ESSAYS ON GENDER DIFFERENCES IN OCCUPATIONAL CHOICES AND COHORT ANALYSIS OF SAVING ADEQUACY

by

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Abstract

The first chapter analyzes how human capital depreciation affects occupational gender segregation. Prior studies are biased because, given an occupational depreciation rate, female workers endogenously choose the duration of leave. I address this problem by proposing an alternative depreciation measure utilizing involuntary job displacement shocks. Using this depreciation proxy along with additional pecuniary and non-pecuniary occupational attributes, I estimate a conditional logit model of occupational choices separately for male and female college graduates using NLSY79 data. The results show that men and women differ largely in selection on many occupational attributes, however, the gender difference in depreciation is statistically insignificant after accounting for additional variance from the generated depreciation regressor.

The second chapter explores the trend of gender differences in selection on occupational mobility. Women who interrupt their career and return to the labor force face the uncertainty of forming a new job match. This uncertainty can be large if the skills they acquired are occupational-specific. I estimate discrete occupational choices by different cohorts using cross-sectional Current Population Survey (CPS) from 1979 to 2008.I find that over the past 30 years, the consideration of occupational mobility has abated in female occupational decisions. In addition, gender gaps in work hours and visual perception also narrow over the past thirty years. Increasing female representation is evident in occupations with high entry barriers, long work hours, and visual intensive tasks.

In the third chapter, we extend the dynamic programming approach used in Scholz, Seshadri, and Khitatrakun (2006) to assess the adequacy of retirement wealth preparation in 2008, using a sample of Americans born before 1954. We examine whether these households have accumulated the wealth necessary to maintain pre-retirement living standards in retirement. Our preliminary results suggest that over 70 percent of the households in our sample had accumulated sufficient resources in 2008. The results suggest a less optimistic view about the adequacy of Americans' retirement preparation than the findings for 1992 in Scholz, Seshadri, and Khitatrakun (2006). Economically disadvantaged households are significantly more likely than others to be under-saving and hence are natural targets for outreach and other efforts to improve financial capabilities.

Chapter 1

The Effects of Human Capital Depreciation on Occupational Gender Segregation

1.1 Introduction

Despite high labor force participation rates, career interruptions are still common among women. Over 41 percent of college-educated women were out of work for more than 6 months at some point, and 23.4 percent had out-of-work spells that totaled two years or more in the fifteen years after receiving a baccalaureate degree. Only 14.1 percent of college-educated men were out of work for at least 6 months at some point, and 3.1 percent had accumulated out-of-work spells of more than 2 years (Goldin and Kuziemko, 2006).[1] Because women are more likely than men to take career breaks to care for their families, they may choose occupations that have lower human capital depreciation to mitigate the wage losses from job interruptions. This consideration is likely to be important for occupations with frequent knowledge-updating requirements, such as sciences, engineering, and finance.[2] Leave patterns and depreciation likely affect the dispersion of gender distributions across occupations. Since occupational segregation results in persistent wage disparities between men and

[1] Table 1 of Goldin (2006) delineates the out-of-work pattern of the entering class of 1976 from the College and Beyond dataset of the Andrew W. Mellon Foundation.

[2] McDowell (1982) estimates how the durability of knowledge influences female career decisions in academia using the the age profile of cited works, i.e. the durability of prior published research papers as cited in current research. He finds that the costs of career interruptions to be largest in physics and chemistry, and lowest in history and English; and the proportion of women in a field is directly related to the durability of the research knowledge in the areas.

women, it is crucial to understand the driving forces of segregation (Groshen, 1991; Blau and Kahn, 2000; Bayard et al., 2003).[3]

Polachek (1981) provides a theoretical framework and empirical evidence to show that women, anticipating spending time out of the labor force, rationally choose occupations with lower wage losses during home-time. England (1982) argues that Polachek's (1981) human capital depreciation hypothesis does not explain occupational gender segregation for two reasons. First, she finds that wage losses during home-time is similar for both male- and female-dominated occupations. Second, occupational choices are similar for women with continuous employment histories and women who interrupt their careers.

The Polachek-England debate led to several follow-up studies. For instance, following England's (1982) specification, Robst and VanGilder (2000) find an insignificant coefficient on the interaction between the percent of female workers in a given occupation and home-time. However, their results change when they replace the continuous home-time variable with an indicator of recent home-time in the prior year. They find that the home-time penalty is higher in occupations with low female representation. Recent research that uses German data also shows contradictory results. Kunze (2012) focuses on workers who participated in apprenticeship training and finds that the depreciation rate is higher in female occupations. In contrast, Görlich and de Grip (2009) and De Grip and Loo (2002) find that the short-run depreciation rate is higher in male occupations than in female occupations in the high-skill labor market.

The inconclusive findings are likely to occur because these studies neglect occupational sorting on other attributes. Gender differences in the preferences for occupational attributes, for instance, can also contribute to occupational segregation. Zafar (2009) and Wiswall and Zafar (2011) elicit subjective expectation information from college students and find that the pecuniary incentive is a more important determinant of college major choices for men

[3] Groshen (1991) finds that after controlling for other forms of segregation, occupational segregation accounts for up to 26 percent of the gender wage gap in services industry. Blau and Kahn (2000) find that occupations and industries together explained 29 percent of the total gender gap. Bayard et al. (2003) find that male-female wage gap is lowered by 25 percent when they control for broad occupation and industry categories.

than for women, and non-pecuniary outcomes (e.g. enjoying coursework) dominate female major choices. Fortin (2008) also finds that gender differences in valuing money and family play a modest but significant role in accounting for the gender wage gap. Hence, sorting on other occupational attributes may mask the effect of sorting on human capital depreciation if these effects cancel each other out.

Another important issue missing from prior studies is the endogeneity between depreciation and home-time. All of these studies take the occurrence or the length of job interruptions of a worker as a given and regress wages on job interruptions to obtain the human capital depreciation rates. Although low depreciation occupations may attract women who anticipate long career interruptions, it could also be the case that being in a low depreciation occupation induces one to take a longer leave. Selection bias also arises because observations of female wage changes are only available for women who return to the labor force.[4] If human capital depreciation rates are in fact higher for female-dominated jobs than for male-dominated jobs, leavers from these female-dominated jobs are likely to remain non-working because higher wage penalties push wage offers below their reservation wages. Therefore, the human capital depreciation estimates may be biased downward for female-dominated jobs without accounting for selection.

My research fills these gaps and contributes to the literature in the following respects. First, I propose an alternative human capital depreciation measure that uses wage losses from unemployment following involuntary job displacements of male workers. Although involuntary job terminations are arguably exogenous, any bias in my depreciation measure due to the selection of male displaced workers (e.g. plants closed in declining industries) is unlikely to cause the result of gender differences in responses to depreciation. In addition,

[4]Polachek (1981) estimates atrophy as the coefficient of home-time in a first-differenced wage equation and regress the atrophy rates on home-time in the second stage. He recognizes the simultaneity issue in the second stage and addresses the problem with the following exclusion restrictions for home-time: potential labor market experience, number of children less than 18, an urban area dummy, a good or excellent health dummy, the age of the youngest child, and an index of labor market demand. Validity of some of these instruments may be questionable–for instance, fertility (number and age of children) can be endogenous to occupational human capital depreciation rates since women in high depreciation occupations may choose to delay fertility to lower her demand for home-time. More importantly, using instruments in the second stage does not address the issue of selection bias in human capital depreciation estimation from the first stage.

I estimate the effect of human capital depreciation on occupational choices by gender while controlling for selection on other occupational characteristics, including wage levels, wage growth, work hours, and occupational tasks (e.g. cognitive tasks, manual tasks). The inclusion of additional occupational attributes helps reconcile the seemingly contradictory results presented in previous studies because I allow multi-dimensional occupational sorting.

This paper investigates how human capital depreciation contributes to occupational gender segregation in the high-skill labor market. The causes of gender segregation likely differ across labor market segments. For instance, occupational gender segregation in the low-skill labor market may be largely explained by male comparative advantages in physical strength, which may be much less pertinent in the high-skill market. To focus on a more homogeneous group, I restrict my sample to college graduates. My empirical approach is to estimate occupational choices in two stages. In the first stage, I estimate occupation-specific human capital depreciation rates as wage changes due to unanticipated work termination shocks by using the Displaced Workers Survey (DWS). In the second stage, using the first stage depreciation estimates and additional occupational attributes, I analyze the discrete occupational choices by college graduates from the National Longitudinal Survey of Youth 1979 (NLSY79) by using a conditional logit model (Mcfadden, 1974; DeLeire and Levy, 2004).[5]

My results show that gender differences are pervasive in wage, wage growth, work hours, and most occupational attributes. However, the gender difference in occupational depreciation is statistically insignificant after adjusting the standard errors to account for additional variance from the generated depreciation regressor in the first stage. This imprecise result makes it difficult to make inferences about the effect of depreciation on gender occupational segregation. The remaining of this paper is organized in the following manner. In Section 1.2, I provide a heuristic theoretical framework. Section 1.3 delineates my empirical strategies, followed by data descriptions in Section 1.4. I present the results in Section 1.5 Finally, Section 1.6 concludes.

[5]The conditional logit model (McFadden, 1974) is a generalized multinomial model widely used to estimate how characteristics of options affect individual choices. For instance, DeLeire and Levy (2004) use this model to estimate the willingness to trade safety hypothesizing that risk averse individuals sort into safer jobs.

1.2 Theoretical Framework

To understand how human capital depreciation influences individual occupational choices, I consider a simple three-period model. Suppose there are only two occupations–A and B–in a perfectly competitive labor market, and skills are nontransferable between these two occupations. Occupation A has a higher human capital depreciation rate than does occupation B. Individuals face occupational choices in the beginning of the first period.

In the first period, individuals choose one occupation and receive its corresponding wage (i.e. w^A or w^B). In the second period, individuals may be hit by a random fertility shock and the probability of having children is p. If individuals have children, they withdraw from the labor market for a period. If individuals do not have children, they continue working and receive the wage offer $w^j + g^j$ in the second period, where g^j indicates the wage growth in one period from the occupation $j = \{A, B\}$. In the last period, children leave, and individuals work again in the same occupation they initially chose. If individuals leave the labor market in the second period, their wage offer upon returning to work in the third period is $w^A(1-\delta) + g^A$ for occupation A, and $w^B + g^B$ for occupation B, where δ represents human capital depreciation for job A and $\delta \in (0, 1]$. Note that the depreciation is normalized to 0 for occupation B.

Assume that individuals are risk-neutral and choose an occupation to maximize their discounted life-time earnings. With the real interest rate at r, the expected net present value of the life-time earnings $E(W^A)$ from occupation A is:

$$\begin{aligned} E(W^A) &= w^A + (1-p)\left[\frac{1}{1+r}\left(w^A + g^A\right) + \frac{1}{(1+r)^2}\left(w^A + 2g^A\right)\right] \\ &\quad + p\left[\frac{1}{(1+r)^2}\left((1-\delta)\, w^A + g^A\right)\right] \qquad (1.2.1) \end{aligned}$$

The net present value of the life-time earnings from occupation B is:

$$\begin{aligned} E(W^B) &= w^B + (1-p)\left[\frac{1}{1+r}\left(w^B+g^B\right) + \frac{1}{(1+r)^2}\left(w^B+2g^B\right)\right] \\ &\quad + p\left[\frac{1}{(1+r)^2}\left(w^B+g^B\right)\right] \end{aligned} \tag{1.2.2}$$

Individuals solve this optimization problem by choosing occupation j^* that satisfies this condition:

$$j^* = \arg\max_{j\in\{A,B\}} \left\{E(W^A), E(W^B)\right\} \tag{1.2.3}$$

The decision rule is that individuals choose occupation A (i.e. $j^* = A$) if the human capital depreciation δ is below the threshold δ^* , and B otherwise:

$$j^* = \begin{cases} A & \text{if } \delta < \delta^* \\ B & \text{if } \delta > \delta^* \end{cases}, \tag{1.2.4}$$

where

$$\begin{aligned} \delta^* &= \frac{1}{pw^A}\left[(1+r)^2 + (1-p)(1+r) + 1\right]\left(w^A - w^B\right) \\ &\quad + \frac{1}{pw^A}\left[(1-p)(1+r) + (1-p)\right]\left(g^A - g^B\right) \end{aligned} \tag{1.2.5}$$

Equation 1.2.5 shows that a higher wage premium or wage growth for occupation A increases the threshold δ^*. As a result, the likelihood of individuals choosing occupation A increases (i.e. the cumulative probability function $F(\delta < \delta^*)$ is increasing in $(w^A - w^B)$ and $(g^A - g^B)$). An equilibrium of non-zero employment for both occupations requires that occupation A has either a higher wage level or higher wage growth (or both) to guarantee that some workers choose occupation A.

The probability of fertility shocks also affects individuals' occupational decisions. The partial derivative of the depreciation threshold δ^* with regards to the fertility probability is negative (i.e. $\frac{\partial\delta^*}{\partial p} < 0$), indicating that a higher fertility probability lowers the depreciation threshold δ^*. As a result, the likelihood of individuals choosing occupation A declines as the fertility probability increases.

There are two empirical implications. First, if men are unaffected by the fertility shocks (i.e. $p = 0$ for men), they continue working in the second period and the depreciation drops out from their decisions rules. Second, among women, if the fertility expectations vary across individuals, low fertility women are more likely than high fertility women to choose occupation A. In other words, two otherwise identical women may choose different occupations if their subjective fertility expectations are different. The effects of fertility across and within gender groups may contribute to segregation.

1.3 Empirical Strategies

I estimate the effects of depreciation on occupational gender segregation using a two-stage approach. In the first stage, I estimate human capital depreciation by occupations and obtain occupational characteristics from a variety of data sources. Utilizing these occupational attributes, I then examine gender differences in occupational choices using a conditional logit model.

1.3.1 First Stage: Human Capital Depreciation

In order to examine how human capital depreciation affects men's and women's occupational choices differently, the first step is to acquire depreciation estimates that are not endogenous to female workers' decisions. I address this issue by proposing an alternative measure using data from the Displaced Workers Survey (DWS). I estimate wage losses incurred by involuntary work terminations as a proxy for human capital depreciation. Human capital may depreciate because individuals become rusty at work after job disruptions or their skills are outdated due to the technological advancement. I broadly define human capital depreciation during job interruptions to include both skill deterioration due to non-use and knowledge obsolescence due to technological changes (Rosen, 2006; De Grip and Loo, 2002). I consider the *total* effect of human capital depreciation without distinguishing the mechanism because workers consider the total wage losses during their separation from employment regardless of the causes.

My estimation relies on displaced male workers because most men maintain continuous work histories. Even in the case of job terminations, they quickly return to work when a new match is formed. Displaced female workers, on the other hand, are much less ideal candidates for depreciation estimation because they, anticipating future leave, may choose low depreciation jobs. Therefore, the fraction of women who return to work after displacement (and hence are observable) may be highly correlated with depreciation by occupation. This female selection may bias depreciation estimates, and therefore, I restrict my sample to male workers in the DWS.

One problem with estimating depreciation by using the data from displaced workers is that wage losses tend to be higher for displacement than for a voluntary leave because employers may perceive displacement as a signal of low productivity. If the probability of getting displaced differs across occupations, being displaced from an occupation with a low displacement rate may send an even stronger signal of low productivity, which could be associated with larger wage losses. The DWS and the Current Population Survey (CPS) data show that, with a few exceptions, the probability of displacement is similar across occupations. Computer analysts and construction workers have a higher probability of being displaced, while managers, social workers, educators, protective service providers, and administrative staff face a lower likelihood of displacement. However, wage losses do not appear to be correlated with the propensity for displacement (i.e. the correlation is -0.01), indicating that the stigma effect is likely to be universal across occupations. Although this stigma effect cannot be separately identified, it does not distort the relative human capital depreciation rates, and does not bias my occupational choice estimates.

Displaced workers in the data provide wage information from their pre-displacement jobs and their current jobs, as well as the year and duration of the displacement. The wage changes between these two jobs encompass two components: wage losses during displacement and wage growth from experience accumulation in the new job. Figure 1.1 provides a graphic illustration of wage changes after job displacement. Human capital depreciation is the rate of wage losses, represented by δ, during the period after displacement (denoted as "leave" on the figure). Estimating human capital depreciation rates recovers the slope (δ) of wage losses during job interruptions.

The duration between wage observations varies across individuals in the data from the DWS. Assume that education was completed before an individual started working. The wage change between the displacement shock (at time t) and the observation from the new job (at time $t+k$, when the wage information in the new job is available) is:

$$\Delta_k w_{ijt} = -\delta_j Leave_{ijt} + \Delta_k g_j \left(Exp_{ijt}\right) + \beta \Delta_k Z_{it} + \Delta_k \varepsilon_{it}, \tag{1.3.1}$$

where $Leave_{ijt}$ is the duration of unemployment for individual i after the job displacement from occupation j, $\Delta_k g_j(\cdot)$ is an occupation-specific function of wage growth in experience, Exp_{ijt} is the accumulation of experience, $\Delta_k Z_{it}$ is a vector of additional covariates including indicators for industry switches (Neal, 1995; Sullivan, 2010), the year of displacement and the survey year to account for year-specific effects. $\Delta_k \varepsilon_{it}$ is the change in *i.i.d.* random shocks.[6]

My primary interest is to recover δ_j from the wage observations of workers who work in the same occupation before and after the displacement.[7] Since $Leave_{ijt}$ and $\Delta_k Z_{it}$ are observable, the parameter of interest, δ_j, can be identified if $\Delta_k g_j \left(Exp_{ijt}\right)$ is also known. Eric French and Taber (2006) estimate the return to experience of low-skilled workers by using a linear approximation. It is well justified in their analysis since their research focuses on young workers. However, a linear approximation is inappropriate for this study because the age distribution of the workers in my data is disperse and the wage profile is highly non-linear. Since the return to experience is not the focus of this paper, I do not specify

[6] The importance of industry-specific human capital is found in prior research (Neal (1995); Sullivan (2010).

[7] The selection problem arises because I focus on workers who were re-employed in the same occupation. In an alternative specification, I include a probit selection equation using workers' pre-displacement industries, occupations, age, race, reasons and the year of displacement to obtain the Inverse Mills ratio as an additional regressor in the wage equation. The depreciation estimates do not change substantially. Because the exclusion restrictions in the selection equation are weak and the results suggest that this selection bias is not the main driving force behind the wage loss results, I report the unadjusted depreciation estimates.

the functional form for the wage growth function $\Delta_k g_j (Exp_{ijt})$, instead I allow it to be flexible. In order to consistently estimate $\Delta_k g_j (Exp_{ijt})$, I need data from workers who work continuously in the same occupation without job interruptions. However, the DWS does not have information on continuous workers' experience and wages prior to the survey date, it can not be used to estimate $\Delta_k g_j (Exp_{ijt})$. Alternatively, I estimate wage growth by using the matched Current Population Survey March Supplements (CPS). I exploit the CPS "outgoing rotation groups" design which allows me to observe the same individuals across a one-year period and create one-year panels of continuous workers across the years that match the DWS sample period.[8] In this rotation groups design, the CPS interviews each household in the sample for four consecutive months, drops them out for the next eight months, and then interviews them again for four more months. Therefore, a substantial proportion of individuals in the sample are observed twice in the same month across two consecutive years. By matching individuals across years, the sample size is large enough to estimate non-parametrically age-specific wage growth rates by occupation.[9]

Once $\Delta_k \hat{g}_j (Exp_{ijt})$ is estimated, and $Leave_{ijt}$ and $\Delta_k Z_{it}$ are observable, δ_j is identified.[10] I assume that wage losses are linear in displacement durations since the maximum span of unemployment after the displacement from this sample is no longer than three years and the sample size is too small to non-linearly estimate occupation-specific depreciation.

1.3.2 Second Stage: Discrete Occupational Choices

In the second stage, I use the depreciation estimates obtained from the first stage to investigate how human capital depreciation affects men's and women's occupational choices.

An individual faces occupational choices among J alternatives in each of T time periods.

[8]I used the CPS March Supplement from 1981 to 2008 to match the DWS sample period. The DWS surveyed respondents' displacement events up to three years prior to the survey year, and hence the earliest displacement observations for 1984 DWS data is in 1981.

[9]I use the second-order Epanechnikov kernel with the Silverman Rule-of-Thumb bandwidth for this non-parametric estimation of age-specific wage growth as a proxy for experience-specific wage growth.

[10]The linear assumption is due to data restrictions. If a large sample is available, this assumption can be relaxed and age- or experience-specific estimates would be feasible.

