship between health outcomes and health insurance coverage (Currie and Madrian, 1999). This is a difficult question to answer since clean identification of health insurance coverage is challenging to obtain. However, evidence has been found of a direct impact between job instability impacts mortality and other health outcomes (Burgard, Brand, and House (2007), Strully (2009), Sullivan and von Wachter(2009)). Those in poor health typically have increased demand for health insurance. Financial losses due a lack of health insurance are lower for those with few assets due to the presence of uncompensated care. Many individuals do not use compensated care, and if they do,

[4] The Henry J. Kaiser Family Foundation (2011)
[5] Author's calculations from the 1996 Survey of Income and Program Participation.
[6] Almost 20% are covered by Medicaid and small fraction are covered through military health care. All calculations from the 1996 SIPP.

it is only after depleting their entire stock of assets[7]. In addition, displaced individuals also are more prone to bankruptcy and have less access to credit (Keys, 2010), which would be necessary to afford expensive health care without insurance.

There are two relationships I explore. The first is how job displacement impacts health insurance coverage. I primarily focus on coverage through an employer pre and post-displacement but also look at other sources of coverage. I use standard methodology to study displaced workers in an event-study framework which allows comparison to the existing literature, and I take advantage of the high periodicity in the Survey of Income and Program Participation which has not been previously exploited. I find that health insurance coverage is lower for displaced workers but within two years of job loss, coverage rates return to their previous levels. I also estimate the impact of displacement on wages in tandem to the analysis of insurance coverage. This helps complete the picture of the impact of job loss within a nationally representative sample and provides comparison to the relevant literature. Last, I document how wages differ by health insurance coverage. Wages recover to their pre-displacement levels within one year and health insurance coverage is associated with higher wages conditional on reemployment.

Previous studies have not come to a concensus about whether coverage recovers post displacement. Gruber and Madrian (1997) find a large, significant difference one year following displacement but others (Lin, 2005; Kosteas and Renna (2009)) have found that within 6 to 12 months there is no significant difference in coverage between the displaced and non-displaced workers. This study adds to the literature by looking at job losers in a stable job market and confirming they are able to recover coverage through an employer. However, the displaced workers are less likely to be covered by insurance and this difference cannot fully be explained

[7] Institute of Medicine (2003)

by either individual or job characteristics. In addition, I confirm findings from previous studies that jobs with health insurance tend to be "better jobs" on average and pay higher wages.

The format of the paper is as follows. Section 2.2 reviews the literature on the effects of job displacement general and on health insurance coverage specifically. Section 2.3 describes the data. Section 2.4 presents estimation strategies and results, and Section 2.5 concludes.

2.2. Literature review

There is a large literature examining the costs from job loss. The primary focus has been direct economic costs and other labor market outcomes: employment, wages, and earnings. Jacobson, LaLonde, and Sullivan (1993) find large long term earnings losses following mass layoffs and von Wachter, Song and Manchester (2011) confirm these results with a more nationally representative sample and find long term earnings losses of 20% up to 15 years following displacement. Schmeider, von Wachter and Bender (2009) find smaller earnings losses during strong economic conditions in Germany.

There has also been recent work looking at the impact of job loss on a variety of health outcomes. Sullivan and von Wachter (2009) find job displacement impacts life expectancy, estimating a loss of 1-1.5 years for those that experience a mass layoff. Burgard, Brand, and House (2007) find job uncertainty increases the incidence of stress-related health conditions and Strully (2009) finds both lower self-reported health status and an increase in the development of new health conditions upon reemployment among displaced workers.

There has been an increase in the study of health insurance coverage as the fraction uninsured continues to rise along with health care costs. Correspondingly, there has been more attention paid to individuals' access to insurance both overall and surrounding job loss particularly in light of the economic downturn. Olson (1992) was the first to explore this question followed by Gruber and Madrian (1997) who examine the impact of Consolidated Omnibus Budget Reconciliation Act of 1985 (COBRA) on health insurance coverage of job leavers.

Olson (1992) uses the Displaced Worker Survey from 1984, 1986, and 1988 to look at the pattern of health insurance associated with job separation and job reattachment. He restricts his analysis to workers who lost their job due to plant closings and permanent layoffs. He reports that the probability a married white male lost health insurance following displacement was 0.2. Single males' health insurance coverage is more adversely affected by job loss than married men. Single male coverage falls to 47% from about 66% with displacement. In addition, he finds displaced workers who were reemployed at the time of a later interview were less likely to be insured through their new job. When estimating the tradeoff between changes in coverage and changes in log wages, he finds that those who gained coverage saw wage gains compared to those uninsured at both points in time. Those who lost coverage, compared to those who maintained insurance, saw wage losses. This suggests higher paying jobs are more likely to offer health insurance.

Gruber and Madrian (1997) use the Survey of Income and Program Participation (SIPP) panels from 1984 to 1988 to evaluate the role of COBRA on the prevalence of health insurance coverage. One provision of COBRA gave employees who separate from their jobs access to their previous employer's group health insurance. They first look at general determinants of coverage and find that unemployment has a large negative effect on coverage, reducing the probability of coverage by about 20% using a linear probability model with individual fixed effects. They also find different effects based on eventual lengths of nonemployment[8]. Those who end up nonemployed the longest experience the sharpest drop in health insurance coverage, even in the initial months following separation. They find the introduction of COBRA increased coverage rates, using the staggered implementation at the state level for identification. The presence of a year of continuation coverage resulted in 2.5 percentage point increase in private insurance coverage. This translates into a reduction of 6.7% in becoming uninsured when transitioning to nonemployment. They also find that COBRA increased nonemployment duration. They argue that continuation benefits should increase mobility and should result in efficiency gains[9]. The availability of continuation benefits increases the probability of separation, where one year of continuation coverage raises the odds of transition from employment to nonemployment from 3.7% to 4.2%, a 14% increase. A secondary analysis finds that having one year of continuation coverage available increased earnings by 8.1%.

Using SIPP panels from 1996 and 2001, Simon (2006) and Simon and Schroder (2006) focus on how displaced workers differ from non-displaced in the period leading up to displacement. They find the displaced experience decreases in coverage starting more than one year prior to displacement. They also compare displaced workers to other workers voluntarily on new jobs and find the displaced workers have lower health insurance coverage. The rationale for the analysis is to eliminate eligibility differences as best as possible since many jobs have a waiting period before new workers are eligible for health insurance. Comparing displaced individuals on new jobs to controls on new jobs, however, is not the counterfactual for the thought experiment, "What would have happened to these individuals' ["the displaced"] health insurance coverage if they had not been displaced?"

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[8] Nonemployed is defined as unemployed or not in the labor force.

[9] Madrian (1994) find evidence of "job-lock" due to employer provided health insurance. In theory, this should reduce efficiency of the economy. Dey [2000] finds that this is the case.

Kosteas and Renna (2009) also focus on differences in eligibility on new jobs which they accomplish by directly control for tenure on a new job. They find the displaced workers' coverage is not different than the control groups' coverage once individuals on new jobs have passed the 6-month tenure mark. This suggests that once individuals have made it through the waiting period to be eligible for insurance, there is no difference in coverage. They use the National Longitudinal Survey of Youth (NLSY) which faces the same difficulties as the Displaced Worker Survey in that there are two years between interviews but provides a longer time period than other panel datasets. However, the NLSY does not allow for a close look at the periods immediately preceding and following displacement which the SIPP provides and will be utilized in this study.

Andersson et al (2011) utilize a combination of survey and administrative data to control more carefully for individual and firm fixed effects using the Current Population Survey in combination with Longitudinal Employer-Household Dynamics data to study the impact of employment instability on health insurance coverage in 1997 through 2001. They find the job losers are less likely to have employer provided health insurance, primarily driven by lower take-up rates. However, they are only able to measure health insurance once for each individual. While they can provide more convincing cross-sectional estimates of health insurance coverage using these fixed effect and matching techniques, they are unable to say much about the dynamics of coverage surrounding job loss.

Lin (2005) uses the Health and Retirement Survey to look at the impact of involuntary job loss for older workers not eligible for Medicare. Older workers are more likely to benefit from the pooling mechanism present in employer-provided health insurance than younger workers and have higher average health care costs. As a result, access to health insurance is probably more important for the elderly. Her findings suggest this high demand group is able to recover health insurance following job displacement during good economic conditions in the late 1990s and early 2000s.

Even with the influx of more recent studies, we still do not have a complete picture of how health insurance coverage is impacted by job loss but only pieces of the puzzle. All of these findings taken together do not come to a unanimous conclusion of whether workers are able to regain coverage following displacement, and it is difficult to reconcile the results due to differences in methodology and data sources.

2.3. Data

To investigate the relationship between displacement, health insurance coverage, and wages, I use the Survey of Income and Program Participation (SIPP) panel from 1996. This is the longest available SIPP panel, covering 48 months, from the end of 1995 or the beginning of 1996 to the end of 1999 or early 2000. Due to its length, this panel can capture the most dynamics surrounding job loss available in all available SIPP panels. Since this data captures individuals during good economic conditions, it is likely that estimates will be upper bounds of the impact of job loss on health insurance. I restrict the sample to individuals 25 to 54 years old. Those younger than 25 are less likely to be on a career job, and workers who are older than 54 may be induced into retirement due to job loss. The transition to retirement is likely a different phenomenon than a transition into unemployment. Individuals living in five states are dropped because state of residence cannot be uniquely identified[10].

There is monthly documentation of both health insurance coverage and employment status in the SIPP. This provides a more detailed picture of each than can be found in other

[10] The five states are Maine, Vermont, North Dakota, South Dakota, and Wyoming.

sources, such as DWS for displacement and the CPS for health insurance coverage. I can follow workers over time as their insurance coverage and job attachments change. The SIPP provides information about type of health insurance coverage and whose name is on the policy. This provides a more detailed analysis of the period surrounding displacement than previous studies of the United States. The typical approach to analyses with the SIPP has been at the wave level, which coincides with individual interviews. Individuals are interviewed every four months and provide retrospective information about the previous three months. Studies have provided strong evidence of "seam bias". (Ham, Li, and Shore-Sheppard, 2007) However, by using differences between treatment and control groups and measuring observations based on time [from displacement], it is possible to use the full set of information contained in the data without seam bias impacting our results. To allow for seam bias and for consistency with the literature, I control directly for reference month in the formal analyses.

To identify a sample of displaced workers, I begin with all job leavers. The interviewer asks these individuals to report a reason for the job ending. Approximately two-thirds of job leavers provide a valid response for job ending. To ensure I capture only exogenous job changes, I can only include in the analysis those with a valid reason for job ending. Displaced workers are those who are on layoff and are not recalled to former employer, those whose employer went bankrupt or sold the business, and those who lost a job due to slack work conditions.

The job loss literature has typically focused on more attached workers with the motivation that the costs of job loss are likely higher for this group. I employ two sample selections to ensure attachment to the labor force. The less stringent follows Gruber and Madrian (1997) who require four consecutive periods of employment for sample inclusion. However, four months lead time may not be sufficient to capture between-group differences.

Therefore, I employ a more restrictive requirement of full employment throughout 1996. This identifies more stable workers in both the displaced and non-displaced samples and provides a more complete picture pre-displacement. Others have found evidence that wages and health insurance coverage fall prior to displacement (e.g. "Ashenfelter dip" for wages, Simon (2006) for health insurance coverage). This provides further motivation to carefully measure baseline differences between the displaced and non-displaced in addition to the effects of displacement[11].

Summary statistics for the full sample [less restrictive labor force criteria] can be found in Table 2.1 by whether an individual is ever displaced. The displaced are slightly younger, less likely to be married, and have less education. White-collar jobs, associated with more education, had fewer displacements than blue-collar jobs historically, although this has changed more recently (Strully, 2009). The displaced have lower levels of employer provided health insurance and similar rates of other coverage. They have fewer work-related health issues, some of which is due to the younger age of the sample.

2.4. Analysis

2.4.1 Overview of Job Displacement and Health Insurance Coverage

Before estimating the impact of job displacement on health insurance coverage, I document the relevant patterns in the population to understand overall trends in displacement and health insurance coverage. Since men are typically the primary earner in a family and likely will provide health insurance to his family, I focus the analysis on men. Traditionally secondary earners, women will be less likely to take-up insurance through their own employer. Therefore, the impact of job loss on health insurance coverage would be much smaller for women. To

[11] Jacobson, LaLonde, and Sullivan (1993) find those who are not part of their mass layoff sample do not exhibit much decline in earnings prior to displacement. This suggests the pre-period may be of less of a concern.

reiterate, I only focus on those who are of prime working age; this sample is past school going age and has not reached early retirement. Farber (2005) provides a good overview of displaced workers but the Displaced Worker Survey cannot provide much information about trends in the late 1990s specifically. He reports a three-year displacement rate of 8% for 1997 to 1999 for working-age men. Using the SIPP, I estimate a monthly displacement rate primarily between 0.1% and 0.6% with a slight decrease between 1996 and 1999. These trends by age group are found in Figure 2.1. In general, younger workers experience a slightly higher displacement rate. The monthly rate reported by the SIPP is consistent with the 3-year average, as the monthly rate from three-year value of 8% is 0.22%. I then look at the fraction covered by employer health insurance during this period. There is an increase in coverage over this time period, particularly for younger workers, shown in Figure 2.2. This is consistent with published CPS statistics on employer provided health insurance (EPHI), although most research and reports have focused on the increase in the uninsured over the longer time period (1990s and 2000s). Younger men see an increase in 5 percentage points from early 1996 through the end of 1999. The trend for coverage from all sources increases in Figure 2.3. More 25-34 year olds are covered at the end of the period, an increase of approximately five percentage points, with slightly smaller gains for the other two age groups. The trends look the same as Figure 1b since EPHI is the predominant source of coverage.

Health insurance is offered more frequently at larger firms, and eligibility for take-up typically depends on tenure at the firm to remove differences in job type. I look at both displacement and EPHI to see how incidence and trends differ among more stable workers. This sample includes workers at firms with at least 25 workers and who have at least 2 years of tenure on their current job. These series are founds in Figures 2.4 and 2.5. There is little change in displacement rates over this time period, and we do not see differences by age present in the full sample figures. This is expected as younger workers are less likely to have long tenure or work at large firms. The displacement rates are also much lower than the overall population. Health insurance coverage is much higher among this sample as expected [Figure 2.5], but we still see big differences by age with the more stable population. Younger individuals are more likely to opt out of coverage since they are healthier on average.

2.4.2 Coverage Transitions around Displacement

How do job loss impact health insurance coverage? What happens before and after a worker is forced to leave his job? I address these questions with three approaches. First, I look at transitions in and out of coverage around the time of displacement. I restrict this table by waves for comparability with the following table which are at the wave level due to data restrictions[12]. I break coverage into three groups – full coverage in wave, some coverage in wave, and no coverage in wave – and compare coverage in the wave prior to displacement and the wave of displacement. Both full coverage and some coverage in the wave of displacement will correspond to losing coverage at displacement; a wave is comprised of four months and coverage is usually lost in the month following displacement [health insurance coverage ends at month's end]. I will explore the timing more carefully in following sections. This summary includes coverage that is not tied directly to employment, such as spousal coverage or individually purchased insurance. These simple transitions are found in Table 2.2. Approximately 10% lost coverage in the wave following displacement, pooling the groups "Full-None", "Full-Some" and "Some-None". "Some" coverage could represents lose due to

[12] Unique information about source of coverage is only at the wave-level not the monthly observation.

displacement or merely instability in coverage. It is important to note that about half maintained coverage. To look at changes in coverage source, I split the sample by the type of coverage pre-displacement and look at their source of coverage following displacement in Table 2.3. For those who were covered through their current employer at time of displacement, 55% remain covered by a current employer and 8% have coverage through their former employer. However, 23% no longer have health insurance from any source, which paints a bleaker picture than the previous table.

The second approach is a descriptive analysis in the spirit of estimating a treatment effect. I look at two groups of individuals who worked through an initial period (1996). The treatment group experienced a displacement in 1997 while the control group is never displaced throughout the sample but is allowed to switch jobs. As mentioned previously, the relevant counterfactual to answer the questions of “how does job loss impact health insurance coverage” is what would have happened if the treatment group was not displaced. They may have stayed on the same job or they may have chosen to leave for another opportunity.

I first document the direct impact of displacement on employment [evidence that ‘treatment’ occurred]. There is a sharp drop in the employment rate between January 1997 and January 1998 for those displaced in 1997 shown in Figure 2.6. For all age groups, employment returns to its original levels by the end of 1999, which is between 2 and 3 years post displacement. It is important to also document the impact of the displacement on wages, as this has been the traditional focus of the job loss literature and helps place this study in the context of the literature. Younger (25-44) displaced workers have lower wages pre-displacement than the control group, but this was not the case for the middle-aged workers (45-54). Figure 2.7 plots average log weekly wages and shows wages recover almost fully following displacement. We might see a larger drop in wages around displacement if the displaced were returning to work at the first possible job opening. During a period of economic boom, displaced workers' reservation wages may not drop during initial unemployment period since they are confident there are plenty of available good jobs. The middle-aged (45-54) workers looked more like the non-displaced in the initial period, and they experience a steeper drop in wages during the displacement period than the younger workers. It is not clear what the impact of displacement is on wages for the younger workers using these simple comparisons; it appears there is no impact of job loss.

Turning the focus to health insurance coverage, I first look at health insurance coverage through current employer in Figure 2.8. Access to the former employer' health care plan is available after displacement through COBRA but is not included in the figure. We see changes in health insurance around the time of displacement, but not a sharp drop in coverage. Since I pool workers with job loss over a twelve-month period, it is hard to know how strong the impact is. Again younger (25-44) displaced workers have lower coverage before displacement while the gap is small or non-existent for the older displaced workers. These simple comparisons of health insurance, wages and employment suggest we must be careful in collapsing working-age men together. Figure 2.9 presents the same comparison for health insurance from any source. Those with other sources of coverage will mute any impact of displacement as will quick re-entry to employment. It looks nearly identical to Figure 2.8, only a small parallel shift upward. Since most individuals have insurance through their employer, changes in this source of coverage will dominate any trends occurring in other sources.

2.4.3 Event Study Approach to Displacement

A common approach to study the impact of job displacement is referred to an event study. Displacement is the event whose impact we are studying, so I pool displacements over the entire SIPP panel, and center the series at the date of displacement. We can control for the date directly in the specification since individuals are displaced at different dates. (Jacobson, LaLonde, and Sullivan, 1993; JLS, henceforth).

The model estimated is:

$$EPHI_{it} = \beta + \Sigma_k \delta_k \cdot D^k_{it} + X_i \cdot \gamma + \pi \cdot State + \tau \cdot Time + \varepsilon_{it} \qquad (1)$$

D^k_{it} are equal to 1 if at time t, the number of months to displacement equals k. Values of k below zero denote observations before displacement. The remaining figures plot k on the x-axis and $\hat{\delta}_k$ on the y-axis. For $\hat{\delta}_k$ to estimate the causal impact of job loss on health insurance, we need ε_{it}, including individual specific α_i to be uncorrelated with both displacement and health insurance coverage. Typically, fixed effects models are used to eliminate bias from unobserved worker heterogeneity in models of wages and earnings. However, with few transitions between health insurance coverage providing little unique variation, estimates would be driven by the "frequent" coverage changers and not be representative of the overall population. Therefore, for health insurance outcomes I do not present results from fixed effects models. Causality will rest on the exogeneity of displacement. In addition, I directly estimate the impact of displacement and drop the first time period. This ensures the remaining δ_k capture the effect of displacement relative to any pre-differences between groups.

I look at simple differences over time in the previous section and want to clearly document the transition between this and the JLS approach. Detailing the relationship between the two approaches is not typically done. I begin with the sample used in Figures 2.6 through

2.9, all workers employed throughout 1996. This is fairly strict restriction in general, but it creates treatment and control groups more similar at baseline. In addition, most studies of job displacement have focused on more stable workers. Since displacement occurs in 1997, the maximum number of months prior to displacement available is 24 but the entire displaced sample will have a minimum of 12 months pre-displacement. Therefore, I only estimate differences up to 12 months prior to displacement to include the full sample in each estimate.

To present the cross-walk between the simple comparisons from the previous section and models that controls for individual and job characteristics, Figure 2.10 recreates Figure 2.8 from the previous section but implements a center at displacement and pools all age groups. This is akin to a simple treatment effect approach of differences-in-differences without using control variables to increase precision of the estimates or explain baseline differences. Figure 2.10 presents three estimates. The first is the raw difference including the difference in levels between the two groups. The remaining models directly estimate the baseline difference since I want to estimate the impact of displacement directly. The second model removes the differences in initial period which provides a parallel shift of the first series. The final model adds a time trend. The control group experiences a slight increase in coverage over the sample [see Figure 2.8], so adding in a time trend increases the difference between the two groups. Since the control group identifies the time trend in each model, I must assume trend of the control group is a valid counterfactual for the displaced sample. There is very little time trend in coverage during this period of economic boom so there is less reason for concern.

We see a sharp decline in coverage starting four months prior to displacement. This could be driven by seam bias. If the respondent is displaced in the final month of the wave, he may report no coverage for the entire wave. As a result, I do not want to stress this finding. There is a continuous increase in coverage as time from displacement increases. These simple estimates suggest insurance coverage recovers almost fully after two years. Coverage levels after two years are approximately five percentage points lower than the initial levels, with the time trend removing half of this difference. As a reference, coverage rates of the treatment group are around 80% with the young slightly lower and the middle aged slightly higher. The maximum impact on coverage occurs in the month following displacement since coverage will be dropped at the end of the month displacement occurs.

I next add controls for both individual and job characteristics since these factors impact the supply and demand of health insurance coverage. These factors could impact coverage outcomes both pre- and post-displacement. I do not want to attribute the raw difference or changes in coverage solely to displacement if coverage is merely correlated with individual or job characteristics. The model without controls is a valid treatment effect estimate of a difference-in-difference approach only if we are confident in the exogeneity of displacement. The individual controls used are age, race, education, work-related disability, marital status and the number of children [split by whether they are under age 6, or ages 6 to 18]. Job controls are limited to two-digit industry and occupation in addition to three categories for firm size. The choice of job characteristics is not straight-forward. Post displacement, current job characteristics are an endogenous outcome, like insurance coverage and wages. It is jointly determined with our outcome variable, employer-provided health insurance. However, the date at which to choose initial job characteristics, which are less endogenous post-displacement, for the treatment and control groups is not immediate. I leave this exploration for future work. In addition, using current job status allows for identical definitions for both treatment and control groups.

Figure 2.11 combines the date fixed effects model from Figure 2.10 with models including controls for individual and job characteristics to show how each set of controls contributes to the difference in coverage experienced by the treatment group at each point in time. We observe a slight decline in coverage in the few months prior to displacement with the sharpest drop occurring just following displacement. We still see a recovery to slightly below pre-displacement coverage levels by two years following displacement. Adding in the control variables suggests the recovery time for coverage is slightly longer than the time-adjusted differences since the solid line is below the dotted line. However, the magnitude of loss is similar after we add in the controls, approximately 15%. Exact values for the “drop” [D_0=1] can be found in Table 2.4. Table 2.4 provides results from a simplified model where the time before and following displacement and broken into categories to provide estimates of pre-differences, the dip before displacement, the drop at and just following displacement and the recovery[13]. Including current job characteristics as controls does not remove initial differences between the displaced and not displaced in health insurance coverage. Furthermore, they do little to explain differences post-displacement although allowing for differences does narrow the gap between the displaced and the control group slightly. This suggests that job type is not responsible for observed difference in insurance coverage through one’s employer. Individual characteristics and a time trend explain almost half of the baseline differences [-7.6% vs. -4.2%] but slightly increase the change the amount of recovery time [-8.6% vs. -5.8%]. The time trend is primarily responsible for the latter whereas the individual characteristics are responsible for baseline differences. This highlights the need to be confident in the controls being a valid counterfactual time trend. The preceding analysis is also performed for coverage from any source. The qualitative findings are not substantially different and results are available upon request.

[13] An analogous table for women can be found in the Appendix B for comparison.