Under the conditional logit framework, the probability that individual i chooses alternative k among j options in period t is:

$$L_{ikt} = \frac{e^{\gamma_t Y_{ikt}}}{\sum_j e^{\gamma_t Y_{ijt}}}, \tag{1.3.2}$$

where Y_{jt} is a vector of observed occupational characteristics (including wage levels, wage growth rates, work hours, tasks required by occupations), and the error term e_{ij} follows an $i.i.d$ extreme value distribution.

The probability that individual i chooses alternative k in period t is:

$$L_{ikt}(\gamma) = \frac{e^{\gamma Y_{kt}}}{\sum_j e^{\gamma Y_{ijt}}} \tag{1.3.3}$$

Note that any individual characteristics that are invariant by choice alternatives drop out from the above equation.

Let j^* denote the alternative that person i chooses in period t. The probability of individual i's observed sequence of choices is the product of standard logits $\prod_t L_{ij^*t}$.

The log likelihood function of the sample is the summation of the individual log likelihood:

$$LL = \sum_i \ln \prod_t L_{ij^*t}. \tag{1.3.4}$$

1.4 Data

I use data from four different sources for the analysis. In the first stage, I obtained pecuniary and non-pecuniary occupational characteristics, including wage levels, wage growth rates, usual work hours, depreciation, and tasks required at work from the Current Population Surveys March Supplements (CPS), the Displaced Workers Survey (DWS), and the Dictionary of Occupational Titles (DOT). In the second stage, I use variables obtained from the first stage to model individual occupational choices by using the National Longitudinal Survey of Youth 1979 (NLSY79). Table 1.1 summarizes the data sources.

1.4.1 Human Capital Depreciation

My primary interest in the first stage is to obtain human capital depreciation rates by occupation. The most comprehensive source of information on the costs of job loss in the U.S. is the Displaced Workers Survey (DWS). I use the DWS biennial surveys from 1984 to 2008 to estimate wage losses during job displacement as a proxy for human capital depreciation. These surveys are supplements to the Current Population Survey (CPS), and they collect information on workers who were displaced from their jobs. Displaced workers are defined as persons 20 years of age and older who lost their jobs because their plants or companies closed or moved, there was insufficient work for them to do, or their positions or shifts were abolished. Respondents are asked if they were displaced at any point during the three calendar years prior to the survey date. These surveys also collect wage information from the pre-displacement job and the current job along with the duration of unemployment following displacement. However, because the information on work hours is unavailable for most observations to create reliable hourly wage rates, I use the weekly earnings of full-time workers for estimation. By restricting my sample to male workers who work full-time in the same occupation after displacement, I obtained 4,341 observations for the human capital depreciation estimation.[11] Depreciation estimates are based on 22 broad occupational categories (excluding the military) following the 2010 Standard Occupational Classification.[12]

Before estimating wage losses during job interruptions, I need to parse out the wage growth component. Since wage growth rates vary substantially at different career stages,

[11] This DWS sample includes all male workers across educational levels. The small sample size prohibits me from estimating occupation-specific depreciation for college graduates. When I include interaction terms between displacement by occupations and an indicator for college graduates, the coefficient estimates of the interaction terms are not statistically different from zero, indicating no systematic differences in depreciation across educational groups. The average annual wage loss across occupations is 11.7 percent for college graduates, similar to the estimate of 11.4 percent for all male workers in my sample. The invariance of depreciation estimates across education levels allows me to use all male workers in the sample for the first stage estimates. In the second stage model, I turn to focus on college graduates' occupational choices.

[12] Source: http://www.bls.gov/soc/major_groups.htm. Note that a few adjustments are made to allow comparability across different occupational codes across four decades. These adjustments include categorizing first-line supervisors and managers in food, sales, building maintenance occupation to the managerial occupation since most of these workers are classified as managers according to Census 1970 occupational codes that are used by NLSY79 up to year 2000.

consistent estimates of experience-specific (or alternatively using age as a proxy for experience for male workers) wage growth rates are required. The small size of the DWS subsample does not allow precise estimates of wage growth by age, and hence I use the CPS data instead. I create one-year panels of continuous workers and use their one-year wage changes to estimate annual wage growth by occupation.

Madrian and Lefgren (1999) point out that matching the CPS observations across periods is challenging for reasons including non-response, mortality, migration, and reporting errors. Since the CPS sampling is at the household level, the same identification codes may be assigned to different individuals across the times when individuals move out and new residents move into the household. To ensure correct matching, I use observations from wave 1-4 in the base year, and match the same individuals in wave 5-8 in the following year. I match individuals across a one-year period by using their household ID, personal line number, sex, and race. I am able to identify 148,548 males who worked full-time and full-year in the same occupation over a one-year period between 1981 and 2008 to match the displacement years from the DWS.[13] I use the one-year panel to estimate age-specific annual wage growth rates by occupation. After teasing out this wage growth component, I am able to identify the depreciation rates by occupation.

1.4.2 Occupational Characteristics

Workers do not consider depreciation rates in isolation. Although workers may prefer a low depreciation occupation, they may still choose a high depreciation job if the financial incentive is large enough to offset the losses from high depreciation. The financial rewards come from two primary sources: wage levels and future wage growth. Suppose there is a trade-off between entry-level wages and future wage growth. Workers' choices may depend on their expected work patterns. If a worker anticipates working briefly and leaving the

[13] The first wave of the DWS used in this paper is from 1984, and it collects retroactive displacement data five years before the survey year. However, since 1994, this retroactive question only went back up to three years. To keep the sample comparable across years, I only keep displacement observations within three years prior to the survey year.

labor force permanently afterwards, an occupation that offers a high entry wage with a low growth prospect may be optimal. However, if the worker temporarily withdraws from the labor market, she may choose between a high entry wage and rapid wage growth, depending on their relative magnitudes.

Wage data from the CPS show a positive 0.08 correlation between entry wages and early wage growth for college graduates.[14] My baseline depreciation estimates are weakly correlated with entry-level wages (0.16), but the depreciation estimates are strongly correlated with early wage growth (0.42). These correlations indicate that higher earnings are associated with higher human capital depreciation. Particularly, high depreciation occupations tend to offer greater wage growth prospects. In order to investigate how individuals choose occupations considering these pecuniary outcomes, I test my models with two sets of measures. The first set of wage measures uses entry-level wages and the 10-year wage growth by occupation. This measure emphasizes the initial wage offer and the wage growth in the early career stage, during which most workers gain substantial wage increases. For the second set of wage measures, I use experience-specific wages and one-year wage growth that evolves as individuals gain experiences. Therefore, this second measure allows individuals with different work histories to face different wage conditions over time.

Individuals also sort into different occupations based on heterogeneous tastes and preferences for a variety of occupational attributes. Particularly, women differ from men in work arrangements. For instance, working women on average work fewer hours than men do on paid work. Bertrand et al. (2010) show that male and female MBA graduates have nearly identical incomes in the beginning of their careers, but the earnings soon diverge primarily due to female career interruptions and shorter weekly hours when children are present.[15] Working mothers may be willing to trade wages for shorter working hours to care for their

[14] Using the CPS March Supplement from 1979 to 2008, I calculate the average entry level wage of new male workers in the age between 22 and 25, who completed at least four year college education but did not obtain any graduate degrees beyond the bachelor level. Early wage growth by occupation comes from the wage differences between these new entrants and male workers with 10 years of experiences (use age as a proxy) who meet the same educational criteria.

[15] Their sample consists of MBAs from the Booth School of Business of the University of Chicago from 1990 to 2006.

children.[16]. If predominantly female occupations coincidentally have low depreciation rates and the low work-hour intensities, the effect of depreciation rates on occupational choices will be overstated. To account for sorting on work-hour intensities, I use the average usual weekly work hours of full-time workers from the CPS between 1979 and 2008.

In order to control for other occupational attributes, I obtain job characteristic measures from the DOT. The data are constructed by the U.S. Department of Labor to provide standardized occupational information across industries. The information on job characteristics is primarily obtained via on-site observations; for jobs that are difficult to observe, information is collected from professional and trade associations. The latest version of the DOT, released in 1991, lists 63 attributes, including worker functions (data, people, things), vocational training required to perform the job, aptitudes, temperaments, interests, physical demands, and work environments. In order to reduce the dimensions of occupational characteristics, I conduct a factor analysis of these 63 DOT variables to obtain five orthogonal factors that account for 74 percent of the variation in occupational characteristics.[17] These five factors can be primarily categorized by: cognitive tasks, motor tasks, interpersonal and physical tasks, visualization, and harsh (e.g. hot or cold) work environments. The factor loadings of these five variables are provided in Table 1.2. These measures are rescaled to follow the standard normal distribution for the interpretation convenience.[18] Table 1.3 summarizes these job characteristics by occupation. Occupations that require the most cognitive skills include legal and scientific professions. Construction jobs demand the highest level of

[16]The trade-off between wages and hours is explained in Altonji and Paxson (1988) There is also evidence of increasing work hours for highly educated and highly paid men from 1979 to 2006 (Kuhn and Lozano (2008))

[17]Similar to Yamaguchi (2012), I use the April 1971 Current Population Survey augmented by the fourth edition of the DOT with the updated occupational characteristics from the revised fourth version in 1991.

[18]The original scales differ substantially across measures. For instance, the aptitude measures are: 1 “The top 10% of the population”, 2 “The highest third exclusive of the top 10% of the population”, 3 “The middle third of the population”, 4 “The lowest third exclusive of the bottom 10% of the population”, and 5 “The lowest 10% of the population”. Physical demands and work environments are indicator of the presence of such characteristics. Prior to conducting the factor analysis, I convert the original measures to a uniform range between 0 and 1, with 1 representing higher requirements of such tasks. The final factor analysis results are rescaled to follow the standard normal distribution for interpretation convenience.

motor skills. Healthcare practitioners possess the strongest ability in a combination of interpersonal and physical tasks. High visualization is a desired aptitude for scientists. Workers in protective services and transportation face the most harsh work environment.

1.4.3 National Longitudinal Survey of Youth 1979

In the second stage, I estimate individual occupational choices by using data from the NLSY79, along with occupational characteristics obtained from the first stage. The long panel of NLSY from 1979 to 2008 is suitable for this study since it covers almost the entire fecundity period for the female sample. Since women are more likely to interrupt careers for family reasons, an ideal dataset for this analysis should cover the period when changes of family formation (e.g., getting married, having children) are likely to occur.[19] Furthermore, in the early waves, the NLSY79 surveys individuals' subjective expectations for future work status at age 35. The subjective expectations for future events are important if individuals, given different human capital depreciation rates associated with occupations, choose early occupations based on such expectations.

The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and were interviewed on a biennial basis thereafter. To focus primarily on college graduates with continuous educational history, I restrict my sample to high-skilled workers who obtain their bachelor's degrees as their terminal degrees prior to 1990 to allow sufficient observations of post-college work histories. I exclude individuals with graduate degrees to construct a more homogeneous sample with the same level of educational attainment. Initially, 1,203 college graduates meet the sample selection criteria, but 79 observations are dropped due to the lack of work information throughout the panel. The final sample consists of 1,124 individuals, approximately half of whom are male. By 2008,

[19]Respondents between 14 and 21 years old were sampled in 1979. By 2008, the age of this cohort is between 43 and 50 years old.

due to funding constraints and sample attrition, my sample has 755 individuals, including 380 men and 375 women.

To remove temporary jobs, I restrict work histories to post-college occupations after individuals make a full-time occupational transition, which is defined as working in an occupation for at least 1,500 hours a year over a one-year period.[20] The summary statistics of the demographics, occupational attributes and distributions of the first job are detailed in Table 1.4. Women and men do not differ in terms of race and ability measured by the AFQT scores, but women are 0.2 years younger than men at their first job. However, the occupational distributions are distinct for men and women. Predominantly male occupations include construction, installation and repair, transportation, farming, legal services, and engineering. Women are highly concentrated in healthcare support, healthcare practice, personal services, education, and administrative support.

The labor force participation rate remained high for both men (97%) and women (85.5%) in 2008, although the majority of the workers experienced certain non-working spells (81% for men, and 94% for women).[21] Job interruption patterns also diverged for men and women and are detailed in Table 1.5. Although a substantial fraction of the men experienced job interruptions, 49 percent had total spells of job interruptions less than one year, and only 6.3 percent had an interruption history for over three years. In contrast, only 34.3 percent of women interrupted their work for less than one year, while 38.9 percent left for longer than three years. By 2008, the average non-working duration among those with job interruptions were 1.28 and 4.85 years for men and women, respectively. The pooled sample includes 14,874 individual-year work observations. Repeated occupational choices by individuals throughout the panel are useful in accounting for unobserved persistent individual preferences.

[20] I construct the work histories by using the weekly work status and the work hours variables.

[21] Percentage of individuals with non-working spells is high because the non-working spells include all job interruptions regardless of the length of spells. Hence, if an individual leaves his or her old jobs, and takes an one-week break before starting working at the new jobs, this one-week break during the job transition is counted towards the non-working spells.

1.5 Results

Human capital depreciation estimates from Equation 1.3.1 are between -.496 to 1.19 log points. The depreciation point estimates are summarized in Table 1.6. The distribution of observations by occupations is uneven from the DWS sample, and the small sample size for some occupations renders the OLS coefficients imprecise. Outliers are likely to be influential when the sample size is small. To alleviate the effect from outliers, I remove the top and bottom 1 percent of the wage change observations from the sample for each year.

The depreciation estimates are inversely correlated (-.20) to the fraction of women in the occupations. Occupations with high human capital depreciation estimates from the OLS regression include: management, social services, and legal services. The high depreciation rates for this set of occupations suggest that wage losses are not entirely driven by technological advancement. For instance, losing business connections is more likely than technological changes to cause the large wage losses among managerial and legal occupations. Business, engineering, arts and media, personal care, sales, office administration, construction, installation, production, and transportation show moderate wage reductions. Many of these jobs require routine skills which are likely to be replaced by machine over time as technology progresses. For instance, Autor et al. (2003) show evidence of decreasing wage rates for routine manual jobs. Occupations that do not suffer wage losses, but instead are associated with wage gains (i.e. δ_j estimates are negative) during job interruptions, include mathematics, sciences, education, health care, protective services, food services, building maintenance, and farming occupations. Most of these wage gain estimates are not statistically significant. However, the large (-.496 log points) wage gain associated with job interruptions from the education occupation is statistically significant at the .05 level.

This statistically significant wage gain for educators is puzzling. If educators lose their jobs because of school closings, they may need to move to another geographical area to find similar jobs. If that is the case, the wage gain may simply be an artifact from the wage changes due to migration. To account for migration, I include an indicator for migration and re-estimate depreciation rates. The results show even larger wage gains for educators after controlling for migration. It indicates that migration is unlikely to be the cause of the wage gains.

Another potential explanation is that wages increase because workers switch to sectors that pay higher wages. After including an indicator for sector switches, the depreciation estimate also shows larger wage gains for educators. Educators remain at the bottom of the depreciation estimates. It is likely that teachers' salaries are protected against wage losses from job displacement because their pay scales are tied to experience. If the wage cannot decrease, it would be more likely to observe positive wage gains after displacement.

Since results from the sensitivity analyses indicate that education is among the occupations with the lowest human capital depreciation rates, I keep the original OLS estimates without rescaling. As long as the relative differences of depreciation estimates by occupation are robust, the qualitative results of the occupational choice estimates will not be affected in the logit framework. The weighted average annual wage loss across all occupation is 8 percent, which is slightly lower than than the findings from the previous literature (Ruhm, 1991; Louis S. Jacobson and Sullivan, 1993; Farber, 1993) because my wage loss estimates tease out the foregone wage growth during unemployment.[22]

Conditional logit estimates with the first set of wage measures, including new entrants' wages and 10-year wage growth, are presented in the upper half of Table 1.7. The coefficients of the entry level wage are positive for both men and women, indicating that pecuniary incentive is an important determinant of occupational choices. The coefficient estimate is much larger for men (2.95) than for women (.947). This result is consistent with prior findings that pecuniary motivations are stronger for men than for women (Fortin, 2008; Zafar, 2009; Wiswall and Zafar, 2011). Men and women differ in their preferences for wage

[22]Ruhm (1991) finds that the weekly earnings of displaced workers were 16 percent lower than those of non-displaced workers in the year following displacement, and still 14 percent lower four years after displacement. Louis S. Jacobson and Sullivan (1993) find that after five years upon the separation, average quarterly earnings losses stood at 25 percent for displaced workers who were separated from long-tenured jobs in Pennsylvania. Farber (1993) finds that relative to non-displaced workers, displaced workers suffered wage losses of 11 percent during the two years immediately following displacement.

growth. Average male workers have a positive coefficient on wage growth (.862). Women, on the other hand, have a negative coefficient on wage growth (-.156), although the point estimate is not significantly different from zero.

The coefficient of human capital depreciation is negative for both men and women. However, the negative response to human capital depreciation appears to be stronger for women (-1.34) than for men (-.822). However, because the second stage estimation is based on the generated depreciation regressor from the first stage, the second-stage standard errors are biased downward without accounting for estimation errors from the first stage. To correct for the additional source of the variance from the first stage, I follow Petrin and Train (2002) and re-draw bootstrap samples for the first stage to account for the additional variance from the first stage. I first repeatedly estimate depreciation rates in the first stage with bootstrap samples from the DWS. For each depreciation estimate from the first-stage bootstrap sample, I re-estimate the second-stage conditional logit model. Standard errors are calculated by adding the additional variance from these bootstrap samples to the second stage results.[23] The corrected standard errors increases by seven times after the adjustment. The large variance from the first stage makes the coefficient estimates of depreciation in the second stage imprecise. As a result, it also makes the inference about gender differences in depreciation difficult. As the result, the coefficient estimates of depreciation for both men and women, as well as the gender difference in depreciation are no longer statistically significant after accounting for the additional variance from the first stage.

This imprecise result is attributable to the large variance from the first stage estimates. The majority of depreciation estimates from the first stage are insignificant. For those insignificant estimates, some are associated with large bootstrap standard errors (e.g. social services and healthcare support) which inflate substantially the adjusted standard errors at the second stage. The statistically insignificant results are most likely attributable to the small sample that pools observations across 24 years in the first stage. The adjusted standard errors make the inference challenging and inconclusive. This drastic change in

[23] I bootstrap 2,000 replications for the first stage.

inferences after accounting for the first stage variance also implies that conclusions from prior studies relying on generated depreciation in the first stage may not be robust after accounting for the first-stage variance.

If women anticipate future family responsibilities and choose low depreciation occupations, there should be distinct patterns for women with and without such responsibilities. In order to understand if human capital depreciation rates have heterogeneous effects within gender, I allow the human capital depreciation rates to interact with the marital status and the presence of children.[24] The conditional logit estimates show that the coefficients on the interaction terms are negative for women and positive for men. However, these coefficient estimates are not statistically significant once the first stage variance is considered (results omitted).

Men and women show different preferences for other occupational attributes. Compared with men, women are less likely to work in occupations with long weekly hours. In addition, women are more likely than men to choose occupations that demand higher cognitive tasks and the combination of interpersonal and physical tasks. Both high-skilled men and women prefer less motor-intensive jobs, and this effect is stronger for women than for men. Moreover, female coefficient for visualization is negative, while men have a positive coefficient. Both men and women prefer not to be working in a harsh work environment.

The results of the conditional logit estimation based on the second set of wage measures (i.e. experience-specific annual log wages and annual wage growth rates) are reported in the bottom half of Table 1.7. The coefficient estimates change slightly for most covariates, but the relative gender differences remain. The coefficient on wage growth changes substantially because this new measure replaces the first 10-year wage growth with the experience-specific annual wage growth. The men's coefficient on wage growth remains insignificantly different from zero, while the women's negative coefficient is statistically significant.

[24] I used two variables related to children–including the indicator for parents after having first child, and the number of children.

1.6 Conclusions

The high-skill labor market remains segregated by gender, in spite of increasing female educational attainment and labor force attachment. Women are highly concentrated in education and healthcare professions but are under-represented in scientific and engineering fields. The most salient difference between men and women in the labor market is the time they spend out of the labor force. Women are still more likely than men to take time off from employment. These job interruptions not only reduce women's earnings significantly through foregone wages during the non-working period, but they also affect female occupational choices through their expectations of future leaves. Anticipating intermittent work, women may choose occupations with low human capital depreciation to mitigate the wage losses during job interruptions.