The previous section pointed to stark differences in wages and health insurance by age both pre- and post-displacement. To follow-up, I look at whether simple demographics and job type can explain the observed age differences or if there is a differential relationship between job displacement and health insurance (and wages) for younger workers. Figure 2.12 presents results from models with only individual level controls. Since current job characteristics do not play a strong role, I proceed with the simpler model. However, adding in job type does not change the findings. Once we control for age, education, disability and family structure, the age differences in coverage disappear. These estimates are noisier due to the smaller sample size but the patterns are fairly consistent across age groups. Younger workers see a sharper decline and less recovery. These results are a muted version of the raw patterns in the data seen in Figures 2.8 and 2.9. In unreported results, differences in disability levels are a primary factor driving differences between age groups for health insurance coverage.

For the full sample of all displaced workers, I present analogous results in tables since the findings are similar. The requirement for sample inclusion is four consecutive months of employment prior to displacement, which will include individuals with less labor force attachment than the previous sample and allow for displacements in the other three years contained in the panel [1996, 1998, and 1999]. Results for EPHI are found in Table 2.6. There is a slight, insignificant decline in coverage prior to displacement, but most of the fall in coverage occurs at displacement and the months immediately following. This group sees a full recovery two years following displacement. However, the less attached workers in the expanded sample have lower levels of insurance coverage leading to baseline differences of -8.9% [Row 1, Column 1 of Table 2.6] for the expanded sample compared to -4.2% in the restricted sample [Row 3, Column1 of Table 2.4]. Due to these baseline differences, it is not surprising they are able to return to this lower coverage rates. For similar reasons, the expanded sample experience a smaller drop in coverage levels in the months immediately following displacement [-15.6% vs. -20% in months 1 to 3 following displacement].

These results are generally consistent with what has previously been found in the literature. Simon (2006) finds a significant difference in baseline coverage more than a year prior to displacement and estimates a decline in coverage leading up to displacement which is a stronger, negative result than this study which finds a small dip prior to displacement. Lin (2005) finds this recovery of insurance coverage within two years as well, although focusing on older workers. The overall finding from this analysis is the further an individual gets past separation, the less of an effect job separation has on health insurance coverage. Two years following displacement post-displacement, displaced workers are not insured much less than the non-displaced in this analysis. In the full sample, the displaced workers are actually end up at coverage levels above baseline levels. This stands in contrast to Gruber and Madrian (1997), who find a drop in coverage at separation and in the few months following separation, at which point the effect flattens out. However, they only analyze through month 12, consider all job separations, voluntary and involuntary, and examine a different time period. They find separators are much less likely to be insured by about 30%. The largest magnitude I find is -16% in the month following separation for the more attached sample. These findings are also consistent with the Kosteas and Renna (2009) who find after 6 months there are no differences in coverage between the displaced and non-displaced.

2.4.4 The effect of job loss and health insurance on wages

When considering reemployment wages after a job loss, it is important to disentangle effect of health insurance from that of past earnings[14]. Conditional on a given marginal product, jobs which offer health insurance should lower wages. However, more productive jobs are more likely to offer health insurance as part of the nonwage compensation[15]. This makes it difficult to disentangle the channels through which health insurance affects wages[16]. This distinction is vital to understanding the mechanisms involved during unemployment and is something to be explored in further research [see Simon (2001) and Stinson (2003) for work on this topic]. In order to address this, a structural model must be developed and evaluated instead of using a reduced-form approach like the current analysis. Difficulties arise because health insurance and wages upon reemployment are jointly determined. As a result, the remaining analysis should be considered a descriptive exercise.

First, I look at the pattern of wages across time in the event-study framework, returning to the original restricted sample of those fully employed in 1996. I estimate (1) with log wages as the dependent variable including both individual controls and an individual fixed effect. The β's from this model are shown in Figure 2.13. Displaced workers experience a 20% loss in weekly wages in the month of displacement with weekly wages returning to their pre-displacement level around one year following displacement. It is important to keep in mind that we are comparing two groups with a substantial attachment to the labor market during a period of economic boom. Estimates of the baseline differences and comparison between models can be found in Table 2.6. Results including current job characteristics are similar, with estimates

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[14] Anderson and Meyer (1997)
[15] Both of these facts are reviewed in Gruber (2002)
[16] Currie and Madrian (1999) for an extensive discussion.

from the category model found in Tables 2.6 and B1 for the restricted and full samples, respectively.

Next, I look at how wage dynamics vary by health insurance status. Initially, I compare those with health insurance and those without coverage on a monthly basis. Figure 2.14 shows the results from this type of comparison. Health insurance status does not have a large impact on the magnitude of wage loss experienced at displacement, approximately a 20% decrease. The results confirm what previous studies have found: in the cross-section, higher wages and the provision of health insurance on the job are positively correlated (e.g. Simon, 2001). Individuals on jobs without health insurance begin at lower wages. These results also show that within a year, wages return to their previous level for both individuals with and without coverage, with perhaps some convergence between the groups.

It is naïve to compare the uninsured with the insured at each point in time. The distinction between the two groups is a result of decisions that each household makes and their underlying preferences. In addition, the comparison in each period allows individuals to move between samples as they gain or lose insurance. Furthermore, it seems probable there are individual-specific unobservable characteristics which change over time, most importantly health. This endogeneity will exert a negative bias on $\hat{\lambda}$ since poor health is negatively correlated with wages due to productivity but positively correlated with the demand for health insurance. Maintaining constant sample definitions throughout the sample addresses these concerns at least partially. The results from previous section suggest coverage begins to drop pre-displacement and I want to allow for this when creating the sample[17]. I split displaced workers by coverage pre- and post-displacement. The first group has full EPHI in months -12 to

[17] It is not known where this dip is due to an actual drop in coverage or seam bias.

-5 ["Have HI"] and the second group does not have full coverage in this time period[18]. The fractions in the overall population are 49.8% and 50.2%. I split the "Have HI" group into two by whether they lost coverage following displacement, defined as less than full coverage in months 1 through 4 following displacement ["Keepers" and "Losers"]. The "Keepers" are 29.6% of the displaced sample and the "Losers" are 20.3%. To display health insurance coverage by categorization, Figure 2.15 plots the average EPHI for each of these groups in the months relative to displacement[19]. There is little change in EPHI for the "keepers" even after the initial period post-displacement. The lowest coverage level in the two years following displacement is 83%, fairly demonstrating strong preferences for coverage. As expected, there is a sharp fall in coverage for the "losers" with the recovery starting in month 4 and recovering to 60%. This suggests that recovery back to original levels is difficult for those who lost their coverage and did not gain coverage through initial job post displacement, since only the employed can be covered by EPHI. In addition, low level of coverage do not appear to be a permanent state as those without full coverage leading up to displacement see increases in coverage levels following displacement. They saw coverage increase from rates of 15% to approximately 50%. Perhaps this group took the opportunity to search for a job with health insurance coverage following displacement.

To estimate (1) I need to select the non-displaced workers by their initial insurance coverage. I restrict the sample to those who had full employer-provided coverage in their first two interview waves, for a total of 8 months. This restriction removes 16% of the control sample, almost all of whom had no coverage through the first 8 months. This allows changes in coverage

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[18] Results from restricting the sample to full coverage for the 12 months pre-displacement look very similar but are slightly noisier due to the smaller sample size.

[19] This does not show $\hat{\delta}_k$ but averages of coverage rates.

for the non-displaced sample that could result from voluntary job changes, for example. This is important since we want to the control group to represent what would have happened in the absence of job displacement. Figure 2.16 presents estimates of the wage model without individual fixed effects to show baseline differences in wages between the three groups. The dynamics shown in Figure 2.16 are not affected by whether individual fixed effects are present or not. Those who did not lose coverage started at a higher baseline and saw little change in wages following displacement. Since they did not lose coverage, it suggests the higher earnings individuals were able to transition into a new job immediately without any negative impact on wages. Both the "Losers" and the "Not fully covered" saw the steep drop in earnings at displacement with a quicker recovery for the "not fully covered".

2.5 Conclusions

This study looked at the impact of job loss on health insurance coverage and how wage outcomes vary by insurance status. This study is the first to look at health insurance coverage pre and post displacement in one framework and use the monthly periodicity available in the SIPP. I find displaced workers see almost a full recovery in employer-provided insurance coverage within two year of displacement. The pre and post-displacement differences in coverage cannot be explained by individual or job characteristics suggesting job losers begin at jobs without health insurance and with lower wages. I also find wages recover to pre-displacement levels with one year of job loss. It is important to keep in mind that these findings represent relationships during strong economic conditions. I also show wages are higher for the insured than the uninsured, providing further evidence that jobs without health insurance are "bad jobs". However, there are pre-differences in wages for those that lose coverage compared to those that maintain coverage, and these unobserved differences could help explain differences in wages by health insurance coverage. It is important to extend this analysis to look at both career women and job losers in poor economic conditions. The experiences of these groups could be vastly different than the results here and we need to expand our knowledge on the relationship between job loss and health insurance.

Figure 2.1. Monthly Displacement Rate, Males
Three Month Moving Average

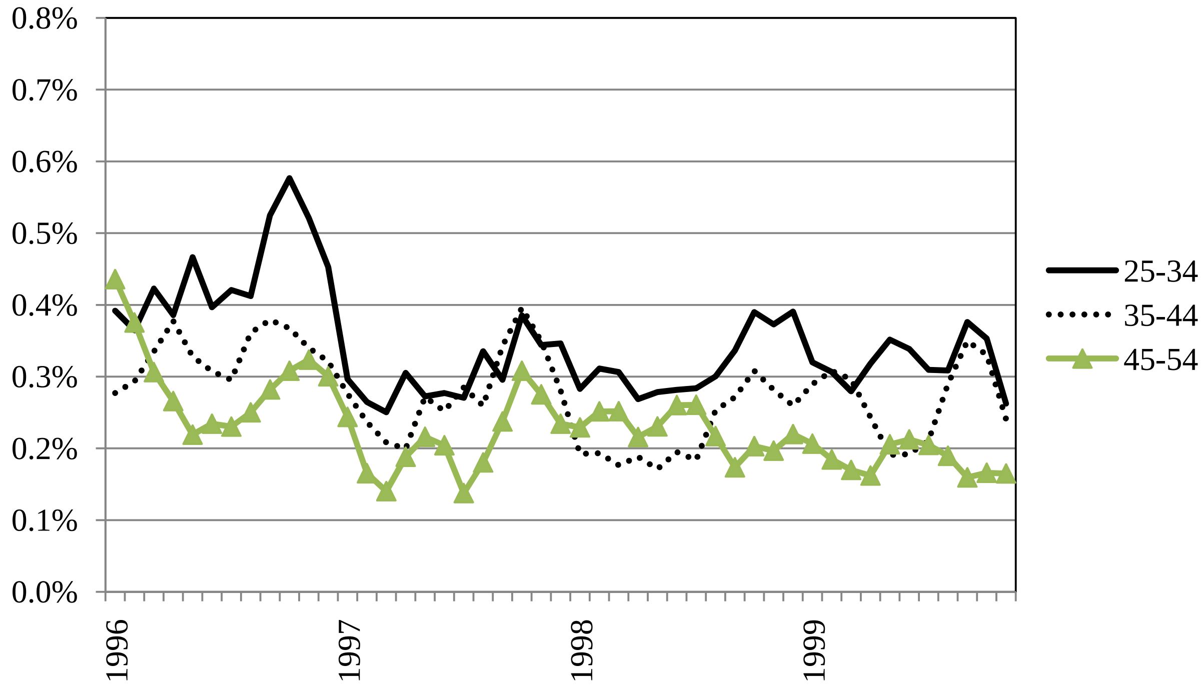

Figure 2.2. Fraction Covered by Own Employer Provided Health Insurance in Each Month, Males

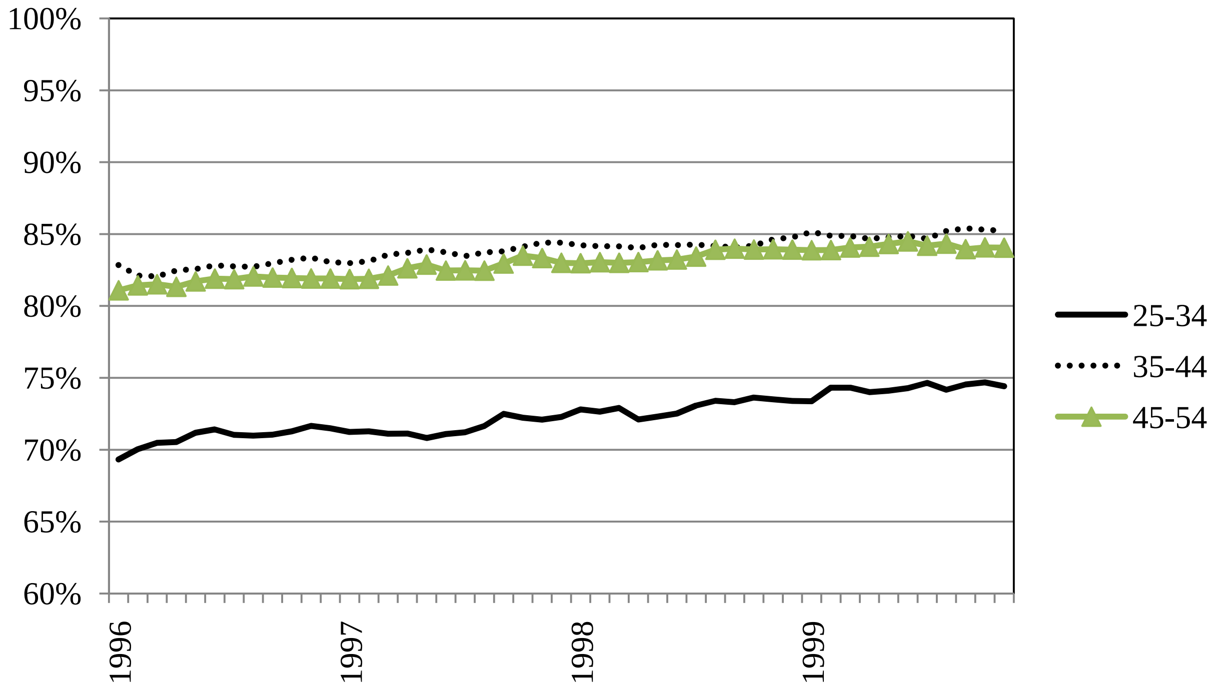

Figure 2.3. Fraction Covered by Any Health Insurance in Each Month, Males

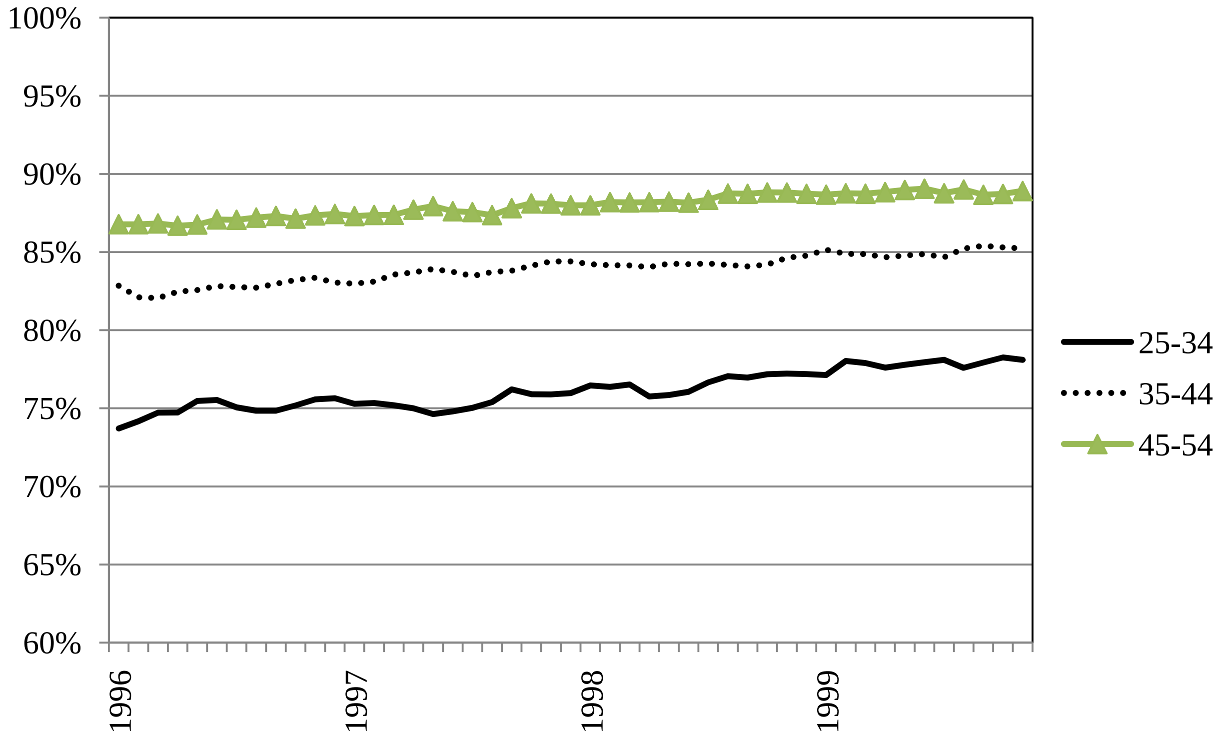

Figure 2.4. Monthly Displacement Rate by age group, Males
Three Month Moving Average
Sample: Individuals at firms with at least 25 employees and 2 years of tenure

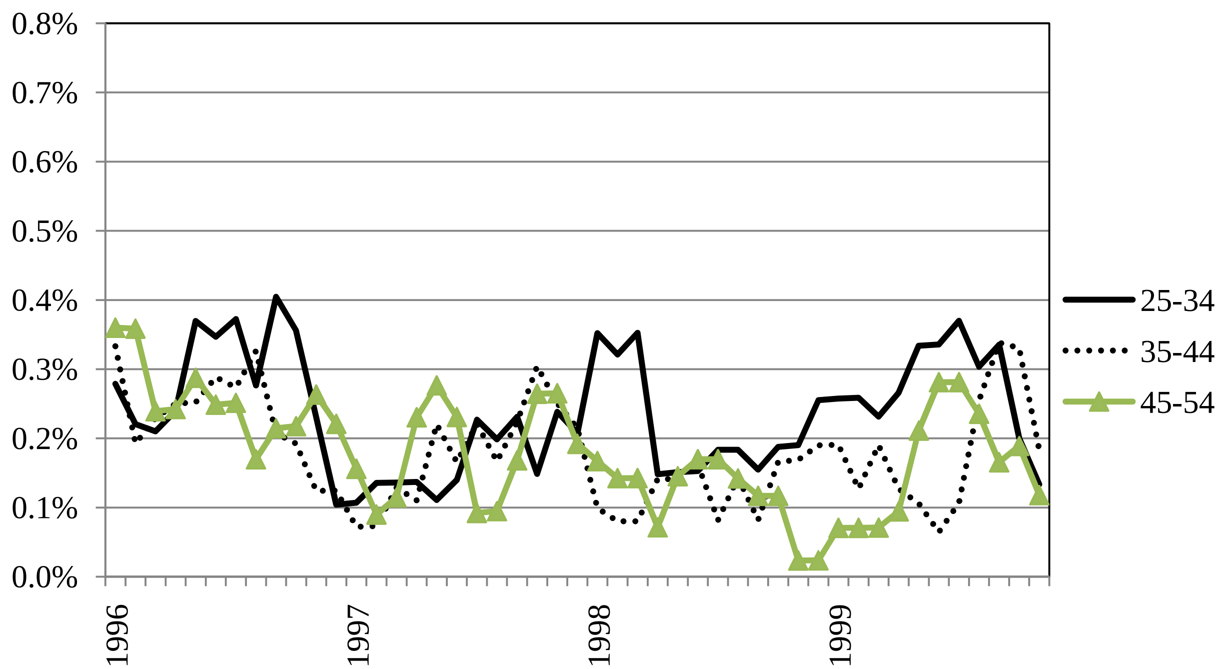

Figure 2.5. Fraction covered by own employer provided health insurance in each month
Sample: Individuals at firms with at least 25 employees and 2 years of tenure

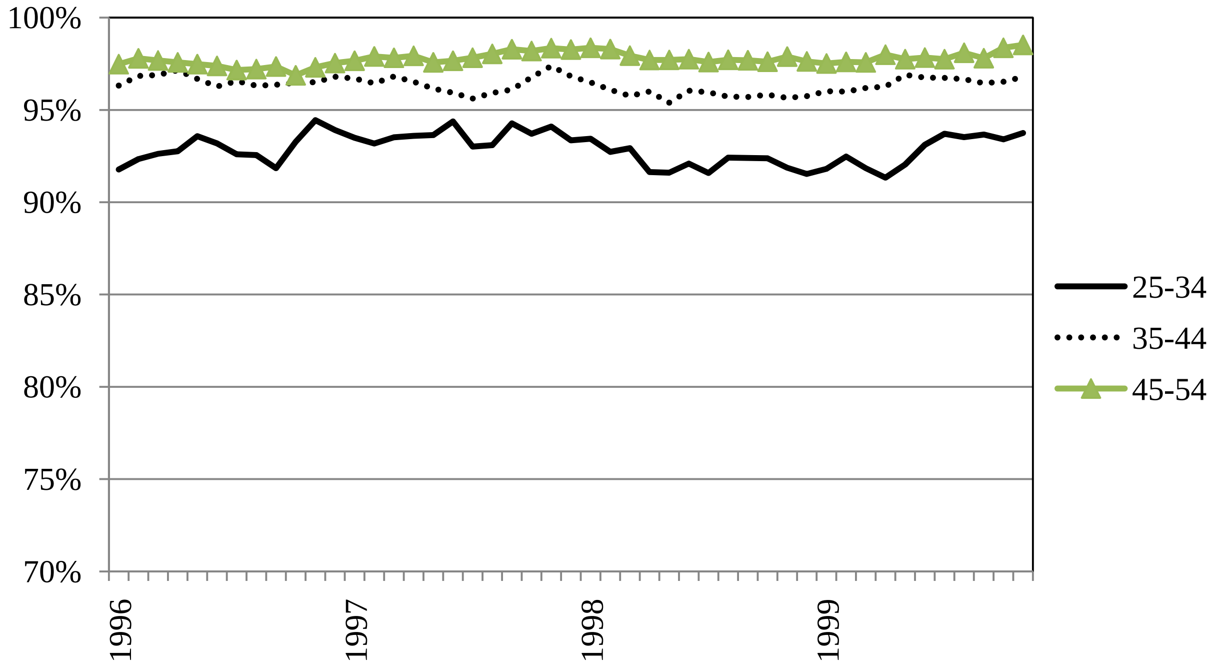

Figure 2.6. Employment Rate, Males
Sample: Those fully employed in 1996.
Treatment group are displaced in 1997 & Control group is never displaced

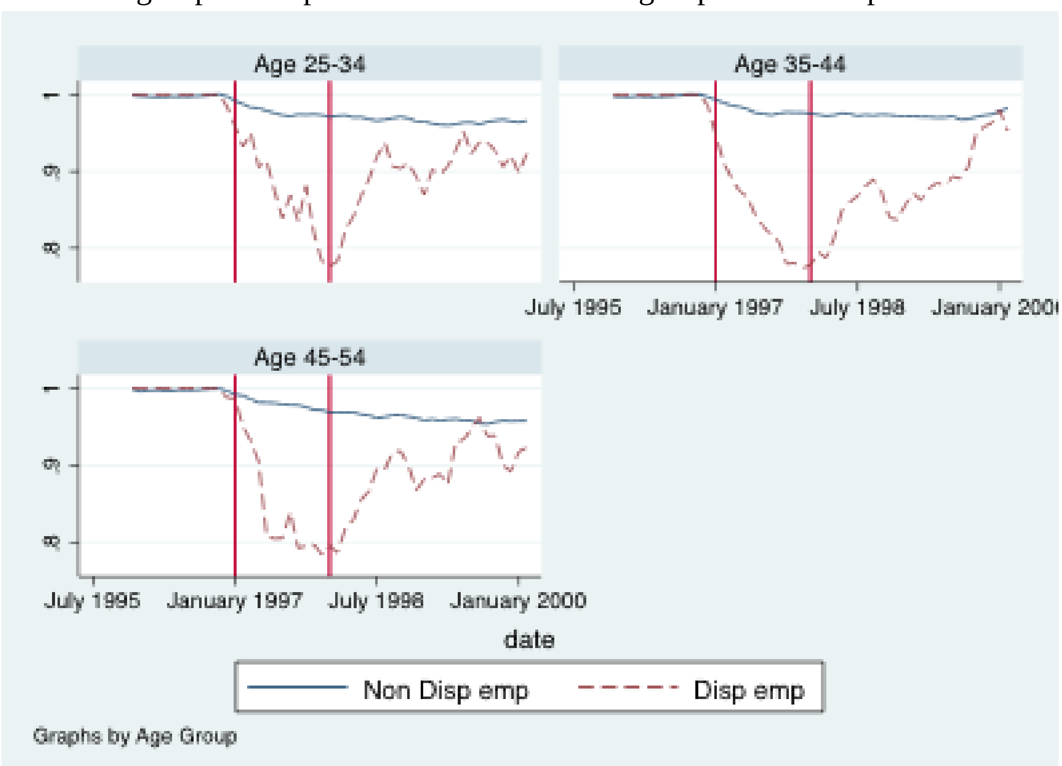

Figure 2.7. Average log weekly wages, Males
Treatment – displaced in 1997 vs. controls – never displaced

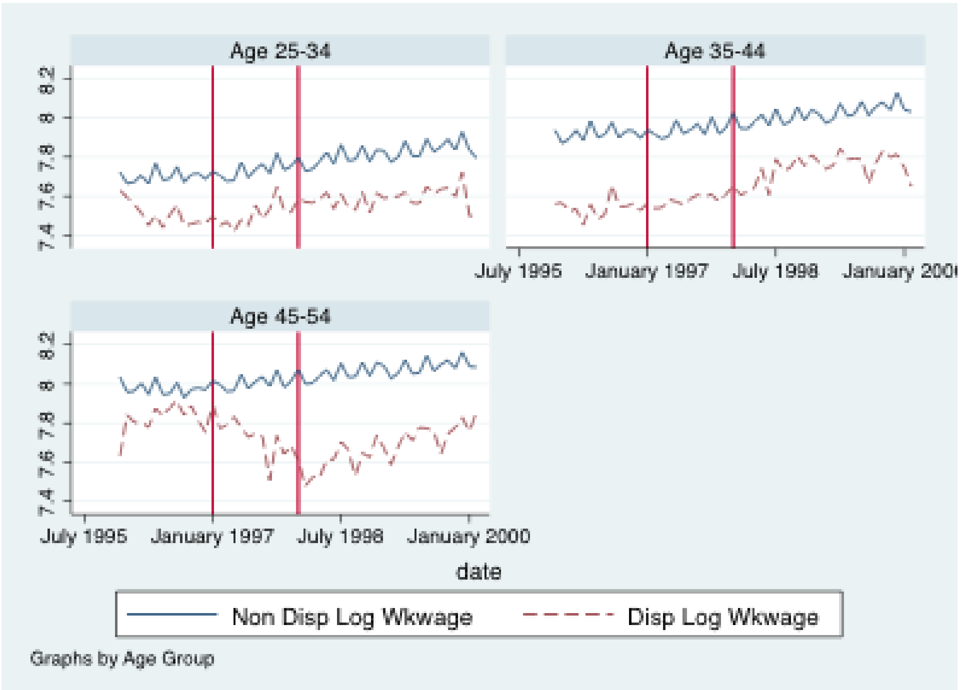

Figure 2.8. Fraction with Own Employer Provided Health Insurance, Males
Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

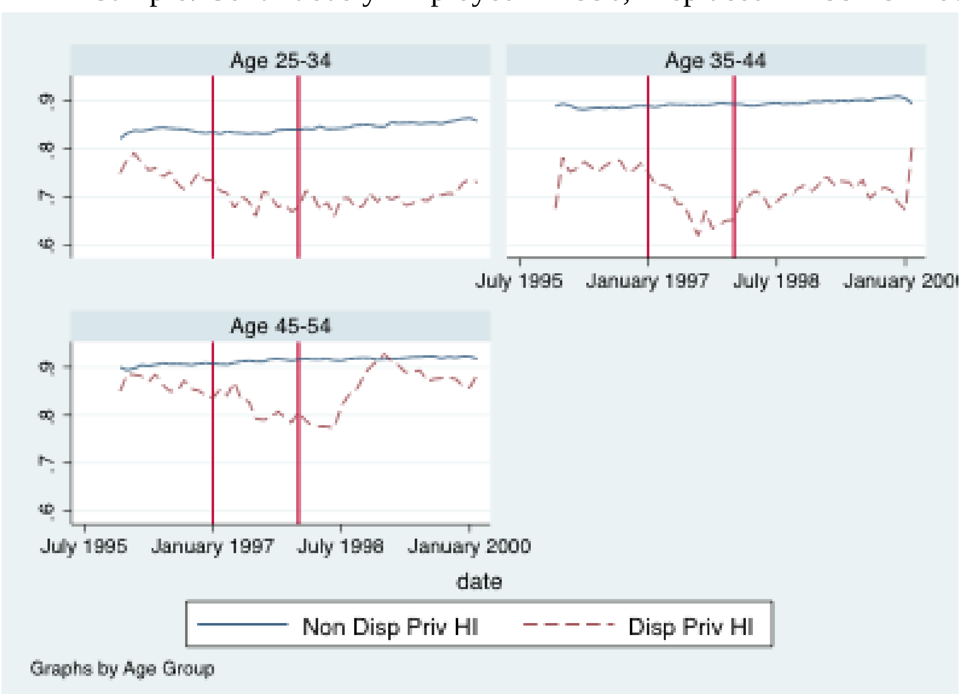

Figure 2.9. Fraction with Any Health Insurance Coverage, Males
Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

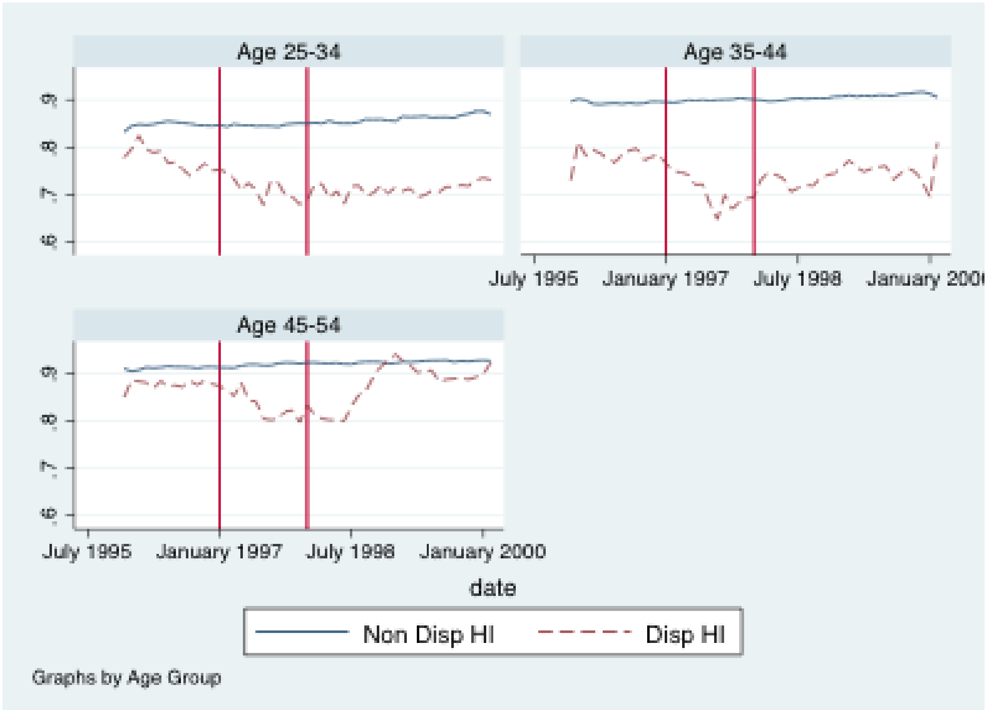

Figure 2.10. Raw Differences in Employer Provided Health Insurance by Time to Displacement
Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

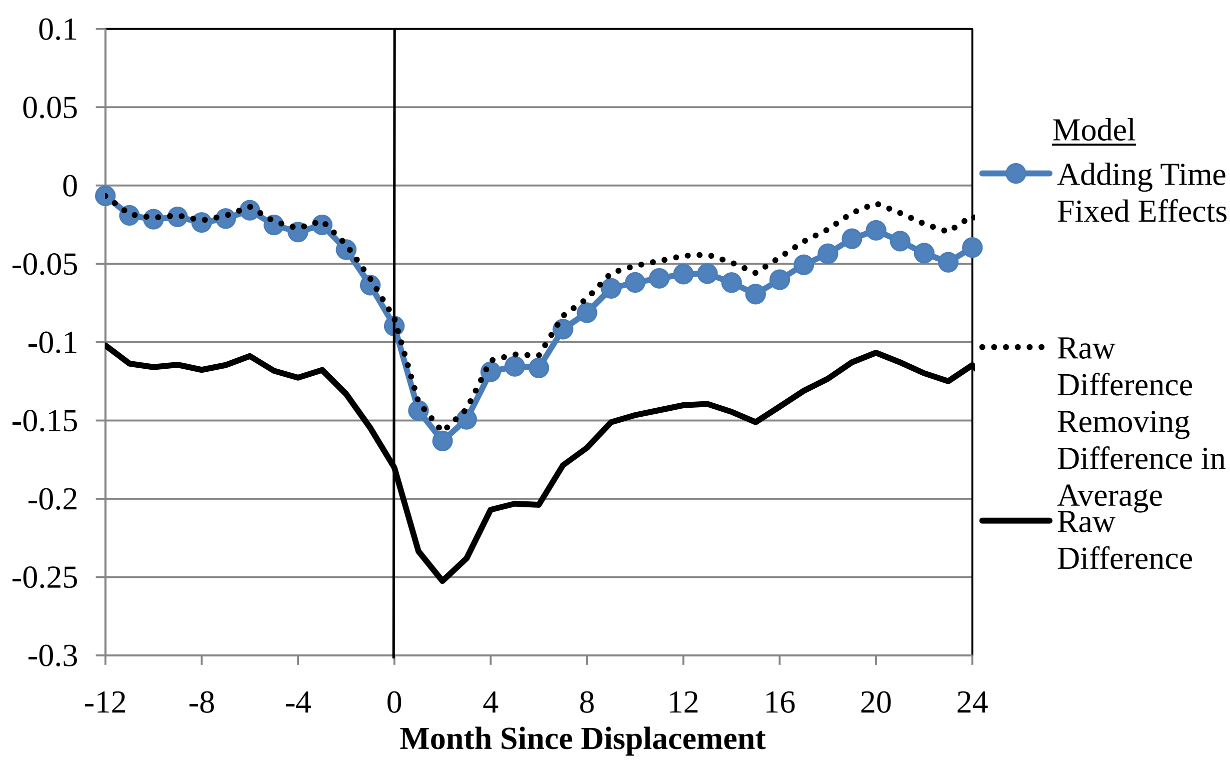

Figure 2.11. Probability of Employer Provided Health Insurance Coverage by Time to Displacement

Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

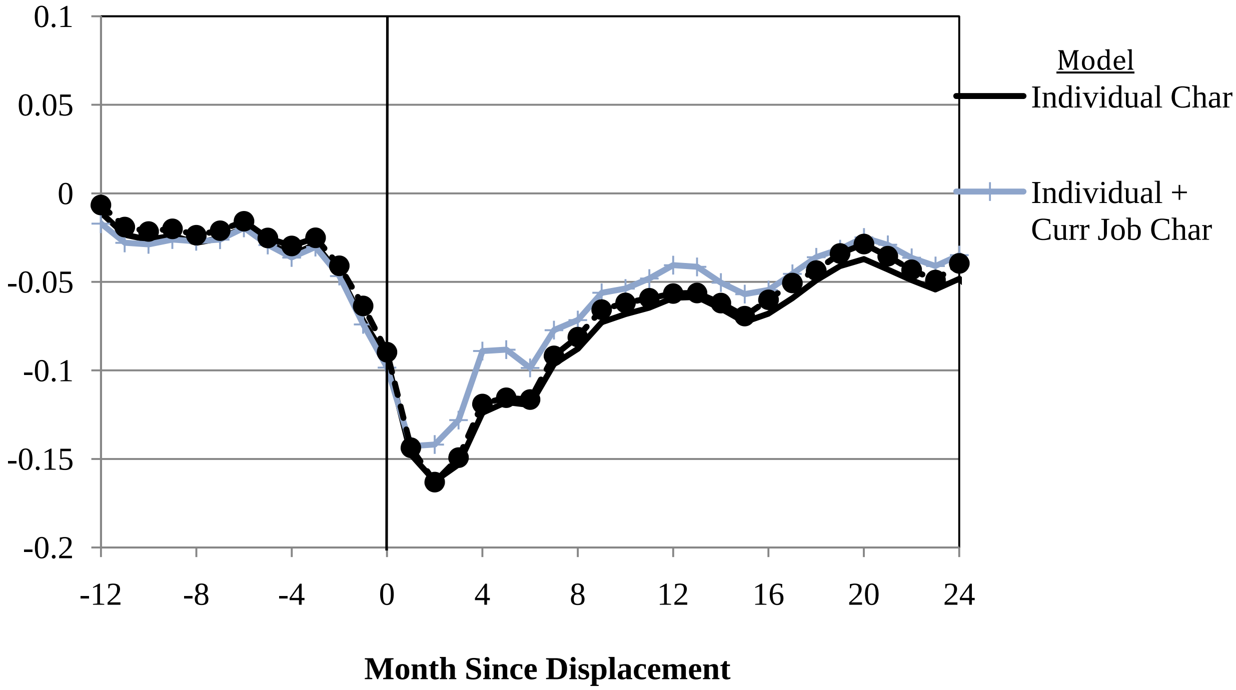

Figure 2.12. Probability of Employer Provided HI Coverage by Month to Displacement and Age Group

Model: Individual Characteristics Only

Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

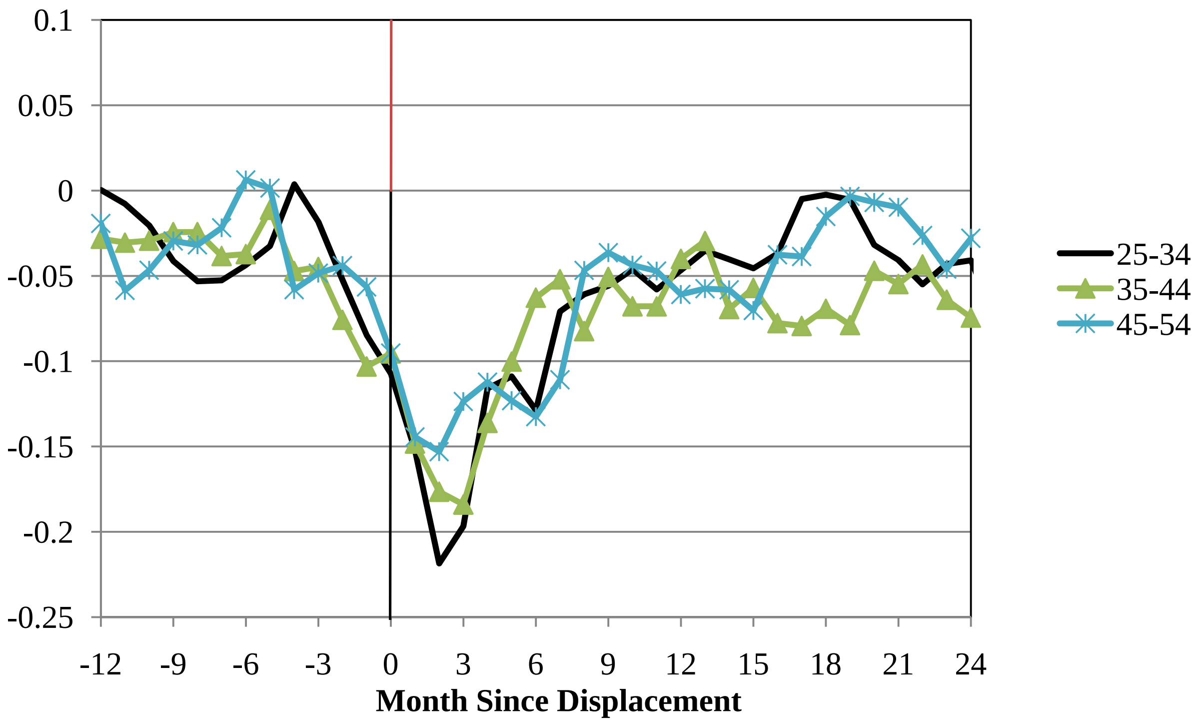

Figure 2.13. Log Weekly Wages by Time to Displacement
Model: Individual Characteristics, Individual FE
Sample: Continuously Employed in 1996, Displaced in 1997 & Never displaced

Figure 2.14. Log Weekly Wages by Time to Displacement and Current Employer Provided Health Insurance Status
Model: Individual Characteristics, Individual FE
Sample: Continuously Employed in 1996, Displaced in 1997 & Never displaced

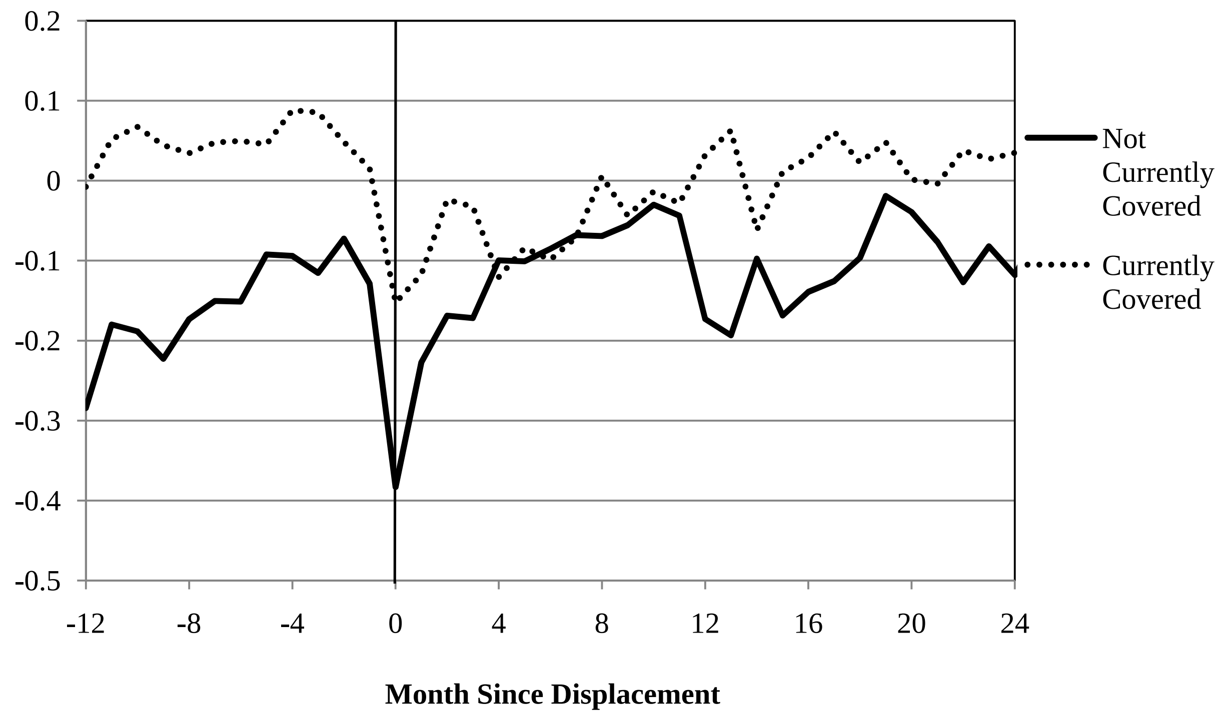

Figure 2.15. Rate of Employer Provided Health Insurance by Status Change near Displacement
Pre-HI: Employer-provided Health Insurance in months 5 through 12 pre-displacement
Post-HI: employer provided health insurance in months 1 through 4 post-displacement

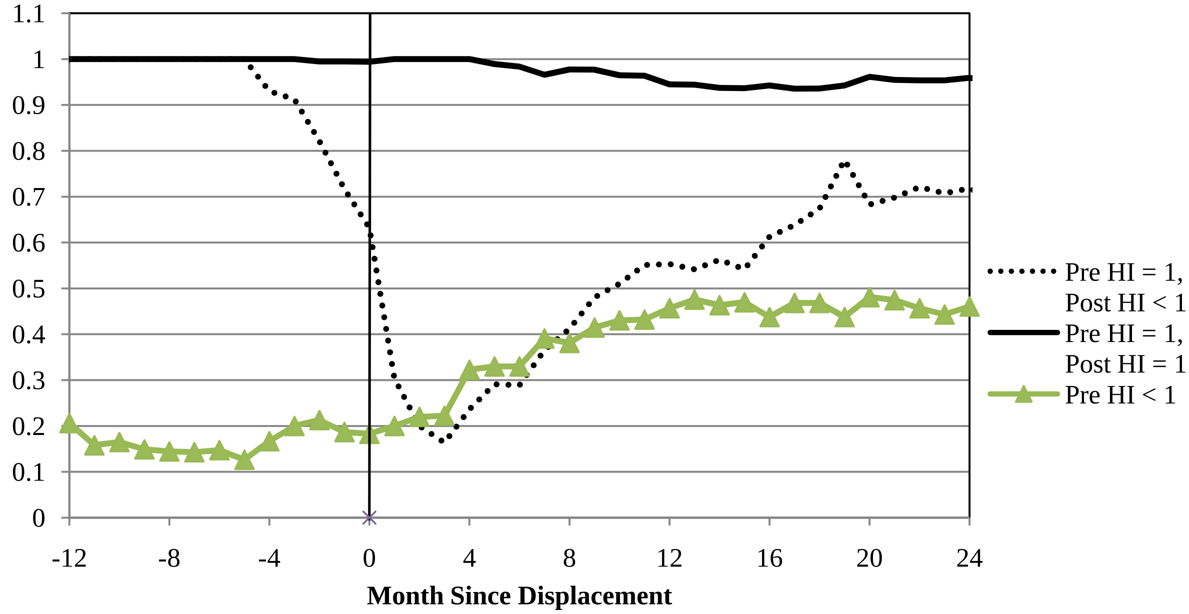

Figure 2.16. Log Weekly Wages by Employer Provided Health Insurance Coverage Change near Displacement
Control Variables: Individual Characteristics
Sample: Non-displaced: All those with Full EPHI in first two waves
Pre-HI: employer provided health insurance in months 5 through 12 pre-displacement
Post-HI: employer provided health insurance in months 1 through 4 post-displacement

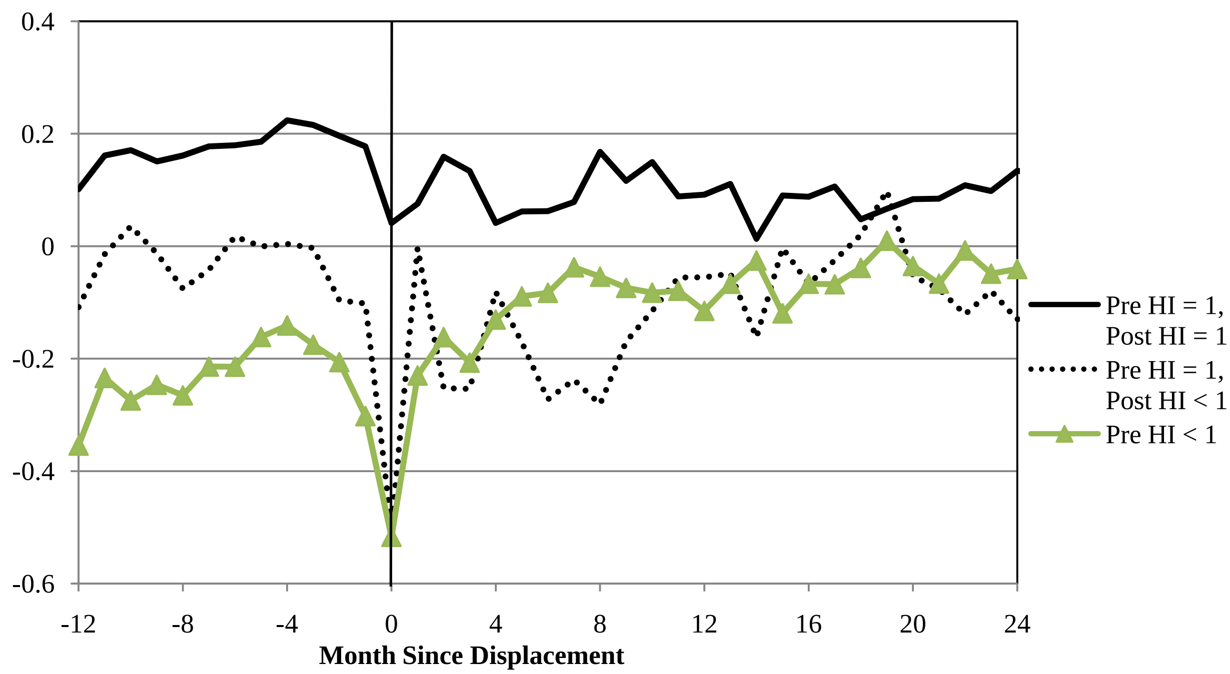

Table 2.1. Summary Statistics of 1996 Survey of Income and Program Participation
Standard Deviation in parentheses