Early studies typically take female job interruptions as a given, and estimate the wage losses during the interruptions. Although women may choose low depreciation occupations because they expect to take an extended duration of leave, the observed results may also be explained by reverse causality: women take longer time off because the costs of job disruptions are low. Furthermore, the likelihood of women returning to work after job interruptions may also differ across occupations; hence, estimating human capital depreciation based on the censored observations may be biased. I propose an alternative depreciation measure using male workers' wage changes after displacement shocks using the Displaced Workers Survey. This new measure is unlikely to be correlated with female occupational selection on depreciation. My estimates show that education, protective services, and farming occupations are associated with wage gains during job interruptions. However, management, social services, and legal services occupations are connected with high wage losses after job displacement.

Another weakness of prior studies is that they neglect the fact that workers sort on other occupational attributes. Even if women are likely to choose low depreciation occupations, women may also prefer occupations with low demands in motor skills. Hence, although labor intensive occupations tend to have low depreciation rates, women are still unlikely to choose these occupations. This is a plausible explanation for England's (1982) non-finding of a monotonic relationship between female representation and depreciation rates across occupations.

Allowing worker sorting on multiple dimensions, I use the estimated occupation-specific human capital depreciation from the DWS and include additional occupational attributes to analyze a discrete occupational choices model. The conditional logit results show that men and women differ vastly in occupational selection on most occupational attributes, including entry-level wages, wage growth, work hours, cognitive tasks, motor tasks, the combination of interpersonal and physical tasks, and visualization. Men show stronger responses than women to pecuniary incentives. Furthermore, men are more likely than women to choose occupations with long work hours, intensive motor tasks, and tasks requiring visualization. Women tend to be working in occupations that demand high cognitive and interpersonal skills. However, gender differences in selection on depreciation are not robust when additional variance from the generated regressor are accounted for. This adjustment of standard errors increases the standard error of the depreciation coefficient by seven times and makes it difficult to make inferences about gender differences in occupational depreciation. To improve the precision of the estimation, tighter first stage estimates are needed. Alternative estimation methods that do not rely on a two-stage design may also worth further investigation.

1.7 Tables and Figures

Table 1.1: Summary of Data Sources

Occupational Characteristics	**Dataset**	**Year**	**Sample**
		Stage 1	
Wage Growth by Age	Merged CPS 1-Yr Panel	1981-2008	Full-time male continuous workers, same job
HC Depreciation Rates	DWS	1984-2008	Full-time male, same occupation
Wage level, Usual Hours	CPS	1979-2008	All full-time
Occupational Attributes	DOT91	1991	All full-time
		Stage 2	
Individual Work History	NLSY79	1979-2008	Complete bachelor degree by 1990

Table 1.2: Factor Loadings from DOT Factor Analysis

Variables	Cognitive Task	Motor Task	Interpersonal and Physical Task	Visualization	Harsh Environment
Data	0.810	0.358	0.137	-0.091	0.101
People	0.704	-0.042	0.302	0.171	0.007
Things	-0.108	0.704	-0.375	0.005	-0.106
Reasoning	0.854	0.376	0.108	0.031	0.000
Math	0.786	0.422	0.070	-0.141	0.032
Language	0.882	0.279	0.108	-0.006	-0.021
Vocational Preparation	0.715	0.562	0.151	-0.126	0.051
Learning	0.820	0.307	0.161	-0.019	-0.027
Verbal	0.899	0.140	0.042	-0.033	-0.008
Numerical	0.735	0.314	-0.056	-0.109	-0.046
Spacial	0.052	0.766	0.090	0.001	-0.007
Form Perception	0.180	0.704	-0.226	-0.041	0.037
Clerical Perception	0.740	0.023	-0.240	0.056	-0.092
Motor Coordination	-0.096	0.539	-0.485	0.149	-0.185
Finger Dexterity	0.040	0.511	-0.607	0.008	-0.069
Manual Dexterity	-0.405	0.578	-0.280	0.065	-0.010
Eye-Hand-Foot Coordinate	-0.446	0.359	0.366	0.301	-0.147
Color Discrimination	-0.159	0.503	0.019	0.388	0.337
Directing	0.640	0.018	0.445	-0.097	0.073
Repetitive Work	-0.579	-0.321	-0.122	0.004	-0.105
Influencing	0.398	-0.205	0.241	0.178	-0.017
Variety	0.178	0.261	0.150	-0.140	0.157
Expressing	0.128	0.051	0.028	0.074	-0.028
Alone	-0.036	0.042	0.041	0.086	-0.072
Stress	-0.006	0.148	0.065	0.293	0.147
Tolerances	-0.174	0.494	-0.378	-0.206	-0.093
Under Instructions	-0.079	-0.095	-0.165	-0.043	-0.091
Dealing with People	0.640	0.018	0.445	-0.097	0.073
Judgement	0.536	0.482	0.173	-0.073	0.099
Strength	-0.658	0.241	0.425	-0.069	0.157
Climbing	-0.458	0.389	0.477	-0.173	-0.242
Balancing	-0.353	0.379	0.339	-0.187	-0.114
Stooping	-0.602	0.171	0.362	-0.145	-0.016
Kneeling	-0.483	0.363	0.386	-0.325	-0.098
Crouching	-0.566	0.257	0.357	-0.279	-0.077
Crawling	-0.203	0.331	0.250	-0.089	0.019
Reaching	-0.549	0.154	-0.360	0.178	0.155
Handling	-0.470	0.121	-0.357	0.182	0.198
Fingering	0.019	0.240	-0.575	0.077	-0.038
Feeling	-0.086	0.366	-0.084	0.131	0.282
Talking	0.682	-0.236	0.205	0.285	0.023
Hearing	0.642	-0.222	0.167	0.296	0.008
Tasting	-0.049	0.064	-0.047	0.096	0.338
Near Acuity	0.273	0.337	-0.424	0.077	-0.121
Far Acuity	-0.176	0.093	0.380	0.611	-0.260
Depth Perception	-0.423	0.570	0.165	0.133	-0.205
Accommodation	0.250	0.341	-0.360	0.037	-0.197
Color Vision	-0.206	0.474	0.095	0.503	0.207
Field of Vision	-0.161	0.061	0.399	0.596	-0.336
Weather	-0.376	0.226	0.461	0.000	-0.208
Cold	-0.190	-0.061	0.044	-0.035	0.307
Hot	-0.263	-0.007	0.013	0.021	0.493
Humid	-0.277	-0.012	0.089	-0.056	0.378
Noise	-0.453	0.323	0.130	-0.024	-0.124
Vibration	-0.054	-0.003	0.012	0.007	-0.025
Atmospheric	-0.313	0.315	0.119	-0.110	0.119
Moving mechanical parts	-0.098	0.253	-0.067	-0.138	-0.013
Electric Shocks	-0.049	0.282	0.084	-0.044	0.061
High Exp Places	-0.143	0.332	0.176	-0.033	0.103
Radiation	0.027	0.040	-0.027	0.021	0.016
Explosive	-0.063	0.134	0.151	0.144	0.241
Toxic Chemicals	-0.108	0.211	0.105	0.038	0.216
Other Environment	-0.334	0.232	0.280	-0.013	0.170

[a] The factor loadings show how the variables are weighted for each orthogonal factor. In this analysis, I reduced the occupational characteristics to five orthogonal factors: cognitive task, motor task, interpersonal and physical task, visualization, and harsh work environment. Each factor is rescaled to followed the standard normal distribution.

Table 1.3: Occupational Characteristics

	Wages 1[a]		Wages 2[b]		Average Weekly Hours	DOT Tasks[c]				
Occupation Groups	New Entrant	10-Yr Growth	Wage	Annual Growth		Cognitive	Motor	Interpersonal and Physical	Visual	Harsh Environment
Managers	10.49	0.621	11.14	0.029	45.76	0.98	-0.38	-0.84	-0.14	-0.23
Business and Finance	10.63	0.424	11.04	0.017	42.75	1.01	-0.28	-1.05	-0.24	-0.36
Mathematicians	10.74	0.374	11.17	0.021	42.59	1.69	-0.52	-1.43	0.34	-0.27
Engineers	10.75	0.341	11.15	0.023	43.18	1.46	-0.49	0.72	0.85	-0.13
Scientists	10.41	0.454	10.96	0.027	43.46	2.06	-0.36	-0.28	1.14	-0.17
Social Services	10.19	0.335	10.43	0.015	45.20	0.83	-0.33	-0.20	-0.84	-0.04
Legal	10.65	0.641	11.10	0.033	45.76	2.30	-0.21	-1.51	-1.03	-0.17
Educators	10.33	0.376	10.71	0.026	43.49	1.17	-0.14	-0.50	-0.65	0.78
Arts and Media	10.41	0.464	10.71	0.017	43.26	1.04	-0.40	0.62	-0.05	0.50
Healthcare Practitioners	10.62	0.494	11.08	0.029	43.64	1.39	-0.29	1.50	-0.35	-0.44
Healthcare Support	9.99	0.623	10.28	0.020	41.47	-0.85	0.03	0.12	-1.05	-0.58
Protective Services	10.54	0.316	10.83	0.011	44.41	-0.22	0.03	-0.41	-0.43	2.38
Food Services	9.93	0.236	10.13	0.010	41.78	-0.78	-0.37	-0.32	-0.39	-0.30
Building Maintenance	10.25	0.172	10.10	0.007	41.38	-1.01	0.92	-0.47	0.12	-0.32
Personal Services	10.04	0.716	10.44	0.019	42.43	-0.98	-0.56	-0.16	-0.88	0.22
Sales	10.52	0.584	10.93	0.020	43.50	-0.02	-0.32	-0.99	-1.00	-0.27
Administrative Staff	10.34	0.401	10.66	0.018	40.95	-0.05	-0.58	0.73	-0.24	-0.37
Farming and Fishing	10.05	0.386	10.09	0.007	46.00	-0.13	1.31	-0.38	0.81	0.29
Construction	10.40	0.340	10.60	0.014	42.51	0.18	1.34	0.41	0.32	0.08
Installation and Repair	10.37	0.419	10.72	0.014	43.02	0.36	1.09	0.96	0.49	-0.31
Production	10.36	0.401	10.67	0.016	42.22	-0.69	-0.07	0.44	0.87	-0.30
Transportation	10.25	0.390	10.54	0.011	43.85	-0.83	0.43	-0.27	-0.06	1.57

[a] New entrants' wage is the mean log wage of male workers aged between 22 and 25 and completed at least four years of college education, but did not pursue any post-college education. Wage growth in the first ten years is the log wage difference between new entrants (male college graduates aged 22-25) and workers with 10 years of experiences (male college graduates aged 32-35).

[b] Log wage and wage growth from Measure 2 are age- specific based on male college graduates . The values shown here are the arithmetic mean values across 40 years of experience groups.

[c] DOT tasks are rescaled to follow the standard normal distribution.

Table 1.4: Summary Statistics of NLSY79

	Men	Women	Difference		
At the first job:					
Percent Non-White	10.0	11.1	-1.0		
AFQT	75.7	74.6	1.0		
Age at First Full-time Job	24.1	23.9	0.2	+	
Obs	554	570			
Weighted (%)	51.3	48.7			
In 2008:					
Obs	380	375			
Weighted (%)	51	49			
Percent working (%)	97	85.5	11.5	**	
First Job Distribution	**Within Male**		**Within Female**		**Percent Female**
	N	%	N	%	%
Managers	93	17.59	67	12.38	40.09
Business and Finance	31	4.96	52	8.85	62.91
Mathematicians	41	7.19	20	5.1	40.30
Engineers	54	9.58	10	1.68	14.32
Scientists	12	1.73	5	0.94	34.15
Social Services	9	1.62	11	1.85	52.06
Legal	3	0.51	1	0.07	11.79
Educators	26	3.88	78	12.22	74.97
Arts and Media	25	4.74	24	6.09	54.96
Healthcare Practitioners	12	1.45	60	9.5	86.15
Healthcare Support	2	0.12	17	2.47	94.98
Protective Services	16	2.22	4	0.46	16.36
Food Services	17	3.43	9	2.29	38.84
Building Maintenance	1	0.29	1	0.23	43.62
Personal Services	5	0.6	12	2.51	79.96
Sales	73	14.16	43	7.82	34.43
Administrative Staff	64	11.36	146	23.71	66.49
Farming and Fishing	10	2.2	1	0.26	10.16
Construction	18	3.93			0.00
Installation and Repair	4	0.61			0.00
Production	18	3.59	7	1.23	24.56
Transportation	20	4.23	2	0.32	6.74
Observations	100	554	100	570	
Weighted %		51.3		48.7	

Standard errors in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 1.5: Leave Patterns by Gender, NLSY79 (2008 wave)

	Men	**Women**
Observations in 2008	380	375
	%	%
Percent w/o Job Interruptions	20.00	6.67
Percent w/ Job Interruptions	80.00	93.33
Interruptions ≤ 1 yr	48.95	34.30
1 yr < Interruptions ≤ 3 yrs	24.74	20.00
Interruptions > 3 yrs	6.32	38.93
Duration of Interruptions	Years	Years
Mean	1.28	4.85
Std. Dev.	1.88	5.75

Table 1.6: Wage Penalty Estimates

	Wage Growth Estimates			Human Capital Depreciation Rate Estimates				
	CPS Observations[a]			DWS Observations[b]		OLS Regression Estimates		
Occupation Groups	**N**	**%**	**Log Point**	**N**	**%**	**Coeffcient(Log Point)**	**Robust S.E.**	**Bootstrap S.E.**
Managers	26,905	18.14	0.075	489	11.47	0.337	(0.0487)**	(0.059)**
Business and Finance	5,864	3.98	0.069	164	3.65	0.050	(0.0903)	(0.089)
Mathematicians	3,725	2.68	0.082	171	4.78	-0.154	(0.0590)**	(0.095)
Engineers	8,685	6.03	0.077	257	6.35	0.024	(0.0593)	(0.039)
Scientists	2,067	1.31	0.034	35	0.75	-0.105	(0.0962)	(0.143)
Social Services	1,887	1.28	0.002	14	0.33	0.496	(0.833)	(0.963)
Legal	1,466	0.97	0.090	32	0.92	1.191	(0.352)**	(0.625)*
Educators	5,010	3.22	0.061	31	0.69	-0.471	(0.218)*	(0.249)*
Arts and Media	1,760	1.21	0.024	88	1.95	0.060	(0.0981)	(0.070)
Healthcare Practitioners	3,042	2.03	0.083	57	1.39	-0.143	(0.146)	(0.295)
Healthcare Support	459	0.31	0.021	6	0.14	-0.084	(0.142)	(0.787)
Protective Services	5,858	3.99	0.045	47	1.13	-0.496	(0.230)*	(0.235)*
Food Services	2,103	1.34	0.008	126	2.76	-0.161	(0.144)	(0.115)
Building Maintenance	3,423	2.23	-0.013	29	0.72	-0.036	(0.216)	(0.398)
Personal Services	605	0.37	-0.014	12	0.20	0.124	(0.300)	(0.389)
Sales	9,029	6.29	0.071	249	5.57	0.049	(0.0740)	(0.060)
Administrative Staff	9,542	6.58	0.036	136	2.80	0.036	(0.0777)	(0.077)
Farming and Fishing	2,015	1.23	0.003	73	1.76	-0.233	(0.119)*	(0.081)**
Construction	7,655	5.00	0.036	821	18.84	0.044	(0.0394)	(0.053)
Installation and Repair	11,792	7.90	0.047	331	7.37	0.094	(0.0480)*	(0.055)+
Production	19,091	13.00	0.030	561	12.49	0.077	(0.0368)*	(0.039)*
Transportation	15,055	10.08	0.048	612	13.92	0.174	(0.0360)**	(0.040)**
Total	148,548	100.00		4,341	100.00			

Standard errors in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

[a] Wage growth rates are estimated nonparametrically by age and occupation group. The average wage growth rate is an arithmetic mean of wage growth rates of all continuous male workers at least 20 years old from the pooled matched one-year CPS panels between 1981 and 2008.

[b] Human capital depreciation estimates are based on male workers who worked in the same occupations after displacement from the DWS 1984-2008.

Table 1.7: Adjusted Standard Errors for Conditional Logit Estimates , NLSY 1979-2008

	NLSY, Women			NLSY, Men				
	Coefficient	**Standard Error**		**Coefficient**	**Standard Error**		**Different by Gender?**	
		Unadjusted	**Adjusted**		**Unadjusted**	**Adjusted**	**Unadjusted**	**Adjusted**
Measure 1:								
New Entrant lnWage	0.947	(0.207)**	(0.563)+	2.952	(0.255)**	(0.444)**	**	**
10-Yr Wage Growth	-0.156	(0.218)	(1.200)	0.862	(0.364)*	(0.966)	*	**
HC Depreciation	-1.340	(0.159)**	(1.096)	-0.822	(0.130)**	(0.903)	*	
Weekly Hours	0.088	(0.0443)*	(0.166)	0.480	(0.0340)**	(0.092)**	**	**
Cognitive Tasks	0.122	(0.0772)	(0.201)	-0.768	(0.0646)**	(0.125)**	**	**
Motor Tasks	-2.147	(0.161)**	(0.471)**	-1.290	(0.158)*	(0.218)**	**	**
Interpersonal and Physical Tasks	0.096	(0.0397)**	(0.137)	-0.265	(0.0422)**	(0.0833)**	**	**
Visualization	-0.781	(0.0855)**	(0.227)**	0.448	(0.0661)**	(0.141)**	**	**
Harsh Environment	-0.501	(0.0796)**	(0.339)	-0.591	(0.0707)**	(0.187)**		
Measure 2:								
lnWage	1.144	(0.178)**	(0.553)**	2.851	(0.225)**	(0.428)**	**	**
Annual Wage Growth	-0.355	(0.118)**	(1.186)	-0.0224	(0.123)	(0.903)	+	**
HC Depreciation	-1.260	(0.163)**	(1.096)	-0.600	(0.141)**	(0.904)	**	
Weekly Hours	0.040	(0.0454)	(0.166)	0.384	(0.0320)**	(0.0914)**	**	**
Cognitive Tasks	0.129	(0.0727)+	(0.199)	-0.713	(0.0591)**	(0.122)**	**	**
Motor Tasks	-2.033	(0.161)**	(0.471)**	-1.011	(0.142)**	(0.206)**	**	**
Interpersonal and Physical Tasks	0.149	(0.0401)**	(0.137)	-0.173	(0.0445)**	(0.0845)**	**	**
Visualization	-0.842	(0.0803)**	(0.225)**	0.307	(0.0603)**	(0.138)**	**	**
Harsh Environment	-0.404	(0.0736)**	(0.338)	-0.490	(0.0675)**	(0.186)**	**	

Standard errors in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

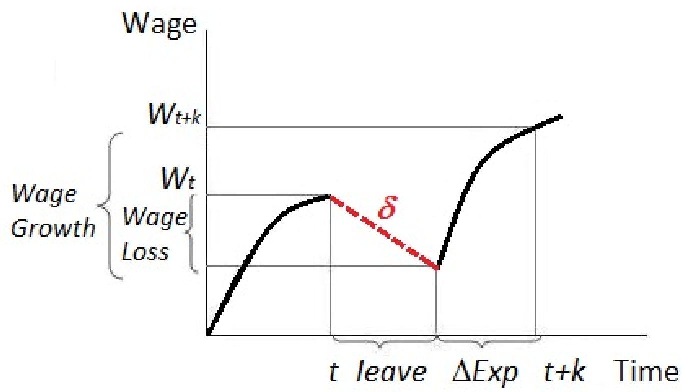


Figure 1.1: Wage Changes for Displaced Workers

Chapter 2

Trends in Female Selection on Occupational Attributes

2.1 Introduction

A surge of female labor force participation marked the most salient change in the labor market since 1960. In 1960, labor force participation rates were 83.3% and 37.3% for men and women, respectively. In 2010, the corresponding rates became 71.2% and 58.6%. The rising female labor force participation was primarily driven by married women whose labor force participation rate increased from 31 percent to 62 percent over the past five decades.[1]

Researchers attribute the rise of female participation in the US labor force in the late 1960s to the introduction of oral contraception (Goldin and Katz, 2002). This new contraceptive technology lowers the costs of investments in long-term career for women because it reduces the uncertainty of pregnancy. Along with rising labor force participation, increases in female investments in education and professional careers were evident. By 1980, the college gender gap in enrollments was reversed (Goldin, 2006), and the representation of women in professional occupations doubled from 18.4 percent in 1960 to 36.4 percent in 1998 (Goldin and Katz, 2000).

Young women's expectations about their future labor market involvement also mirrored the increasing return to human capital and career opportunities for women. The National Longitudinal Survey of Young Women (NLS68) and the National Longitudinal Survey of Youth 1979 (NLSY79) both asked whether respondents would be either "married, at home, with family" or "at work" when they were 35 years old. These surveys show that young

[1]Source: U.S. Bureau of Labor Statistics, Bulletin 2217; and unpublished Basic Tabulations, Table 12.

women who expected to be in the paid labor force at age 35 increased from below 35 percent in 1968 to over 80 percent by 1980 (Goldin, 2006).

These changes in women's attitudes towards family and career are reflected not only in their subjective expectations but also in their career interruption patterns. Caring for young children has been a primary cause for women to interrupt their career. Figure 2.1a shows that the out-of-labor-force rate of women without young children remains relatively stable over time. In contrast, the rate of withdrawing from the labor force among young mothers (women under age 40) with children less than 5 years old diminishes over time (Figure 2.1b). In addition, compared with women with no young children (Figure 2.2a), mothers with young children who remain in the labor force also show larger growth in their labor supply through the increasing number of weeks at work over time (Figure 2.2b).

One major policy change that may have a direct effect on young mothers' leave pattern is related to the maternity legislation. The 1993 Family and Medical Leave Act (FMLA) allows eligible mothers to take up to 12 weeks of unpaid leave and return to their pre-childbirth jobs. Prior to the federal legislation, similar maternity mandates were available in 12 states and the District of Columbia (Baum II, 2003). Previous studies find that maternity leave with job protection increases the likelihood of women returning to their old jobs (Klerman and Leibowitz, 1994; Rönsen and Sundström, 1996; Ondrich et al., 1996; Gregg and Waldfogel, 2005). Berger and Waldfogel (2004) find that eligible mothers in the US are more likely to take maternity leave up to 12 weeks, and return more quickly to work after 12 weeks. Baum II (2003) finds that maternity leave legislation increases the number of mothers who eventually returned to their pre-childbirth jobs.

Laughlin (2011) documented the maternity leave and employment patterns of first-time mothers from 1961 to 2008. Among women who gave first birth during 1961-1965, 44 percent worked during pregnancy. In 2006-2008, over 65 percent of first-time mothers worked during their pregnancy. Among women who worked during pregnancy, only 17 percent returned to work in three months for the 1961-1965 cohort, but 59 percent of the 2005-2007 cohort returned to work in three months. The percentage of women who worked during pregnancy and returned to work in 12 months after giving the first birth is 26 percent and 79 percent for the 1961-1965 cohort and the 2005-2007 cohort, respectively.

The increasing labor supply of mothers with young children likely accounts for the change of the age profile of female labor supply. In 1960, only 29 percent of married women between age 25 and 34 were in the labor force, and the age profile of married women's labor force participation followed a twin-peak pattern with an evident drop in the middle during the childrearing ages. The labor force participation rate of this demographic group increased sharply to 81.3% in 2010.[2] As more young mothers decided to stay in the labor force when their children are young, this twin-peak labor force participation pattern disappeared after the 1980s.

Career disruptions reduce workers' wages through the loss of human capital (Mincer and Ofek, 1982; Kunze, 2012) and impede employment prospectives (Gagliarducci, 2005). Recent evidence (Yamaguchi, 2012; Sanders, 2012; Sanders and Taber, 2012) suggests that human capital is a complex multi-dimensional concept, and different occupations tend to require largely different mixtures of different skills. If a worker's particular skill deteriorated substantially during her job interruption, and that skill is crucial in performing the old job, she may become incapable in performing her old job when she return to work. However, if her other skills remain intact or are mostly preserved, her human capital could still be highly valued by other occupations. Hence, skill transferability and job mobility can be important considerations if women eventually return to the labor market. Occupations that help accumulate general skills which are applicable in a wide range of other occupations may be desirable if workers' labor market participation is intermittent.

In the past, women may have invested heavily on general skills that can be transferred among occupations, given women's high likelihood and long duration of job interruptions. With the increasing female labor force attachment, the return from investments in specialized skills may increase relatively faster for women than for men. As a result, skill specificity that

[2]Source: U.S. Census Bureau, Statistical Abstract of the United States: 2012.

discouraged women from entering particular occupations in the past may have a diminishing effect on women's occupational decisions over time.

To investigate the relationship between female career interruptions and skill transferability, I exploit three measures related to job mobility–entry barriers, turn-over rates, and task similarities. The first measure captures the fraction of the inflow of workers from other occupations. The larger fraction of workers transferring from other occupations, the lower the barriers are for workers to enter the occupation. The second variable measures the outflow of workers to other occupations. This variable differs conceptually from the first measure since occupations with low entry barriers may not always be a stepping stone for workers to move into other occupations. For example, a dead-end job may be easy to enter but it leads workers to nowhere. The third variable measures the "distance" of tasks among occupations. If the tasks required to perform two occupations are similar, workers are likely to transfer their skills from one job to the other.

Focusing on the trend of the gender differences in sorting on occupational attributes, I estimate discrete occupational choices under the conditional logit framework for different cohorts using cross-sectional data from the Current Population Survey (CPS) from 1979 to 2008. My analysis shows that skill specificity associated with job entry barriers has become decreasing concern in female occupational decisions. Also, the gender differences in work-hour intensities, visualization tasks, and occupational mobility to other occupations also appear to narrow over time. In contrast, gender differences in other dimensions, such as entry wage-level, wage growth, cognitive skills, motor skills, interpersonal and physical tasks, harsh work environment, and task similarities do not show discernible trends. In addition, the evidence of increasing female participation in occupations with high skill entry-barriers, including legal professionals and healthcare practitioners, appears to support the prediction of the diminishing effect of skill specificity on female occupational choices.

2.2 Method and Data

I estimate a conditional logit model using the March Supplements of the Current Population Survey data by year. The Current Population Survey (CPS) is the primary source of labor force statistics for the population of the United States. Hence, analyses using this data across time can shed light on the overall changes in the trend of the US labor market.

Under the conditional logit model, the probability that individual i chooses alternative k among j options in period t is:

$$L_{ikt} = \frac{e^{\gamma_t Y_{ikt}}}{\sum_j e^{\gamma_t Y_{ijt}}}, \tag{2.2.1}$$

where Y_j are the job characteristics associated with occupation j, and t represents each cohort in time t. The vector of Y_j include three job mobility measures, wage levels, wage growth, weekly work hours, cognitive tasks, motor tasks, interpersonal and physical tasks, visualization, and harsh work environment. The error term e_{ij} follows an $i.i.d$ extreme value distribution.

Let j^* denotes the occupation chosen by individual i. The log likelihood function of the sample is the summation of the individual log likelihood:

$$LL = \sum_i \ln L_{ij^*t}, \tag{2.2.2}$$

The objective is to identify the γ_t for each cohort in different years from 1979 to 2008 by maximizing the log likelihood function. By running this conditional logit model by year, I am able to obtain the coefficient estimates for each year and show the trend over time.

To observe occupational mobility, I create a one-year panel from the CPS cross-sections relying on the survey's rotation group design. Observing the occupational outcomes of the same individuals in two consecutive years, I extract information of mobility in and out from occupations. However, these unconditional job mobility estimates are noisy measures of both the aggregate economic shocks and workers' selection on unobserved occupational characteristics. Particularly, transferring into an occupation with an upward wage trajectory results in a very different economic outcome from moving to a job with huge wage losses. To capture less noisy measures of desirable job mobility, I condition the occupational inflows and outflows on job transfers with positive wage changes. A large fraction of the inflow of workers through other occupations into an occupation with wage gains is a clear desirable occupational benefit. However, the measure of the occupational outflow is more difficult to interpret. Although the ability to move to other occupations with wage gains may indicate that the occupation is associated with wide marketable skills, it may also imply that many outside options are more attractive than this current occupation. Hence, the sign of the coefficient of occupational turn-over rates is ambiguous.

An alternative measure of skill transferability across occupations is the similarity of tasks required to perform occupations. If the intensity of tasks and skills required to perform two occupations are similar, workers are likely to transfer their skills between these occupations. I exploit the occupational task information from the revised fourth edition of the Dictionary of Occupational Titles (DOT) in 1991. DOT lists 63 attributes, including worker functions (data, people, things), vocational training required to perform the job, aptitudes, temperaments, interests, physical demands, and work environments. I use Principal Coordinates Analysis to calculate the task distances among occupations at the 1990 Census three-digit occupational code level. I define occupational transferability as the weighted number of occupations within one standard deviation of occupational distances for each occupation. The more job opportunities within the close proximity, the more likely one may transfer from one occupation to another.

This analysis focuses on high-skilled workers under age 40 because women at the age range are most likely to interrupt their career to care for young children. Since mothers with young children showed the most striking pattern of changes in labor supply, individuals in this group are also most likely to alter their occupational choices as their labor market attachment increases. To control for any gender-neutral time trend, I also include men in my sample to show the changes in gender differences over time. I restrict my analysis on the high-skill labor market because the labor market is likely to be segmented by educational attainment. Increases in educational wage premiums had caused the widening of the the U.S.

wage inequalities (surveyed in Katz and Autor (1999)) since the late 1970s. Although the growing inequality slowed down in the last 15 years (Card and DiNardo, 2002), employment growth differed sharply in the 1990s versus the 1980s, with more rapid growth of employment in jobs at the bottom and top relative to the middle of the skill distribution (Autor et al., 2006). Restricting my sample to college graduates allows me to focus on a more homogeneous labor group.

The sample size of college graduates, including individuals with graduate degrees, under age 40 from the pooled CPS 1979-2008 is 270,985. The size of annual samples grows from 7,306 in 1979 to 11,719 in 2008. Table 2.1 shows the gender distribution of the sample by year. It is evident that fewer women than men obtained a college degree in 1979. However, the gender gap reversed in 1991, and more female college graduates were observed in recent years. Goldin and Katz (2002) illustrate that contraception technology reduces the costs of investments in education. The increasing participation of women in higher education may have fundamentally altered the underlying ability distributions of female college graduates over time. Female college graduates from earlier cohorts may represent a more selected group than their comparable peers in the 2000s. However, it will bias my estimation from finding results of a narrowing gender gap in skill specificity over time because the cost of home-time increases with abilities. Since female college graduates from earlier cohorts are more likely coming from the right tail of the ability distribution, compared with female college graduates in recent years, their cost of trading career for family would be higher. Hence, if the results indicate that the gender gap in selection on skill specificity diminishes over time, the true effect is likely to be even larger without the ability redistributions among female college graduates.

2.3 Results

Figure 2.3 plots the gender difference coefficient of low occupational entry barriers across time. The gender difference showed a downward trend and move from 10.6 to 4.07 over this period. Although women are still more likely than men to choose occupations with lower entry barriers, the gender difference narrows. Occupations with the highest entry barriers are legal professionals and healthcare practitioners. The point estimates do not necessary differ from one year to another throughout the entire period. Typically, coefficients from adjacent years are not statistically different from each other. However, the point estimates for most years after 2000 are statistically different from those before 1990. Occupations with the highest entry barriers are legal and medical professions. Over the past thirty years, women in legal professions approximately quadrupled from 12 percent to 46 percent, and the percentage of women in healthcare practice also grew from 49 percent to 69 percent over this same period (see Figure 2.4 and 2.5).

The coefficient of occupational turn-over rates is negative for both men and women. The negative coefficient indicates that this variable likely captures undesirable occupational attributes associated with the occupations. Also, high turn-over rates may suggest that such occupations are transitory and may have limited long-term development opportunities. Occupations with high fractions of workers leaving for other occupations include administrative support and healthcare support. This turn-over rate measure is highly correlated with the entry-barrier measure (.67). Hence, workers' preferences for low entry-barriers offset the effect of high turn-over rates in a variety of occupations. Figure 2.6 shows that the gender difference in the coefficient of occupational turn-over rates remained relatively stable until 2000, and the difference started to narrow. The gender difference in turn-over rates in the last three years from 2006 to 2008 appears to be significantly smaller than those before 1990.

With regards to the skill transferability measure, women are also more likely than men to choose occupations that are similar to other occupations. In other words, the proximity to other occupations is a highly desired occupational attribute to women. However, this gender difference in the coefficient of skill transferability remains stable and hovers between 2 and 3.5 over the sample period (see Figure 2.7).

Figure 2.8 shows that the gender differences in selection on usual work hours also narrows over time. It is not surprising to observe the narrowing gender gap in selection on work hours, given the increasing female investments in education and stronger labor market attachment. Occupations that demand long hours of labor input include: legal professionals, farmers, and managers, and they were traditionally male-dominated occupations. Female representation in legal and managerial professions increased substantially over this period. Female managers grew from under 25 percent in 1979 to 46 percent in 2008, and women in legal professions almost increase by four times. However, female participation in farming has stagnated and remained under 20 percent although less than 1 percent of college graduates worked in farming occupations. Figure 2.4, 2.9, and 2.10 showed the time trend of female representation in these three occupations.

The other major narrowing gender gap is related to visualization tasks. This "visualization" factor comes primarily from the DOT measures of far acuity, field of vision, color vision, and color discrimination. It is most valued in sciences and engineering occupations– both were over-represented by men. Women tend to choose occupations that do not require intensive visualization tasks. Figure 2.11 presents that the gender difference in coefficient of visualization narrowed from -.926 in 1979 and to -.237 in 2008. Although male domination persists in the engineering field, women gain substantial traction in the field and the female share grows from 3.5 percent to 15.1 percent over the past three decades (see Figure 2.13). Women in scientific occupations across life, physical, and social sciences also increase from 25.6 percent in 1979 to 44.6 percent in 2008 (see Figure 2.12).

Women are more likely than men to choose occupations with low entry wages. This result is consistent with prior findings that pecuniary motivations are stronger for men than for women (Fortin, 2008; Zafar, 2009; Wiswall and Zafar, 2011). The coefficient estimate of gender difference in response to entry-level wages is relatively stable and the difference oscillates between -4 and -3 (Figure 2.14).

Female workers, on the other hand, are more likely to choose occupations with larger wage growth rates. This result differs from the estimates in Chapter 1. Note that individuals with graduate degrees are included here but excluded in the analysis in Chapter 1. Because the entry-level wage is defined as the mean wage among college graduates between age 22 and 25, the entry-wage is relatively lower for occupations that typically require graduate degrees and internships. For instance, the mean entry-level wage for healthcare practitioners is approximately 11 to 12 percent lower than the initial wage for computer analysts and engineers. But the 10-year wage growth rate is substantially larger for medical practitioners than for computer analysts and engineers. Since healthcare practitioners are predominantly female, the coefficient estimate reflects the fact that women tend to choose medical occupations that are associated with a steep upward wage trajectory. Figure 2.15 shows fluctuations of the gender difference in selection on wage growth, but the differences across years are mostly statistically insignificant.

The gender differences in selection on cognitive skills, motor skills, and harsh work environment are persistent and no noticeable trends are observed (Figure 2.16, 2.17, and 2.18).

Discussions of education reforms center on addressing the under-representation of women in science, technology, engineering, and sciences (STEM). From the above analysis, since STEM occupations tend to have moderate turnover rates of workers both in and out from these occupations, it is clear that job entry barriers and occupational mobility are not the primary reasons preventing women from entering these occupations. However, the narrowing gender gap in occupational selection on visualization requirement coincides with the growing representation of women in occupations with high visualization requirement, including sciences and engineering. There is no evidence of increasing female participation in computer analysis and mathematics occupations.

2.4 Discussions and Conclusions

This chapter examines the time trend of gender differences of occupational selection on multiple occupational characteristics between 1979 and 2008. I find that over the past 30 years, the considerations of occupational mobility have abated for women in choosing occupations. Women in 1979 were much more likely than their peers in 2008 to leave the labor market for an extended period of time, and hence were more likely to choose occupations with more general skills that are applicable in other occupations when they return to the labor market. This skill transferability concern may be a reason why women were less likely to be attorneys and doctors in the past. With increasing female labor market attachment, occupational transferability has become a diminishing concern for women. Rapid growth of female representation in legal and healthcare professions corroborates the prediction of the narrowing gender difference in selection on occupational mobility. This change in preferences for occupational mobility is gender specific due to the drastic growth of female labor force attachment in the past few decades. Male selection on occupational mobility is relatively stable over time, and hence the narrowing gender difference is entirely attributable to changes in female occupational sorting.

The stronger female labor market attachment also reflect women's increasing participation in occupations that demand long work hours. Women's reallocation of time from home to market production allows them to choose time-demanding occupations. Indeed, the rapid increase in female representation in these hour-intensive occupations, such as managers, attorneys, and doctors, provides suggestive evidence that the narrowing gender gap in work hours changes the gender distributions in these occupations.

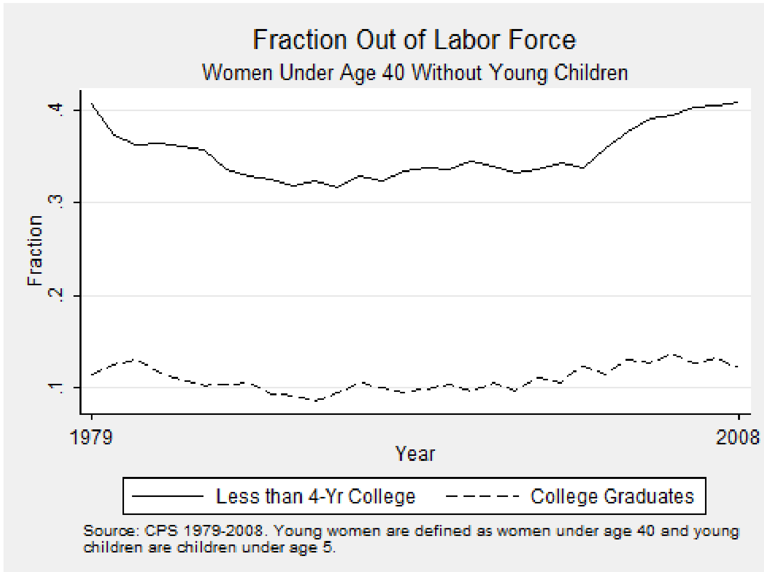
I also find that the gender difference in selection on visualization diminishes over the past thirty years. The increasing likelihood of women choosing occupations that require intensive visualization tasks is associated with the growth of female representation in sciences and engineering occupations. In contrast, there is little change of gender differences in cognitive skills, motor skills, and harsh work environment. While women develop stronger preferences for visualization tasks, the gender differences in other occupational attributes persist over time. Future research on preference formation may shed light on the causes of the these changing and unchanging gender differences.

2.5 Appendix: Figures and Tables

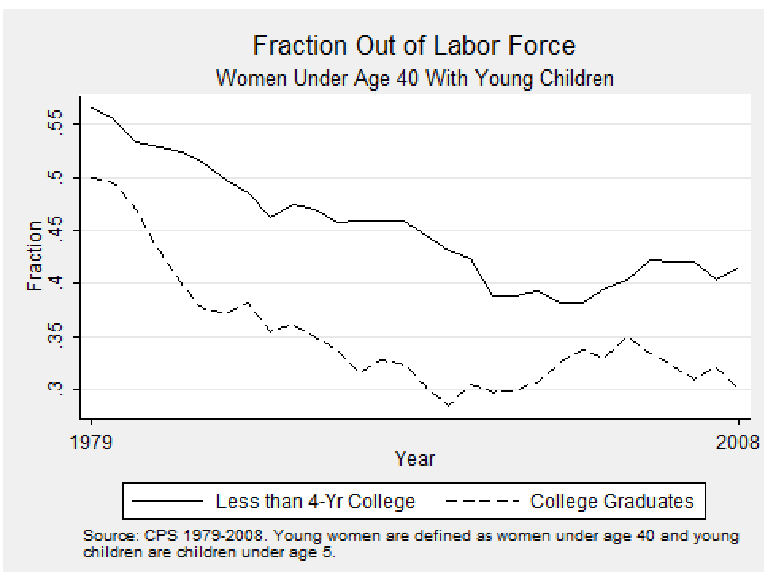
Table 2.1: Sample Size: CPS 1979-2008

Year	Male	Female	All
1979	4,263	3,043	7,306
1980	5,082	3,850	8,932
1981	5,137	3,877	9,014
1982	4,667	3,563	8,230
1983	4,806	3,832	8,638
1984	4,883	4,016	8,899
1985	4,954	4,199	9,153
1986	5,016	4,263	9,279
1987	4,865	4,251	9,116
1988	4,587	4,198	8,785
1989	4,247	4,022	8,269
1990	4,487	4,399	8,886
1991	4,210	4,369	8,579
1992	4,067	4,183	8,250
1993	4,116	4,169	8,285
1994	3,949	3,933	7,882
1995	4,045	4,123	8,168
1996	3,415	3,604	7,019
1997	3,393	3,604	6,997
1998	3,424	3,632	7,056
1999	3,382	3,666	7,048
2000	3,454	3,633	7,087
2001	5,613	5,968	11,581
2002	5,586	6,028	11,614
2003	5,333	5,800	11,133
2004	5,214	5,774	10,988
2005	5,090	5,884	10,974
2006	5,037	5,887	10,924
2007	5,189	5,985	11,174
2008	5,371	6,348	11,719
Total	136,882	134,103	270,985

The sample is restricted to college graduates under age 40.