	Displaced	Never Displaced
Employer Provided Health Insurance Coverage	59.1% (49.2%)	74.0% (43.8%)
Any Insurance Coverage	63.6% (48.1)	78.8% (40.9%)
Age	35.9 (8.56)	37.4 (8.74)
Black	9.9% (29.8)	11.3% (31.6%)
Hispanic	14.8% (35.6)	10.6% (30.8%)
High School	38.7% (48.7)	33.7% (47.3%)
Some College	28.7% (45.2)	27.9% (44.9%)
At least a College Degree	15.0% (35.7)	25.8% (43.8%)
Married	59.1% (49.2)	63.4% (48.2%)
Disability	17.2% (37.7)	19.7% (39.8%)
Average Wage in First Wave	$1,781 ($2,116)	$2,240 ($2,736)
# Observations	2,932	22,436

Table 2.2. Health Insurance Transitions Around Displacement, Full Sample of Male
Displaced Workers

[Joint Probability] [Row Marginal Prob]	Full Coverage	Some Coverage	No Coverage	TOTAL
Full Coverage	34.6% 78.8%	1.0% 2.3%	7.5% 17.1%	43.9% 100%
Some Coverage	1.3% 4.6%	26.1% 91.9%	1.0% 3.5%	28.4% 100%
No Coverage	3.7% 13.1%	1.7% 6.0%	22.5% 80.8%	27.8% 100%

# of individuals = 2,932

Table 2.3. Coverage Transitions – Pre and Post Displacement, Full Sample of Male Displaced Workers
[Marginal probabilities within pre-displacement type]

Pre-Displacement Source Of Coverage [Fraction of Population]		Post Displacement Source of Coverage [Marginal Row Probability]: None	Dependent	Current Employer	Former Employer	Other	[Total]
	None 33.6%	72.9%	2.5%	16.1%		8.5%	[100%]
	Dependent 12.3%	10.7%	70.2%	13.7%		5.4%	[100%]
	Current Employer 40.3%	22.5%	7.5%	54.9%	7.5%	7.6%	[100%]

Number of Individuals = 2,122

Table 2.4. Probability of Employer Provided Health Insurance, Restricted Sample
Sample: Employed in 1996
Treatment group: Displaced in 1997

		Change to Baseline						
	Baseline	Months Pre-Displacement		Displace-ment	Months Post-Displacement			
MODEL		-12 to -5	-4 to -1	0	1 to 3	4 to 11	12 to 23	24+
Raw Difference	-7.6% (3.3%)	-3.0% (2.5%)	-7.9% (2.9%)	-13.5% (3.3%)	-19.0% (3.3%)	-12.8% (3.6%)	-6.2% (2.7%)	-5.8% (3.7%)
Date Fixed Effects	-6.9% (3.3%)	-3.3% (2.5%)	-8.7% (2.9%)	-14.2% (3.3%)	-19.7% (3.3%)	-13.7% (3.6%)	-7.4% (2.7%)	-7.4% (3.7%)
Individual	-4.2% (3.3%)	-3.7% (2.5%)	-8.9% (2.9%)	-14.4% (3.3%)	-20.0% (3.3%)	-14.3% (3.6%)	-8.1% (3.7%)	-8.6% (4.6%)
Indiv + Current job	-7.0% (3.0%)	-3.3% (2.3%)	-8.8% (2.7%)	-13.4% (3.2%)	-12.5% (3.2%)	-7.0% (3.4%)	-2.9% (3.5%)	-3.6% (4.3%)

Table 2.5. Probability of Employer Provided Health Insurance, Full Sample
Sample includes all Displaced and never displaced workers with at least 4 months of employment

		Change to Baseline							
	Baseline	Pre-Displacement			Displace-ment	Months Post-Displacement			
MODEL		-24 to -13	-12 to -5	-4 to -1	0	1 to 3	4 to 11	12 to 23	24+
Indiv	-8.9%	2.4%	0.0%	-6.2%	-11.2%	-15.6%	-10.0%	2.5%	0.1%
	(1.9%)	(1.6%)	(1.8%)	(1.9%)	(2.0%)	(2.1%)	(2.3%)	(2.3%)	(2.3%)
Indiv + Current job	-10.9%	1.9%	0.0%	-9.9%	-14.9%	-13.6%	-5.9%	0.0%	1.8%
	(1.6%)	(1.4%)	(1.6%)	(1.7%)	(1.7 %)	(1.7%)	(1.8%)	(2.0%)	(1.9%)

Table 2.6. Log Weekly Wages, Restricted Sample
Sample: Employed in 1996
Treatment group: Displaced in 1997

		Change to Baseline						
	Baseline	Pre-Displacement		Displace-ment	Months Post Displacement			
MODEL		-12 to -5	-4 to -1	0	1 to 3	4 to 11	12 to 23	24+
Individual	-14.8%	-1.7%	0.2%	-24.9%	-8.3%	-4.8%	-3.3%	-1.7%
	(3.8%)	(2.9%)	(3.7%)	(4.9%)	(4.5%)	(4.1%)	(4.2%)	(5.0%)
Individual, FE	-----	-0.6%	2.2%	-21.8%	-10.1%	-4.8%	-0.5%	-1.0%
	-----	(2.5%)	(3.2%)	(4.4%)	(4.1%)	(3.7%)	(3.7%)	(4.0%)
Individual +	-11.7%	-2.3%	-0.2%	-25.5%	-6.8%	-4.2%	-1.6%	-0.2%
Current Job	(3.6%)	(2.9%)	(3.6%)	(4.9%)	(4.3%)	(3.8%)	(4.0%)	(4.9%
Individual +	-----	-0.8%	1.6%	-22.3%	-9.6%	-4.9%	-0.4%	-0.6%
Current Job, FE	-----	(2.6%)	(3.2%)	(4.4%)	(4.1%)	(3.6%)	(3.6%)	(4.0%)

Chapter 3: Accounting for Changes in the Economic Well-being of Elderly Women

3.1. Introduction

Policymakers and researchers have spent much time discussing the plight of old age women and their well-being (e.g. Ferber 1993, Munnell 2004, US General Accounting Office 1997, Weaver 1997). Older women have a much higher poverty rate than men, mostly due to the high poverty rates of women who are currently not married. There are many reasons which cause women to be at a disadvantage in old-age regardless of marital status. Some of these are: a priority of care-giving which reduces the number of years spent in the labor market, lower average earnings, lower mortality, and a greater propensity to work part-time (Munnell, 2004). We have observed pronounced changes in labor force outcomes of females – particularly married women: increased participation, higher wages, and increased educational attainment (Goldin, 2006)). These changes do not seem to have translated into more retirement security. One possible reason we have not seen a pronounced decline in poverty for elderly women could be an increase in the fraction of the female elderly population who are either divorced or never married. These two groups have higher poverty rates than other women[1]. Related, some have asked whether the Social Security system is doing enough for women, even though women currently benefit more than men due to spousal and survivor benefits. However, since many women do not claim Social Security based on their own earnings history (Levine et al, 2000b) and Social Security benefits make up the bulk of the income for many elderly couples (Social Security Administration, 2010), we might expect to see a dampened impact of the increase in female LFP on old age poverty.

[1] In contrast, Bedard and Deschenes (2005) find that once negative selection into divorce is accounted for, divorced women are in fact economically better off than those never divorced.

Finally, due to population aging, poverty rates may rise simply as a result of the demographic shift. Since there are a variety of potential explanations for the changes in poverty rates, it is important to use a framework that incorporates all factors.

Historically, the elderly have had a much higher poverty rate than the rest of the population. On average, this is no longer true. The risk for poverty has been mitigated by the increasing generosity of Social Security over the past several decades (Engelhardt and Gruber, 2006). We need a better understanding of the channels which lead to elderly poverty if we aim to design policy targeted at increasing the economic well-being of elderly women. This is particularly pressing given the fattest part of the baby boom cohort will be 65 in 2020 (Hurd 1990). Women at all ages have higher rates of poverty than men. Gender differences in elderly poverty rates have barely narrowed over time even though on many other fronts the gender gaps have been closing significantly [see Figure 3.1]. Differences in income between elderly men and women are similar now to what they were 50 years ago, even though women are working in much higher numbers than ever before in most age groups (Even and MacPherson, 2004). Furthermore, as the overall poverty has fallen over time for the elderly, there have not been corresponding drops in within group poverty (i.e. those with high school diploma or widows) over the same time period. This observation lends itself to a hypothesis of composition shifts being the primary cause of falling elderly poverty.

This study focuses on the relationship between individual characteristics and the economic well-being of elderly females. I choose to focus on women since they are more at-risk than elderly men. It aims to quantify the relative importance of different factors which have been associated with economic well-being. I ask how changes in individual characteristics contribute to the evolution of poverty of elderly women. It is an accounting exercise at heart.

First, I examine the impact of changes in the distribution of age, education, and marital status on the change in poverty from 1975 to 2005. These factors are very commonly cited as determinants of poverty. I create counterfactual poverty rates using the distribution from an initial year and look at how poverty would have progressed over time had the composition of the elderly population remained constant. This is only a first step in understanding the decline in poverty. We can investigate the relationship between behavioral choices and poverty more carefully in future research. As a follow-up exercise, I project poverty rates forward given the changes in age and education distribution anticipated for the elderly over the next 20 years. I also look at the impact of these factors and measures of labor market activity on changes in the income distribution of elderly women from 1995 to 2005. Finally, I look directly at the predicted impact of changes to the labor force and marital status over the life-cycle on poverty.

To preview the results, I find changes in educational attainment, particularly the fall in women with less than a high school diploma, plays the largest role in the evolution of poverty. It may not be the case that education, per se, protects women from poverty in the same way that marriage protects from poverty through risk sharing and combined incomes since the difference in poverty rates between those married and not married is striking. It is more likely that education is a proxy for higher earnings capacity and retirement benefits which directly impact poverty in old age. I also find the continued increase in educational attainment will continue to push the poverty rate lower over the next two decades. Overall changes to the distribution marital status plays almost no role in explaining the change in poverty rates over the past three decades due to small offsetting effects of the shift from widowed to married and from married to divorced. It is definitely not the case that marital status does not play a role in determining the *level* of poverty, it appears less important in explaining the *evolution*. Shifts in the age distribution have small positive effects on poverty trends. Decomposing of the income distribution confirms the importance of education and also points to a very important role of labor supply. Analyzing the income distribution sheds light on the role of marital status but changes in marital status do not appear to have significant impacts on the bottom tail of the income distribution. The overall changes observed in the income distribution due to shifts in the factor [age, marital status, and education] distributions are an increased density in the upper tail and less mass in the middle of the distribution. Finally, I find that increased marital volatility will like put positive pressure on poverty likelihood in old age, but this is offset by increased average lifetime wages and labor force experience. As a result, there is little impact in the long run on expected poverty outcomes.

This study only begins to fill a gap which exists in the literature on economic well-being in old age. With the baby boom approaching retirement, current work has focused on the financial pressure this will place on Medicare and Social Security without contemplating the impacts on the elderly themselves. We know very little about how women in this generation will fare in old-age given their large increases in education attainment and labor force participation over their lifetime. Previous work has suggested the role of Social Security will mute the impact of these changes. However, this study suggests that education and labor force participation have an impact in their own right. There are too many issues to address comfortably in one study, but this work attempts to shed light on questions we need to answer in the future.

The remainder of the paper is as follows: Section 3.2 provides background information and a review of the relevant literature, Section 3.3 describes the data, Section 3.4 contains the poverty analysis, Section 3.5 contains the income distribution reweighting, Section 3.6 presents the analysis of the impact of labor force behavior and marital status over the life-cycle on projected poverty and Section 3.7 concludes.

3.2. Background

Many research areas are relevant to the current study. This review will focus on the measurement of poverty and what we know about the determinants of old-age economic well-being, focusing on women. In addition, I review studies focused on poverty at other ages which use a similar empirical strategy. Noticeably absent are studies which focus on old-age behavioral outcomes which impact economic well-being such as labor supply, retirement and Social Security claiming, as treatment of these topics is outside the scope of the current study. However, these are all important decisions which have a strong bearing on economic well-being in old age. For example, increases in labor force participation and average wages of women will increase their own retired worker benefits from Social Security.

The first section of the analysis focuses on poverty rates, so we need to be clear on what is meant by poverty, how we measure it, and its shortcomings. Poverty measures whether a family's pre-tax and pre-transfer income falls below a certain threshold that is dependent on age and family structure. There are many complaints about this measure, such as it fails to account for taxes, transfers, and health care expenditures, it is an absolute not relative measure, and it does not summarize the entire distribution. However, it does provides a good snapshot of economic well-being and in the interests of comparability, this study will use the official definition developed in 1963-64 and still used by the Census Bureau today. The official Census policy is:

> "Following the Office of Management and Budget's (OMB) Statistical Policy Directive 14, the Census Bureau uses a set of money income thresholds that vary by family size

> and composition to determine who is in poverty. If a family's total income is less than the family's threshold, then that family and every individual in it is considered in poverty. The official poverty thresholds do not vary geographically, but they are updated for inflation using Consumer Price Index (CPI-U). The official poverty definition uses money income before taxes and does not include capital gains or noncash benefits (such as public housing, Medicaid, and food stamps).[1]"

From 1967 to 1985, there was a growth of social insurance, which provided a variety of cash transfers to the elderly. During this time period, poverty of the elderly declined 12 percentage points (Sawhill, 1988). The fall in poverty for the elderly continued until about 2000. This increase in well-being does not seem to have favored one age group over another, perhaps the oldest old if anyone. The recession during the 1980s was fairly mild for the elderly unlike the non-elderly, pointing to a protective role of Social Security. Engelhardt and Gruber (2006) investigate this claim and find, using variation from the 'notch' cohort, the declines in poverty are caused by the increased generosity of Social Security[2]. Their results suggest that the fall in poverty rates is driven by the married elderly. While this is reassuring that social programs do their job, there is little reason to believe that poverty will continue to fall if Social Security remains the primary safety net. Social Security faces major financial challenges in the decades to come. Given these results, we would expect to poverty rise if benefits are scaled back. In addition, their results suggest non-married individuals are more at risk, as increased Social Security benefits did not reduce poverty for this group.

Many point to marital status as an important factor in determining the incidence of poverty. It protects the elderly through pooling resources, division of labor, and risk sharing. In 2004, almost 30% of unmarried women ages 65 and older are living below 125% of the appropriate poverty threshold, compared to only 8% of married women (Karamcheva and

[1] http://www.census.gov/hhes/www/poverty/povdef.html

[2] It is important to keep in mind that this study is identified off the `notch' generation, cohorts born between 1917 and 1921.

Munnell, 2007). This reflects that marital status is closely tied to available Social Security benefits for women. Two-thirds of women claim some form of spousal benefits (Meyer et al, 2006) and 98% of spousal and survivor benefits[3]. For these women, marital status is more important than employment status or history – their earnings histories do not matter because their benefits are calculated using their husbands' work history.

Many studies have pointed to events in old age which lead to the incidence of poverty, such as widowhood and poor health (Holden and Zick, 1998; Karamcheva and Munnell, 2007). However, it could be the case that many women are poor in old age because they have been poor much of their life or they have been living on the brink of poverty over their lifetime. Entering old age without earnings or assets may be more important than widowhood or health issues. Choudhury and Leonesio (1997) investigate this with the National Longitudinal Survey of Mature Women. Their results suggest living in poverty earlier in life is a strong determinant of poverty for women ages 62-69. Previous poverty experiences explain more of the variation than events from later in life, like widowhood, earnings loss, divorce or the onset of health issues for either the husband or wife. However, couples who are more likely to be widowed have lower income than those who remain intact over a period of time (Karamcheva and Munnell, 2007). Low income can reflect low education or earnings capacity on the part of husband or wife or potentially worse health of the husband. They find those who are widowed had husbands in poorer health well before his death, and they find the poverty of widows is due to both pre-widowhood economic status and the death of husband.

Levine et al (2000a) also look at determinants of economic well-being, measured using projected retirement income since their data contains the near-elderly. They find lifetime labor attachment and health status are important factors, but they are unable to evaluate how these

[3] Favreault and Sammartino (2002)

factors compare to old-age events due to their research design looking at those ages 51 to 61 years of age. Their findings are consistent with Karamcheva and Munnell (2007). The results are driven by the unmarried because married couples have the same projected retirement income just as poverty status is defined at the family level. A related study suggests that the gender gap in anticipated retirement income could be closed by raising the educational attainment of women to that of men (Mitchell et al, 1999). Unfortunately, it is difficult to place these two studies in context with other studies since they cannot examine old-age outcomes. However, their findings point to a strong role of labor supply and education which inform the current analysis.

A few studies have looked at the impact of compositions changes like this study on poverty of children and the working-age population. Ross et al (1987) follow a decomposition analysis of poverty rates, looking at the impact of changes in the age, sex, and race composition. For working age families, shifts in demographic characteristics placed upward pressure on the poverty rates from the 1950s to the 1970s. Cancian and Reed (2002) directly control for labor force participation when looking at the evolution of poverty as both measures can be observed in the same year for the working-age population. They find while demographic shifts and changes in family composition alone would have increased poverty, the increase in female labor supply, particularly those with young children, served to force the poverty level down. As a result, there was little observed change in poverty rates. This is consistent with Ross et al (1987) for a more recent time period. Sawhill and Thomas (2002) and Thomas and Sawhill (2001) ask similar questions but use a slightly different methodology and find that having a household head work full-time [instead of part-time] would reduce child poverty from 13% to 7.5% and having the same fraction of children in female-headed households as in 1970 would reduce the poverty of children to 9.5%. Hoynes et al (2006) also find a strong relationship between female labor force participation and poverty rates of working-wage women from 1980 to 2003. Due to concerns of reverse causality, they do not emphasize the magnitude of the results but maintain the data show a strong correlation. These results taken together suggest that economic well-being of elderly women could increase in the future if poverty is persistent as multiple authors have found (e.g. Stevens, 1999).

3.3. Data

For the first set of analyses, I will use data from the Annual Demographic (March) Supplement from the Current Population Survey from the 1976 to 2006. This data provides detailed information on personal and family income for the previous calendar year, so the data represents 1975 to 2005. The analyses focus on women who are 65 and older. Focusing on this age range avoids most complications arise when comparing workers to non-workers since most women who were working will have left the labor force by this age. Only 5.3% of women 65 and older are still working full time, and another 7.3% are working part-time. In comparison, only 7.2% of women 70 and older are in the labor force at all[4]. Most women also will have claimed Social Security benefits by this age as well so differences in well-being are taking into account the level of Social Security benefits received. In 2004, 94.1% of women claimed Social Security benefits by age 65 (Munnell and Soto, 2005).

For the final analysis looking at the relationship between marital and labor force history and poverty outcomes/projections, I use a dataset from the Census Bureau which matching survey data with administrative data on earnings history. The data merges (1) a pared down version of the Survey of Income and Program Participation (SIPP) data from the 1990s (1990-

[4] Author's calculations from the March 2005 CPS file.

1993, 1996), (2) the Summary Earnings Records (SER) and Detailed Earnings Records (DER) from the Internal Revenue Service, and (3) the Master Beneficiary Record (MBR) from the Social Security Administration[5]. This project is housed at the Census Bureau. The project's goal was to merge demographic variables to the administrative data. In most cases, administrative data is missing this key information. Since not all individuals from the SIPP can be matched to administrative data, missing values are imputed to the final data. Four different imputations are performed, and final estimates must average the four sets of results and calculate standard errors to account for the imputation. These datasets are referred to as the Gold Standard files. Details on this process are specified in Abowd et al (2006). Importantly, the SIPP data contains a full marital history up to the creation of a fourth marriage including dates and reason for marriage ending. The SER contain earnings records from 1951 to 2003, up to the maximum facing payroll taxes. Finally, the MBR contains information on the type of initial benefit received from Social Security in addition to the date benefits were initially paid.

3.4 Analysis

3.4.1 Overview of Poverty

To provide background about poverty levels and trends before moving onto the decomposition exercise, Figure 3.1 presents average poverty for men and women from 1975 to 2005. Confirming other studies, there is large decline for both men and women until 1996 for men and 2000 for women but little narrowing of the gender difference. Over the whole period, poverty falls from about 12% to 8% for men and 18% to 14% for women. The minimum poverty rate for women is 12.6% in 2000 and a maximum in 1981 of 19.2%. Men experience a minimum of

[5] An application for the publicly available data can be found at http://www.census.gov/sipp/synth_data.html. Questions can be directed to hhes.synthetic.data.use.list@census.gov.

6.9% in 1996 and a maximum of 11.8% in 1975 and 1981. The levels in 2005 are more than one percentage point higher than their minimum, suggesting the falling trend is reversing even in advance of the economic and financial crisis in 2007-2008.

Since part of the focus of this study is the impact of education and marital status on poverty, it is important to understand how poverty varies between groups defined by these characteristics before exploring the time trend. For an overview, Figure 3.2 graphs poverty rates of women who have either a high school or college diploma by whether they are married. Poverty varies widely by education and as noted in the introduction, there was little trend in poverty over this period within each group. If anything, the recent trend has been positive for women who are not married. For the not married, those with only a high school degree are approximately 50% more likely to fall below the poverty line than those with a college degree. Education plays little role for married women. Presumably, her husband's education would have a stronger impact.

3.4.2 Reweighting of Poverty Rates

The evolution of poverty rates can be expressed as a combination of two time series. The first is changes in the composition of the population: how has the prevalence of different groups changed over time? The second is the group-specific poverty rates. Using marital status to demonstrate, I start with the poverty rate in a given year for women in each marital status (married, widowed, divorced, separated, and never married) and then weight these group-specific poverty rates by the fraction of the population which falls into each category to calculate the overall poverty rate. Below, t denotes year, M is the number of marital categories, and wgt_{mt} is the fraction of group *m* in the population in year *t*. the overall poverty rate can be then written as:

$$pov_t = \sum_{m=1}^{M} pov_{mt} \cdot wgt_{mt}$$

Noting this rewriting, I can treat the weights as a choice variable and use an alternate weight. The group-specific poverty rates are weighted instead using wgt_{mk} from year $k \neq t$. This creates a counterfactual poverty rate which answers the question, "What would the poverty rate have been if the composition of the population corresponded to the year *k*?" This is sometimes referred to as a shift share analysis. Making a couple of substitutions, the counterfactual poverty rate can be written as:

$$pov_{kt} = \sum_{m=1}^{M} pov_{mt} \cdot wgt_{mk}$$

In this example, the poverty rates for each marital status move over time while the distribution of characteristics remains constant in year *k.* Allowing cell-level poverty to move over time is crucial, for there may be public policies, technological change, or industrial composition changes which will impact on group differentially. For the reweighting, I focus on three characteristics which have been closely tied to the incidence of poverty: age, marital status and education. In this setup, education can be thought of as a proxy for earning capacity or potential.

The key assumption in creating counterfactual poverty rates is the group-specific poverty rates do not change as a result of the change in characteristics. Considering education in particular, this assumption is a bit strong. Poverty is likely to change as a result of the distributional changes in educational attainment. We need to keep this in mind when examining the results and know the impact of education may not be as large as the following analysis suggests. Those with less than a high school education are being left behind as educational attainment continues to rise and technological change reduces the supply of low wage jobs (Autor et al, 2006). Poverty may increase as a result of increased competition for low-wage jobs. In contrast, with a supply and demand framework of the labor market, the opposite should occur as the supply of low educated workers falls. The latter should not impact poverty since few highly educated individuals experience poverty but the former could have an impact. These are just two examples of why we need to be wary when interpreting the findings and why it is not immediately clear what the overall bias would be.

Before looking at the impact of shifts in the age distribution on poverty, I present the changes in composition seen over time. There are significant changes in the age distribution for women aged 65 and older seen in Figure 3.3. Most prominently, there is a large increase in the fraction 80 and older. This comes as no surprise due to the increase in life expectancy observed over the past few decades. There is also a slight up-tick in the fraction ages 75 to 79. As a results, we observe a fall in the percentages for the other two age groups, ages 65 to 69 and 70 to 74. Due to these changes, an increase in poverty due to these shifts is likely since the oldest individuals tend to have a higher poverty rate than the "young" old. Figure 3.4 graphs the overall poverty, and the poverty rates given the age distribution in both 1975 and 2005. Maintaining the same age distribution as in 1975 would have led to a slight increase in poverty by 2005 but no more than a 5% increase. We also see a greater difference between the counterfactuals in 1975 compared to 2005. This indicates the difference in poverty between groups has narrowed over time, the distribution is less important than previously.

Large changes in educational attainment have occurred with more change expected in the future with the retirement of the baby boom generation. Figure 3.5 presents the fraction of elderly women with less than a high school diploma, with a high school diploma, those with some college attendance, and those with at least a college degree. There was drastic fall in the fraction of elderly women with less than a high school degree, a flattening of the fraction with a high school diploma, and slow, steady increases in the fraction of women with more than a high school education. These changes would all point to a fall in the poverty rate due to these shifts. This is what we see in Figure 3.6. The poverty rate would have changed very little in the absence of changes in educational attainment in the absence of cyclical movements.

Given the striking results about the impact of changes in the education distribution, it is natural to wonder what is it about educational attainment that lead to the reduction in poverty? I form a hypothesis by examining the changes in the distribution in tandem with the cell-specific poverty rates. Those without a high school diploma have an average poverty rate of over 20% throughout the whole time period, while their share fell from over 60% to approximately 25% of the elderly female population. Since those with at least a high school diploma all have a poverty rate around 10%, the natural candidate is the decrease in those without a high school diploma. To examine this more formally, I create the following counterfactual poverty rates. Like the previous analysis, I allow the within-cell (education) poverty rates to change over time, reflecting greater economic conditions. I hold constant the fraction with a high school diploma or less and the fraction with some college and college degree at their 1975 levels. However, I allow the ratio of LTHS to HS change in each year. To do this, I calculate the ratio of LTHS/HS in each year and scale it by the fraction of (LTHS+HS) present in 1975. This results in a counterfactual poverty rate primarily grounded in the 1975 education distribution but allowing the dropouts to shift to completion of high school. The results shown in Figure 3.7 find this shift in educational attainment is primarily responsible for the fall in poverty observed between 1975 and 2005.

Since education cannot directly impact poverty, it is useful to have an idea of income differences by education to see where the transmission occurs. Focusing solely on the low-educated individuals, I compare non-married women with a high school diploma and those without. Married women are less impacted by their own educational attainment; the message is clearer focusing on the not married. Across most income sources, those with a high school diploma have higher outcomes. They are more likely to work, and receive slightly higher wages when they do. They have higher Social Security payments, and this gap has been widening over time. We even see a difference in the incidence of pension benefits. Among those that receive benefits, average pension income is higher for those with more education. The difference in the pension benefit level is likely due to higher lifetime earnings.

There were been fundamental changes in marriage and divorce rates over this time period in addition to increased life expectancy. These changes will each have an impact on the observed distribution of marital status. As shown in Figure 3.8, the shifts to the marital status distribution were pronounced. The fraction of widowed women fell due to increases in the incidence of divorce and increased life expectancy of men. It is unclear if these shifts can be considered as substantial as the changes in age and education. However, even small changes in marital status could have an impact on poverty since the incidence varies largely between groups. However, Figure 3.9 shows very little of the change in poverty can be attributed to overall shifts in distribution of marital status. Since the 1975 counterfactual is greater than observed poverty in 2005, the average impact of shifts in marital status is slightly negative. There are likely offsetting trends with the increases in married women and decreases in widows placing negative pressure on the poverty rate and the increase in divorced women placing positive pressure. This combination is likely driving the observed null result of marital status on the evolution of poverty.

To evaluate these potentially offsetting factors, I repeat a similar exercise to the one used above that looks at the shift from LTHS to HS. I look at two shifts in the marital distribution. The first is the shift from widowed to married. As men live longer, more women still married in old age. Second, I look at the shift from married to divorced or separated. These two changes will have opposite impacts on poverty with the first reducing poverty and the second increasing. We see this is exactly the case in Figure 3.10, although the impact on poverty incidence is not very large. Shifts in marital status, while significant, are not as dramatic as the shifts in education. The fraction widowed has fallen approximately 10 percentage points and the fraction divorced has risen by approximately 8 percentage points. Divorced women tend to have slightly higher poverty rates than widowed women, from 1 to 9 percentage points higher.

Figure 3.11 summarizes these results by graphing the counterfactual distribution holding the {age·education·marital status} distribution constant. Not surprisingly, the {age·education·marital} status graphs do not look much different than the age·education distribution graphs. The only observable difference is after 2000. When holding the full joint distribution constant, we see the changes in marital status place slight downward pressure on the overall poverty rate.

3.4.3 Poverty Projections (I)

While the previous section helps us understand changes which have already occurred, we are also interested in what will happen in the future. We know that the increase in educational attainment has continued past the current retirees, and the shifts in age distribution will continue with the retirement of the baby boomers. As a result, we would like know how the poverty rates will shift in the coming years a result of these changes. It is fairly straightforward to project counterfactual poverty rates given changes in age and education if we ignore differential mortality. Changes to age and educational attainment are not possible or are unlikely in old-age, respectively. Assuming mortality is random across groups will create a upper bound of poverty since those who are poor are more likely to die earlier, e.g. those with less education.

It is not straightforward to project poverty keeping marital status fixed because, inherently, marriage rates change over time due to death and divorce. In 1995, 65.9% of 55 to 64 years old women were married but in 2005, only 54.3% of this cohort was married [observed at ages 65 to 74]. If we keep marital status fixed, we understate the true incidence of poverty. To include marital status in the exercise, I would have to estimate marital transitions. For these reasons and in light of the finding from the previous section that marital status had little role in explaining trends in historical poverty levels, I present projections based on the shifts of the age and education distribution.

There are data limitations which only allow us to project poverty for those ages 65 to 79. Beginning in 2002, the CPS no longer identified the age of individuals 80 years of age and older. They currently use two classifications, 80 to 84 and 85+. This creates problems when trying to project the anticipated distribution of age and education in the future using the current distribution of younger ages. Due to this restriction, I focus only on those whose age can be identified more precisely, those between 65 to 79.

In a sense, this section is the opposite of the previous section. Earlier, I allowed cell-specific poverty rates to change over time and fixed the weights. In this section, I allow the weights to change over time but hold the cell-specific poverty rates fixed. This will answer the question, “What do we expect poverty to be in the future if cell-specific poverty remains constant by the cell shares change over time?” This is shown below:

$$pov_t = \sum_{g=1}^{G} pov_{g,06} \cdot wgt_t \quad t = 2005, \ldots, 2025$$

This is best illustrated with an example. To project the poverty rate in 2010 for women ages 65 to 79, I use the age-specific poverty rate from 2005. One cell in pov_t is 65 year old women with a high school education. I calculate the poverty rate for this group in 2005. I use the fraction of women ages 60 to 74 who are 60 years old with a high school education in 2005 as the weight. The women who are 60 to 74 in 2005 will be 65 to 79 in 2010.

The first assumption necessary for this exercise is mortality is random across cells, so the {age·education} distribution of 60 to 74 year olds in 2005 is a good estimate of the {age·education} distribution of 65 to 79 year olds in 2010. As I project further into the future, the actual sample will be younger than the ‘predicted’ sample as the older individuals die off at a higher rate than the younger individuals in the sample. Over time, more higher educated as mortality rates higher. Both of these factors cause the estimates presented to overestimate the ‘actual’ poverty rate. Comparing the 2010 predictions to the reported 2010 poverty rates in the CPS, we see this is the case, 11.5% in Table 3.1, column 2 vs. 9.8%[6].

In addition to assuming that mortality is random across cells, I assume the cell-specific poverty rate prevailing in 2005 is the same as will prevail in the future. This is reasonable given that cell-specifi poverty rates have not changed much over the past thirty years. I cannot follow cyclical patterns, but these are temporary fluctuations which are not as informative in understanding the underlying ‘true’ trends in poverty.[7] I use the average poverty from 2003 to

[6] http://www.census.gov/hhes/www/cpstc/cps_table_creator.html
[7] They would be useful in evaluating how well social programs protect against poverty in an economic downturn.

2005 as a robustness check but this has little impact on the findings. Table 1 provides projections of poverty until 2025 for women 65 to 79 given the anticipated changes in the age and education distributions. Allowing the age distribution to evolve over the next 20 years to 2025 has little impact on elderly female poverty. There is a small positive trend in the average age of women 65 to 79 but the majority of shift is coming from the increase in 80+ category as life expectancy continues to increase. A fall from 12.13% to 12% is predicted as a result of age shifts, a reduction of only 1%. However, by allowing age and education distribution evolve together, we observe a fall in poverty to 9.54%, a reduction of more than 21%.

3.5. Reweighting the Income Distribution

Given the criticism directed at poverty rates that they only presents a snapshot of well-being combined with the goal of investigating the role of labor force participation, I next look changes to the income distribution for elderly women between 1995 and 2005. Reweighting the income distribution is the same in spirit as the previous analysis and asks the question, "What would the income distribution of elderly women look like if women received the income in 2005 given the distribution of attributed in 1995?"

I examine changes to personal income since I am focused on the impact of changes in characteristics within the female population[8]. Income is typically shared at the family level and the preceding analysis used a family-level measure, poverty, since that measure is typically considered in policy analysis. I could do the reweighting of the income distribution at the family level as well. As we are focused on female economic well-being, we need to know how women are contributing to their own outcomes. There is little reason to believe the remainder of family

[8] All income values will be in log form as the distribution of log income is more symmetric than the distribution of income.

income will respond to female characteristics as strongly as her personal income. The primary sources of personal income are wages, pensions, Social Security and other public support programs.

For the income analysis, I follow the familiar DiNardo, Fortin, and Lemieux (1996) methodology (henceforth, DFL) to reweight the income distribution. Their approach asks the question, "What would the income distribution look like if characteristic *z* had remained at a previous distribution [and the distribution of income remained as it is today for characteristic *z*]?" Implicit in this type of analysis is ignoring the impact of the shift in characteristic *z* on the income distribution in general equilibrium. One advantage of this approach is I can account for more factors at once than the previous exercise, particularly factors which are not defined at the individual level. For instance, I can control for the fraction of women who were working at age 55 or at age 60 by birth cohort and educational attainment to control for general trends in the labor force participation of women. I also account for those who are currently working, either full-time or part-time, at the time of interview as wages and salary are a key component of income for those working. Other control variables include our previous explanatory factors: age, education, and marital status. I also include race and region of the country as baseline controls.

To formalize what is meant by reweighting of the income distribution, I need to begin with an expression for the density of current income. The overall density can be written as a combination of the conditional densities:

$$\begin{aligned} f_t(inc) &= \int_{z\in\Omega_z} dF(inc, z \mid t_{inc,z} = t) \\ &= \int_{z\in\Omega_z} f(inc \mid z, t_{inc} = t)\, dF(z \mid t_z = t) \end{aligned}$$

Next I define a hypothetical density, where income distribution for each group, defined by control variables, *z*, comes from 2005 but the distribution of attributes is from 1995[9].

$$f(inc;t_{inc}05,t_z=05)=\int_{z\in\Omega_z} f(inc\,|\,z,t_{inc}=05)dF(z\,|\,t_z=95)$$

$$=\int_{z\in\Omega_z} f(inc\,|\,z,t_{inc}=05)\psi_z(z)dF(z\,|\,t_z=05)$$

where the reweighting fuction, $\psi_z(z)$, is:

$$\psi_z(z)=\frac{dF(z\,|\,t_z=95)}{dF(z\,|\,t_z=05)}.$$

The notation is explicit in showing the counterfactual density as the true density of income in 2005 weighted using $\psi_z(z)$. What remains is estimating the reweighting function, $\psi_z(z)$. To proceed with this estimation, it is useful to rewrite $\psi_z(z)$ using Bayes' rule:

$$\psi_z(z)=\frac{\Pr(t_z=1995\,|\,z)}{\Pr(t_z=2005\,|\,z)}\bullet\frac{\Pr(t_z=1995)}{\Pr(t_z=2005)}$$

For estimation of $\psi_z(z)$, I estimate a probit model with an indicator for 2005 as the dependent variable, using the sample of data from both 1995 and 2005 and control variables as noted above. Interpreting the probit results is not natural.

The income analysis focuses on women between the ages 65 to 79. This restriction is for two reasons. The first is the desire to control for cohort LFP at ages 55 and 60. Previous years of the CPS are used to estimate cohort specific LFP. Women who are 75 in 1995 are assigned the LFP of women who were 55 in 1975. The second is the inability to separate out year of age past 79 as previously discussed. The control variables used are age, education, marital status, the interaction of marital status and education, region of residence, current full-time or part-time employment, average LFP of birth cohort at age 55 and 60 by education, and an indicator for

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[9] The following discussion is drawn from DiNardo, Fortin, and Lemieux (1996).

working at any point in the previous calendar year. Given I am interested in separating out the effects of each characteristic, I do the reweighting in a step-by-step fashion. Figures 3.13-3.16 go through the step-by-step process.

I present the density of log real income for both 1995 and 2005 in Figure 3.12. The distribution shifted to the right over the ten-year period. Poverty fell from approximately 15% to 13% between these two years for the full 65 and older population. Over the time period, the income distribution has also become more spread out, increasing income inequality experienced by elderly women. The Gini coefficient for personal income increased from 0.417 to 0.444 between 1995 and 2005.

I start with what would be different in 2005 if the age distribution had remained as it was in 1995. On average the sample is slightly older in 2005 but the averages masks the fact that in 2005, there were relatively more individuals at ages 65 and 66 and more at ages 75 through 79. Unfortunately, I cannot investigate the full shifting of the age distribution, since most changes occurred for those 80 year old or more. Therefore, we only observe small differences between the reweighted distribution and the original 2005 distribution, seen in Figure 3.13. The shift is to the right at almost all points of the income distribution, showing an increase in average income but little change in inequality.

Figure 3.14 shows the difference between the age reweighting and the reweighting of age and education. There are sharp differences near the median income and a reduction of inequality due to a shift left in the upper half of the distribution and a small shift left in the bottom third of the distribution. The shift left in the upper and lower third of the distribution is likely due to fewer college graduates and more LTHS individuals in 1995. Near the median, there is an increase in density, due to more individuals with less than high school diploma, for the peak of their log income distribution is a bit larger than 8.

The impact of the shift in marital status is presented in Figure 3.15. Recall there has been an increase in the fraction of divorcees, a reduction in the fraction of widows, and an increase in the fraction married in the 10 year period. The results of this are a reduction of the peak created by the low education group, and a slight shift right for those in the 3rd quartile of the income distribution. The increase in the fraction never married contributes to the appearance of a right peak, as does the increase in divorcees. The decrease in the fraction of widows is partially responsible for the decline in the left peak. Due to the variety of changes in marital patterns and income varying widely by marital status, a bimodal distribution of income results.

The goal of the current analysis, other than expanding to a full income distribution instead of a summary measure, is to include a measure of LFP since average female labor market activity continued to change, even for older women, during the decade in question. Figure 3.16 presents the final reweighting, providing the addition of labor force measures. In general, holding fixed current and past LFP makes the distribution more equal. There is now more mass in the center of the distribution.

Changes in individual characteristics can account for a significant portion of the shift in income from 1995 to 2005. However, there are large changes in income distribution within these groups which will account for the remainder of the shifts. In addition, Figure 3.17 suggests the factors I focused on are not responsible for changes in the bottom tail of the distribution, income values below $4,500 in 1995 dollars. Changes due to shifts in the ‘factor’ distributions have the most impact in the middle and upper portions of the income distribution. Two key pieces distinguish this from the previous poverty analysis: first, we are unable to control for the oldest individuals – perhaps the most at-risk for poverty. Second, the income reweighting only focuses on a recent period and, therefore, misses drastic shifts in factors which occurred between 1975 and 1995. Looking back at Figure 3.11, there are changes in poverty outcomes between 1995 and 2005 that changes in the distribution of age, education, and marital status cannot account for. In light of the finding that changes to current and past LFP do not impact the lower tail of the distribution, the income and poverty reweighting analyses appear consistent with one another.

There are two caveats to keep in mind when performing this type of reweighting analysis. While they have been discussed previously, they cannot be stressed enough. The first is the control variables could be proxying for the true causal connection, if any. The second is any impact to the group-specific income distribution in general equilibrium due to the shifts in characteristics are ignored. Any results of supply and demand (particularly relevant in the labor market) which has results from the change in the educational attainment will not be accounted for here and may in fact confound our results. We can see this by focusing on those with less than a high school diploma[10]. The supply of LTHS women has fallen. This should increase the demand for labor market for the skill set, and as a result, average income should rise at the bottom of the distribution. However changes in technology and the industry structure of the economy also play a role in determining wages for low-skilled women (Autor et al, 2006; Blau and Kahn, 1997). These factors are outside the scope of this study but important to keep in mind.

The order in which we chose to do the reweighting is arbitrary, but as a robustness check, I reverse the order to ensure the conclusions remain the same. For the most part, this is the case. Age has little impact, labor force plays a larger role in explaining the shift since it now goes first,

[10] This was previously discussed. I revisit it here because its implications in the context of the income distribution are ever more visible than in the poverty case.

and the role of education is diminished once we have controlled for labor force behavior and marital status. Since labor force activity has a more plausible, direct link to economic status, it is reassuring that education plays a smaller role after allowing for changes in labor force behavior.

3.6. Projecting Poverty using Earnings and Marital History

To incorporate measures of marital and labor force history into the analysis, I use data from the Census Bureau called the Synthetic SIPP. It combines a subset of questions from the Survey of Income and Program Participation including a detailed marital history with administrative data containing a full earnings history and information on Social Security claiming. This allows me to relate marital status and labor force participation over the life-cycle to economic well-being in old-age which almost no other data sources allow. I only observe old-age outcomes for a small set of birth cohorts who are present in the survey data during old-age. Therefore, I have a sample of poverty outcomes from 1990 to 1999. I use this sample of women to estimate a relationship between earnings history, marital history and poverty between the ages of 65 and 69. The model I estimate is:

$$Pov65\_69_i = \alpha + \beta \cdot X_i + \gamma Z_i + u_i$$

I use average poverty from ages 65 to 69 for each individual to provide a more detailed description of the level of economic well-being each woman faces. Someone who experienced poverty at every age between 65 and 69 faces a different outlook than someone who only experienced poverty once. In addition, this approach removes the need to control directly for age. This will be useful when projecting poverty for younger cohorts. The base control variables, X_i, are race and education and are included in each model. Z_i contains contain a subset of all marital status and labor force history measures available, with each model using a different set of Z_i. Using the regression estimates, I predict future poverty rates for younger cohorts who reach age 62 between 1996 and 2018. To include as many cohorts as possible in the regression and projections, I limit measures of labor force and marital history to experiences from an individual's 3rd and 4th decades (age 30-50). This ensures that younger cohorts can be included in the projection analysis since I need to observe them until age 50. Earlier ages cannot be included due to data limitations on earnings history, where the first year included is 1951. I use models with different sets of controls to look at how changes in the characteristics of successive cohorts impacts predicted future poverty outcomes. Younger cohorts have stronger labor force history and more volatile marital histories, on average. The underlying assumption is the relationship between marital history or labor force history and poverty in old-age is not changing over time. This may be a strong assumption but one which probably understates the impact of changes to marital and labor force history. For older generations, LFP and wages over the life-cycle probably has a weaker impact on elderly poverty than for younger generations and vice versa for marital history. Therefore, if we expect the relationship between wages, for example, and poverty outcomes to strengthen, then we would expect poverty to fall further than this exercise suggests. This is also likely as more women rely on their own Social Security benefits in old-age.

The results in Figure 3.18 present projections for cohorts born between 1931 and 1953 by the types of controls included in each model. I present average poverty between ages 65 and 69 for the cohorts used to estimate the model, women born between 1925 and 1930, as a baseline. The values range between 11 and 14%. All values to the right of the solid vertical line are model projections for cohorts *not* used in estimating the regressions. Using only race and education as model controls suggests a similar slow decline in projected poverty as found in an earlier section.

There are two primary categories the remaining controls fall into. Either descriptions of marital status over the life cycle or measures of average wages and labor force experience. The controls used to look at marital history are the number of marriages, age at the first seven changes in marital status, the type of change in marital status, and the fraction of one's 30s and 40s spent married, divorced, widowed or never married[11]. I initially add the marital controls and labor force controls separately to see the effect from each type of measures in isolation. This is the type of exercise you could perform with the public release SIPP for marital history. Younger cohorts spent much less of their 30s and 40s married and much more of these decades divorced or never married. The results in Figure 3.18 [the dashed line] present at how we expect poverty progress given the changes in marital status over the life-cycle. The projections suggest a moderate impact of marital instability on poverty for future cohorts. There is an initial decline and then slow flattening of average poverty between ages 65 and 69. The regression estimates describe the relationship between lifetime marital status and old-age poverty for cohorts where marriage was commonplace over the life-cycle, where approximately almost 90% of women's 30s and 40s were spent married. This falls to approximately 75% for the youngest cohorts included in the projections. Since future generations spend less time married, the relationship between poverty in old age and marital status over the life-cycle may fundamentally change.

The opposite holds true for changes in labor force participation and earnings over the life-cycle. Here we see a slower initial decline followed by a sharper fall in poverty for those born between 1935 and 1945 with a flattening for the youngest cohorts[Figure 3.18, line with triangles]. This later decline is likely due to the drastic changes that have occurred for the youngest cohorts in LFP and wages. The controls used are the number of years employed during 30s and 40s, the average overall and nonzero wage in each decade, and average nonzero wage

[11] A detailed list of controls can be found in the Data Appendix.

over all years worked. The women included in this analysis are referred to as the "roots of the [female labor force] revolution" by Claudia Goldin (2006). These women had rising expectations for their labor force participation once constraints to employment for married women were relaxed and attained more education than cohorts before them.

To focus on the effects of marital status and labor force activity in isolation ignores the fact that marital status and labor force behavior in each period are jointly determined. Therefore, I need to estimate models with both sets of factors. I interact measures of labor force activity with marital status outcomes to allow for flexibility in the how marital status and labor force choices interact over the life-cycle since I cannot observe other factors over the life-cycle (e.g. children and job characteristics). The projections from this interacted model look like a combination of the previous two sets of results. There is a strong, continuous fall in poverty expected over time with a flattening occurring starting with those born in the late 1940s. It is reassuring that labor force decisions over the life-cycle exert an independent effect on poverty even after a wide range of marital history variables have been accounted for. But it is important to note that marital status has its own strong impact on old age outcomes. Both of these results are crucial to understanding old-age economic outcomes. Further research can investigate what old age income sources are impacted by marital factors and which are primarily determined by labor force choices over the life-cycle.