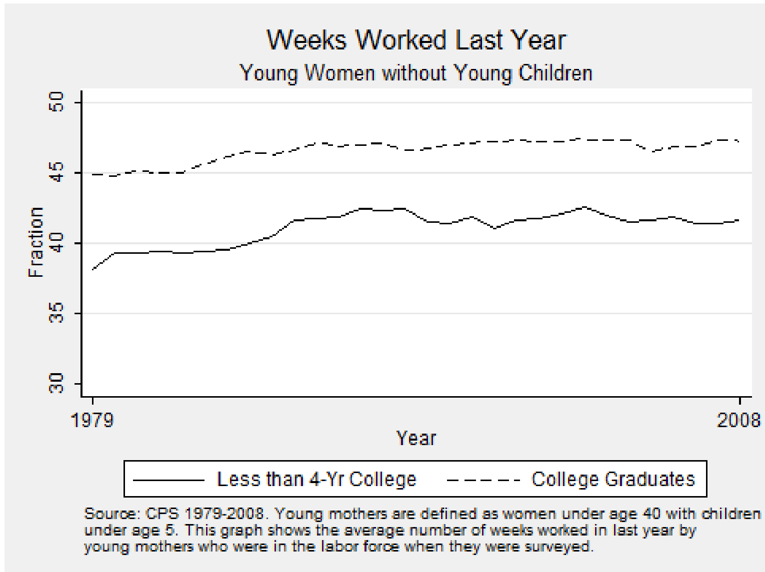


(a) Women Under 40 w/o Young Children

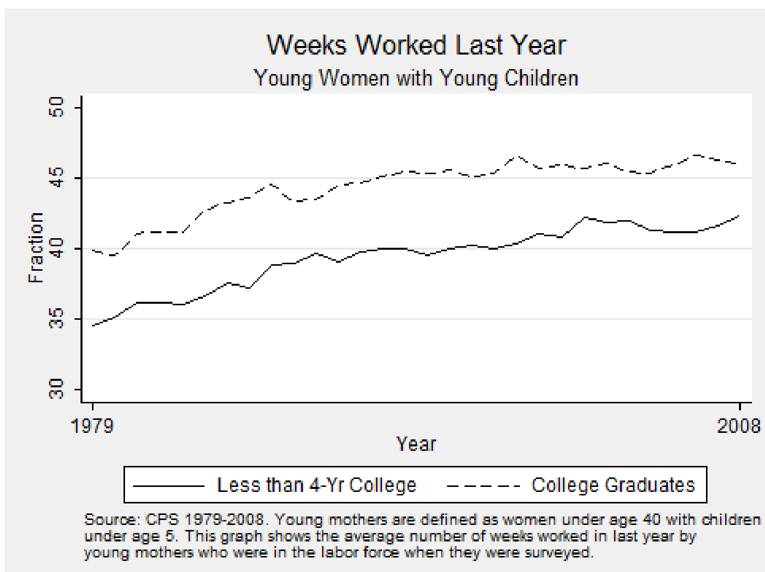


(b) Women Under 40 w/ Young Children

Figure 2.1: Women Under 40 and Out of Labor Force, CPS 1979-2008



(a) Women Under 40 w/o Young Children



(b) Women Under 40 w/ Young Children

Figure 2.2: Weeks Worked Last Year: Women Under 40 and in the Labor Force, CPS 1979-2008

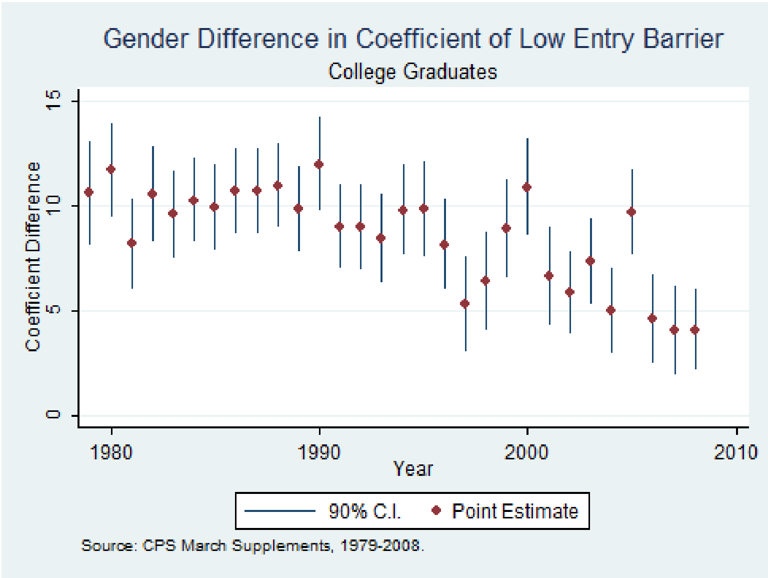


Figure 2.3: Trends of Gender Gap in Entry Barrier Coefficient

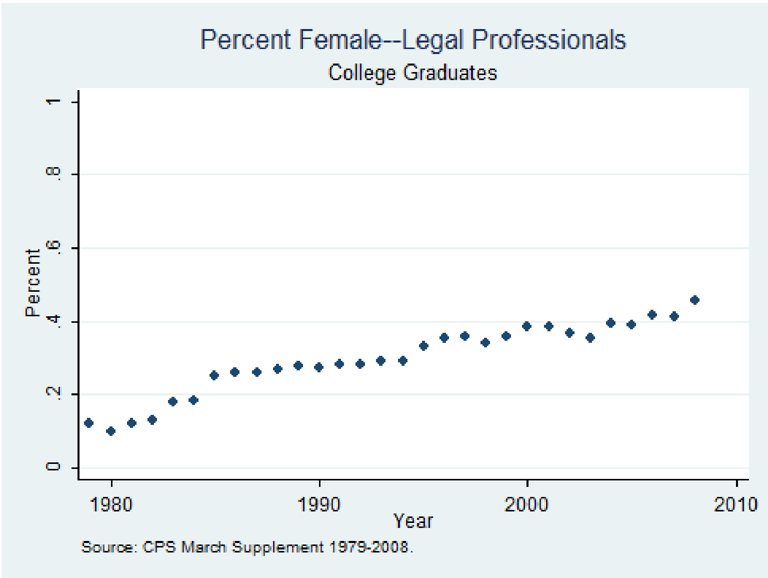


Figure 2.4: Fraction of Women in Legal Occupations

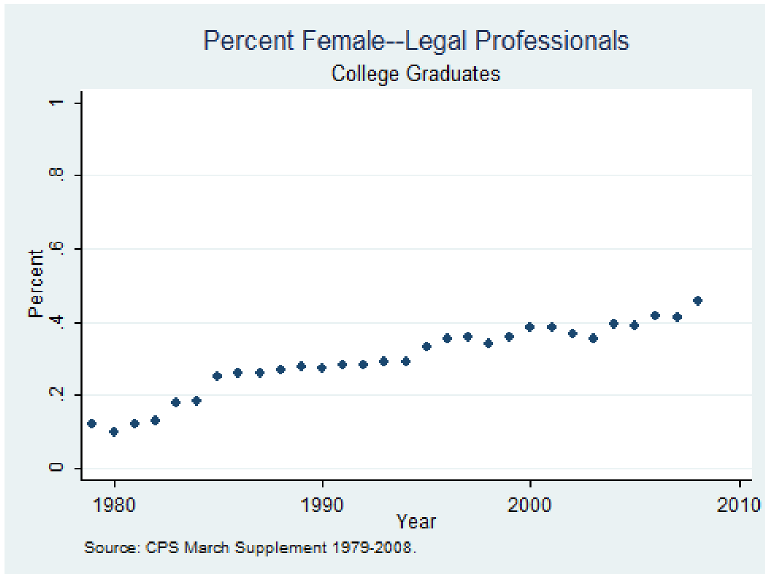


Figure 2.5: Fraction of Women in Healthcare Practice Occupations

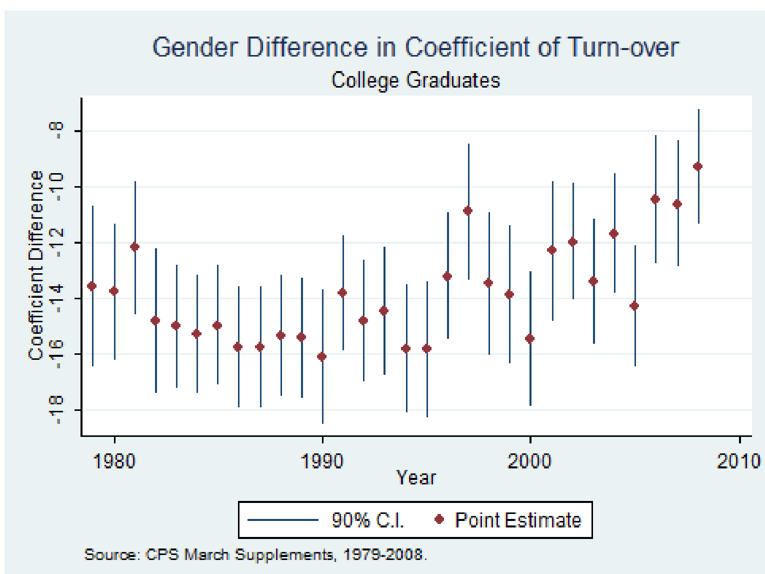


Figure 2.6: Trends of Gender Gaps in Turn-over Coefficient

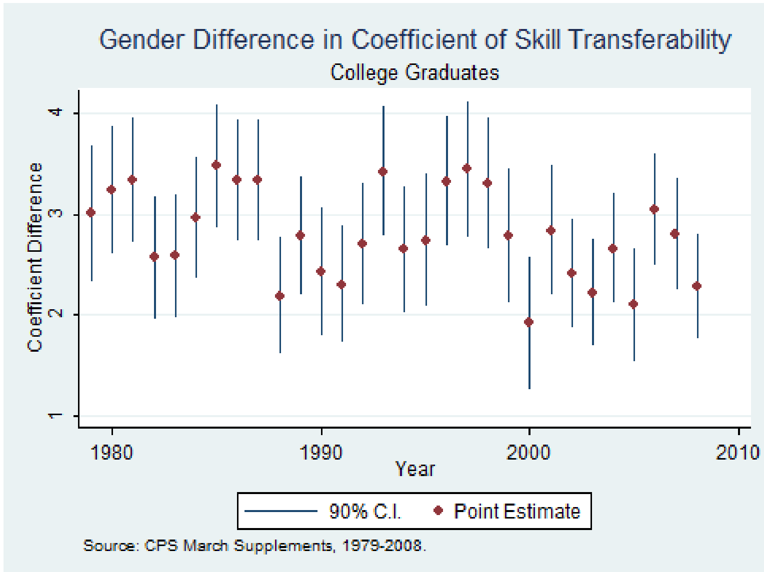


Figure 2.7: Trends of Gender Gaps in Skill Transferability Coefficient

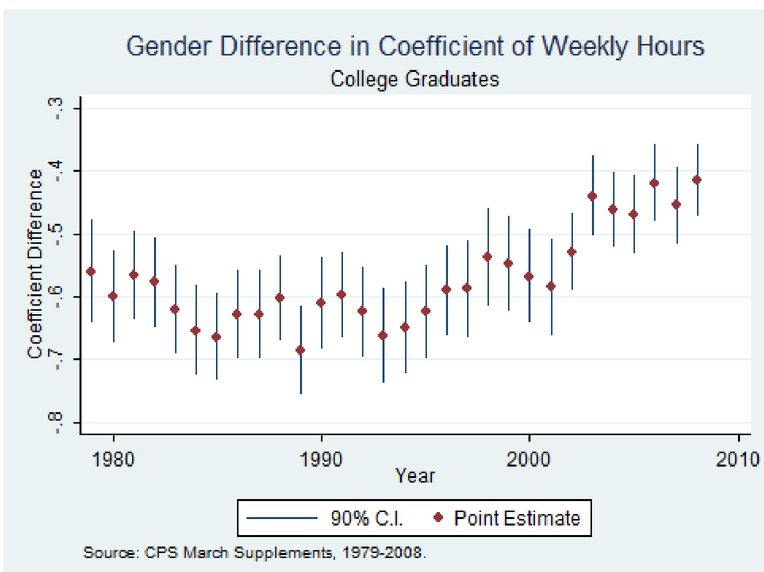


Figure 2.8: Trends of Gender Gaps in Work Hours Coefficient

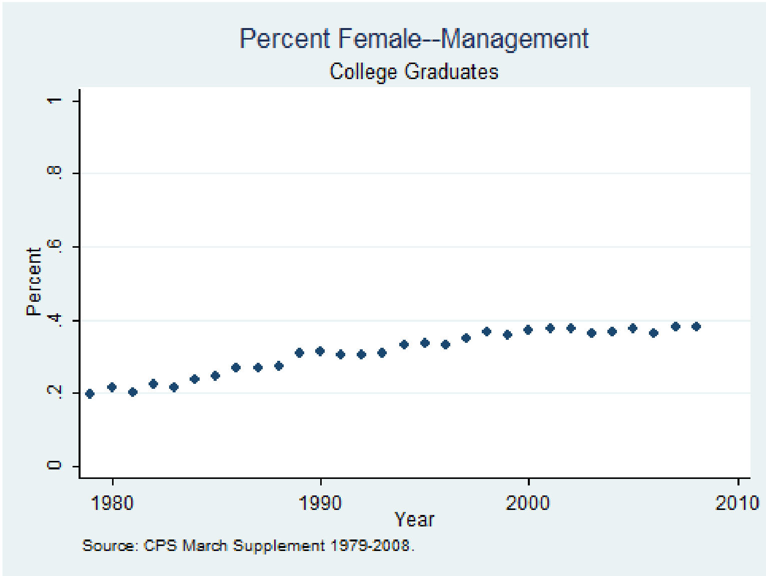


Figure 2.9: Fraction of Women in Managerial Occupations

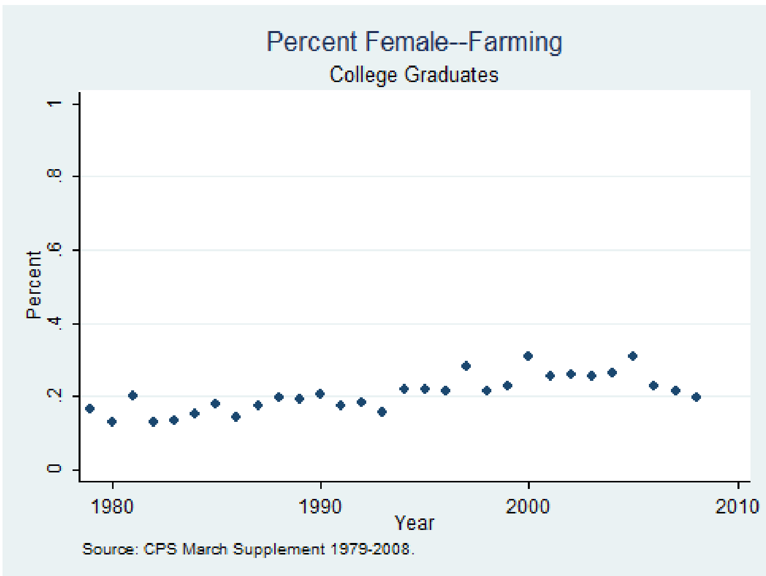


Figure 2.10: Fraction of Women in Managerial Occupations

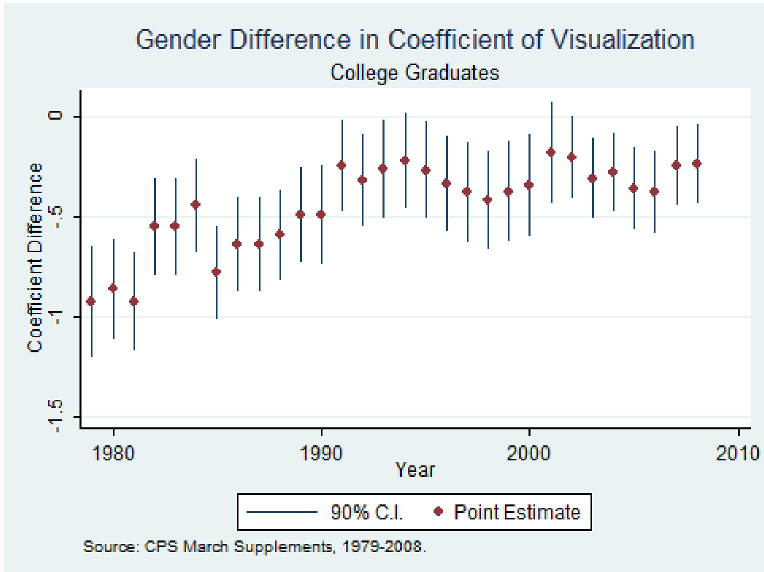


Figure 2.11: Trends of Gender Gaps in Visualization Coefficient

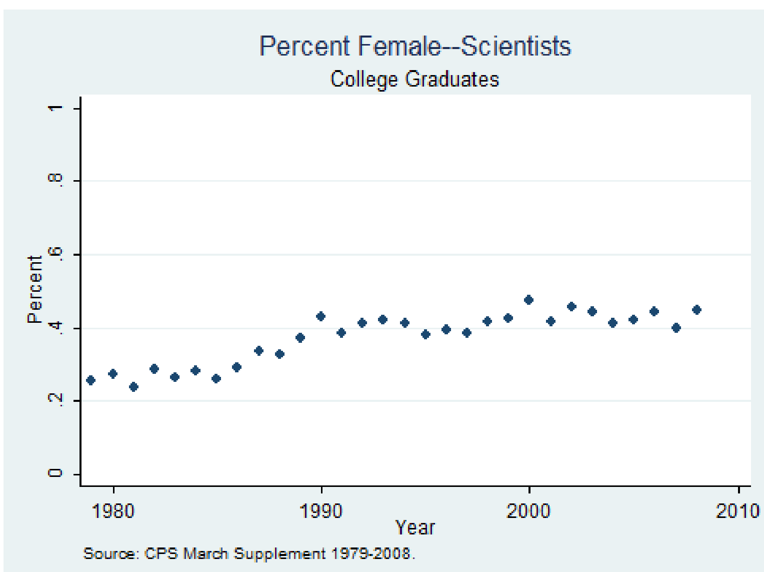


Figure 2.12: Fraction of Women in Science Occupations

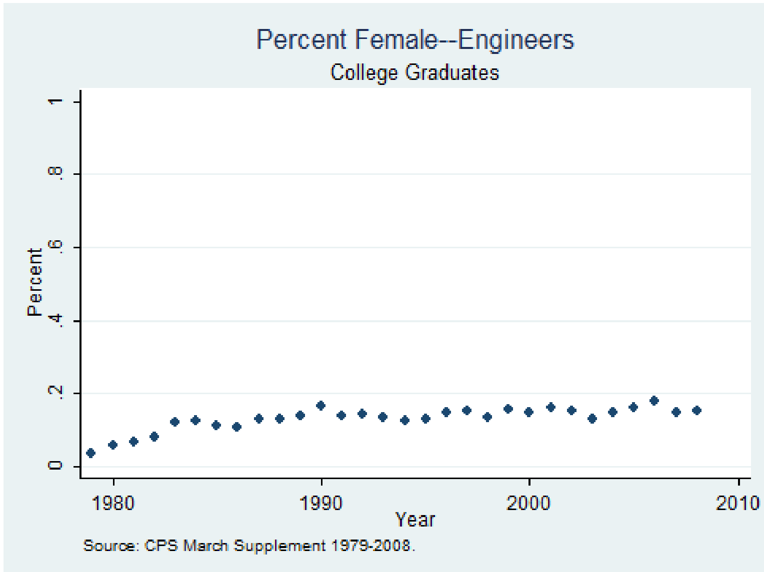


Figure 2.13: Fraction of Women in Engineering Occupations

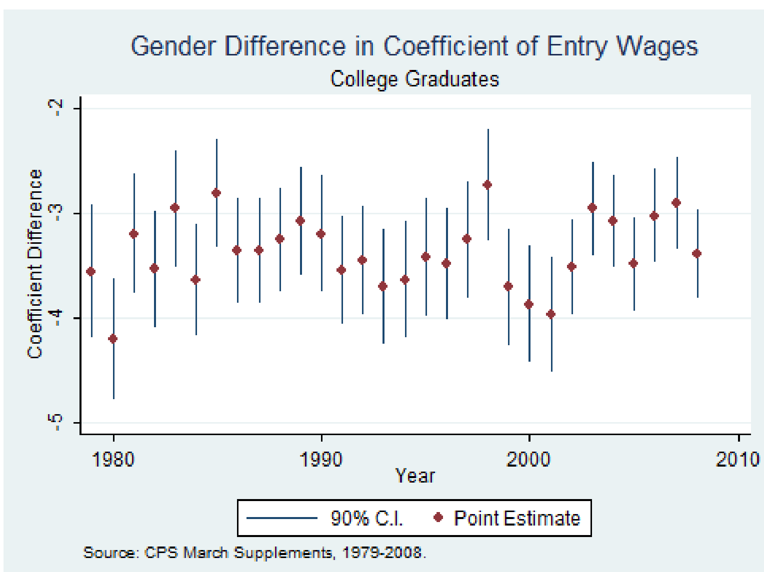


Figure 2.14: Trends of Gender Gaps in Entry Wage Coefficient

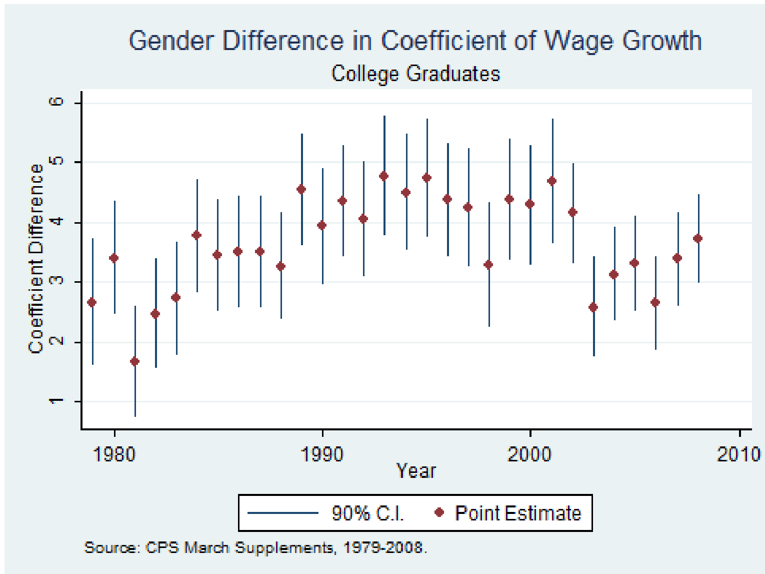


Figure 2.15: Trends of Gender Gaps in Wage Growth Coefficient

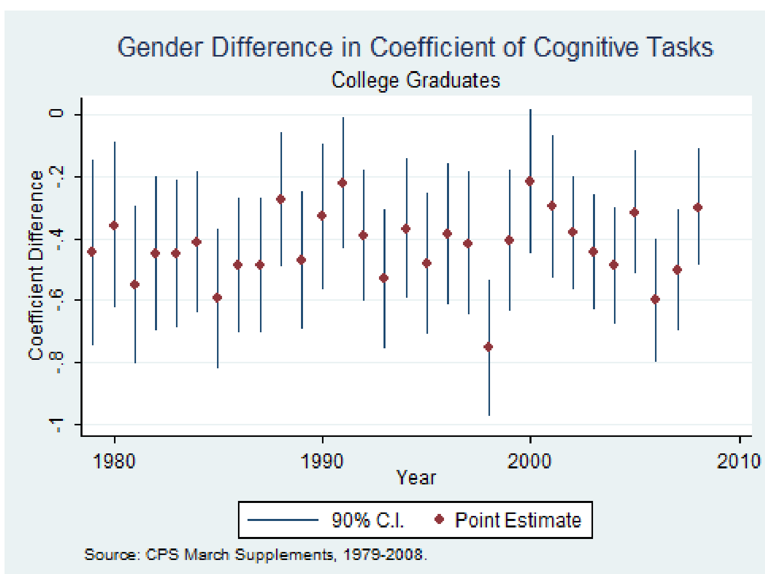


Figure 2.16: Trends of Gender Gaps in Cognitive Task Coefficient

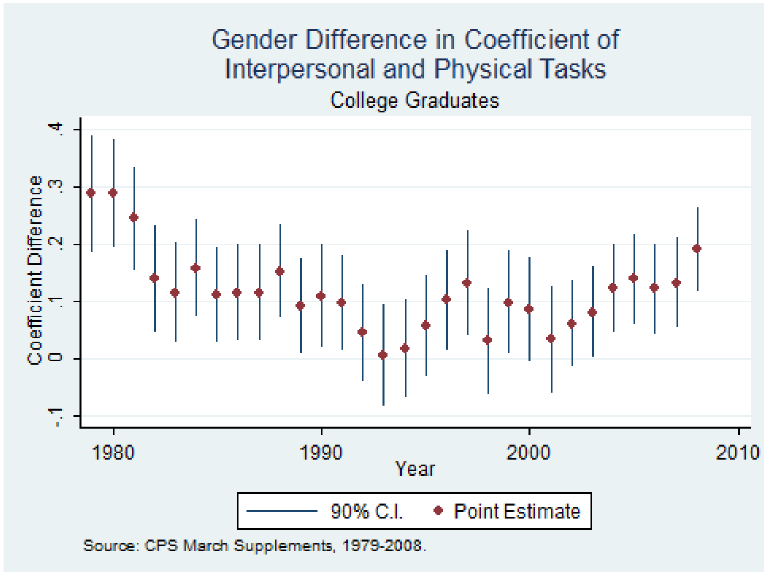


Figure 2.17: Trends of Gender Gaps in Interpersonal Skill Coefficient

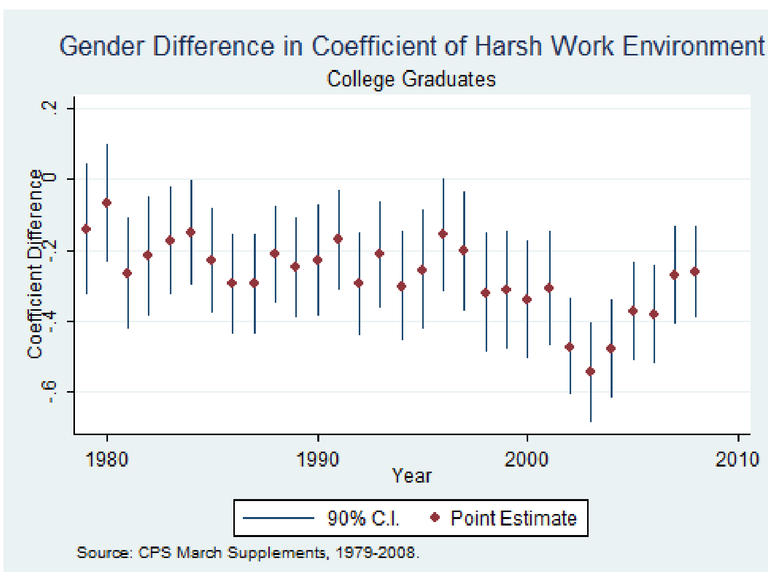


Figure 2.18: Trends of Gender Gaps in Work Environment Coefficient

Chapter 3

Are Baby Boomers Saving Less Adequately Than Earlier Cohorts?

With William G. Gale, John Karl Scholz, and Ananth Seshadri

3.1 Introduction

There is widespread concern expressed in newspapers and in public policy and academic studies that a substantial fraction of Americans are preparing poorly for retirement. The headlines of newspaper articles – two examples are “Debt-Squeezed Gen X Saves Little” (O’Shaughnessy, 2008) or “Retirement’s Unraveling Safety (Russakoff, 2005) Net” –suggest that individuals or the institutions that people rely on for retirement security are falling short. Journalists likely take cues from the financial services industry and from writing by academics and other opinion leaders. An article in the 2007 McKinsey Quarterly (Court and Forsyth, 2007) states “One finding of our research was a segmentation indicating that only about a quarter of the boomers are financially prepared for their twilight years” (page 106). Munnell et al. (2008) calculate the National Retirement Risk Index and show that “even if households work to age 65 and annuitize all their financial assets, including the receipts from reverse mortgages on their homes, 44 percent will be ‘at risk’ of being unable to maintain their standard of living in retirement.”[1] A widely cited statistic from the National Income and Product Accounts (NIPA), the personal saving rate as a fraction of disposable personal

[1] As additional examples, see “A Nation in Debt,” (Whitehead, 2008) and “The Great Seduction.” (Brooks, 2008)

income, has declined steadily since the early 1980s. The personal saving rate was 13.2 percent in 1986, but it was negative in 2002, 2005 and 2006, the only negative years since 1932.

But developing rigorous, systematic evidence on the degree to which people are preparing sensibly for retirement is difficult. In the first part of this chapter we briefly summarize and interpret some of the evidence on the adequacy of retirement wealth accumulation. A key building block for many studies is the "replacement rate" concept. For reasons discussed below, we think replacement rates do not provide a sensible underpinning for assessing retirement financial preparedness. We also present descriptive evidence on wealth holdings across U.S. birth cohorts and subjective attitudes about their financial circumstances in retirement. This descriptive evidence does not seem consistent, in our view, with dire assessments of poor financial preparation.

In the second part of the chapter we extend the dynamic programming approach used in Scholz et al. (2006) to assess the adequacy of retirement wealth preparation in 2008, using a sample of Americans born before 1954. We examine whether this group of households have accumulated the wealth necessary to maintain pre-retirement living standards in retirement. Our results suggest that more than 70 percent of the households in our sample had accumulated sufficient resources in 2008. Economically disadvantaged households are significantly more likely than others to be under-saving and hence are natural targets for outreach and other efforts to improve financial capabilities. There is no systematic cohort difference in meeting the optimal wealth targets.

If these results hold as we incorporate a broader set of households and conduct additional specification checks, they suggest a somewhat less optimistic view about the adequacy of American's retirement preparation than the findings for 1992, the focal year in Scholz et al. (2006). There they found, for households born between 1931 and 1941, that 15.6 percent of the sample had accumulated wealth below their optimal targets in 1992 (and the magnitude of the conditional deficits were somewhat smaller than what we find in 2008).

3.1.1 A brief (selective) overview of the existing literature

There are two major elements to data-based analyses that conclude Americans are saving too little for retirement. The first is the declining, sometimes negative NIPA personal saving rate figures. The second are studies that make use of the workhorse financial planning concept of replacement rates.

3.1.1.1 NIPA Saving Rates

There are difficult issues, capably discussed in Gale and Sabelhaus (1999), with the NIPA's effort to measure personal saving. One important item is that accrued (and realized) capital gains are excluded from the saving measure. Thus, increases in consumption caused by an appreciating stock market or appreciating housing wealth would result in falling NIPA personal saving rates. Investment in consumer durables is also not treated as personal saving, and Gale and Sabelhaus (1999) note that "From the perspective of economic theory, the line between personal and corporate saving is thin and somewhat arbitrary." They write, after looking at both data from the NIPA and Flow of Funds Accounts, that "The official personal saving measures do not measure wealth accumulation in the form of capital gains. . . . They provide inconsistent treatment of durable goods, payments from corporations, inflation, and taxes. They are affected by demographic factors, and they provide no information on the distribution of saving across households." They conclude that both the NIPA and Flow of Funds measures substantially overstate the decline in personal saving in the period they study, and they conclude one should not make inferences about the saving behavior of individual households based on the aggregate NIPA or Flow of Funds personal saving rate.

3.1.1.2 Replacement Rates

The replacement rate – the amount of income in retirement needed to maintain pre-retirement living standards – is a workhorse concept in the financial planning literature. Typical advice suggests that replacement rates should be 70 to 85 percent of pre-retirement income.[2] Target replacement rates are less than 100 percent for three reasons. First, upon retirement, households typically will face lower taxes than they face during their working years, if for no other reason than Social Security is more lightly taxed than wages and salaries. Second, households typically also save less in retirement than they do during their working years, so saving is a smaller claim on available income. Third, work related expenses generally fall in retirement.

Low income households are thought to need higher replacement rates than high income households because, prior to retirement, they have lower tax burdens, so the difference in tax treatment between Social Security and wages and salaries is less consequential, and they likely devoted less in pre-retirement income to saving than their more affluent counterparts (Dynan, Skinner, and Zeldes, 2004), hence the reduction in taxes and saving experienced in retirement will be less substantial for these households.

Many studies use replacement rates as their standard for assessing the adequacy of wealth accumulation. Court and Forsyth (2007), for example, write that "Our analysis also indicates that 60 percent of boomers will need to work (following formal retirement) just to maintain 80 percent of their current consumption." Munnell et al. (2008) is perhaps the most ambitious study of wealth accumulation using the replacement rate concept. They conclude that under a best case scenario, 44.5 percent of American households will be at risk of being unable to maintain their standard of living in retirement.

Munnell et al. (2008) make strong assumptions to go from the Survey of Consumer Finances (SCF) – a high quality cross-sectional dataset on household wealth – to an assessment about the adequacy of wealth accumulation at retirement.[3] They take the components of net worth observed for each household in the SCF and extrapolate these to age 65 and then

[2] Applications will use different measures of pre-retirement income, such as income in the year immediately prior to retirement, average income during the working life, or income in the "n years" immediately prior to retirement.

[3] For more details on their approach, see Munnell, Webb, and Delorme (2006). Munnell et al. (2008) provide evidence for Late Boomers (born 1955-64) and GenXers (1965-72). Our data do not cover these cohorts. Forecasting problems likely increase with the length of the forecast and the optimal wealth accumulation at younger ages tends to be low, both because of children and upward sloping age-earnings profiles.

annuitize net worth. This provides the numerator of the statistic they compare to the replacement rate target. The denominator of the statistic is lifetime income, which they need to impute from the SCF cross-section. To do this they assume all men and women in the SCF have the median earnings profile (anchored by their observed earnings in 2004), calculated from restricted social security earnings records from the Health and Retirement Study. There is, of course, a great deal of variation in earnings realizations across households. With estimates of the numerator and denominator, they designate a household as being "at risk" if their replacement rate is 10 percent below a target that varies between 65 percent for high-income singles to 85 percent for low- income one-earner couples. The target averages 73 percent across all households.

Given the often substantial idiosyncratic and aggregate shocks that households receive in middle and older ages, it is unclear how accurately the wealth extrapolations will mimic the actual wealth holdings of SCF households upon retirement. Hence, the resources available to households in retirement may be misstated. They are also likely to have substantial forecast errors (both positive and negative) in estimates of lifetime earnings, particularly when anchored by the earnings reports found in a single cross-section of data. But unlike many forecasting exercises, this is not a case where upside errors cancel out downside errors, leaving an arguably plausible average estimate. Those whose lifetime earnings are overstated are more likely than they should be to be classified as being at risk. To see why, consider a household that, by assumption, has accumulated exactly the retirement resources needed to maintain living standards. If the forecast of lifetime earnings is overstated, which likely will occur in roughly half the cases, the household will appear to have insufficient wealth, not because wealth accumulation is too low but because the estimate of lifetime earnings (and hence, pre-retirement living standards) is overstated. If earnings forecast errors are substantial and symmetric, it is perhaps not surprising that upwards of 50 percent of the population is found to be at risk.

The replacement rate concept is also flawed in that it ignores the role that children play in optimal life-cycle wealth decisions nor do they account for timing of income and wealth shocks, that may affect optimal wealth accumulation if households face credit constraints. Scholz and Seshadri (2009) provide a detailed analysis of the effects children have on optimal wealth accumulation.

To summarize, the replacement rate is a conceptually flawed benchmark for retirement planning. Moreover, the assumptions needed to calculate household replacement rates with some datasets are severe. A natural alternative is to use insights from the life-cycle model, augmented to account for fundamental factors affecting most households, such as demographic changes and uncertainty about future earnings, medical expenses, and longevity. The drawbacks to this approach, done correctly, are computational complexity and the data demands, which among other things, require information on annual earnings over individuals' lifetimes. But the lifecycle model is the appropriate conceptual benchmark, as lifecycle consumption decisions maximize lifetime well-being, subject to lifetime resource constraints. We emphasize the fact that we do not need to assume that people follow the lifecycle model for our approach to be informative. Rather, the lifecycle model provides a rigorous normative benchmark – if household wealth exceeds the lifecycle target, they are on-target for being able to maintain their pre-retirement living standards in retirement. Put less intuitively, they will be able to equate the discounted marginal utility of consumption across periods.

3.1.1.3 Several Lifecycle Papers Suggest Most Americans are Preparing Well for Retirement

Hubbard et al. (1995) and Engen and Uccello (1999) use life-cycle models to simulate the expected distribution of wealth for representative household types. Hubbard et al. (1995) note that when realistic features of the tax and transfer system are modeled, the distribution of optimal wealth that results from the life-cycle model matches the distribution observed in data. Engen and Uccello (1999) conclude, using their best judgment regarding model and data, that "households are largely saving adequately, but other interpretations are possible."

Scholz et al. (2006) go a step further, and examine the household-specific implications of an augmented lifecycle model. They found that fewer than 20 percent of households born between 1931 and 1941, members of the original Health and Retirement Study (HRS) cohort, had less wealth than would be suggested by an optimal household-specific target. These targets were computed from a model incorporating uncertain earnings, uncertain lifespan, end-of-life health shocks, supplemented with Social Security earnings records and other economic and demographic data from the HRS. The wealth deficit of those who were undersaving was generally small. A critical unresolved issue, however, is the degree to which these results hold for other cohorts, particularly those born after 1941.

Love et al. (2008) study the wealth trajectories of households in retirement, showing they do not decumulate wealth as quickly as one would expect from the no-uncertainty life-cycle model. They show that while wealth in levels falls with age for elderly households in the HRS, "annuitized" wealth does not. Annuitized wealth reflects both the steady flow of annual income that could be drawn from a given level of wealth and the fact that as years go by, remaining lifespan will (generally) fall. Rising annuitized wealth as households move through their retired years is not the pattern one would expect to see in the data if people systematically were saving too little for retirement.

3.1.2 Descriptive evidence on the adequacy of saving

There are three pieces of descriptive evidence that provide additional perspective on the degree to which Americans are preparing well for retirement. The first shows the net worth held by the typical member of broadly specified birth cohorts, at comparable ages. If some birth cohorts are preparing well, while others are doing less well, one might expect to see evidence of this when comparing cohort patterns of wealth accumulation over time.

The second simply compares the wealth, lifetime income, and wealth-to-income ratios of HRS cohorts. As the HRS has matured, new cohorts have been added. The 2008 version of the data, which we rely on for this chapter, includes households from the AHEAD cohort, born before 1924; Children of Depression Age (CODA) cohort, born between 1924 and 1930; the original HRS cohort, born between 1931 and 1941; the War Baby cohort, born between 1942 and 1947; and the Early Boomer cohort, born between 1948 and 1953. Again, if there are substantial differences in behavior between HRS birth cohorts, one might expect to see clues in the descriptive data.

The third makes use of two subjective questions posed in the HRS to retired households: (a) how satisfied are you with retirement, and (b) how are the retirement years compared to before? A comparison of responses to these questions, and how they relate to net worth may be revealing about the degree to which people have prepared well for retirement.

3.1.2.1 Cohort Patterns of Wealth Accumulation

Figure 3.1 shows data from the Survey of Consumer Finances (from 1962 and every three years between 1983 and 2004) for two population cohorts: households who are age 25 to 39 when we begin to follow them, and households who are age 40 to 54. We plot the evolution of median net worth for 25 to 39 year olds in 1962, in 1983 (there is no SCF-like survey conducted in the 1970s), and in 1992. We also plot the evolution of median net worth for the three older cohorts: those who were 40 to 54 in 1962, 1983, and 1992.

Each symbol in the Figure plots the median net worth at the middle age in the given age band (for example, households age 40 to 54 are plotted as if they were 47 years old). The figures show the evolution of median net worth for the same sets of households over time, since (aside from mortality, immigration and emigration) we know households who are 25 to 39 in 1962 (as defined by the head's age) will be 46 to 60 in 1983, 52 to 66 in 1989, and so on until their final observation as 67 to 81 year olds in 2004.

There are three noteworthy aspects of Figure 3.1. First, the cohort defined as 40 to 54 in 1962 (the line marked by "⧫" in the lower right portion of the figure) has significantly lower net worth than the other cohorts. Individuals in this cohort were children or young adults during the Depression and were young adults during World War II. Opportunities for human capital acquisition and wealth accumulation were more limited for this cohort than they were for subsequent cohorts. Second, median net worth grows steadily for each cohort. The patterns shown here are difficult to reconcile with assertions that living standards for typical Americans are declining.