3.7. Conclusion

The economic well-being of elderly women, or lack there of, has been a topic of great interest, particularly in the past few decades. Many explanations have been put forth as reasons for elderly females' precarious economic position. However, few studies have been able to rigorously explore and evaluate a variety of factors in one framework. This study attempts to fill this gap by examining changes in poverty and income distribution and evaluating four different determinants of poverty. It seems some popular explanations of poverty do not appear to be responsible for the large fall in poverty rates seen over the past few decades. Age and marital status play little role in explaining the changes investigated in this study. Marital status does seem to have a more central role in explaining movements in the income distribution above the poverty line. A more plausible culprit is the role of economic factors. Education is a general yet imperfect proxy for economic status and capacity. There is a strong relationship between the changes in education and labor force behavior over time, and these factors both play a role in economic outcomes in old age. Changes in educational attainment and labor force participation can help us most understand the drastic reduction in poverty in old age. However, there are likely still very strong roles for both age and marital status in determining an individual's likelihood of falling below the poverty line. It is important to think more carefully about how increased volatility in marital status will impact old-age economic well-being other than through Social Security benefits. It is clear marital status plays a role in determining outcomes but understanding the channels through which it operates is of utmost importance.

In the future, I want to evaluate these results in the context of other studies, in particular, Engelhardt and Gruber's (2006) evaluation of the relative importance of Social Security in reducing poverty. I want to compare the direct role of Social Security to other factors. In addition, future research can investigate the channels through which labor force behavior, education, and marital status over the life-cycle impact economic status. Is it pensions, Social Security, or savings behavior which has the largest impact on old-age economic well-being?

Policy prescriptions from this analysis are not new. The results suggest encouraging marriage and work for females will be best to increase their economic well-being in old age. However, a note of caution is appropriate when investigating overall trends: there may be a good mechanical reason that needs to be considered when thinking about the impact of behavioral choices like the impact of aging.

Figure 3.1 Poverty by Sex for Individuals ages 65 and older, 1975-2005

Figure 3.2: Poverty Rates by Education and Marital Status, Females 65 and older

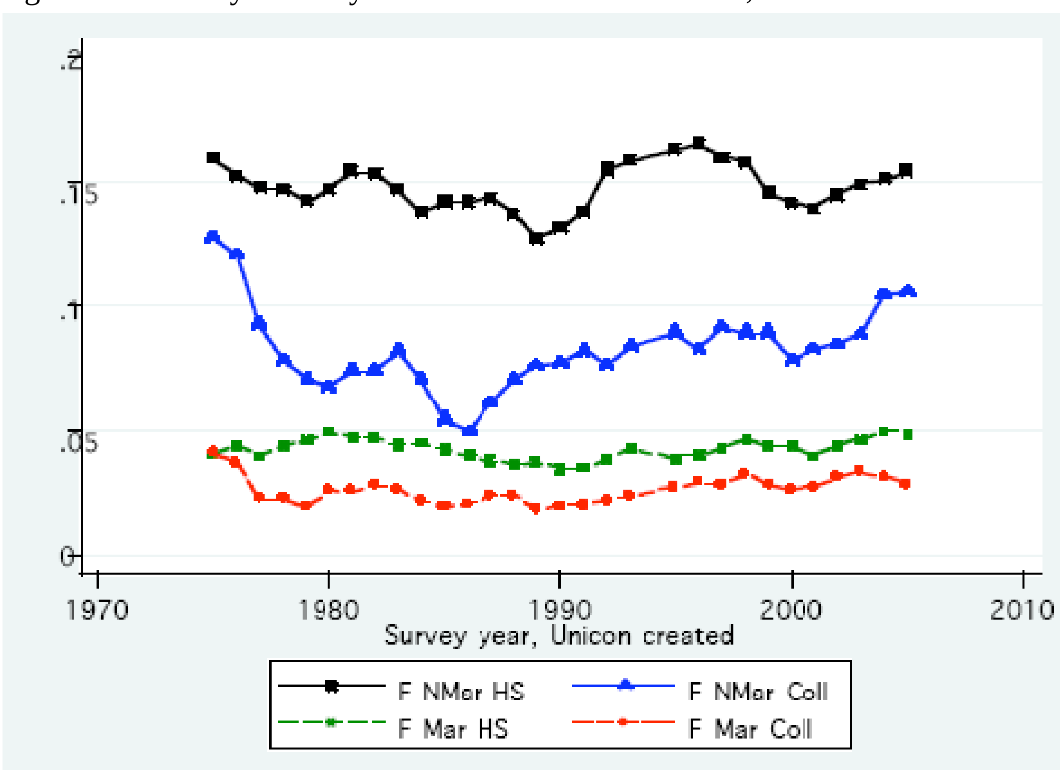

Figure 3.3: Age distribution of Women ages 65 and older,1975-2005

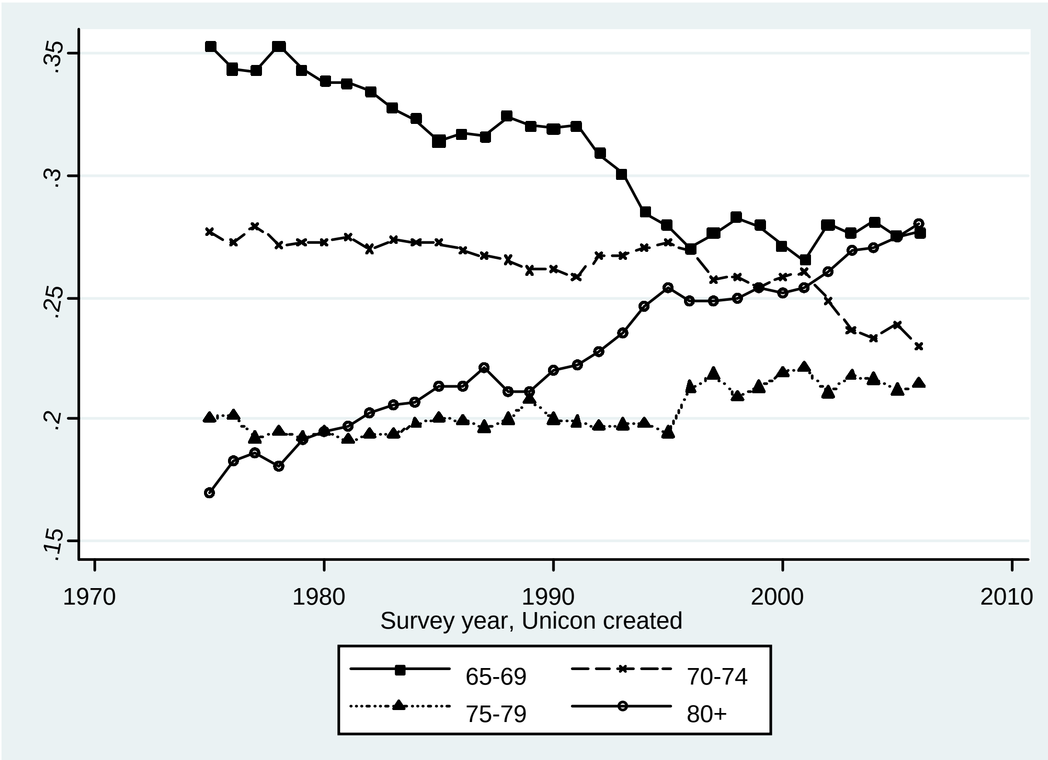

Figure 3.4. Actual and Counterfactual Poverty rates
Maintaining age distribution from 1975 and 2005

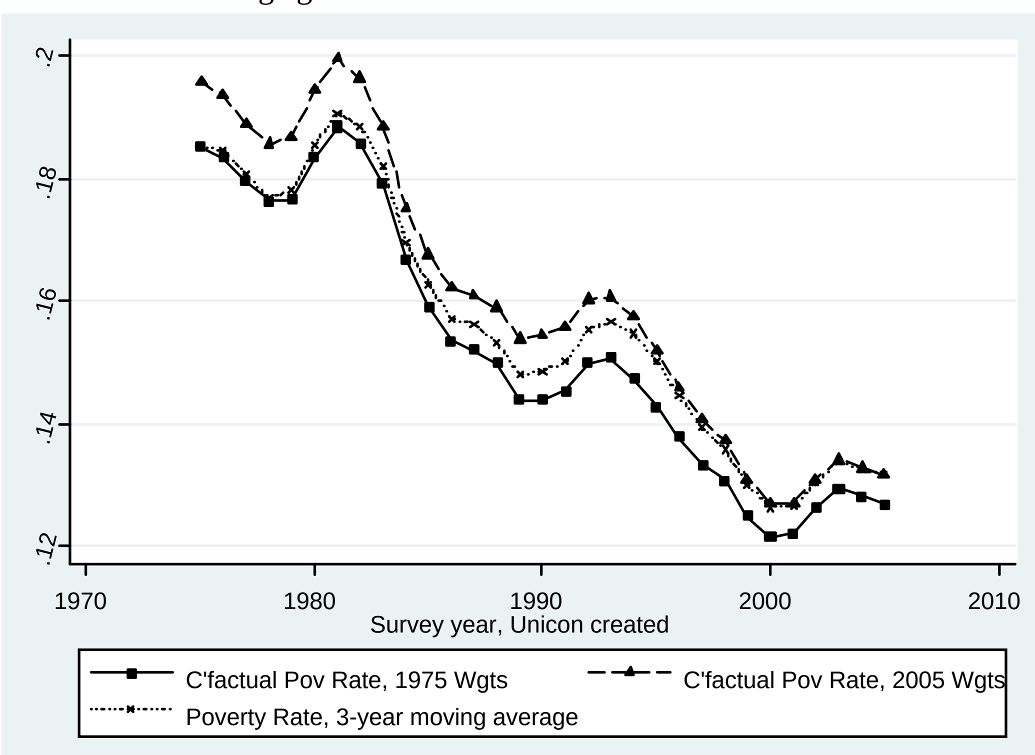

Figure 3.5. Education distribution of Women 65+, 1975-2005

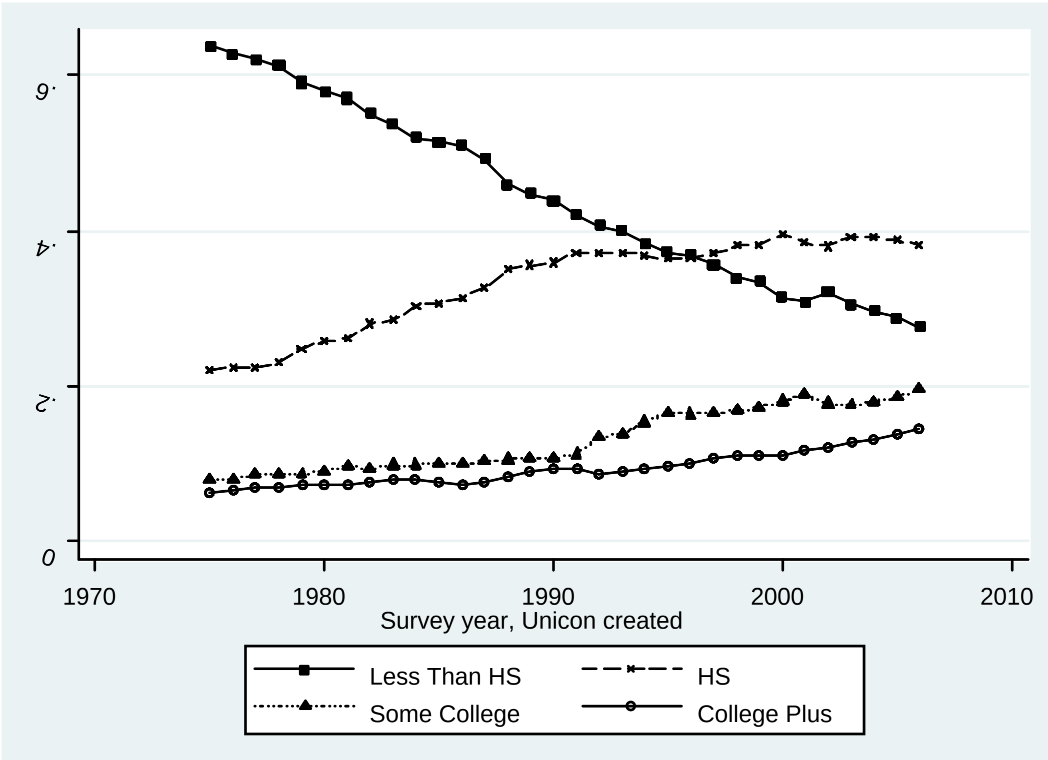

Figure 3.6. Actual and Counterfactual Poverty rates
Maintaining education distribution from 1975 and 2005

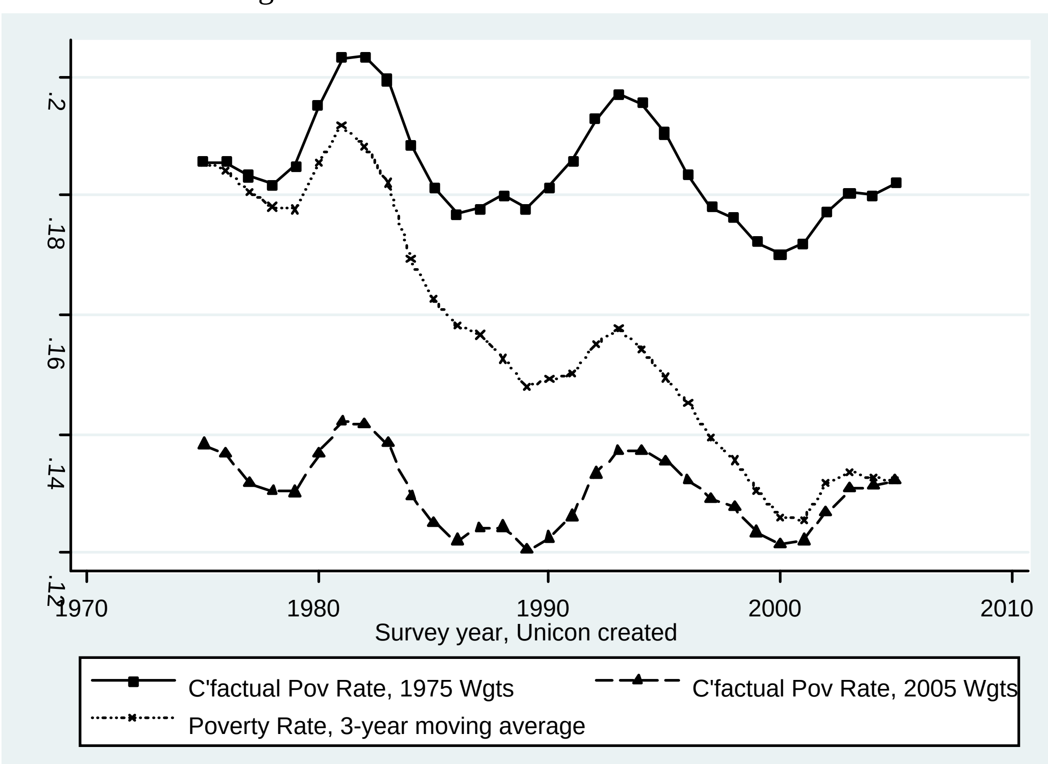

Figure 3.7. Actual and Counterfactual Poverty Rates
Comparing the Impact of shift from LTHS to HS only to the Original 1975 education distribution

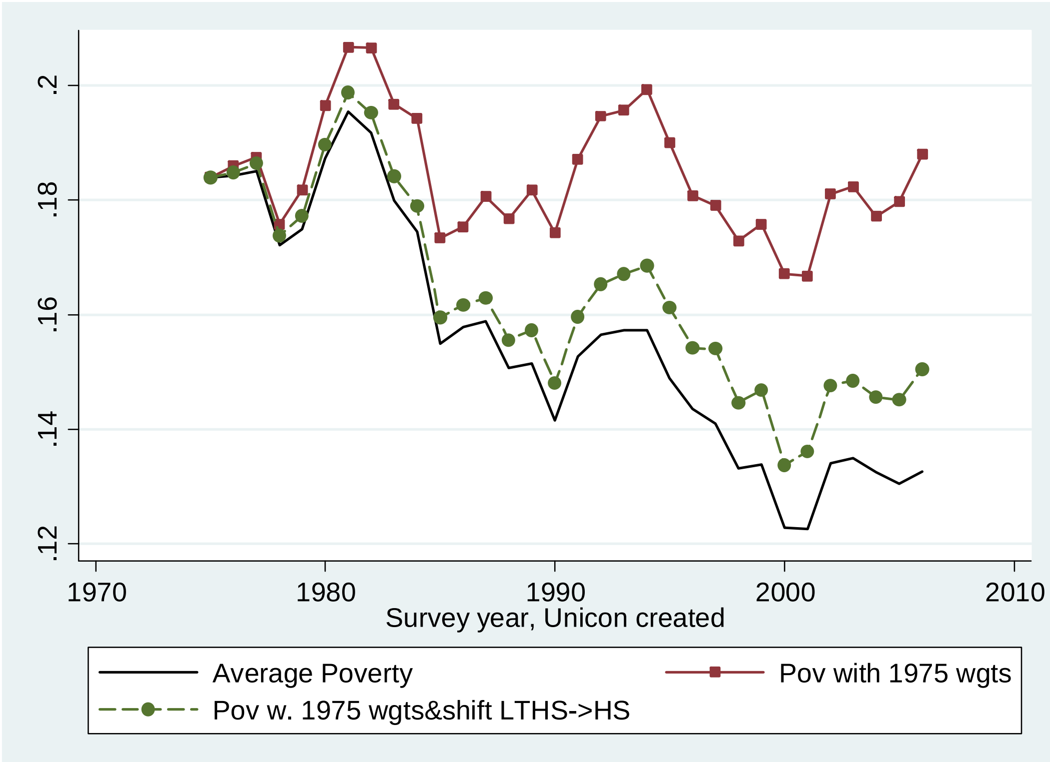

Figure 3.8. Distribution of Marital Status for Women ages 65 and older, 1975-2005

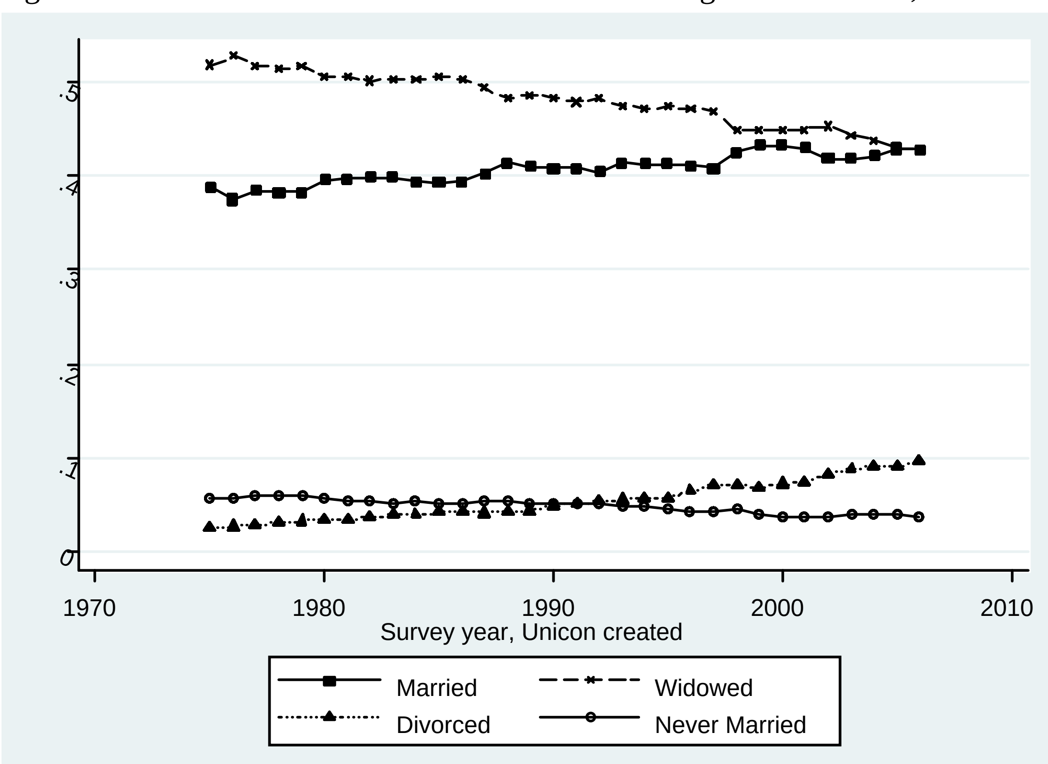

Figure 3.9. Actual and Counterfactual Poverty rates
Maintaining Marital Status distribution from 1975 and 2005

Figure 3.10. Actual and Counterfactual Poverty Rates
Impact of the shift from Widows to Married and from Married to Divorced

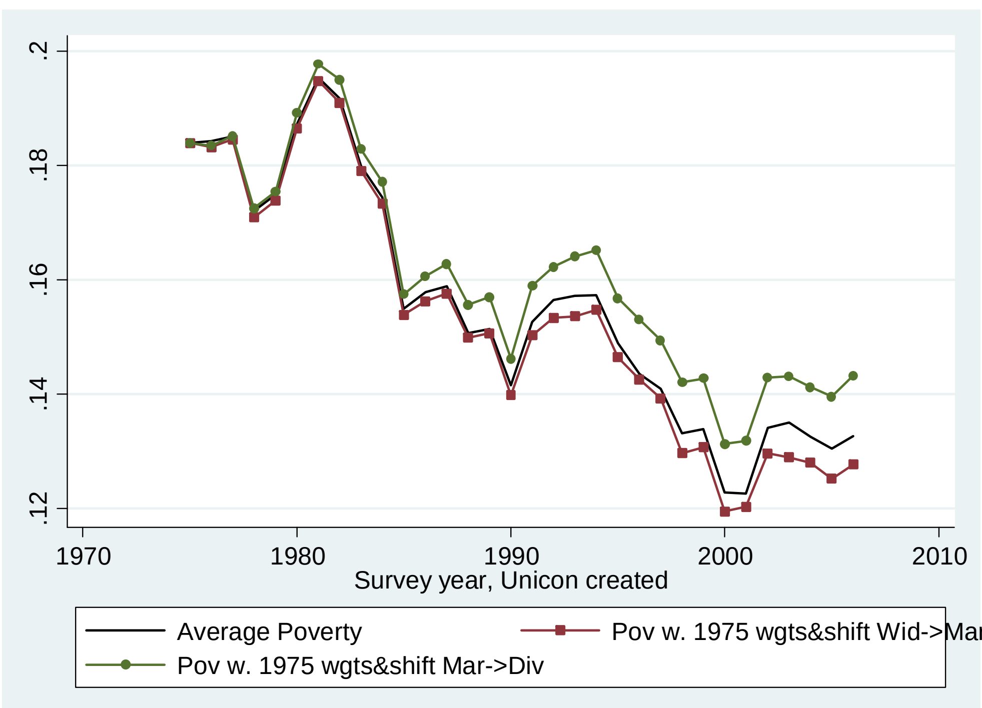

Figure 3.11. Actual and Counterfactual Poverty rates
Maintaining Age, Education, and Marital Status distribution from 1975 and 2005

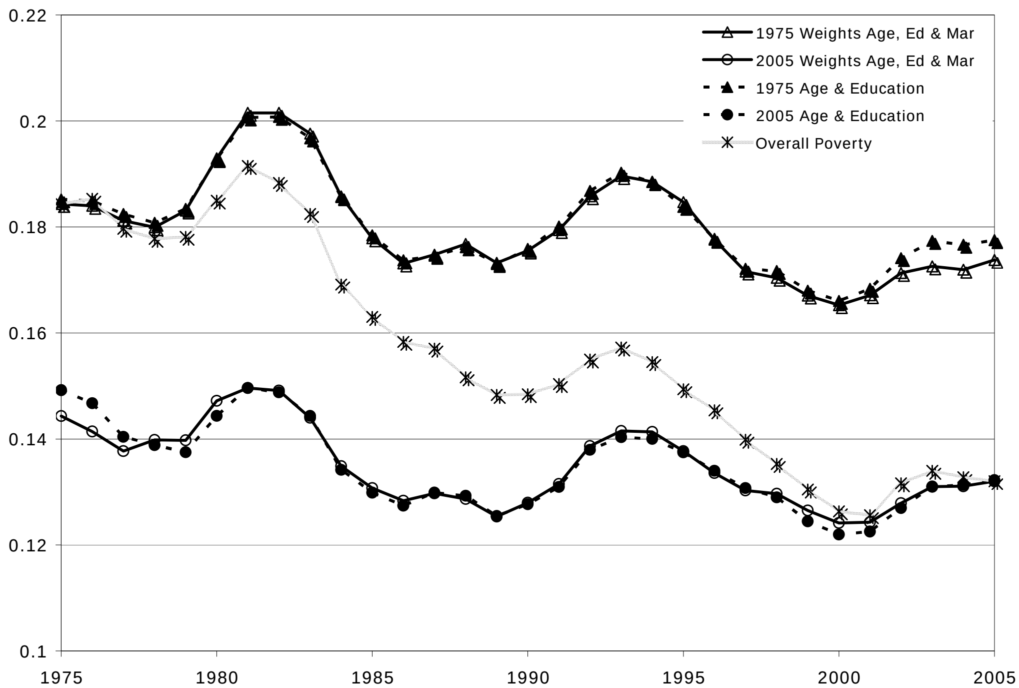

Figure 3.12: Log Personal Income, Women ages 65-79, 1995 and 2005

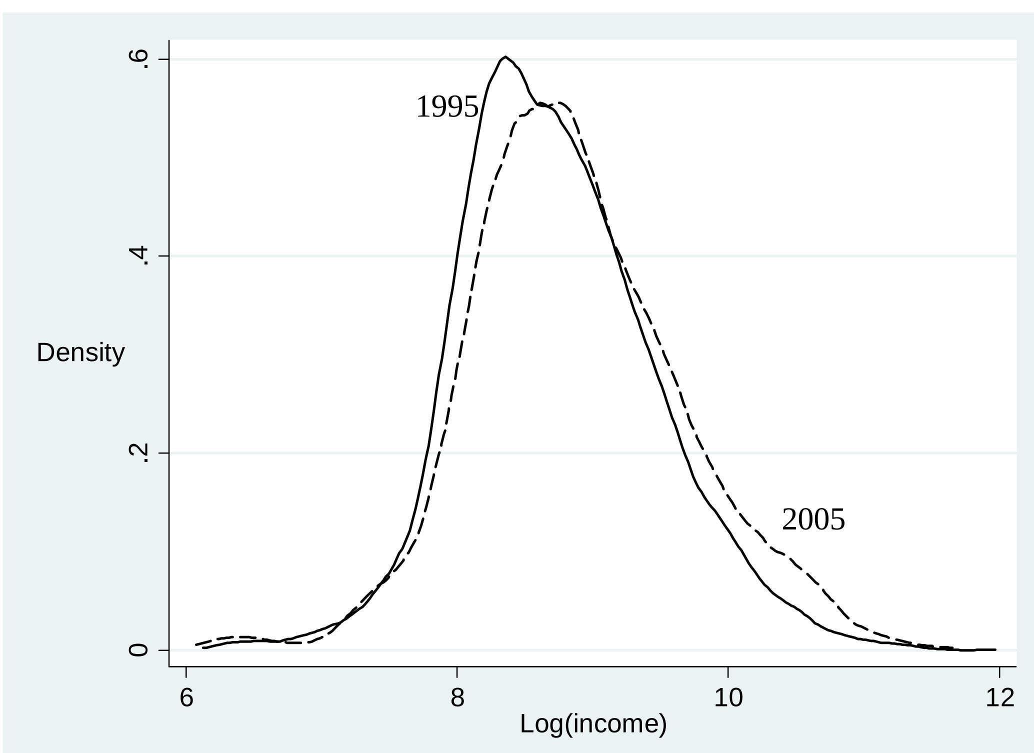

Figure 3.13. Impact of Age Distribution, DFL reweighting

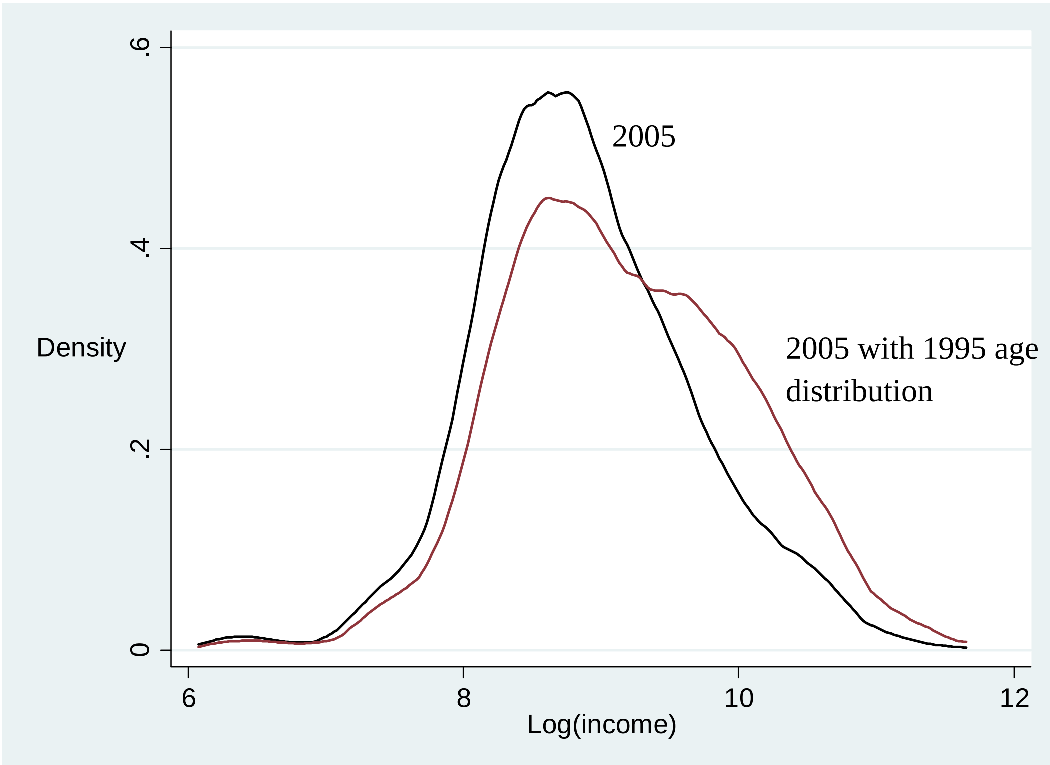

Figure 3.14. Impact of Education Distribution, DFL reweighting

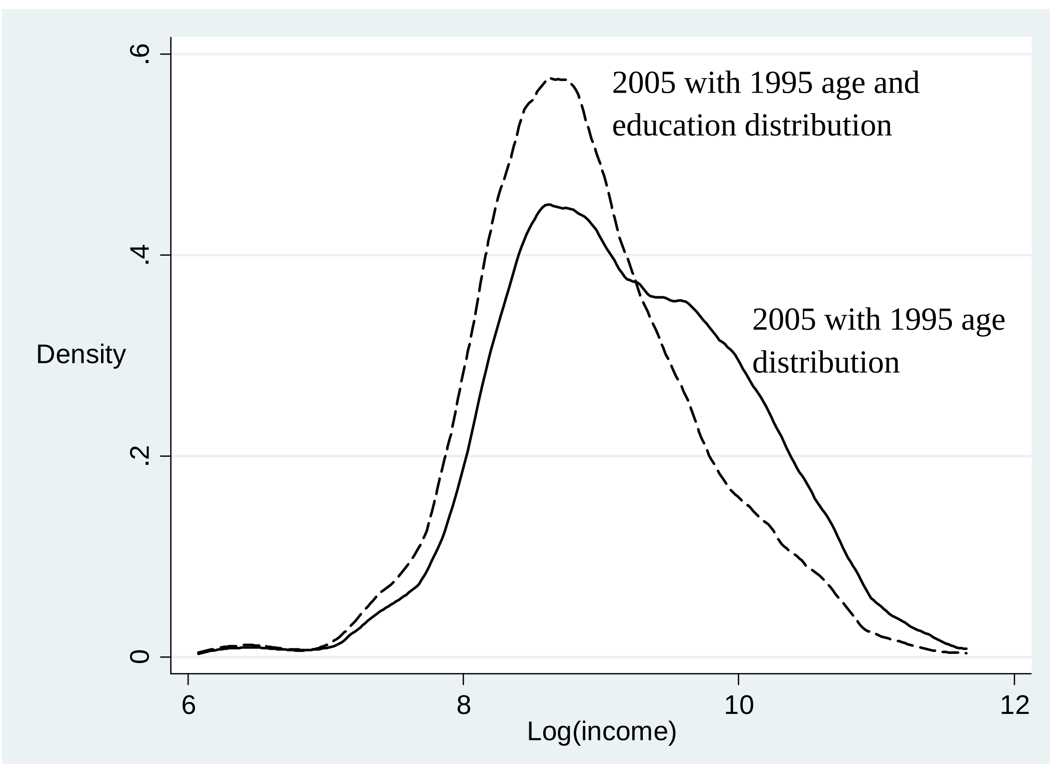

Figure 3.15. Impact of Marital Status Distribution, DFL reweighting

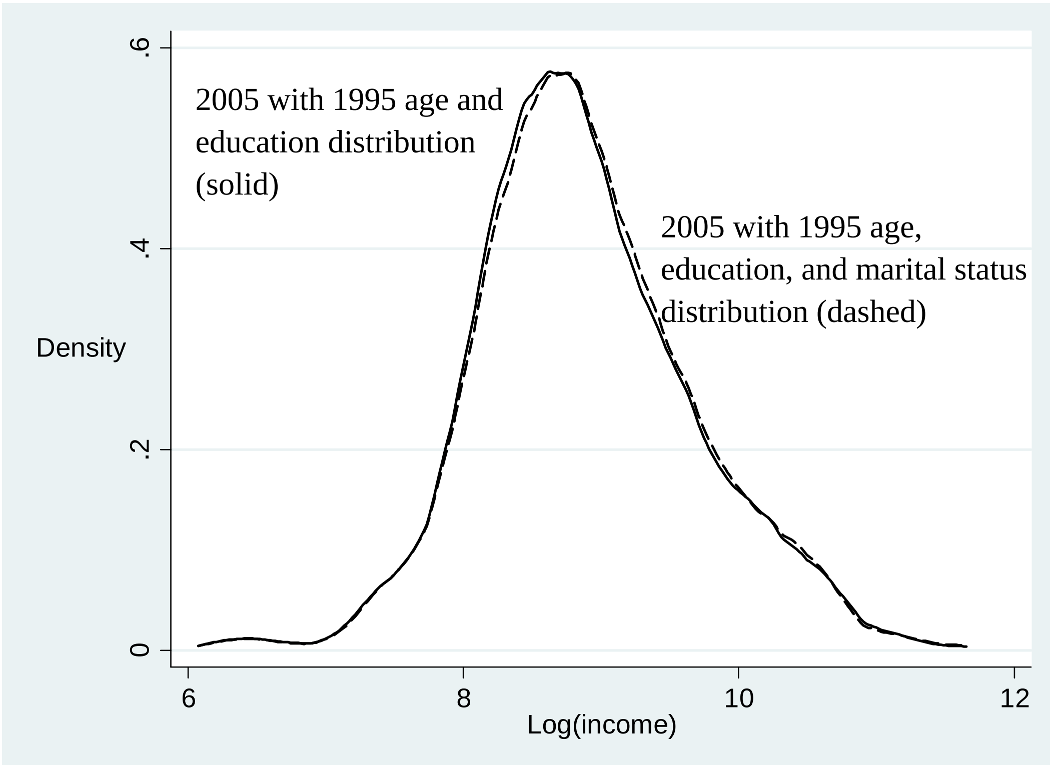

Figure 3.16. Impact of Changes in Labor Force Participation, DFL reweighting

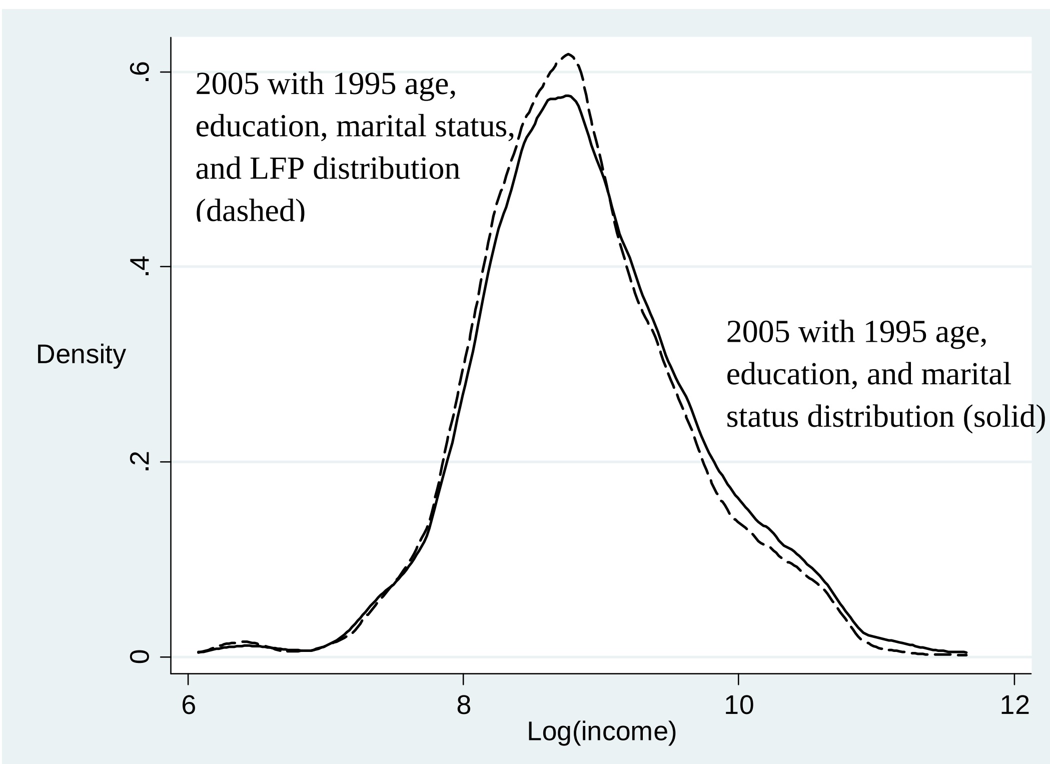

Figure 3.17. Comparing Log Income in 1995 & 2005 to Log Income in 2005 with DFL weights

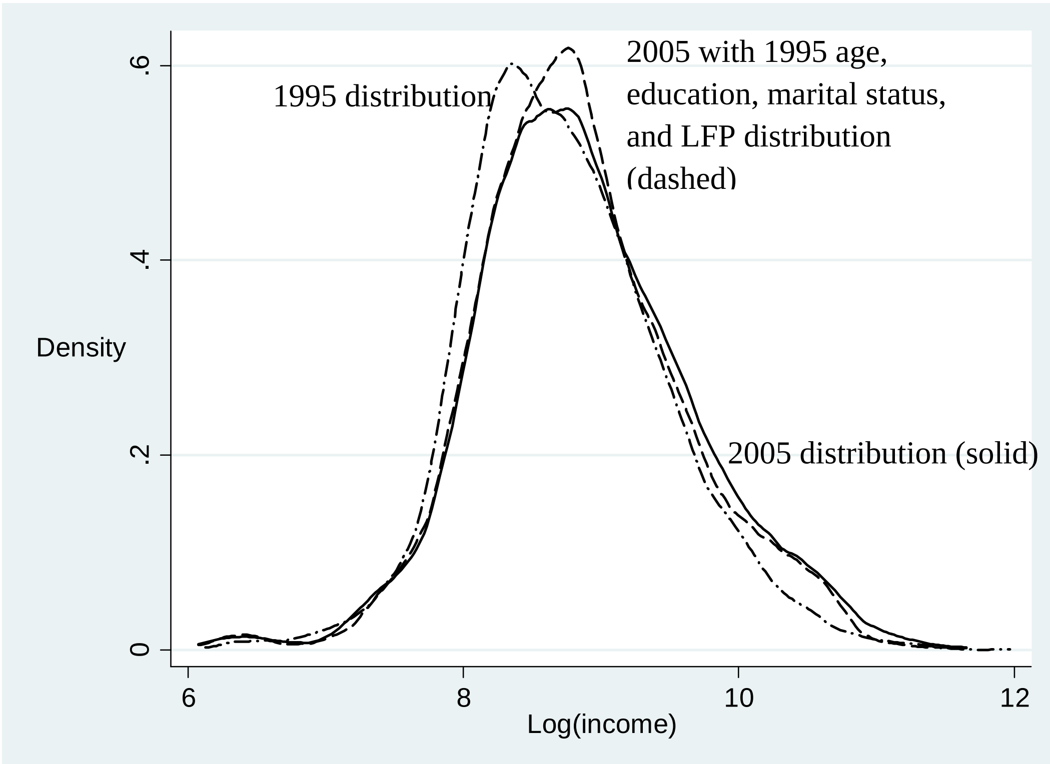

Figure 3.18. Actual and Predicted Poverty at ages 65-69

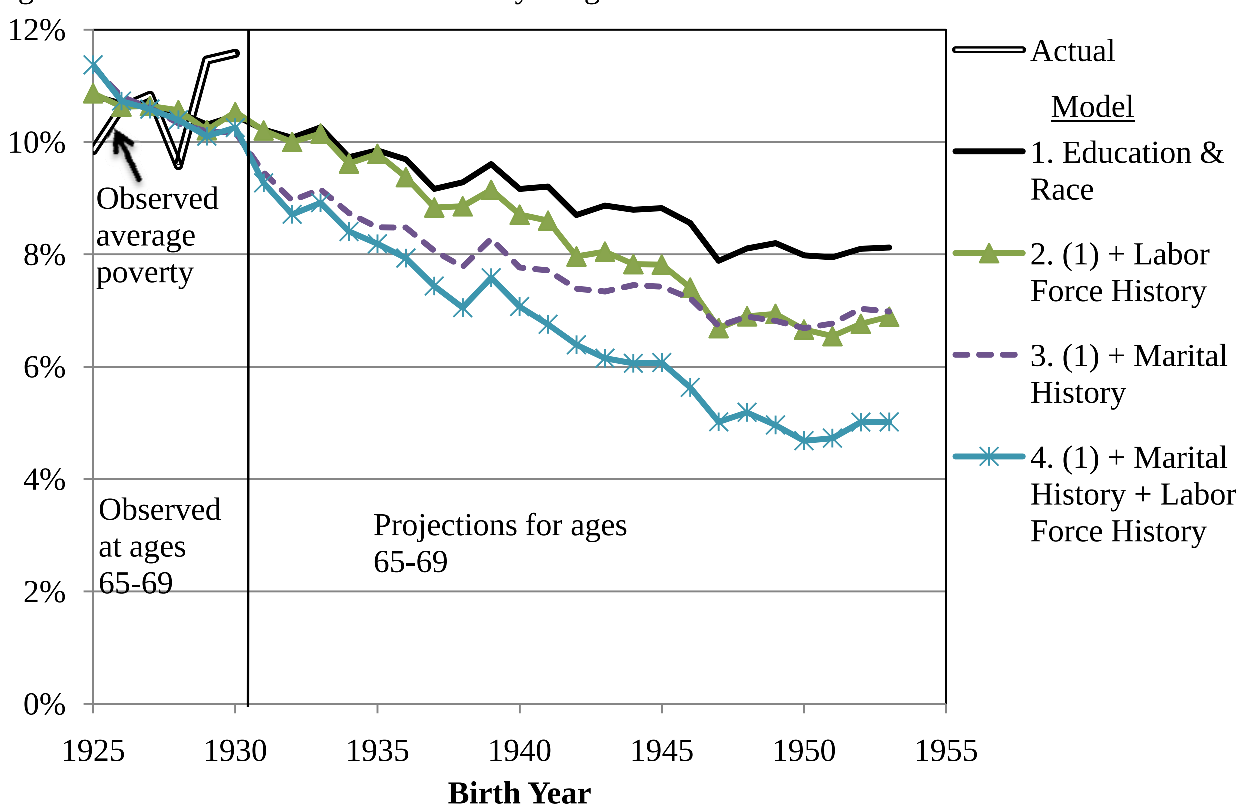

Table 3.1 Projections of Female Poverty Rates, ages 65 to 79

Year	Age distribution only	Age and education
2006	12.13	12.13
2007	12.09	12.00
2008	12.04	11.83
2009	12.08	11.76
2010	12.04	11.51
2011	12.04	11.36
2012	12.02	11.14
2013	11.97	10.93
2014	11.97	10.92
2015	11.96	10.60
2016	11.99	10.40
2017	11.98	10.29
2018	11.97	10.16
2019	12.02	10.11
2020	11.96	9.86
2021	11.98	9.81
2022	12.00	9.75
2023	12.02	9.65
2024	12.02	9.59
2025	12.00	9.54

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Appendix A

Synthetic versions of the data are made available to researchers for analysis, while the final analysis must be performed at the Census Bureau by government employees. The variables on the synthetic files are synthesized to protect the anonymity of the individuals, but "should reproduce characteristics of the underlying confidential data". There are 16 implicates of the data, and we can think of each as a dataset of imputed values. Estimates from the synthetic implicates are averaged for final estimates from the imputed data. Calculation of the standard errors takes into account the imputation process (Abowd et al, 2006). This is a new type of data set and an additional value of this analysis will be to evaluate how well the data implicates perform. The synthetic implicates do not reproduce the claiming distribution very well as they smooth over claiming spikes at ages 62 and 65. Despite this shortcoming, estimates of the baseline model from the synthetic data is very similar to results from the Gold Standard files.