Third, each successive cohort ends up with somewhat more wealth after the last two periods of observation (in 2001 and in 2004) than the cohort before it. To see this, at any given age (fixing age on the horizontal axis), the most recently born of the given age group has greater net worth (read straight down, which holds age constant). This shows that net worth (in levels) is growing across cohorts, even through the period of weak economic and stock market performance between 2001 and 2004. Each cohort appears to be mimicking the behavior of the previous cohort, though they appear to be accumulating somewhat more. If people are systematically making important mistakes by accumulating too little for retirement, the mistakes seem to be occurring across all cohorts.

3.1.2.2 Wealth and Income Across HRS Cohorts

Table 3.1 provides data from the HRS on wealth accumulation and lifetime income across cohorts. Start with the RAND version of the HRS which includes 30,548 individuals. Of these 28,978 are either the household head (household member with highest lifetime earnings) or the primary spouse of the household head. The primary spouse is defined as the spouse to whom the head has been married the longest. Individuals are considered single if either: a) they report never having been married, or b) they were married one time but for less than 10 years. Earnings records from the Social Security Administration are a key element in our analysis so we drop households in which either the head or the primary spouse did not agree to release their earnings history. This selection process leaves 13,776 individuals, 12,600 of whom are married and 1,176 of whom are single; a total of 7,476 unique households. Of these we drop 75 households because their earnings history is insufficient to estimate the household fixed effect in the earnings model or because the gender of the household head and the primary spouse is the same which would affect eligibility for Social Security and government transfers. This leaves 7,401 households, 6,282 of which are married and 1,119 that are single.[4] The table provides useful magnitudes for interpreting the model-based

[4]The resulting numbers of households with non-missing net worth values are 3,975, 3,702, 5,757, 5,362, 5,039, 5,338, 4,934, and 4,544 for year 1992, 1994, 1998, 2000, 2002, 2004, 2006, and 2008, respectively.

simulation results shown later. Slightly over half of the sample is from the original HRS cohort born between 1931 and 1941. Scholz et al. (2006) and Haider and Solon (2000) suggest the observed characteristics of those in the original HRS cohort who agreed to release their data are very similar to those who do not. The original HRS cohort was intensively studied in Scholz et al. (2006). It is useful to have these households in the sample, since they allow us to compare our new results for the original HRS cohort with the results from our earlier work. The sample size of the AHEAD cohort is smaller due the attrition by mortality. The remaining portion of the sample is roughly evenly split between the remaining three cohorts.

The age of head column shows the age ranges that are used when drawing samples for the new HRS cohorts. AHEAD and CODA households will clearly be affected by survivorship bias: some members of this cohort will have died, and mortality is likely correlated with household resources. Hence, the AHEAD and CODA sample will likely be composed disproportionately of wealthier, higher-income members of the cohort.

Median net worth is a comprehensive wealth measure, reflecting the value of stocks, bonds, mutual funds as well as other financial instruments, the value of houses and real estate (less the associated debt), and defined contribution pension fund balances. The patterns of net worth are not conclusive. Early boomers have much less net worth than their counterparts in the HRS and War Babies cohorts, which could be consistent with the idea that this group of households is failing to prepare appropriately for retirement. Of course, we expect there to be a natural lifecycle pattern of wealth accumulation. Households in the early baby boom cohort typically will be in the paid labor market for more than a few years. Moreover, many will have children who have recently left the household. As emphasized by Scholz and Seshadri (2009), children have a substantial, negative effect on wealth accumulation. Hence, we expect there to be a great deal of wealth accumulated in the high-earning years between the time children leave the house and when they retire. Moreover, we expect retired households to decumulate wealth. Hence, the patterns of net worth in Table 3.1 may be precisely what we would expect to see for life-cycle households.

The median lifetime income column is the sum of real household life earnings up to 2004.[5] Most households in the oldest three cohorts have retired: for these cohorts, income is higher, the younger the household. Members of the War Babies and Early Boomers will typically work more years in the paid labor market. The final column of Table 3.1 reports the median of the ratio of net worth to cumulative earnings to date. As with the net worth (in levels) figure, the ratios may be consistent with problems in wealth accumulation, or may reflect precisely the pattern we would expect to see if the lifecycle model capably summarizes behavior. In descriptive regressions where wealth-to-income is the dependent variable, and conditioning variables include age and indicator variables for educational attainment, defined benefit pensions for the husband and wife, and indicators for cohort, the cohort indicators are insignificant, individually and jointly. The final section of the chapter takes a more rigorous look at patterns of wealth accumulation across cohorts and by individual.

3.1.2.3 Subjective Views of Financial Satisfaction in Retirement

HRS respondents were asked two questions about their subjective views of retirement. The responses are summarized in Table 3.2. It is critical to understand that few households in the younger cohorts – the War Babies and Early Boomers – are actually retired. Those who are retired in these cohorts likely incurred some health or employment shock that led to unexpected negative changes in economic circumstances. For this reason, the samples are quite small in these cohorts. Also, there are many fewer responses to the retirement comparison question than to the retirement satisfaction question.

Over the entire population, only 6 percent of households find retirement not at all satisfying. Eleven percent of households find their living standards worse in retirement than they were prior to retirement. Responses to these subjective questions, while far from definitive, are consistent with the idea that households in the HRS are on track to achieving financially

[5]We have imputed earnings for households whose reported earnings are capped by the social security earnings limit. Our approach follows Scholz et al. (2006).

secure retirements, particularly over the portions of the sample (the AHEAD, CODA, and HRS cohorts) where there are substantial numbers of retirees.

3.2 Model-Based Calculations of the Adequacy of Wealth Accumulation

To avoid confusion about the specific model we have in mind, we start this section by describing our baseline model that incorporates uncertain lifetimes, uninsurable earnings, uninsurable medical expenses, and borrowing constraints.

We assume a household derives utility $U(c)$ from period-by-period consumption in equivalent units, and $g(A_j, K_j)$ is a function that adjusts consumption for the number of adults A_j and children K_j in the household at age j .[6]

Let c_j and a_j represent consumption and assets at age j. With probability p_j the household survives into the next period, so the household survives until age j with probability $\prod_{k=S}^{j-1} p_k$, where $\prod_{k=S}^{j-1} p_k = 1$ if $j - 1 < R$. At age D , $p_D = 0$. The discount factor on future utilities is β . Expected lifetime utility is then

$$E\left[\sum_{j=S}^{D} \beta^{j-s} g(A_j, K_j) U(c_j / g(A_j, K_j))\right]$$

The expectation operator E denotes the expectation over uncertain future earnings, health expenditures, and life span.

Consumption and assets are chosen to maximize expected utility subject to the constraints,

$$y_j = e_j + r a_j + T(e_j, a_j, j, n_j),\ j \in \{S, ..., R\}, \tag{3.2.1}$$

[6] Married households in 2004 are modeled as making their lifecycle consumption decisions jointly with their partner throughout their working lives. They become single only if a spouse dies. Similarly, single households in 2004 are modeled as making their lifecycle consumption decisions as if they were single throughout their working lives.

$$y_j = SS\left(\sum_{j=S}^{R} e_j\right) + DB\left(e_R\right) + ra_j + T_R\left(e_R, \sum_{j=S}^{R} e_j, a_j, j, n_j\right),\ j \in \{R+1, \ldots, D\}, \tag{3.2.2}$$

$$c_j + a_{j+1} = y_j + a_j - \tau(e_j + ra_j), j \in \{S, \ldots, R\} \tag{3.2.3}$$

$$c_j + a_{j+1} + m_j = y_j + a_j - \tau\left(SS\left(\sum_{j=S}^{R} e_j\right), DB\left(e_R\right) + ra_j\right), j \in \{R+1, \ldots, D\} \tag{3.2.4}$$

Equation 3.2.1 and 3.2.2 define taxable income for working and for retired households.[7] Equation 3.2.3 and 3.2.4 show the evolution of resources available for consumption. In these constraints e_j denotes labor earnings at age j. $SS(\cdot)$ are social security benefits, which are a function of aggregate lifetime earnings, and $DB(\cdot)$ are defined benefit receipts, which are a function of earnings received at the last working age. The functions $T(\cdot)$ and $T_R(\cdot)$ denote means-tested transfers for working and retired households. Transfers depend on earnings, social security benefits and defined benefit pensions, assets, the year, and the number of children and adults in the household, n . Medical expenditures are denoted by m_j and the interest rate is denoted by r.[8] The tax function $\tau(\cdot)$ depicts total tax payments as a function of earned and capital income for working households, and as a function of pension and capital income plus a portion of social security benefits for retired households.

We simplify the problem by assuming households incur no out-of-pocket medical expenses prior to retirement and face no pre-retirement mortality risk. Therefore, the dynamic programming problem for working households has two fewer state variables than it does for retired households. During working years, the earnings draw for the next period comes from

[7] In the baseline model, we define a household's retirement date for those already retired as the actual retirement date for the head of the household. For those not retired, we use the expected retirement date of the person who is the head of the household. The head is defined as being the person with the highest lifetime earnings.

[8] Medical expenses are drawn from the Markov processes $\Omega_{jm}(m_{j+1}|m_j)$ for married and $\Omega_{js}(m_{j+1}|m_j)$ single households. Medical expenses drawn from the distribution for single households are assumed to be half of those drawn from the distribution for married couples.

the distribution Φ conditional on the household's age and current earnings draw. We assume that each household begins life with zero assets.

We briefly discuss several key modeling decisions. Further discussion is given in Scholz, Seshadri, and Khitatrakun (2006). We use constant relative risk-averse preferences, so $U(c) = \frac{c^{1-\gamma}}{1-\gamma}$, when $\gamma \neq 1$. In our baseline parameterization, we set the discount factor as $\beta = 0.96$ and the coefficient of relative risk aversion (the reciprocal of the intertemporal elasticity of substitution) to $\gamma = 3$. We assume an annualized real rate of return of 4 percent.

Our equivalence scale comes from Citro and Michael (1995) and takes the form $g(A_j, K_j) = (A_j + 0.7K_j)^{0.7}$, where A_j indicates the number of adults and K_j indicates the number of children in the household. This scale implies that a two parent family with 3 children consumes 66 percent more than a two parent family with no children. There are other equivalence scales, including ones from the Organization for Economic Cooperation and Development, Department of Health and Human Services (Federal Register, Volume 56, Number 34, February 20, 1991) and Lazear and Michael (1980).[9] The corresponding numbers for these equivalence scales in this example are 88 percent, 76 percent, and 59 percent. Our scale lies in between these values.

We model the benefits from public income transfer programs using a specification suggested by Hubbard, Skinner and Zeldes (1995). The transfer that a household receives while working is given by $T = max\{0, \underline{c} - [e + (1+r)a]\}$, whereas the transfer that the household will receive upon retiring is $T_R = max\{0, \underline{c} - [SS(E_R) + DB(e_R) + (1+r)a]\}$. This transfer function guarantees a pre-tax income of $\underline{c}$, which we set based on parameters drawn from Moffitt (2002).[10] We assume through this formulation that earnings, retirement income, and assets reduce public benefits dollar for dollar.

[9] OECD equivalence scales are accessible on http://www.oecd.org/eco/growth/OECD-Note-EquivalenceScales.pdf.

[10] The $\underline{c}$ in the model reflects the consumption floor that is the result of all transfers (including, for example, SSI). Moffitt (2002) provides a consistent series for average benefits received by a family of four from 1960 to 1998. We assume that the parameters for years prior to 1960 and after 1998 are the same as the closest year for which we have data. We adjust (and verify) amounts for different family sizes using equivalence scales.

We aggregate individual earnings histories into household earnings histories. Earnings expectations are a central influence on life-cycle consumption decisions, both directly and through their effects on expected pension and social security benefits. The household model of log earnings (and earnings expectations) is $\log e_j = \alpha^i + \beta_1 AGE_j + \beta_2 AGE^2 + u_j$, where $u_j = \rho u_{j-1} + \epsilon_j$ and e_j is the observed earnings of the household i at age j in 2004-dollars, α^i is a household specific constant, $AGEj$ is age of the head of the household, u_j is an $AR(1)$ error term of the earnings equation, and ϵ_j is a zero-mean $i.i.d.$, normally distributed error term. The estimated parameters are $\alpha^i, \beta_1, \beta_2, \rho$ and σ_ϵ . They are available on request.

We divide households into six groups according to marital status, education, and number of earners in the household, giving us six sets of household-group-specific parameters.[11] Estimates of the persistence parameters range from 0.69 for one-earner married couples without college degrees to 0.74 for married households with two earners, in which the highest earner has at least a college degree.

The specification for out-of-pocket medical expenses for retired households is given by

$$\log m_t = \beta_0 + \beta_1 AGE_t + \beta_2 AGE^2 + u_t, \tag{3.2.5}$$

$$u_t = \rho u_{t-1} + \epsilon_j,\ \epsilon_j \sim N(0, \sigma_\epsilon^2), \tag{3.2.6}$$

where m_t is the household's out-of-pocket medical expenses at time t (the medical expenses are assumed to be 1 if the self-report is zero or if the household has not yet retired),AGE_t is age of the household head at time t, u_t is an $AR(1)$ error term and ϵ_j is white-noise. The parameters to be estimated are $\beta_0, \beta_1, \beta_2, \rho$, and σ_ϵ^2. We estimate the medical-expense specification for four groups of households: (1) single without a college degree, (2) single with a college degree, (3) married without a college degree, and (4) married with a college degree, using eight waves of the HRS.

[11]The six groups are (1) single without a college degree; (2) single with a college degree or more; (3) married, head without a college degree, one earner; (4) married, head without a college degree, two earners; (5) married, head with a college degree, one earner; and (6) married, head with a college degree, two earners. A respondent is an earner if his or her lifetime earnings are positive.

We solve the dynamic programming problem by linear interpolation on the value function. For each household in our sample we compute optimal decision rules for consumption (and hence asset accumulation) from the oldest possible age (D) to the beginning of working life (S) for any feasible realizations of the random variables: earnings, health shocks, and mortality. These decision rules differ for each household, since each faces stochastic draws from different earnings distributions (recall that the earning expectation parameter, α^i , is household specific).

Household-specific earnings expectations also directly influence expectations about social security and pension benefits. Other characteristics also differ across households: for example, birth years of children affect the scale economies of a household at any given age (as determined by the equivalence scale). Consequently, it is not sufficient to solve the life-cycle problem for just a few household types.

3.2.1 Steps Needed to Develop the Analysis Sample

The Health and Retirement Study (HRS) is sponsored by the National Institute of Aging and conducted by the University of Michigan with supplemental support from the Social Security Administration. The HRS is a national panel study with an initial sample (in 1992) of 12,652 persons in 7,702 households. It oversamples blacks, Hispanics, and residents of Florida. The baseline 1992 study consisted of in-home, face-to-face interviews of the 1931–41 birth cohort and their spouses, if they were married. Follow up interviews have continued every two years through 2008. As the HRS has matured, new cohorts have been added.

Our analysis starts with the RAND version of the HRS which includes 30,548 individuals and aggregates HRS data for respondents and spouses across waves into a single analysis file with consistent variable definitions across waves.[12] Of these 28,978 are either the household head (household member with highest lifetime earnings) or the primary spouse of the household head. The primary spouse is defined as the spouse to whom the head has been

[12] Source: http://hrsonline.isr.umich.edu/modules/meta/rand/index.html, the site requires registration with the HRS.

married the longest. Individuals are considered single if either: a) they report never having been married, or b) they were married one time but for less than 10 years. We add core HRS measures to the RAND data, including information about child ages, defined contribution pension benefits from past and current jobs, and defined benefit pension coverage from past and current jobs. We transform the data from respondent level into household level and add household-level pension data. We calculate Social Security benefits for each member of the household based on the earnings history for respondents, respondents' living spouses and deceased spouses.

The Social Security Administration provides detailed earnings records for those HRS respondents who grant explicit permission. This restricted-access data provide a direct measure of earnings realizations and lifetime income. These measures allow for the estimation of household's expectations of future earnings. They also allow us to simulate accurately social security benefits for the respondent and spouse or for the couple, if the benefit would be higher. Since earnings records from the Social Security Administration are a key element in our analysis, we drop households in which either the head or the primary spouse did not agree to release their earnings history. Note that because we do not have information on transfer payments prior to 1992 (the first wave of the HRS) or on earnings outside the Social Security system, our measures of lifetime earnings are less then perfect.

3.2.2 Optimal Wealth Accumulation Across HRS Cohorts

Table 3.3 presents information on mean and median optimal wealth targets, the percentage of households in each HRS cohort that has accumulated less than their optimal target, and the median net worth shortfall, conditional on failing to meet the optimal target. The targets represent the amount of non-DB pension, non-social security net worth that the household should have accumulated, at the time we observe them in the 2008 HRS, to be on track to equate the discounted marginal utility of consumption over their remaining life. The sample includes 4,462 households, and the sample sizes for AHEAD, CODA, HRS, WB, and EBB are 342, 709, 2,164, 675, and 572, respectively

In addition to assuming the preference parameters discussed above, we assume that the social security system that households anticipate when making annual consumption decisions is the one in effect in 2008 and the health shocks households experience in old age are the ones we estimate based on eight waves of out-of-pocket medical expenses from the HRS cohorts (these shocks are correlated through an AR(1) error term). Presenting the optimal wealth targets as we have done assumes, implicitly, that housing wealth is fungible and can be used to support consumption in old age.

The first column of the upper panel in Table 3.3 shows the mean level of optimal wealth for households in each HRS cohort. The optimal amounts peak for the WB cohort, and then it falls as households age, as households presumably decumulate wealth in retirement.

The second column of the upper panel shows the median optimal net worth targets across cohorts. The fact that mean targets far exceed the median targets shows the wealth distribution is highly skewed. But the qualitatively similar pattern across cohorts is apparent. Median optimal targets are lowest for the AHEAD cohort, and peak in the EBB cohort, whose average age in the 2008 HRS is 57. The median targets then decline as households move through retirement.

Columns 3 and 4 of the upper panel provide the first formal estimates of the degree to which households outside the original HRS cohort are preparing well for retirement. Overall, 29.9 percent of households have net worth that is below their optimal targets. Conditional on not meeting the targets, the magnitude of the deficit is $96,897. Recall, the fact that people are at or above their optimal targets means simply that they are in position, given their social security and defined benefit entitlements, to maintain the discounted marginal utility of consumption over time. If a household had, for example, a living standard below the poverty line during their working years, they would still likely have a below poverty income during retirement, even when they have met their optimal targets. Thus, "optimal" does not necessarily imply socially desirable: it simply suggests that given available resources, people are not consuming more than they should if they wish to maximize lifetime utility.

These results differ somewhat from the results of Scholz et al. (2006). There they found that 15.6 percent of the HRS cohort had accumulated less than their optimal targets in 1992, and the median conditional deficit in 1992 was $5,260 (in 1992 dollars). Hence, we find a somewhat larger fraction of households below their optimal targets in this preliminary analysis than the results in of Scholz et al. (2006).

3.2.3 Are Baby Boomers Saving Less Adequately Than Earlier Cohorts?

At first glance of Table 3.3, a higher fraction of the Early Baby Boomers (45.6 percent of the 572 households) at age 55 to 60 in 2008, appear to save less adequately than earlier cohorts. However, examining the optimal saving rates using data from earlier waves, we find that, consistently across cohorts, households are in fact more likely to miss their optimal wealth targets when they were young than in their old age. As a result, the fraction of households from the EBB cohort that misses the optimal wealth target in 2008 appears to mirror the wealth accumulation pattern of other cohorts at a comparable age. For instance, 41.8 percent of the original HRS cohort between 51 and 61 years old in 1992 missed their optimal wealth target. Similarly, 38.6 percent of the War Babies between 55 and 60 years old in 2004 were unable to meet the saving target.

We examine the correlates of undersaving by estimating descriptive probit regressions, where the dependent variable takes the value one if the household's net worth is less than the optimal target. Since we are interested in investigating if the baby boomers are systematically saving less adequately than previous cohort, we analyze the probit regressions separately for year 2004, 2006, and 2008, in which the EBB cohort are part of the HRS survey. Table 3.4 shows that the EBB cohort is no more likely than other cohorts to be under-saving in 2004. The results change slightly for 2006 and 2008. Although the EBB cohort is no more likely than AEAHD and CODA cohorts to be under-saving, it is more likely than the HRS original cohort in 2006 and 2008 as well as the WB cohort in 2008 to miss the optimal saving target.