Figure A1. Expected Lifetime Retired Worker Benefits, by Discount Rate

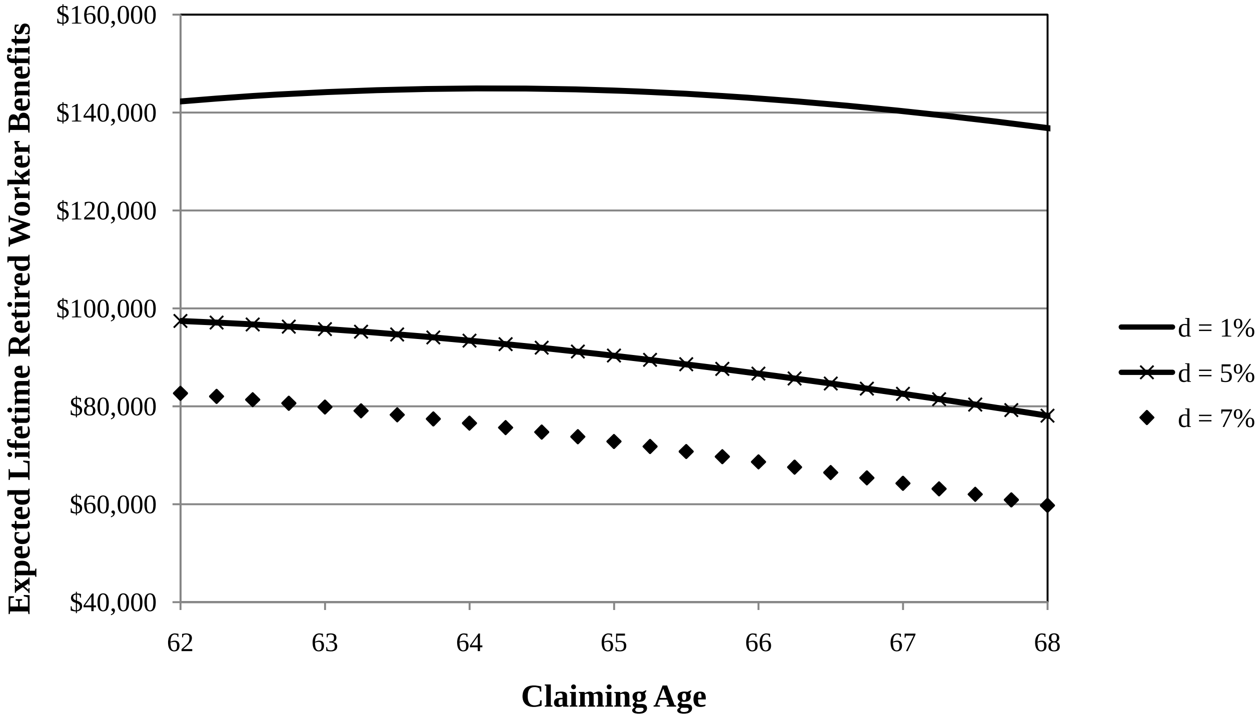
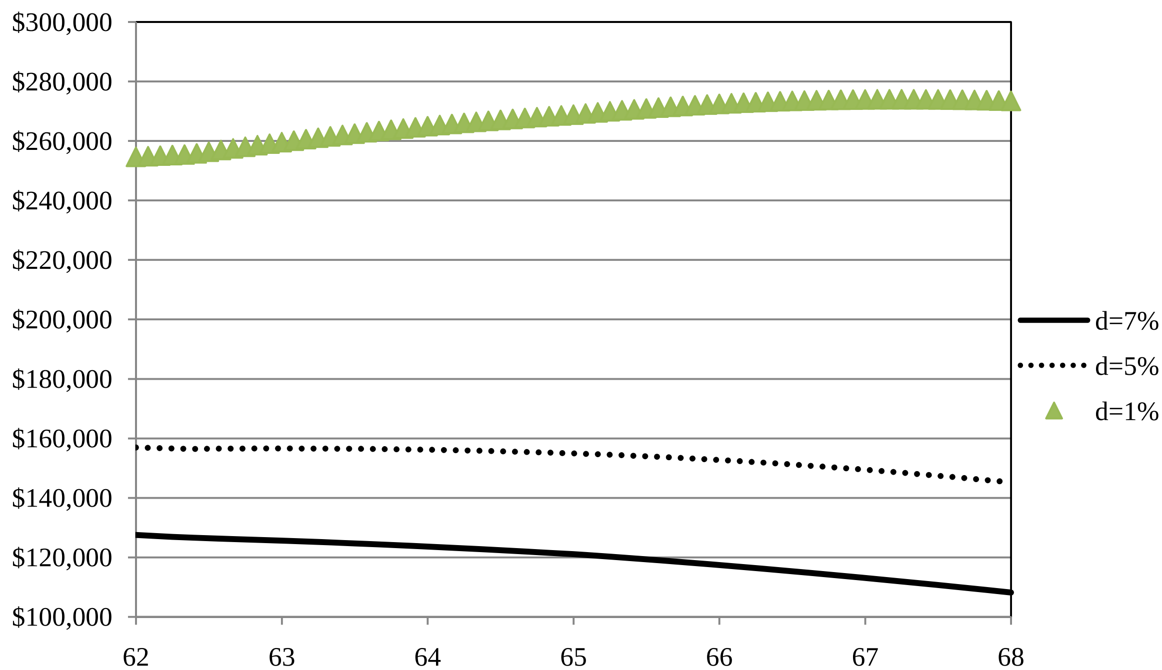
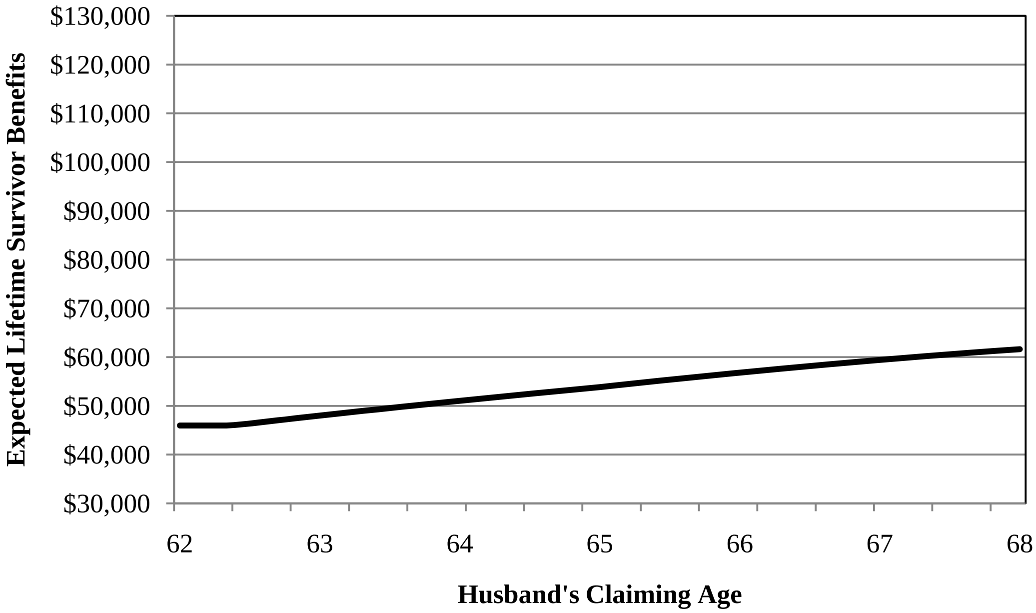


Figure A2. Total Household Expected Benefits, by Discount Rate



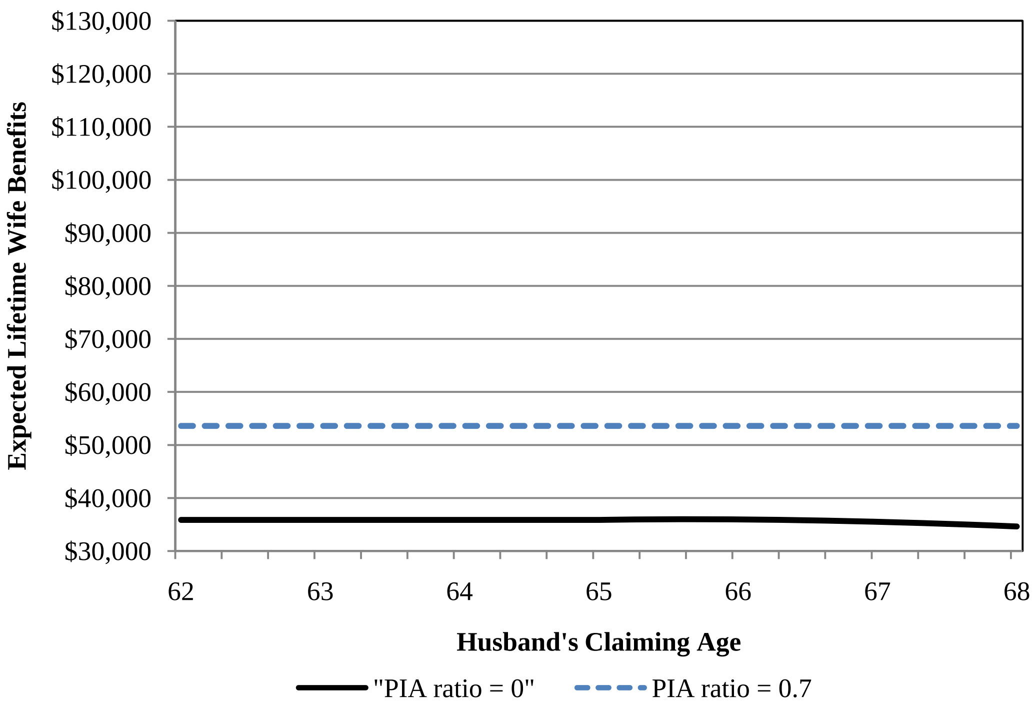
Note: Wife PIA = 0

Figure A3. Expected Survivor Benefits



Note: For males with PIA of $963 born in 1937; NRA = 65 and DRC = 6.5%; wife 3 years younger.

Figure A4. Expected Wife Benefits



Note: For males with PIA of $963 born in 1937; NRA = 65 and DRC = 6.5%; wife 3 years younger.

PIA Ratio = Wife PIA/Husband PIA.

Figure A5. Distribution of PIA Ratio

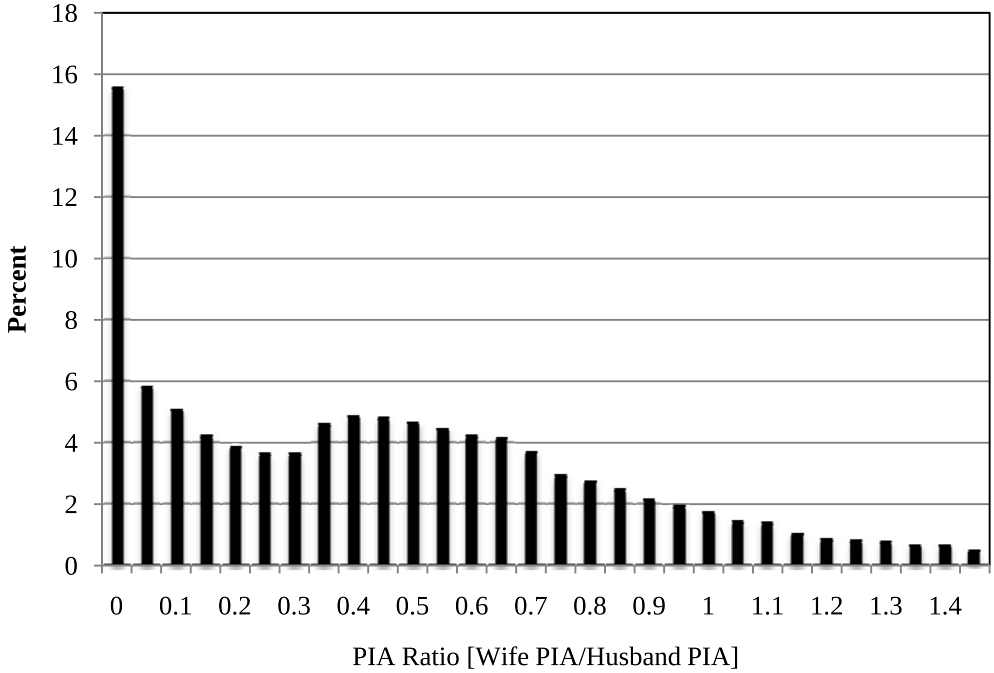


Figure A6. Expected Lifetime Retired Worker Benefits, by Normal Retirement Age (NRA)

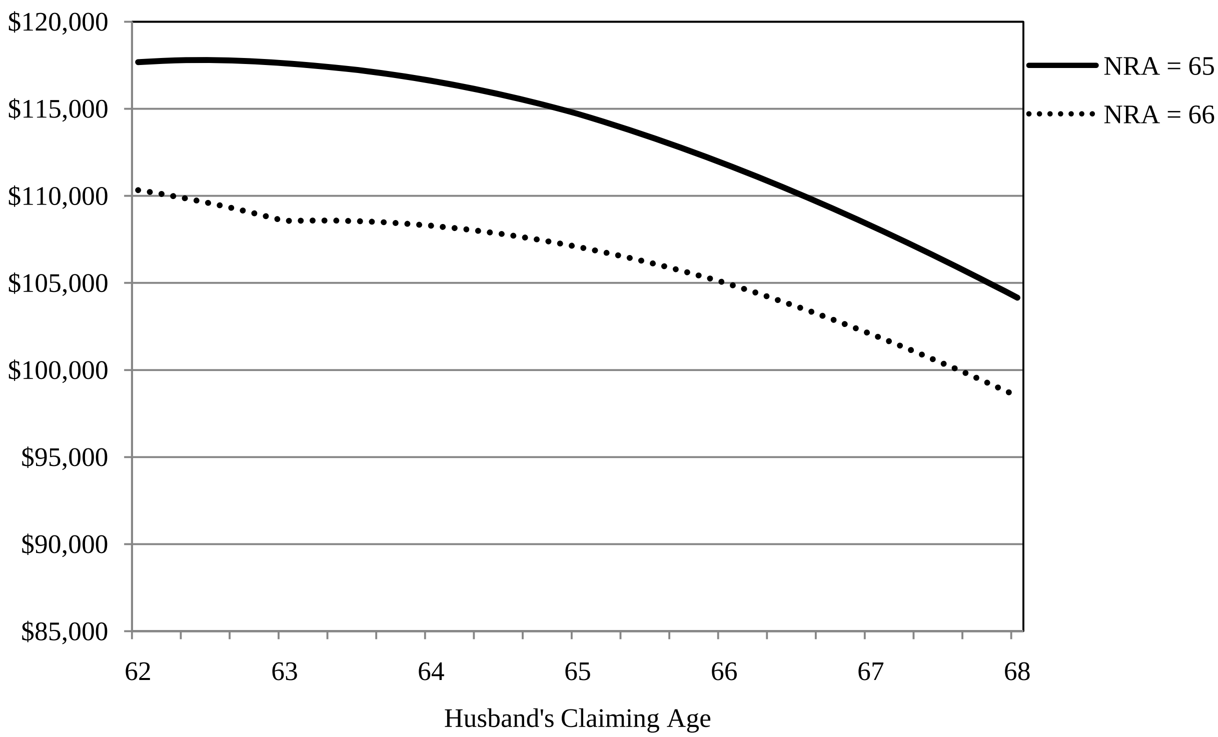
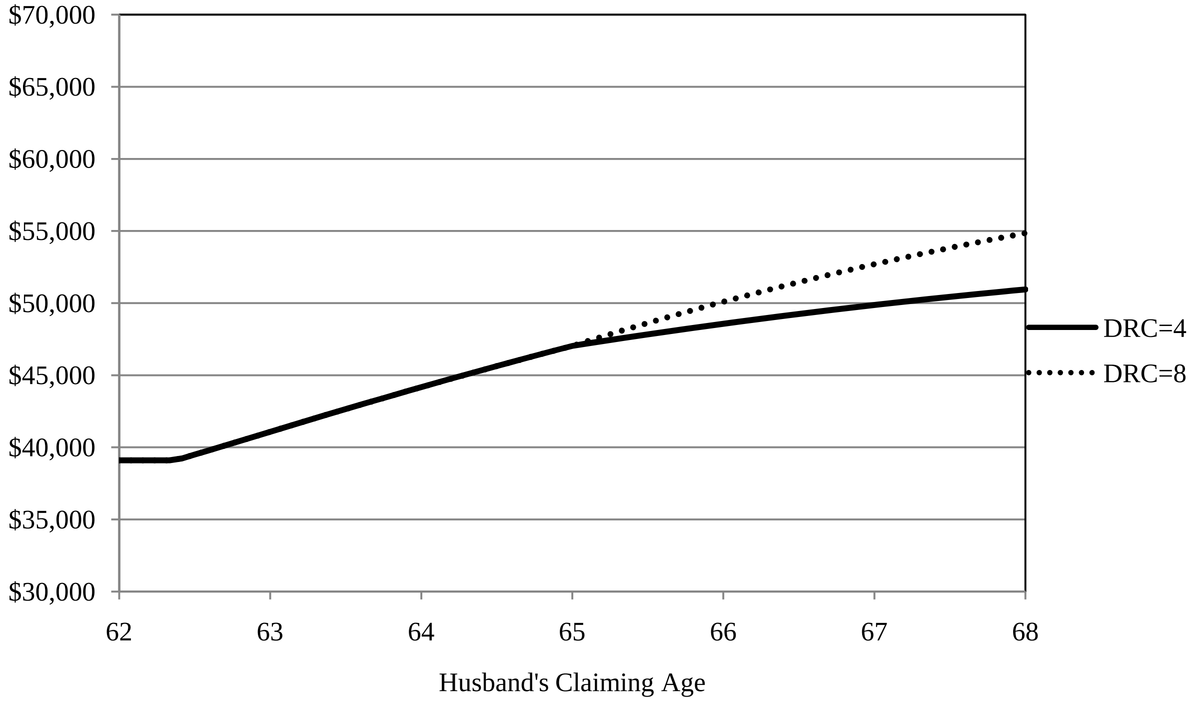
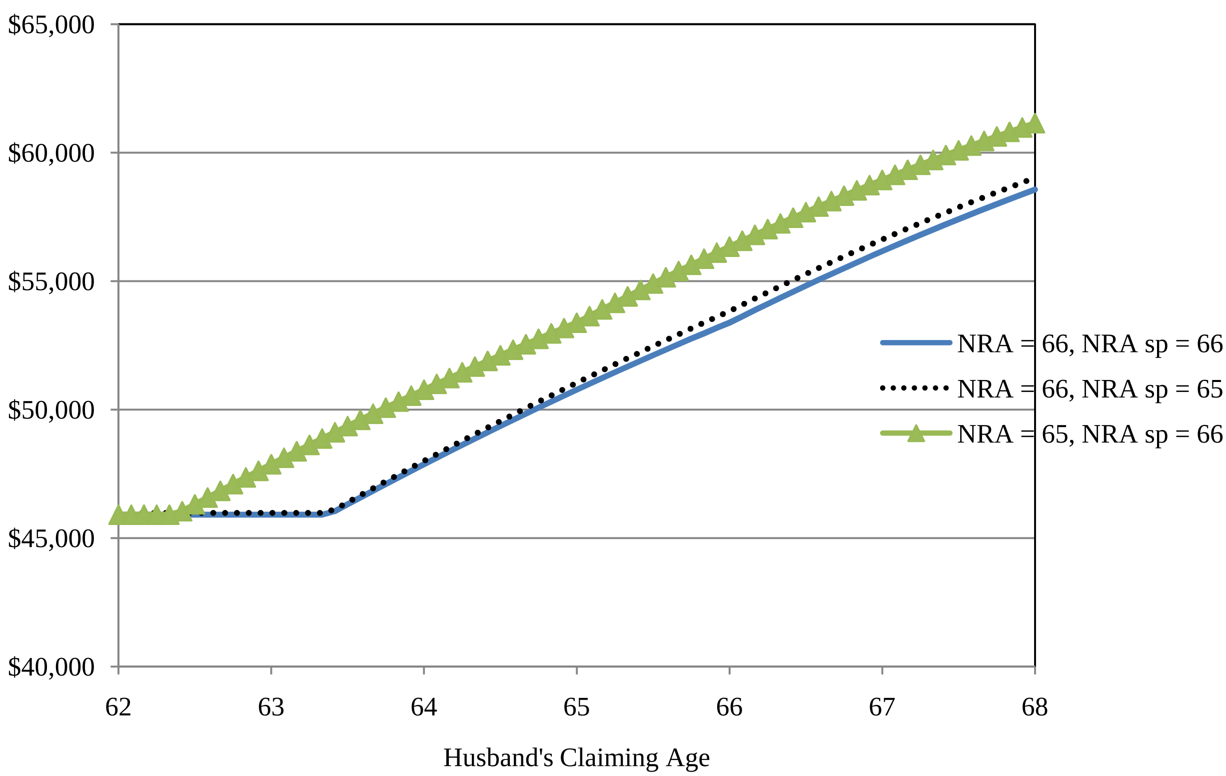


Table A7. Expected Survivor Benefits by Delayed Retirement Credit (DRC)



Note: For males with PIA of $963 born in 1937, NRA = 65, and wife 3 years younger.

Table A8. Survivor Benefits by NRA of Husband and Wife



Appendix B

Survey of Income and Program Participation Data Notes

Following Gruber and Madrian (1997), I drop individuals who have a job but are not at work. In addition, those who are business owners are dropped, since a model of health insurance would likely differ for these individuals. In any case, coverage of the self-employed is a topic to be explored in other research. The SIPP documentation claims that three variables (plus a time variable) will uniquely identify observations in the data. However, this is not the case. About 10% of the sample had to be removed because the identifiers used in the SIPP were not able to distinguish between two people in the same household.

Variables used to create disability index

Receiving some type of disability payments, Disability as a reason for: the receipt of Social Security, receipt of different type of pensions, receipt of worker's compensation, reason for working part-time, had a physical or mental condition which limits work, application for AFDC, application for WIC, application for food stamps, application for General Assistance, application for other welfare, application for SSI, or receipt of veteran's payment.

Table B1. Log Weekly Wages by Time to Displacement, Full Sample, Males

Sample includes all Displaced and never displaced workers with at least 4 months of employment

Change to Baseline

	Baseline	Months Pre-Displacement			Displace-ment	Months Post-Displacement			
MODEL		-24 to -13	-12 to -5	-4 to -1	0	1 to 3	4 to 11	12 to 23	24+
Indiv	-13.3%	-0.8%	-2.7%	-6.7%	-37.1%	-14.0%	-6.3%	-1.5%	2.8%
	(2.4%)	(2.0%)	(2.3%)	(2.5%)	(3.1%)	(2.8%)	(2.7%)	(2.9%)	(3.2%)
Indiv, FE	----	2.6%	3.0%	1.8%	-25.9%	-9.3%	-0.3%	4.4%	6.7%
		(1.7%)	(1.9%)	(2.0%)	(2.6%)	(2.3%)	(2.1%)	(2.2%)	(2.5%)
Indiv + Current Job	-9.1%	-1.0%	-3.7%	-7.8%	-38.2%	-13.7%	-6.0%	-1.8%	1.8%
	(2.2%)	(1.9%)	(2.2%)	(2.3%)	(3.0%)	(2.6%)	(2.4%)	(2.6%)	(2.9%)
Indiv + Current Job, FE	----	2.3%	2.4%	0.8%	-26.9%	-9.4%	-0.4%	4.1%	6.4%
		(1.6%)	(1.8%)	(2.0%)	(2.6%)	(2.3%)	(2.1%)	(2.2%)	(2.5%)

Table B2. Employer Provided Health Insurance by Time to Displacement, Restricted Sample, Females

Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

Change to Baseline

	Baseline	Months Pre-Displacement		Displace-ment			Months Post-Displacement	
MODEL		-12 to -5	-4 to -1	0	1 to 3	4 to 11	12 to 23	24+
Raw Difference	-4.8%	0.6%	-1.2%	-7.7%	-11.8%	-8.6%	-2.1%	-4.3%
	(4.0%)	(2.9%)	(3.6%)	(3.4%)	(3.9%)	(4.2%)	(4.4%)	(5.1%)
Date Fixed Effects	-9.2%	0.7%	-2.9%	-9.1%	-15.1%	-14.5%	-8.1%	-8.7%
	(4.0%)	(2.9%)	(3.6%)	(3.5%)	(3.9%)	(4.2%)	(4.5%)	(5.2%)
Individual	-6.5%	-0.0%	-3.9%	-9.2%	-15.3%	-15.1%	-8.8%	-10.3%
	(3.9%)	(2.8%)	(3.6%)	(3.4%)	(3.9%)	(4.3%)	(4.5%)	(5.1%)
Indiv + Current job	-7.9%	-0.0%	-5.1%	-10.0%	-7.8%	-5.1%	-1.6%	-3.2%
	(3.5%)	(2.7%)	(3.4%)	(3.2%)	(3.6%)	(3.8%)	(4.0%)	(4.5%)

Table B3. Log Weekly Wages by Time to Displacement, Restricted Sample, Females

Sample: Continuously Employed in 1996, Displaced in 1997 & Never Displaced

Change to Baseline

	Baseline	Pre-Displacement		Displacement	Months Post Displacement			
MODEL		-12 to -5	-4 to -1	0	1 to 3	4 to 11	12 to 23	24+
Individual	-6.7%	-3.5%	3.4%	-31.5%	-14.9%	-7.6%	-11.3%	-12.6%
	(5.9%)	(5.1%)	(4.9%)	(7.5%)	(7.8%)	(5.9%)	(6.9%)	(8.5%)
Individual, FE	-----	-0.1%	0.0%	-26.4%	-18.1%	-12.0%	-13.7%	-10.5%
	-----	(3.7%)	(3.9%)	(6.3%)	(7.0%)	(4.8%)	(6.1%)	(6.4%)
Individual +	-6.8%	-2.8%	-2.2%	-28.2%	-12.2%	-4.1%	-8.0%	-8.2%
Current Job	(5.3%)	(4.7%)	(4.5%)	(7.2%)	(7.6%)	(5.6%)	(6.3%)	(7.7)%
Individual +	-----	-0.1%	0.0%	-25.7%	-16.5%	-10.5%	-12.2%	-9.3%
Current Job, FE	-----	(3.5%)	(3.8%)	(6.3%)	(7.0%)	(4.7%)	(5.9%)	(6.1%)

Appendix C

Full set of labor force history and marital history controls used in projections are:

Existence of 1st and 2nd marriages and whether ended in widowhood and divorce; existence of 3rd and 4th marriages; fraction of 30s spent married, divorced, widowed or never married; fraction of 40s spent married, divorced, widowed or never married; age of 1st through 7th change in marital status (and interacted with experience in 30s and 40s); fraction of 30s married interacted with average wages in 30s and years worked in 30s; fraction of 40s married interacted with average wages in 40s and years worked in 40s; # of years employed in 30s, # of years employed in 40s, average (nonzero) earnings between ages 30 and 50, average earnings between ages 30 and 50 including zeros, average wage in 30s, average wage in 40s, average nonzero wage in 30s, average nonzero wage in 40s