One potential explanation for the lower propensity for missing the optimal wealth target by HRS and WB cohorts in these years may be due to the sharp declines in household consumption after retirement that are documented in prior studies (Bernheim et al., 2001; Hurst, 2008). As all HRS households became at least 65 years old in 2006, and the WB cohort started to enter age 65 in 2008, their consumption may in fact drop substantially at the typical retirement age at 65. This consumption discontinuity has been puzzling as it violates the consumption smoothing prediction by the economic theory. As the retiring cohorts decumulate their wealth at a slower rate in the golden years, the elderly households become more likely to meet or exceed the optimal target.

Note that this difference in saving adequacy across cohorts was eliminated once we pooled all the observations across waves for estimation, indicating that the results in one particular year may be noisy due to measurement errors or random shocks that are cohort-specific.

Households from the lowest income quintile appear to be most likely to meet their saving target since their saving target is sufficiently low. For households in the second to fifth income quintiles, income appears to be positively correlated with the likelihood of meeting the optimal wealth targets. African American and single households are more likely than others to be undersaving. Even though we have already conditioned on lifetime income quintiles, education attainment is also strongly, negatively correlated with undersaving. Catholic households are less likely to be undersaving.

The net worth information is only available after 1992 in the HRS survey. As a result, we do not observe the wealth accumulation pattern of older cohorts in their early ages. However, solving the dynamic optimal problem, we are able to obtain the optimal wealth targets by year for each individual household. To exploit the optimal output, we supplement this analysis using the actual wealth data from the SCF in 1962 and every three years between 1983 and 2007. First, we construct two groups that are perfectly comparable in their age range in different years from the HRS. After showing the wealth accumulation by these two groups with the available data from the HRS, we map out the wealth profile from the SCF against the optimal wealth trajectory derived from the HRS model. Our first cohort consists of the HRS original cohort because it provides the most complete biannual wealth information from 1992 to 2008. The HRS cohort were 51 to 61 years old in 1992, and we call it the "Parents" group. To compile a perfectly comparable group with this same age range, we use households between 51 and 61 years old in 2004, including partial war babies and entire early baby boomers, labeled as the "Baby Boomers".[13] Table 3.5 shows the summary statistics of these two groups from the HRS data. There are 3,937 observations for Parents and 1,187 observations for the Baby Boomers from the HRS sample in 1992 and 2004, respectively. Both mean and median wealth targets are slightly lower for the Baby Boomers than for the Parents. At the age between 51 and 61, 43 percent of the Parents failed to meet their wealth targets in 1992, and 39 percent of the Baby Boomers were unable to save up to their optimal targets in 2004. The conditional deficits for households that missed the wealth targets are similar for the two groups– \$108,605 for the Parents and \$101,459 for the Baby Boomers (in \$2008).

Figure 3.2 shows the actual wealth profile for Parents and Baby Boomers by age. It is clear that the wealth accumulation trajectory is similar in the overlapping early ages across these two groups from the HRS. We further plot the actual median wage profile against the median optimal targets separately for these two groups. Figure 3.3a and 3.3b show that the median wealth accumulation by these two groups are mostly above the median optimal targets throughout different ages. The gap between the actual and the optimal median targets appears to widen after age 60 for the Parents. Figure 3.4 and 3.5 present the SCF median net worth against the optimal wealth target from the HRS model. The pattern is very similar for both Parents and Baby Boomers–the actual median wealth tracks on or above the optimal targets for both groups across ages. Although we do not observe the Parents' net worth in early age from HRS, Figure 3.4 shows that, the equivalent group of Parents in the SCF actually accumulated the wealth that tracked the optimal wealth targets

[13]Although the HRS original cohort is not literally old enough to be the "Baby Boomer's" parents, the 12-year age gap between these two groups still serve as a good benchmark to identify any discernible changes across cohorts.

derived from our model using the HRS data. This outcome indicates that our model works well for the same age group across different datasets.

3.3 Conclusions

There is a considerable amount of discussion in the popular media and in policy and academic writing that Americans are doing a poor job preparing for retirement. This perception is reinforced by low (and sometimes negative) personal saving rates in the National Income and Product Accounts for selected years over the past decade, and perhaps recent disruptions in the housing, credit, and stock markets, and slow economic growth. But efforts to assess the adequacy of wealth accumulation require an objective standard to reach conclusions. The workhorse standard has been the replacement rate. But replacement rates are a conceptually flawed measure. We argue instead that the lifecycle model provides a natural, normative tool for assessing the adequacy of wealth accumulation.

In earlier work, Scholz et al. (2006) showed the original HRS cohort, those born between 1931 and 1941, had overwhelmingly met or exceeded their optimal wealth targets in 1992. But an important unanswered question remained: do our findings apply to households born in other cohorts? Munnell, Webb and Golub-Sass (2008) argue that the answer is "no." But for reasons discussed earlier, we think their work is not the last word on this topic.

In this chapter we present preliminary evidence from the HRS making use of a broader age range of households. This includes two cohorts older than the original HRS cohort (the AHEAD and CODA) and two cohorts younger than the original HRS cohort (the War Babies and Early Baby Boomers).[14] The approach used in our analysis is data intensive. It requires social security earnings histories and data on fertility, because one cannot develop a suitable measure of pre-retirement living standards without knowing the annual flow of resources that households received during their working lives and the composition of households when income arrives. Through the procedures the HRS has established for researchers to gain

[14] We again emphasize the sample restriction in this draft that the primary earner in each household is retired and at least one household member has at least 30 years of earnings in the restricted social security data. These restrictions will be relaxed in subsequent drafts.

access to HRS respondents' social security earnings records, we are able to acquire the necessary data for a broader set of HRS cohorts and apply the methodology in Scholz et al. (2006).

Our preliminary evidence suggests that 30 percent of HRS households have net worth that is below their optimal targets. Conditional on having accumulated too little, the magnitude of the deficits is $95,656. While the results suggest that some households will need to ratchet their living standards downward in retirement, most Americans are, by and large, preparing sensibly, given the existing generosity of social security, Medicare, and pension arrangements. We have additional work to do to explore the robustness of our results, particularly the ability of households to comfortably weather unusually large out of pocket medical expenses (recall, households in the model are hit with out of pocket medical expenses after retirement – the magnitude of these shocks are estimated using eight HRS waves of data). But we see little in the descriptive data or our model-based analyses that leads us to think that households are making large, systematic errors in their financial preparation for preparation.

3.4 Appendix: Figures and Tables

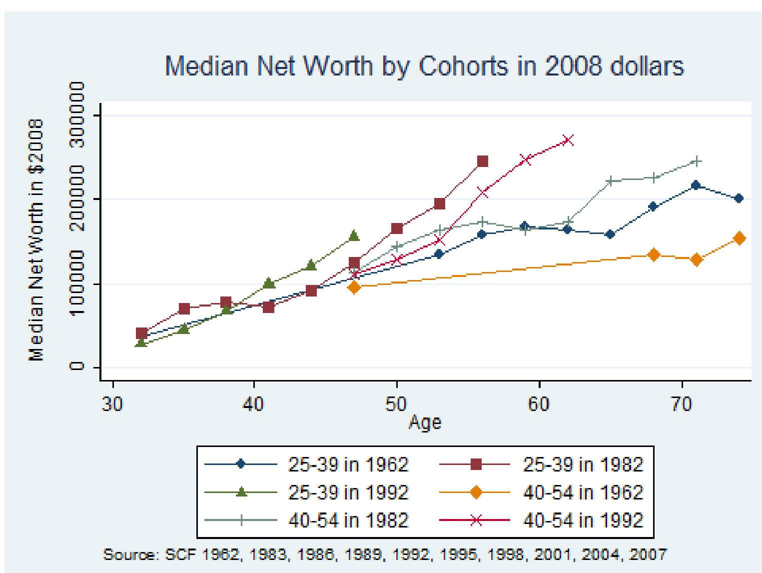


Figure 3.1: Median Net Worth by Cohort, 2008 Dollars

Table 3.1: Household Wealth of the HRS Cohorts, 2008 dollars

	Born Between	Observations	Age of Household Head	Mean Actual Wealth	Median Actual Wealth	Median Lifetime Income	Median Wealth to Income Ratio
AHEAD	1890-1923	342	88	644,160	271,500	1,898,569	0.173
CODA	1924-1930	709	81	703,511	314,000	2,122,285	0.157
HRS	1931-1941	2,164	72	708,551	308,000	2,210,309	0.144
WB	1942-1947	675	63	570,197	243,600	2,122,249	0.117
EBB	1948-1953	572	57	389,874	146,200	1,696,781	0.100
Full Sample		4,462	68	597,476	251,100	2,050,491	0.127

Table 3.2: Subjective Views of Retirement Financial Well-being, HRS Cohorts, 2008

	How satisfying is retirement?			Retirement years compared to before?		
	Very	Modestly	Not at all	Better	Same	Worse
AHEAD	63.7 percent	30.2 percent	6.1 percent	46.1 percent	34.3 percent	19.7 percent
CODA	58.8	37.6	3.6	40.9	43.1	16.0
HRS	59.7	35.1	5.2	49.0	39.6	11.4
War Babies	56.6	35.7	7.7	61.1	30.7	8.3
Early Boomers	29.0	49.8	21.1	51.8	31.1	17.1
Overall	57.9	35.9	6.3	53.1	35.8	11.1

Table 3.3: Optimal and Actual Net Worth in 2008 and Percentage Failing to Meet Their Optimal Targets, HRS Cohorts

Cohort	Mean Optimal Wealth Target	Median Optimal Wealth Target	Percentage Below Optimal Target	Median Conditional Deficit
AHEAD	74,132	59,636	16.4	-53,723
CODA	139,252	108,251	18.9	-69,359
HRS	154,303	93,790	22.5	-76,245
WB	232,126	152,976	33.0	-109,315
EBB	230,805	168,601	45.6	-108,289
Full Sample	185,258	119,597	29.6	-95,656
Cohort	Mean Actual Wealth	Median Actual Wealth	Observations	Age of Household Head
AHEAD	644,160	271,500	342	88
CODA	703,511	314,000	709	81
HRS	708,551	308,000	2,164	72
WB	570,197	243,600	675	63
EBB	389,874	146,200	572	57
Full Sample	597,476	251,100	4,462	68

Table 3.4: Correlates of Under-Saving: HRS 2004, 2006, and 2008

Year	2004		2006		2008	
Covariates	Coefficient (Marginal Effects)	S.E.	Coefficient (Marginal Effects)	S.E.	Coefficient (Marginal Effects)	S.E.
AHEAD	0.042	(0.112)	-0.065	(0.091)	-0.063	(0.095)
CODA	0.058	(0.085)	-0.048	(0.073)	-0.078	(0.071)
HRS	-0.012	(0.051)	-0.093*	(0.047)	-0.109*	(0.048)
WB	0.012	(0.034)	-0.033	(0.032)	-0.072*	(0.032)
2nd Income Quintile	0.253**	(0.033)	0.233**	(0.034)	0.223**	(0.033)
3rd Income Quintile	0.262**	(0.034)	0.222**	(0.036)	0.193**	(0.034)
4th Income Quintile	0.245**	(0.035)	0.190**	(0.036)	0.168**	(0.035)
5th Income Quintile	0.223**	(0.038)	0.200**	(0.039)	0.153**	(0.037)
Age	-0.010**	(0.003)	-0.008	(0.003)	-0.008*	(0.003)
Male	0.006	(0.024)	0.023	(0.023)	-0.009	(0.024)
Black	0.180**	(0.031)	0.157**	(0.032)	0.081**	(0.031)
Nonwhite, Not Black	0.141**	(0.049)	0.086+	(0.048)	0.047	(0.048)
GED	0.049	(0.043)	0.038	(0.043)	0.037	(0.042)
High School Grad	-0.083**	(0.023)	-0.062**	(0.023)	-0.078**	(0.024)
Some College	-0.106**	(0.025)	-0.117**	(0.023)	-0.102**	(0.025)
College or Above	-0.211**	(0.023)	-0.18**	(0.023)	-0.159**	(0.025)
Number of Children	-0.012*	(0.005)	-0.006	(0.005)	-0.010+	(0.005)
Single	0.158**	(0.033)	0.161**	(0.034)	0.135**	(0.032)
Catholic	-0.038*	(0.020)	-0.050*	(0.019)	-0.043*	(0.020)
Jewish	-0.031	(0.063)	-0.094+	(0.056)	-0.093	(0.066)
No Religion	0.037	(0.033)	0.001	(0.032)	-0.022	(0.031)
Other Religion	-0.042	(0.071)	-0.119*	(0.055)	0.065	(0.084)

Table 3.5: Optimal and Actual Net Worth and Percentage Failing to Meet Their Optimal Targets–Parents v.s. Baby Boomers

Cohort	Age and Year	Observa-tions	Mean Optimal Wealth Target	Mean Actual Wealth	Median Optimal Wealth Target	Median Actual Wealth	Percentage Below Optimal Target	Median Condi-tional Deficit
Parents	51-61 in 1992	3,937	218,723	393,682	165,975	191,057	43.1	-108,605
Baby Boomers	51-61 in 2004	1,187	194,654	410,783	137,567	169,826	38.8	-101,459

Source: HRS 1992 and 2004.

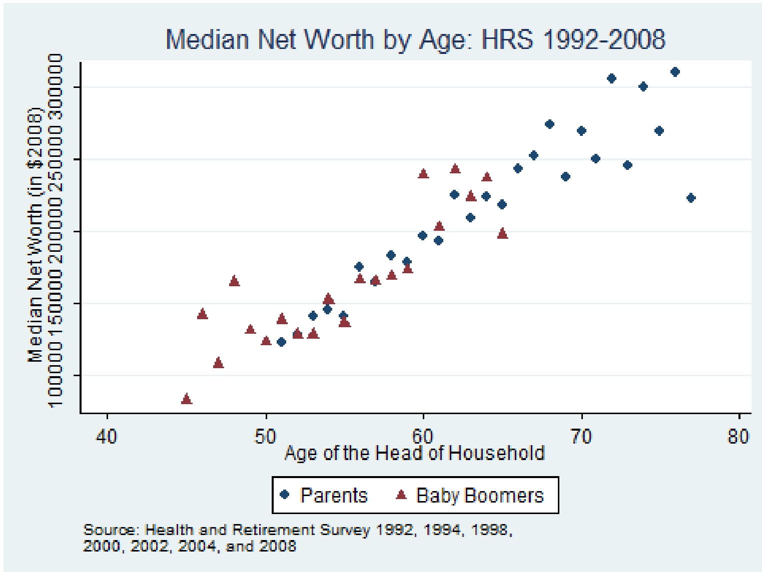
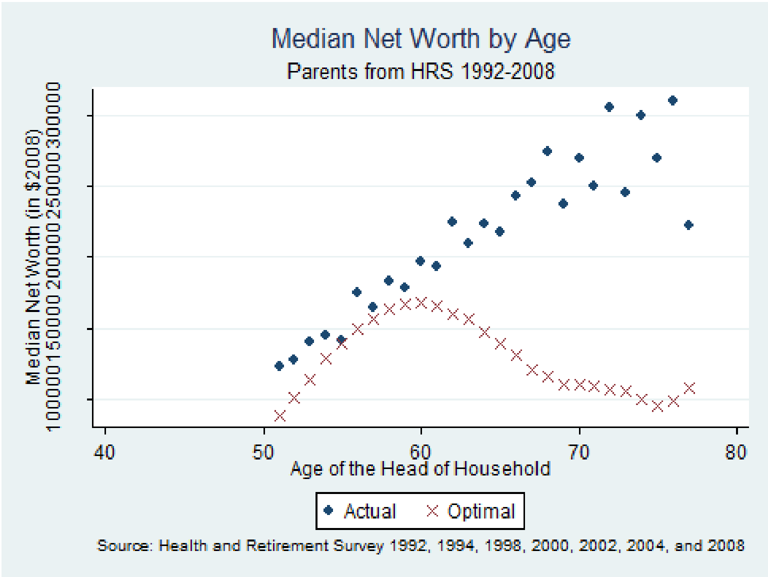
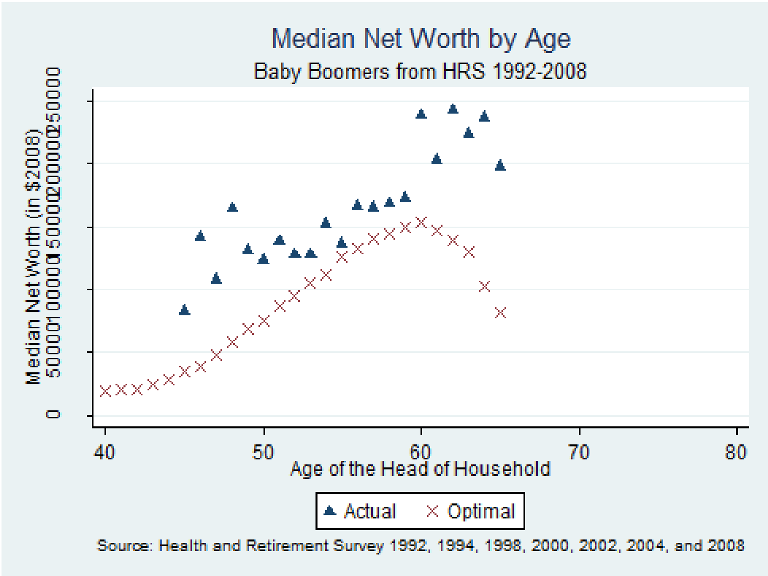


Figure 3.2: Actual Median Net Worth by Age



(a) Median Wealth by Age: Parents



(b) Median Wealth by Age: Baby Boomers

Figure 3.3: HRS Actual and Optimal Median Wealth Profile

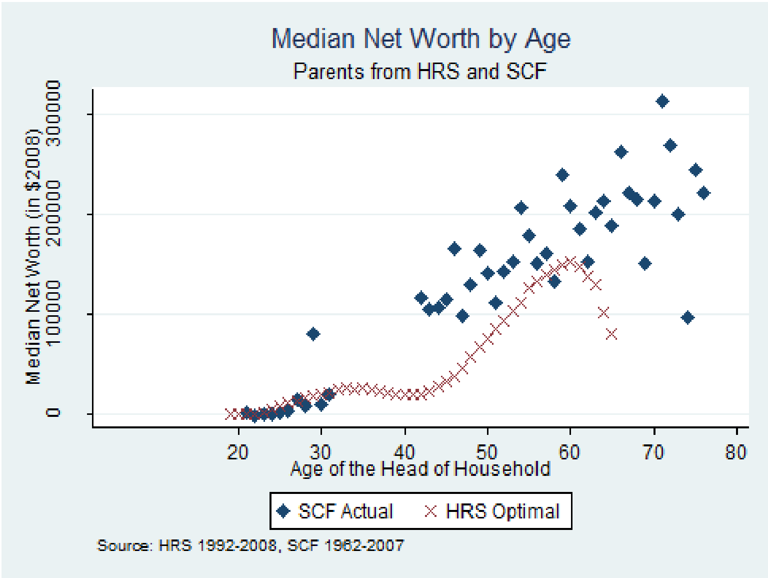


Figure 3.4: SCF Actual Median Wealth and HRS Optimal Wealth Profile: Parents

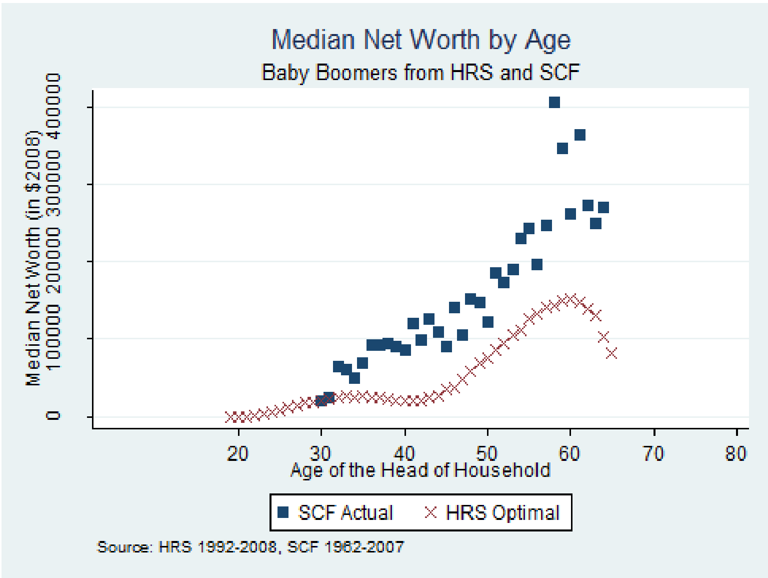


Figure 3.5: SCF Actual Median Wealth and HRS Optimal Wealth Profile: Baby Boomers

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